Detection of Valve Leakage in Reciprocating Compressor Using Artificial Neural Network (ANN)

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ABSTRACT

In the present work, Artificial Neural Networks (ANN) techniques are being applied for detection of valve leakage in reciprocating compressor. It has been experienced that replacement of defective valves before they cause further damage can greatly reduce maintenance and production costs. In the past, valve problems were unnoticed until process flow instruments showed a reduction in flow or when compressors became noisy or overheated. These symptoms usually did not occur until the very last stages of valve degradation. By this time the compressor frequently was damaged because of valve parts were being ingested into the cylinder and thus causing piston ring or liner damage. The application of Artificial Neural Networks technique identifies the most practical yet sensitive form of signature to use for trend monitoring and will additionally help the system to accept the fact that a compressor is malfunctioning without the aid of additional instruments capable of establishing credibility.

Key Words: Artificial Neural Network, valve leakage, valve degradation, signature, trend monitoring.

1. INTRODUCTION

Artificial Neural Network (ANN) is a computing system made up of number of simple, highly interconnected nodes or processing elements, which process information by its dynamic state response to external inputs. The ANN maps a set of input patterns on to a corresponding set of output patterns. The network accomplishes this mapping by first learning from a series of past examples. The network then applies what it has learnt to a new input pattern to predict the appropriate output. Typical faults are being introduced or simulated in the reciprocating compressor components. The cylinder pressure signature is monitored. The information is subsequently trained to output a response when a particular level of deterioration is encountered in the unit.

Miles and Ramsey (1992) had carried out preliminary investigations on reciprocating compressor trouble shooting and fault diagnosis. The effect of faults like leaking valves and piston rings, vibration of valve springs, delayed closing of discharge valve, etc. studied by Chlumsky (1965). Yadava *et al* (1985) had experimentally shown these effects on pressure pulsations. Matsumura *et al* (1992) described analysis of indicator diagram as a method to diagnose valve malfunction which can not be predicted in advance. Woollatt (1993) has indicated that the comparison of pressure-volume diagram of healthy and defective compressor can indicate the types of defects. Manepatil (1996) suggested mathematical simulation of the compressor cycle. Patterson (1995), Rich (1991) and Wasserman (1989) helped to work on Artificial Neural Network (ANN).

The aim of this paper is to use the ANN techniques for identifying the most practical yet sensitive form of signature used for trend monitoring so as to avoid more serious damage to the reciprocating compressor. The failure of valves of reciprocating compressor can result in more serious damage to the compressor because of the ingestion of the valve parts in to the cylinder, which can result in piston or liner damage. Artificial Neural Networks techniques, Functional Link Network (FLN) is used for pattern recognition of pressure signal and to classify that weather the leakage is in suction valve or discharge valve and Back Propagation Algorithm (BPA) is used to predict the amount of leakage in the respective valve in terms of percentage.

2. COMPRESSOR

2.1 Compressor Detail:

Table-1 shows the specifications of a single stage reciprocating compressor, which has been used for simulating the detection of valve leakages.

2.2 Common Faults in Reciprocating Compressor:

Majority of the problems in a reciprocating compressor exist because of the valve leakages. Discharge valves are normally subjected to most severe conditions in the reciprocating compressor.

2.3 Pressure – Time Diagram for two faults:

The two major faults have been considered for the study of reciprocating compressor. The simulated healthy pressure–time diagram of reciprocating compressor is shown in *figure-1*. First the leakage in suction valve, whose diagram in comparison with healthier one, is shown in *figure-2* while f*igure-3* represents the second fault, i.e., the discharge valve leakage.

3. ARTIFICIAL NEURAL NETWORK (ANN)

3.1 Use of ANN for Trend Monitoring:

In the present work, the simulated healthy expansion process of compressor in pressure-time coordinate has been predicted using *Functional Link Network (FLN)* as ANN tool for pattern recognition. On the basis of the comparison of this simulated healthy expansion process of compressor with actual expansion process, whether the leakage is in suction or discharge valve can be determined. The percentage of leakage, on the basis of pressure deviation at a particular instant of time, has been predicted by using *Back Propagation Algorithm (BPA)*.

3.2 Functional Link Network (FLN):

FLN is a single layer network, i.e. number of neurons in the layer equals to the output variables. The architecture of FLN is shown in *figure-4*. The neurons of the output layer are non-sigmoid. The network is trained via delta rule. The basis of the network is Mc Lourin's series. Following enhanced type of sets can be assumed.

$X, X^2, X^3\ldots,$ or $X, \mathrm{Sin}\,(\pi X), \mathrm{Cos}\,(\pi X), \mathrm{Sin}\,(2\pi X), \mathrm{Cos}\,(2\pi X) \ldots,$ or $Xi, Xi.Xj, \ldots\ (j \geq i)$, etc.

The prediction of healthy expansion process of compressor using FLN has been used, in which X1=1, X2=t, X3= t^2 X4= $t^3$and X5= $t^4$are the inputs, W1, W2, W3, W4, W5 are the weights and P is the output. Initially, low random values of weights have been taken and are subsequently trained by flow diagram of FLN as shown in *figure-6*. The trained weights from FLN are as follows:

W1 = 0.979721, W2 = -2.236767, W3= 1.239925, W4 = 0.539985 and W5 = - 0.309054.

The predicted healthy signal from FLN has been compared with the simulated signal. If the input signal from compressor is going towards *lower* side to the healthy signal the leakage is in *suction* valve and if the input from compressor going *upper side* with respect to healthy signal, the leakage is in *discharge* valve.

3.3 Back Propagation Algorithm (BPA):

The Back Propagation Algorithm (BPA) is a fully connected, layered, feed-forward network, which has been shown in *figure-5*. In this figure, there are unit activation levels of input, hidden and output units and weights on connections between the input and hidden units and hidden and output units. This network has three layers. Each unit in one layer is connected in the forward direction to every unit in the next layer, then on to the output layer. The existence of hidden units allows the network to develop complex feature detectors, or internal representation.

The back propagation network starts with initialization of a random set of weights for input-output pair as shown in *figure-7*. The network adjusts its weights each time it sees an input-output pair. Each pair requires two stages: a forward pass and a backward pass. The forward pass involves presenting a sample input to the network and letting activations flow until they reach the output layer. During the backward pass, the network's actual output (from the forward pass) is compared with the target output and error estimates are computed for the output units. The weights connected to the output units can be adjusted in order to reduce those errors. The error estimates of the output units

can be used to derive error estimates for the units in the hidden layers. Finally, errors are propagated back to the connections stemming from the input units. The BPA updates its weights incrementally, after seeing each input-output pair. After it has seen all the input-output pairs (and adjusted its weights that many times), one epoch has been completed. Training a back propagation network usually requires many epochs. The training set for training the low random values weights (both input and output are normalized), are given in *table-2* and *table-3* for suction valve and discharge valve respectively. The trained weights from BPA for leakages in s*uction valve* are given below:
Input Weights: W1=-1.030214, W2= 1.435114 and W3= 1.153805.
Output Weights: W4= -1.723355, W5= 1.060080 and W6= 0.661403 and in *discharge valve* are given below:
Input Weights: W1=-1.030214, W2= 1.435114 and W3= 1.153805.
Output Weights: W4= -1.723355, W5= 1.060080 and W6= 0.661403.

4. RESULTS

4.1 Prediction of Healthy Process:

Figure-8 represents the trained signature of the healthy expansion process. FLN has been used to predict the pressures at different times which are given in *table-4*. Some of the values of predicted pressure from FLN for healthy expansion process have been compared with the values of simulated pressure as shown in *table-5.*

4.2 Trend Shift for Leakage in Suction or Discharge Valve:

The signal i.e. pressure signal coming from compressor, will go towards *lower* side for the leakages in *suction* valve, as shown in *figure-9* for 2%, 3%, and 4% leakages while will shift on *upper* side of healthy signal for the leakages in *discharge* valves as shown in *figure-10* for 1.5%, 1%, 0.7% and 0.5% leakages.

4.3 Prediction of Percentage of Leakage:

The *table-6* represents comparison between percentage leakages as obtained from BPA with the simulated leakages for *suction* valve at particular time. Similarly, the *table-7* represents comparison between percentage leakages as obtained from BPA with the simulated leakage for *discharge* valve at particular time.

5. CONCLUSIONS

- The result data from tables 5, 6 and 7 are very close to the simulated data, i.e., the pattern recognition of pressure signal from FLN and quantification of percentage of leakages for suction and discharge valves from BPA. Therefore, ANN (combination of FLN and BPA) may be a good tool for early detection of valve leakages.
- The application of Artificial Neural Networks (ANN) technique will additionally help the system to accept the fact that a compressor is malfunctioning without the aid of additional instruments capable of establishing credibility.
- In the present work, the ANN presented in the form of computer program only. In future, these computer programs can be used with computer interfacing for online monitoring of the compressor.

Table-1: Cylinder and valve parameter

Cylinder Parameters:	*Unit*	*Value*	
Compressor Speed	rpm	750	
Cylinder Bore	m	0.127	
Connecting Rod Length / Crank Radius	n = l/r	20/5 = 4	
Cylinder Clearance	m	0.014	
Suction plenum chamber diameter	m	0.09	
Discharge plenum chamber diameter	m	0.098	
Piston head diameter	m	0.12	
Discharge pressure	Pa	444000	
Wall temperature	K	373	
Valve Parameters:		*Suction*	*Discharge*
Mass of valve plate + 1/3rd spring mass	Kg	0.770	0.0536
Spring stiffness of valve	KN/m	9.04	21.3
Initial force on valve plate	N	27	49.58
Permitted valve lift	mm	1.34	1.72
Effective diameter of valve plate	m	0.132	0.102
Effective area of valve plate	mm ²	4168	4831
Valve discharge coefficient	-	0.7	0.7

Table – 2: Normalized value of leakage and pressure difference as training set for suction valve leakage detection.

Sr. No.	*Normalized Pressure difference at particular instant (P/Pmax) ΔP max = 122890.46 Pa*	*Normalized Leakage (L/Lmax) Lmax = 4%*
1	1.0000000	1.00
2	0.8224067	0.75
3	0.5122435	0.50
4	0.0000000	0.00

Table – 3: Normalized value of leakage and pressure difference as training set for discharge valve leakage detection.

Sr. No.	*Normalized Pressure difference at particular instant (p/pmax) ΔP max = 36241.8506 Pa*	*Normalized Leakage (L/Lmax) Lmax = 1.5%*
1	1.000000	1.0000
2	0.588759	0.6667
3	0.376601	0.4667
4	0.197678	0.3333

Table - 4: Prediction of pressure at arbitrary time's through FLN

Time (sec)	*Predicted Pressure from FLN (Pa)*
0	439662
0.000278	412192.2
0.001296	319406.8
0.002037	260090.4
0.002222	246415.7
0.004074	135641.8
0.004537	115540.8
0.006018	71731.67
0.006574	63197.94
0.0075	58169.98
0.008518	65123.23
0.009537	83923.71
0.01	95949.91

Table - 5: Comparison of predicted pressure from FLN & simulated pressure

Time (sec)	*Predicted Pressure from FLN (Pa)*	*Simulated Pressure (Pa)*
0	439662	448762.5
0.002037	260090.4	264153.9
0.002222	246415.7	244353.7
0.004074	135641.8	112377.2
0.006574	63197.94	57533.13
0.01	95949.91	95718.65

Table - 6: Comparison between leakages from BPA with the simulated leakage for *suction* valve at particular time

Pressure difference (Pa) in suction at particular instance 0.0025 sec	*% of Leakage from BPA*	*Simulated % of Leakage*
122890.46	3.822838	4.0
101065.94	3.082928	3.0
62949.84	2.011082	2.0
0	- 0.003740	0

Table - 7: Comparison between leakages from BPA with the simulated leakage for *discharge* valve at particular time

Pressure difference (Pa) in discharge at particular instance 0.0025 sec	*% of Leakage from BPA*	*Simulated % of Leakage*
36241.85	1.39742	1.5
21337.72	0.976751	1.0
13648.72	0.724536	0.7
7164.22	0.498519	0.5

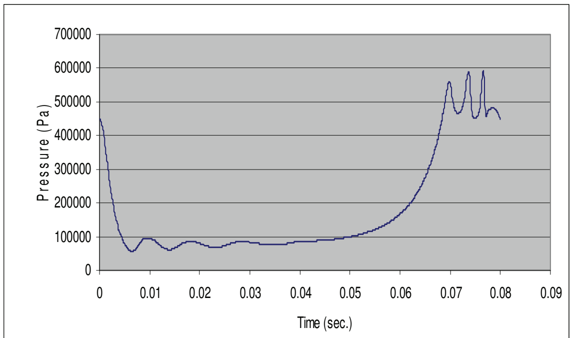

Figure-1: Simulated Compressor with Healthy valves

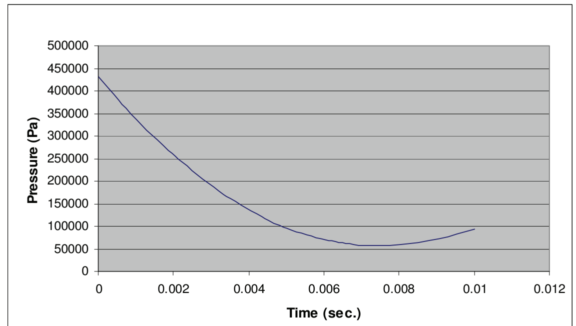

Figure-8: Healthy expansion process from FLN

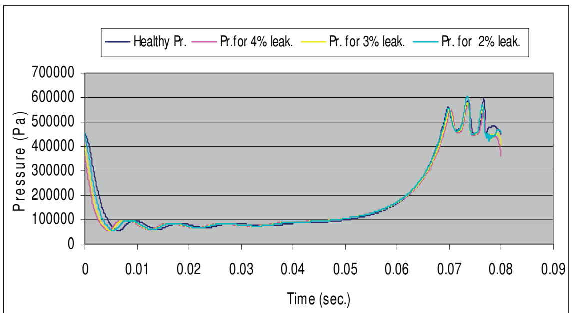

Figure-2: Simulated Faulty suction valve

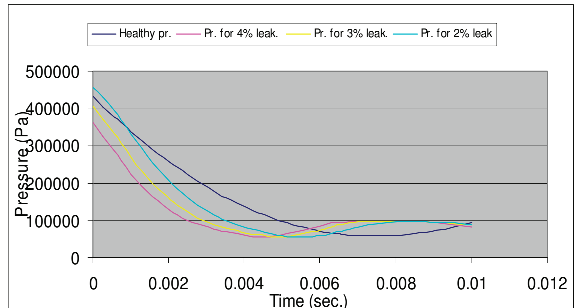

Figure-9: Simulated Suction valve leakage

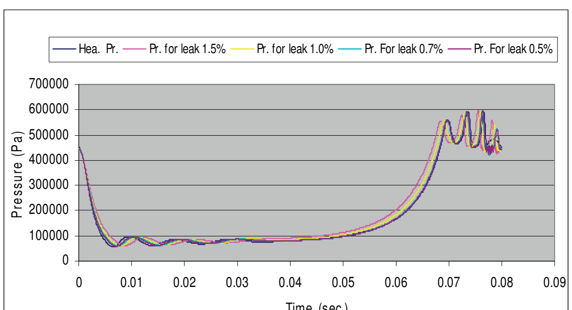

Figure-3: Simulated Faulty Discharge valve

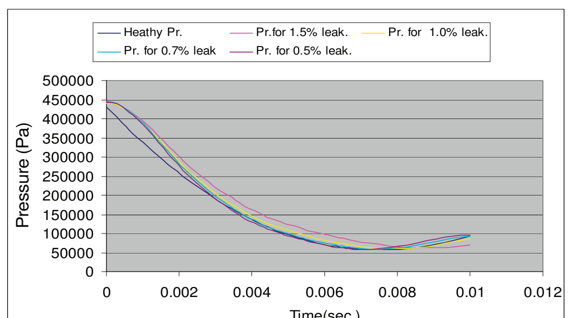

Figure-10: Simulated Discharge valve Leakage

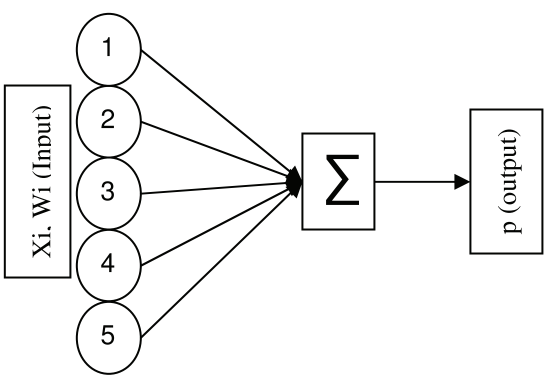

Figure - 4: Architecture of Functional Link Network (FLN)

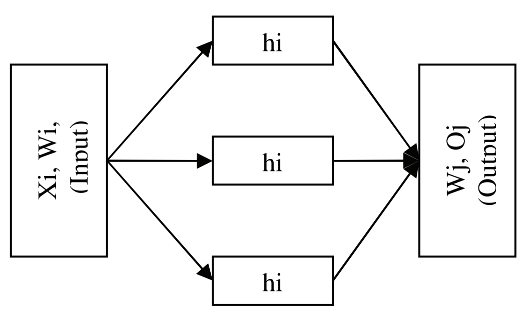

Figure - 5: Architecture of Back Propagation Algorithm (BPA)

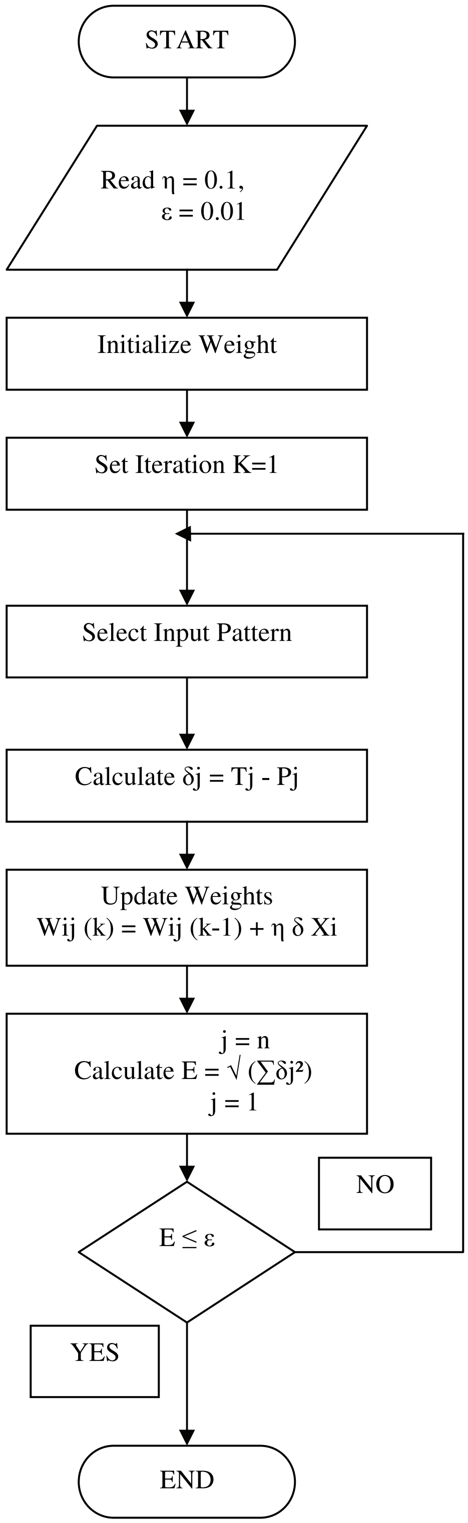

Figure - 6: Flow Chart for Functional Link Network

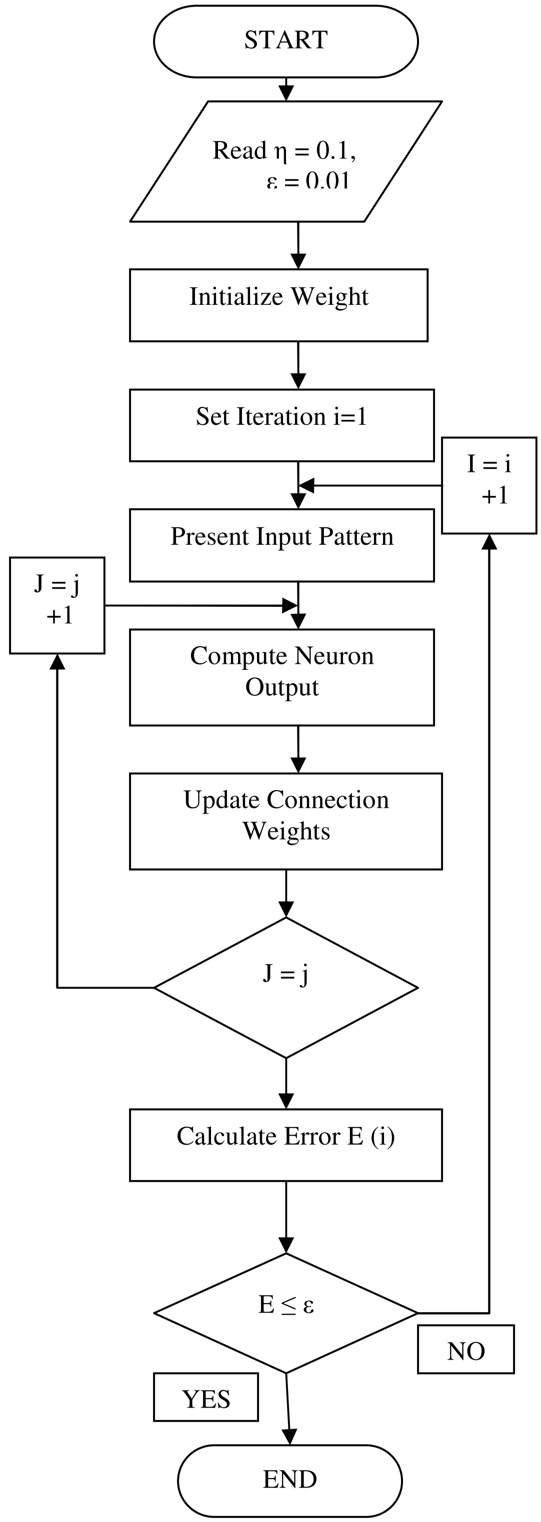

Figure - 7: Flow Chart for Back Propagation Algorithm

NOMENCLATURE

E	error	
h	hidden activation	
O	neurons	
p	pressure	(Pa)
Δp	pressure difference	(Pa)
P	actual output activation	
t	time	(seconds)
T	desired output activation	
W	weights	
X	input	
ANN	Artificial Neural Network	
FLN	Functional Link Network	
BPA	Back Propagation Algorithm	

Greek Symbols:

δ	error gradient
ε	tolerance
η	learning rate

Suffix:

i	input
j	output
max	maximum

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