MODELLING AND CONTROL OF A PNEUMATIC MOTOR USING NEURAL NETWORKS

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Abstract

A considerable amount of interest has been shown by researchers in the control of pneumatic drives over the past decade, for two main reasons, firstly, the response is very slow and the inability to attain set points is high due to hystiresis and secondly, the dynamic model of the system is highly non-linear, which greatly complicates controller design and development. To address these problems, two streams of research efforts have evolved; (i) using conventional methods to develop a modelling and control strategy, (ii) adopting a strategy that does not require mathematical model of the system.

This paper presents an investigation into the modelling and control of an air motor incorporating a pneumatic equivalent of the electric H-bridge. The pneumatic H-bridge has been devised for speed and direction control of the motor. The system is divided into three regions called low speed, medium speed and high speed. The system is highly nonlinear in the low speed region. Linear parametric models characterising the two linearised operating regions (medium and high speed) of the motor are developed using parametric estimation techniques and local controllers are developed using a pole-assignment design. A neuro-model and controller are

developed for the low speed region. A gain scheduling strategy is devised for controlling the system in the three regions.

1. Introduction

Industrial processes, is in general, require objects to be moved, manipulated or subjected to some force. The use of electrical equipment, such as DC motors, or mechanical equipment via devices driven by air (pneumatics) or liquids (hydraulics) normally achieves these tasks.

Air motors are compact, lightweight sources of smooth vibration-less power. They start and stop almost instantly, and are unaffected by continuous stalling or overload, and thus are suitable for intermittent operation. Air motors are relatively cheap, easy to maintain, and have the versatility of variable speed, high starting torque, are intrinsically safe in hazardous areas, and will operate in exceptionally bad environments [**3, 7, 10 & 15]**. Some of the advantages of air motors over electric motors include the following [**3]**:

- Since air motors do not require electric power, they can be used in volatile atmospheres.
- Air motors generally have high power density, so a smaller air motor can deliver the same power as its electrical counterpart.
- Unlike electric motors, many air motors can operate without the need for auxiliary speed reducers.
- Overloads that exceed stall torque generally cause no harm to air motors. With the electric motor, overloads can trip circuit breakers, so an operator must reset them before restarting the equipment.
- In contrast to electric motors, which utilise expensive and complicated speed controls, speed of an air motor can be regulated through simple flow-control valves.
- The motor torque can vary simply by regulating the input pressure.

- Air motors do not need magnetic starters, overload protection, or the host of other support components required by electric motors, and
- Air motors generate much less heat than electric motors.

Section 2 provides a brief description of the experimental set up utilised in this study. Section 3 briefly describes the modelling approach. Section 4 discusses the implementation of the control strategy and presents experimental assessment of the performance of the control strategy. The paper is concluded in section 5.

2. System set up

The control system for the air motor is shown schematically in Figure 2.1. The computer (PC) with the auxiliary hardware is used to source out and read all plant devices. All electrical devices are externally powered.

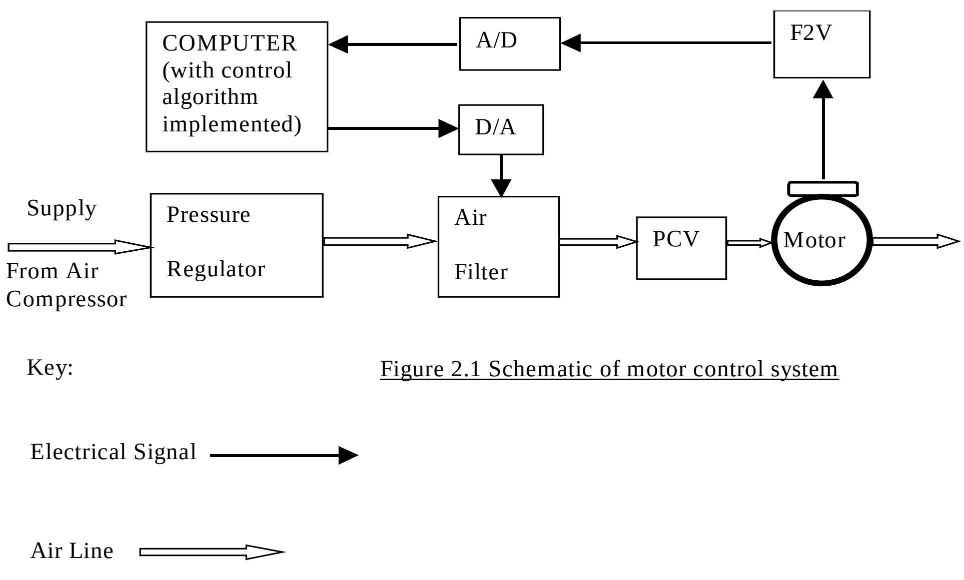


Figure 2.1 Schematic of motor control system

Coding the control algorithm is straightforward. However, it is always advisable to consider factors such as realisation, actuator nonlinearities and computational delay to minimise controller sensitiveness to errors.

3. Modelling approach

A black box identification approach was adopted for modelling the system. This involved several tests using data obtained from a speed of 0 to 380 rev/min, termed the un-identified speed region using neural networks. There are number of nonlinear models that are potentially suited to this problem. In this investigation, a nonlinear autoregressive model with exogenous inputs [NARX] **[8]**, which provides a concise representation of a wide class of non-linear systems, is employed. The NARX models are also referred to in the literature by various other names such as one-step-ahead predictor or as series-parallel model.

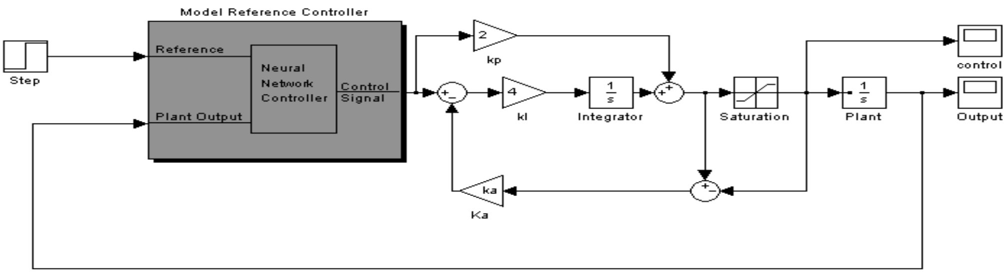


Figure 3.1 Neural network and simulink schematic of air motor control system

Many control system outputs of the actuator can saturate. This is because the dynamics of the real actuator are limited, for an air motor valve will saturate when it is fully opened or closed. The solution to this problem is the integrator windup, circuit which turns off the integral action when the actuator saturates. The PI controller method is easier to implement as it does not require a separate nonlinearity but uses the saturation itself. The effect of the anti-windup is to reduce the overshoot and the control effect on the feedback. It’s omission may lead to distortion in response in practical systems.

3.1 Neuro PI controller of the air motor

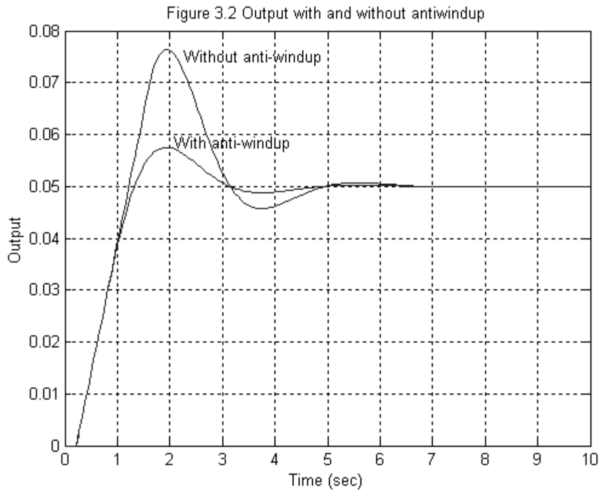
The air motor system has been identified and modelled from real input/ output data using neural networks. The system output model was found to fall within ±0.05. This means that the system's nonlinear PI controller must be limited within this range. The anit-wndup PI controller is implemented using standard transfer function for the plant.

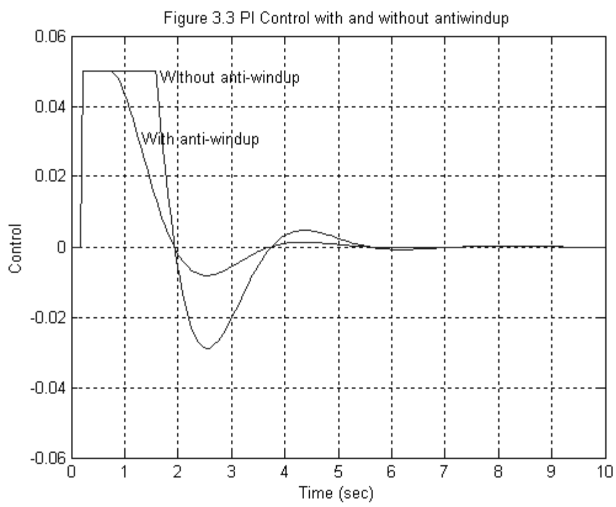
$$G(s) = \frac{1}{s}$$

and a PI controller would be

$$D_c = k_p + \frac{k_I}{s} = 2 + \frac{4}{s}$$

The simulink presentation of the system is shown in figure 3.1 and system's output and control effect in figures 3.2 and 3.3 respectfully





The main features of NARX identification with neural networks are symbolically indicated in Figure 3.4.

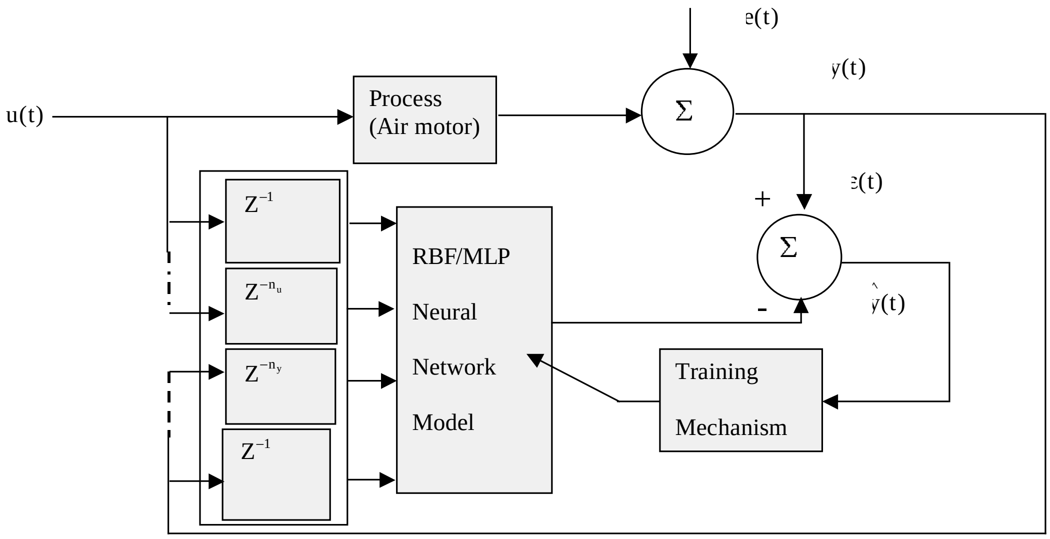


Figure 3.4 NARX model identification with neural networks

The mathematical non-linear model is of the form:

$$y(t) = f\{y(t-1),\cdots y(t-n_y), u(t-1)\cdots u(t-n_u)\} + e(t) \qquad (3.1)$$

where $y(t)$ is the output, $u(t)$ is the input and $e(t)$ accounts for the uncertainties such as possible noise, unmodelled dynamics and n_y, n_u are the maximum lags in the output and input respectively. The $e(t)$ term is assumed to be a zero mean white noise sequence and $f(\bullet)$ is some vector valued non-linear function of $y(t)$ and $u(t)$ respectively.

If the model is good enough to identify the system without incorporating the noise term or considering the noise as an additive at the output, the model can be represented as a NARX form **[9 & 17]**. The system's noise term $(e(t))$ can be replaced by the prediction error or residual ($\varepsilon(t)$) term and equation (1) can then be re-written as:

$$y(t)=f\{y(t-1),\cdots y(t-n_y),u(t-1)\cdots u(t-n_u)\}+e(t) \tag{3.2}$$

where the residual is defined as:

$$\varepsilon(t)=y(t)-\hat{y}(t) \tag{3.3}$$

$\hat{y}(t)$ is the model-predicted output.

4. Implementation

Other models to identify the linear operating region of the system were obtained with speed ranging from 385 to 680. These speeds were divided into: 385 to 543, medium speed and 543 to 680 rev/min, high speed. Speeds below 385 are regarded as low speed region and are identified using neural networks. Accordingly, the auto-regressive moving average with exogenous input (ARMAX) type model was used to characterise the medium speed and high speed and operating regions of the system. This is given as:

$$\mathrm{A}(\mathrm{z}^{-1})\mathrm{y}(\mathrm{t})=\mathrm{z}^{-\mathrm{k}}\mathrm{B}(\mathrm{z}^{-1})\mathrm{u}(\mathrm{t})+\mathrm{C}(\mathrm{z}^{-1})\varsigma(\mathrm{t}) \tag{4.1}$$

where

$$\mathrm{A}(\mathrm{z}^{-1})=1+\mathrm{a}_1\mathrm{z}^{-1}+\ldots+\mathrm{a}_{\mathrm{n}_\mathrm{a}}\mathrm{z}^{-\mathrm{n}_\mathrm{a}}$$

$$\mathrm{B}(\mathrm{z}^{-1})=\mathrm{b}_1+\mathrm{b}_2\mathrm{z}^{-1}+\ldots+\mathrm{b}_{\mathrm{n}_\mathrm{b}}\mathrm{z}^{-\mathrm{n}_\mathrm{b}+1}$$

$$\mathrm{C}(\mathrm{z}^{-1})=1+\mathrm{c}_1\mathrm{z}^{-1}+\ldots+\mathrm{a}_{\mathrm{nc}}\mathrm{z}^{-\mathrm{n}_\mathrm{c}}$$

$\mathrm{z}^{-\mathrm{k}}$ represents the system delay, and $\mathrm{u}(\mathrm{t})$, $\mathrm{y}(\mathrm{t})$ and $\varsigma(\mathrm{t})$ represent the system input, output and zero-mean white noise signals.

To estimate parameters of the model in equation (4), a least squares (LS) algorithm is utilised **[16]**. A pseudo-random binary sequence (PRBS) input signal is used to excite the system and 1000 input/output data points are collected for estimation of the model parameters. To ensure that the model is an adequate representation of the characteristics of the system, it is validated through a number of tests. These include:

- *Significance of parameters*: An estimated parameter is significant if it is greater in magnitude than its corresponding standard deviation.
- *Correlation tests*: For a model to be acceptable, the auto-correlation of the residuals is required to be white. Moreover, the cross-correlation between the input sequence and a white noise sequence should be zero. The approximate 95% confidence interval at $\pm 1.96/\mathrm{N}$, where N represents the number of data points, can be used to test this.

  Estimation and test set: Divide the data into estimation set and test set, where the model is estimated with a set of data and then tested over a different set of data.

The above five tests as defined by equations (4.2-4.6) should be satisfied if the $u(\bullet)$'s and $y(\bullet)$'s are used as network input nodes.

$$\phi_{\varepsilon\varepsilon}(\tau) = \mathrm{E}[\varepsilon(t-\tau)\varepsilon(t)] = \delta(\tau) \tag{4.2}$$

$$\phi_{u\varepsilon}(\tau) = \mathrm{E}[u(t-\tau)\varepsilon(t)] = 0 \qquad \forall\tau \tag{4.3}$$

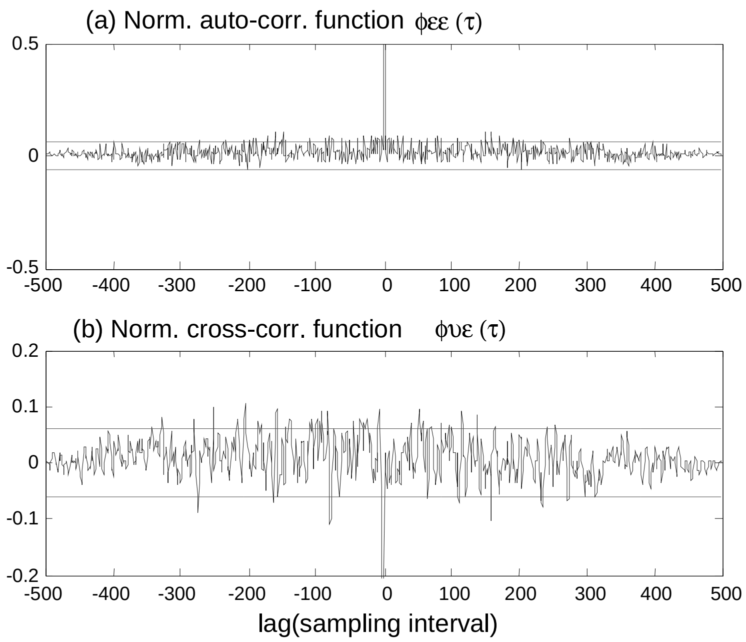
$$\phi_{u^2\varepsilon}(\tau) = \mathrm{E}\left[\left(u^2(t-\tau) - u^{-2}(t)\right)\varepsilon(t)\right] = 0 \qquad \forall\tau \tag{4.4}$$

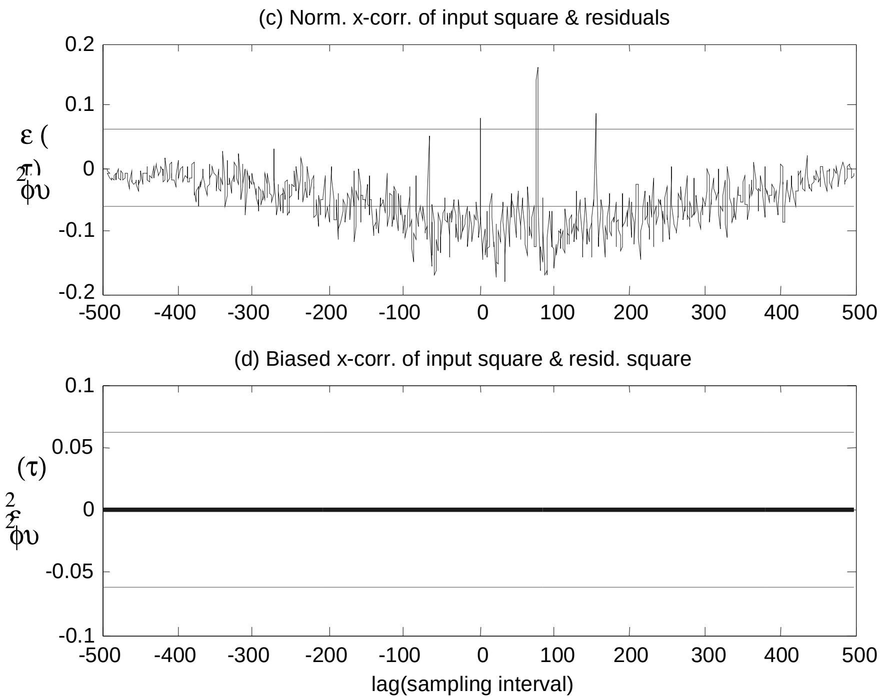
$$\phi_{u^2\varepsilon^2}(\tau) = \mathrm{E}\left[\left(u^2(t-\tau) - u^{-2}(t)\right)\varepsilon^2(t)\right] = 0 \qquad \forall\tau \tag{4.5}$$

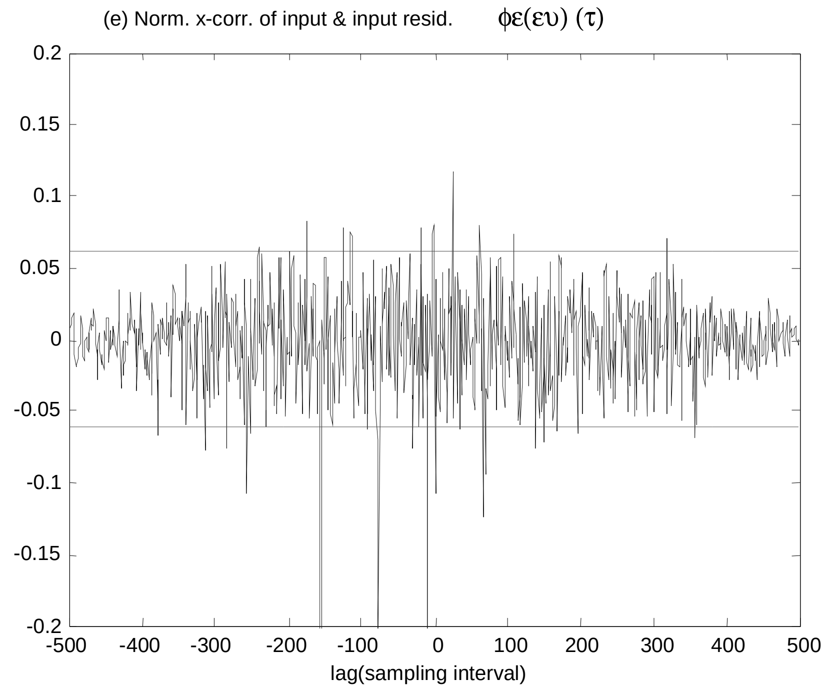
$$\phi_{\varepsilon(\varepsilon u)}(\tau) = \mathrm{E}[\varepsilon(t)\varepsilon(t-1-\tau)u(t-1-\tau)] = 0 \qquad \tau \geq 0 \tag{4.6}$$

where $\phi_{u\varepsilon}(\tau)$ indicates the cross-correlation function between $u(t)$ and $\varepsilon(t)$, $\varepsilon u(t) = \varepsilon(t+1)u(t+1)$, and $\delta(t)$ is an impulse function.

The first two tests were adequate to test the model validity in the case of linear modelling but not sufficient to validate nonlinear models. As a result of this, higher order correlation tests are also included since this study is about a non-linear model. The above five tests as defined by equations (4.2-4.6) should be satisfied if the $u(\bullet)$'s and $y(\bullet)$'s are used as network input nodes.







5. Conclusion

An investigation into real-time modelling and control of a radial piston type air motor has been presented. The air motor has been characterised by local models corresponding to the low-speed, medium speed and high-speed operating regions. Linear parametric models of the system have been obtained and validated using the least square parameter estimation algorithm. Neural networks have been used to model the low speed section of the system.

A gain scheduling control strategy has been adopted for the system. Local controllers for the medium speed and high-speed operating regions of the system have been designed using a pole-assignment design approach. The set point and command tracking ability of the local controllers have been evaluated and verified within simulation studies as well as experimentally. It has been shown that each controller performs to a satisfactory level. Furthermore, the switching ability of the scheduler has been demonstrated and it has been shown that the scheduler selects the correct local controller for an operating region and smooth transition between the three local controllers is achieved.

It has been demonstrated that speed regulation of the air motor can be achieved with the pneumatic H-bridge in real-time. It has been noted that the motor characteristics incorporate hysteresis at the low-speed region. Accordingly, the performance of the devised linear control method at the lower set points in the low-speed region has not been as good as for medium and higher speeds. Future research, using adaptive neuro-fuzzy control will investigate this aspect.

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