

SysIdentPy: A Python package for System Identification using NARMAX models

Wilson Rocha Lacerda Junior¹, Luan Pascoal da Costa Andrade¹, Samuel Carlos Pessoa Oliveira¹, and Samir Angelo Milani Martins^{1, 2}

¹ GCoM - Modeling and Control Group at Federal University of São João del-Rei, Brazil ² Department of Electrical Engineering at Federal University of São João del-Rei, Brazil

DOI: [10.21105/joss.02384](https://doi.org/10.21105/joss.02384)

Software

- [Review](#) ↗
- [Repository](#) ↗
- [Archive](#) ↗

Editor: [David P. Sanders](#) ↗

Reviewers:

- [@Shibabrat](#)
- [@dawbarton](#)

Submitted: 20 May 2020

Published: 02 October 2020

License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#)).

Summary

The field of System Identification (SI) aims to build mathematical models for static and dynamic behavior from experimental data (Ljung, 1987). In particular, nonlinear system identification has become a central issue in the SI community, and from the 1950s onwards many methods have been proposed. In this respect, NARMAX (Nonlinear AutoRegressive Moving Average with eXogenous input) models are among the most well-documented and used model representation of dynamical systems (Billings, 2013).

The NARMAX model was proposed by (Billings & Leontaritis, 1981; Chen & Billings, 1989; Leontaritis & Billings, 1985) and can be described as

$$y_k = \mathcal{F}[y_{k-1}, \dots, y_{k-n_y}, x_{k-d}, x_{k-d-1}, \dots, x_{k-d-n_x} + e_{k-1}, \dots, e_{k-n_e}] + e_k, \quad (1)$$

where $n_y \in \mathbb{N}^*$, $n_x \in \mathbb{N}$, $n_e \in \mathbb{N}$, are the maximum lags for the system output and input respectively; $x_k \in \mathbb{R}^{n_x}$ is the system input and $y_k \in \mathbb{R}^{n_y}$ is the system output at discrete time $k \in \mathbb{N}^n$; $e_k \in \mathbb{R}^{n_e}$ represents uncertainties and possible noise at discrete time k . In this case, \mathcal{F} is some nonlinear function of the input and output regressors and d is a time delay typically set to $d = 1$.

Although there are many possible approximations of $\mathcal{F}(\cdot)$ (e.g., Neural Networks, Fuzzy, Wavelet, Radial Basis Function), the power-form Polynomial NARMAX model is the most commonly used (Billings, 2013; Khandelwal, Schoukens, & Tóth, 2020):

$$y_k = \sum_{i=1}^p \Theta_i \times \prod_{j=0}^{n_x} a_{k-j}^{b_i, j} \prod_{l=1}^{n_e} e_{k-l}^{d_i, l} \prod_{m=1}^{n_y} y_{k-m}^{a_i, m} \quad (2)$$

where p is the number of regressors, Θ_i are the model parameters, and a_i, m, b_i, j and $d_i, l \in \mathbb{N}$ are the exponents of the output, input and noise terms, respectively.

The following example is a polynomial NARMAX model where the nonlinearity degree is equal to 2, identified from experimental data of a DC motor/generator with no prior knowledge of the model form, taken from (Lacerda Junior, Almeida, & Martins, 2017):

$$y_k = 1.7813y_{k-1} - 0.7962y_{k-2} + 0.0339x_{k-1} - 0.1597x_{k-1}y_{k-1} + 0.0338x_{k-2} + 0.1297x_{k-1}y_{k-2} - 0.1396x_{k-2}y_{k-1} + 0.1086x_{k-2}y_{k-2} + 0.0085y_{k-2}^2 + 0.0247e_{k-1}e_{k-2} \quad (3)$$

The Θ values are the coefficients of each term of the polynomial equation.

Polynomial basis functions are one of the most used representations of NARMAX models due to several interesting attributes, such as (Aguirre, 2004; Billings, 2013):

- All polynomial functions are smooth in \mathbb{R} .
- The Weierstrass approximation theorem (Weierstrass, 1885) states that any continuous real-valued function defined on a closed and bounded space $[a, b]$ can be uniformly approximated using a polynomial on that interval.
- They can describe several nonlinear dynamical systems (Billings, 2013), including industrial processes, control systems, structural systems, economic and financial systems, biology, medicine, and social systems (Aguirre, 2004; Billings, 2013; Boynton, Balikhin, Wei, & Lang, 2018; Chiras, Evans, & Rees, 2001; Fung, Wong, Ho, & Mignolet, 2003; Guo, Guo, Billings, & Wei, 2016; Kukreja, Galiana, & Kearney, 2003; Lacerda Junior, Martins, Nepomuceno, & Lacerda, 2019; Martins & Aguirre, 2016).
- Several algorithms have been developed for both structure selection and parameter estimation of polynomial NARMAX models.
- Polynomial NARMAX models can be used both for prediction and inference. The structure of polynomial NARMAX models are easy to interpret and can be related to the underlying system, which is not a trivial task when using, for example, neural or wavelet functions.

Estimating the parameters of NARMAX models is a simple task if the model structure is known *a priori*. However, usually there is no information on what terms one should include in the final model, and selecting the correct terms has to be part of the system identification procedure. Thus, the identification of NARMAX models is twofold: selecting the most significant regressors given a dictionary of candidate terms, which relies on model structure selection algorithms, and estimating their parameters.

SysIdentPy

SysIdentPy is an open-source Python package for system identification using polynomial NARMAX models. The package can handle SISO (Single-Input Single-Output) and MISO (Multiple-Inputs Single-Output) NARMAX model identification and its variants such as NARX, NAR, ARMAX, ARX, and AR models. It provides various tools for both model structure selection and parameter estimation including classical algorithms, e.g., forward regression orthogonal least squares and extended least squares orthogonal forward regression; parameter estimation using ordinary least squares, recursive algorithms and adaptive filters; the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Khinchin's law of iterated logarithm criterion (LILC), and Final Prediction Error (FPE) methods for model order selection (Haber & Keviczky, 1999); regression metrics; and residual analysis. The reader is referred to the package documentation for further details.

SysIdentPy is designed to be easily expanded and user friendly. Moreover, the package aims to provide useful tools for researchers and students not only in the SI field, but also in correlated areas such as Machine Learning, Statistical Learning and Data Science. Recently, an R package was published (Ayala, Gritti, & Santos Coelho, 2020) with tools to model dynamic systems using NARMAX models. However, to the best of our knowledge, SysIdentPy is the first open-source package for system identification using NARMAX models in Python. Moreover, SysIdentPy includes recursive and gradient methods for parameter estimation, e.g., recursive least squares, affine least mean squares, sign-sign least mean squares and many others that are not available in the above-mentioned R package. Also, the user can choose between four methods for model order selection, which is not possible with the mentioned R package.

Example

The following is an example of how to use SysIdentPy to build a NARMAX model from data. For simplicity, the example uses simulated data with 1000 samples, generated using the method `get_miso_data`:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sysidentpy.polynomial_basis import PolynomialNarmax
from sysidentpy.metrics import root_relative_squared_error
from sysidentpy.utils.generate_data import get_miso_data

x_train, x_valid, y_train, y_valid = get_miso_data(n=1000,
                                                  colored_noise=False,
                                                  sigma=0.001,
                                                  train_percentage=90)
```

Assuming that there is no information regarding what system generated the data, a dictionary of candidate terms must be created by defining the nonlinearity degree of the polynomial function and the maximum lag of the input and output terms. These parameters are, respectively, `non_degree`, `ylag`, `xlag`. The Akaike Information Criterion is chosen for model order selection and the least squares method is used for parameter estimation:

```
model = PolynomialNarmax(non_degree=2,
                        order_selection=True,
                        ylag=2, xlag=[[1, 2], [1, 2]],
                        info_criteria='aic',
                        estimator='least_squares',
                        )
```

The user can also run a SISO example by replacing `get_miso_data` with `get_siso_data` and the `xlag` values with an integer or a list of integers. If one wants to estimate the parameters using, for example, the recursive least squares algorithm, just set `estimator` to `'recursive_least_squares'`. Replacing the AIC method with BIC, for example, can be done analogously by replacing `'aic'` with `'bic'`.

The `fit` method is used to obtain the model and `predict` to validate the model using new data. The metric to evaluate is the relative root squared error. To get the root mean square error metric, for example, import it using `from sysidentpy.metrics import root_mean_square_error` and replace the root relative squared error method with it.

```
model = PolynomialNarmax(non_degree=2,
                        order_selection=True,
                        ylag=2, xlag=[[1, 2], [1, 2]],
                        info_criteria='aic',
                        estimator='least_squares',
                        )

model.fit(x_train, y_train)
yhat = model.predict(x_valid, y_valid)
rrse = root_relative_squared_error(y_valid, yhat)
print(rrse)
```

The `model.results` and `model.residuals` statements return the polynomial model obtained using the fit method and plot the results for qualitative analysis.

```
results = pd.DataFrame(model.results(err_precision=8,
                                   dtype='dec'),
                      columns=['Regressors', 'Parameters', 'ERR'])

print(results)
ee, ex, extras, lam = model.residuals(x_valid, y_valid, yhat)
model.plot_result(y_valid, yhat, ee, ex)
```

The table below and Figure 1 are the output of the aforementioned example. Table 1 details the regressors chosen to compose the final model, its respective parameters and the error reduction ratio (ERR), which measure the contribution of each regressor to explain the system output. ERR values can be interpreted as a feature importance metric. Figure 1 depicts the simulation of model prediction and the validation data as well as the autocorrelation of the model residues and the cross-correlation between the input and the residues.

Regressors	Parameters	ERR
$x_2(k-1)$	0.6000	0.90482955
$x_2(k-2)x_1(k-1)$	-0.3000	0.05072675
$y(k-1)^2$	0.3999	0.04410386
$x_1(k-1)y(k-1)$	0.1000	0.00033239

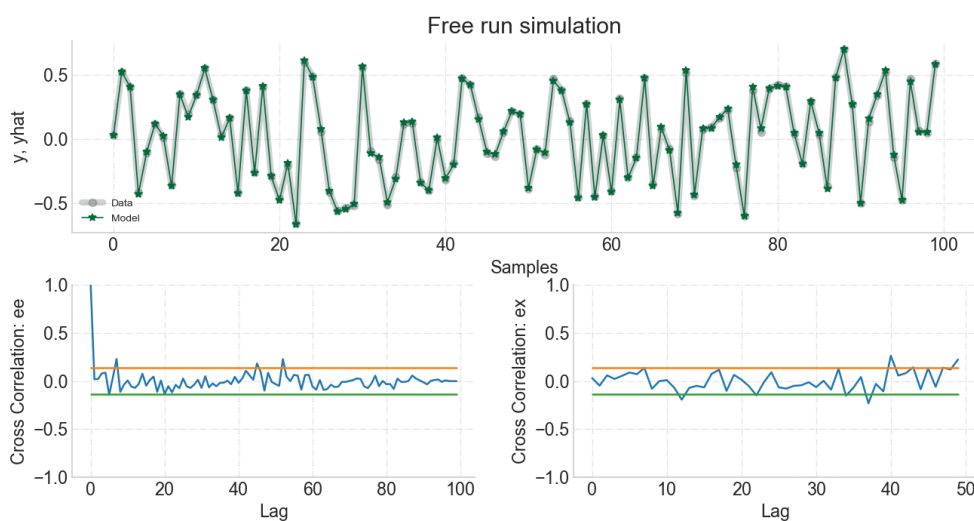


Figure 1. Results from modeling a simulated system available with the *SysIdentPy* package. Free run simulation (validation data vs. model prediction), autocorrelation of the residues and cross correlation between residues and the input.

For more information and examples of how to build NARMAX models and its variants using different methods for parameters estimation, model order selection and many more, see the package documentation.

Future work

Future releases will include new methods for model structure selection of polynomial NARMAX models, new basis functions, multiobjective model structure selection and parameter

estimation algorithms, new adaptive filters, frequency domain analysis, and algorithms for using NARMAX models for classification problems.

References

- Aguirre, L. A. (2004). *Introdução à identificação de sistemas—técnicas lineares e não-lineares aplicadas a sistemas reais*. Editora UFMG.
- Ayala, H. V. H., Gritti, M. C., & Santos Coelho, L. dos. (2020). An r library for nonlinear black-box system identification. *SoftwareX*, 11, 100495.
- Billings, S. A. (2013). *Nonlinear system identification: NARMAX methods in the time, frequency, and spatio-temporal domains* (p. 574). Chichester: John Wiley & Sons.
- Billings, S. A., & Leontaritis, I. J. (1981). Identification of Nonlinear Systems Using Parameter Estimation Techniques. In *Proceedings of the IEEE conference on control and its application* (pp. 183–187).
- Boynnton, R., Balikhin, M., Wei, H., & Lang, Z. (2018). Applications of NARMAX in space weather. In *Machine learning techniques for space weather* (pp. 203–236). Elsevier. doi:[10.1016/b978-0-12-811788-0.00008-1](https://doi.org/10.1016/b978-0-12-811788-0.00008-1)
- Chen, S., & Billings, S. A. (1989). Representations of non-linear systems: The NARMAX model. *International Journal of Control*, 49(3), 1013–1032. doi:[10.1080/00207178908559683](https://doi.org/10.1080/00207178908559683)
- Chiras, N., Evans, C., & Rees, D. (2001). Nonlinear gas turbine modeling using NARMAX structures. *IEEE Transactions on Instrumentation and Measurement*, 50(4), 893–898.
- Fung, E. H. K., Wong, Y. K., Ho, H. F., & Mignolet, M. P. (2003). Modelling and prediction of machining errors using ARMAX and NARMAX structures. *Applied Mathematical Modelling*, 27(8), 611–627. doi:[10.1016/s0307-904x\(03\)00071-4](https://doi.org/10.1016/s0307-904x(03)00071-4)
- Guo, Y., Guo, L. Z., Billings, S. A., & Wei, H.-L. (2016). Ultra-orthogonal forward regression algorithms for the identification of non-linear dynamic systems. *Neurocomputing*, 173, 715–723. doi:[10.1016/j.neucom.2015.08.022](https://doi.org/10.1016/j.neucom.2015.08.022)
- Haber, R., & Keviczky, L. (1999). *Nonlinear system identification. 2. Nonlinear system structure identification* (Vol. 7). Springer Science & Business Media.
- Khandelwal, D., Schoukens, M., & Tóth, R. (2020). A tree adjoining grammar representation for models of stochastic dynamical systems. *arXiv preprint arXiv:2001.05320*. doi:[10.1016/j.automatica.2020.109099](https://doi.org/10.1016/j.automatica.2020.109099)
- Kukreja, S. L., Galiana, H. L., & Kearney, R. E. (2003). NARMAX representation and identification of ankle dynamics. *IEEE transactions on biomedical engineering*, 50(1), 70–81. doi:[10.1109/tbme.2002.803507](https://doi.org/10.1109/tbme.2002.803507)
- Lacerda Junior, L., W. R., Almeida, V. M., & Martins, S. A. M. (2017). Identificação de um motor/gerador cc por meio de modelos polinomiais autorregressivos e redes neurais artificiais. In *XIII simpósio brasileiro de automação inteligente* (pp. 1–6). Porto Alegre.
- Lacerda Junior, W. R., Martins, S. A. M., Nepomuceno, E. G., & Lacerda, M. J. (2019). Control of hysteretic systems through an analytical inverse compensation based on a narx model. *IEEE Access*, 7, 98228–98237. doi:[10.1109/access.2019.2926057](https://doi.org/10.1109/access.2019.2926057)
- Leontaritis, I. J., & Billings, S. A. (1985). Input-output parametric models for non-linear systems – part i: Deterministic non-linear systems; part ii: Stochastic non-linear systems. *International Journal of Control*, 41(2), 303–328; 329–344.

- Ljung, L. (1987). *System identification: Theory for the user*. Prentice-hall. doi:[10.1016/0005-1098\(89\)90019-8](https://doi.org/10.1016/0005-1098(89)90019-8)
- Martins, S. A. M., & Aguirre, L. A. (2016). Sufficient conditions for rate-independent hysteresis in autoregressive identified models. *Mechanical Systems and Signal Processing*, 75, 607–617. doi:[10.1016/j.ymssp.2015.12.031](https://doi.org/10.1016/j.ymssp.2015.12.031)
- Weierstrass, K. (1885). Über die analytische darstellbarkeit sogenannter willkürlicher functionen einer reellen veränderlichen. *Sitzungsberichte der Königlich Preußischen Akademie der Wissenschaften zu Berlin*, 2, 633–639.