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A NOVEL METHOD FOR THE PERFORMANCE MODELING OF A GAS TRANSMISSION COMPRESSOR

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ABSTRACT

This paper presents the application of feed forward neural networks to the performance modeling of a gas transmission compressor. Results of compressor model testing suggest that compressor speed can be estimated to within $\pm 2.5\%$. The neural network property of function approximation is used to predict compressor speed for given process constraints and instrument input sets. The effects of training set size, instrument noise, reduced input sets and extrapolation from the training domain, are quantified. Various neural network architectures and training schema were examined. The embedding of a neural network into an expert system is also discussed. A neural network can be re-trained to reflect changing compressor characteristics. A global saving in compressor fuel gas of 1% could prevent the production of 6 million tonnes of CO₂ per year, [1].

INTRODUCTION

In the UK, gas is produced from offshore oil and gas fields. The gas is pipelined ashore to reception terminals where it is treated to remove entrained liquids and corrosive elements. Once treated, the gas is dispatched to a distribution grid for supply to industrial and domestic customers or to storage. The daily production of gas from the offshore fields may be supplemented by drawing down on the stored supplies. Hence gas may be moved from storage facilities to meet varying demand. Compressors are critical components, in transmission systems, to transport gas from its point of production, or storage, to the consumer. They provide the mechanism to move large quantities of gas around the network to meet instantaneous demand and to replenish local storage.

Gas pipeline transportation compressor stations generally use variable speed, centrifugal compressors operating in a

parallel configuration. It is necessary to control the compressors to meet consumer demand but also to prevent unstable operation. Unstable operation can result in compressor surge, which can cause significant damage or even complete failure of the compressor. Compressors are high capital cost components and are expensive to replace. Loss of compression capacity can incur commercial penalty for failure to meet demand or consequent loss of business.

Current compressor control philosophy pivots around prevention of surge or anti-surge control. Prevention of damage to high capital cost equipment is a key control driver but other factors such as environmental emissions restrictions require most efficient use of fuel. This requires reliable and accurate performance control.

NOMENCLATURE

y	output function
x_j	j^{th} input parameter
w_j	j^{th} input weighting
w_o	bias parameter
a	artificial neuron activation level
$\sigma(a)$	function of activation level
θ	activation level threshold
ρ	logistic function 'density' parameter
E_{Sn}	peak percentage speed training error
S_{n95}	average speed training error, rpm (95% confidence level)
σ	average speed training error variance, rpm
r	average correlation coefficient
ψ	isentropic head coefficient
Φ	flow coefficient

CURRENT COMPRESSOR CONTROL PHILOSOPHY

Centrifugal compressors exhibit small discharge pressure variations for large changes in compressor flow rate. This performance characteristic can accommodate swings in customer demand whilst maintaining relatively steady supply pressures. However, this same characteristic makes the control of parallel compressors problematic, as a slight change in pipeline pressure can result in compressor instability.

White 1972 [2] described a compressor control technique that uses a linear relationship between compressor pressure rise and the square of the compressor inlet actual volume flow rate. Staroselsky, 1979 [3] developed the technique, to define and control compressor operating point (COP), relative to the compressor surge point. This has become a *de facto* industry standard method of compressor anti-surge control and has resulted in compressor performance control becoming implicit in anti-surge control. A schematic representation, adapted from Liptak 1995 [4], for controlling parallel compressors is shown in Figure 1.

A surge variable is computed, from process measurements and compressor speed, in the anti-surge controller which is then downloaded to a load-sharing controller. If the surge variable approaches the surge limit value then anti-surge controlling action may be invoked. This could involve ‘blowing off’ gas from the compressor discharge or re-circulating gas from the discharge to the inlet via an anti-surge control valve.

The load-sharing controller calculates a control action, to keep the surge variable at a predetermined set point for the compressor operating closest to its surge limit point. Each compressor speed set point is then set to maintain the compressors surge variable at the same value, away from the surge limit point.

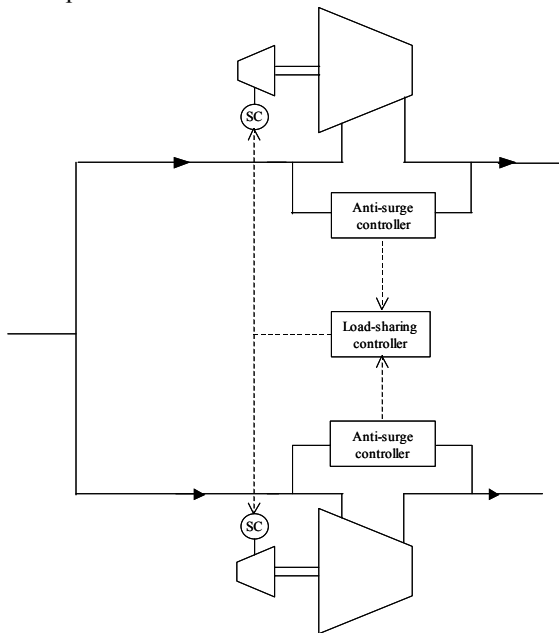


Figure 1 – “Equidistant” Load Sharing

Hence each compressor operates with the same surge variable value set to maintain each COP at the same “distance” from their respective surge limit points. This is often referred to as “equidistant” load sharing. This method of control is efficient in preventing compressor instability, but may mean that COP is not efficient in terms of fuel consumption.

Cordiner 1997 [5] described the use of Fuzzy Logic as a means of advising individual COP to improve load sharing, in terms of fuel consumption, between a bank of compressors, used in natural gas compression stations. The work suggested neural networks could be used to ‘optimise’ operating point selected by the Fuzzy control system. This was the starting point for research by Pearson 2001 [6], described in this paper.

COMPRESSOR PERFORMANCE CHARACTERISTICS

Performance characteristics can be represented in several ways. Godse 1989 [7], summarized some of them as: actual inlet volume flow rate vs. discharge pressure or pressure ratio or polytropic head. Variable speed compressor performance characteristics are shown in Figure 2, for constant suction pressure, temperature and gas density. The performance characteristics are multi-valued functions of compressor discharge pressure and compressor inlet actual volume flow rate.

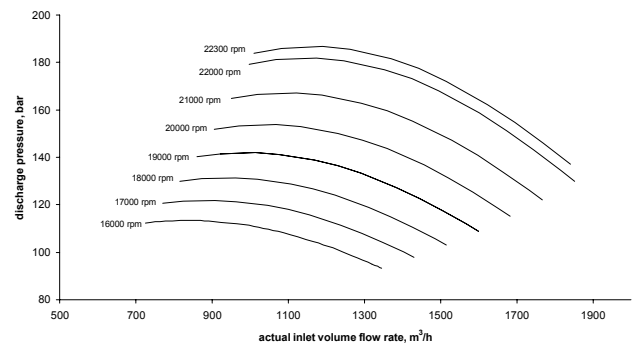


Figure 2 – Compressor Performance Characteristics

Where characteristics follow the affinity laws they can be reduced to a single *universal speed curve*, if isentropic head is used as the discharge variable. To obtain this curve the actual inlet volume flow rate and isentropic head are normalized against compressor speed and speed squared respectively. The performance characteristics, for the compressor shown in Figure 2, are plotted as a universal speed curve in Figure 3.

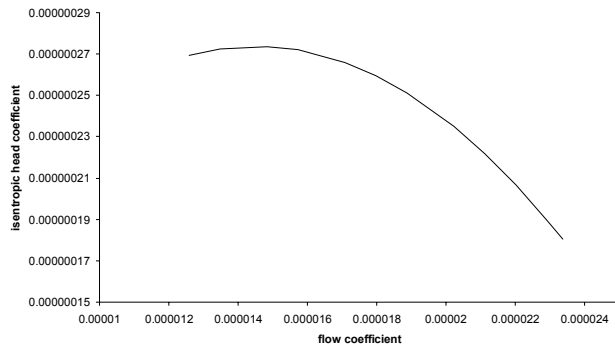


Figure 3 – Universal Speed Curve

PROPERTIES OF FEEDFORWARD NEURAL NETWORKS

Feed forward networks have “signal” paths that do not loop back on themselves, i.e. there is no feedback signal within the network, Gurney 1997 [8]. This type of network requires supervised training. Supervised training enables a network to “learn” the underlying relationships in training sets. If the training data presented represents a function, then the network is a *function approximator*. Similarly if the training set represents a decision plane then the network is a *classifier*.

Cheng and Titterington 1994 [9], point out the similarities between the diagram of a single perceptron, Figure 4, and a form of multiple linear regression, equation (1).

$$y = w_0 + \sum_j w_j x_j \quad (1)$$

The specific perceptron shown in Figure 4 is a Threshold Logic Unit or TLU as described by McCulloch & Pitts 1943 [10]. The output, y , from this unit is a change in state, or logic level, which is changed when the accumulation, a , of weighted input activity, $\sum w_j x_j$, exceeds a threshold, θ .

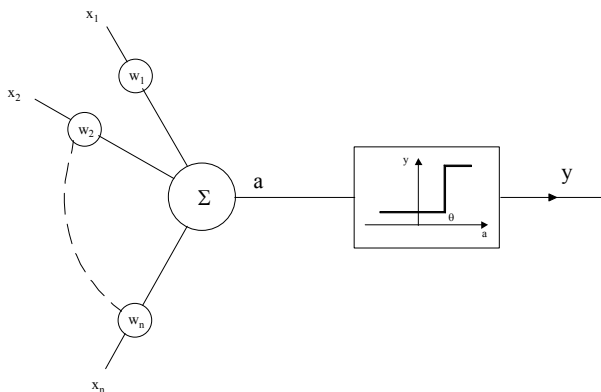


Figure 4 – Diagram of a TLU Perceptron

The “step” function output can be replaced with a “softer” function, such as a logistic sigmoid function, equation 2, as shown in Figure 5.

$$y = \sigma(a) \equiv \frac{1}{1 + e^{-\frac{(a-\theta)}{\rho}}} \quad (2)$$

This allows the perceptron output to represent an ‘analogue’ function of the input combinations.

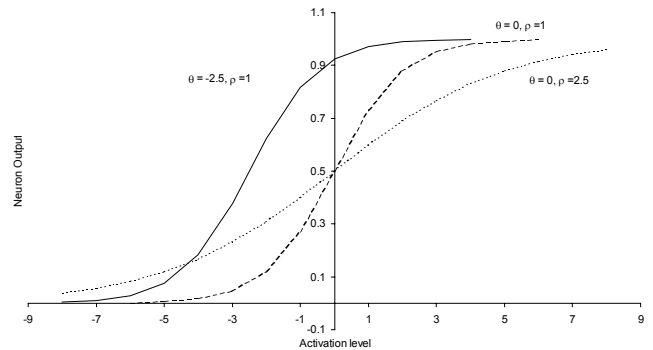


Figure 5 – Logistic Sigmoid Function

Varying the bias, θ , changes the output level for a given activation input level. Varying the function density term, ρ , changes the sensitivity of the output to changes in input. The output function of a perceptron can be the sigmoid function described, or a radial function as found in a Radial Basis Function (RBF) artificial neuron, or a simple linear function. If the output neuron has a linear activation function the output can be thought of as a *superposition* of the hidden layer perceptron outputs.

A typical, multi-layer perceptron neural network architecture is shown in Figure 6. The network shown has 6 inputs, 5 perceptrons in a hidden layer and a single output perceptron. Hornik 1989 [11] identified that a three layer neural network could represent the mapping between any input and output set, i.e. it could act as a universal approximator.

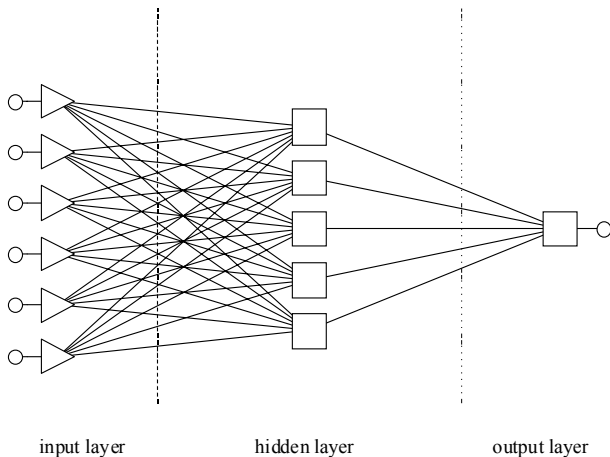


Figure 6 – Typical Feed forward Neural Network

The architecture of a neural network is primarily a function of the complexity of data set it is to represent and the method of training used. Werbos 1979 [12] described an error back-propagation technique using the, δ , delta rule. The general procedure for training a neural network is an iterative series of step as follows:

- Training data is presented to the neural network.
- An error is derived by comparing the corresponding output of the network with the training data value, giving rise to an error value.
- The weights of the neural network are manipulated such that this error is minimised.

These training steps are repeated until the mean error for the training set is minimised. Error function optimisation schemes such as Quasi-Newton, Levenberg-Marquardt and conjugate gradient descent are also used for supervised training. These schemes are described in Haykin 1994 [13] and Bishop 1995 [14]. It is customary to use a validation data test to prove that the network has achieved an optimal solution over the input domain. The separate validation set of data is usually derived from the same data pool as the training data. If the validation set error is comparable with the training set error then training continues. If the training error continues to fall whilst the validation error does not fall, this is indicative of over training i.e. the network is being trained to approximate the training data set patterns but not other patterns, from the same vector space, which are in the validation set. Over training can occur for a variety of reasons but in particular if training set size is too small or input/output training set relationships are complex. Cheng [9] refers to this method of validation as cross validation.

USING NEURAL NETWORKS TO REPRESENT COMPRESSOR PERFORMANCE CHARACTERISTICS

A series of tests were devised to assess the effectiveness of neural networks when used to represent compressor performance characteristics. The tests ranged from the ideal case of modeling an exact compressor head map to modeling a random set of compressor operating points. Two different sets of compressor performance characteristics were used to train neural networks. The first set used for initial, qualitative testing was atypical, non-fan law data. The second set of characteristics closely corresponded to the Fan Laws. For empirical testing, data subsets were generated using the methods described by Godse [7]. The testing used a trained neural network to estimate compressor speed required to deliver a specified gas flow rate against a constraining discharge pressure, for variable compressor inlet conditions of gas pressure, temperature and molecular weight.

Given the complexity of neural network architectures and the diversity, and complexity, of training methods, a proprietary package, Trajan Neural Network Software [15], was used to design a series of neural networks for each data set. The package contained an Intelligent Problem Solver (IPS), which would design and test tens of neural networks, varying by architecture and training method, for each data set. The network with the least training error was taken as the most representative of the compressor characteristics and performance metrics were recorded for this network. Design and testing of neural networks was under taken thirty one times and average performance metrics deduced for these networks at 95% confidence levels. Peak error was taken as the maximum error from the thirty one “most representative” networks.

Qualitative, Exploratory Testing

The first compressor data set consisted of compressor data that did not conform to the Affinity Laws. This data set was used with the IPS to train around one hundred neural networks, for the same compressor characteristics, at notionally fixed values of temperature, pressure and gas molecular weight. Differential pressure was used to represent the square of compressor inlet actual volume flow rate. It was found that 93% of the “most representative” neural network architectures were multilayer perceptron types. A typical architecture is shown in Figure 7. The network architecture shows six inputs: inlet pressure; inlet temperature; gas molecular mass, inlet volume flow rate differential pressure; outlet pressure; outlet temperature. The input combinations are processed through six fully connected hidden nodes feeding a single output representing compressor speed.

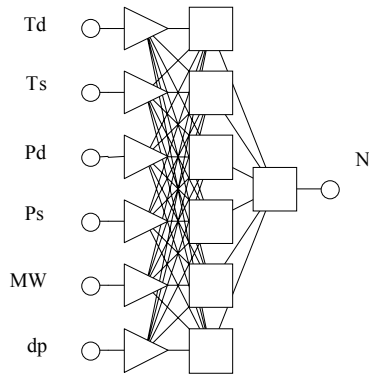


Figure 7 – Typical six input neural network

The results of the qualitative testing are summarised in Figure 8, which shows a variable speed compressor performance characteristics represented by the continuous lines. The neural network estimates of speed are shown as data points.

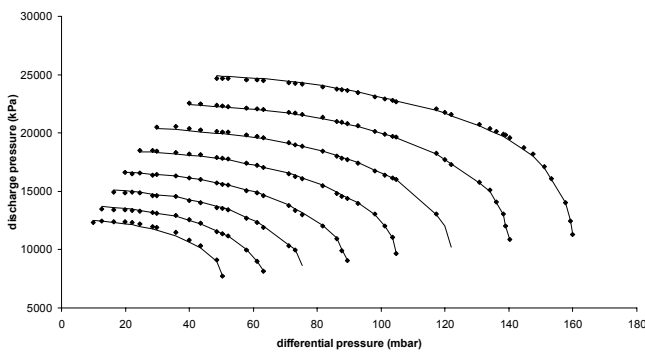


Figure 8 – Neural Network Speed Estimates

Empirical Testing

Five basic data sets were generated to assess neural network training performance for:

- a.) variations in training set size ('clean' data Set 1a-c, all sets);
- b.) inclusion of instrumentation noise in the input/output signals; (Sets 2a – full input set)
- c.) training on random operating points (Sets 3a-b);
- d.) training on random operating points with extended input sets i.e. gas composition in place of molecular mass; (Sets 3c-d)
- e.) use of input subsets used for training; (Set 2b – reduced input set, Set 5) ;
- f.) extrapolation over the full performance characteristic range from a restricted range training set. (Set 4)
- g.) normalized data set (universal speed curve) (Set 5)

Testing Data Set 1

Three data set sizes were used as follows: 96 data-points representing the actual default compressor performance points - 12 actual inlet volume / isentropic head data pairs for each of eight constant speed lines, (set 1(a)); the original set supplemented with interpolated points, 184 points in total, (set1(b)) and the original set supplemented with interpolated points, 496 in total, (set1(c)). For set 1(b) linear interpolation was applied to the flow coefficient such that original data points were bisected. For set 1(c), the flow coefficient range was split into 61 linear intervals, giving 62 points per constant speed line. A summary of results is presented, in Table 1, for the 'clean' data sets.

Data Set	No of points	E_{Sn} %	S_{n95} rpm	σ rpm	r	Over trained / total networks
1a	96	+3.2 -4.5	+182 -191	99	0.999011	43/74
1b	184	+1.5 -1.9	+170 -149	72	0.999502	11/42
1c	496	+1.3 -1.1	+125 -97	41	0.999828	6/37

Table 1 – Data Set 1 Results

Testing Data Set 2

Instrument noise levels were selected to represent typical instrument uncertainties as follows: $\pm 0.25\%$ of span for pressure transmitters; $\pm 0.5\%$ of span for temperature transmitters; $\pm 0.1\%$ span for differential pressure transmitters; $\pm 0.25\%$ of reading for molecular mass and $\pm 0.25\%$ of reading for speed transmitters.

Randomly distributed instrument uncertainty levels were generated with a mean of 0% and standard deviation corresponding to 95% or 2σ confidence levels. The uncertainty levels were then applied to the instrument range or spot reading, as appropriate, to create a noise component. The noise component was then added to the nominal input value to give the "noisy" input. Results for 'noisy' inputs are shown in Table 2.

Data Set	No of points	E_{Sn} %	S_{n95} rpm	σ rpm	r	Over trained / total networks
2a	496	+1.4 -1.5	+160 -161	58	0.99658	2/33
2b	496	+1.1 -1.4	+158 -165	59	0.999621	1/32

Table 2 – Data Set 2 Results

Testing Data Set 3

Four random data sets were generated. Each of the four sets included neural network inputs of suction pressure and temperature; discharge pressure and temperature; differential pressure and a training target of compressor speed. Set 3(a) and 3(b) contained 500 and 1000 data points respectively, and an additional input of molecular mass to represent gas characteristics. Set 3(c) contained 1000 data points and an additional 21 inputs, one for each of the gas components identified in AGA8, to represent gas characteristics. Set 3(d) contained 1000 data points and an additional 10 inputs, one for each gas component typically identified by an on-line gas chromatograph, to represent gas characteristics. Results of testing the sets are shown in Table 3.

Data Set	No of points	E_{Sn} %	S_{n95} Rpm	σ rpm	r	Over trained / total networks
3a	500	+2.5 -1.9	+161 -170	49	0.999663	4/35
3b	1000	+2.0 -2.4	+194 -218	40	0.999769	1/32
3c	1000	+2.0 -2.5	+169 -273	51	0.999655	6/37
3d	1000	+1.8 -2.6	+173 -228	47	0.999696	11/42

Table 3 – Data Set 3 Results

Testing Data Set 4

Data set 4 contained a limited training data set for testing neural network extrapolation performance. The individual data-points in the limited training set are shown against the complete performance characteristics in Figure 9. Results of extrapolation testing are shown in Table 4.

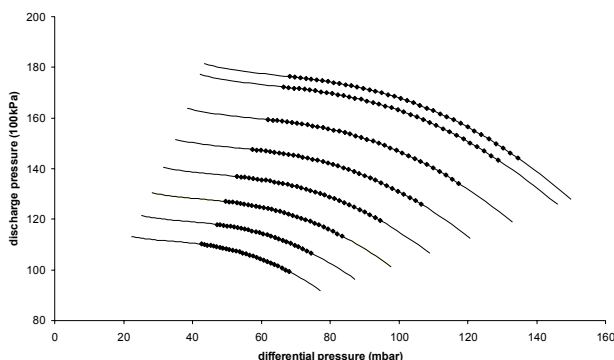


Figure 9 – Extrapolated Data Set

Data Set	No of Points	E_{Sn} %	S_{n95} Rpm	σ rpm	r	Over trained / total networks
4	496	+1.6 -4.8	+137 -629	176	0.995927	2/33

Table 4 – Data Set 4 Results

Testing Data Set 5

Training was undertaken using only normalised flow and isentropic head coefficients, Set 5(a). Only five networks were trained and the average training error exceeded 2000 rpm in each case. Since only five networks were trained peak, mean and standard deviation of the network errors are tabulated. The data set contained the 96 points generated for data set 1c. The errors for normalised training data only are summarised in Table 5.

Network no.	Peak errors %	Mean error %	Error s.d. Rpm
1	+28 / -12	4.0	2187
2	+21 / -18	2.2	2197
3	+15 / -23	1.4	2189
4	+22 / -16	0.8	2195
5	+25 / -13	2.9	2185

Table 5 – Data Set 5a Results

Further training was undertaken with the normalised data set but the inputs were augmented with suction pressure, suction temperature, discharge temperature and molecular mass, Set 5(b). Results are shown in Table 6. Input subsets were enabled and input combinations are summarised in Table 7.

Data Set	No of points	E_{Sn} %	S_{n95} Rpm	σ rpm	r	Over trained / total networks
5b	96	+4.6 -2.3	+426 -324	122	0.998414	9/40

Table 6 – Data Set 5b Results

No. of Inputs	Input combinations	No. of networks	Average s.d. Rpm
6	$\phi, \psi, T_d, T_s, P_s, MW$	1	152
5	ϕ, ψ, T_d, P_s, MW	1	138
5	$\phi, \psi, T_d, P_s, T_s$	3	128
4	ϕ, ψ, T_d, P_s	3	113
4	ϕ, ψ, T_d, T_s	1	95
4	ϕ, ψ, T_d, MW	2	113
4	ψ, T_d, MW, T_s	1	122
3	ϕ, ψ, T_d	8	109
3	ψ, T_d, P_s	1	142
3	ψ, T_d, MW	1	137
2	ψ, T_d	9	132

Table 7 – Data Set 5b Input Combinations

Further training was undertaken with discharge pressure replacing head coefficient, Set 5(c). Results of Data Set 5(c) testing are shown in Table 8 and input combinations are shown in Table 9.

Data Set	No of points	E_{Sn} %	S_{n95} Rpm	σ rpm	r	Over trained / total networks
5c	96	+3.3 -2.6	+164 -262	100	0. 998987	17/48

Table 8 – Data Set 5c Results

No. of Inputs	Input combinations	No. of networks	Average s.d. Rpm
6	$\phi, T_d, T_s, P_s, P_d, MW$	1	96
5	ϕ, T_d, P_s, P_d, MW	1	87
5	ϕ, T_s, T_d, P_s, P_d	4	77
4	ϕ, T_d, P_d, P_s	2	110
4	ϕ, P_d, T_d, T_s	3	94
4	ϕ, P_d, T_d, MW	1	91
3	ϕ, P_d, MW	1	139
3	ϕ, P_d, T_d	17	102
2	ϕ, T_d	1	118

Table 9 – Data Set 5c Input Combinations

A fixed input combination of flow coefficient, discharge pressure and discharge temperature was tested, Data Set 5d, results shown in Table 10.

Data Set	No of points	E_{Sn} %	S_{n95} Rpm	σ rpm	r	Over trained / total networks
5d	96	+2.8 -1.9	+166 -198	75	0.999432	16/47

Table 10 – Data Set 5d Input Combinations

DISCUSSION

Variations in Training Set Size

In all cases, the training : validation : testing set split was 50% : 25% : 25%. Hence for a 200 point data set, 100 points would be used for training, 50 points for validation and 50 points for neural network testing. Cross validation was used to assess whether or not over training had occurred. A summary of incidence of over training, in terms of training set size, is shown in Table 11.

The table suggests non-linear decrease in incidence of over-training as the training set size increase. For the same basic data set, the addition of simulated noise further reduces incidence of over-training. For a random data set, equivalent to continuously varying inputs, the results suggest that an over-training incidence of 3 in 100 will be experienced.

Data set	Training set size (no. of points)	Peak error (%)	Incidence of Over-training (%)
Basic 1a	48	+3.2 / -4.5	58
Basic 1b	92	+1.5 / -1.9	26
Basic 1c	248	+1.3 / -1.1	16
Noisy 2 a	248	+1.4 / -1.5	6
Noisy 2b	248	+1.1 / -1.4	3
Random 3a	250	+2.5 / -1.9	11
Random 3b	500	+2.0 / -2.4	3
Random 3c	500	+2.0 / -2.5	16
Random 3d	500	+1.8 / -2.6	26
Extrap. 4	248	+1.6 / -4.8	6
Normalised 5 (aug. inputs)	48	+4.6 / -2.3	23
Normalised 5 (ϕ, ψ, T_d aug. inputs)	48	+3.3 / -2.6	35
Normalised 5 (ϕ, P_d, T_d)	48	+2.8 / -1.9	35

Table 11: Incidence of Over training vs. Training set size

Training set size does not appear to significantly influence accuracy of the neural network predictions above 250 points.

As the number of inputs increase e.g. between sets 3(b) and 3(d) the accuracy performance is similar but the incidence of over-training increases.

In a field implementation the input signals to the neural network will be measured process variables. The measurement will include random noise largely defined by the instrumentation uncertainty levels.

Effects of instrument Noise

Comparing sets 1(c) and 2 (a), typical instrument noise levels appear to marginally degrade accuracy and variance levels but greatly reduce incidence of over training, by approximately two thirds.

Training on random operating points

Training with random data (set 3(a), within the operating envelope) degraded peak error performance from around $\pm 1.5\%$ to around $\pm 2.5\%$ but with improved variance performance, from 58 rpm to 49 rpm. Doubling training set size to 1000 data points (set 3(b)) further improved variance performance to 40 rpm and reduced incidence of over training by around two thirds half.

Data set 3(c) and 3(d) used an extended gas properties inputs. Increasing the number of inputs increased the incidence of over training and degraded variance performance. It should be noted that this “degraded performance” can still estimate compressor speed to around $\pm 2.5\%$.

Extrapolation from a restricted training set

The constant speed at which the peak -ve and +ve errors occur are shown in Figure 10 and Figure 11 respectively. The constant speed line is shown as the solid line with the training points. The broken line shows the neural network compressor speed estimate.

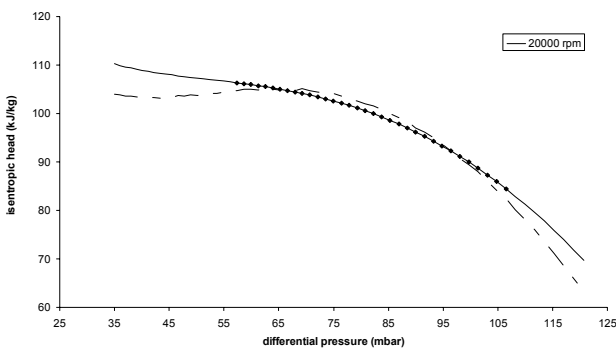


Figure 10 - Peak negative extrapolation error

Peak negative error is -4.8% occurring at a training speed of 20000 rpm.

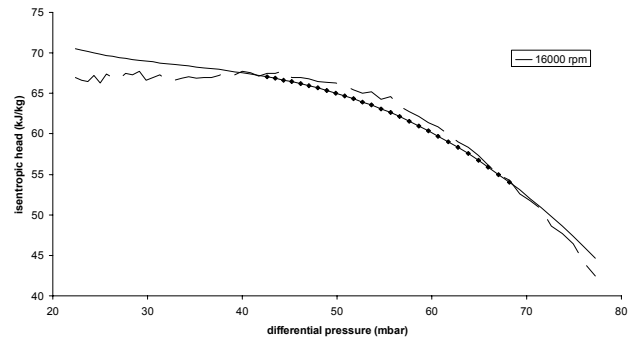


Figure 11 - Peak positive extrapolation error

Peak positive error, of $+1.5\%$, occurs at a training speed of 16000 rpm. Extrapolation is possible but could result in an asymmetrical, negative biased speed error of up to approximately 5%.

Training with normalised performance data

Training with only isentropic head and flow coefficients resulted in large errors in compressor speed estimates. Errors generated were one order of magnitude greater than neural networks when trained with absolute engineering units. The plot of the isentropic head vs. flow coefficient, the “universal speed” curve, is a multi-valued function in terms of compressor speed. It is possible to have several values of compressor speed at constant flow or isentropic head coefficient value. The universal speed curve and associated neural network estimated speeds are plotted for one neural network trained on normalised data is shown in Figure 12.

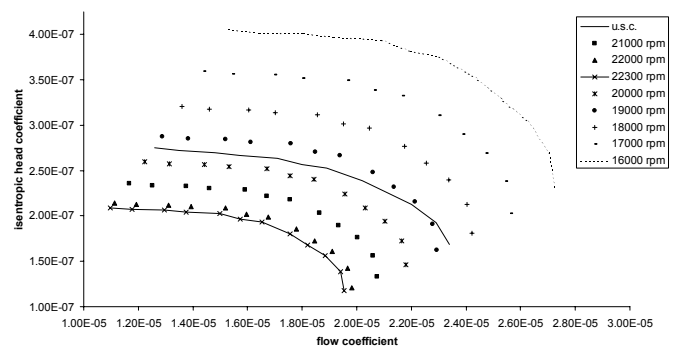


Figure 12 - Normalised data neural network performance

The neural network creates a separate curve for each compressor speed where one, universal curve is expected. The neural network can represent the shape of the curve but cannot

locate it in vector space. Plots of compressor speed, estimated from normalised data augmented with discharge temperature are shown in Figure 13 and Figure 14.

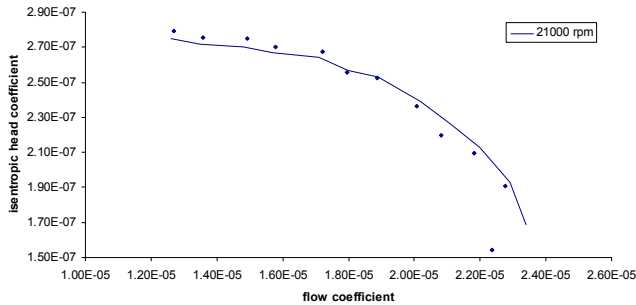


Figure 13 - T_d Augmented Input, peak -ve error

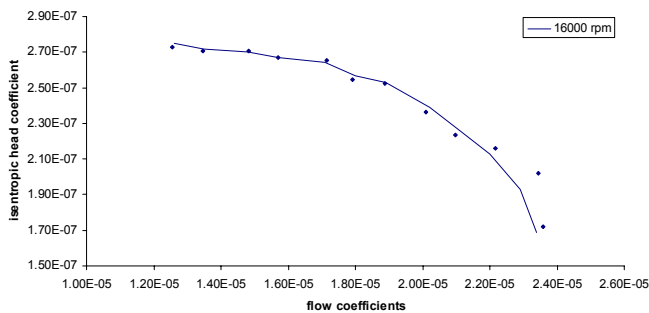


Figure 14 - T_d Augmented Input, peak +ve error

Normalised inputs of isentropic head and flow coefficient can be used to represent the universal speed curve when an augmenting input such as discharge temperature is added.

Further testing was undertaken with flow coefficient as the only normalised input. Compressor speed estimates were marginally improved, but frequency of over training increased by around 50%. More than 50% of the networks trained produced an input subset of flow coefficient, discharge pressure and discharge temperature. Training with the combination of flow coefficient, discharge pressure and discharge temperature was undertaken. Compressor speed estimates were within $\pm 3\%$ with an average error standard deviation of 75 r.p.m. Levels of over-training were consistent with reduced training set size at around 35%.

Analogy with other rotating systems

Henderson & Pearson 1997 [16] described a steady-state control scheme for a micro-hydrogenerator set. This method used the force balance equilibrium characteristics of the generator set and electrical load. Transient control was

implemented by other systems but improvements to transient response were suggested by the use of under or over correction of steady state loading, see Henderson & Pearson 1998 [17].

In a compressor system the characteristics are less well defined and affected by plant external to the system including process load. The compressor, however, exhibits the same tendency to settle at a natural equilibrium operating point. If the compressor characteristics are well known then the compressor speed can be set based on load constraints of capacity throughput and pressures.

The recycle valve in an anti-surge control system can be thought of as load control of the compressor where opening the re-cycle valve reduces the “load” on the compressor. There are similarities between the derivative control action described for the generator set [17] and a quick opening solenoid compressor recycle valve that improves surge control response.

Implementing Neural Network Based Performance Control

Effective performance control needs to hold the compressor at some operating point where capacity throughput and/or pressure constraints are met. This is likely to be achieved through the use of a steady state control scheme where averaging the performance control can meet longer term control objectives against plant transients. Performance control and anti-surge control are complimentary: effective, longer-term performance control should reduce the propensity of the compressor to surge and effective anti-surge transient control improves the effectiveness of the compressor in meeting performance objectives. Effective performance control therefore requires a composite control strategy.

Neural network estimates of compressor speed must be confirmed either by an operator, or expert rules, in a composite expert system. Safe operation of any plant equipment is of paramount importance, as discussed by Cordiner [5]. One element of an Expert System must centre around Safety/Protection. Decisions regarding the “representativity” of compressor speed estimates are needed to identify whether or not neural network re-training is required. A neural network, in the forms described, can be used as a basis for Model Predictive Performance Control. Some form of performance monitor, which may simply trend performance residuals, is required to trigger neural network training updates by the Expert System. As with Knowledge Based systems, Gonzalez & Dankel [18], some form of COP database and data filtering or data validation techniques will be required.

The approach of embedding neural networks and fuzzy logic rules within compressor control and monitoring strategies is discussed by many authors including, recently Vachtsevanos [19], Cordiner [5] and Botros [20].

CONCLUSIONS

The results of the testing are clearly indicative that neural networks can “learn” compressor head characteristics. The most rigorous test case, comprising a random data set of operating points, suggest that compressor speed can be estimated to within $\pm 2.5\%$ of the speed required to meet a given flow rate for a given discharge pressure constraint.

The “most representative” neural network design returned the lowest training error in each of the thirty-one tests conducted for each data set. Neural network architecture is overwhelmingly biased toward multi-layer perceptron, feed forward networks. This was found in the initial research phase and during the numerical testing. The difference in performance between similar neural networks is related to training algorithm employed.

Results of testing suggest that a data set size of 500 points can train a neural network to estimate compressor speed to $\pm 2.5\%$, Table 11. The use of gas components as inputs in place of molecular mass fall within this error band, but increase incidence of over-training, possibly related to more complex network architectures.

Extrapolation from the middle third of the flow coefficient range is possible but the error band increases to $\pm 5\%$ and the error distribution is biased toward underestimating compressor speed, Figures 10 and 11. This type of error would tend to move the compressor toward surge for a fixed discharge pressure constraint.

The use of normalised flow and head coefficient data for training neural networks is possible but the speed curves are reversed as shown in Figure 12. An augmenting input is required to locate the universal performance curve in absolute vector space. Use of head and flow coefficients augmented with discharge temperature, as inputs, accounted for 26% of neural network “best network” design. Use of head coefficient and discharge temperature accounted for 29%, Table 7. Error levels are similar to those reported for the actual number of training points, 48 in number. Augmented input performance is shown in Figures 13 and 14.

It may be possible to reduce the instrumentation associated with compressor control to three: flow rate measurement; discharge pressure and discharge temperature. Neural network training using flow coefficient, discharge pressure and discharge temperature indicate compressor speed can be estimated to within $\pm 3\%$ using these measurements alone, as indicated in Table 9.

The research, testing and results described in this paper are novel and form the basis of a novel performance control scheme for compressors. The method of controlling COP using neural networks falls into the category of model predictive control, where the compressor performance is estimated using a neural network trained on actual compressor data. This technique can be viewed as in incremental improvement in control technology as described by Botros 1994 [21].

Neural network learning capability implies that changing compressor performance characteristics can be accommodated

without specific expert intervention. The performance control set point, of compressor speed, can be expressed in terms of absolute engineering units without the need for translation relative to the compressor surge limit.

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