# Nonlinear Black-box System Identification through Neural Networks of a Hysteretic Piezoelectric Robotic Micromanipulator


**Helon V. Hultmann Ayala*, Didace Habineza**, Micky Rakotondrabe**, Carlos E. Klein*, Leandro S. Coelho*,*****

** Industrial and Systems Eng. Graduate Program, Pontifical Catholic University of Paraná, Curitiba, 80215-901, Brazil*
*** Department of Automatic Control and Micromechatronic Systems (AS2M), FEMTO-ST Institute, University of Franche-Comté / CNRS / ENSMM / UTBM, Besançon, France*
**** Electrical Eng. Graduate Program, Federal University of Paraná, Curitiba, PR 81531-980, Brazil*
*(Tel: +554132711333. E-mails: helon.ayala@pucpr.br; didace.habineza@femto-st.fr; mrakoton@femto-st.fr; carlos.klein@volvo.com; leandro.coelho@pucpr.br)*



**Abstract:** Piezoelectric micromanipulators are used in applications with precise and high dynamics positioning. This recognition is thanks to their high resolution, bandwidth and stiffness. Its nonlinear behavior, however, complicates the design of robust control laws with respect to no or imprecise sensing. In this context, this work presents the identification of a piezoelectric micromanipulator through nonlinear black-box neural networks with data acquired in a laboratory setup. A comparison is made regarding the model complexity. The results show the accuracy of the models, their statistical validity and that they were able to capture the dynamics of the micromanipulator adequately.



*Keywords:* robotic micromanipulators, piezoelectric actuator, hysteresis, nonlinearity, artificial neural networks, system identification.


## 1. INTRODUCTION

Micromanipulation has received great deal of attention in the last two decades. It provides tools for various fields in science in order to actuate in the micrometer scale, such as positioning of objects for microscopic devices, driving tools in microsurgery and actuating in microelectromechanical systems (MEMS). In the biomedical engineering field, examples are in vitro fertilization and gene abnormalities identification (Gordon and Laufer, 1988; Cohen et. al., 1993). Piezoelectric actuators were widely used for the purpose of micromanipulation, due to their quick time for response, stiffness and the total amplitude of force it is able to exert (Cao and Chen, 2014; Agnus et al, 2013). Among the most used micromanipulators are piezoelectric micromanipulators. They offer a very high resolution of positioning (down to nanometers is possible), a high bandwidth (up to tens of kHz) and a high stiffness and thus a high manipulation force.

However some difficulties are faced by the designer whenever building control systems to accurately drive piezoelectric actuated micromanipulators. Indeed, the presence of hysteresis, creep and badly damped vibration render difficult the synthesis of the controllers (Xie et al 2009; Rakotondrabe et al 2008). Therefore, these phenomena are undesirable features when considering piezoelectric devices for the high precision control of such devices. Among them, hysteresis is the principal source of nonlinearity and the most studied for piezoelectric manipulators (Devasia, Eleftheriou and Moheimani, 2007; Hassani, Tjahjowidodo and Do, 2014). The nonlinearity problem with modeling piezoelectric actuators becomes more salient when one considers the environment at a micrometer scale, where a priori one has to resort to open loop control to actuate on such devices as sensing is either not possible due to the lack of space. In this scenario, a good model may be employed and can provide good estimates of the position of the tip for control purposes and avoid the shortcomings of sensing. In this case, the model should be precise enough as to account for the dynamical changes of the actuators during operation.

However, due to the nonlinear behavior of piezoelectric actuators, obtaining a good mathematical abstraction is a difficult task. Estimating nonlinear systems is a very broad problem as it is impossible to propose a structure able to describe efficiently every possible nonlinear system. Hence, the scope is often reduced to focus on nonlinear model structure with black box setup. Models based on the computational intelligence approaches, such as fuzzy systems (Takagi and Sugeno, 1985) and artificial neural networks (Haykin, 2009) may present a good approximation for nonlinear plants. These methods have the property of universal approximation and are thus good choices for nonlinear mappings in the context of system identification (Hartman, Keeler and Kowalski, 1990; Hunt, Haas and Murray-Smith, 1996).

Among these computational intelligence techniques reported in system identification applications, the artificial neural network, or more specifically, dynamic neural network based on Nonlinear AutoRegressive models with eXogenous inputs (NARX models) model structure, has been widely adopted due to its proven record of performance especially for nonlinear, complex systems (Han, Wang and Qiao, 2013; Kar et. al., 2014).

On the other hand, according to the specific literature on the area, piezoelectric actuator modelling may be classified into (i) mathematical models or (ii) system identification models (Hassani, Tjahjowidodo and Do, 2014). The first category includes Preisach, Krasnosel'skii–Pokrovskii, Prandtl–Ishlinskii, Maxwell-Slip and Bouc–Wen and Duhem models. They are composed by closed-form mathematical equations with a given number of parameters, which are adjusted to adhere to the dynamics of the system to be modeled. System identification stands for the techniques which are able to interpolate a flexible surface to the input and output data of the model. Among other criteria, these techniques may be classified into white and black-box models, depending on the knowledge of the system used in the modelling process. Grey-box models stand in between those two extremes (Ljung, 1999; Billings, 2013).

In this paper, a nonlinear neural network black-box model for system identification with sigmoidal activation functions has been applied for identifying the unknown process parameters when applied to a hysteretic piezoelectric robotic manipulator. We consider to have no *a priori* knowledge about the system to be identified and use thus solely input and output data from experimentation in order to build a model. That is, we do not use any knowledge regarding the hysteresis, creep or any other nonlinear behavior of the actuator in the modeling process. This gives flexibility for the designer as he does not have to define *a priori* any kind of parameter related to any given type of nonlinearity. To this end, the unknown process is modeled as a NARX process and the parameters of this model are obtained using the approximation capabilities of the single layer neural network, which were illustrated by the results. We analyze several configurations in order to test linear against nonlinear models, where the later showed better statistical results. Specifically, the tests based on correlation of the residuals pointed that the nonlinear models were better able to capture the dynamics of the system, being so a better choice for the designer as the test indicated that the residuals were random at the end of the identification procedure.

The rest of the paper is organized as follows. Section 2 gives the description of the piezoelectric actuator and the experimental setup. Basic knowledge regarding nonlinear black-box system identification and model validation are given in Section 3. The results and conclusion are depicted in Sections 4 and 5, respectively.

## 2. PIEZOELECTRIC ROBOTIC MANIPULATOR

The experimental setup employed in this paper is based on a piezoelectric robotic micromanipulator. The micromanipulator is a cantilever with rectangular section and has two layers one of which is based on PZT (lead zirconate titanate) piezoelectric material and the other one is based on non-piezoelectric layer (nickel). The piezoelectric layer is also called active layer and the non-piezoelectric one is called passive layer (Fig.1.(a)). When a voltage $u(t)$ is applied to the active layer, it expands or contracts following the direct piezoelectric effect. Due to the interface between the two layers, this expansion/contraction generates a bending $y(t)$ of the overall cantilever, as depicted in Fig.1.(b). The cantilever can therefore be considered as a system having an input $u(t)$ and an output $y(t)$.

Piezoelectric cantilevers are widely employed for robotic micromanipulation or robotic microassembly thanks to the very high resolution (down to nanometers), the high bandwidth (in excess of the kHz) and the high stiffness they can offer to satisfy the requirements in these tasks (Agnus et. al., 2013; Rakotondrabe, 2013; Rakotondrabe et. al., 2010). Fig.1(c) pictures a photography of a piezoelectric robotic micromanipulator. This micromanipulator, which will be used for further experiments, has the following active dimensions (length, width, thickness): 15mm×2mm×0.3mm. The thickness of the piezoelectric layer is 0.2mm whilst that of the passive layer is 0.1mm.

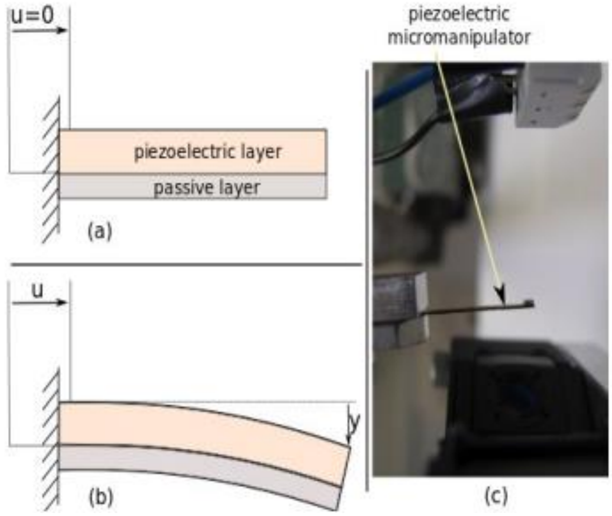

Fig. 1. The piezoelectric robotic micromanipulator. (a) and (b): principle. (c): a photography.

## 3. NONLINEAR BLACK-BOX SYSTEM IDENTIFICATION

The aim for the mathematical modelling is the construction of high fidelity models that could represent the real behavior for the real observed system. Classifying the model by the construction approach one can have models white-box, gray-box and black-box. White-box models are used when there is access to the system natural laws (chemistry, physics) and there is no available experimental data. Black-box in other hand is used when there is no previous knowledge on the system natural laws or behavior, but the prerequisite for its usage is the availability of experimental information. Finally, the gray-box models are constructed partly by the white-box and part by the black-box approaches.

The prerequisite to use the black-box approach is the availability of experimental data, which is obtained by exciting the system and acquiring output data useful for system identification. On the other hand, system identification is an area of knowledge focusing the study of alternative techniques for mathematical modeling. The characteristic for those techniques is that there is no or very low need of previous knowledge about the system to be modeled and consequently those methods are taken also as black-box modeling or empirical modeling (Ljung, 1999). The steps for a system identification can be represented as: i) dynamic test and data acquirement, ii) choice of mathematic representation and model structure, iii) structural parameter estimation, iv) model validation.

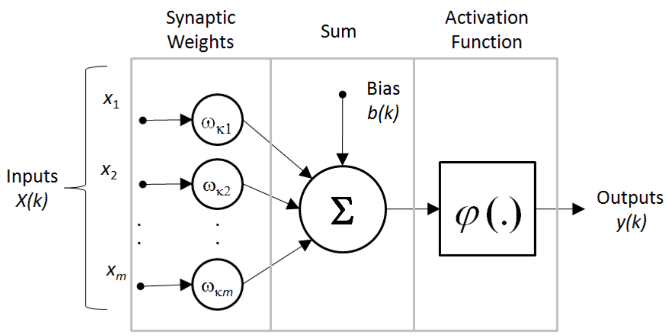


Fig. 2. Artificial neuron (*Haykin, 2009).*

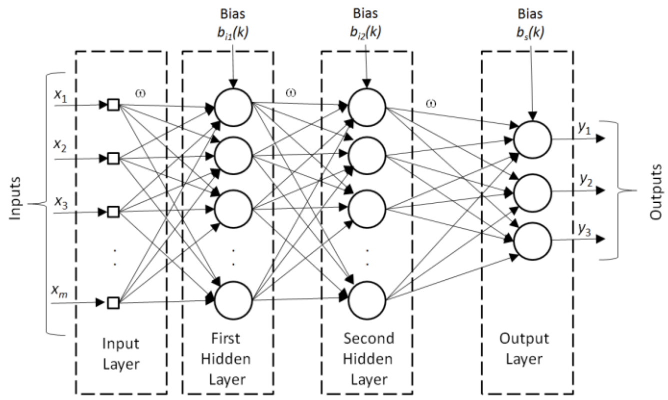


Fig. 3. Network topology (*Haykin, 2009).*

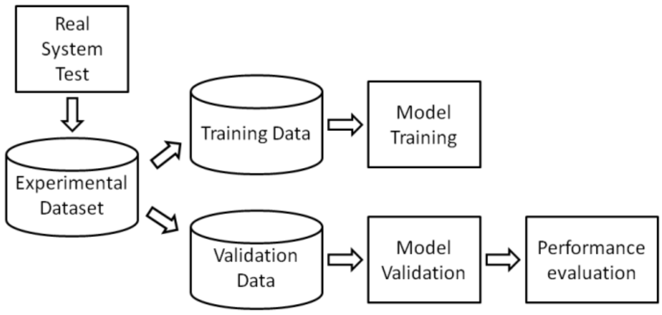


Fig. 4. Framework to apply ANN in system identification.

### *3.2 NARX models*

The abbreviation NARX stands for non-linear auto regressive with exogenous input. Non-linear once the model shall deal with a non-linear system representation. Auto regressive due to the representation based on the latest system input/output status and with exogenous input to take the noise and uncertainties in consideration.

Taking a discrete system where the inputs are represented by $u(k)$ and the outputs are $y(k)$. One NARX model which stand for this system will be in the form (Wang, 2014):

$$\begin{aligned} y(k) = f\,(&u(k), u(k-1),\ldots, \\ &u(k-\mathrm{Nu}), y(k-1),\ldots, y(k-\mathrm{Ny})) \end{aligned}, \qquad (1)$$

where $k$ is the discrete time step, $\mathrm{Nu} \geq 0$ and $\mathrm{Ny} \geq 0$ are the input and the output orders used in the NARX model. The function $f(.)$ stands for a non-linear function, in general. Using an artificial neural network, ANN, to approximate the non-linear function $f(.)$, one can build a so called NARX neural network. ANNs like Jordan (Jordan, 1986) and Elman (Elman, 1990) are recurrent networks which can deal with non-linearity. The recurrence ability, that means some model outputs from latest discrete steps can be taken as a valid inputs, will bring the net the auto-regressive and exogenous parts.

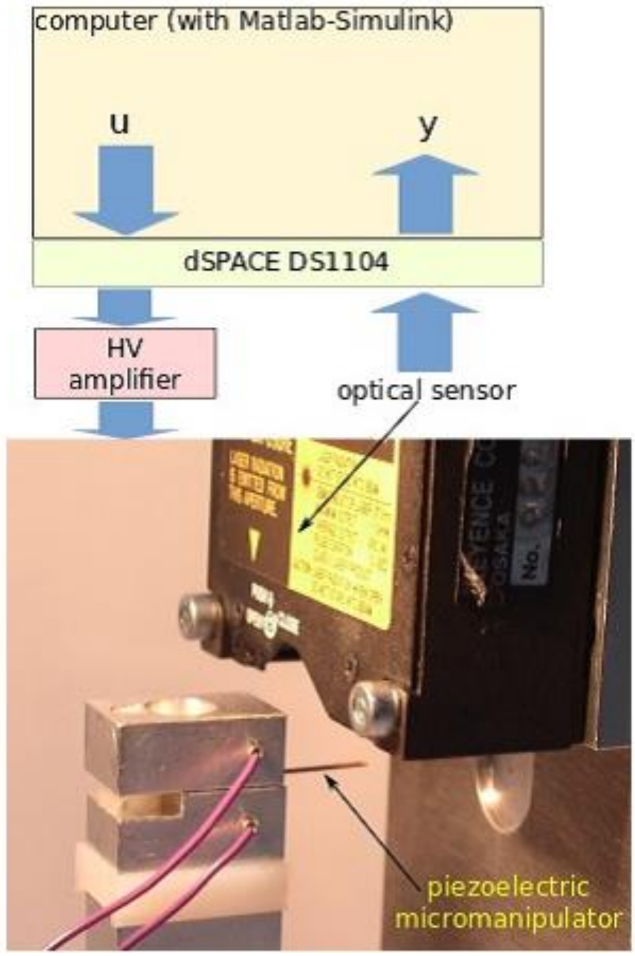


Fig. 5. Diagram of the experimental setup.

### *3.3 Artificial neural networks*

An artificial neural network is a massively parallel-distributed processor that has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects: i) knowledge is acquired by the network through a learning process, ii) interconnection strengths known as synaptic weights are used to store the knowledge, (Haykin, 2009).

As a network, the ANN is based on a singular structure called neuron. Each neuron have 1 to $m$ inputs, $x(k)$, which are multiplied by unique synaptic weights, $\omega(km)$. All scaled inputs, by their respective weights, are then sum each other and with one bias factor, $b(k)$. Finally, the result is applied to an activation function which gives the final neuron result, $y(k)$. The artificial neuron representation is shown on figure 2.

The artificial neuron can be mathematically represented as:

$$y(k) = \varphi(b(k) + \sum_{j=1}^{m} \omega_{kj} x_j) \tag{2}$$

The ANN is arranged in layers. Each layer can have its own number of neurons. The complexity of the system and the wanted accuracy will demand the number of needed neurons for each network layer and the number of neuron layers to the model. Figure 3 is presenting one network structure with one input layer, two hidden layers and one output layer.

Despite the fact that the ANN have a good generalization ability, that means the capacity to deal with new stimuli different than the one used for learning, one shall be aware that once the model accuracy is structure dependant it is not possible to be sure all new situations will be handled correctly. The best rule is: a model which was trained to a system behavior can only deal with the known behavior and so if the real system is not properly mapped, then the representativeness will be defective.

### *3.4 Artificial neural networks applied to system identification*

A common framework to use ANNs in the system identification shall follow the steps: i) plan and check the variables to acquire and carefully check the stimuli given to the system in order to capture the systems behavior; ii) experiment the system in order to record the database; iii) split the database in order to have a dataset for train the system and another dataset to validate the system; iv) select the best network structure, tune the constructive parameters and train the model; v) use the validation dataset and simulate the system; vi) compare the validation output with the real systems output and calculate a performance index. Figure 4 is presenting the framework.

The last step on black-box modeling is the validation. Once the model was built using a portion of the original experimental data set, validation is then performed with the remaining part of the original set. The model validation output is evaluated using a performance index. There are some metrics available like mean squared error, MSE, mean absolute percentage error, MAPE, and multiple correlation coefficient, $R^2$. This paper elected the multiple correlation coefficient to be used once it does not depend on scale to be interpreted.

$R^2$ is an index in the unitary range where the unity stands for a hundred percent of following and the null answer represents the worst case. It is calculated by:

$$R^2 = 1 - \frac{\sum_{k=1}^{N} (\hat{y}_k - y_k)^2}{\sum_{k=1}^{N} (y_k - \bar{y}_k)^2} \tag{3}$$

where $k$ stands for the discrete time step, $y_k$ is the real output on time step $k$, $\hat{y}_k$ is the estimated output on time step $k$, and $\bar{y}_k$ is the mean real output up to time step $k$.

## 4. RESULTS

The present section is devoted to report the results obtained when nonlinear black-box system identification with neural networks is applied to model the piezoelectric system. Both the methodology and the description of the system were given respectively in Sections 2 and 3.

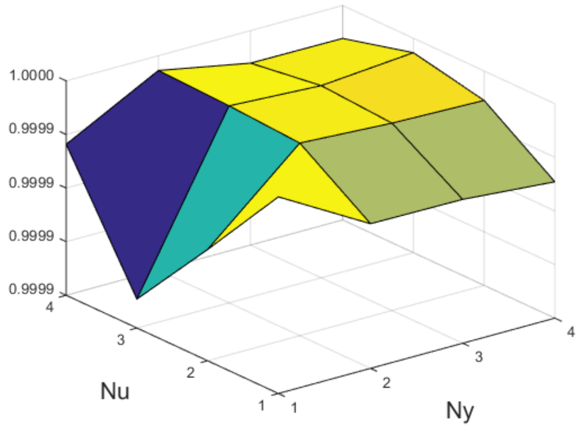


Fig. 6. Multiple correlation coefficients in the validation phase in simulation for the neural network model with varying orders on the input and outputs of the system.

### *4.1 Data acquisition*

For the experimental tests, the piezoelectric robotic micromanipulator in Fig.1(c) has been integrated in a benchmark that contains the following materials: (i) the piezoelectric micromanipulator itself; (ii) a computer with Matlab-Simulink software for generating the driving voltage $u(t)$ and for acquiring the measured signal $y(t)$; (iii) a dSPACE board that serves as interface between the computer and the external (the dSPACE is a DS1104 capable of working at high frequency – in excess of 10MHz); (iv) a high-voltage (HV) amplifier that amplifies the voltage from the computer before sending it to the piezoelectric micromanipulator (the amplifier A400DI from FLC company, can furnish up to +/-200V); and (v) an optical displacement sensor (LK2420 from Keyence company) which is used to measure the deflection (displacement) $y(t)$ of the micromanipulator. The sensor is set to have a 100 nm of precision and in excess of 2kHz of bandwidth, which are sufficient enough for the characterization carried out in this paper and sufficient to account for the dynamics of the micromanipulator.

The sampling time for the whole acquisition system, i.e. the computer/Matlab-Simulink and the dSPACE board, is set to be 0.5 ms (2kHz of sampling frequency). Fig. 5 depicts the diagram of the whole experimental setup. We recorded in total 10 s, what generated 200,000 samples. Afterwards we processed the data and found that 50,000 data were enough for modelling the manipulator, which were split into estimation and validation datasets as we will discuss in the next subsection.

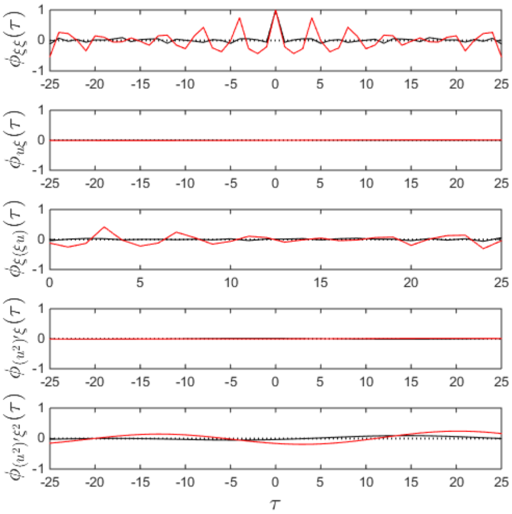


Fig. 7. Residual statistical test in the case of Ny = Nu = 1 (red) and Ny = Nu = 4 (black) (95% margin in dotted lines).

*4.2 Numerical experiments*

We tested NARX models with neural networks varying the order of the delays on both the input and the output in order to check the accuracy with the respect to the possible space of the inputs of the model. Namely, we set the number of lags on the input and the output from 1 to 4. The number of neurons was fixed at 10 neurons with sigmoidal activation function by experimenting on the data. The modelling procedure was implemented computationally on MATLAB with standard available functions. We split the 50,000 data into two datasets, namely estimation and validation datasets, in 50% ratio.

For all possible pairs of number of lags on both the input and output of the system, the multiple correlation coefficient obtained were very close to one for the estimation and validation phases in prediction and simulation. In the case of validation phase and in simulation (usually the most difficult scenario), the metric returned 0.9999 for all pairs of lags on the input and the output, as illustrated in Figure 6.

Even though the accuracy is very high in all cases tested, in simulation run and in the validation phase, the statistical properties of the residuals of the model with orders equal to 1 are not adequate. Figure 7 shows the tests based on the autocorrelation of the residuals and on higher order correlation function between the input and the residuals (Billings, 2013; Chap. 5) for the models with orders equal to 1 and 4. It is possible to see that the former model was not able to capture adequately the dynamics of the system, while the later gave adequate results for the correlation tests. Thus, the model with orders equal to 4 is more reliable in a statistical sense, as the tests shown in Figure 4 indicate that the dynamics have been adequately captured.

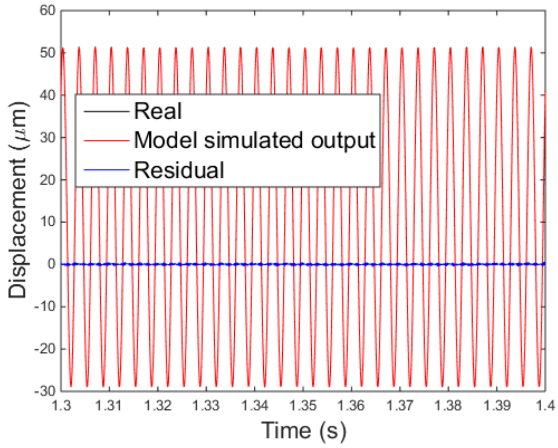


Fig. 8. Measured output response, model simulation and respective residual in the validation phase (a) and zoomed around 1.35 sec (b), in the case of Ny = 4 and Nu = 4

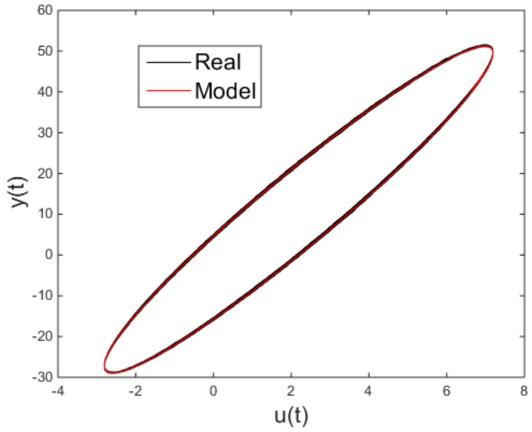


Fig. 9. Measured and simulated output versus the input for the model with Ny = Nu = 4. Note that the hysteretic behaviour has been adequately captured.

The precision of the model with Ny = Nu = 4 can also be checked in Figures 8 and 9. The former picture shows the original data, simulated predictions (where the predictions are calculated based on previous predictions and the measured output data is used only to initialize the predictions) and the residuals. It is possible to see that the predictions are almost indistinguishable from the original output data. In Figure 9 we have the plot of the output versus the input, in order to analyse the quality of the predictions with respect to the hysteretic behaviour of the system. One can see that the nonlinear characteristic of the system was properly captured by the model.

It is important to note that we also tried linear ARX models with all possible sets of orders from 1 to 10 in the input and the output. However, even though the multiple correlation metrics indicated that the models were very accurate (they were similar as in the nonlinear models), the correlation tests were not satisfied by any of the models. Thus, we omitted the graphical results for the case of linear models as the tests indicated that the models are not valid in a statistical sense.

## 5. CONCLUSION

In the present paper, we showed an experimental test bench to perform data acquisition for the purpose of acquiring data for system identification. Moreover, we employed black-box system identification techniques in order to define the quality of the models by varying their complexity. We found out that the nonlinear models were able to capture adequately the dynamics of the system. On the other hand, the linear models showed to be insufficient to capture the model dynamics. This happened in spite of the fact that the models are accurate enough in terms of the multiple correlation metric. We used, though, the tests based on the autocorrelation of the residuals and higher order cross-correlation between the residuals and the input to infer that there was still dynamics left in the residuals – a highly undesirable feature in a model – even though the predictions were accurate. Building accurate models is important in the scope of micromanipulators as we may use richer information when providing feedback for the positioning controllers with the models avoiding, thus, the use of expensive sensors in such scale.

As future works, we shall focus on the improvement of such models by exploiting the universal approximation capabilities of the neural networks. Moreover, we shall employ also evolutionary algorithms in order to perform the search of the parameters with global search techniques and define as project parameters the inputs of the model and its complexity as well. Being so, the designer is not required to perform tedious and error prone procedures to build models.

## ACKNOWLEDGEMENTS

This work has been partially supported by CAPES (Brazilian research agency) through a PROSUP scholarship.

## REFERENCES

Agnus, J., et. al. (2013) Robotic Microassembly and micromanipulation at FEMTO-ST, *Journal of Micro-Bio Robotics*, 8(2), 91-106.

Billings, S.A. (2013) Nonlinear system identification: NARMAX methods in the time, frequency, and spatio-temporal domains. West Sussex, United Kingdom: John Wiley & Sons Ltd.

Cao, Y., Chen, X.B. (2014) A survey of modeling and control issues for piezo-electric actuators. *Journal of Dynamic Systems, Measurement, and Control*, 137(1), pp. 1-13.

Cohen, J., Alikani, M., Adler, A., Reing, A., Ferrara, T. A., Kissin, E. and Anderson, C. (1993) Application of Micromanipulation in the Human. In Vitro Fertilization and Embryo Transfer in Primates Serono Symposia, Springer-New York, pp. 246-278.

Devasia, S., Eleftheriou, E. and Moheimani, S.R. (2007) A survey of control issues in nanopositioning. *IEEE Transactions on Control Systems Technology*, 15(5), pp. 802-823.

Elman, JL. (1990) Finding structure in time. *Cognitive Science*, 14: pp. 179-211.

Gordon, J. W. and Laufer, N. (1988) Applications of micromanipulation to human in vitro fertilization. *Journal of Assisted Reproduction and Genetics*, 5(2), 57-60.

Han, H.-G., Wang, L.-D. and Qiao, J.-F. (2013) Efficient self-organizing multilayer neural network for nonlinear system modeling, *Neural Networks*, 43, pp. 22-32.

Hartman, E., Keeler, J.D. and Kowalski, J.M. (1990) Layered neural networks with Gaussian hidden units as universal approximations. *Neural Computation*, 2(2), pp. 210-215.

Hassani, V., Tjahjowidodo, T. and Do, T.N. (2014) A survey on hysteresis modeling, identification and control. *Mechanical Systems and Signal Processing*, 49(1), pp. 209-233.

Haykin, S.S. (2009) *Neural networks and learning machines*. 3rd Ed. Pearson Education. Upper Saddle River, USA.

Hunt, K.J., Haas, R. and Murray-Smith, R. (1996) Extending the functional equivalence of radial basis function networks and fuzzy inference systems. *IEEE Transactions on Neural Networks*, 7(3), pp.776-781.

Jordan, MI. (1986) Attractor dynamics and parallelism in a connectionist sequential machine, *Proc. Eighth Annual Conf. of the Cognitive Science Society*, Amherst, MA, pp.531–546.

Kar, S., Das, S. and Ghosh, P.K. (2014) Applications of neuro fuzzy systems: a brief review and future outline. *Applied Soft Computing*, 15, pp. 243-259.

Ljung, L. (1999) *System identification: theory for the user*. 2nd. ed. Upper Saddle River, NJ: PTR Prentice Hall.

Rakotondrabe, M. (2013) *Smart materials-based actuators at the micro/nano-scale: characterization, control and applications*, Springer-Verlag, New York.

Rakotondrabe, M., Clévy, C. and Lutz, P. (2008) Hysteresis and vibration compensation in a nonlinear unimorph piezocantilever, IEEE/RSJ International Conference on Intelligent Robots and Systems, Nice France, pp: 558-563.

Rakotondrabe, M., Ivan, I.A., Khadraoui, S., Clévy, C., Lutz, P. and Chaillet, N. (2010) Dynamic displacement self-sensing and robust control of cantilevered piezoelectric actuators dedicated to microassembly tasks, IEEE/ASME International Conference on Intelligent Mechatronics, Montreal Canada, pp:557-562.

Takagi, T. and Sugeno, M. (1985) Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man and Cybernetics*, SMC-15(1), pp. 116-132.

Wang, H. ,Song, G. (2014) Innovative NARX recurrent neural network model for ultra-thin shape memory alloy wire, *Neurocomputing* 134, pp. 289-295.

Xie, H., Rakotondrabe, M. and Régnier, S. (2009) Characterizing piezoscanner hysteresis and creep using optical levers and a reference nanopositioning stage, *Review of Scientific Instruments*, 80(4), 046102.