Neuro-Fuzzy: Multivariable Identification of a Pumping System with Variable Demand

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Abstract. This work used intelligent techniques to identify an automated water pumping system with variable demand for the development of intelligent controllers. Two multivariable and non-linear models were developed based on Artificial Neural Networks (ANN) and Neuro-Fuzzy (NF). The objective is to enable simulations of operation scenarios, analysis, design and implementation of control algorithms. Experiments were carried out throughout the system's operating region to build a robust database, used in training. For validation, new tests were conducted with new operating points. The models were evaluated using performance criteria such as RMSE, NRMSE, FPE and Fit. The results show fits greater than 99%. It is concluded that intelligent techniques are superior in comparison to parametric and mathematical models in the multivariable and non-linear identification of pumping systems for simulation and dynamics prediction purposes.

Keywords: Pumping system; Artificial Neural Network; System identification; Hydraulic system.

1 Introduction

Water supply systems (WSS) comprise a set of equipment aimed at supplying water, covering domestic, industrial and public consumption (Gomes [1]). WSS face challenges arising from hourly variation in demand, influenced by society's consumption patterns. These challenges include significant fluctuations in service pressures and increased electrical energy consumption. In periods of low demand, pumps that were designed to operate at nominal speeds supply the network with excessive pressures and increase energy consumption and the risk of damage to pipes. On the other hand, in times of high demand, pressure drops occur. WSS presents challenges in terms of design and analysis, making it unfeasible to instrument and conduct experiments throughout the WSS due to financial costs and operational complexity. However, developing a computational model that represents its characteristics is an advantageous solution. Global models allow predicting anomalous behavior, simulating operating scenarios, correcting data, replacing failed sensor measurements or reducing the quantity, in addition to identifying patterns and assisting in the development of control algorithms (Moscinski and Ogonowski [2]). WSS exhibit significant daily and seasonal variations, making it possible to simulate scenarios based on computational models. This allows maintenance to be planned proactively, ensuring water supply in critical situations.

System identification techniques involve the construction of computational dynamic models based on measured data (Ljung [3]). With the advancement of computational techniques, models based on classical mathematics became obsolete in the identification of many dynamic systems (Moreira *et al.* [4]). The use of parametric models to identify linear systems or those with few nonlinearities is common. Cavalcanti *et al.* [5] modeled a WSS using SISO (single input - single output) parametric models, ARMAX (Autoregressive with

Exogenous Input Averages) showed better performance compared to ARX (Autoregressive with Exogenous Inputs) and Transfer Functions. Coutinho [6] conducted a comparative analysis of MISO modeling (two inputs) of a photovoltaic WSS using artificial neural networks (ANN) and polynomial models. ANN showed RMSE 45 times lower.

Some modeling techniques were employed to identify parameters that affect the energy efficiency of WSS. Gandhi *et al.* [7], Simpson and Marchi [8] and Fecarotta *et al.* [9] developed a mathematical model based on the CMB affinity laws for yield. Nazif *et al.* [10] used genetic algorithms to obtain a model aimed at managing pressure in WSS with variable demand. Walski and Creaco [11] developed an algorithm based on mathematical analysis of CMB efficiency to optimize the configuration of the pumping system. Other studies addressed the development of mathematical (Feng *et al.* [12]; Ha *et al.* [13]) and parametric (Meunier *et al.* [14]) models for linear hydraulic systems. However, these works highlight significant limitations of these methods, especially when they involve non-linearities or multiple variables. This suggests that complex hydraulic systems, with non-linearities and multivariables, can be better represented by ANN and NF.

The demand for more efficient methods has boosted the use of models based on artificial intelligence, ensuring better performance in identifying systems and parameters. Several studies highlight the robustness and applicability of ANN and NF in modeling dynamic systems (Gonçalves *et al.* [15]; Sierra *et al.* [16]; Nourani *et al.* [17]; Gao *et al.* [18] and Pillonetto *et al.* [19]). These techniques have also been applied to pumping systems to analyze and improve energy efficiency. Meirelles *et al.* [20] employed an ANN-based metamodel to estimate the pressures of nodes in a network to calibrate the computational model of an WSS.

Modeling pumping systems with variable demand has not been investigated with ANN and NF in the literature. This work uses these techniques in the multivariable and non-linear identification of an experimental WSS system with variable demand. Global models are developed, validating and using them in scenario simulations, analyzes and implementation of control algorithms, such as adaptive and open loop.

2 Methodology

Experiments were conducted across the entire operating range, manipulating the two input variables (frequency and VRP angle) and monitoring two output variables (pressure and flow) to develop the global model. Table 1 summarizes the modeled variables, their global range and the range of variation used in the experiments. To ensure that the database covers the system characteristics, the frequency was varied randomly within a pre-established range, taking into account the system characteristics to avoid sudden accelerations of the CMB. The settling time, chosen according to the inertial characteristics of the system, was 30 seconds to reach steady state. A longer time is chosen without compromising the quality of the data. To avoid the aliasing effect, caused by a low sampling frequency, a sampling frequency equal to 20 [Hz] was used, higher than the Nyquist criterion to avoid the aliasing effect. Fast sampling is preferred (Ljung [3]).

Table 1. Description of the ranges of variables used in the tests.

Data	Description
Global operating range of input variables	$20 < f_1 < 50\ Hz$ and $0 < \emptyset_{VRP} < 90º$
Delta of variation of input variables	$3 < \Delta f_1 < 5\ Hz$ and $\Delta\emptyset_{VRP} = 5º$

2.1 Experimental system

An instrumented bench (Fig. 1) designed to emulate a WSS with variable demand was used. The system input variables are the inverter electrical frequency and the Pressure Reducing Valve Angle (VRP). The VRP is responsible for vertically shifting the pipe curve and changing the water demand, causing the controller to act at the CMB speed to control the pressures at the set-point. The output variables, related to the CMB, are the holding pressure, the flow and the active power. A Supervision and Data Acquisition System (USB-6229) is used to acquire plant data and control the frequency inverter and VRP. A frequency converter (SE ALIVAR 31) is responsible for adjusting the speed of the CMB (3 HP). The LABVIEW platform is used. Sensing is done by three pressure transducers (PTX 7217) and one electromagnetic flow transducer (VMS Pro 038), as well as a signal sent by the frequency converter to read the active power of the CMB and one sent by the VRP to indicate the opening angle.

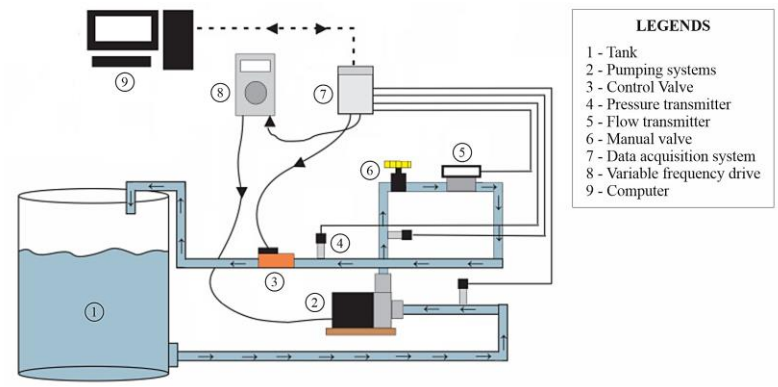

Figure 1. Schematic of the experimental bench capable of emulating WSS with variable demand.

2.2 Training and Validation

An iterative algorithm was used to reduce the error in training the ANN and NF models. Fig. 2(a) shows the architecture of the developed ANN, organized into three layers: input, intermediate and output. The input layer receives the signals, while the processing takes place in the intermediate layer, with the weighted weights (W), also acting as a rule extractor. At the output layer, the result is completed and the signal is fed back to the input, in an iterative process, aiming to reduce the error. The end of training is determined by the number of iterations or the final allowable error. The training algorithm was backpropagation. The number of intermediate layers and neurons per layer was estimated by increasing both until satisfactory results were achieved.

Fig. 2(b) illustrates the architecture of the developed NF system. The algorithm is made up of five layers that are part of the training process. The first layer calculates the degree of relevance (w1 and w2) with which the inputs (x1 and x2) satisfy the values or linguistic terms associated with these nodes. In the second layer, each node corresponds to a rule and calculates to what degree (Ai,j) the consequent of the rule is being met, that is, the implications of the premises. The third layer is responsible for performing vector normalization ($\overline{w_1}$ e $\overline{w_2}$). In the fourth layer, the outputs of the neurons (Pressure and Flow) are calculated by the product of the values of the rule's consequents. In the last layer, the respective output is calculated. Backpropagation is used with the backpropagation of the squared error in training. The NF algorithm limits the number of layers of the Neural network to one, the order of the model was changed through the number of Membership Functions (MF), which represents the number of neurons in the intermediate layer. The non-linear system required adopting MF Gaussians to reduce the number of neurons.

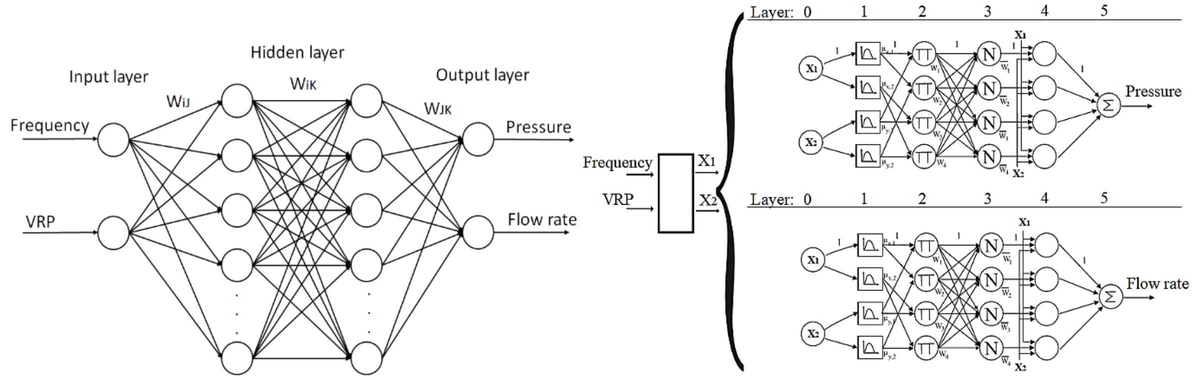

Figure 2. Architecture of the ANN Multiple Input – Multiple Output (MIMO) (a) and the NF MIMO system (b).

Model validation is linked to the agreement it presents with the system. Stating that a model has been validated depends more on qualitative rather than quantitative criteria. Thus, the model may have good characteristics for prediction, but be terrible for simulation. Therefore, it must be evaluated for each application.

One parameter estimation method is the Final Prediction Error (FPE), where the model parameters are chosen in order to minimize the difference between the model output (prediction) and the measurement (Eq. (1)) (Ljung [3]).

$$\epsilon(t,\theta) = y(t) + \hat{y}(t|\theta) \tag{1}$$

Other metrics were used to evaluate the performance of the models, Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE) and Adjustment Percentage (FIT) (Eq. (2)). These indicators are general and seek to indicate a global parameter of the model, such as the average error percentage.

$$Fit = \left(1 - \frac{1}{P\sum_{K=1}^{P}} \left|y^k - \hat{y}^k\right|\right) * \frac{100}{\hat{y}^k} \tag{2}$$

where y^k or y and $\hat{y}^k$ or $\hat{y}$ are respectively the desired output and the output obtained by the model for the k-th input and P is the total number of training or validation pairs (i.e., cross-validation).

3 Results

Two models were developed: i) fixed demand (SIMO) with varying flows and pressures, but constant VRP; ii) variable demand (MIMO) with variable flows and pressures and VRP. The results are divided into three parts. The first describes the experimental procedures and the results obtained in the development of the databases used in the training and validation of each model. Afterwards, the steps taken in training and validation are discussed and performance indicators are analyzed.

3.1 Database Development and Training

The experimental procedure for developing the training and validation database of the SIMO models consisted of varying, according to Table 1, the frequency of the CMB converter with the observation of the output variables, Pressure and Flow. Increasing frequency steps were inserted up to the upper limit, and then decreasing steps were inserted. The VRP angle was kept constant at 30º. The experimental data for training have a total of 5,700 pairs. For validation, 3,120 new pairs were used. There is no upper limit for the amount of validation data, which should represent more than 20% of the data. No filters were used in the ANN and NF modeling data.

The complexities of the MIMO model are due to the number of variables and the nonlinearities of the demand variation. The variation of the VRP angle changes the demand, resulting in the vertical displacement of the pipe curve and adds a variable and severe nonlinearities to the model, due to the hydraulic characteristics of the valve. The experimental procedure was similar to the previous one, varying the frequency in increasing steps until the limit of the variable, followed by the gradual variation of the VRP angle (Table 1). The relationship between the output and input variables of the training data has 61,850 pairs. For validation, 19,700 pairs were used.

An interactive training process was performed to obtain the structural configuration (number of layers and neurons) with the highest percentage of model FIT. A ranking of the best results was obtained by varying the training parameters for the MIMO model. An initial number of neurons per layer was selected, increasing them as necessary. The ANN obtained better results with a low number of neurons in the first layer and a high number in the second. The results of the NF model did not show a common trend in the two outputs analyzed. With pressure as the output, a high number of MF was preferred for the VRP angle. For the flow rate, a low number of MF was preferred for the angle, so intermediate amounts of MF were chosen. In general, the models presented FITs higher than 96%, excellent values for simulations of the pumping system and development of control algorithms.

3.2 Model response

The neural structure of the SIMO models was defined according to the procedures described in 3.1. Fig. 3 illustrates the responses of the SIMO models tested with training and validation data for the NF (5 Gaussian MF) and for the ANN (two layers with 8 and 5 neurons and tangential activation function). It was observed that the computational costs of the models developed in the NF are higher. Thus, it is convenient to reduce the number of neurons in the intermediate layer to values lower than those found in the ANN models, still obtaining superior FITs. Table 2 shows the performance of the models, with superior FITs for the intelligent models. However, prediction was not a positive point for these models, precisely because they presented extra difficulties in modeling the delay in their training stage. Thus, in low complexity situations (SIMO), the parametric models presented better results and are recommended for applications when the objective is prediction. For simulations and scenario analysis, the intelligent models are better because they have low stationary errors and high FITs. In this work, the order of the parametric models was defined through a cost function proposed by Ljung [3], relating the order of the model to the FIT and FPE.

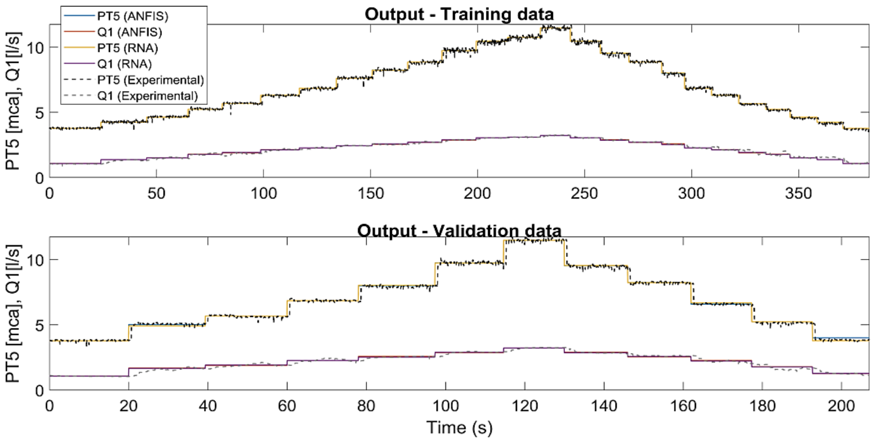

Figure 3. Response of SIMO (Single Input-Multiple Output) models with training (a) and validation (b) data.

Table 2. Performance data of SIMO computational models evaluating pressure and flow output (Q).

Model	RMSE	NRMSE	FPE	FIT (%)
ARX	0.75 (0.07)	666.7e-5 (21.5e-5)	669.5e-5 (21.6e-5)	73.01 (84.42)
ARMAX	0.61 (0.08)	628.9e-5 (21.21e-5)	633.5e-5 (21.3e-5)	88.01 (89.84)
NF (ANFIS)	0.026 (0.008)	17.8e-5 (19.5e-5)	843.5e-5 (191e-5)	99.95 (99.72)
RNA	0.0260 (0.008)	18.1e-5 (19.9e-5)	844.9e-5 (190.7e-5)	99.94 (99.20)

Fig. 4 illustrates the response of the MIMO models with training and validation data. The NF with 3 Gaussian MFs for each input variable and the ANN with two layers with 8 and 5 neurons and tangential activation function. The good adjustment of the curves was notable, and there were no problems with overfit. The system flow rate presented a longer transient period than that presented by the pressure. Thus, the model adjustment in these regions was impaired, mainly when the validation data were tested. In order to mitigate the error in the transient region, delays (k and k-1) were inserted into the model. However, no satisfactory transient regions were observed for the flow rate with validation data, which may result in reduced FPE performance, analyzed in Table 3.

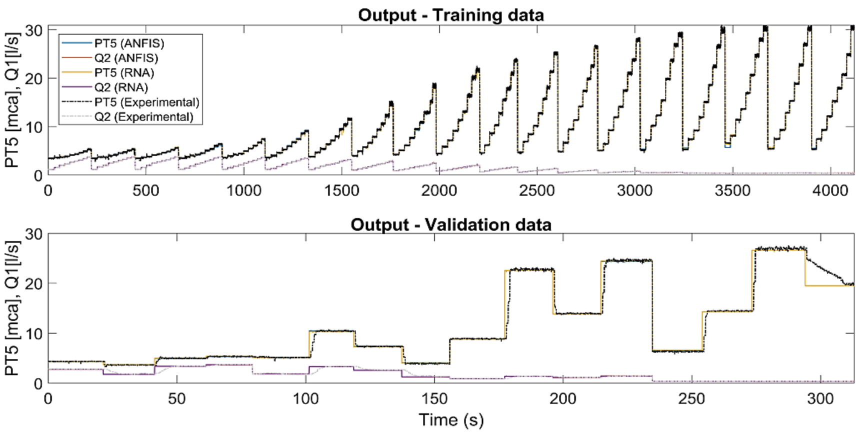

Figure 4. Response of MIMO (Multiple Input - Multiple Output) models with training (a) and validation (b) data.

Fig. 5 illustrates the percentage error per sample in the training of the Neural MIMO and NF models. Some peaks were noted, mainly due to the low adjustment in transient regions; however, the average error was less than 2%, which highlights the robustness of the AI-based models.

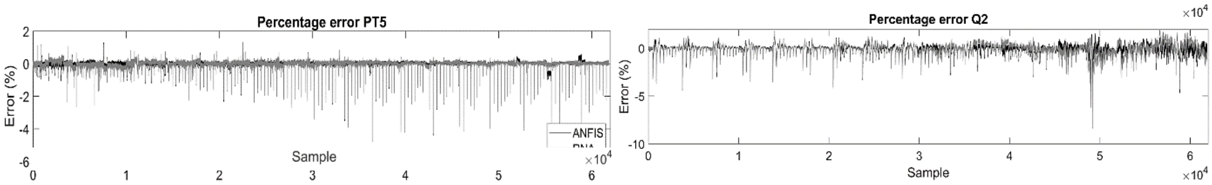

Figure 5. Percentage error per sample of the MIMO RNA (a) and NF (b) models.

Table 3 shows the comparison of performance indicators of the MIMO models, with the superiority of the intelligent models, mainly in the Fit and RMSE. The parametric models presented unsatisfactory results in the identification of multivariable and nonlinear systems. They were designed to model only linear systems and, in general, SISO. The use of models based on computational intelligence aimed to eliminate the deficiencies found in the parametric models for simulation and prediction. With excellent results for applications in multivariable and nonlinear hydraulic systems.

Tabela 3. Dados de performance dos modelos MIMO avaliando a saída da pressão e vazão.

Model	**RMSE**	**NRMSE**	**FPE**	**FIT (%)**
ARX	1.11 (0.46)	476e-5 (44.8e-5)	0.0476e-5 (44.8e-5)	22.18 (53.06)
ARMAX	0.91 (0.50)	960e-5 (98.7e-5)	96040e-5 (98.8e-5)	19.00 (39.43)
NF (ANFIS)	0.14 (0.0049)	0.11e-5 (0.10e-5)	333.6e-5 (183e-5)	99.86 (99.99)
RNA	0.13 (0.0054)	0.11e-5 (0.09e-5)	343.1e-5 (192.6e-5)	99.87(99.99)

3.3 Model analysis

The obtained computational models are directed to analysis and simulation, with the objective of developing control strategies and algorithms for operational efficiency, considerably reducing the energy consumption of the pumping system. The development of a model that relates the operating parameters to the energy efficiency of the system results in an effective tool for the energy analysis of the system in different operating scenarios. A surface of the behavior of the WSS can be obtained through the NF computational model (Fig. 6). We show how the interrelation of the input and output variables occurs. The analysis shows the graphical behavior of the system with the change of scenario, and helps to determine safe operating limits. Furthermore, the development of control algorithms, such as open loop or adaptive control, starts from the system model.

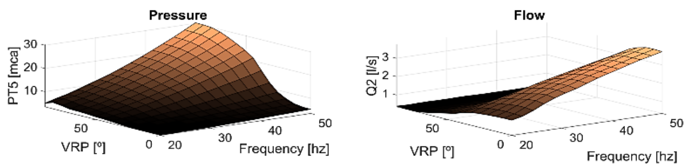

Figure 6. Dynamic response surfaces of WSS.

4 Conclusions

As an alternative to parametric models, which have deficiencies in modeling multivariable systems with nonlinearities, this work proposes the use of ANN and NF to identify a nonlinear and multivariable WSS. Two comparative analyses were conducted with the parametric techniques. Initially, a CMB is identified as a way to demonstrate the ability of parametric models to model systems with few nonlinearities. Subsequently, the CMB is modeled with the addition of a variable (VRP) that adds severe nonlinearities to the model. Only the intelligent models present satisfactory results. The results of the cross-validation with the performance indicators show the superiority of the intelligent models. It is possible to improve the performance of the parametric models by increasing their respective orders, as a consequence, an increase in the computational cost is observed. The analysis of the intelligent models shows that the NF has little superiority in prediction compared to the ANN. This is observed when the objective is simulation, the intelligent models present similar performance. ANN are preferable, because they present lower computational costs. However, they do not allow good interpretability of the dynamic characteristics of the system, which is achieved with NF systems.

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