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A new MIMO ANFIS-PSO based NARMA-L2 controller for nonlinear dynamic systems

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ABSTRACT

The proposal of this study is a new nonlinear autoregressive moving average, NARMA-L2 controller, which is based on an adaptive neuro-fuzzy inference system, ANFIS architecture. The new control configuration employs Sugeno-type fuzzy inference system FIS submodels to map input characteristics to the output of a dynamic and nonlinear system. The commonly used learning algorithm, which is called a hybrid method (Backpropagation and Least Square Error), has been carried out as well as particle swarm optimisation (PSO) approach, in order to select the optimal parameters of the ANFIS submodels. Once the system has been modelled efficiently and accurately, the proposed controller is designed by rearranging the generalised submodels. The controller performance is evaluated by simulations conducted on a binary distillation column, which is characterised by a nonlinear and dynamic behaviour. The obtained results show that the PSO-ANFIS based NARMA-L2 achieved more efficient modelling and control performances when compared with other controllers. These controllers include ANN-based NARMA-L2, (PD, PI and PID like) fuzzy-tuned by GA and PSO and traditional PID, which are also implemented to the column for comparison. Stability and robustness of the proposed controller regarding system inputs variance have also been tested by applying asynchronous setpoints of both inputs of the process.

1. Introduction

As a result of the worldwide ambition for more reliable attainment of high product quality, more efficient use of energy, tighter safety, and environmental regulations, industrial processes have evolved over recent years into very complex, highly nonlinear and integrated systems (Ogunnaike, 1994).

Rigorous demands like these naturally lead to more difficult and challenging control problems for today's industrial control engineers; problems requiring more efficient solutions than can be achieved by only conventional techniques. It also required inter- and cross-disciplinary research, development, as well as collaboration in both industry and academia. Cooperation between control and other disciplines has been consistently fruitful (Samad and Annaswamy, 2011).

A big drive has been seen in the academic community to design new control systems, either by traditional or contemporary methods. Introducing an intelligent control system can be the key factor in improving performance as well as deal better with challengeable features of nonlinear and complex processes, although linear-based control systems are frequently used. In general, reasonable performance is attained over a narrow operating range, however, when a wide range of process tasks is a prerequisite, the nonlinearities become more critical, and the control performance is sacrificed (Mahfouf et al., 2002).

Intelligence based methods emerged two decades ago to act as an effective solution in many applications; several comprehensive reviews had been written showing that its importance and widespread applications (Gani et al., 2016; Precup and Hellendoorn, 2011; Chandrasekaran et al., 2010). From a control viewpoint, when nonlinearity, uncertainty or control difficulties as a result of dynamic behaviour, which may bring severe complications to analysis and synthesis. Artificial Neural Networks (ANNs) and Fuzzy Logic (FL) are employed considerably in order to deal with such challenges. One of the strongest arguments for the use of intelligence-based controllers is their ability to exploit the tolerances for uncertainty and nonlinearity, in order to achieve robustness and controllability, as well to being affordable solutions (Precup and Hellendoorn, 2011). In addition, many intelligent-hybrid approaches have been innovated to provide an efficient solution to widespread problems (Shamshirband et al., 2014; Caraveo et al., 2016; Amador-Angulo et al., 2016).

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Advances in computer science and electronic technologies have facilitated control engineers to apply intelligent-based controllers due to (Samad and Balas, 2003):

1. Design and implementation of electronic circuits with a powerful performance with information processing.
2. Significant development in simulation platforms and computer-aided software that enables control designers to build and further design various efficient configurations of control as well as process systems.

In 1974, Mamdani first applied fuzzy based controllers for laboratory-scale steam engines (Mamdani, 1974), a year after his work with Assilian (Mamdani and Assilian, 1975) had proved the superiority of fuzzy based controllers over the fixed based controllers on DDC algorithms. Later on, the process control designers extended Mamdani's innovative work in order to design and implement various control systems to deal more efficiently with a different application of more complex real-world processes. The so-called 'Mamdani fuzzy model' was reported as intuitive with a widespread acceptance inference system. Around a decade later, Takagi and Sugeno proposed another fuzzy model that could map any smooth, nonlinear function to any prescribed precision, within any compact set. This model is presented by a set of fuzzy 'IF–THEN' rules. The rules of the so-called Takagi–Sugeno (T–S), fuzzy model characterise the local linear input–output relationships of any nonlinear system. When this proposed fuzzy model is applied, it gave a reasonable performance in a water cleaning process, as well as a converter in a steel-making process (Takagi and Sugeno, 1985). Both the Mamdani and T-S models have been successfully implemented in various applications. Comprehensive reviews have been written about Fuzzy controllers; types, effectiveness applications (Precup and Hellendoorn, 2011; Tai et al., 2016).

Neural networks have also a remarkable approximation ability that has inspired many researchers to propose a new controller that can use the prediction performance of those networks in control configurations. One of the most remarkable configurations is nonlinear autoregressive moving average technique, NARMA-L2, proposed by Narendra and Mukhopadhyay (1997) by introducing an efficient solution to the problems that cause slow performance of backpropagation training algorithms. The main idea of the NARMA-L2 controller is using approximate models that represent a dynamic process, by training ANN offline and then designing the NARMA-L2 controller by rearranging the trained ANN model. The obvious advantage of the NARMA-L2 controller is that it does not require an additional submodel to be trained, as is required in other neuro-controllers, such as Model Reference Adaptive Control, MRAC, and Model Predictive Controller, MPC (De Jesus et al., 2001).

More recently, other new controllers have been proposed and applied in different fields. Some contributions are referred to in the following by Piltan et al. (2011), who proposed and implemented a SISO fuzzy estimating sliding mode controller on a robot manipulator, Particle swarm optimisation PSO, used as an optimisation tool to adjust the sliding function. Valikhani and Sourkounis (2014) used a novel control method based on an emotional decision-making process, which occurs in mammalian brains. The so-called brain emotional learning-based intelligent controllers, BELBIC, are applied to control twice-fed induction generator used in wind turbine systems. Shen et al. (2014) introduced a new adaptive solution to neural tracking control problems by proposing a novel neural control for a class of uncertain pure-feedback nonlinear systems.

NARMA-L2 based controllers have been recently gaining enormous interest amongst researchers in different areas. Necsulescu et al. (2007) designed a MIMO NARMA-L2 controller, together with output redefinition techniques for controlling the flight of an unmanned aerial vehicle, UAV. The results showed a good and stable performance of the proposed controller. Fourati et al. (2015) controlled a bioreactor with an NARMA-L2 controller and proved that the trajectory tracking performance obtained was better than with the use of the inverse neural model controller. Valluru et al. (2012) implemented NARMA-L2 controller on a series of DC motors, in order to regulate speed. The performance index of the proposed controller outperformed a PID controller. Uçak and Günel (2016) proposed a novel NARMA-L2 controller based on online Support Vector Regression, SVR. The proposed controller was tested on a bioreactor system, its performance compared with a PID controller. Jalil and Darus (2013) used an NARMA-L2 to control the vibration of a flexible beam structure, with non-collocated sensor-actuator placement.

This study proposes a new design of MIMO NARMA-L2 controller, based on FIS approximation submodels at the identification of the process to be controlled. ANFIS configuration is used into the FIS submodels and trained separately by a hybrid method (Bp-LSE) and Particle Swarm Optimisation, to find the optimal parameters of the FISs. This proposed controller has been implemented, followed by testing on a binary distillation column, which exhibits nonlinear and dynamic behaviour.

2. Distillation modelling

2.1. Process description

Oil refineries, as well as other chemical and petrochemical plants, widely use the process of distillation. The chemical compounds in a mixture are separated into their individual component chemicals using distillation columns. These types of columns operate extensively in the petroleum, natural gas, liquid and chemical industries (Smith, 2012). However, the process utilised in these columns is very energy intensive columns. The Department of Energy in the USA published a report and showing that distillation columns are the largest consumers of energy in the chemical industry. Typically, they account for 40% of the energy consumed by all petrochemical plants. Even with this high energy consumption, distillation is still widely utilised for this separation and purification method (Luyben, 2013).

Fig. 1 shows the schematic diagram of a binary distillation column. The feed mixture is separated into two products; one is a distillate or overhead, and the other is the bottom product. Heat is supplied to the column via a reboiler, in order to vaporise the liquid in the base of the column. The vapour goes up through trays inside the column to reach the top. The vapour then liquefies in the condenser. Liquid from the condenser drops into the reflux drum. Finally, the some of the distillate product is removed from this drum as a pure product. The rest of the liquid is fed back near the top of the column as reflux, while another product is produced at the bottom.

2.2. Model representation

The modelling and simulation of the binary distillation column used in this study is based on Luyben model (Luyben, 1999, 2013) with the following considerations:

1) No chemical reactions occur inside the column
2) There is constant pressure
3) Binary mixture
4) Constant relative volatility
5) No vapour hold-up occurs in any stages
6) Constant hold-up liquid at all trays
7) Perfect mixing and equilibrium for vapour-liquid at all stages

Hereafter, the mathematical equations of the model can be written per stage by as following:

On each tray (excluding reboiler, feed and condenser stages):