MODELLING AND SIMULATION OF AN AIR MOTOR SYSTEM USING EXTENDED RADIAL BASIS ALGORITHM

Rapelang Marumo[1] and M. O. Tokhi[2]
[1]University of Botswana
Department of Mechanical Engineering
Private Bag UB0061, Gaborone. Botswana
Email: marumorr@mopipi.ub.bw
[2]The University of Sheffield
Department of Automatic Control & Systems Engineering
Mappin Street. Sheffield. UK

This article proposes a new modelling scheme using extended radial basis function (RBF) and adaptive neuro-fuzzy filter for handling nonlinear uncertainties of an air motor servo valve. This model combines the fast model development ability of RBF and the adaptation capability of adaptive neuro-fuzzy inference system (ANFIS) used instead of the well known conventional modelling techniques. The ANFIS structure provided parameter partitioning and better performance under transient response to handle the problem of disturbance attenuation. The pneumatic H-bridge, characterising a pneumatic servo valve has been devised for speed and direction control of the motor and the system characteristics conveniently divided into three main regions; of low speed (below 390 rev/min), medium speed (390 to 540 rev/min) and high speed (540 to 680 rev/min). The system is highly non-linear in the low speed region and hence the need to use an adaptive intelligent based modelling technique arises. Simulation results has proven that for an air motor system with uncertainty and perturbed noise, the RBF-ANFIS model scheme performed well and out past its conventional counterpart by far.

Keywords: Identification, Simulation Modelling Radial Basis Function, Pneumatic Valve

1   INTRODUCTION

The nonlinear friction, especially the friction behaviour at velocity reversal, is a big obstacle for high precision motion model and control of a pneumatic actuator system. Thus, the dynamic model structure for friction compensation is necessary. The valve nonlinearities are complicated and it is necessary to consider their integral nonlinear effect. The term conventional control is used to refer to theories and methods that were developed in the past decades to control dynamical systems, primarily described by differential difference equations and mainly used PID controllers. In fact, it is well known that there are control problems that cannot be adequately formulated and studied in the form of differential equations. To address these problems in a systematic way led researchers to develop a number of methods that are collectively known as intelligent control methodologies. In this context, the term intelligent control has come to mean some form of control using fuzzy logic, neural network and/or genetic algorithm methodologies. However, intelligent modelling does not restrict itself only to those methodologies. Research into intelligent modelling incorporates and integrates different techniques and concepts from different disciplines including identification, modelling and simulation theory, computer science and cybernetics.

1.1   Conventional Modelling Techniques

In this investigation, parametric identification of the air motor system with simple least squares and recursive least squares techniques is considered. The experiments involve development of plant model, predicted model, computation of error between the plant model and the predicted model and analysis of correlation function tests.

1.2   Simple Least Squares in the Low Speed Region

Fig. 1 shows the actual and predicted response of the system at low speed, and Fig.2 shows the corresponding output error.
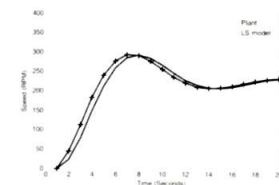

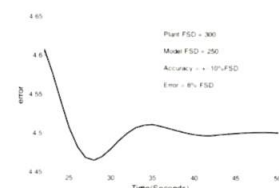Figure 1: Response of low speed data to simple least squares

Figure 2: Error between actual and predicted output

Linear least squares or simple least square is a conventional method, which finds the line

minimising the sum of the squared distance between the observed points and the fitted line. This method of fitting ensures that the estimates of the slope and the intercept parameters of the model have some desirable statistical properties. The experiment involves using the MATLAB program that loads in data that contains the inputs and outputs the air motor system. Using this data, the system model can be estimated. The best mean-squared error level of 0.02222505 was achieved. The order of the system can be approximated to be about 2 or 3. Using this original data, the system can be estimated. By using training and test data, auto correlation function results were observed to be white. The simplest model that showed the best fit was an ARMAX model with and or $\text{ARMAX}(2\ 2\ 1\ 1)$.

1.3   Recursive Least Squares in the Low Speed Region

In this section, the MATLAB program was used again to load the input-output data and run it using RLS algorithm. The objective is to look for the minimum value of the integral absolute errors. The concept of this approach is to plot the actual and the predicted output and see how the parameters converge within RLS algorithm. Main parameters are the system's input-output data, the forgetting factor and the covariance matrix. The algorithm is developed from the following pseudo codes:

$$P = P - P * X * \left(\left(1 + X' * P * X \right)^{\hat{}} (-1) \right) * X' * P$$
$$\text{theta} = \text{theta} + P * X * \left(\text{yt} - X' * \text{theta} \right)$$

(1)

The RLS type used in this study is the forgetting factor type. The concept of forgetting is such that older information is gradually discarded in favour of the most recent information or giving less weight to older data and more weight to recent data [1]. RLS results are shown in Fig. 3. The model order was found to be in the order of 3. The results were achieved using RLS with a forgetting factor 0.95.
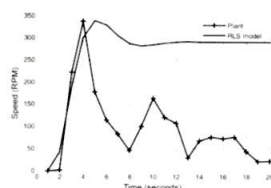

Figure 3: Actual and predicted output

1.4   Intelligent based modelling techniques

Considerable research is currently being devoted to intelligent modelling techniques for systems that are ill defined, poorly understood or highly nonlinear

such as pneumatic drives. However, application of intelligent modelling to pneumatic drives is not wide spread. Knowledge of the system behaviour is required for construction of a scheme for modelling and simulation of the pneumatic system. Radial basis function neural network (RBF-NN) is a special class of multi-layer feed forward networks, widely used with supervised learning algorithms to solve non-linear engineering problems. Radial basis networks may require more neurons than standard feed forward back propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed forward networks. They can also work best when many training vectors are available. Both simple NN and adaptive neural fuzzy inference system (ANFIS) can be used to identify a dynamic system, but ANFIS has two preferred merits over simple NNs for its ability for parameter partitioning. ANFIS has the ability to integrate process dynamics as well as human knowledge expressed in linguistic form. Results show that ANFIS has faster learning speed and higher identification accuracy than a simple NN identifier. The strategy adopted here with a neuro-fuzzy system is to find the parameters of a fuzzy system by means of learning methods obtained from NNs. A common way to apply a learning algorithm to a fuzzy system is to represent it in a special neural-network-like architecture. Then a learning algorithm, such as back propagation, can be used to train the system. Adaptive neuro-fuzzy system architecture with two inputs and one output is shown in Fig. 4. The single –value fuzzification, Gaussian membership function, and product inference and centre average defuzzification in the fuzzy logic are adopted.
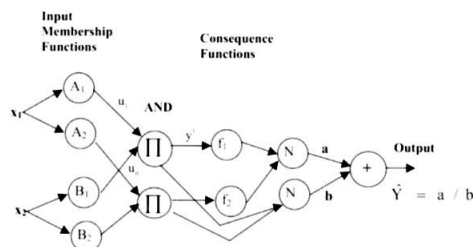

Figure 4: Sugeno-Mamdani type fuzzy inference systems

The fuzzy model in Fig.4 can be seen as a layered structure (network), similar to artificial neural networks. Hence this approach is usually referred to as neuro-fuzzy modelling [2].

1.5   Related work

Many attempts have been made to introduce simplified models in order to construct a model-based air motor controller [3]. A common method has been to approximate non-linear dynamics of the air motor into linear (ideal) models assumed to have

sufficiently small uncertainty [4]. Studies on modelling of pneumatic systems, especially locally linearised modelling, can be found in the literature [5]. Linear and nonlinear dynamics of the dynamic model of a pneumatic actuator forms the platform and the launching pad point of the motion control algorithms of the air motor system in this study. [6]. There are numerous researchers who have focused their efforts on different issues of modelling of pneumatic servo systems. The issues include but are not limited to the following:. Air flow: a normal pneumatic valve does not behave like a simple nozzle. The mathematical model of the valve airflow must be produced specifying the flow capacity of the pneumatic fluid power valves. Valve modelling: there is little work found in the literature on this topic. The valve's input/output behaviour has significant influence on the servo control system. Analysis of pneumatic valve model parameters reveals that, the valve model contains two friction parts, namely static part and dynamic part. Friction parameters may be identified using evolutionary strategies [7, 8]. Air motors are compact, lightweight sources of smooth power with relatively less vibration. They are not affected by continuous stalling or over load; they start and almost stop instantly. They play a very significant part as prime movers because they are relatively cheap, easy to maintain and have versatility of variable speed and high starting torque. They are intrinsically safe in hazardous areas and will operate in exceptionally harsh environments. When a state feedback controller is used to control pneumatic servo systems, it is impossible in practice to determine the control gains theoretically because of the high nonlinearities of the system and the uncertainty in system modelling. Knowledge of the system behaviour is required for construction of a scheme for modelling and simulation of the pneumatic system. Radial basis function neural network (RBF-NN) is a special class of multi-layer feed forward networks, widely used with supervised learning algorithms to solve nonlinear engineering problems. This paper reports on recent advances on scientific findings and application of intelligent techniques as alternative methods of modelling and simulation of an air motor. The paper is organized as follows: Section 2 provides a brief description of the experimental set up utilized in this study. Section 3 briefly describes the modelling approach. Section 4 presents experimental assessment of the performance and the implementation of the RBF-NN modelling strategy. The paper is concluded in Section 5.

2   SYSTEM SET UP

The computer (PC) with the auxiliary hardware is used to source out and read all plant devices. All electrical devices are externally powered. At the centre of the motor is a tri-lobed cam mounted on the

motor output shaft. There are four pistons radially positioned and acting on the cam, which reciprocate in fixed cylinder liners. Rolling contact in the cam is made by sealed needle roller bearings. The action of the piston on the cam converts linear force to rotational motion. As the piston reciprocates, a channel in the face of the seal pad connects two ports formed in the liner. A series of channels are formed in either flank of the motor-cylinder block. The channels link the control port in the cylinder liners to the piston chamber of the adjacent end piston. An annular manifold is formed in each of the flank faces of the cylinder block. These manifolds are connected to motor inlet/output ports. A flow control valve is linked to the motor ports. The function of the valve is to control the direction and rate of airflow through the motor. Normally, actuation of the valve is achieved by a proportional solenoid but in this work, the solenoid has been replaced by a pneumatic H-bridge. A cutaway view of the motor is shown in Fig. 5.
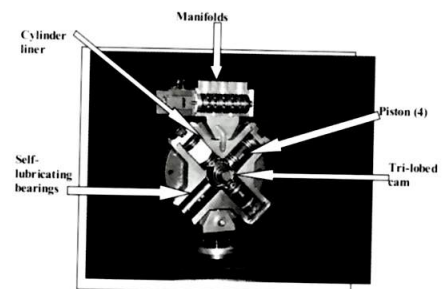

Figure 5: Cutaway view of radial piston air motor

Coding the control algorithm is straightforward. However, it is always advisable to consider factors such as realization, actuator nonlinearities and computational delay to minimize controller sensitiveness to errors. An optical encoder is mounted on the extension of the output shaft of the motor. The encoder transmits information that allows motor speed and direction to be detected. An optical encoder is a non-contacting rotary to digital converter. The optical converter is useful for position feedback and manual interface. The encoder converts real time shaft angle, speed and direction into Transistor-Transistor Logic (TTL) compatible quadrature outputs with or without index. The motor speed is measured by a shaft encoder, which represents the measured speed in terms of frequency. The encoder uses optical sensors to provide a series of pulses that can be translated into motion, position or direction. A stationary light emitting diode (LED) is mounted so that its light will continually be focused through the glass disk. A light activated transistor is mounted on the other side of the disk so that it can detect the light from the LED. This disk is mounted to the shat of the motor whose position is being sensed, so that when it turns, the disk turns. When

the disk lines up so that the light from the LED is focused on the phototransistor, the phototransistor will go into saturation and an electrical square wave pulse will be produced. The frequency to voltage (F2V) converter transforms the frequency from the shaft encoder to a voltage in the range 0 to 5 V. This analogue voltage is then converted into binary form by an A/D converter, which the computer can now read. The controller uses this measured speed along with other variables to generate a control signal. A D/A converter converts the control signal from binary into analogue voltage. This analogue voltage when applied to the pressure control valve (PCV) either increases or decreases the air pressure to the motor, thus controlling the speed of the motor. Many of the applications of neural networks, particularly in the area of non-linear system identification and control, reduce the problem of approximating unknown functions of one or more variables of discrete measurements [9]. A number of authors have established that multi-layer feed forward neural networks, with a variety of activation functions, serve as universal approximators. In the case of modelling the low frequency dynamics of the air motor, RBF-NN has been chosen. This is a form of neural networks, which can be designed very quickly and find an exact solution. A trade off is that the behaviour of such networks may be extremely complex.

3   SYSTEM IDENTIFICATION

Before controlling the system, the system must be identified. System identification is one of the most fundamental requirements for many engineering and scientific applications. The objective of system identification is to find exact or approximate models of dynamic systems based on observed input and output data. These input and output data can be obtained through experimental work, simulation or directly collected from the plant. Many identification methods have been reported in the literature. These include least squares (LS) method, prediction error method (PEM) and recursive least squares (RLS) method. Some of these methods, however, have the potential risk of getting stuck at local minima, which often result in poorly identified models. The risk increases as the parameters of the AR part are close to the MA part [10]. For highly non-linear optimisation problems, methods to avoid convergence to local minima are sought. The parametric identification of the air motor is realised in this investigation by minimising the prediction error of the actual output and the predicted output. In this article system identification has been used to obtain local parametric models for the plant in three distinct regions, termed low, medium and high speed region. Models obtained in the high speed and medium speed regions are good. However, the model obtained in the low speed region is not very good.

There are two main reasons for models obtained at low speed region:
•   Hysteresis is more dominant in the low speed region than in medium and low speed regions
•   The plant is very sensitive in this region and the combination of these two effects made the plant rather difficult to model using conventional modelling approaches.

The results obtained from the low speed leads to some interesting conclusion that, the plant need to be modelled using some form of intelligent modelling techniques to deal with the dead band and hysteresis, which is strongly present in the region. As a result, the need to use neural networks, to model low speed dynamics of the air motor system sufficed.

Once a model of the physical system is obtained, it can be used for solving various problems such as, to control the physical system or to predict its behaviour under different operating conditions [11]. A number of techniques have been devised by many researchers to determine models that best describe input / output behaviour of a system. In many cases when it is difficult to obtain a model structure for a system with traditional system identification techniques, intelligent techniques are desired that can describe the system in the best possible way [12]. The system characteristics are divided into three main regions, namely low speed (below 390 rev/min), medium speed (390 to 540 rev/min) and high speed (540 to 680 rev/min). The system is highly non-linear in the low speed region and hence a neuro-model using extended radial basis neural networks is proposed.

3.1   RBN-NN-Learning Algorithms

A generalized regression network (GRNN) is proposed to model the system in the low speed range. The GRNN is basically a two-layer network with a radial basis function in the first layer and a special linear output layer [13]. The task of a learning algorithm for the RBF is to select the center and find a set of weights that make the network perform the desired mapping. A number of learning algorithms commonly used for this purpose include but not limited to the following:
•   Random center selection and a least square algorithm
•   The orthogonal least square
•   Clustering and a least square algorithm
•   Nonlinear parameter optimization
In this work parameter generalization benchmarks comparing the performance of feed forward networks, GRNN are provided. The purpose of these benchmarks is to aid the user in selecting the appropriate algorithm for their problem. For training purposes, the input patterns (collected data) were normalized to unit length to ensure they fell within the required range of -1 to 1. Each network was

trained on the profile of a normal event data set, split into training, verification and test set, to allow precise network prediction accuracy. Subsequently the networks were given a series of dataset that they have never seen before, to determine their arbitrary pattern generalization and their ability to track the desired output. . The first layer is designed to receive a set of input data for the first 500 data points. The second layer receives inputs for data points ranging from 501 to 1000 data points. The first layer has tangsig output in the hidden layer and the second layer has a logsig transfer function in the hidden layer output. Details of these algorithms can be found in [14]. A diagram of the GRNN architecture is shown in Fig 6.
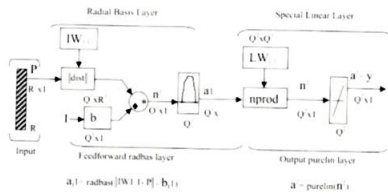

Figure 6: Air motor GRNN structure with Gaussian node

The dimensions in Fig. 6 have the following definitions:
- PR represents an $R \times 2$ matrix defining the minimum and maximum values of R inputs
- IW represents the new input weight matrix
- Q is the number of neurons in the layer
- LW is the new $Q \times R$ weight matrix
- b is a new $Q \times 1$ bias vector
- n is the number of network layers
- $\|dist\|$ denotes distance between vectors

In Fig. 6, the $\|dist\|$ box accepts the input P, plus the input matrix $IW^{1.1}$ and produces a vector having Q^1 elements. The elements are the distances between the input vector and vectors $IW^{1.1}$ formed from the weight matrix. The bias vector b^1 and the output of the are $\|dist\|$ combined with the MATLAB operator (dot*), which does the element-by-element multiplication. The selection of a representative training set is very important when training a neural network (NN). The most critical ability of an NN is its ability to generalize to data to which it has never been exposed [15]. For this generalization to be realized, a training set must be constructed, which is very representative of the entire dataset. For this study, the generation of the training set was done through an experimental data collected from the air motor rig.
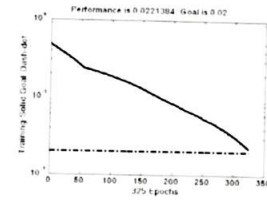

Figure 7: Performance curve showing RBF convergence

Fig. 7 shows the net performance curve on training set. It can be observed that the network tends to converge with sum-squared error (SSE) of 0.022 after 325 epochs. After convergence has been achieved, the network is tested with estimating data set of the remaining 500-input/output data set that the network has never seen. An SSE of 0.037 was obtained after 325 epochs, indicating a 1.5% error. The results are convincingly promising and show that RBF network arbitrarily approximates and learns the parameters in the hidden layer together with those in the output layer and can hence be implemented for further model development. It must be noted that for best network measurement and performance results, the mean squared error is a good criterion to use. However, in this study, SSE produced performance measurement results are adequate enough to be used for further model development.

4   MODEL ANALYSIS AND IMPLIMENTATION

The input variables of the NNs were chosen on the basis of physical laws that describe the behaviour of the pneumatic motor and on the basis of the effect of the inputs on parameters and performance of NNs. Moreover, the effects of functional form of input variables were tested. Following these tests, together with the maximum air pressure (4.5 bar), some combinations of input parameters, measured at variable load were chosen: maximum speed, medium speed and low speed. Maximum pressure was chosen because it is a good indicator of the fluid state while the value of quantities of speed inputs change due to variable load demand. Three different RBF algorithms were investigated in order to determine the type of network most suitable for modelling the air motor system.

4.1   Non-parametric Identification Techniques

In a system identification exercise the input signals must be persistently exciting so that they provide sufficient information in the response. Various modelling techniques can be used with neural networks to identify nonlinear dynamic systems. Nonlinear autoregressive moving average process with exogenous input (NARMAX) model (also known as error model) is one of them. Literature has revealed that, if the plant input and output data are

available, the NARMAX model is a suitable choice for modelling nonlinear systems with suitable neuro-learning algorithms. The NARMAX model is mathematically expressed as:

$$\hat{y}(t) = f[(y(t-1), y(t-2), \cdots, y(t-n_y), u(t-1), u(t-2),$$
$$\cdots, u(t-n_u), e(t-1), e(t-2), \cdots, e(t-n_e)] + e(t) \qquad (2)$$

where:

$u(t)$, $\hat{y}(t)$ and $e(t)$ represent the output vector determined by the past values of the system input vector, output vector and noise respectively n_y, n_u, and n_e represent associated maximum lags respectively, $f(\square)$ represents the system mapping constructed with a NN such as multi-layered perceptron (MLP) together with appropriate activation function and learning algorithm [16].
If the model is good enough to identify the system without including the noise term, then it can be represented as NARX model and expressed as:

$$\hat{y}(t) = f[(y(t-1), y(t-2), \cdots, y(t-n_y),$$
$$u(t-1), u(t-2), \cdots, u(t-n_u)] + e(t) \qquad (3)$$

4.2   Validating the Model

An identified model should never be accepted until it has been thoroughly validated. A common measure of predictive accuracy of model used in system identification is to compute the one ahead step (OSA) prediction of the system output. This can be expressed as:

$$\hat{y}(t) = f(u(t), u(t-1), \cdots, u(t-n_u), y(t-1), \cdots, y(t-n_y)) \qquad (4)$$

where $f(\square)$ represents a nonlinear function, u and y are the input and output samples respectively. The residual or error between the output and its prediction is given by:

$$\varepsilon(t) = y(t) - \hat{y}(t) \qquad (5)$$

Often $\hat{y}(t)$ will be a relatively good prediction of $y(t)$ over the estimation set, even if the model is biased, because the model was estimated by minimising the prediction errors. Another method to evaluate the predictive capability of the fitted model is to compute the model predicted output (MPO). This can be expressed as:

$$\hat{y}_d(t) = f(u(t), u(t-1), \cdots, u(t-n_u), \hat{y}_d(t-1) \cdots, \hat{y}_d(t-n_y)) \qquad (6)$$

$$\varepsilon_d(t) = y(t) - \hat{y}_d(t) \qquad (7)$$

If only lagged inputs are used to assign network input nodes, then:

$$\hat{y}(t) = \hat{y}_d(t) \qquad (8)$$

The implication that if the fitted model behaves well for OSA and MPO does not necessarily imply that the model is unbiased. The prediction over a different set of data often reveals that the model could be significantly biased. One way to overcome this problem is by splitting the data set into two sets, estimation set and test set. The first half (estimation set) is used to train the NN and the output computed. The NN usually tracks the system output well and converges to a suitable error minimum. New inputs (test set) are presented to the trained NN and the predicted output is observed. If the fitted model is correct, then the network will predict well for the prediction (test) set. In this case the model will have captured the underlying dynamics of the system. If both OSA and MPO of a fitted model are good over the estimation and prediction data sets, then most likely the model is unbiased. A more convincing method of model validation is to use correlation tests. If a model is adequate then the prediction error $\varepsilon(t)$ should be unpredictable from (uncorrelated with) all linear and nonlinear combinations of past inputs and outputs.

4.3   Correlation Functions

An alternative approach for model validation constitutes auto correlation and the cross correlation tests. If a model is adequate then the residual or prediction errors $\varepsilon(t)$ should be unpredictable from (uncorrelated with) all linear and non-linear combinations of past inputs and outputs. Derivation of simple tests, which can detect these conditions, is complex, but it can be shown that for non-linear systems the following five-correlation conditions should hold [17]. 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 adequate, the correlation tests in equations (9) to (13) have to be satisfied.

$$\phi_{\varepsilon\varepsilon}(\tau) = E[\varepsilon(t-\tau)\varepsilon(t)] = \delta(\tau) \qquad (9)$$

$$\phi_{u\varepsilon}(\tau) = E[u(t-\tau)\varepsilon(t)] = 0 \quad \forall \tau \qquad (10)$$

$$\phi_{u^2\varepsilon}(\tau) = E[(u^2(t-\tau) - u^2(t))\varepsilon(t)] = 0 \quad \forall \tau \qquad (11)$$

$$\phi_{u^2\varepsilon^2}(\tau) = E[(u^2(t-\tau) - u^2(t))\varepsilon^2(t)] = 0 \quad \forall \tau \quad (12)$$

$$\phi_{\varepsilon(u\varepsilon)}(\tau) = E[(\varepsilon(t)\varepsilon(t-1-\tau) - u(t-1-\tau)] = 0 \quad \tau \geq 0 \quad (13)$$

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 is an impulse function. For linear models, however, only the first three tests above are sufficient. Theoretically, the above tests indicate that the auto correlation function (ACF) of the residuals should be white, and the cross-correlation (CCF) between the input sequence and a white noise sequence should be zero. In practice, the approximate 95% confidence interval at $\pm 1.96/\sqrt{N}$ can be used to test the above. Testing model variance over a different data sequence. It is important to note that it is easy to fit a model to data that appears to predict well over the data set used for estimation. Even bad models exhibit this property. It is much more difficult to get correct model, the model that describes the dynamics of the underlying system and not one data set.

4.4   RBF Model Development

Since all validity correlation tests are acceptable, the next step is to develop the system model using real input/output data. In this case, there are 500 input/output data points providing a set of 500 radbas neurons. It is observed that untrained radbas neuron vaguely detect input data vectors presented to them but cannot arbitrarily interpolate reasonably well, to create an explicit radbas profile. The next step is to train 500-input/output data set out of 1000. The trained data is then simulated with the remaining 500 unseen data set to produce input/output radbas network (PT).
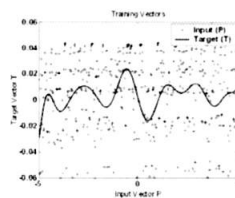

Figure 7: Radial basis function

Fig. 8 shows how as many radbas neurons as there are input vectors in P can be created. This provides a set of radbas neurons in which each neuron acts as a detector for a different input vector. Therefore, if there are Q input vectors, then, there will be Q neurons.

The transfer function for the radial basis neuron is:

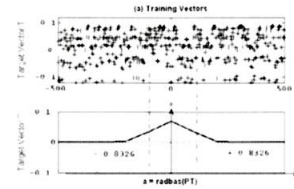Radbas: $(PT) = e^{-(PT)^2}$ (14)

Figure 8: RBF (P, T)

The radial basis function has a maximum output of 0.8 when its input is 0. As the distance between weight and input decreases, the output increases. During training, the neuron was given a bias 'b' of 0.1 and a spread of 8.326. The net input can be expressed as: $sqrt(-\log(0.4))$. Therefore its output would be: $0.1 \times 8.326 \times 0.6$ i.e. 0.5 for any input vector at vector distance of 8.326 ($0.8326/b$) from its weight. Each bias in the first layer was set to 0.8326 per spread. This gives radial basis functions that cross 0.5 at weighted inputs of $\pm$ spread. This determines the width of an area in the input space to which each neuron responds. Fig. 8 also shows how a single radial basis transfer function (RBTF) can be utilized to represent a radial basis output for a selected data set. This is the initial stage to design RBF networks and subsequent radbas neurons are then created one after the other until a satisfactory radial basis model is achieved. For this study, 3 data sets were selected; representing three ranges of the air motor speed and their respective outputs are as presented in Fig.9.
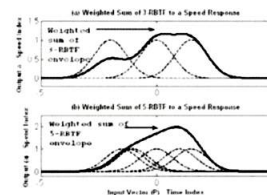

Figure 9: Three & five - RBF model

Fig. 9 shows radial basis outputs for these data sets with their weighted sum of responses. Three radial basis neurons do not give a perfectly smooth weighted sum of RBTF envelope and to overcome this shortfall, a radial basis neuron insertion technique is adopted, whereby extra two RBTFs are added at the beginning and the end of the weighted sum of RBTF envelope. The results give a linear five-RBTF model, which is adequate to represent the response of the air motor for the whole data range (low, medium and high speed range). Also, in Fig. 9 a comparison of a three - RBTF model between a five - RBTF model and their respective weighted sum of RBTF responses is shown. A response with many radial basis neurons, give smoother perfectly more linear weighted sum of RBTF output. Therefore, for this study a five - RBTF model (Fig. 9) is the obvious choice. However, there is a trade off

between the two choices, a three – RBTF model gives faster response with nonlinear weighted sum of RBTF envelope while a five – RBTF model gives a slower response with a perfectly linear RBTF envelope. During training, three – RBTFs converged in 100 seconds while five – RBTFs converged in 325 seconds. This means that five - RBTFs are slower to operate because they use more computation to do their function approximation or classification.
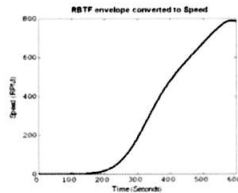

Figure 10: Air motor five - RBTF linear output

Fig. 10 shows the output of the five - RBTF, which represents the air motor speed over the whole data set. Further observations and analysis of Fig. 10 show that using radial basis algorithms enables the air motor system to attain linear operating conditions in less than 200 seconds. In a practical context, these results exhibit instantaneous starting characteristics. These results demonstrate that neural networks are able to handle nonlinearities due to system's hysterisis and can thus be used to control the air motor to attain set point speeds.

4.5 Extended RBF recurrent model

Simple radial basis function network produced reasonably good and promising results. In analogy with conventional RBF feed forward network and the development of RBF recurrent networks then suffices. The design of a context layer to which patterns can be copied directly following the learning algorithm, provides for a good comparison of trained inputs of the second layer. This is achieved by the design of the staggered two-delay outputs fed back as inputs of the first layer and second layer respectively. A diagram of the extended RBF architecture is shown in Fig 11.
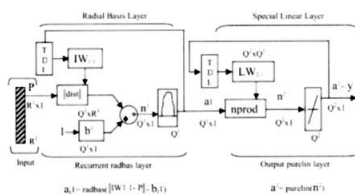

Figure 11: Air motor two -layer recurrent RBF network

Tapped delay lines consist of a complete memory temporal encoding stage followed by a (dot*) radbas operator. The tapped delay line (TDL) is needed to make full use of the designed neural network. The

output of the TDL is an N-dimensional vector, made up of the input signal at the current time, or the previous input signal. The combination of a TDL and a linear network such as purelin, which create a good linear filter. This has the advantage of ease of mathematical analysis and training regimes. As a result, the three networks of the compared algorithms all have tapped delay lines. The dimensions in the above have the following definitions: PR represents matrix defining the minimum and maximum values of R inputs, TDL tapped delay lines, S number of neurons in the layer, IW, new input weight matrix, LW the layer matrix, output vector, b new bias vector, n number of network layers and D number of delay lines.

4.6 Implementation and Results

The air motor system has three approximate speed regions. The low speed region ranges from 0 RPM to 350 RPM, non-linear region. The medium and high speed regions are approximated from 350 RPM to 540 RPM and 540 RPM to 600 RPM respectively, linear region. Collected data, corresponding to the above speed ranges are chosen to be a set of PRBS shifting between [-850 and –900, -900 and –1050, -1050 and 1300] counts for low, medium and high speed respectively. Figure 12 shows the ramping up and ramping down characterisation of the air motor speed within predefined DC counts regions.
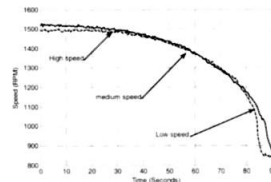

Figure 12: Ramp up and ramp down characterisation of air motor system

This characterisation is desirable to because when the ramp matches the ramp down characterisation, it is a good indication that the system is identifiable by conventional methods, especially within the bounded regions. Furthermore, the bounded regions help to determine the operating regions of the air motor. For ease of clarity, parameters shown in Fig. 12 can be presented in a tabular form. Table 1 shows the three regions in terms of ADC count, DAC count and RPM.

In this investigation, identification of the air motor system using conventional methods such as simple least squares and recursive least squares techniques is considered. The experiments involved development of plant model, predicted model, computation of error between the plant model and the predicted model and analysis of correlation function tests.

Table 1: Boundary definitions of three speed
regions

Region	Input pressure (DAC counts)	Output speed (ADC counts)	RPM
High speed	1100 to 1300	1450 to 1500	450 to 700
Medium speed	900 to 1100	1200 to 1450	350 to 430
Low speed	700 to 900	800 to 1200	0 to350

The results obtained from the low speed leads to
some interesting conclusion that, the plant need to be
modelled using some form of intelligent modelling
techniques to deal with the dead band and hysteresis,
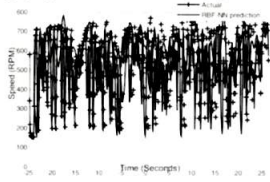which is strongly present in the region.

Figure 13: Actual and predicted output

Results of various modelling techniques have been
validated through a range of tests including
input/output mapping, training and test validation,
mean squared error, sum square error for RBF and
correlation tests. Modelling of systems with
nonlinearities and little physical insight is a domain
of black-box models showing universal
approximating capabilities such as RBF -GNN.
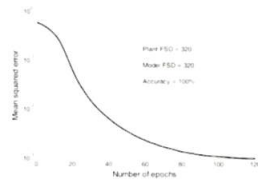Pneumatic drives belong to this kind of systems.

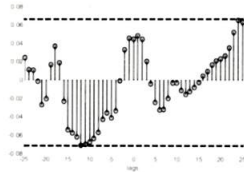Figure 14: Error between actual and predicted
output

Figure 15: Auto-correlation test

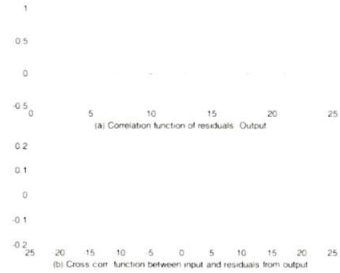Figure 16 Cross-correlation of residuals and
input

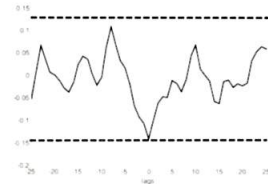Figure 17: Cross-correlation of residuals
square and input

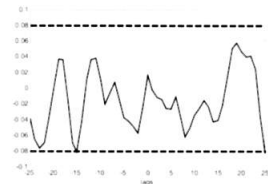Figure 18: Cross-correlation of residuals
square and input square

Figure 19: Cross-correlation of residuals and
(input*residuals)

Comparing the results with those Section 1, reveals
that intelligent modelling techniques such RBF-GNN
perform better than simple least squares and RLS in
modelling and identification of air motor dynamics at
low speed. Furthermore, the introduction of hybrid
intelligent modelling techniques such as ANFIS has
shown that performance achieved using neuro-fuzzy
is much faster than RBF-GNN alone. It is therefore
evident to conclude that, intelligent modelling is a
partnership of modelling techniques such as RBF-
GNN and ANFIS, where each of the partner
contributes to a distinct need of a problem performs
better than each partner alone. Intelligent modelling
techniques are also evolutionary rather than
revolutionary and in this respect, the principal
contributions are complementary rather than
competitive. Accordingly, intelligent modelling
approaches are an alternative to conventional
techniques and hence their application must be tried
when there is a prove that conventional methods do
not yield meaningful results.

5   CONCLUSION

A strategy of applying the radial basis function
networks to recognize time varying patterns has been
presented. The ability of neural networks has been

used in the identification of a pneumatic motor in the low speed region. The effectiveness of this strategy was validated using model validity correlation tests, which were all within the 95% confidence limit. Neural network modelling and simulation techniques presented in this paper show that, given sufficient number of hidden neurons, the RBF-NN can approximate a continuous function to an arbitrary accuracy. However, because the number of radial basis neurons is proportional to the size of the input space, and the complexity of the problem, RBF-NN algorithm can be prohibitively too large. Tuning the various number of parameters, i.e. radius, centers etc, can get quite complicated as is shown in combining regression trees and RBF network insertion. Choosing the right centers (for the hidden layer) is of critical importance although there are a number of ways to solve this unsupervised learning problem, such as using competitive learning. A new recurrent RBF network, which takes the network input and past outputs as augmented input adaptively, learns the parameters in the hidden layer together with those in the output layer. This has the advantage of ease of mathematical analysis and training regimes and outstanding performance in recursive function approximation and estimation. It is therefore recommended that, parametric and non-parametric models of the air motor system based on intelligent modelling techniques, thus developed and validated will be used in subsequent investigations for the development of control strategies for air motor control at low speed regions.

REFERENCES

1.   Tokhi, M.O., Al-Miskiry, M. and Brisland, M. Real-time control of air motors using a pneumatic H-bridge, Control Engineering Practice, 9, No. 4, pp. 449-457, 2001.

2.   Vahidi, A. Stefanopoulo A. and Peng, H.,. Recursive least squares with forgetting for online estimation of vehicle mass and road grade: theory and experiments [online], available from World Wide Web: http://ghost.engin.umich.edu/JournalPaperMassGrade_Final.pdf

3.   Jang, J.-S. R., Sun, C.-T. and Mizutani, E. Neuro-Fuzzy and Soft Computing, Prentice Hall, Upper Saddle River, NJ., 1997.

4.   Tokhi, M .O., Reynolds I. N. and Brisland, M. Real-time control of a radial piston air motor. IFAC World Congress, Barcelona, 21 – 26 July 2002.

5.   Marumo R. and Tokhi, M.O. Modelling and Control of a Pneumatic Motor, Proceedings of the First African Control Conference, December, Cape Town, South Africa pp. 100-112, 2003.

6.   Marumo R. and Tokhi, M.O. Modelling and Simulation of an Air Motor using Elman Neural Networks, Proceedings of the Fourth IASTED International Conference on Modelling, Simulation, and Optimization, August, Kauai, Hawaii, USA pp. 160-164, 2004.

7.   Sorli M. and Parstorelli, S. Performance of a pneumatic force controlling servo system: influence of valves conductance. Robotic and autonomous systems, 30, p 283-300, 2000.

8.   Choi, S.H. Lee C.O. and Cho, H.S Friction compensation control of an electro pneumatic servo valve by using an evolutionary algorithm, Proc. of the Institute of Mechanical engineers, part I: Journal of systems and control engineering, vol. 214, No. 3, p 173-184, 2000.

9.   Kadirrkamanathan G.P. Liu, V. and. Billings, S.A Variable neural networks for adaptive control of nonlinear systems, IEEE Trans. Syst., Man, Cybern. C, 29, pp.34-43, 1999.

10. Narendra K.S and Parthasarathy, K. Identification and control of dynamics systems using neural networks, IEEE Trans. Neural Networks, 1, pp.4-27, 1990.

11. Sze, T.L System identification using radial basis neural networks, PhD thesis, Department of Automatic Control and Systems Engineering, The University of Sheffield, Sheffield, UK, 1995.

12. Elanayar, S.V.T. and Yung, C.S. Radial basis function neural networks for approximation and estimation of non-linear stochastic dynamic systems. The IEEE Transaction on Neural networks, 5, (4), pp. 594-603, 1994.

13. Demuth H. and Beale M. Neural networks toolbox user's guide v.4 (The MathWorks, Inc. 2000).

14. Chen, S., Cowan, C.F.N. and Grant, P.M. Orthogonal least squares learning algorithm for radial basis function networks. IEEE Transactions on Neural Networks, 2, (2), pp.302-309, 1991.

15. Shaheed, M. H. Neural and genetic modelling, control and real-time finite element simulation of flexible manipulators, PhD thesis, Department of Automatic Control and System Engineering, The University of Sheffield, Sheffield, UK, 2000.

16. Garrett A. and Dobbs R., Defining neural network parameters for prediction of head movements in virtual environment applications [online], available from world wide web: http://cnts.uia.ac.be/conll98/pdf/073078sc.pdf

17. Billings, S.A & Voon, W. Correlation-based model validity tests for nonlinear models. International Journal of Control, 44, 235-244, 1986.