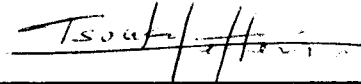


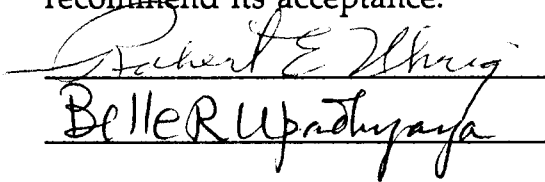
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A NEURAL NETWORK METHODOLOGY FOR CHECK VALVE
DIAGNOSTICS

A Thesis
Presented for the
Master of Science
Degree
The University of Tennessee, Knoxville

Michael T. Travis
December 1991

DEDICATION

This thesis is dedicated to my parents and my grandparents for their support and encouragement throughout my entire education. I dedicate this thesis to them since I can only begin to return to them the many things they have given to me.

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ABSTRACT

The emerging computational tools of artificial neural networks are applied to the area of check valve diagnostics. Recent years have seen increased attention to check valves as a result of several valve failures in safety-related systems in nuclear power plants, demonstrating the need for a non-intrusive method for monitoring check valves. A neural network methodology has been developed for check valve diagnostics using data from a test flow loop. The methodology developed uses an artificial neural network architecture which couples both unsupervised and supervised learning networks in a unified structure.

The results of this research demonstrate the ability of the coupled-network methodology to be applied to check valve diagnostics, more specifically the check valve operating condition. This methodology shows improved results over other self-organizing neural networks investigated (competition, self-organizing map, and probabilistic neural networks). The results of this methodology can be improved using various methods to represent the input data.

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CHAPTER 1

INTRODUCTION

1.1 Background On Check Valves

A check valve is a self-contained, self-actuating device which has no external means to indicate its internal position or operation. Figure 1 shows the structure of a swing-type check valve and its internal components. The check valve internals consist of the valve seat, valve disc, stud pin, hinge arm, hinge pin, and the backstop. Other types of check valves include piston-lift, tilting-disc, ball, and duo-check valves.

Thousands of valves are used in a nuclear power plant (NPP), several hundred of which are crucial to the integrity of the defense barrier for isolation of leaks and prevention of the release of radiation to the public [1]. Check valves are used throughout a nuclear power plant to prevent reverse flow in the event of a pipe break and to separate high-pressure systems from low-pressure systems. Hundreds of check valves are located throughout the piping system of a nuclear power plant. Table 1 lists the general locations of check valves in a NPP and the approximate number of valves used in these areas [2]. Each valve has the potential for developing problems due to component wear effects from aging and service.

1.2 Degradation and Failure of Check Valves

Continued component degradation leads to check valve failure, causing concern for plant availability (since plant shutdown is necessary for

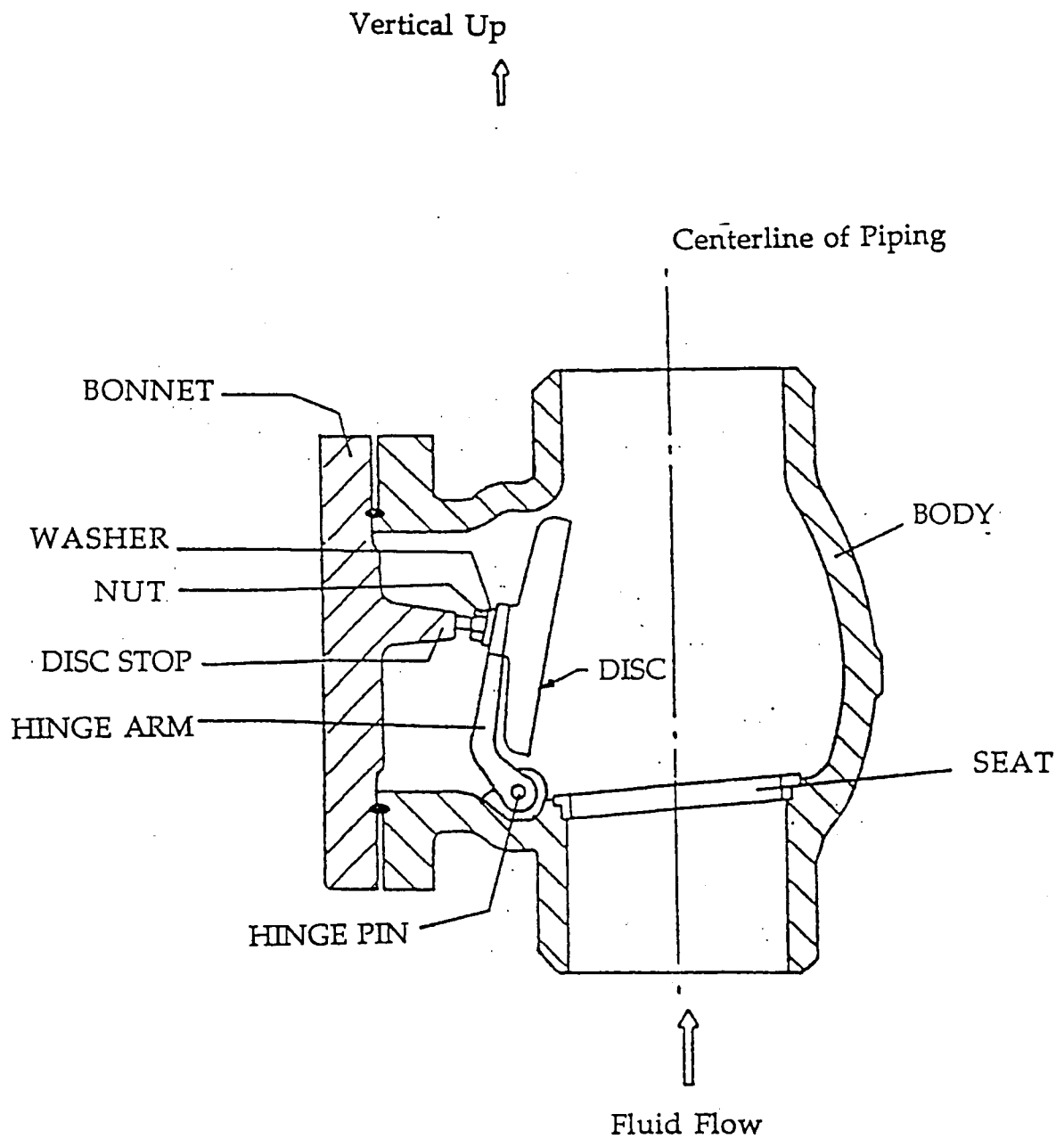


Figure 1: Diagram of A Swing Check Valve.

Table 1: Typical Valve Locations and Applications in a Nuclear Power Plant.

Reactor Type	Reactor System	Number of Valves	Valve Size (inches)
BWR	Low-pressure core spray	10 - 18	2 - 28
	High-pressure coolant injection	10 - 14	4 - 24
	Low-pressure coolant injection [Includes residual heat removal and containment spray]	10 - 21	4 - 24
	BOP systems	200 - 400	0.5 - 24
PWR	Auxiliary feedwater	4 - 23	4 - 8
	Containment spray	4 - 14	6 - 14
	High-pressure coolant injection	12 - 28	2.5 - 4
	Low-pressure coolant injection and residual heat removal	5 - 14	8 - 10
	BOP systems	200 - 400	2 - 60

maintenance) and safety. The most common problem associated with the failure of check valves results from system flow oscillations or system piping vibrations. The most significant sources of check valve failure due to system operation failure to have the minimum velocity required to lift the disc to the full-open and stable position, failure to have the minimum distances from upstream disturbances, vortex shedding from the valve seat and the trailing edge of the valve disc, and pump induced pulsations. Other sources include high velocity through the valve seat, control valve and orifice cavitation, and water hammer in piping systems. These operating conditions induce check valve component degradation and may lead to check valve failure [3].

Failure of check valves can cause serious power plant component damage such as overpressurization of low pressure systems, steam binding of auxiliary feedwater pumps, and damage from water hammer conditions [4]. Increased attention to check valves in recent years resulted from several valve failures in safety-related systems causing plant shutdown. Consequently, there is a strong need for verifying their operational integrity. Check valve monitoring methods can be generalized into two classes: intrusive and non-intrusive.

1.3 Check Valve Monitoring Methods

The traditional method of teardown and inspection is an intrusive method for monitoring check valves. The valve is disassembled and the components are inspected. This procedure provides accurate diagnosis of the check valve internals. However, if a valve is operating in a normal condition, teardown and reassembly of it may introduce degradation leading to failure of the valve.

Since intrusive methods may introduce problems, industry has focused on developing nonintrusive methods for check valve monitoring. Three major methods have been established: acoustic emissions monitoring (AEM), ultrasonic inspection (UTI), and magnetic flux signature analysis (MFSA). Several utilities and vendors have performed extensive studies on these monitoring methods. Two methods developed more recently by Oak Ridge National Laboratory are the external AC magnet (EACM) method and the external DC magnet (EDCM) method [5]. The ability of these methods to detect the most common check valve problems is listed in Table 2 (indicated by either 'Yes', 'No', or not necessarily 'NN').

Table 2: Effectiveness of Nonintrusive Check Valve Monitoring Methods.

Check Valve Problem	AEM	MFSA	UTI	EACM	EDCM
<u>Internal Degradations</u>					
Hinge pin wear	Yes	Yes	Yes	Yes	Yes
Disc stud wear	Yes	Yes	Yes	Yes	Yes
Disc-hinge arm wear	Yes	Yes	Yes	Yes	Yes
Cavitation	Yes	No	No	No	No
<u>Disc Position</u>					
Fully open	NN	Yes	Yes	Yes	Yes
Fully closed	NN	Yes	Yes	Yes	Yes
Intermediate positions	No	Yes	Yes	Yes	Yes
Flutter	NN	Yes	Yes	Yes	Yes
Backstop or seat contact	Yes	Yes	Yes	Yes	Yes
<u>Loose or Missing Internal Parts</u>					
Parts not moving	No	Yes	Yes	Yes	Yes
Dislodged parts	No	Yes	Yes	Yes	Yes
<u>Leakage</u>					
Seat leakage	Yes	No	No	No	No
Reverse leakage	Yes	No	No	No	No
External leakage	Yes	No	No	No	No

Acoustics emission technology has been applied by Advanced Technology Engineering Systems, Inc. in developing COMANDD (Checkvalve Operation Monitoring AND Diagnostic System). This system provides time and frequency displays of the raw data acquired by the system and time delay processing for impact location. Software provides analysis such as shock pulse analysis for periodic events, histograms for pattern recognition techniques, and waterfall plots for overall vibration analysis [6]. Acoustic emission and magnetic flux signature analysis methods are combined by Liberty Technologies in QUICKCHECK, a check valve diagnostics system. The acoustic signals are represented by three separate signals: the high-frequency envelope, the low-frequency acoustic signal, and the total acoustic signal. The magnetic trace is used in conjunction with the acoustic envelope trace for monitoring the valve open/close stroke [7].

Acoustic emissions are generated when solids contact each other or when gases or liquids flow through pipes and fittings. These emissions can be detected using piezoelectric accelerometers or microphones which respond to pressure waves over wide frequency ranges. The acoustic signal can be analyzed for determining the integrity of the valve. Magnetic flux signature analysis uses a permanent magnet placed on a moving part inside the check valve. A Hall-effect gaussmeter sensor outside of the check valve detects the magnitude of the magnetic field (constant and varying) produced by the magnet. MFSA is nonintrusive except for the initial placement of the magnet within the check valve [5]. For ultrasonic inspection of check valves, an ultrasonic signal (a high-frequency sound wave) is generated by a transmitting transducer located outside the valve body. This signal is transmitted through the valve and is reflected by the internal components

back to the receiving transducer. Time analysis of the reflected wave yields information about disc position [8].

The external AC magnet method uses two wire coils attached to the body of the check valve at different locations. A fixed-frequency electric current source is connected to the transmitter coil producing a magnetic field. The receiver coil senses the magnetic field transmitted through the valve and warped by the valve body and internals. A measurable current is induced in the coil by the magnetic field. The external DC magnet method uses one or more DC magnetic fields produced externally by permanent magnets or by coils carrying DC current. A Hall-effect probe is used to detect the DC magnetic fields transmitted through the valve. The EDCM method is similar to MFSA, except that this method is totally non-intrusive [8].

1.4 Automation Techniques for Plant Diagnostics

Non-intrusive techniques for check valve diagnostics are a viable alternative to past techniques since they eliminate the wear induced by physical inspection. These methods also lend themselves to techniques for automating check valve diagnostics. Automation of power plant diagnostics has already been applied to systems such as motor-operated valves [9], boilers, turbines, and environmental controls [10]. Since preventive and corrective maintenance procedures can cost as much as 25 percent of a power plant's total production costs [10], predictive maintenance procedures are receiving increased attention. Automation of check valve diagnostics would prove beneficial for valves located in high-radiation areas by reducing exposure of workers and for early detection of valves with potential problems.

1.5 Application of Artificial Neural Networks for Check Valve Diagnostics

Artificial neural networks (ANNs) have demonstrated remarkable success in pattern recognition and classification problems [11]. ANN technology has been applied to many aspects of nuclear power plant performance, such as prediction of power and process variables [12] and plant component diagnostics [13]. ANNs can also be used for non-intrusive evaluation systems to make rapid and reliable evaluations to identify potential problem areas for human evaluation [14]. Such success demonstrates the potential for neural network application to check valve diagnostics.

The emerging computational tools of artificial neural networks are applied to develop a neural network methodology for check valve diagnostics. Using experimental check valve data from a test flow loop, the objective is to develop an ANN to detect check valve operating conditions based on input data from the experimental tests. ANN learning algorithms are investigated as well as techniques for representing the data.

The methodology developed utilizes unsupervised and supervised learning networks in a unified structure. A self-organizing network using the K-means algorithms is used to organize the input data into clusters of similar patterns. The centroids of the clusters are then used to train a backpropagation network to output a coded representation of the test condition. This approach demonstrates improved results over other networks investigated. The results of this methodology can be improved by utilizing the concepts of fuzzy logic to represent the input data.

CHAPTER 2

NEURAL NETWORK THEORY

2.1 Definition of An Artificial Neural Network

An artificial neural network (ANN) is an information processing system whose structure is inspired by methods of information processing believed to exist in the brain. An ANN is composed of a large collection of simple processing units interconnected with variable weights or strengths which result in excitatory or inhibitory responses. These processing units (artificial neurons or neurodes) take information from sensors or other artificial neurons, process this information, and transmit an output signal.

Neural network models are specified by three factors: the topology of the network, the characteristics of the neurodes, and the learning rules. The learning rules specify two things, an initial set of connection weights and how to adapt the weights during network training [15]. ANNs use logical parallelism with serial operations. ANNs have substantial fault tolerance resulting from large numbers of processing units and primarily local interconnectivity. Thus, damage to a few neurodes does not necessarily impair the overall performance of the network.

2.2 The Biological Neuron and the Artificial Neuron

A simple diagram of a biological neuron is given in Figure 2. The output of a neuron is transmitted to other neurons through interconnections called axons which branch out to connect with other neurons via axon collaterals. The axon collateral connects to the part of the neuron called a

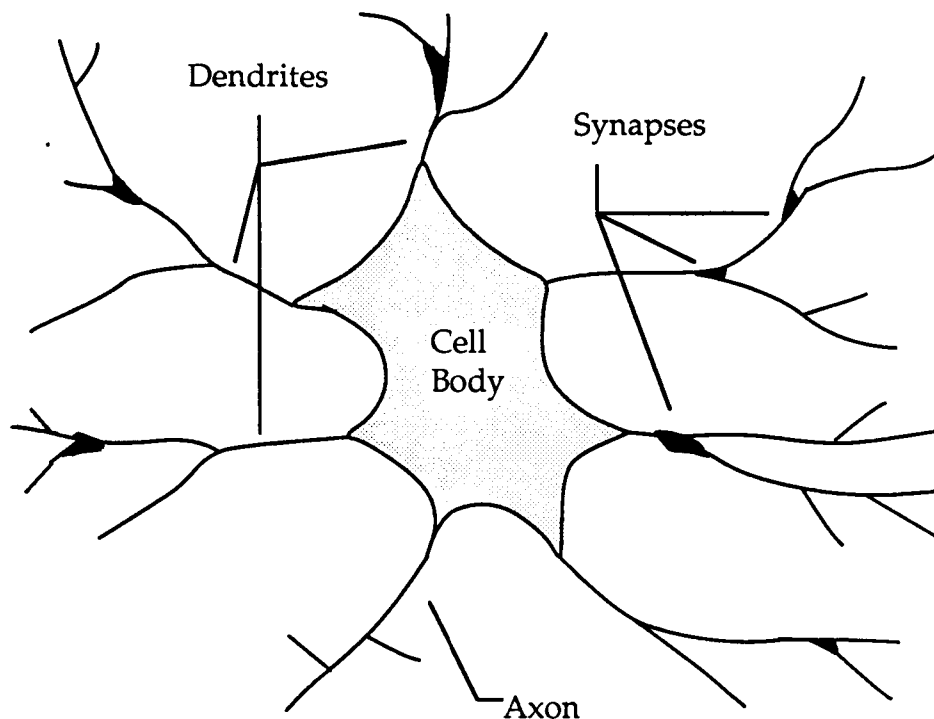


Figure 2: Illustration of a Biological Neuron.

dendrite. This point of connection is called the synapse, which has differing strengths, or synaptic weights, and can be either adaptive or plastic. The synapses produce either an excitatory or inhibitory effect on the activity of the neuron. If the total activation transmitted by the dendrites exceeds a threshold limit, the neuron transmits its output signal along its axon to other neurons [16].

The processing units, or neurodes, of an artificial neural network perform in a similar manner. Figure 3 illustrates the neural network processing unit. Input signals (x_i) from either sensors or from the outputs of other neurodes, are multiplied by their respective weights (w_i) and summed (net_k). The result is then passed through a nonlinear transfer (or activation) function to produce an output (O):

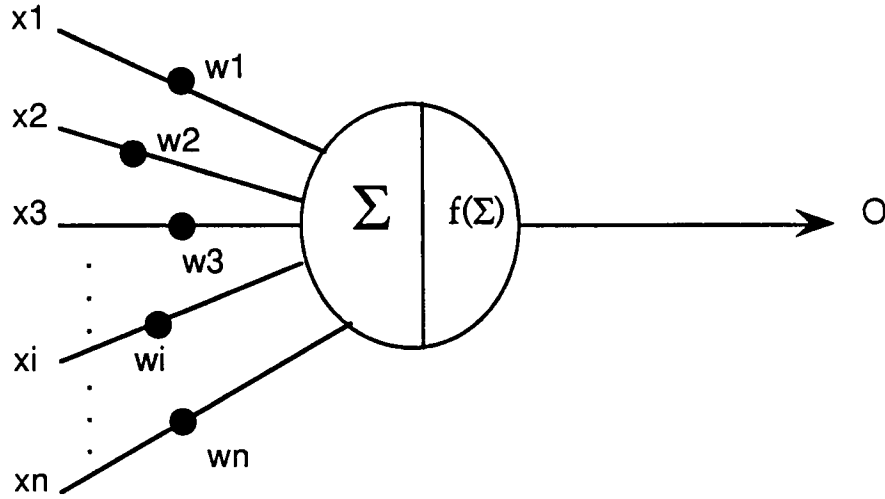


Figure 3: Diagram of an Artificial Neural Network Processing Unit.

$$O = f_k(\text{net}_k) = f_k\left(\sum_{i=1}^n x_i w_i\right) \quad (2.1)$$

Four commonly used activation functions are linear, ramp, step, and sigmoid. The sigmoid activation function is used in this thesis and is given by:

$$f(\text{net}_k) = \frac{1}{1 + \exp\left[-\frac{\text{net}_k}{\theta_0}\right]} \quad (2.2)$$

The sigmoidal slope of the activation function is given by θ_0^{-1} .

2.3 Classification of Artificial Neural Networks

Artificial neural networks can be classified according to their learning algorithms into two categories: *unsupervised* and *supervised* learning. An unsupervised learning algorithm will self-organize a set of input patterns into groups of patterns called clusters based on a measure of similarity. As a result, a large number of patterns can be separated into several clusters. A supervised learning algorithm adjusts its connection weights and thresholds

to represent the knowledge contained in a set of associated input/output pairs. The objective is to minimize the sum of the square of the output errors averaged over all patterns. Different rules are used to make corrections to the ANN weights [17].

2.4 Artificial Neural Networks With Unsupervised Learning

Unsupervised learning in neural networks means that the network has no knowledge of the correct output for an input pattern to be used for training. These networks are generally modeled after neurobiological systems. Several models using unsupervised learning have been people trying to model learning in parts of the brain. One model, the Kohonen network, uses competition between output nodes to classify output patterns. Other models for unsupervised learning include the self-organizing map (an adaption of competition) and the Grossberg outstar [18].

2.4.1 A Euclidean-Distance-Based Self-Organizing Network

One approach to a self-organizing network, although it is not an ANN in the strictest sense, is an algorithm which self-organizes a set of input patterns based on a Euclidean distance (ED). The square of the Euclidean distance from a new pattern vector X to the j^{th} cluster center is:

$$ED_j^2 = \sum_{i=1}^n (B_{ij} - X_i)^2 \quad (2.3)$$

where (B_{ij}) are the coordinates of the cluster centroid. A new pattern is assigned to the cluster for which ED^2 is the smallest, provided that it also satisfies the similarity test:

$$ED_{j^*} < \text{cluster radius} \quad (2.4)$$

If these conditions are met, the centroid coordinates of cluster j^* are adapted to include the new pattern. Otherwise, a new cluster is formed by the pattern. This method of organizing data is referred to as the K-means algorithm for clustering. The structure of this type of self-organizing network is illustrated in Figure 4, where the minimum distance classifier shown assigns the cluster number to which the input pattern is most similar. The connections shown in the figure do not represent connections with weights; instead, they are used to illustrate the flow of information through this algorithm.

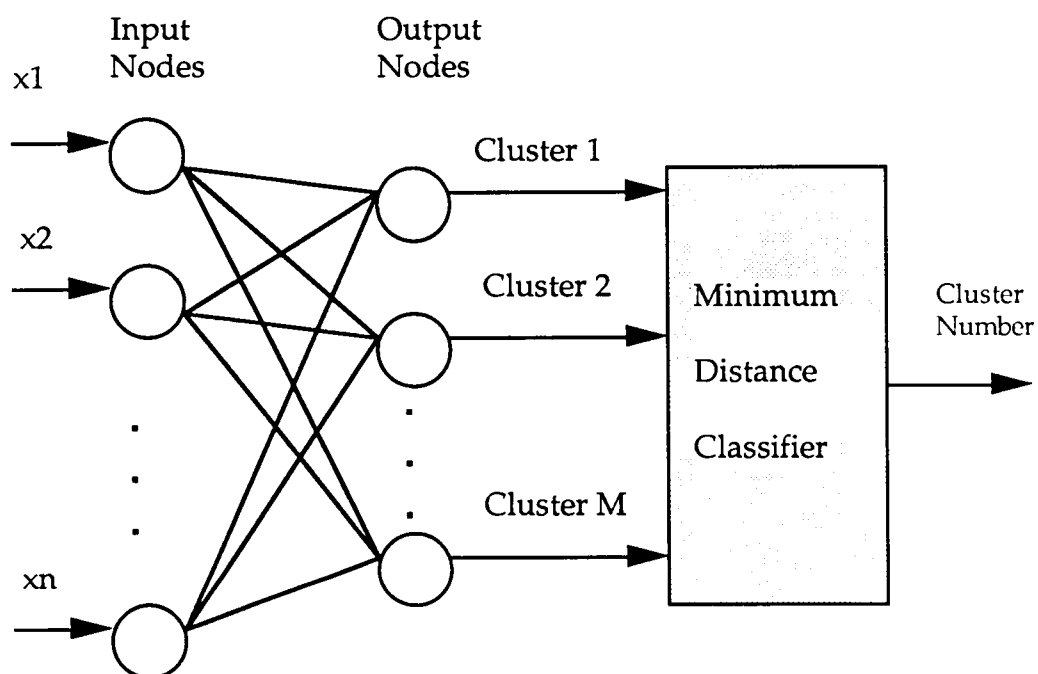


Figure 4: Diagram of a Euclidean-Distance-Based Self-Organizing Network.

2.4.2 The Competitive Filter Network

Another self-organizing neural network, developed by Teuvo Kohonen, is the Kohonen network, or competitive filter network [19]. The competitive layer of neurodes in this network uses lateral inhibition. Each input vector in a set of patterns is presented to the network. Each neurode in the competitive layer computes its total response from the input vector, and the neurode with the strongest response is designated the winner. The winning neurode and its neighbors adjust their weights according to:

$$\delta W_{ij}(t) = R * A_j(t) * [A_i(t) - W_{ij}(t)] \quad t = 0,1,2,... \quad (2.5)$$

for each neurode j , where W_{ij} is the connection weight from neurode i to neurode j , R is the learning rate, and A is the response (or activation) of a neurode from the input vector. The weight vector for the j^{th} neurode is then normalized typically such that its length is equal to one [16].

2.4.3 The Self-Organizing Map

A further modification of the competitive filter network incorporates the Euclidean distance between the input vector and the weight vector of the winning neurode. This network was also developed by Kohonen and is called the self-organizing map. In a similar fashion, input patterns are presented to the network. After determination of the winning neurode, the weights are adjusted according to

$$\delta W_{ij}(t) = R * H_{ci}(t) * [A_i(t) - W_{ij}(t)] \quad t = 0,1,2,... \quad (2.6)$$

where $H_{ci}(t)$ is a function of the distance between neurode j and the neurode with the maximum activation and is given by

$$H_{ci}(t) = h_o(t) e^{-\frac{\| r_i - r_c \|^2}{\sigma^2(t)}} \quad (2.7)$$

with $h_0(t)$ and $s(t)$ as decreasing functions of time. The coordinates of the winning neurode and neurode i are represented by r_c and r_i , respectively [19].

2.5 Artificial Neural Networks With Supervised Learning

Supervised learning in neural networks uses associated input/output pairs. Thus, the network can determine if its output is correct and can apply its learning law to adjust its weights. The most widely used learning law of this type is the Delta rule, which is a gradient-descent learning rule. Further modification of this rule yields the Generalized Delta rule used in the backpropagation of error for more complex network structures [20].

2.5.1 The Backpropagation Network

One ANN which uses supervised learning is the backpropagation network. This network uses the Generalized Delta Rule to adjust the connection weights. The error of any output unit k is

$$e_k = t_k - o_k \quad (2.8)$$

where t_k is the target output and o_k is the actual output. The total error for the pattern is

$$E = \frac{1}{2} \sum_{k=1}^m (t_k - o_k)^2 \quad (2.9)$$

The correction to the weight of the connection between node k and node j is

$$\Delta W_{kj} = \eta \delta_k o_j \quad (2.10)$$

where the error signal δ_k at an output unit k is given by

$$\begin{aligned} \delta_k &= (t_k - o_k) f'(\text{net}_k) \\ \delta_k &= (t_k - o_k) o_k (1 - o_k) \quad \text{for sigmoid with } \theta_0 = 1. \end{aligned} \quad (2.11)$$

The values of the deltas for hidden layer (j) nodes can be inferred from deltas at an upper layer. The error is propagated backward to yield

$$\delta_j = o_j (1 - o_j) \sum_{k=1}^m \delta_k W_{kj} \quad (2.12)$$

and

$$\Delta W_{ji} = \eta \delta_j o_i, \quad (2.13)$$

where, η , is the learning rate parameter. Using the momentum term (α) allows increased learning rate without oscillations by making the correction at step (n+1) dependent on the correction at step n, yielding

$$\Delta W_{kj(n+1)} = \eta \delta_k o_j + \alpha \Delta W_{kj(n)} \quad (2.14)$$

These corrections are calculated for all patterns and averaged over the entire set of patterns, then corrections are made. The process continues until the value of the error function is reduced to an acceptable level [21]. Figure 5 illustrates a backpropagation network with two hidden layers.

2.5.2 The Probabilistic Neural Network

Another approach to a supervised learning neural network replaces the sigmoidal transfer function with an exponential function. This network, called the Probabilistic Neural Network (PNN), is capable of computing nonlinear decision boundaries for classification based on the Bayes strategy [22]. Figure 6 shows the organization of a neural network for pattern classification using the PNN approach. Input signals from the input units pass to the pattern units, each of which forms a dot product of the input vector X with a weight vector W_i ,

$$Z_i = X \cdot W_i \quad (2.15)$$

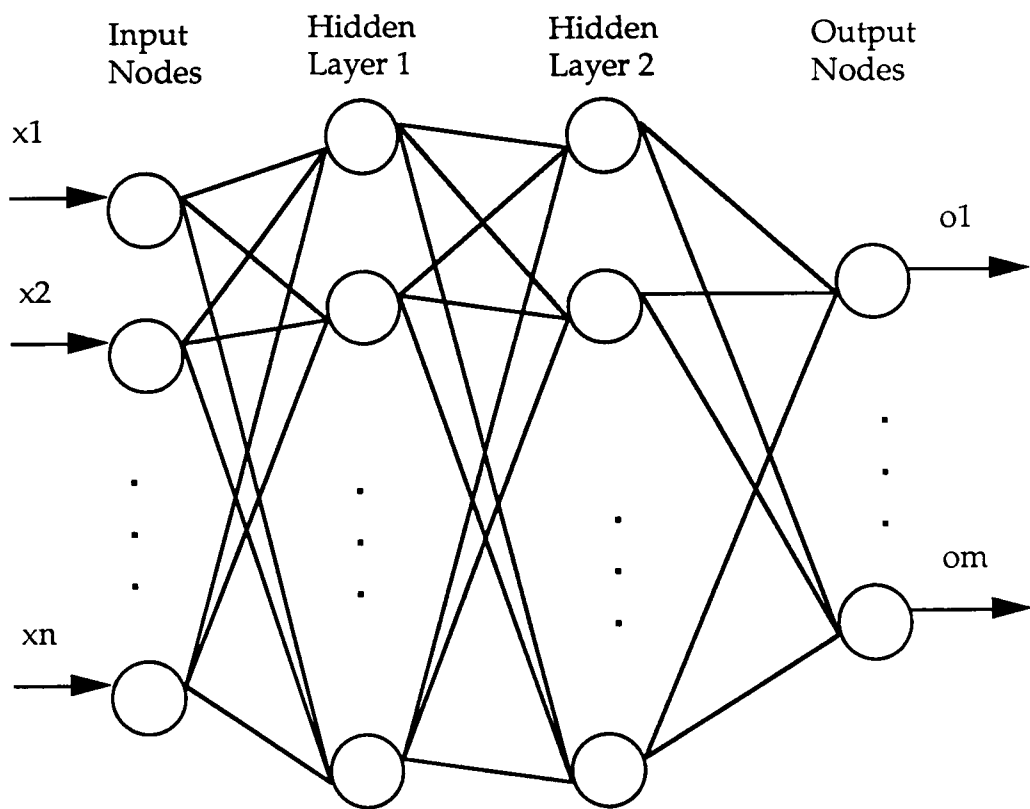


Figure 5: Backpropagation Network With Two Hidden Layers.

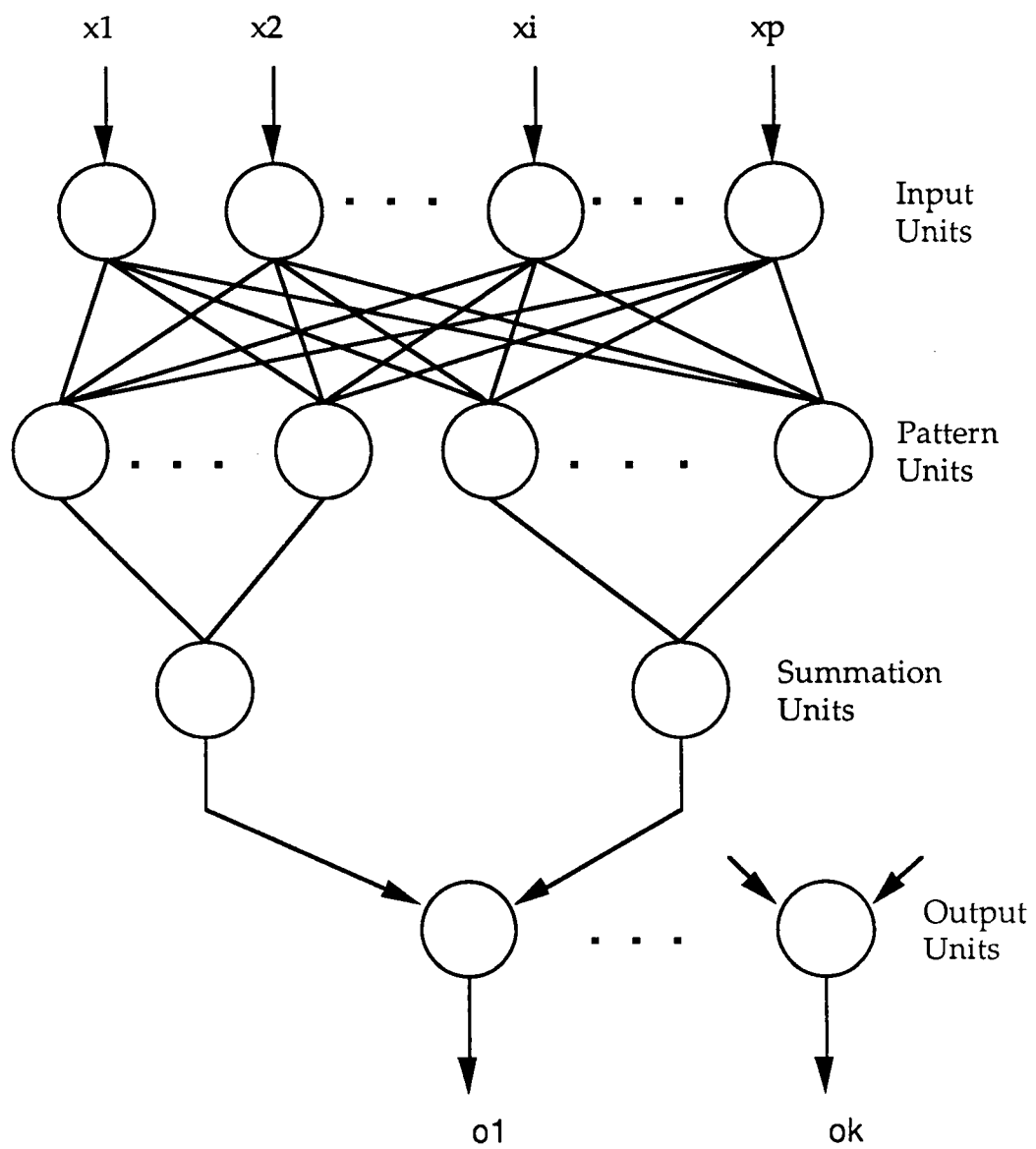


Figure 6: Organization of a Probabilistic Neural Network.

An exponential transfer function is applied to Z_i and the result is transmitted to the summation units. If both X and W_i are normalized to unit length, the exponential can be represented as

$$f(Z_i) = \exp \left[\frac{-(W_i - X)' (W_i - X)}{2\sigma^2} \right] \quad (2.16)$$

where σ is a smoothing parameter. The summation units sum the inputs from the pattern units which correspond to the category from which the training pattern was selected. The output units are two-input units which produce binary outputs and have a single weight, C_k , given by

$$C_k = \frac{h_{Bk} l_{Bk}}{h_{Ak} l_{Ak}} \frac{n_{Ak}}{n_{Bk}} \quad (2.17)$$

where

n_{Ak} = number of training patterns from category O_{Ak}

n_{Bk} = number of training patterns from category O_{Bk}

l_{Ak} = loss associated with making the decision O_{Ak}

l_{Bk} = loss associated with making the decision O_{Bk}

h_{Ak} = *a priori* probability of occurrence of patterns from category O_{Ak}

h_{Bk} = *a priori* probability of occurrence of patterns from category O_{Bk}

The network is trained by setting the weight vector W_i in one of the pattern units equal to each X pattern in the training set. The pattern unit's output is then connected to the appropriate summation unit [23].

CHAPTER 3

PROBLEM DESCRIPTION

3.1 Objective

The objective of this research is to demonstrate the applicability of artificial neural networks to check valves for diagnostic evaluation. More specifically, a neural network methodology for check valve diagnostics based on the valve operating condition is developed using experimental data from a check valve flow loop.

3.2 Experimental Data

The experimental data for network training was obtained from a flow test loop at Utah State University through the Nuclear Industry Check Valve (NIC) Group. The processed data used for network training is listed in Table B1 of Appendix B. The flow loop, illustrated in Figure 7, consists of the check valve, a pump, an interchangeable venturi, and instrumentation for acquiring data. The data from this flow loop is in tabular form and contains information for seven variables: *flow, upstream pressure, pressure difference* (DP across valve), *downstream pressure, velocity, disc position, and fluctuation*. The average values for these variables are recorded in the data tables. A disc motion code is also available consisting of seven possible codes, listed in Table 3, which may be present simultaneously.

A total of 639 experimental tests were conducted using different valve sizes and types. As seen in Table 4, the check valves range in size from 4 to 24 inches and can be grouped into three types: swing check valves, duo check

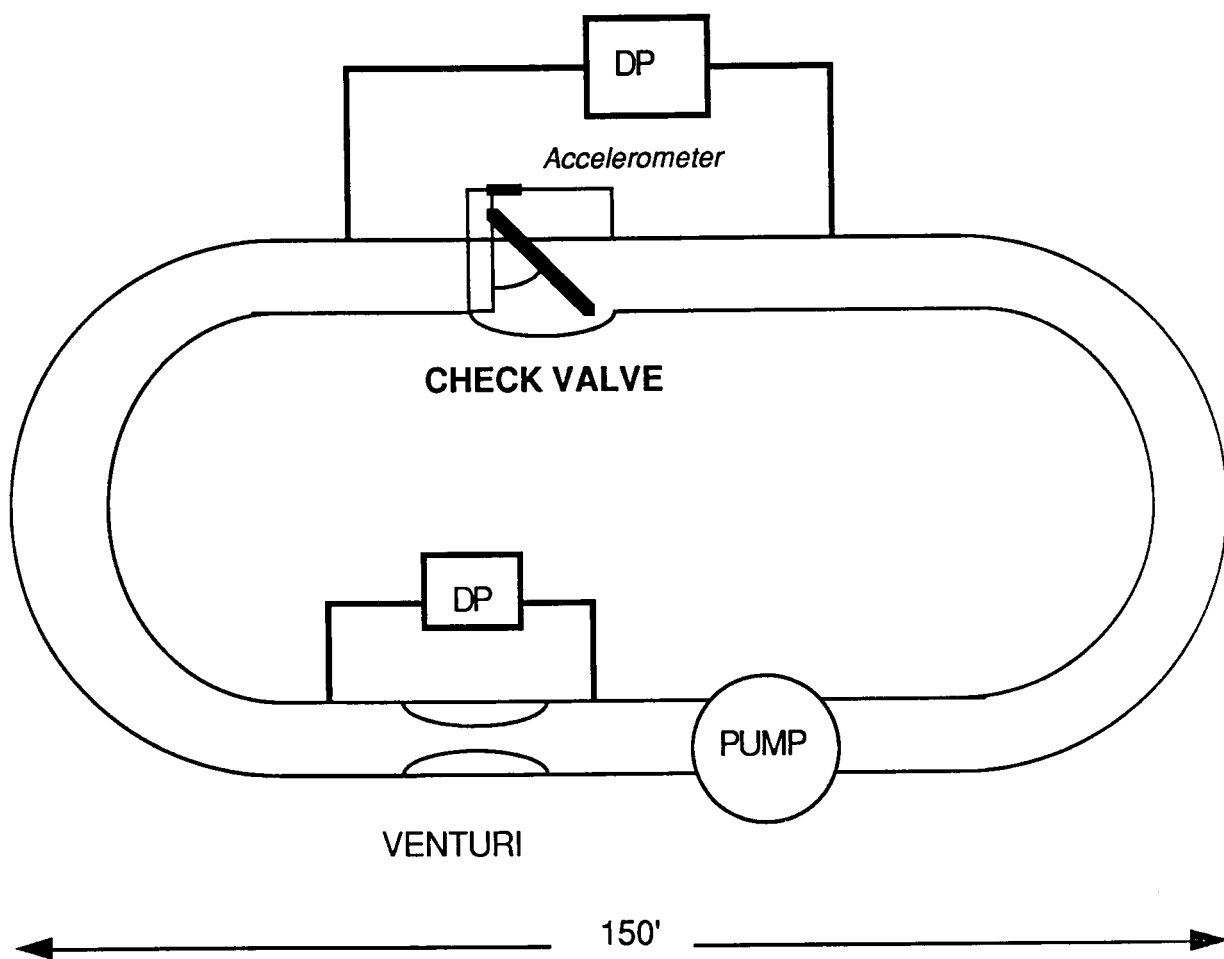


Figure 7: Diagram of Test Flow Loop at Utah State University.

Table 3: Disc Motion Codes and Their Definitions.

Disc Motion Code	Motion Represented
1	Arm rotating about hinge pin.
2	Disc rotation about stud pin.
3	Wobble about stud pin.
4	Lateral movement, hinge arm.
5	Rocking of hinge arm.
6	Vertical disc movement on stud pin.
7	Vertical assembly movement.

Table 4: Types and Sizes of Check Valves Used at Utah State University.

Valve Size (inches)	Type of Check Valve
4	Velan Swing Check Valve
6	Powell Swing Check Valve Crane Tilt-Disc Check Valve
10	Crane Swing Check Valve Velan Swing Check Valve Mission Duo Check Valve
12	ValMatic Tilt-Disc Check Valve
16	Rockwell Tilt-Disc Check Valve
20	Atwood Morill Swing Check Valve
24	Atwood Morill Swing Check Valve ValMatic Tilt-Disc Check Valve

valves, and tilt-disc check valves. Table 5 shows the degradation conditions of the valves for which the test conditions are evaluated and for which data is available. The test conditions of the valves can be classified in seven main categories: *zero flow*, *near seat*, *30% flow*, *75% flow*, *pump trip/start*, *tapping*, and *backseated*. These main categories and the test conditions which are classified in them are listed in Table 6. Along with these conditions are subconditions such as with/without turbulence and with/without cavitation.

Table 5: Degradation Conditions of Check Valves Tested.

Degradation Condition	Degree of Degradation
New Valve	-----
Hinge Pin Wear	Loose HP 7.5% 15% 30% 15% on one HP, other HP new 15% left HP, 30% right HP
Stud Pin Wear	15% 30%
Hinge Pin and Stud Pin Wear	30%
Missing Disc	-----
Disc in Bottom of Valve	-----
Disc Stuck Open	30% Open 68% Open 100% Open
Mission Duo CV Only	
1/2 Disc Stuck Open	-----
No Spring	-----
No Spring + 15% Pin Wear	-----

Table 6: Test Conditions Evaluated for Check Valves.

General Conditions	Specific Test Conditions
Zero Flow	Zero Flow 3% Flow
Near Seat	Near Seat Seat Leakage Seat Tapping
30% Flow	30% Flow
75% Flow	75% Flow
Pump Trip/Start	Pump Trip/Start
Tapping	Tapping 100% Flow Touching Open With Turbulence Flutter
Backseated	Backseated Max. Backseated Maximum Flow

3.3 Neural Network Methodology for Check Valve Diagnostics

The NIC data is utilized to demonstrate the applicability of neural networks to the area of check valve diagnostics (valve operating conditions). More specifically, a neural network methodology for check valve diagnostics is developed using selected variables from the data set for input to a neural network with the test condition as the desired output. The methodology is implemented using the NNET neural networks environment package on a PC and is examined utilizing the NIC data. The investigation of some approaches required the use of other neural network environment packages since the NNET environment has limited network learning algorithms. The software packages used were the NeuralWorks software on a PC and the PLEXI software on a Sun Sparc IV workstation.

The first aspect of neural network research involving real-world data is how to present the data to the network for training. A study is performed to compare the use of the raw data with the use of other representations. In addition to the necessity of determining how data should be represented, the selection of data to be used for network training is also important. Both aspects of data implementation are developed within this research.

Once the selection and representation of the data has been determined, the neural network is chosen for application. The choice of the neural network focuses on two aspects of neural networks. First, the type of network to be used must be determined. This aspect focuses on the many learning algorithms used in neural networks. The second aspect to neural networks consists of selecting the architecture of the network, i.e., the number of layers and the number of neurodes used in the layers.

CHAPTER 4

METHODOLOGY

4.1 Selection of Data Variables

From the NIC data tables seven variables were initially chosen for network training: *flow, upstream pressure, pressure drop across the valve, velocity, percent open, fluctuation, and the disc motion code*. The downstream pressure was not used since the combination of the upstream pressure and the pressure drop already contains the information of this variable. This method yielded an input vector with 13 components in the following order: one value each for flow, upstream pressure, pressure drop, velocity, percent open, and fluctuation; and seven values representing the disc motion codes.. The disc motion code represents seven possible conditions which are each represented in the input vector by a value of 1.0 if present or by a value of 0.0 if not present. After initial studies, the disc motion code was removed from the input vector resulting in six input variables. Using these six variables, the goal is to develop a neural network which will give a coded form in the output representing the test condition corresponding to the input pattern presented to the network. Six test conditions are of interest in developing the methodology for check valve diagnostics: zero flow, near seat, 30% flow, 75% flow, tapping, and backseated. The pump trip/start condition was not utilized since the method of reaching this condition would only be useful for transient analysis of the actual signals for the variables. Also, this test condition does not represent a diagnostic condition of the check valve.

4.2 Coupling of Unsupervised and Supervised Learning Networks

The first method applied to check valve diagnostics couples unsupervised and supervised learning networks in a unified architecture as shown in Figure 8. This method is implemented using the NNET neural networks environment, developed by AI Ware, on a PC and is examined through the utilization of the NIC data. The unsupervised network of NNET is not a "true" neural network; instead, it is simply a self-organizing algorithm. This network is discussed in Appendix A. This algorithm is utilized to form clusters containing similar patterns by applying the K-means clustering algorithm to the input data. The centroids of the clusters formed by the self-organizing network are then used as input to a backpropagation network. The backpropagation network is trained to produce an output which is a coded form representing the test condition. Once trained, the original patterns used for clustering are used to test the backpropagation network for accuracy.

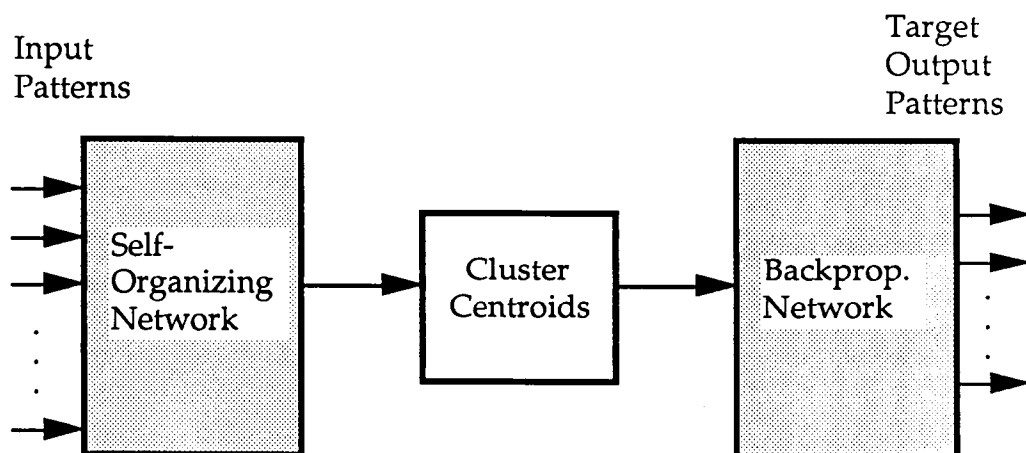


Figure 8: Structure of System Coupling A Self-Organizing Algorithm and A Backpropagation Network.

Using seven variables for input (flow, upstream pressure, pressure drop, velocity, percent open, fluctuation, and disc motion code), a training file of 73 patterns with 13 components was established from the data for the 10" Crane swing check valve. The raw values from the NIC data were used for constructing the pattern file. The patterns were normalized from -1.0 to +1.0 using the input normalization feature of NNET. The cluster radius was adjusted to reduce the number of clusters formed with the pattern set. As a result of the clustering results, training of a backpropagation network on the cluster centers was not performed.

The disc motion code information was removed from the training patterns leaving six input values (flow, upstream pressure, pressure drop, velocity, percent open, and fluctuation) for the first 65 patterns. The remaining eight patterns of the 73-pattern set were removed until the usefulness of the stuck disc degradation condition was evaluated. The data values were normalized from -1.0 to +1.0 using the input normalization feature of NNET. The cluster radius was adjusted to reduce the 65 patterns to 19 clusters. The centroids of these clusters were used to train a backpropagation network using a three-bit binary code for the respective test condition as the target output. With a three-bit binary code, a maximum of eight codes can be produced, and the target output patterns are listed in Table 7. The output patterns were normalized from 0.10 to 0.90. The backpropagation network consisted of six input nodes, one hidden layer with 10 nodes, and three output nodes. The network was trained with a system error tolerance of 0.000025, and after training, the network was tested using the 65 patterns.

Table 7: Target Output Patterns for Backpropagation Training Based on Clustering of 65 Patterns.

Test Condition	Target Output
Tapping	1 0 0
Backseated	0 1 0
Near Seat	0 0 1
Zero Flow	0 1 1
75% Flow	1 1 0
30% Flow	1 0 1

Although the NNET software package has an input normalization feature, the data for the remaining valve sizes and types in the data set must be normalized independently. Since this cannot be done with the normalization feature of NNET, it was necessary to normalize the data and then create the file. Independent normalization prevented any classification by valve size and also provided a further hint to the network regarding the test condition. To test the effect of this normalization scheme, the 65 patterns from the 10" Crane swing check valve were normalized from zero to one. The cluster radius of the self-organizing network was adjusted to reduce the 65 patterns to 19 clusters. The centroids of the resulting clusters were used to train a backpropagation network using the desired output codes used earlier. The backpropagation network used the same structure as before: six input nodes, one hidden layer with 10 nodes, and three output nodes. The output was normalized from 0.10 to 0.90. The network was trained until the system error reached 0.000025 and was then tested using the 65 patterns used for clustering.

The data for the remaining valves were used to create a training file with 451 patterns, and the data values were normalized from zero to one.

The cluster radius of the self-organizing network was adjusted to reduce the 451 patterns to 124 clusters and to 62 clusters. The centroids of the 124 clusters were used to train a backpropagation network with six input nodes, one hidden layer with 20 nodes, and three output nodes. The network was trained for five test conditions, each represented by a three-bit binary code given in Table 8 with the values being normalized from 0.10 to 0.90. Two tolerances for the system error were used, 0.001 and 0.0005. For both system error values, the 451 patterns were used to test the network.

Table 8: Target Output Patterns for Backpropagation Training Based on Clustering of 451 Patterns.

Test Condition	Target Output
Zero Flow & Near Seat	0 0 1
30% Flow	1 0 1
75% Flow	1 1 0
Tapping	1 0 0
Backseated	0 1 0

The centroids of the 62 clusters were used to train a backpropagation network with the same architecture and the same five test conditions. After the system error was reduced to 0.0001, the 451 patterns were used for testing the network. Three other approaches were used with this network, two utilizing the belief value and another using fuzzy output values for the backpropagation network. Each pattern created using the NNET pattern editor has a belief value associated with it. The belief value is the confidence that the user has in the validity of the association of an input/output pair and takes values from zero (no confidence) to one (full confidence). The belief value for the centroid of mixed-pattern clusters was adjusted by two methods.

The first method adjusted the belief value according to the statistics of the dominant patterns. For example, a cluster with six tapping patterns, two backseated patterns, and one 75% flow pattern would have its centroid classified as a tapping pattern with a belief value of 0.667. The second method changed the belief value of patterns for clusters with a large number of patterns classified wrong from its value in the first method to 0.30. The resulting pattern files from both methods were used to train a backpropagation network with six input nodes, twenty hidden layer nodes, and three output nodes. The networks were trained using the same five target output patterns normalized from 0.10 to 0.90 and a system error tolerance of 0.0001. After training, the 451 patterns were used for network testing. The third method incorporates a five-bit fuzzy code at the output of the backpropagation network. Each bit in the output represents the degree of membership the pattern has in one of the five test conditions. For pure clusters, the code has a value of 1.0 for its corresponding category and a value of zero for the remaining four bits. For mixed-pattern clusters, the value of 1.0 is assigned to the majority pattern. All other values are assigned by taking the statistics of the patterns and rounding up the value to one decimal place. This method is illustrated in Figure 9 which shows the method of representation and two example patterns. Part (b) of the figure shows the code for a cluster of only 30% flow patterns. A value of 1.0 is assigned to the position for 30% flow and values of 0.0 are assigned to all other positions. Part (c) shows the code for a cluster with one 75% flow, six tapping, and two backseated patterns. A value of 1.0 is assigned to the position for tapping (majority pattern), a value of 0.20 is assigned to the position for 75% flow ($1/9 = 0.11 \sim 0.20$), and a value of 0.30 is assigned to the position for backseated

Zero Flow & Near Seat	30% Flow	75% Flow	Tapping	Backseated
--------------------------	----------	----------	---------	------------

(a)

0.0	1.0	0.0	0.0	0.0
-----	-----	-----	-----	-----

(b)

0.0	0.0	0.20	1.0	0.30
-----	-----	------	-----	------

(c)

Figure 9: Illustration of: (a) Fuzzy Output Code for Backpropagation Training, (b) Example Pattern for a Cluster With Only 30% Flow Patterns, (c) Example Pattern for a Mixed-Pattern Cluster With Two Backseated, Six Tapping, and One 75% Flow Patterns.

($2/9 = 0.22 \sim 0.30$) The output code values were normalized from 0.10 to 0.90 using the output normalization feature of NNET. This pattern file was used to train a back propagation network with six input nodes, 20 hidden layer nodes, and five output nodes. The network was trained for a system error tolerance of 0.0005, after which the 451 patterns were used to test the network. For analyzing the test results, the pattern was classified to the category which had the highest degree of membership in the output.

4.3 Training A Backpropagation Network Using Pattern Averaging

Another approach to developing a methodology for check valve diagnostics consisted of training a backpropagation network using an average

pattern for each of the six test conditions. This procedure is an attempt to determine if a representative pattern for each of the six test conditions can be found using the average pattern approach. Six average patterns with six inputs were calculated by averaging all the mean values listed in the data tables for each of the six variables over all patterns belonging to a specific test condition in the first 65 patterns. These patterns were normalized from zero to one and were used to train a backpropagation network with six input nodes, ten hidden nodes, and three output nodes using the six desired output patterns listed earlier in Table 6 normalized from 0.10 to 0.90. The network was trained with a system error tolerance of 0.000025. After training, the network was tested using the 65 patterns.

To test the effect of nodes in the hidden layer on the results, the six patterns were used to train a backpropagation network with six input nodes, 15 hidden nodes (50% increase), and three output nodes. Using the same desired outputs, the network was trained with a system error tolerance of 0.000025 and then tested with the 65 pattern set. The network was trained to further reduce the system error to 0.000005 and tested using the 65 pattern set.

4.4 Clustering of Check Valve Data Using A Competition Network

Other self-organizing networks were investigated to determine whether they could cluster the data with better results. The first network investigated was the competition network available in the PLEXI neural networks environment on a Sparc IV workstation. Using the 451 patterns normalized from zero to one, a competition network with six input nodes and 150 nodes in the competition layer was trained for 45,100 iterations (100 passes through the data set). After training, the network was tested using the

451 patterns. The results were analyzed by recording the patterns and their corresponding firing node. The network was trained further for a total of 451,000 iterations (1000 passes through the data set) and tested with the 451 patterns.

4.5 Clustering of Check Valve Data Using A Self-Organizing Map

Another network used was the self-organizing map which is also available with the PLEXI neural networks environment. This network also consisted of six input nodes and a self-organizing layer with 150 nodes. The network was trained for 45,100 iterations and tested with the 451 patterns. The results were analyzed in a similar fashion as the results of the competition network. The network training continued for a total of 451,000 iterations, and the network was tested on the 451 patterns.

4.6 Application of the Probabilistic Neural Network

The probabilistic neural network (PNN) is one type of a neural network classifier [16] and is available in the NeuralWorks neural network environment on a PC. The PNN was applied to the check valve diagnostics problem using the 73 patterns for the 10" Crane swing check valve. The 73 patterns were normalized from zero to one and were used to train a PNN network with six input nodes, 73 hidden nodes (or pattern nodes), and six output nodes (one for each test condition). The target output patterns consisted of zeros in all positions except one which represented the category and took the value of one. The test conditions and their respective target patterns are listed in Table 9. The PNN network was trained for 30,000 iterations and then tested using the 73 patterns.

Table 9: Target Output Values for the Probabilistic Neural Network.

Test Condition	Target Output
Zero Flow	1 0 0 0 0 0
Near Seat	0 1 0 0 0 0
30% Flow	0 0 1 0 0 0
75% Flow	0 0 0 1 0 0
Tapping	0 0 0 0 1 0
Backseated	0 0 0 0 0 1

4.7 Data Representation Methods for Coupled Unsupervised and Supervised Learning Networks

Returning to the method of clustering data and using the cluster centroids to train a backpropagation network, three methods of representing the data were investigated. These methods were investigated using the first set of 73 patterns. The first method used the six input variables normalized from zero to one. The cluster radius was adjusted to reduce the 73 patterns to 24 clusters and to 12 clusters. For both cases, the cluster centroids were used to train a backpropagation network for five test conditions. The backpropagation network consisted of six input nodes, 12 hidden nodes, and three output nodes. The target output patterns for the test conditions are given in Table 10 and were normalized from 0.10 to 0.90 for training. The network was trained for two system error tolerances, 0.0010 and 0.0001, after which the 73 patterns were used to test the network.

The second approach utilized the concepts of fuzzy logic and membership functions to represent the six variables. Fuzzy logic aims at modeling the imprecise modes of reasoning that are an essential part of the human ability to make rational decisions in an environment of uncertainty

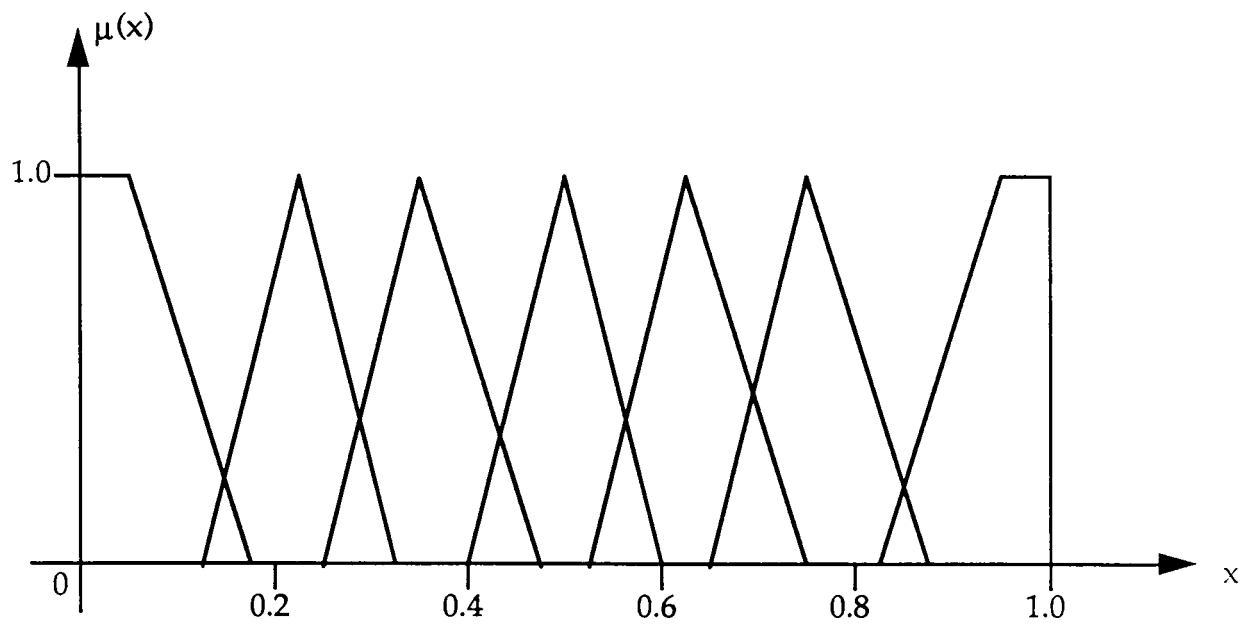
Table 10: Target Output Values for Backpropagation Training Based on Clustering of 73 Patterns.

Test Condition	Target Output
Zero Flow & Near Seat	1 0 0
30% Flow	0 1 0
75% Flow	0 0 1
Tapping	1 0 1
Backseat	0 1 1

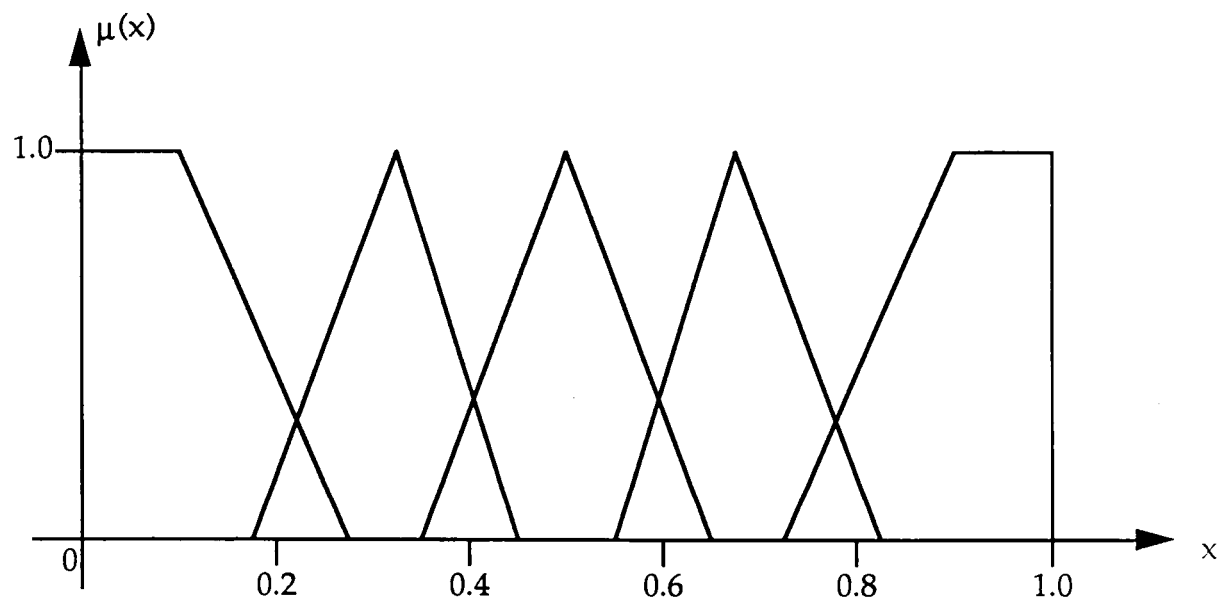
and imprecision [24]. Membership functions are used to represent the degree to which an element belongs to a set. Thus, membership in a set is not a well-defined boundary but a continuous scale gradually sliding in and out of the set [25].

The two membership functions are illustrated in Figure 10. The first membership function consists of seven values evenly distributed from zero to one. This membership function was applied to variables which exhibited a good variation of values over the range of zero to one. Three variables were described by this membership function: flow, upstream pressure, and velocity. The second membership function consists of five values evenly distributed from zero to one. This membership function was applied to variables which had values distributed over the range of zero to one, but also had values more centralized around a few specific values. Three other variables were described by this membership function: pressure drop, percent open, and fluctuation.

The normalized values for each of the six variables was transformed into an input vector of 36 values. The variables using the seven-value membership function were each translated to seven values representing the



(a)



(b)

Figure 10: Membership Functions Used to Represent the Check Valve Data Variables: (a) Flow, Upstream Pressure, and Velocity, (b) Pressure Drop, Percent Open, and Fluctuation.

degree of membership of the variable's value to each of the seven fuzzy values. The variables using the five-value membership function were each similarly translated to five values. The first seven bits of the input vector represent the degrees of membership of the flow variable, the next seven bits represent the upstream pressure variable, the next five bits represent the pressure drop variable, the next seven bits represent the velocity variable, the next five bits represent the percent open variable, and the final five bits represent the fluctuation variable.

The first approach utilizing this data translated the 73 pattern set into 73 fuzzy patterns of 36 values. The cluster radius of the self-organizing network was adjusted to reduce the 73 patterns to 24 clusters and 12 clusters. The centroids of these clusters were used to train a backpropagation network with 36 input nodes, 72 hidden nodes, and three output nodes. The same target outputs shown in Table 10 were used with this network. The network was trained with two system error tolerances, 0.0010 and 0.0001, after which the 73 fuzzy patterns were used to test the network. The pattern file was expanded to 179 fuzzy patterns, limited by the available memory of the computer used. The cluster radius was adjusted to reduce the 179 patterns to 24 clusters. The centroids of these clusters were used to train a backpropagation network with the same architecture used with this method for the 73 patterns. The network was trained using two system error tolerances, 0.001 and 0.0001, and after both tolerances were reached, the network was tested using the 179 pattern set.

The second approach applied the membership functions to the cluster centroids formed using the six input values for clustering. The 73 patterns were reduced to 24 clusters and 12 clusters as before by adjusting the cluster

radius of the self-organizing network. The membership functions were applied to the centroids of these clusters as in the first approach. The 24 six-value centroids were translated to 24 36-value fuzzy patterns, and the 12 six-value centroids were translated to 12 36-value fuzzy patterns. The fuzzy patterns were used to train a backpropagation network with 36 input nodes, 72 hidden nodes, and three output nodes. The target outputs shown in Table 10 were also used with this network. Two system error tolerances were applied to this network, 0.001 and 0.0001. After each system error was reached, the 73 patterns were used to test the network.

CHAPTER 5

RESULTS AND ANALYSIS

5.1 Results From Coupled Unsupervised and Supervised Learning Networks

The results from using the cluster centroids from the self-organizing network to train a backpropagation network with the test condition code as the output are discussed in this section. The results are divided into three sections, representing the initial studies conducted in this research. The results focus on the input variables used for analysis with the first data set and the expansion of the study using the entire set of data.

5.1.1 Use of the Disc Motion Code Information

The effects of varying the cluster radius of the self-organizing algorithm using the 73 patterns with 13 inputs and normalized from -1.0 to +1.0 are given in Table 11. The cluster radius was varied from 0.70 to 1.10. Analysis of the 23 clusters formed for a cluster radius of 1.10 revealed that the data had been clustered according to the disc motion code (DMC). As a result, mixed-pattern clusters were formed solely on this basis causing erroneous results. Two possible reasons for this effect are evident. First, seven of the 13 inputs were used to represent the DMC information and may have put more emphasis on the DMC than for the other six variables. Second, and more likely, the extreme values of zeros and ones (-1.0 and +1.0 after normalization) used to indicate the absence or presence of these features would cause the results obtained. By using the extreme representation, the Euclidean distance will increase significantly for patterns with differing DMCs

Table 11: Results of Varying the Cluster Radius of Self-Organizing Network for 73 Patterns With 13 Inputs.

Cluster Radius	Number of Clusters Formed	Reduction Factor
0.70	34	2.15
0.80	30	2.43
0.90	27	2.70
1.10	23	3.17

even though they may be of the same test condition. The DMC was not used in other experimentation and was not used for backpropagation training.

5.1.2 Normalization Scheme Results

The effects of the normalization schemes can be observed in Tables 12 and 13. The effects of varying the cluster radius on clusters formed from 65 patterns with six inputs is shown in Table 12 for both normalization schemes. As expected, the smaller normalization range $[0,1]$ required a smaller cluster radius to produce an equal number of clusters for a particular cluster radius with $[-1,1]$ normalization. The results of using cluster centers for training a backpropagation network for test conditions is given in Table 13. The results show that for a given number of clusters, network architecture, and system error, the normalization has no effect on the results of the backpropagation network since both networks produced an 8% error during testing on the 65 patterns. Not observable in the result tables is the fact that both networks classified the same patterns wrong, also showing no effect of normalization.

Table 12: Results of Varying the Cluster Radius for 65 Patterns With Six Inputs for Two Normalization Ranges.

Normalization Range [min,max]	Cluster Radius	Number of Clusters Formed	Reduction Factor
[-1.0,+1.0]	0.50	19	3.42
	0.60	17	3.82
	0.70	16	4.06
	0.80	14	4.64
[0.0,+1.0]	0.25	22	2.95
	0.28	19	3.42
	0.35	16	4.06

Table 13: Results of Backpropagation Training on Cluster Centroids for Two Normalization Ranges.

Normalization Range [min,max]	Number of Clusters Applied	Backpropagation Structure			System Error	Percent Wrong
		<u>In</u>	<u>Hidden</u>	<u>Out</u>		
[-1.0,+1.0]	19	6	10	3	0.000025	8.0
[0.0,+1.0]	19	6	10	3	0.000025	8.0

5.1.3 Results for 451 Patterns

The results of varying the cluster radius for the 451 patterns from the total data set are shown in Table 14. For a cluster radius of 0.25, the 451 pattern set was reduced to 124 clusters, a larger degree of compression than achieved for the 65 pattern set. The results of backpropagation network training on cluster centroids for 124 and 62 clusters are given in Table 15. For the network architecture used with the 124 cluster centroids, a reduction of the system error by 50% produced no effect on the number of patterns

Table 14: Results of Varying the Cluster Radius for 451 Patterns With Six Inputs.

Cluster Radius	Number of Clusters Formed	Reduction Factor
0.10	292	1.54
0.20	173	2.61
0.25	124	3.64
0.30	95	4.74
0.40	62	7.27
0.50	33	13.67

Table 15: Results of Backpropagation Training on Cluster Centroids From 451 Patterns.

Number of Clusters	Backpropagation Structure			System Error	Percent Wrong	Note
	<u>In</u>	<u>Hidden</u>	<u>Out</u>			
124	6	20	3	0.0010	6.0	-----
124	6	20	3	0.0005	6.0	-----
62	6	20	3	0.0001	11.8	-----
62	6	20	3	0.0001	11.8	First belief value method
62	6	20	3	0.0001	12.4	Second belief value method
62	6	20	3	0.000022	13.3	Second belief value method
62	6	20	5	0.0005	13.1	Fuzzy output code

classified wrong, which remained 6%. Using 62 cluster centers with the same network architecture and a system error reduced by 80% resulted in 11.8% of the patterns classified wrong, almost doubled by cutting the number of clusters in half. Also seen in Table 15 are the results of other approaches applied to the 62 cluster centers. The first method of adjusting the belief value made no difference in the results; however, the second belief value approach showed an increase in patterns classified wrong to 12.4%. Reducing the system error with the second belief value approach further increased the patterns classified wrong to 13.3%. Application of the fuzzy output code to the backpropagation network showed an increase to 13.1% patterns classified wrong.

5.2 Results From Pattern Averaging

The results of training a backpropagation network on the six average test condition patterns for the 65 pattern set are given in Table 16. Using the same network architecture and system error tolerance, this approach resulted with a 20% pattern error. Using 50% more nodes in the hidden layer and the same system error, the pattern error increased slightly. Reducing the system error by 80% produced no change in the pattern error. These results demonstrate that the test conditions cannot be represented by using the average pattern as a prototype.

5.3 Results for the Competition Network and Self-Organizing Map

The clustering results from the competition network and the self-organizing map using 451 patterns are given in Table 17. Both networks were investigated for clustering ability and were not used with other network

Table 16: Results of Backpropagation Training on Six Average Patterns From 65 Patterns.

Backpropagation Structure			System Error	Percent Wrong
<u>In</u>	<u>Hidden</u>	<u>Out</u>		
6	10	3	0.000025	20.0
6	15	3	0.000025	21.5
6	15	3	0.000005	21.5

Table 17: Clustering Results of 451 Patterns Using Competition and Self-Organizing Map Networks.

Network Type	Network Structure		Number of Iterations	Number of Clusters Formed	Number of Mixed-Pattern Clusters
	<u>Input</u>	<u>Output</u>			
Competition	6	150	45,100	53	26
Competition	6	150	451,000	48	24
Self-Org. Map	6	150	45,100	96	43
Self-Org. Map	6	150	451,000	100	43

types. For 100 passes through the data set, the competition network produced 53 clusters with 49.1% being mixed-pattern clusters. The self-organizing map produced nearly twice the number of clusters with a lower percentage being mixed-pattern clusters (44.8%). Further training of the self-organizing map showed only a slight improvement in the results. The mixed-pattern clusters also showed a large degree of confusion regarding the test condition. For example, 30% flow patterns in a zero flow cluster and 30% flow, 75% flow, and tapping patterns in one cluster. The patterns within each cluster have not been analyzed to determine if these networks are clustering on the basis

of information other than the test conditions, e.g. degradation conditions of the check valve.

5.4 Results From the Probabilistic Neural Network

The results of the probabilistic neural network (PNN) used for classifying the 73 patterns are given in Table 18. After training for 30,000 iterations, the PNN resulted in a high error on recall, 20.5%. Considering there was no data compression for training, the PNN does not demonstrate any ability to classify the patterns according to test condition. Analysis of the patterns misclassified showed that the PNN had difficulty in distinguishing the near seat patterns from the zero flow patterns and in distinguishing the tapping patterns from the backseated patterns.

Table 18: Results of the Probabilistic Neural Network Using 73 Patterns With Six Inputs.

Network Structure			Number of Iterations	Percent Wrong
<u>Input</u>	<u>Hidden</u>	<u>Output</u>		
6	73	6	30,000	20.5

5.5 Data Representation Effects

The results of using the clustering approach with the first data set of 73 patterns is shown in Table 19. Two degrees of reduction were compared using the cluster centers for backpropagation training, 24 clusters and 12 clusters. Using the same network architecture and system error tolerances, the higher degree of compression showed a significant increase in the percent of patterns classified wrong. Decreasing the system error for the lesser degree of

Table 19: Results of Backpropagation Training on Cluster Centroids From 73 Patterns.

Number of Clusters	Network Structure			System Error	Percent Wrong
	<u>In</u>	<u>Hidden</u>	<u>Out</u>		
24	6	12	3	0.0010	4.1
24	6	12	3	0.0001	4.1
12	6	12	3	0.0010	26.0
12	6	12	3	0.0001	27.4

compression improved results; however, for the larger degree of compression, the results were not improved.

Table 20 shows the results of using the 36 fuzzy input representation of the six variables for clustering and then using the cluster centroids of the fuzzy patterns to train a backpropagation network. Comparing the results for 24 clusters with the results of the 24 clusters from six inputs shows no change in the percent of patterns classified wrong, using different networks for the same system error tolerance. For 12 clusters, this approach shows a significant decrease in the pattern testing error over the results for the six-input results. The results of this same method using the set of 179 patterns are given in Table 21. Reducing the patterns to 24 clusters, shows a large increase in the percent of patterns classified wrong; however, this error is smaller than the error produced from the 73 patterns clustered to 12 clusters which is a smaller degree of compression.

The results of using the 36 fuzzy inputs from the 73 pattern set for application after the 73 patterns are clustered are given in Table 22.

Comparing the results applied for a clustering from 73 patterns to 12 clusters

Table 20: Results of Backpropagation Training on Cluster Centroids From 73 Patterns Using 36 Fuzzy Inputs at the Self-Organizing Network.

Number of Clusters	Network Structure			System Error	Percent Wrong
	<u>In</u>	<u>Hidden</u>	<u>Out</u>		
24	36	72	3	0.0010	4.1
24	36	72	3	0.0001	4.1
12	36	72	3	0.0010	11.0
12	36	72	3	0.0001	11.0

Table 21: Results of Backpropagation Training on Cluster Centroids From 179 Patterns Using 36 Fuzzy Inputs at the Self-Organizing Network.

Number of Clusters	Network Structure			System Error	Percent Wrong
	<u>In</u>	<u>Hidden</u>	<u>Out</u>		
24	36	72	3	0.0010	21.23
24	36	72	3	0.0001	24.58

Table 22: Results of Backpropagation Training on Cluster Centroids From 73 Patterns Using 36 Fuzzy Inputs at the Backpropagation Network.

Number of Clusters	Network Structure			System Error	Percent Wrong
	<u>In</u>	<u>Hidden</u>	<u>Out</u>		
24	36	72	3	0.0010	2.7
24	36	72	3	0.0001	2.7
12	36	72	3	0.0010	23.3
12	36	72	3	0.0001	19.2

show a smaller percentage of patterns classified wrong using the 36 fuzzy inputs for the backpropagation network. Further reduction of the system error shows a larger improvement in the results for the fuzzy input approach.

CHAPTER 6

CONCLUSIONS

The applicability of artificial neural networks for check valve diagnostics has been demonstrated. The neural network methodology developed couples unsupervised and supervised learning networks in a unified structure. The centroids of clusters formed by the unsupervised network were used to train a backpropagation network to produce the corresponding test condition in the output. This method demonstrated improved results compared to other approaches, producing a 12% testing error for a reduction factor of 7.27 for 451 patterns.

Although showing success for check valve diagnostics, this methodology has one research decision to be made by the user, the degree of compression to be used for clustering the data. This decision is reflected in determining the size of the cluster radius. Experimental results demonstrate that larger degrees of data compression cause a larger number of the data patterns to be mis-classified into mixed-pattern clusters. As a result, most of these patterns are classified wrong by the backpropagation network. Since this is a subjective decision, analysis should be performed to determine the proper degree of compression to be implemented. Selection of the cluster radius also removes from the network its ability to truly self-organize the data, since the user has already forced a constraint on the network. Such a constraint may force the network to organize the data along lines other than the test condition.

Other networks were investigated; however, these networks proved less effective than the first methodology. Both the competition network and the self-organizing map demonstrated a large percentage of mixed-pattern clusters. Further study may show organization of patterns on a basis other than the test condition. The probabilistic neural network resulted in a larger pattern error than the coupled-network methodology. The failure of these networks further demonstrates the ability of the coupled-network methodology for check valve diagnostics.

Use of the disc motion code (DMC) information with the other six variables yielded clusters of mixed patterns based solely on the DMC. The result is due to the extreme values used to represent the DMC; however, it demonstrates no relation between the DMC and the test condition. Removing the DMC information yielded improved clustering results for the test condition. Normalization of these data patterns for two normalization ranges, $[-1.0, +1.0]$ and $[0.0, +1.0]$, showed no difference in clustering or backpropagation results.

Methods of representing the data using the concepts of fuzzy logic showed improved results over using the six input variables for the first set of 73 patterns. Two approaches with fuzzy input values were investigated, both of which showed improvements in the testing results. Expansion of the second method to the entire data set of 451 patterns should reduce the error of the system.

The overall results from this research clearly demonstrate the applicability of artificial neural networks for check valve diagnostics. Furthermore, a neural network methodology for check valve diagnostics has been developed with favorable results. As with other diagnostic applications,

neural networks can also be applied to check valves, an important component of nuclear power plants. A system developed by incorporating the concepts of two areas of artificial intelligence, fuzzy logic and artificial neural networks, can improve the overall results of a check valve diagnostic system.

The results of all networks investigated demonstrate that there may be some problems inherent in the experimental data. More significant are the results from the Kohonen networks, which had difficulty organizing the input data according to the test condition. The coupled methodology resulted in higher degrees of pattern error for higher degrees of data compression, suggesting that the data has wide variations within the test condition categories.

CHAPTER 7

FUTURE WORK

The experimental check valve data has uses other than those presented in this research. Future work with this data will consist of many investigations. First, an in-depth parametric study should be performed for data representation methods. Second, the check valve data should be used to develop a diagnostic model of the check valve process. Third, the competition network and the self-organizing map should be investigated further for application to check valve diagnostics. Fourth, a parametric study of the effect of network architecture should be conducted. Fifth, a sensitivity study should be performed to determine important parameters for check valve diagnostics.

The parametric study of data representation may focus on three schemes: six input variables, 36 fuzzy inputs for clustering, and 36 fuzzy inputs for backpropagation training after clustering of the six-input patterns. Each of the representations should be applied to the first set of 73 patterns and to the entire set of 451 patterns. The data sets should be clustered for two reduction factors: three and six. In each case, the cluster centroids should be used to train a backpropagation network to yield the test condition as output.

The diagnostic model is illustrated in Figure 11. The check valve can be considered a process with four inputs (flow, upstream pressure, pressure drop, and velocity) and four outputs (downstream pressure, percent open, fluctuation, and test condition). A backpropagation network should be developed using the experimental data to model the check valve. This task

needs to be implemented using the same approach for developing the backpropagation network for test conditions. Input patterns will be clustered, and cluster centroids will be used to develop a diagnostic model.

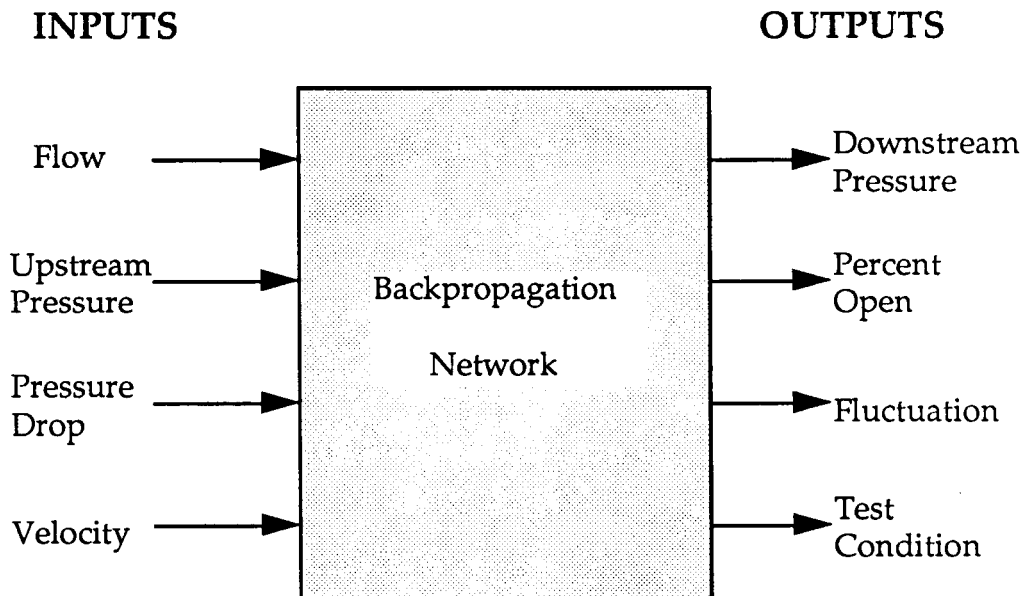


Figure 11: Diagram of A Backpropagation Network For A Diagnostic Model.

An in-depth study should be performed using the competition network and the self-organizing map. This investigation must focus on two main aspects. First, the architecture of the networks should be investigated. Of interest is expanding the number of nodes in the Kohonen layer to approximately equal the number of patterns used for training, thus allowing the network to freely organize the data. Second, the organization of the data by these networks should be studied to determine the features of the patterns in clusters.

Other studies may focus on effects of network architecture on the testing results through varying, for example, the number of hidden layers and the number of nodes in hidden layers. Once a satisfactory network is established, a sensitivity study may be conducted to determine important variables for check valve diagnostics. A sensitivity study may also be conducted for the diagnostic model.

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APPENDICES

APPENDIX A

DISCUSSION OF SOFTWARE USED IN RESEARCH

A.1 NNET Neural Networks Software

NNET is an artificial neural networks environment for personal computers developed by AI Ware, Incorporated. This ANN environment allows the user to implement unsupervised learning, supervised learning, and associative memory (recall and decision) tasks. Through the user interface, the user is provided with full system capabilities through an on-screen application which does not require the user to write any programming code. NNET can also be executed from C code or be placed into other systems through the programming interface.

The unsupervised learning algorithm of NNET is implemented on the basis of Euclidean distance. The square of the Euclidean distance from a new pattern X to the j^{th} cluster center B_j is

$$ED_j^2 = \sum_{i=1}^n (b_{ij} - x_i)^2 \quad (\text{A.1})$$

where b_{ij} are the coordinates of the cluster centroid. A pattern is assigned to the cluster for which ED_j is the smallest provided that it is less than the cluster radius. If these conditions are not met, a new cluster is formed. The unsupervised learning scheme implemented with NNET is shown in Figure A1. The minimum distance classifier shown assigns the cluster number to which the input pattern is most similar.

The supervised learning feature on NNET provides two approaches. The first approach is implemented with a backpropagation network. The generalized delta rule is used to make adjustments to connection weights based on associated input/output pairs. The network parameters available for adjustment are learning rate, momentum term, sigmoidal slope, and system error. The system error is the average of the square of the difference between

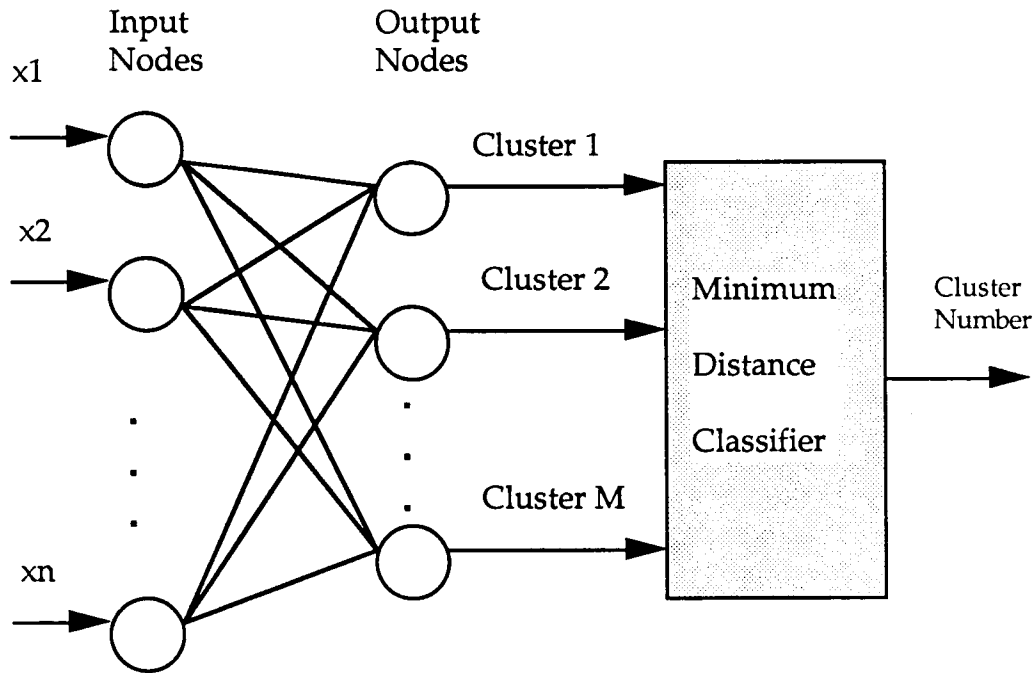


Figure A1: Diagram of NNET Unsupervised Learning Network.

the outputs and the targets for all nodes for each pattern. Figure A2 illustrates a general network utilizing backpropagation training.

A second approach for supervised learning provided by NNET implements an algorithm for a functional-link network. The functional link approach enhances the original input signal with additional inputs that are either higher order terms of the original inputs (joint activation) or functions of the original inputs (functional expansion). Utilization of functional enhancement does not usually require hidden layers for learning and usually increases the learning rate. The two enhancement modes may be used singly, in combination, or recursively. The number of terms generated from a joint activation of order k is

$$\text{number of JA}(k) \text{ terms} = \sum_{k=1}^n C(n,k) \quad (\text{A.2})$$

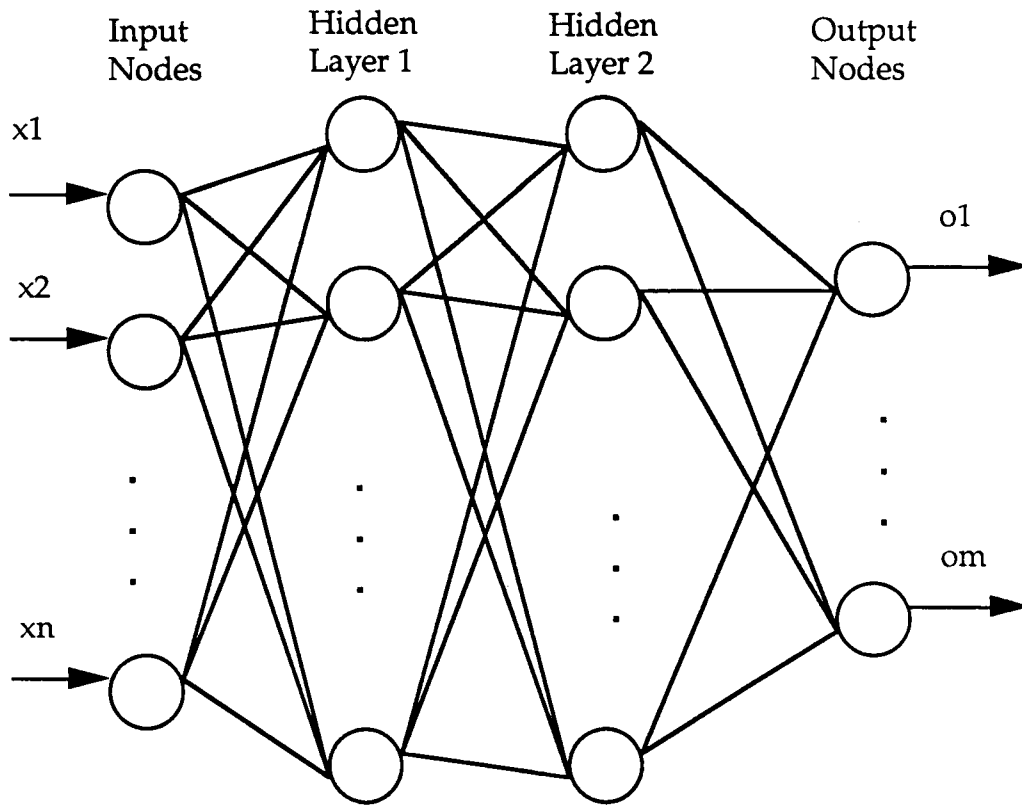


Figure A2: Diagram of a General Backpropagation Network.

where n is the number input features before enhancement and

$$C(n,k) = \frac{n!}{k! (n-k)!} \quad (\text{A.3})$$

The number of terms generated from a functional expansion of order k is

$$\text{number of FE}(k) \text{ terms} = n (2k + 1) \quad (\text{A.4})$$

Figure A3 illustrates a supervised learning network using joint activation enhancement of second order for three input features.

A.2 The PLEXI Neural Networks Software

PLEXI is a graphics oriented neural networks environment. The software version utilized in this research is installed on a Sun Sparc IV workstation. Neural networks are constructed through a graphically rich user

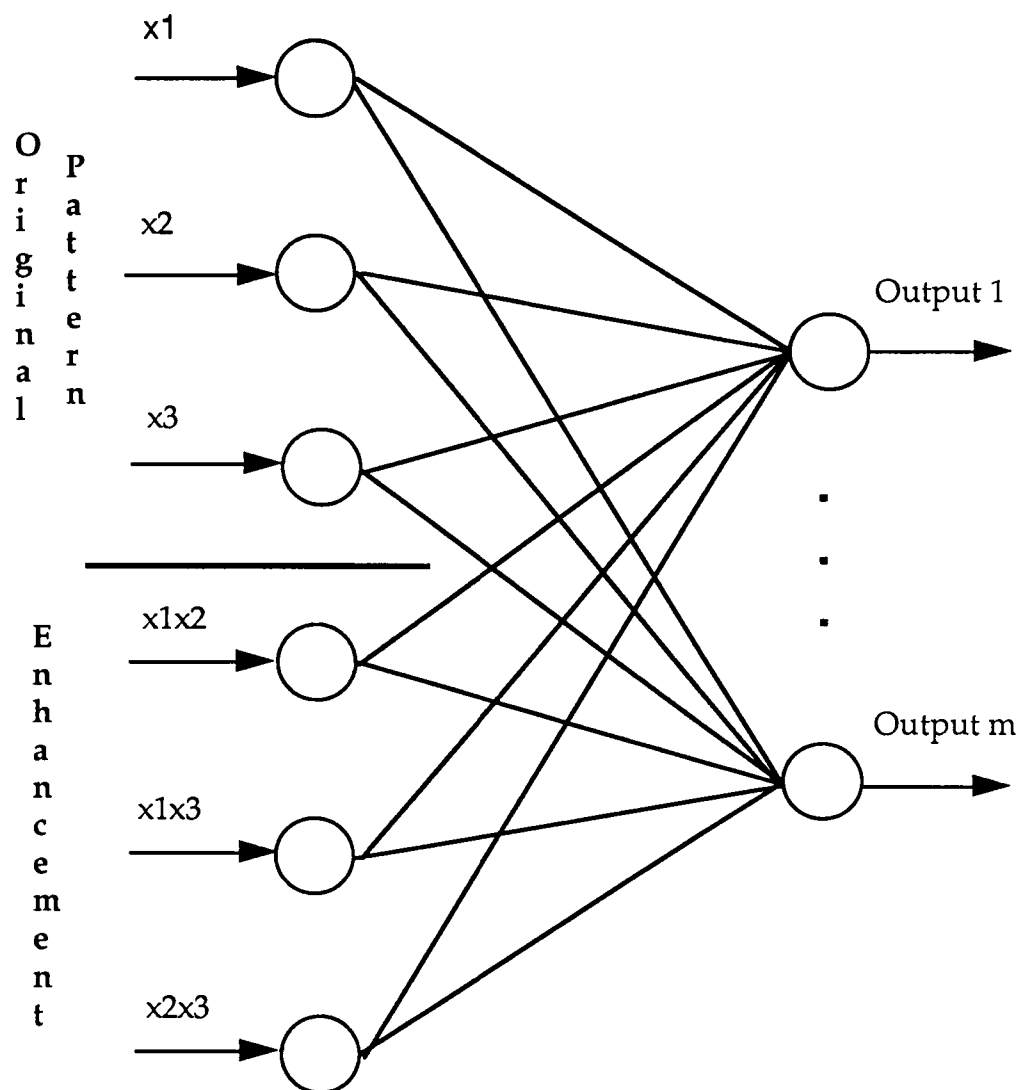


Figure A3: Supervised Learning Network With Joint Activation Enhancement of Second Order.

interface using two basic components, layers and connections. A layer is organized as a two-dimensional array of processing units that share common transfer and learning functions. A connection between two layers is a "bundle" of elemental links between the processing units in both layers. The attributes of network components can be edited through menus. Also, graphical displays can be added to any state variable of a network component.

Seven network models are readily available through the PLEXI environment. Two of these models use the Kohonen learning law: competition and the self-organizing map. Three models are variations of the delta learning rule: simple backpropagation, backpropagation, and fast bipolar backpropagation. The remaining models are bidirectional associative memory (BAM) and Hopfield memory. In addition to these seven models, PLEXI allows the user to develop others through its pull-down menus and its graphical environment.

The two networks utilized for check valve diagnostics are the competition network and the self-organizing map (SOM). The competition network model in PLEXI implements a weight update scheme where for each unit j :

$$\delta W_{ij} = R * A_j * (A_i - W_{ij}) \quad (A.5)$$

and normalizes W_j such that $\|W_j\| = L$. L is usually equal to one, but it is available as an argument for this learning law. The SOM is a variation of the competition learning law which also incorporates the Euclidean distance from the "winning" unit (the unit with maximum activation) to the unit for which the weights are being adjusted. The weights for each unit j are adjusted according to:

$$\delta W_{ij} = R * S(s,j,j_{\max}) * (A_i - W_{ij}) \quad (A.6)$$

where $S(s,j,j_{\max})$ is a function of the distance between unit j and the winning unit given by

$$S(s,j,j_{\max}) = e^{-\frac{d^2}{s^2}} \quad (\text{A.7})$$

In Equation A.7, d is the distance in unit coordinates and s is a controlling constant for the amount of "spread" and is available as an argument for this learning law. As with competition, the W_j are normalized such that $\|W_j\| = L$, with L usually equal to one.

APPENDIX B

PROCESSED CHECK VALVE DATA FROM UTAH STATE UNIVERSITY

(The data listed in this appendix is not the raw data obtained from Utah State University. This data has been processed and there is no means through which the original data can be recovered using these values.)

Table B1: Processed Check Valve Test Data From Utah State University.

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
1	10" Swing	None	Zero Flow	0.000000	0.211800	0.013800	0.000000	0.000000	0.000000
2	10" Swing	None	Tapping	0.719700	0.059100	0.120300	0.719700	1.000000	0.124700
3	10" Swing	None	75% Flow	0.251300	0.192400	0.030400	0.251400	0.732800	0.250500
4	10" Swing	None	30% Flow	0.141200	0.204800	0.022100	0.141300	0.333000	0.040100
5	10" Swing	None	Near Seat	0.013500	0.210400	0.013800	0.013500	0.033900	0.000000
6	10" Swing	None	Tapping	0.724800	0.202900	0.188100	0.724800	1.000000	0.040100
7	10" Swing	None	Tapping	0.657000	0.532500	0.101000	0.656700	0.993000	0.124700
8	10" Swing	None	75% Flow	0.254400	0.298700	0.033200	0.254200	0.732800	1.000000
9	10" Swing	None	Backseated	0.989500	0.012400	0.249000	0.989700	1.000000	0.000000
10	10" Swing	None	Backseated	0.989500	0.081300	0.203300	0.989700	1.000000	0.000000
11	10" Swing	None	Tapping	0.919400	0.042800	0.218500	0.919300	0.989000	0.250500
12	10" Swing	None	Tapping	0.919400	0.042800	0.218500	0.919300	0.989000	0.250500
13	10" Swing	None	75% Flow	0.229800	0.311600	0.030400	0.229900	0.732800	0.250500
14	10" Swing	None	30% Flow	0.135500	0.000000	0.022100	0.135300	0.333000	0.124700
15	10" Swing	None	30% Flow	0.135500	0.000000	0.022100	0.135300	0.333000	0.124700
16	10" Swing	None	Zero Flow	0.000000	0.713700	0.000000	0.000000	0.003000	0.000000
17	10" Swing	None	Zero Flow	0.000000	0.713700	0.000000	0.000000	0.003000	0.000000
18	10" Swing	30% Hinge Pin	Zero Flow	0.000000	0.211800	0.000000	0.000000	0.067800	0.000000
19	10" Swing	30% Hinge Pin	Tapping	0.803700	0.000700	0.143800	0.803600	1.000000	0.007600
20	10" Swing	30% Hinge Pin	75% Flow	0.306600	0.181900	0.034600	0.306400	0.750700	0.467500
21	10" Swing	30% Hinge Pin	30% Flow	0.162000	0.201700	0.026300	0.161800	0.376900	0.234300
22	10" Swing	30% Hinge Pin	Near Seat	0.013000	0.210800	0.013800	0.013100	0.003000	0.000000
23	10" Swing	30% Hinge Pin	Backseated	0.974500	0.090500	0.214400	0.974300	1.000000	0.000000
24	10" Swing	30% Hinge Pin	Tapping	0.786800	0.111300	0.178400	0.786800	0.985000	0.936000
25	10" Swing	30% Hinge Pin	Tapping	0.864300	0.034600	0.224100	0.864300	0.979100	0.467500

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
26	10" Swing	30% Hinge Pin	75% Flow	0.293800	0.305800	0.037300	0.293800	0.750700	0.467500
27	10" Swing	30% Hinge Pin	30% Flow	0.157400	0.287100	0.024900	0.157200	0.376900	0.374200
28	10" Swing	30% Hinge Pin	Near Seat	0.013900	0.793100	0.013800	0.014000	0.097700	0.003000
29	10" Swing	30% Stud Pin	Zero Flow	0.000000	0.200600	0.000000	0.000000	0.003000	0.000000
30	10" Swing	30% Stud Pin	Tapping	0.626700	0.095400	0.085800	0.626900	0.989000	0.500000
31	10" Swing	30% Stud Pin	75% Flow	0.220500	0.195900	0.027700	0.220100	0.732800	0.250500
32	10" Swing	30% Stud Pin	30% Flow	0.125600	0.205200	0.019400	0.125500	0.333000	0.007600
33	10" Swing	30% Stud Pin	Near Seat	0.029900	0.207600	0.013800	0.029900	0.066800	0.001100
34	10" Swing	30% Stud Pin	Backseated	1.000000	0.033400	0.225400	1.000000	1.000000	0.000000
35	10" Swing	30% Stud Pin	Tapping	0.400900	0.171100	0.362400	0.401100	0.962100	0.500000
36	10" Swing	30% Stud Pin	75% Flow	0.220500	0.616600	0.030400	0.220100	0.732800	0.500000
37	10" Swing	30% Stud Pin	30% Flow	0.126500	0.415600	0.020700	0.126400	0.333000	0.400200
38	10" Swing	30% Stud Pin	Near Seat	0.032400	0.599100	0.013800	0.032600	0.066800	0.080300
39	10" Swing	30% HP & SP	Zero Flow	0.000000	0.197800	0.000000	0.000000	0.003000	0.000000
40	10" Swing	30% HP & SP	Backseated	0.982100	0.072000	0.226800	0.981300	1.000000	0.000000
41	10" Swing	30% HP & SP	Tapping	0.646700	0.551200	0.095400	0.646500	0.991000	0.000000
42	10" Swing	30% HP & SP	Tapping	0.680300	0.236800	0.139700	0.680500	0.985000	0.803700
43	10" Swing	30% HP & SP	75% Flow	0.263000	0.747500	0.030400	0.263100	0.785600	0.401300
44	10" Swing	30% HP & SP	75% Flow	0.280900	0.352500	0.036000	0.280800	0.785600	0.535800
45	10" Swing	30% HP & SP	30% Flow	0.136400	0.866800	0.022100	0.136200	0.356900	0.267900
46	10" Swing	30% HP & SP	30% Flow	0.143700	0.165500	0.023500	0.143700	0.356900	0.401300
47	10" Swing	30% HP & SP	Near Seat	0.017700	1.000000	0.012400	0.017700	0.000000	0.001100
48	10" Swing	15% Hinge Pin	Zero Flow	0.000000	0.211100	0.000000	0.000000	0.003000	0.000000
49	10" Swing	15% Hinge Pin	Backseated	0.991000	0.061500	0.222700	0.991100	1.000000	0.000000
50	10" Swing	15% Hinge Pin	Tapping	0.645600	0.545300	0.092700	0.645500	0.990000	0.517400

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
51	10" Swing	15% Hinge Pin	Tapping	0.730000	0.242600	0.156300	0.729900	0.985000	0.776600
52	10" Swing	15% Hinge Pin	75% Flow	0.247700	0.691400	0.030400	0.247700	0.758700	0.388300
53	10" Swing	15% Hinge Pin	75% Flow	0.267900	0.354800	0.034600	0.267700	0.763700	0.776600
54	10" Swing	15% Hinge Pin	30% Flow	0.141000	0.659900	0.022100	0.140900	0.345000	0.259200
55	10" Swing	15% Hinge Pin	30% Flow	0.146700	0.395700	0.023500	0.146900	0.388800	0.259200
56	10" Swing	15% Hinge Pin	Near Seat	0.029700	0.682100	0.013800	0.029900	0.057800	0.001100
57	10" Swing	15% Stud Pin	Zero Flow	0.000000	0.209900	0.000000	0.000000	0.003000	0.000000
58	10" Swing	15% Stud Pin	Backseated	0.886400	0.236800	0.177000	0.886200	1.000000	0.000000
59	10" Swing	15% Stud Pin	Tapping	0.741000	0.453000	0.124500	0.741100	0.994000	0.124700
60	10" Swing	15% Stud Pin	Tapping	0.726900	0.233300	0.156300	0.726700	0.994000	0.500000
61	10" Swing	15% Stud Pin	75% Flow	0.234800	0.830500	0.029000	0.234600	0.738800	0.160500
62	10" Swing	15% Stud Pin	75% Flow	0.231500	0.366500	0.030400	0.231300	0.738800	0.250500
63	10" Swing	15% Stud Pin	30% Flow	0.123500	0.659900	0.022100	0.123600	0.333000	0.000000
64	10" Swing	15% Stud Pin	30% Flow	0.128400	0.162000	0.020700	0.128300	0.333000	0.124700
65	10" Swing	15% Stud Pin	Near Seat	0.027100	0.697300	0.011100	0.027100	0.061800	0.001100
66	10" Swing	Disc Stuck 30%	Zero Flow	0.000000	0.209000	0.000000	0.000000	0.302100	0.000000
67	10" Swing	Disc Stuck 30%	Backseated	0.886400	0.180700	1.000000	0.886200	0.302100	0.000000
68	10" Swing	Disc Stuck 30%	Tapping	0.741000	0.335000	0.647300	0.741100	0.302100	0.000000
69	10" Swing	Disc Stuck 30%	75% Flow	0.242200	0.679300	0.067800	0.242100	0.302100	0.000000
70	10" Swing	Disc Stuck 30%	75% Flow	0.240500	0.114100	0.069200	0.240200	0.302100	0.000000
71	10" Swing	Disc Stuck 30%	30% Flow	0.119900	0.794300	0.018000	0.119900	0.302100	0.000000
72	10" Swing	Disc Stuck 30%	30% Flow	0.119500	0.216900	0.018000	0.119400	0.302100	0.000000
73	10" Swing	Disc Stuck 30%	Near Seat	0.026500	0.870300	0.001400	0.026600	0.302100	0.000000
74	12" Tilt-Disc	30% Hinge Pin	Zero Flow	0.000000	0.190400	0.000000	0.000000	0.285700	0.000000
75	12" Tilt-Disc	30% Hinge Pin	Backseated	0.953400	0.624000	1.000000	0.953700	1.000000	0.000000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
76	12" Tilt-Disc	30% Hinge Pin	Tapping	0.546000	0.478400	0.200000	0.546300	0.982100	0.333300
77	12" Tilt-Disc	30% Hinge Pin	Tapping	0.341600	0.139200	0.088000	0.341300	0.928600	1.000000
78	12" Tilt-Disc	30% Hinge Pin	75% Flow	0.274200	0.921600	0.176000	0.273900	0.785700	0.083300
79	12" Tilt-Disc	30% Hinge Pin	75% Flow	0.262700	0.427200	0.088000	0.262600	0.785700	0.166700
80	12" Tilt-Disc	15% Hinge Pin	Zero Flow	0.000000	0.190400	0.000000	0.000000	0.000000	0.000000
81	12" Tilt-Disc	15% Hinge Pin	Backseated	1.000000	0.635200	0.944000	1.000000	1.000000	0.000000
82	12" Tilt-Disc	15% Hinge Pin	Tapping	0.487800	0.444800	0.136000	0.487400	0.982100	0.500000
83	12" Tilt-Disc	15% Hinge Pin	Tapping	0.462700	0.000000	0.064000	0.462100	0.982100	1.000000
84	12" Tilt-Disc	15% Hinge Pin	75% Flow	0.279800	0.913600	0.176000	0.279500	0.785700	0.083300
85	12" Tilt-Disc	15% Hinge Pin	75% Flow	0.272600	0.844800	0.152000	0.272500	0.785700	0.500000
86	12" Tilt-Disc	15% Hinge Pin	30% Flow	0.070900	0.955200	0.096000	0.071600	0.428600	0.000000
87	12" Tilt-Disc	15% Hinge Pin	30% Flow	0.073300	0.654400	0.080000	0.073000	0.428600	0.000000
88	12" Tilt-Disc	Disc Stuck 100%	Zero Flow	0.000000	1.000000	0.000000	0.000000	1.000000	0.000000
89	12" Tilt-Disc	Disc Stuck 100%	Backseated	0.953400	0.668800	0.912000	0.953700	1.000000	0.000000
90	12" Tilt-Disc	Disc Stuck 100%	Tapping	0.495000	0.910400	0.240000	0.494400	1.000000	0.000000
91	12" Tilt-Disc	Disc Stuck 100%	75% Flow	0.277000	0.921600	0.080000	0.276700	1.000000	0.000000
92	12" Tilt-Disc	Disc Stuck 100%	75% Flow	0.274200	0.472000	0.056000	0.273900	1.000000	0.000000
93	12" Tilt-Disc	Disc Stuck 100%	30% Flow	0.071300	0.955200	0.008000	0.071600	1.000000	0.000000
94	12" Tilt-Disc	Disc Stuck 100%	30% Flow	0.070500	0.408000	0.008000	0.070200	1.000000	0.000000
95	4" Swing	None	Zero Flow	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000
96	4" Swing	None	Seat Leak	0.272100	0.039100	0.000000	0.274700	0.149000	0.000000
97	4" Swing	None	Backseated	0.966000	0.592200	0.880000	0.968000	0.971400	0.000000
98	4" Swing	None	Touching	0.775500	0.670400	0.600000	0.778700	0.958700	0.250000
99	4" Swing	None	Touching	0.877600	0.385500	0.640000	0.874700	0.956600	0.250000
100	4" Swing	None	75% Flow	0.680300	0.743000	0.520000	0.680000	0.760500	0.250000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
101	4" Swing	None	75% Flow	0.673500	0.712300	0.520000	0.674700	0.718400	1.000000
102	4" Swing	None	30% Flow	0.394600	0.871500	0.360000	0.392000	0.380900	0.250000
103	4" Swing	None	30% Flow	0.387800	0.865900	0.360000	0.386700	0.359800	0.250000
104	4" Swing	None	Near Seat	0.000600	1.000000	0.400000	0.000000	0.106800	0.125000
105	4" Swing	None	Zero Flow	0.000000	0.000000	0.000000	0.000000	0.106800	0.000000
106	4" Swing	None	Touching	0.966000	0.290500	0.560000	0.965300	0.250000	0.950300
107	4" Swing	Loose H.P.	Zero Flow	0.000000	0.195500	0.640000	0.000000	0.000000	0.000000
108	4" Swing	Loose H.P.	Backseated	0.972800	0.589400	0.880000	0.973300	0.971400	0.000000
109	4" Swing	Loose H.P.	Touching	0.775500	0.691300	0.600000	0.778700	0.965100	0.500000
110	4" Swing	Loose H.P.	Touching	0.932000	0.371500	0.680000	0.933300	0.965100	0.500000
111	4" Swing	Loose H.P.	75% Flow	0.680300	0.740200	0.520000	0.677300	0.760500	0.250000
112	4" Swing	Loose H.P.	75% Flow	0.666700	0.717900	0.520000	0.669300	0.739400	0.250000
113	4" Swing	Loose H.P.	30% Flow	0.394600	0.858900	0.360000	0.394700	0.380900	0.050000
114	4" Swing	Loose H.P.	30% Flow	0.394600	0.856100	0.360000	0.394700	0.380900	0.025000
115	4" Swing	30% Hinge Pin	Zero Flow	0.000000	0.195500	0.640000	0.000000	0.000000	0.000000
116	4" Swing	30% Hinge Pin	Backseated	1.000000	0.578200	1.000000	1.000000	1.000000	0.000000
117	4" Swing	30% Hinge Pin	Touching	0.857100	0.564200	0.720000	0.858700	0.985700	0.500000
118	4" Swing	30% Hinge Pin	Touching	0.775500	0.212300	0.560000	0.776000	0.971400	0.250000
119	4" Swing	30% Hinge Pin	75% Flow	0.619000	0.782100	0.480000	0.616000	0.628600	0.250000
120	4" Swing	30% Hinge Pin	75% Flow	0.625800	0.768200	0.480000	0.626700	0.628600	0.250000
121	4" Swing	30% Hinge Pin	30% Flow	0.408200	0.865900	0.360000	0.408000	0.342800	0.500000
122	4" Swing	30% Hinge Pin	30% Flow	0.381000	0.877100	0.360000	0.378700	0.314300	0.500000
123	4" Swing	30% Stud Pin	Zero Flow	0.000000	0.195500	0.000000	0.000000	0.000000	0.000000
124	4" Swing	30% Stud Pin	Backseated	0.932000	0.625700	0.880000	0.930700	0.971400	0.000000
125	4" Swing	30% Stud Pin	Touching	0.693900	0.681600	0.600000	0.690700	0.945400	1.000000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
126	4" Swing	30% Stud Pin	75% Flow	0.666700	0.600600	0.520000	0.664000	0.841100	0.250000
127	4" Swing	30% Stud Pin	75% Flow	0.653100	0.578200	0.520000	0.656000	0.841100	0.000000
128	4" Swing	30% Stud Pin	30% Flow	0.374100	0.486000	0.360000	0.376000	0.450400	0.250000
129	4" Swing	30% Stud Pin	30% Flow	0.381000	0.514000	0.360000	0.381300	0.450400	0.125000
130	4" Swing	15% Hinge Pin	Zero Flow	0.000000	0.015400	0.000000	0.000000	0.000000	0.000000
131	4" Swing	15% Hinge Pin	Backseated	0.938800	0.617300	0.880000	0.936000	0.971400	0.000000
132	4" Swing	15% Hinge Pin	Tapping	0.898000	0.539100	0.720000	0.896000	0.959700	1.000000
133	4" Swing	15% Hinge Pin	75% Flow	0.639500	0.770900	0.520000	0.640000	0.691700	0.500000
134	4" Swing	15% Hinge Pin	75% Flow	0.632700	0.745800	0.520000	0.632000	0.668400	0.250000
135	4" Swing	15% Hinge Pin	30% Flow	0.374100	0.865900	0.360000	0.376000	0.342100	0.500000
136	4" Swing	15% Hinge Pin	30% Flow	0.374100	0.854700	0.360000	0.373300	0.342100	1.000000
137	4" Swing	15% Hinge Pin	Near Seat	0.001700	0.980400	0.280000	0.002700	0.085700	0.000000
138	4" Swing	Disc Stuck 100%	Zero Flow	0.000000	0.998600	0.000000	0.000000	1.000000	0.000000
139	4" Swing	Disc Stuck 100%	Backseated	0.959200	0.597800	0.920000	0.962700	1.000000	0.000000
140	4" Swing	Disc Stuck 100%	75% Flow	0.666700	0.745800	0.440000	0.669300	1.000000	0.000000
141	4" Swing	Disc Stuck 100%	75% Flow	0.666700	0.731800	0.440000	0.664000	1.000000	0.000000
142	4" Swing	Disc Stuck 100%	30% Flow	0.387800	0.870100	0.160000	0.386700	1.000000	0.000000
143	4" Swing	Disc Stuck 100%	30% Flow	0.381000	0.854700	0.160000	0.384000	1.000000	0.000000
144	10" Duo	None	Zero Flow	0.000000	0.330600	0.000000	0.000000	0.000000	0.000000
145	10" Duo	None	Backseated	0.981300	0.736100	0.798100	0.981600	1.000000	0.142900
146	10" Duo	None	Tapping	0.994900	0.541700	0.840400	0.995000	0.984600	0.285700
147	10" Duo	None	75% Flow	0.432600	0.800000	0.338000	0.432300	0.761500	0.028600
148	10" Duo	None	75% Flow	0.439800	0.647200	0.356800	0.439800	0.784600	0.214300
149	10" Duo	None	30% Flow	0.147700	0.508300	0.192500	0.831000	0.523100	0.000000
150	10" Duo	None	30% Flow	0.104600	0.225000	0.122100	0.104500	0.328400	0.142900

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
151	10" Duo	None	75% Flow	0.426900	0.150000	0.079800	0.426400	0.701500	0.428600
152	10" Duo	None	100% Flow	0.974500	0.266700	0.596200	0.974900	0.992500	0.714300
153	10" Duo	None	100% Flow	0.802400	0.013900	0.169000	0.802700	0.985100	1.000000
154	10" Duo	None	Tapping	0.974500	0.455600	0.662000	0.974900	1.000000	0.142900
155	10" Duo	30% Hinge Pin	Zero Flow	0.000000	0.266700	0.000000	0.000000	0.000000	0.000000
156	10" Duo	30% Hinge Pin	Backseated	0.975900	0.744400	0.802800	0.975800	1.000000	0.028600
157	10" Duo	30% Hinge Pin	Tapping	0.959800	0.633300	0.774600	0.959900	0.985100	0.071400
158	10" Duo	30% Hinge Pin	75% Flow	0.413900	1.000000	0.305200	0.413900	0.813400	0.028600
159	10" Duo	30% Hinge Pin	75% Flow	0.439800	0.555600	0.338000	0.439800	0.791000	0.028600
160	10" Duo	30% Hinge Pin	30% Flow	0.145900	0.588900	0.178400	0.821600	0.373100	0.000000
161	10" Duo	30% Hinge Pin	30% Flow	0.003200	0.000000	0.018800	0.003300	0.307100	0.285700
162	10" Duo	30% Hinge Pin	75% Flow	0.424400	0.694400	0.061000	0.423900	0.857100	0.571400
163	10" Duo	30% Hinge Pin	Open	0.975900	0.550000	0.586900	0.975800	0.992900	0.571400
164	10" Duo	30% Hinge Pin	Tapping	0.752400	0.480600	0.159600	0.752500	0.978600	0.571400
165	10" Duo	30% Hinge Pin	Tapping	0.981300	0.727800	0.680800	0.981600	0.985700	0.142900
166	10" Duo	30% Hinge Pin	Zero Flow	0.000000	0.322200	0.000000	0.000000	0.000000	0.000000
167	10" Duo	30% Hinge Pin	Tapping	0.967700	0.758300	0.638500	0.968200	1.000000	0.142900
168	10" Duo	30% Hinge Pin	Tapping	0.770000	0.416700	0.596200	0.770100	0.985300	0.571400
169	10" Duo	30% Hinge Pin	Tapping	0.975900	0.488900	0.647900	0.975800	0.992600	0.285700
170	10" Duo	30% Hinge Pin	75% Flow	0.449200	0.641700	0.328600	0.449000	0.808800	0.142900
171	10" Duo	30% Hinge Pin	75% Flow	0.445600	0.150000	0.122100	0.445700	0.808800	0.285700
172	10" Duo	30% Hinge Pin	30% Flow	0.152000	0.883300	0.206600	0.152200	0.308800	0.071400
173	10" Duo	30% Hinge Pin	30% Flow	0.152000	0.308300	0.065700	0.152200	0.257400	0.285700
174	10" Duo	30% Hinge Pin	Seat Tap.	0.083400	0.358300	0.234700	0.285700	0.022100	0.014300
175	10" Duo	1/2 Disc Stuck	Backseated	1.000000	0.691700	1.000000	1.000000	1.000000	0.071400

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
176	10" Duo	1/2 Disc Stuck	Tapping	0.816700	0.447200	0.455400	0.816900	0.970800	0.714300
177	10" Duo	1/2 Disc Stuck	Tapping	0.970500	0.566700	0.873200	0.970700	0.985400	0.428600
178	10" Duo	1/2 Disc Stuck	75% Flow	0.436200	0.419400	0.314600	0.436500	0.795600	0.071400
179	10" Duo	1/2 Disc Stuck	75% Flow	0.440500	0.366700	0.079800	0.440600	0.817500	0.428600
180	10" Duo	1/2 Disc Stuck	30% Flow	0.147000	0.805600	0.183100	0.826300	0.416100	0.000000
181	10" Duo	1/2 Disc Stuck	30% Flow	0.149800	0.022200	0.375600	0.149700	0.401500	0.285700
182	10" Duo	No Spring	Zero Flow	0.000000	0.205600	0.000000	0.000000	0.692300	0.000000
183	10" Duo	No Spring	Backseated	0.981300	0.741700	0.469500	0.981600	1.000000	0.000000
184	10" Duo	No Spring	Tapping	0.790200	0.355600	0.323900	0.790100	0.946200	0.428600
185	10" Duo	No Spring	Tapping	0.970500	0.455600	0.431900	0.970700	0.953800	0.142900
186	10" Duo	No Spring	75% Flow	0.426200	0.461100	0.103300	0.426400	0.953800	0.000000
187	10" Duo	No Spring	75% Flow	0.438400	0.236100	0.314600	0.438100	0.915400	0.428600
188	10" Duo	No Spring	30% Flow	0.150200	0.700000	0.056300	0.150500	0.915400	0.000000
189	10" Duo	No Spring (NS)	30% Flow	0.148000	0.172200	0.352100	0.148000	0.784600	0.285700
190	10" Duo	NS, 15% Pin	Backseated	0.986700	0.672200	0.464800	0.986600	1.000000	0.285700
191	10" Duo	NS, 15% Pin	Tapping	0.835800	0.336100	0.338000	0.836100	0.977800	0.857100
192	10" Duo	NS, 15% Pin	Tapping	0.942900	0.497200	0.413100	0.943100	0.966700	0.571400
193	10" Swing	None	Zero Flow	0.000000	0.229700	0.000000	0.000000	0.000000	0.000000
194	10" Swing	None	Seat Leak	0.000000	0.229700	0.000000	0.000000	0.008300	0.000000
195	10" Swing	None	Backseated	1.000000	0.385100	1.000000	1.000000	1.000000	0.000000
196	10" Swing	None	Tapping	0.860600	0.783800	0.923700	0.860400	0.997200	0.166700
197	10" Swing	None	Tapping	0.706900	0.398600	0.305100	0.706900	0.986200	0.500000
198	10" Swing	None	75% Flow	0.396800	0.540500	0.957600	0.396700	0.740300	0.166700
199	10" Swing	None	75% Flow	0.445100	0.435800	0.584700	0.444900	0.787300	1.000000
200	10" Swing	None	30% Flow	0.149700	0.425700	0.703400	0.149400	0.292800	0.041700

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
201	10" Swing	None	30% Flow	0.146000	0.104700	0.830500	0.146100	0.306600	0.333300
202	10" Swing	30% Hinge Pin	Zero Flow	0.000000	0.469600	0.000000	0.000000	0.085400	0.000000
203	10" Swing	30% Hinge Pin	Backseated	0.986300	0.756800	0.728800	0.986100	1.000000	0.000000
204	10" Swing	30% Hinge Pin	Tapping	0.820300	0.587800	0.678000	0.820400	0.996400	0.166700
205	10" Swing	30% Hinge Pin	Tapping	0.750600	0.317600	0.093200	0.751000	0.996400	0.500000
206	10" Swing	30% Hinge Pin	75% Flow	0.402100	0.959500	0.720300	0.402400	0.811400	0.333300
207	10" Swing	30% Hinge Pin	75% Flow	0.432800	0.547300	0.567800	0.432700	0.743800	0.500000
208	10" Swing	30% Hinge Pin	30% Flow	0.158700	0.966200	0.661000	0.159200	0.359400	0.041700
209	10" Swing	30% Hinge Pin	30% Flow	0.159100	0.496600	0.016900	0.159200	0.291800	0.500000
210	10" Swing	15% Hinge Pin	Zero Flow	0.000000	0.462800	0.000000	0.000000	0.000000	0.000000
211	10" Swing	15% Hinge Pin	Backseated	0.986300	0.473000	0.703400	0.986100	1.000000	0.000000
212	10" Swing	15% Hinge Pin	Tapping	0.791900	0.804100	0.669500	0.791800	0.996800	0.166700
213	10" Swing	15% Hinge Pin	Tapping	0.786300	0.067600	0.135600	0.786100	0.971200	0.500000
214	10" Swing	15% Hinge Pin	75% Flow	0.407500	0.723000	0.720300	0.407300	0.717900	0.333300
215	10" Swing	15% Hinge Pin	75% Flow	0.411500	0.729700	0.567800	0.411400	0.682700	0.500000
216	10" Swing	15% Hinge Pin	30% Flow	0.163100	0.290500	0.661000	0.163300	0.246800	0.041700
217	10" Swing	15% Hinge Pin	30% Flow	0.156700	0.570900	0.033900	0.156700	0.246800	0.833300
218	10" Swing	15% Stud Pin	Zero Flow	0.000000	0.381800	0.000000	0.000000	0.000000	0.000000
219	10" Swing	15% Stud Pin	Backseated	0.977000	0.804100	0.678000	0.977100	1.000000	0.000000
220	10" Swing	15% Stud Pin	Tapping	0.852600	0.858100	0.661000	0.853100	0.997200	0.083300
221	10" Swing	15% Stud Pin	Tapping	0.732200	0.432400	0.076300	0.732200	0.994500	0.416700
222	10" Swing	15% Stud Pin	75% Flow	0.403500	0.979700	0.711900	0.403300	0.723000	0.166700
223	10" Swing	15% Stud Pin	75% Flow	0.421800	0.668900	0.525400	0.422000	0.695300	0.333300
224	10" Swing	15% Stud Pin	30% Flow	0.162100	0.787200	0.661000	0.162400	0.268700	0.041700
225	10" Swing	15% Stud Pin	30% Flow	0.161700	0.459500	0.000000	0.161600	0.293600	0.333300

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
226	10" Swing	30% Stud Pin	Zero Flow	0.000000	0.435800	0.000000	0.000000	0.000000	0.000000
227	10" Swing	30% Stud Pin	Backseated	0.967700	0.831100	0.694900	0.967300	1.000000	0.000000
228	10" Swing	30% Stud Pin	Tapping	0.847300	0.763500	0.661000	0.847300	0.997200	0.083300
229	10" Swing	30% Stud Pin	Tapping	0.762600	0.223000	0.067800	0.762400	0.991600	0.333300
230	10" Swing	30% Stud Pin	75% Flow	0.577900	0.918900	0.703400	0.578000	0.916400	0.333300
231	10" Swing	30% Stud Pin	75% Flow	0.574500	0.851400	0.330500	0.574700	0.922000	0.416700
232	10" Swing	30% Stud Pin	30% Flow	0.159100	0.797300	0.661000	0.159200	0.292500	0.083300
233	10" Swing	30% Stud Pin	30% Flow	0.158100	0.695900	0.016900	0.158400	0.325900	0.333300
234	10" Swing	30% HP, 30% SP	Zero Flow	0.000000	0.429100	0.000000	0.000000	0.000000	0.000000
235	10" Swing	30% HP, 30% SP	Backseated	0.977000	0.760100	0.711900	0.977100	1.000000	0.000000
236	10" Swing	30% HP, 30% SP	Tapping	0.844600	0.344600	0.678000	0.844900	0.996700	0.083300
237	10" Swing	30% HP, 30% SP	75% Flow	0.416100	1.000000	0.711900	0.416300	0.797300	0.083300
238	10" Swing	30% HP, 30% SP	75% Flow	0.585200	0.898600	0.420000	0.585300	0.870400	0.500000
239	10" Swing	30% HP, 30% SP	30% Flow	0.157700	0.729700	0.661000	0.157600	0.318900	0.166700
240	10" Swing	30% HP, 30% SP	30% Flow	0.159100	0.462800	0.050800	0.159200	0.299000	0.500000
241	16" Tilt Disc	None	Zero Flow	0.000000	0.215400	0.000000	0.000000	0.000000	0.000000
242	16" Tilt Disc	None	Backseated	1.000000	0.130800	1.000000	1.000000	1.000000	0.000000
243	16" Tilt Disc	None	Tapping	0.855200	0.092300	0.706800	0.855200	0.996700	0.054100
244	16" Tilt Disc	None	Tapping	0.796600	0.023100	0.022600	0.796500	0.947400	0.410800
245	16" Tilt Disc	None	75% Flow	0.541900	0.765400	0.766900	0.541800	0.736800	0.054100
246	16" Tilt Disc	None	75% Flow	0.595700	0.319200	0.285700	0.595500	0.766400	0.454100
247	16" Tilt Disc	None	30% Flow	0.177700	1.000000	0.624100	0.177300	0.299300	0.000000
248	16" Tilt Disc	None	30% Flow	0.180100	0.553800	0.285700	0.179800	0.292800	0.054100
249	16" Tilt Disc	None	Seat Leak	0.004500	0.219200	0.503800	0.005000	0.000000	0.000000
250	16" Tilt Disc	15% Hinge Pin	Zero Flow	0.000000	0.215400	0.000000	0.000000	0.000000	0.000000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
251	16" Tilt Disc	15% Hinge Pin	30% Flow	0.208800	1.000000	0.676700	0.208500	0.301800	0.000000
252	16" Tilt Disc	15% Hinge Pin	75% Flow	0.573900	0.826900	0.782000	0.574300	0.753000	0.000000
253	16" Tilt Disc	15% Hinge Pin	75% Flow	0.568800	0.350000	0.353400	0.569300	0.725600	0.216200
254	16" Tilt Disc	15% Hinge Pin	30% Flow	0.203400	0.742300	0.353400	0.203500	0.317100	0.027000
255	16" Tilt Disc	15% Hinge Pin	100% Flow	0.837700	0.207700	0.195500	0.837700	0.987800	0.162200
256	16" Tilt Disc	15% Hinge Pin	100% Flow	0.848800	0.576900	0.804500	0.848900	0.987800	0.027000
257	16" Tilt Disc	15% Hinge Pin	Zero Flow	0.000000	0.215400	0.000000	0.000000	0.009100	0.000000
258	16" Tilt Disc	15% Hinge Pin	100% Flow	0.848800	0.576900	0.804500	0.848900	0.987800	0.054100
259	16" Tilt Disc	30% Hinge Pin	Zero Flow	0.000000	0.211500	0.000000	0.000000	0.000000	0.000000
260	16" Tilt Disc	30% Hinge Pin	Touching	0.912200	0.516500	0.812000	0.912600	0.987200	0.135100
261	16" Tilt Disc	30% Hinge Pin	Touching	0.914300	0.000000	0.000000	0.913900	0.953800	0.540500
262	16" Tilt Disc	30% Hinge Pin	75% Flow	0.686200	0.734600	0.782000	0.686600	0.751300	0.189200
263	16" Tilt Disc	30% Hinge Pin	75% Flow	0.709100	0.250000	0.233100	0.709100	0.764100	1.000000
264	16" Tilt Disc	30% Hinge Pin	30% Flow	0.283600	0.980800	0.661700	0.283400	0.287200	0.108100
265	16" Tilt Disc	30% Hinge Pin	30% Flow	0.294500	0.742300	0.391000	0.294600	0.284600	0.459500
266	24" Tilt Disc	None	Zero Flow	0.000000	0.229700	0.000000	0.000000	0.000000	0.000000
267	24" Tilt Disc	None	Backseated	0.957400	0.258000	0.718200	0.957400	1.000000	0.000000
268	24" Tilt Disc	None	Tapping	0.526300	0.197900	0.638000	0.526500	0.973200	0.400000
269	24" Tilt Disc	None	Tapping	0.511300	0.000000	0.573900	0.511600	0.973200	0.200000
270	24" Tilt Disc	None	75% Flow	0.348400	0.962900	0.638000	0.348400	0.785700	0.100000
271	24" Tilt Disc	None	75% Flow	0.350900	0.558300	0.631200	0.351000	0.803600	0.300000
272	24" Tilt Disc	None	30% Flow	0.060200	1.000000	0.630000	0.060000	0.357100	0.010000
273	24" Tilt Disc	None	30% Flow	0.050100	0.321600	0.628900	0.050300	0.303600	0.020000
274	24" Tilt Disc	Disc Stuck 68%	Zero Flow	0.000000	0.252700	0.000000	0.000000	0.680000	0.000000
275	24" Tilt Disc	Disc Stuck 68%	Backseated	0.721800	0.015900	1.000000	0.721900	0.680000	0.000000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
276	24" Tilt Disc	Disc Stuck 68%	Tapping	0.536300	0.098900	0.812100	0.536800	0.680000	0.000000
277	24" Tilt Disc	Disc Stuck 68%	Tapping	0.503800	0.010600	0.741100	0.894600	0.680000	0.000000
278	24" Tilt Disc	Disc Stuck 68%	75% Flow	0.348400	0.224400	0.704500	0.348400	0.680000	0.000000
279	24" Tilt Disc	Disc Stuck 68%	75% Flow	0.355900	0.088600	0.579600	0.356100	0.680000	0.000000
280	24" Tilt Disc	Disc Stuck 68%	30% Flow	0.055600	0.240300	0.616300	0.055500	0.680000	0.000000
281	24" Tilt Disc	Disc Stuck 68%	30% Flow	0.059500	0.056500	0.595600	0.059400	0.680000	0.000000
282	24" Tilt Disc	15% Hinge Pin	Zero Flow	0.000000	0.252700	0.000000	0.000000	0.000000	0.000000
283	24" Tilt Disc	15% Hinge Pin	Backseated	0.959900	0.021200	0.780100	0.960000	1.000000	0.000000
284	24" Tilt Disc	15% Hinge Pin	Tapping	0.503800	0.159000	0.644900	0.894600	0.990700	0.200000
285	24" Tilt Disc	15% Hinge Pin	Tapping	0.501300	0.010600	0.572700	0.501300	0.981500	1.000000
286	24" Tilt Disc	15% Hinge Pin	Zero Flow	0.000000	0.252700	0.000000	0.000000	0.000000	0.000000
287	24" Tilt Disc	15% Hinge Pin	75% Flow	0.373500	0.219100	0.704500	0.373500	0.870400	0.100000
288	24" Tilt Disc	15% Hinge Pin	75% Flow	0.368400	0.091900	0.600200	0.368400	0.851900	0.600000
289	24" Tilt Disc	15% Hinge Pin	30% Flow	0.056500	0.240300	0.634600	0.056800	0.222200	0.000000
290	24" Tilt Disc	15% Hinge Pin	30% Flow	0.067700	0.093600	0.606000	0.067700	0.240700	0.100000
291	24" Tilt Disc	15% One HP	Zero Flow	0.000000	0.252700	0.000000	0.000000	0.111100	0.000000
292	24" Tilt Disc	15% One HP	Backseated	1.000000	0.030000	0.768600	1.000000	1.000000	0.000000
293	24" Tilt Disc	15% One HP	Tapping	0.523800	0.151900	0.647200	0.523900	0.992100	0.200000
294	24" Tilt Disc	15% One HP	Tapping	0.501300	0.024700	0.562400	0.501300	0.984100	0.800000
295	24" Tilt Disc	15% One HP	75% Flow	0.348400	0.219100	0.657500	0.348400	0.841300	0.100000
296	24" Tilt Disc	15% One HP	75% Flow	0.350900	0.125400	0.614000	0.351000	0.841300	0.600000
297	24" Tilt Disc	15% One HP	30% Flow	0.057500	0.238500	0.633400	0.057400	0.349200	0.000000
298	24" Tilt Disc	15% One HP	30% Flow	0.058200	0.053000	0.611700	0.058100	0.317500	0.100000
299	24" Tilt Disc	7.5% Hinge Pin	Zero Flow	0.000000	0.252700	0.000000	0.000000	0.000000	0.000000
300	24" Tilt Disc	7.5% Hinge Pin	Backseated	0.962400	0.026500	0.769800	0.962600	1.000000	0.000000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
301	24" Tilt Disc	7.5% Hinge Pin	Tapping	0.523800	0.151900	0.647200	0.523900	0.990400	0.200000
302	24" Tilt Disc	7.5% Hinge Pin	Tapping	0.506300	0.024700	0.000000	0.506500	0.980800	0.800000
303	24" Tilt Disc	7.5% Hinge Pin	75% Flow	0.348400	0.220800	0.656400	0.348400	0.826900	0.100000
304	24" Tilt Disc	7.5% Hinge Pin	75% Flow	0.345900	0.130700	0.610500	0.345800	0.788500	0.500000
305	24" Tilt Disc	7.5% Hinge Pin	30% Flow	0.055400	0.240300	0.633400	0.055500	0.250000	0.000000
306	24" Tilt Disc	7.5% Hinge Pin	30% Flow	0.058200	0.053000	0.611700	0.058100	0.192300	0.100000
307	24" Swing	None	Zero Flow	0.000000	0.990100	0.000000	0.000000	0.054000	0.000000
308	24" Swing	None	Flutter	1.000000	0.388900	0.803700	1.000000	0.981000	0.600000
309	24" Swing	None	Flutter	0.961800	0.438300	1.000000	0.961400	0.999000	0.800000
310	24" Swing	None	75% Flow	0.559000	0.821000	0.384600	0.558800	0.728900	0.400000
311	24" Swing	None	75% Flow	0.559000	0.802500	0.000000	0.558800	0.728900	0.800000
312	24" Swing	None	30% Flow	0.149300	0.963000	0.228100	0.149500	0.297000	0.200000
313	24" Swing	None	30% Flow	0.142300	0.975300	0.000000	0.142200	0.288000	0.400000
314	24" Swing	15% Hinge Pin	Zero Flow	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000
315	24" Swing	15% Hinge Pin	Flutter	0.958300	0.456800	0.814300	0.958000	0.972600	0.800000
316	24" Swing	15% Hinge Pin	Flutter	0.927100	0.487700	0.000000	0.926700	0.991500	1.000000
317	24" Swing	15% Hinge Pin	75% Flow	0.576400	0.784000	0.363400	0.576100	0.812000	0.400000
318	24" Swing	15% Hinge Pin	75% Flow	0.548600	0.790000	0.000000	0.548700	0.774200	0.800000
319	24" Swing	15% Hinge Pin	30% Flow	0.149300	0.969100	0.228100	0.149500	0.339900	0.200000
320	24" Swing	15% Hinge Pin	30% Flow	0.135400	0.981500	0.000000	0.135500	0.292700	0.600000
321	24" Swing	None	Zero Flow	0.000000	0.993800	0.000000	0.000000	0.000000	0.000000
322	24" Swing	None	Flutter	0.975700	0.000000	0.824900	0.975400	0.959900	0.400000
323	24" Swing	None	Flutter	0.885400	0.537000	0.000000	0.885200	0.979100	0.800000
324	24" Swing	None	75% Flow	0.569500	0.796300	0.538500	0.569400	0.825600	0.400000
325	24" Swing	None	75% Flow	0.552100	0.808600	0.000000	0.552100	0.787100	0.800000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
326	24" Swing	None	30% Flow	0.145800	0.963000	0.421800	0.145600	0.345600
327	24" Swing	None	30% Flow	0.142300	0.975300	0.000000	0.673700	0.326300
328	24" Swing	30% Hinge Pin	Zero Flow	0.000000	0.993800	0.000000	0.000000	0.000000
329	24" Swing	30% Hinge Pin	Flutter	0.972200	0.382700	0.782500	0.972000	0.975900
330	24" Swing	30% Hinge Pin	Flutter	0.913200	0.487700	0.000000	0.913200	1.000000
331	24" Swing	30% Hinge Pin	75% Flow	0.576400	0.784000	0.458900	0.576100	0.824000
332	24" Swing	30% Hinge Pin	75% Flow	0.562500	0.790100	0.000000	0.562200	0.799900
333	24" Swing	30% Hinge Pin	30% Flow	0.170200	0.975300	0.313000	0.170200	0.400000
334	24" Swing	30% Hinge Pin	30% Flow	0.142300	0.981500	0.000000	0.142200	0.328000
335	20" Swing	None	Zero Flow	0.000000	1.000000	0.000000	0.000000	0.000000
336	20" Swing	None	Backseated	0.987800	0.368900	0.996800	0.887000	0.995600
337	20" Swing	None	Tapping	0.780500	0.606600	0.827700	0.700400	0.991700
338	20" Swing	None	Tapping	0.788600	0.606600	0.000000	0.708100	0.989800
339	20" Swing	None	75% Flow	0.422800	0.893400	0.703700	0.379600	0.748600
340	20" Swing	None	75% Flow	0.398400	0.885200	0.574900	0.357900	0.744800
341	20" Swing	None	30% Flow	0.122000	0.975400	0.647300	0.109500	0.293300
342	20" Swing	None	30% Flow	0.126000	0.975400	0.574900	0.113000	0.301000
343	20" Swing	None	Zero Flow	0.000000	1.000000	0.000000	0.000000	0.000000
344	20" Swing	None	Backseated	0.996000	0.377000	0.985500	0.996500	0.995600
345	20" Swing	None	Tapping	0.739900	0.639300	0.822900	0.739800	0.988000
346	20" Swing	None	Tapping	0.735800	0.672100	0.574900	0.735700	0.991700
347	20" Swing	None	75% Flow	0.365900	0.901600	0.713400	0.366100	0.730400
348	20" Swing	None	75% Flow	0.365900	0.901600	0.574900	0.366100	0.734300
349	20" Swing	None	3% Flow	0.012200	0.983600	0.629600	0.012400	0.026900
350	20" Swing	None	30% Flow	0.122000	0.983600	0.640900	0.121800	0.288300

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
351	20" Swing	None	30% Flow	0.130100	0.975400	0.574900	0.130100	0.319100	0.250000
352	20" Swing	15% Hinge Pin	Zero Flow	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000
353	20" Swing	15% Hinge Pin	Backseated	0.955300	0.418000	0.948500	0.955300	0.995600	0.000000
354	20" Swing	15% Hinge Pin	Tapping	0.845500	0.549200	0.858300	0.845800	0.991600	0.500000
355	20" Swing	15% Hinge Pin	Tapping	0.772400	0.631100	0.574900	0.772800	0.967500	0.625000
356	20" Swing	15% Hinge Pin	75% Flow	0.406500	0.893400	0.715000	0.406700	0.702500	0.375000
357	20" Swing	15% Hinge Pin	75% Flow	0.418700	0.877000	0.574900	0.419100	0.714600	0.750000
358	20" Swing	15% Hinge Pin	30% Flow	0.105700	0.975400	0.653800	0.105900	0.257000	0.125000
359	20" Swing	15% Hinge Pin	30% Flow	0.109700	0.975400	0.574900	0.110100	0.261000	0.500000
360	20" Swing	15% , 30% HP	Zero Flow	0.000000	0.983600	0.000000	0.000000	0.000000	0.000000
361	20" Swing	15% , 30% HP	Backseated	1.000000	0.000000	1.000000	1.000000	0.995600	0.000000
362	20" Swing	15% , 30% HP	Tapping	0.817100	0.573800	0.868000	0.817500	0.991500	0.500000
363	20" Swing	15% , 30% HP	Tapping	0.800900	0.582000	0.574900	0.801100	0.989400	0.500000
364	20" Swing	15% , 30% HP	75% Flow	0.406500	0.877000	0.731100	0.406700	0.740500	0.375000
365	20" Swing	15% , 30% HP	75% Flow	0.414700	0.868900	0.574900	0.414900	0.740500	0.625000
366	20" Swing	15% , 30% HP	30% Flow	0.126000	0.975400	0.647300	0.126000	0.279800	0.125000
367	20" Swing	15% , 30% HP	30% Flow	0.122000	0.975400	0.574900	0.121800	0.304500	0.500000
368	20" Swing	30% Hinge Pin	Zero Flow	0.000000	0.983600	0.000000	0.000000	0.000000	0.000000
369	20" Swing	30% Hinge Pin	Backseated	0.979700	0.409800	0.977500	0.980000	0.995600	0.000000
370	20" Swing	30% Hinge Pin	Tapping	0.800900	0.598400	0.842200	0.801100	0.995600	0.375000
371	20" Swing	30% Hinge Pin	Tapping	0.792700	0.606600	0.574900	0.792800	1.000000	0.375000
372	20" Swing	30% Hinge Pin	75% Flow	0.410600	0.885200	0.711800	0.410800	0.726100	0.250000
373	20" Swing	30% Hinge Pin	75% Flow	0.402400	0.868900	0.574900	0.402600	0.726100	1.000000
374	20" Swing	30% Hinge Pin	30% Flow	0.113800	0.975400	0.644100	0.113600	0.239100	0.125000
375	20" Swing	30% Hinge Pin	30% Flow	0.113800	0.983600	0.574900	0.113600	0.252200	0.375000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
376	6" Swing	None	Max. Flow	1.000000	1.000000	1.000000	1.000000	0.000000
377	6" Swing	None	Tapping	0.230700	0.200700	0.230700	0.991900	0.200000
378	6" Swing	None	Tapping	0.203500	0.805600	0.203300	0.967500	0.600000
379	6" Swing	None	75% Flow	0.142200	0.801300	0.142000	0.739800	0.100000
380	6" Swing	None	75% Flow	0.120300	0.801300	0.120700	0.731700	0.600000
381	6" Swing	None	30% Flow	0.062000	0.814300	0.062000	0.300800	0.100000
382	6" Swing	None	30% Flow	0.060500	0.818600	0.078100	0.276400	0.400000
383	6" Swing	30% Stud Pin	Zero Flow	0.000000	0.000000	0.000000	0.000000	0.000000
384	6" Swing	30% Stud Pin	Max. Flow	0.988700	0.671700	0.988800	1.000000	0.000000
385	6" Swing	30% Stud Pin	Tapping	0.226900	0.967600	0.078100	0.976900	0.100000
386	6" Swing	30% Stud Pin	Tapping	0.201200	0.978400	0.000000	0.976900	0.600000
387	6" Swing	30% Stud Pin	75% Flow	0.139200	0.978400	0.115200	0.692300	0.100000
388	6" Swing	30% Stud Pin	75% Flow	0.121800	0.978400	0.078100	0.707700	0.400000
389	6" Swing	30% Stud Pin	30% Flow	0.060500	1.000000	0.092900	0.376900	0.100000
390	6" Swing	30% Stud Pin	30% Flow	0.057500	1.000000	0.078100	0.330800	0.400000
391	6" Swing	15% Hinge Pin	Zero Flow	0.000000	0.105800	0.000000	0.000000	0.000000
392	6" Swing	15% Hinge Pin	Max. Flow	0.983400	0.680300	0.983300	1.000000	0.000000
393	6" Swing	15% Hinge Pin	Motion	0.232200	0.961100	0.078100	0.896600	0.400000
394	6" Swing	15% Hinge Pin	Tapping	0.202000	0.961100	0.078100	0.875900	1.000000
395	6" Swing	15% Hinge Pin	75% Flow	0.141500	0.965400	0.115200	0.689700	0.100000
396	6" Swing	15% Hinge Pin	75% Flow	0.124100	0.974100	0.078100	0.565500	0.400000
397	6" Swing	15% Hinge Pin	30% Flow	0.065800	0.989200	0.100400	0.393100	0.100000
398	6" Swing	15% Hinge Pin	30% Flow	0.042400	0.991400	0.078100	0.200000	0.400000
399	6" Swing	30% Hinge Pin	Zero Flow	0.000000	0.071300	0.000000	0.000000	0.000000
400	6" Swing	30% Hinge Pin	Tapping	0.194400	0.969800	0.078100	0.926400	0.200000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
401	6" Swing	30% Hinge Pin	Tapping	0.202000	0.952500	0.078100	0.202000	0.920200	0.800000
402	6" Swing	30% Hinge Pin	75% Flow	0.143000	0.965400	0.119000	0.143300	0.681000	0.100000
403	6" Swing	30% Hinge Pin	75% Flow	0.124100	0.969800	0.078100	0.124000	0.607400	0.600000
404	6" Swing	30% Hinge Pin	30% Flow	0.066600	0.991400	0.100400	0.066700	0.386500	0.200000
405	6" Swing	30% Hinge Pin	30% Flow	0.061300	0.995700	0.078100	0.061300	0.312900	0.400000
406	6" Swing	None	Zero Flow	0.000000	0.071300	0.000000	0.000000	0.000000	0.000000
407	6" Swing	None	Tapping	0.226900	0.965400	0.078100	0.227300	0.969200	0.200000
408	6" Swing	None	Tapping	0.206500	0.965400	0.078100	0.206000	0.907700	0.800000
409	6" Swing	None	75% Flow	0.146700	0.969800	0.115200	0.146700	0.738500	0.100000
410	6" Swing	None	75% Flow	0.125600	0.969800	0.078100	0.126000	0.715400	0.600000
411	6" Swing	None	30% Flow	0.068800	0.991400	0.100400	0.069300	0.384600	0.100000
412	6" Swing	None	30% Flow	0.066600	0.995700	0.078100	0.066700	0.446200	0.400000
413	6" Swing	15% Stud Pin	Zero Flow	0.000000	0.071300	0.000000	0.000000	0.000000	0.000000
414	6" Swing	15% Stud Pin	Tapping	0.232200	0.961100	0.078100	0.232000	0.984600	0.020000
415	6" Swing	15% Stud Pin	Tapping	0.202700	0.965400	0.078100	0.203300	0.953800	0.400000
416	6" Swing	15% Stud Pin	75% Flow	0.147500	0.965400	0.115200	0.147300	0.723100	0.200000
417	6" Swing	15% Stud Pin	75% Flow	0.121000	0.974100	0.078100	0.121300	0.661500	0.600000
418	6" Swing	15% Stud Pin	30% Flow	0.068800	0.991400	0.100400	0.069300	0.369200	0.020000
419	6" Swing	15% Stud Pin	30% Flow	0.064300	0.993500	0.078100	0.064000	0.392300	0.400000
420	6" Tilt Disc	None	Zero Flow	0.000000	0.004800	0.000000	0.000000	0.000000	0.000000
421	6" Tilt Disc	None	Max. Flow	0.991700	0.278600	0.967000	0.992200	1.000000	0.000000
422	6" Tilt Disc	None	Tapping	0.574700	0.766700	0.000000	0.575100	0.987700	0.200000
423	6" Tilt Disc	None	Tapping	0.548800	0.771400	0.000000	0.548900	0.975300	0.600000
424	6" Tilt Disc	None	75% Flow	0.428600	0.857100	0.245400	0.428300	0.765400	0.000000
425	6" Tilt Disc	None	75% Flow	0.396600	0.883300	0.000000	0.396700	0.765400	0.500000

Table B1: (Continued)

Pat. No.	Valve Size & Type	Valve Degradation	Test Condition	Flow	Upstream Pressure	Pressure Drop	Velocity	Percent Open	Fluctuation
426	6" Tilt Disc	None	30% Flow	0.044700	0.997600	0.047600	0.044700	0.296300	0.000000
427	6" Tilt Disc	None	30% Flow	0.048000	1.000000	0.000000	0.047600	0.284000	0.000000
428	6" Tilt Disc	30% Hinge Pin	Zero Flow	0.000000	0.000000	0.750900	0.000000	0.000000	0.000000
429	6" Tilt Disc	30% Hinge Pin	Max. Flow	0.989000	0.276200	1.000000	0.989300	0.901200	0.000000
430	6" Tilt Disc	30% Hinge Pin	Tapping	0.572000	0.766700	0.000000	0.572200	0.888900	0.500000
431	6" Tilt Disc	30% Hinge Pin	Tapping	0.553800	0.771400	0.000000	0.554200	0.888900	1.000000
432	6" Tilt Disc	30% Hinge Pin	75% Flow	0.438500	0.857100	0.157500	0.438500	0.925900	0.000000
433	6" Tilt Disc	30% Hinge Pin	75% Flow	0.394400	0.881000	0.000000	0.394700	0.679000	0.700000
434	6" Tilt Disc	30% Hinge Pin	30% Flow	0.051800	0.992900	0.054900	0.051500	0.284000	0.000000
435	6" Tilt Disc	30% Hinge Pin	30% Flow	0.046300	1.000000	0.000000	0.046200	0.259300	0.000000
436	6" Tilt Disc	15% Hinge Pin	Zero Flow	0.000000	0.000000	0.750900	0.000000	0.000000	0.000000
437	6" Tilt Disc	15% Hinge Pin	Max. Flow	0.993900	0.269000	0.992700	0.994200	0.888900	0.000000
438	6" Tilt Disc	15% Hinge Pin	Tapping	0.571400	0.776200	0.000000	0.571700	0.888900	0.000000
439	6" Tilt Disc	15% Hinge Pin	Tapping	0.555400	0.776200	0.000000	0.555200	0.864200	0.700000
440	6" Tilt Disc	15% Hinge Pin	75% Flow	0.431900	0.866700	0.293000	0.431700	0.654300	0.000000
441	6" Tilt Disc	15% Hinge Pin	75% Flow	0.402100	0.881000	0.000000	0.402000	0.703700	0.500000
442	6" Tilt Disc	15% Hinge Pin	30% Flow	0.050200	1.000000	0.051300	0.050600	0.296300	0.000000
443	6" Tilt Disc	15% Hinge Pin	30% Flow	0.050200	1.000000	0.000000	0.050100	0.284000	0.100000
444	6" Tilt Disc	None	Zero Flow	0.000000	0.000000	0.750900	0.000000	0.000000	0.000000
445	6" Tilt Disc	None	Max. Flow	1.000000	0.271400	0.981700	1.000000	1.000000	0.000000
446	6" Tilt Disc	None	Tapping	0.572000	0.761900	0.000000	0.572200	0.987700	0.000000
447	6" Tilt Disc	None	Tapping	0.549900	0.776200	0.000000	0.550300	0.938300	0.800000
448	6" Tilt Disc	None	75% Flow	0.435200	0.861900	0.190500	0.435100	0.777800	0.000000
449	6" Tilt Disc	None	75% Flow	0.403800	0.876200	0.000000	0.404000	0.777800	0.600000
450	6" Tilt Disc	None	30% Flow	0.050200	0.995200	0.062300	0.050600	0.284000	0.000000
451	6" Tilt Disc	None	30% Flow	0.049600	1.000000	0.000000	0.049600	0.284000	0.000000

VITA

Michael Todd Travis was born in Dickson, Tennessee on June 24, 1966. He attended elementary schools in Charlotte, Tennessee and graduated from Dickson County High School in May 1984. In September 1984 he entered Tennessee Technological University and received the degree of Bachelor of Science in Electrical Engineering in December 1989. The following January he entered The University of Tennessee and received the degree of Master of Science in Nuclear Engineering in December 1991. He is a member of Eta Kappa Nu, the electrical engineering honor society, and Tau Beta Pi, the national engineering honor society.