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Evaluation of ML Algorithms for System Dynamics Identification of Aircraft Pressure Control System

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Abstract

In this work we study the behaviour of aircraft integrated air management system and internal pressure control system. Our goal is to investigate the capabilities of novel data-driven algorithms for system identification. Pressure control system is critical for aircraft operations, because detected faults lead to flight cancellation and maintenance, while in-flight faults or improper pressure regulation can substantially worsen crew or passenger flight conditions or even lead to a catastrophe. The main algorithm studied is Sparse Identification of Nonlinear Dynamics, which identifies nonlinear dynamical systems from data promoting sparsity in the solution. We benchmark SINDy with other state of the art data-driven regression techniques, such as feed-forward neural network and random forest and show that in many cases SINDy performs better despite high noises and insufficient data. In the end we formulate further steps for improving the quality of the results in order to use them in model predictive control framework and for anomaly detection.

1. Introduction

With the advances of microelectronics and different methods for data analysis, it becomes possible to collect, store, and process a lot of operational data in a complex system. The result of this analysis could be used for maintenance planning in order to prevent any system failures and to decrease maintenance costs, or to increase control precision for the most critical operational parameters.

Thresholding technique is the simplest and the most widely used method for health analysis. It can reliably define up and down states of the system, but fail to detect prefault system states, that often have complex criteria, and by definition cannot diagnose any latent faults. Model-based approaches involve explicitly constructed model of system operation, which is often hard or impossible to use due to the lack of model flexibility and unknown exact operational conditions. Data-driven health analysis on the other hand can infer model of the system using operational data. It is an active research subject in academic community and already finds many practical applications in aerospace (Basora, Olive, & Dubot, 2019). One of the promising applications of data-driven health analysis is the detection of pre-fault states. These states are difficult to formalise, and do not require immediate actions. The latter can be used for establishing condition-based planning and maintenance.

Because faults occur rarely on a real system, there is a lack of prefault operation data, and thus it is often difficult to construct a robust data-driven classifier. One of the approaches to overcome this obstacle is to construct a model of nominally operating system and detect any discrepancies between the model and measured data. This approach is widely known as anomaly detection or novelty detection. Many different methods can be used to construct a model of studied system, including simple autoregressive models, ARIMA, different types of recursive neural networks, DMD, or others. However, these methods could be sensitive to noises and outliers in the training data, or have issues with interpretability, as in the case with neural networks. It also may be difficult to detect latent faults with this approach, because they often pollute the training data and thus may be included into nominal model.

In order to use this problem statement in a realistic setting, one needs to train the algorithm on all the nominal states of the system that are available. In test phase the algorithm marks all the states that are sufficiently different from seen nominal states for the operator to consider whether they should be treated as nominal or not, after which the algorithm should be retrained using either only new data or from the scratch, depending on the algorithm used.

In case the model can predict system behaviour, this model can also be used for model predictive control, which is a control technique based on finite-horizon optimisation of predicted system behaviour with respect to control strategy. In this approach, a finite window prediction is used to choose the best next control input to the system (Agachi, Cristea, Csavdari, & Szilagyi, 2016).

Although the behaviour of natural or human-made systems may be very complex, the structure of governing differential equations is often quite simple. This observation in combination with sparse regression techniques inspired the development of sparse identification of nonlinear dynamical systems (SINDy) method (Brunton, Proctor, & Kutz, 2016). This method often requires less data than neural networks for fitting the model (Kaiser, Kutz, & Brunton, 2018) and often gives interpretable results in terms of parsimonious system of governing differential equations. It was shown by Kaheman in (Kaheman, Kutz, & Brunton, 2020) that the method is sufficiently accurate for controlling double pendulum on a cart and other systems with complex dynamics.

The main function of Integrated Air Management System (IAMS) is the control of many environmental conditions for crew and equipment operation on board of an aircraft, such as temperature, pressure, and chemical composition. Additional functions may include air preparation for wing ice-protection system and rare gas subsystem of fuel system. Depressurisation or overpressurisation IAMS failures may cause a catastrophe, so there are strict requirements for redundancy and technical diagnosis problems are considered relevant.

Traditionally, IAMS gets the pressurised air from aircraft engine compressor, cools it to the necessary temperature, and controls the pressure in the cabin. Main components of IAMS include Bleed Air System, Environmental Control System, Air Distribution System, and Cabin Pressure Control System. Some modern systems may also use separate electrical compressors instead of getting the air from the engine.

Typical technical diagnosis problems, such as fault detection and identification, and remaining useful life estimation, are relevant for IAMS. However, system states (up state, down state, etc.) are defined using thresholding rules, and require certain actions from control system or crew members. Many fault localisation problems are also solved using direct methods, e.g. using a certain pre-flight or ground diagnostics test procedure. For these types of faults many advanced techniques are not needed. By leveraging operational data, data-driven methods could potentially be used for faults that cannot be easily identified and require dismantling or disassembly of subsystems, or additional instruments for that. They can be used for assessing fault probability thus decreasing the time for unnecessary dismantling and installation of subsystems.

Analysis shows that a significant number of flight accidents occur due to the impact of flight hazards on the aircraft crew. (Ho, 1975) shows that rapid change in cabin pressure might lead to spontaneous pneumothorax. Typical symptoms include chest pain and shortness of breath. Its occurrence in aviation may result in the abort of a mission, a serious accident, or a major disaster. Another study (Hussein, Abdel Tawab, Lotfi, Fayad, & Elsisy, 2019) indicates that because of exposure of aircrew to rapidly changing ambient pressures barotrauma is considered to be the most frequent medical problem related to aeroplane travel and has been mentioned as a causal element in aviation accidents. In general the number of medical emergencies onboard aircraft is increasing as commercial air traffic increases and the general population ages, becomes more mobile, and includes individuals with serious medical conditions (Hu, Cowl, Baqir, & Ryu, 2014). Rapid change in cabin pressure during flying can cause ear-drum pain and perforation, vertigo, and hearing loss. It has been estimated that 10% of adults and 22% of children might have changes to the ear drum after a flight (Wright, 2015). According to the "Federal Aviation Regulations Part 25 – Airworthiness Standards: Transport Category Aircraft" pressurised cabins must have a means by which the pressure differential (difference between external and internal pressure) can be rapidly equalised. Moreover, modern trend towards the introduction of supermaneuvrability in combat aircraft leads to an increase in the rate of change of pressure difference. In (Sukhov & Timoffeev, 2019) the need to use new methods and approaches to the synthesis of pressure control algorithms is indicated. It is an active research subject in academic community with multiple approaches being used to find the best method. L_1 adaptive controller which consists of three components: state predictor, adaptive law and control law, was successfully used in (Cooper, Cao, & Jiong, 2017) to mitigate the effect of nonlinearities in pressure control system. In (Wang, Qian, & Ma, 2012) fuzzy PID controller was used to obtain higher control accuracy for cabin pressure. Although these works show good results both of them were conducted in simulated environment without any use of hardware-in-the-loop simulation.

The purpose of this project is to identify the behaviour of an aircraft pressure control system in different conditions during ground tests for the purposes of predictive control and anomaly detection. We show the applicability of SINDy for system identification and compare the results by different methods, and identify further steps to improve the results.

The rest of the paper has the following structure: in section 2 we will describe the main structure of pressure control system, its operation, and conducted testing procedures; in sec-

Figure 1. Test facility overview

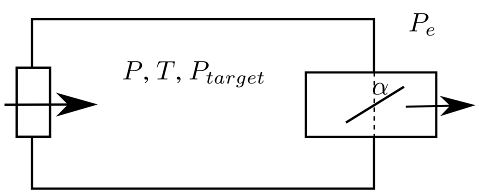

Figure 2. Schematic view of a cabin pressure control system

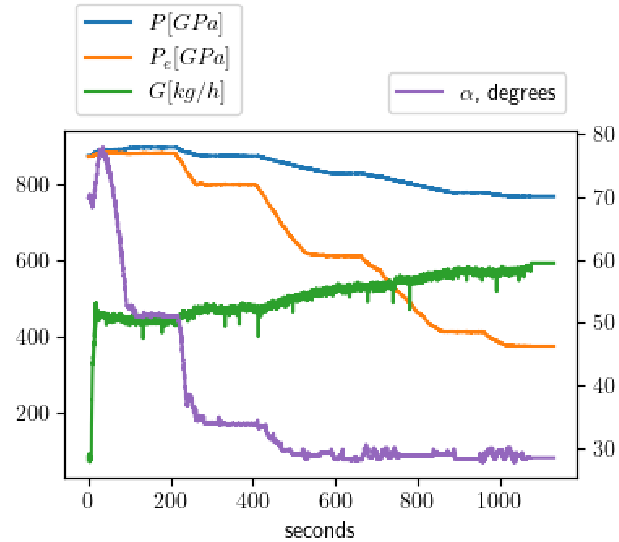

Figure 3. Sample test profile.

tion 3 we will briefly describe the operation of SINDy and other methods we used for benchmarking; then, in section 4 the results of the work will be presented; finally, in section 5 we will formulate the conclusions and possible further steps for this research.

2. Experiment Setup

The test facility is built for testing of aircraft pressure control system at different operational modes. The pressure control system under consideration closely resembles that installed on an operational aircraft. An overview of the facility is shown in Fig. 1, and structure of conducted experiment is shown in Fig. 2. Main components include pressurised cabin, external atmosphere simulator, and two pressure control valves operating under the same control law.

System operation can be formalised as follows:

$$\dot{P} = a(G - f(P - P_e, \alpha)) \quad (1)$$

$$\dot{\alpha} = g(P, P_{target}, P_e, \dot{P}, \alpha), \quad (2)$$

where P – cabin pressure, P_e – external atmospheric pressure, G – inflow into the cabin, f – flow through pressure control valve, α – valve opening angle (same for both valves), The former equation determines system dynamics, while the latter one is the control algorithm.

During the tests different aircraft scenarios could be modelled, such as ascent, descent, takeoff and landing, different manual control modes. An example test profile is shown in fig. 3. Inflow measurement noise can be attributed to its measurement method, which relies on velocity estimation in the air duct using Pitot tube, while oscillations of valve opening angle are imposed by its control strategy.

Table 1. Tests used in this study

Scenario	Number of runs
Ascent	4
Descent	2
Takeoff	5
Landing	11

The experimental data used in this study is shown in table 1. All of the experiments were conducted in 2 month period in the same test facility.

In this work we will build a regression model for the first equation in 1 using different data driven methods for model predictive control and anomaly detection, and benchmark the quality of corresponding models.

Table 2. Correlation matrix of the measurements

	α	P	ΔP	G	$\dot{P}$
α	1.00	0.28	-0.63	0.09	-0.03
P	0.28	1.00	-0.70	-0.22	-0.04
ΔP	-0.63	-0.70	1.00	0.34	-0.14
G	0.09	-0.22	0.34	1.00	-0.08
$\dot{P}$	-0.03	-0.04	-0.13	-0.08	1.00

Table 3. Statistical parameters of measured data

Parameter	α	P	ΔP	G	$\dot{P}$
Mean	39	830	0.22	640	0.01
Standard deviation	14	50	0.13	165	0.23

2.1. Data description

A well-known Darcy–Weisbach equation (Brown, 2002) for a flow in a pipe is

$$\frac{\Delta P}{L} = f_D \frac{\rho v^2}{2D}, \tag{3}$$

where $\frac{\Delta P}{L}$ is pressure gradient in a pipe, f_D — Darcy friction factor, ρ — air density, v — flow velocity, D — pipe diameter, while air mass flow Q and thus rate of cabin pressure change $\dot{P}$ is proportional to pipe flow velocity $\dot{P} \propto Q = Fv\rho$ Assuming turbulent flow in outflow duct, and taking into account that f_D is nearly constant in turbulent flow (Moody, 1944), equation (3) suggests to use $\sqrt{\Delta P}$ as one of the features.

To sum up equations (1) and (3), the following features are used for model training: $\sqrt{\Delta P} = \sqrt{P - P_e}$ — square root of cabin excessive pressure, P — total cabin pressure, G — cabin inflow rate, $F = 1 - \cos\alpha$ — fraction of opened cross-sectional area in pressure control valve.

3. METHODS

In this section we will discuss several methods we used for system identification from test data. As a baseline predictor we used null hypothesis which predicts $\dot{P} = 0$ with respect to any argument.

Another simple algorithm for benchmark is random forest. This model was trained with 50 estimators.

3.1. SINDy

Sparse Identification of Nonlinear Dynamics (Brunton et al., 2016) is a novel method that leverages the observation that in most systems only a few terms define system dynamics. The method have shown very strong noise robustness and is well suited for limited training data scenarios (Kaiser et al., 2018). It was successfully used for learning model predictive control for double pendulum balance (Kaheman et al., 2020) and for condition monitoring of wind-induced vibration of a suspension bridge (Li et al., 2018) in combination with clustering in order to distinguish different operational modes.

First, it is assumed that the RHS of governing differential equations can be represented as a linear combination of a number of functions from some dictionary:

$$\dot{x}_k = \Theta(x^T)\xi_k, k = 1 \dots n, \tag{4}$$

where $x = (x_1 \dots x_n)^T$ is a vector of phase space variables, $\Theta(x) = (\theta_1(x) \dots \theta_m(x))$ is a library of candidate terms, ξ_k is a sparse vector of coefficients that control which functions from the library are included into the model.

In order to calculate matrix of model coefficients $\Xi = (\xi_1 \dots \xi_n)$ from experimental data, it is possible to construct the matrix of derivatives

$$\dot{\boldsymbol{X}} = \begin{bmatrix} \dot{x}_1(t_1) & \dot{x}_2(t_1) & \dots & \dot{x}_n(t_1) \\ \dot{x}_1(t_2) & \dot{x}_2(t_2) & \dots & \dot{x}_n(t_2) \\ \vdots & \vdots & \ddots & \vdots \\ \dot{x}_1(t_m) & \dot{x}_2(t_m) & \dots & \dot{x}_n(t_m) \end{bmatrix} \tag{5}$$

and the matrix of values of functions from the dictionary

$$\Theta(\boldsymbol{X}) = \begin{bmatrix} 1 & \theta_1(x(t_1)) & \dots & \theta_k(x(t_1)) \\ 1 & \theta_1(x(t_2)) & \dots & \theta_k(x(t_2)) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \theta_1(x(t_m)) & \dots & \theta_k(x(t_m)) \end{bmatrix} \tag{6}$$

Then Eq. (4) can be rewritten in simple form

$$\dot{\boldsymbol{X}} = \Theta(\boldsymbol{X})\Xi + \eta \boldsymbol{Z}, \tag{7}$$

where Z is a matrix of i.i.d. Gaussian entries with zero mean, and η is noise magnitudes, which is added because Eq. (4) doesn't hold exactly with measured data. Because library of candidate functions Θ is usually large, this is fundamentally an overdetermined regression problem with noise where we seek a sparse matrix Ξ. This problem can be solved with sparsity promoting regression techniques such as LASSO, or sequential shrinkage as proposed in (Brunton et al., 2016).

In this work we used polinomial library of features for this method, which means that family of functions Θ can be described as $\Theta = x_1^{r_1} x_2^{r_2} \dots x_n^{r_n}$, where x_i are individual features described in section 2.1.

3.2. Feed-forward Neural Network

We chose a feed-forward neural network as one of the methods for a benchmark due to their popularity and ability to fit to very complex functions. In order to leverage the structure of underlying differential equation (4), we used an architecture shown in fig. 4. The data was normalized prior to training. We used 100 neurons with sigmoid activation in hidden layer to introduce nonlinearities and 0.5 dropout rate as a sample to show its behaviour, however, it was found to be very similar in a wide range of hyperparameters. Finally, the network was trained using ADAM optimizer with learning rate of 0.002 and 10 epochs. Further training did not increase training and validation scores.

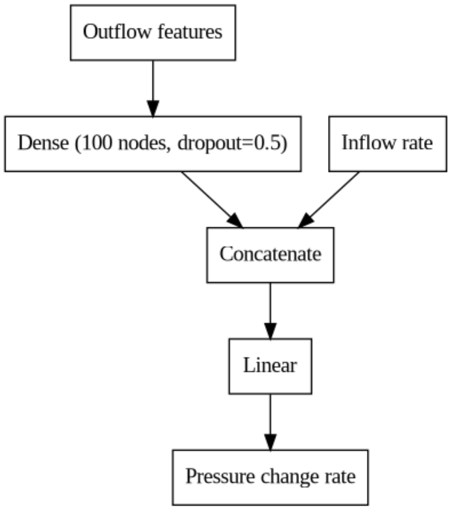

Figure 4. Employed neural network architecture.

Table 4. Metrics comparison of different system identification methods

Method	RMSE	MAE	R^2 coef.
NULL	0.21	0.15	-0.32
RF	0.22	0.16	-0.4
SINDy	0.17	0.14	-1.7
FF NN	0.2	0.15	-5.2
LSTM RNN	0.23	0.16	-9.5

3.3. LSTM Recurrent Neural Network

Another popular and flexible model for sequence modeling and prediction is long short term memory recurrent neural network. We used one layered implementation with 50 hidden nodes with sigmoid activations and one linear neuron as output. The model was trained with ADAM optimizer with learning rate of 0.002.

In contrast to feed-forward NN, LSTM NN quickly overtrained after 20 epochs of training.

4. Results

The results are summarised in table 4. The metrics of the algorithms were obtained using 5-fold cross-validation using each time series as a sample.

We can see thatR^2 coefficient is negative, which means that original data variance is higer than prediction accuracy for all the models we were able to infer from available experiments.

Some of the models are shown in figures 5, 6, 8.

We can see that SINDy can to a certain degree explain variance in $\dot{P}$, which is connected to slight changes in valve angle α, which is used for pressure control, whereas other models dealt with that problem less successfully. Moreover, the iden-

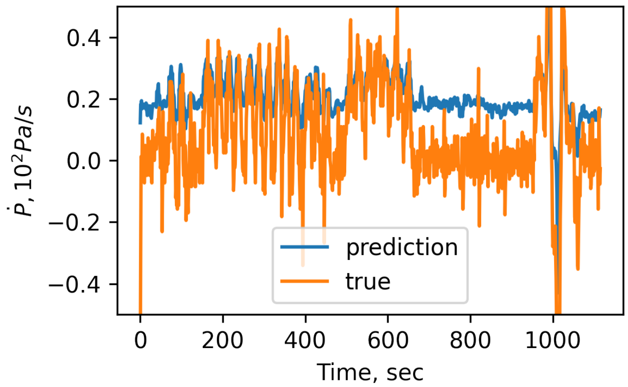

Figure 5. SINDy model cross validation for $\dot{P}$

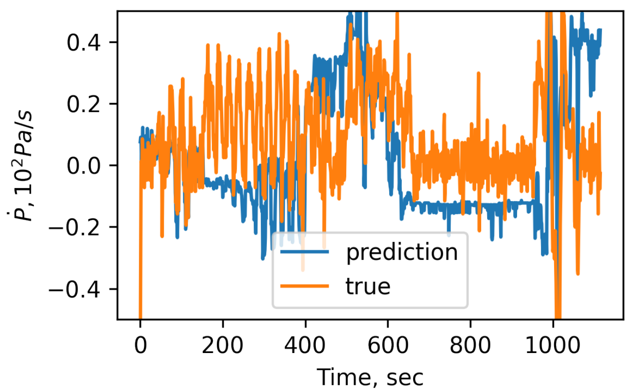

Figure 6. Random forest model cross validation for $\dot{P}$

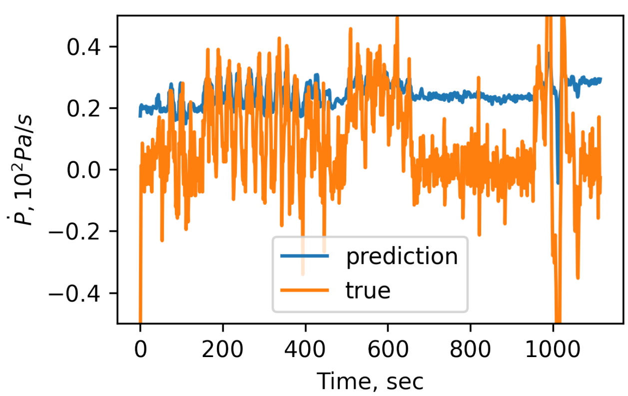

Figure 7. Feed-forward neural network model cross validation for $\dot{P}$

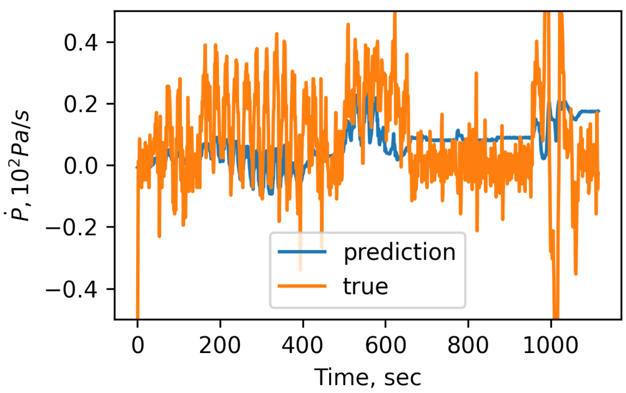

Figure 8. Recurrent neural network with LSTM neurons model cross validation for $\dot{P}$

tified model can be easily written as

$$\begin{aligned}\dot{P} = &-4.2961 + 0.006P + 0.002G + 16.289F \\ &+ 6.942\sqrt{\Delta P} + -0.020PF + -0.011P\sqrt{\Delta P} \\ &+ 0.002G\sqrt{\Delta P} + 1.108F^2 + -24.006F\sqrt{\Delta P} \\ &+ 1.452\Delta P,\end{aligned}$$

where cabin excess pressure $\Delta P = P_e - P$ measured in atmospheres, open area fraction in pressure control valve $F = 1 - \cos\alpha$, inflow rate G measured in kg/hour, and $\dot{P}$ measured in hectopascals per second. Although the resulting model does not correspond to physical reality and thus must be strictly cross-validated to be used in a real case, it may be essential to have an explicit model for usage in model predictive control scenarios to ensure controller safe and predictable operation.

There are multiple possible reasons for poor models quality: poor choice of functional family to represent the differential equation (1), the absence of system temperature readings and corresponding errors in measurement of G, or more complex system behaviour, such as additional latent variables dynamics. Because neural networks represent a very flexible functional family, poor choice of functional family is unlikely. The most straightforward way to improve the models is to remove possible biases and noises that are imposed by current measurement techniques. We consider temperature reading crucial for correct inflow rate calculation based on pitot tube readings.

5. Conclusion

None of the models we built in this study was sufficiently better than null hypothesis to be used in model predictive control framework. Medium model quality can be explained by different ambient temperatures that were not measured in the test facility during different tests. This can cause significant difference between true and measured specific inflow rates, because constant temperature was used in its calculations.

The development of a model even for a relatively simple system using existing data proved to be a non-trivial task. We believe that in order to further improve the results of system identification test procedures have to be modified. In particular some other parameters should be monitored, such as temperature in the cabin and temperature inside the inflow air duct. Correspondingly, in order for the system to be usable on board of the aircraft, similar instruments will have to be installed. It is also desirable to decrease inflow measurement noise.

Nevertheless, as a result of this study we have shown that SINDy method gives better and more interpretable models than other data-driven methods, such as random forest and neural networks. This feature may be important for applications in model predictive control of critical aircraft components. It allows to ensure necessary function properties, such as smoothnes, which is difficult to do in case of neural networks.

6. Acknowledgements

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