Available online at www.sciencedirect.com
ScienceDirect
Energy Procedia 82 (2015) 316 – 321
Energy Procedia

ATI 2015 - 70th Conference of the ATI Engineering Association

Assessment of an identification strategy for the prediction of the dynamics of two-phase flows

A. Fichera[a]*, A. Pagano[a]

[a]Dipartimento di Ingegneria Industriale, Universitò degli Studi di Catania

Abstract

The present study aims at assessing a flexible and light modeling methodology specifically oriented to the short-term prediction of the dynamics of the void fraction of experimental two-phase flows. The proposed strategy consists in the assessment and optimisation of a generalised NARMAX model for the input-output identification of the dynamics of the experimental time series of the void fraction, detected through a high resolution resistive probe during an extensive experimental campaign. Such a model has been implemented by means of Multilayer Perceptron artificial neural networks, trained using input-output data detected during experiments expressing different flow patterns. Reported results show that a satisfactory agreement is reached between simulated and experimental data, showing that the model is able to predict two-phase flow dynamics.

Peer-review under responsibility of the Scientific Committee of ATI 2015

Two-phase flow; NARMAX identification strategy; predictive neural model;

1. Introduction

Several basic industrial processes, ranging from power generation, chemical and processing plants to oil pipelines, present heat and mass transfer applications of two phase flows. The type of flow pattern and the transitions among them indeed represent critical factors for the process performances; therefore, great importance is devoted to flow patterns analysis, identification and classification. Referring to the case of two phase flows in pipes, bubbly, slug, churn and annular flows are the main classes of flow patterns reported in typical classifications [1-5].

* Corresponding author. Tel.: +39 0957382450
E-mail address: afichera@dii.unict.it

Peer-review under responsibility of the Scientific Committee of ATI 2015
doi:10.1016/j.egypro.2015.12.039

A main problem in the identification of the flow patterns is represented by the intrinsic nonlinear nature of the dynamics due to the interaction of several complex phenomena.

In [6], preliminary analyses of the experimental time series have shown the existence of strange attractors for some of the flow patterns, such as cap and slug flows, while a deeper insight was shown to be required for the attractors of more complex flow patterns, such as those of churn and annular flows. In consideration of the high resolution of the experimental time series required for an appropriate adoption of nonlinear techniques, in [7] a resistive impedance probe was assessed for the measure of the local void fraction in air-water two-phase flows in vertical pipes, with the aim of achieving high spatial and temporal resolution while reducing the influence of noise and other disturbing phenomena. With the aim of assessing an identification tool based on the topology of the attractor in state space, in [8] the authors proposed a novel approach aiming at reducing the complexity of the attractor structure whilst minimizing the influence of noise-like high order dynamics, such as travelling waves and ripples on the liquid film that envelopes the air flow or dispersed bubbles in aerated liquid slugs. In particular, the basic concept of strategy relies on the technique known as Singular Value Decomposition (SVD) proposed by [9] and shown to be robust and effective in the field of thermal fluid dynamics for the analysis of single-phase liquid flows [10] as well as for gas-liquid [11, 12] and gas-solid [13] two-phase flows.

The present study proposes a preliminary analysis of an identification strategy for the short-term prediction of void fraction time series. In particular, a generalized NARMAX model, i.e. a Nonlinear Auto-Regressive Moving Average with eXogenous input [14-15], is assessed on the basis of input-output experimental measurements. With respect to classical models based on the governing equations expressing the relationship among the variables and the parameters of a given system, which are prone to parameter uncertainty, one of the main advantages of the NARMAX approach consists in the possibility of avoiding an exact determination of model parameters and of their unpredictable variations. Therefore, it may represent a powerful tool when, as a consequence of the nonlinear interactions of involved phenomena, it is not possible to achieve a deep physical knowledge of the process and an exact determination of model parameters. Moreover, a *generalized* form of the NARMAX model can be easily implemented by means of a Multilayer Perceptron, i.e. a neural network trained through a classical back-propagation algorithm. In fact, the great potentiality offered by generalized NARMAX models in terms of predictability of complex nonlinear dynamics in thermal fluid systems were discussed by the authors in several other cases [16-18]. The identification strategy has been applied to the experimental void fraction time series that have already be discussed in [7-8], together with the characteristic of the experimental apparatus which, for brevity is not reported.

2. NARMAX model

Identification strategies of various kind by means of input-output measurements are commonly used in many situations in which it is not necessary to achieve a deep mathematical knowledge of the system under study but it is of interest to predict the time evolution of the system dynamic. This is often the case in diagnostic systems and in control applications, where satisfactory predictions of the system dynamics and sufficient robustness to parameter uncertainty are the main (or unique) requirements. Due to their strongly nonlinear nature, parameter variations and uncertainty play a fundamental role on the dynamics of two-phase flows which, in fact, are very difficult to be modeled with accuracy. Therefore, an identification approach based on input-output measurements indeed represents an interesting reliable option. One way of obtaining the identification of a nonlinear system consists of the characterization of its output at a given instant, y(k), by using a NARMAX model (Nonlinear Auto-Regressive Moving Average with eXogenous inputs) [15], which for SISO (Single Input - Single Output) systems writes:

$$y(k)=F[y(k-1), \ldots, y(k-n_y), u(k-1), \ldots, u(k-n_u)] \quad (1)$$

where $y(\cdot)$ and $u(\cdot)$ are respectively the output and the input at the generic time sample and n_y and n_u are the number of previous steps of the system output and input, respectively, that is necessary to take into account, and which depend on the model order. A NARMAX model in such a form is able to represent a discrete time invariant non-linear system in a region around an equilibrium if the system has lumped parameters and can be described by a linear model in a neighborhood of the equilibrium. A NARMAX model is said to be *generalized* if it is valid for different equilibria and even for piece-wise linear function F. An efficient way for the assessment of a generalized NARMAX model is to take advantage of the potentiality of the Multilayer Perceptron Neural Network [19], which does not require the linearisation around equilibria. In fact, the approximation of the nonlinear function F through combination of sigmoidal functions, as that performed by a neural network, is valid also for piecewise continuous functions. The greater flexibility offered and the wide number of operating conditions detected during the experimental phase (corresponding to different regions of state space) make the neural network approach suitable for the aims of this work.

Concerning the neural architecture, the Multilayer Perceptron is a class of feed-forward network used for function approximation made up by one or more hidden layers interposed between the input and output layers, with each layer formed by simple computing units, called nodes or neurons. For a neural network with n inputs and m outputs, the global input-output relationship is a function $NN{:}R^n \rightarrow R^m$. During the training of the network, the weights w_i connecting the nodes are recursively updated in order to minimize a cost function that, generally speaking, is related or coincides with the prediction error. At the end of training, the function $NN{:}R^n \rightarrow R^m$ is definitely determined. Cybenko demonstrated that NN can uniformly approximate any continuous function $F{:}D \subset R^n \rightarrow R^m$, where D is a compact subset of R^n [20] and this observation ensures that the function F in equation (1) can be approximated by a neural network, so that:

$$y(k) \approx NN[y(k-1), \ldots, y(k-n_y), u(k-1), \ldots, u(k-n_u)] \quad (2)$$

Once that the training of the neural network has been completed it should be ready to simulate the entire set of the system dynamics encompassed by the conditions learned during the training.

In order to validate the model it is necessary to evaluate the properties of the errors that affect the prediction of the outputs of the model. Such an analysis can be accomplished by verifying that the autocorrelation function of the normalised error $\varepsilon(t)$, namely $\phi_{\varepsilon\varepsilon}(t)$, assumes the values 1 for $t=0$ and 0 elsewhere; in other words, it is required to the function to behave as an impulse. This condition is, of course, ideal and in practice it is sufficient to verify that $\phi_{\varepsilon\varepsilon}(t)$ falls in a confidence band usually fixed at the 95%, i.e. $\phi_{\varepsilon\varepsilon}(t)$ should remain within the range $1.96 \cdot N^{-0.5}$, with N delimiting the window of data on which $\phi_{\varepsilon\varepsilon}(t)$ is observed [21].

The aim of this paper was to predict the dynamical behavior of the void fraction time series under different air and water mass flow rates, determining, in particular, different flow structures; therefore, the structure of the neural model was chosen accordingly, considering, in particular, the lack of preliminary knowledge on the order of the system dynamics. This lead to choose the strategy of creating an entire family of neural networks implementing generalized NARMAX models with order n_y growing from 3 to 11. Such a strategy allows also for the identification of the order of the system dynamics, which can be assumed to correspond to that of the model with the best prediction performance, i.e. that with optimal characteristics of the error. Therefore the structure of the NARMAX model can be described as:

$$[vf(k)] = F\,[vf(k-1), vf(k-2), \ldots, vf(k-n_y)] \quad (3)$$

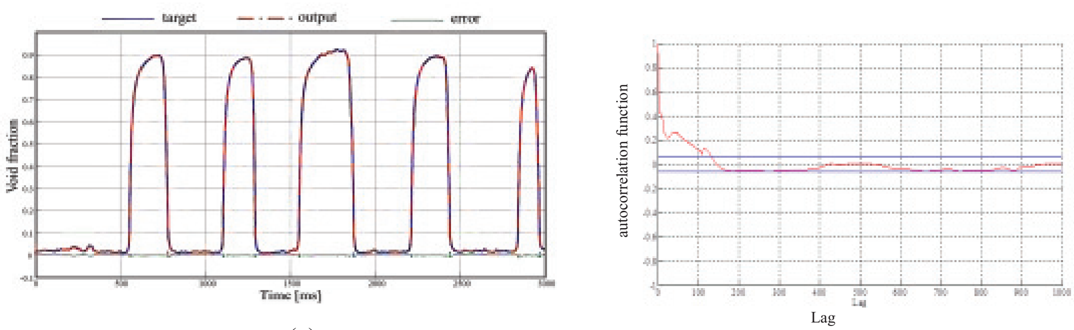
where the $vf(k)$ represents the measured void fraction at time step k, i.e. the output of the system that the model aims at predicting. For each model order, a family of three-layered neural networks has been trained. The input layer contains a number of neurons corresponding to the n_y arguments of $F(.)$, which are fed by the instantaneous variables comparing in the right hand side of equation (3) and do not perform any transformation of their values; they are connected to the neurons of the unique hidden layer of nonlinear neurons, performing an input-output transformation following the tangent-sigmoid function and, then, feed the output layer, with only one neuron, i.e. the model prediction in the left-hand side of equation (3), which transforms its input according to the pure-line function. Within the family of neural networks implemented for each order of the NARMAX model, the number of neurons of the hidden layer has been progressively increased until the network with optimal prediction performance (within the specific family) has been found.

The neural models were trained using the Levenberg–Marquardt rule [22] and feeding it in batching, in order to ensure higher training performances. The number of epochs varied from network to network because the training was performed testing contemporary the neural network with a checking data set, in order to validate the training and to avoid over-fitting.

For each model order, n_y, the training set was created with input vectors corresponding to a piece of the void fraction time series encompassing n_y time steps, being the output the one-step ahead value of the time series. In particular, the training vectors were created extracting three separated pieces of 1000 samples from the void fraction time series, chosen with the aim of describing different waveforms expressing the most recurrent patterns within the time series, for 27 experimental conditions over the entire set of observed conditions in order to span the entire set of experimental conditions reported in [7]. Each piece of time series was preliminary decimated considering 1 out of 3 data, for an actual length of 333 data, in order to account for the dominant patterns of the system dynamics while reducing the dimension of the data set and suppressing high-frequency noisy components. Both testing and checking data sets were created analogously to the training set but within the entire set of experimental conditions so as to ensure an appropriate evaluation of the generalization capability of the NARMAX model in the prediction of conditions not learned during the training.

3. Results and discussion

The neural network was made of three layers, in particular 11 neurons the 6th model order ensured the lowest error (both in terms of the mean value, very close to zero, and of the mean absolute value).



(a) (b)

Fig. 1. (a) Comparison between the experimental time series and the neural network prediction; (b) autocorrelation function of the prediction error.

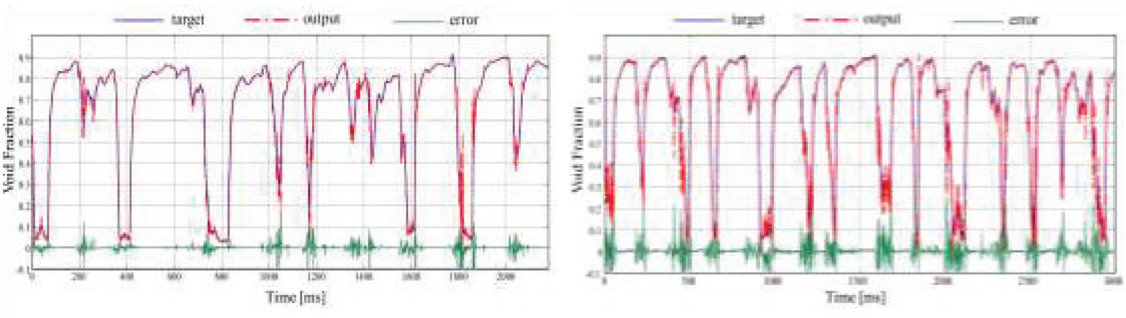
Fig. 1 shows the comparison between the experimental time series of void fraction and the corresponding neural network prediction in testing for operating condition 7, slug flow, (air flow =4 l/min, water mass flow = 3.7 l/min). The plot on the right of the same figure reports the autocorrelation function, $\phi_{\varepsilon\varepsilon}(t)$, of the prediction error for the same data. Both these plots evidence that the neural network predictions are satisfactory and indicate that the training was sufficiently wide and ensured adequate generalisation properties. The satisfactory correspondence between experimental and simulated data was obtained for the whole set of operating conditions considered in this study, whose results were perfectly consistent with those presented in Fig. 1.

The neural model was recursively used in order to verify its ability to autonomously describe the time evolution of the void fraction, feeding the neural model with its own predictions from previous steps.
In Figure 2 comparisons between the actual output and the 3 and 6 steps ahead predictions are respectively reported. It must be noticed that for $q=3$ (corresponding to a prediction step of 9 ms) the simulated time series satisfactory approximates the experimental data. For $q=6$ (prediction steps of 18 ms) the approximation is, as expected, progressively worsened. Nevertheless, the model is still able to reveal the occurrence of the dominant patterns of the oscillations of the void fraction time series and, therefore, can be used to extend the prediction capability. In particular, it must be noticed that the quality of the prediction is worsened with respect to low amplitude oscillations but remains in the overall satisfactorily for the high amplitude patterns; these are of course good news in view of the design of a predictive tool based on the neural network, as high amplitudes of the void fraction can be in general associated to the fundamental characteristic of the flow patterns. Indeed, this observation is useful also to point out that the optimal choice for the number of recursive predictions, q, depend on the specific application of the predictive model.

Conclusions

This paper aimed at assessing a flexible and light modeling methodology specifically oriented to the short-term prediction of the dynamics of the void fraction of experimental two-phase flows. This represents the first step towards the design of a predictive tool based on the neural network of the global structure of the flow pattern for given input conditions of the mass flow rate of the two phases. The input-output identification of the dynamics of the experimental time series of the void fraction, detected through a high resolution resistive probe during an extensive experimental campaign, has been obtained through a generalized NARMAX model. Such a model has been implemented by means of Multilayer Perceptron artificial neural networks, trained using input-output expressing different flow patterns. Results of the simulations show that the model is able to give a satisfactory description of the experimental data.

Moreover, the developed neural model was used in a recursive scheme in order to test its ability to perform wider term predictions. In fact, though predictive capabilities are limited to a few steps ahead, the length of satisfying predictions is indeed adequate for the implementation of the neural model in a more complex predictive scheme, which ensures wider prediction opportunities.



(a) (b)

Fig. 2 Simulated and actual output of the void fraction for prediction steps (a) $q = 3$ and (b) $q=6$.

References

[1] Dukler AE, Hubbard MG. The characterization of flow regimes for horizontal two phase flow. Proc Heat Transfer Fluid Mech Inst 1966, **1**:100–121.
[2] Jones OC, Zuber N. The interrelation between void fraction fluctuations and flow patterns in two phase flow. Int J Multiph Flow 1975, **2**: 273–306.
[3] Costigan G, Whalley PB. Slug flow regime identification from dynamic void fraction measurement in vertical air–water flows. Int J Multiph Flow 1997, **23**: 263–282.
[4] Mi Y, Ishii M, Tsoukalas LH. Vertical two-phase flow identification using advanced instrumentation and neural networks. Nucl Eng Design 1998, **184**: 409–420.
[5] Qi FS, Yeoh GH, Cheung SCP, Tu JY, Krepper E, Lucas D. Classification of bubbles in vertical gas–liquid flow: Part 1 – an analysis of experimental data. Int J Multiph Flow 2012, **39**: 121–134.
[6] Cantelli L, Fichera A, Guglielmino ID, Pagano A. Non-Linear Dynamics of Air-Water Mixtures in Vertical Pipes: Experimental Trends. Int J Bifurc Chaos 2006, **16-9**: 2749-2760.
[7] Cantelli L, Fichera A, Pagano A. A high-resolution resistive probe for nonlinear analysis of two-phase flows. J Thermodynamics 2011, **2011**: paper 491350, p. 10.
[8] Fichera A, Pagano A. A dynamics-based tool for the analysis of experimental two-phase flows. Int J Heat Fluid Flow 2013, **44**: 735-744.
[9] Broomhead DS, King GP. Extracting Qualitative Dynamics from Experimental Data. Physica D 1986, **20**: 217-236.
[10] Cammarata G, Fichera A, Pagano A. Nonlinear analysis of a rectangular natural circulation loop. Int Comm Heat Mass Transfer 2000, **27 (8)**: 1077-1089.
[11] Drahos J, Tihon J, Serio C, Lubbert A. Deterministic chaos analysis of pressure fluctuations in a horizontal pipe at intermittent flow regime. Chem Eng J 1996, **64**: 149–156.
[12] Ajbar A, Al-Masry W, Ali E, Prediction of flow regimes transitions in bubble columns using passive acoustic measurements. Chem Engineering and Processing 2009, **48**: 101-110.
[13] Stuart Daw C, Lawkins WF, Downing DJ, Clapp NE. Chaotic characteristics of a complex gas-solids flow. Physical Review A 1990, **41(2)**: 1179-1181.
[14] Narendra KS, Parthasarathy K. Identification and control of dynamical systems using neural networks. IEEE Trans Neural Networks 1990, **1(1)**: 4–21.
[15] Chen S, Billings SA, Grant PM. Representations of non-linear system: the NARMAX model. Int J Control 1989, **49(5)**:1013–32.
[16] Fichera A, Pagano A. Neural network-based prediction of the oscillating behaviour of a closed loop thermosyphon. Int J Heat Mass Transfer 2002, **45**: 3875-3884.
[17] Cammarata L, Fichera A, Pagano A. Neural prediction of combustion instability. Applied Energy 2002, **72**: 513-528.
[18] Biserni C, Fichera A, Guglielmino ID, Lorenzini E, Pagano A. A non-linear approach for the analysis and modelling of the dynamics of systems exhibiting Vapotron effect. Int J Heat Mass Ctransfer 2006, **49**: 1264-1273.
[19] Chen S, Billings SA, Grant PM. Non-linear system identification using neural networks. Int J Control 1990, **51(6)**: 1191–214.
[20] Cybenko G. Approximation by superpositions of a sigmoidal function. Math Control, Signals and Systems 1989; **2**: 303–14.
[21] Billings SA, Jamaluddin HB, Chen S. Correlation based model validity tests for non-linear models. Int J Control 1986; **44**: 235–44.
[22] Boggs PT, Byrd RH, Schnabel RB. A stable and efficient algorithm for non-linear orthogonal distance regression. SIAM J Sci Stat Comp 1987; **8**: 1052–1078.

Biography

Alberto Fichera is full professor of "Fisica Tecnica Industriale" at the University of Catania (Italy), he is the Coordinator of the Master of Degree of Management Engineering. He teaches Energy Management at University of Catania. He is author of about 160 papers published in various reviewed journals and proceedings conferences