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USE OF NEURAL NETWORKS TO MONITOR POWER PLANT COMPONENTS

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ABSTRACT

A new methodology is presented for nondestructive evaluation (NDE) of check valve performance and degradation. Artificial neural network (ANN) technology is utilized for processing frequency domain signatures of check valves operating in a nuclear power plant (NPP). Acoustic signatures obtained from different locations on a check valve are transformed from the time domain to the frequency domain and then used as input to a pretrained neural network. The neural network has been trained with data sets corresponding to normal operation, therefore establishing a basis for check valve satisfactory performance. Results obtained from the proposed methodology demonstrate the ability of neural networks to perform accurate and quick evaluations of check valve performance.

INTRODUCTION

Check valves came in the forefront of utility attention in 1986. That year a number of check valve failures caused damages to important NPP systems at several plants. As a result INPO issued Significant Operating Experience Report (SOER) 86-3, "Check Valve Failure or Degradation." Three years later the U.S. Nuclear Regulatory Commission Generic Letter 89-04, "Guidance on Developing Acceptable In-Service Testing Programs," made mandatory the inclusion of check valves in station preventive maintenance programs. Furthermore, an industry user group called the Nuclear Industry Check Valve Group (NIC) was established for exchanging information related to the application, testing, and maintenance of check valves[1].

Check valve failures have been identified as important contributors to water hammer events, overpressurization of low pressure systems, as well as steam binding of auxiliary feedwater pumps[1,2]. The need to verify operability of a check valve is the main issue in a valve maintenance program. A common practice followed widely in the nuclear industry consists of valve disassembly and inspection. It is very common in a nuclear plant for 10 to 30 valves to be disassembled per outage. This particular preventive maintenance approach raises a number of serious questions such as, maintenance-induced failures, and prolonged outages. It becomes apparent that the introduction of nondestructive evaluation techniques will significantly reduce the cost of the preventive maintenance program. In addition computer-based diagnostics will incorporate human expertise and assist in decision making process concerning the status of the check valve under investigation[3].

Swing check valves are self-contained, self-actuating valves that have no external operator to indicate their internal position or movement[2]. Three methods have been developed for check valve monitoring, namely: acoustic emission, ultrasonic inspection, and magnetic flux signature analysis. All three methods have been developed as means of providing check valve condition related information (e.g., disc position, disc motion, seat leakage, etc.). The most widely used technique is that of acoustic emission where mechanical stress (sound) waves that propagate through materials are monitored. These waves are the results of occurrences (events) such as impacts, flow, and leakage[4].

In the proposed methodology two acoustic signatures are obtained from every check valve. The information comes from two accelerometers located on the valve body near the Hinge Pin (HP) and the Back Stop (BS). The auto power spectral densities (APSDs) of both acoustic signals are calculated and used as input and desired output to a neural network. The data sets have been acquired from a large boiling water reactor (BWR).

METHODOLOGY FOR VALVE MONITORING USING ANNs

In order to detect possible anomalies in a check valve, the acoustic time series from both the Hinge Pin and the Back Stop accelerometers are transformed to the frequency domain through a Fast Fourier Transform (FFT) and the outcome is the APSD of both signals. The <u>APSD of the Hinge Pin</u> of a trouble-free valve is used as <u>input</u> to a neural network and the <u>APSD of the Back Stop</u> as desired <u>output</u>. An overall schematic representation of the ANN architecture along with the input-ouptut patterns is shown in Figure 1. There is a number of reasons supporting the particular data pre-processing as well as the ANN configuration applied.

A time series representation is very difficult to manipulate. Unimportant effects may alter the actual shape of the time series making it different from the expected one. The information carried in a time series is not easily detectable and extractable in the time space[5,6]. A frequency representation gives the advantages of data compression, satisfactory time series representation, and realistic information representation. All the phenomena contributing to the acoustic signatures may be easily identified in the frequency domain through the shape of the power spectral density of the time series under investigation[6]. Furthermore, the HP accelerometer is located ahead of the SP accelerometer both in space and time. Hence, the information recorded by the HP accelerometer should appear in the BS accelerometer recordings with a slight time lag and a minimum alteration caused by wave mode superposition.

Before calculating the APSDs it is imperative to check the time series for stationarity[5,6,7]. The time stationarity of the acoustic signals was checked through the Power Spectra of the acoustic signatures and concluded that the time series could be considered as stationary and the ergodic theorem was applicable. Therefore the Auto Power Spectral Densities of both time series could be calculated. The acoustic signatures were previously digitized with a sampling interval of $4 * 10^{-5}$ seconds and a total digitization time of 100 seconds. The 25 KHz sampling frequency is considered adequate for eliminating aliasing effects on the digitized signal for frequencies below 12.5 KHz[7].

The Hinge Pin APSD consists of 128 points which were used as network input (input layer with 128 nodes) and the corresponding 128 points of the Back Stop Pin APSD were set as the network expected response (output layer with 128 nodes). The network as shown in Figure 1, has 300 nodes in the hidden layer and the three layers are fully connected. The training algorithm is Backpropagation with generalized delta rule and momentum term[8] as it is being supplied from the Plexi software package. Initially the connection weights and the activation were randomized into the interval -0.3 to 0.3. Training the network for 5,000 cycles, a sum square error of 0.03 was attained. Results obtained after training the network for 10,000 cycles are identical to those after 5,000 training cycles.

Check Valve Data

In 1991, a utility carried out acoustical monitoring of many important check valves in a large BWR by simultaneously tape recording acoustic signals from piezoelectric accelerometers mounted near the hinge pins and the back stops of the valves. This data were processed and interpreted by experts within the company and its contractors. Most valves were characterized by these experts as "satisfactory," but a few were characterized as "unsatisfactory." By a judicious matching of identical valves in identical environments (some deemed as being "satisfactory" and some as being "unsatisfactory") it was possible to apply the methodology described above. It is recognized that this procedure is not identical to comparing the same valve "before" and "after" failure, or during progressive failure over time. However, recent applications of this same methodology to progressive failure over a period of months of a large (1000 HP) reactor coolant pump bearing confirmed the validity of this methodology[9]. This work demonstrates how this methodology can be applied to check valves. Two data sets acquired from the large BWR, designated as Set I and Set II, were processed and used for developing and testing the proposed neural network methodology for check valve monitoring. Each set has a number of valves at a known condition.

SET I

Set I is composed from two 30" Duo check valves manufactured by MISSION, a Division I Standby Service Water/Normal Service Water isolation valve (mark number **1SWP*V326**), and a Division II Standby Service Water/Normal Service Water isolation valve (mark number **1SWP*V327**). Acoustic emission data taken from **1SWP*V326** indicate that the acoustic signature of this valve is typical of a normal valve. The acoustic signature of **1SWP*V327** exhibits multiple impacts occurring each second. The later valve was dismantled and inspected, revealing a number of malfunctions which were identified and fixed by the maintenance crew. The **1SWP*V326** valve acoustic data was used as reference of appropriate valve behavior, and the ANN was trained with this data establishing a neural network model of appropriate valve behavior.

Seven separate time samples were extracted from each particular signal. Each signal subset has a total of 100,000 points, corresponding therefore to a 4 second interval of the actual signal time. The time locations these signals were extracted from, are listed in Table 1 below. The APSD of every signal subset was calculated by dividing each signal subset into groups consisting of 256 points. A FFT was then calculated for every 256 points. A total of 390 distinct FFTs were calculated for each subset of 100,000 points, and the resultant APSD for the whole subset was the average of the 390 independent APSDs. The Hanning window as it is supplied from the Global Lab software package was used for the FFTs[10].

Table 1: Extracted Signal Intervals for Set I

TIME STEP NUMBERING	ACTUAL TIME INTERVALS (sec)
500,000 - 599,999	20 - 24
800,000 - 899,999	32 - 36
1,000,000 - 1,099,999	40 - 44
1,500,000 - 1,599,999	*60 - 64*
1,800,000 - 1,899,999	72 - 76
2,000,000 - 2,099,999	80 - 84
2,200,000 - 2,299,999	88 - 92

The APSD calculated for the time interval 60 - 64 seconds of the trouble-free valve signature (**1SWP*V326**) was used for training the network. The rest of the time intervals from the **1SWP*V326** valve, as well as the equivalent intervals from the **1SWP*V327** valve have been used for network testing. Considering that the FFT size is 256, the digitization frequency is 25 KHz and the Fourier Transform is a periodic function, we may conclude that the frequency range of interest is 0 - 12.5 KHz which is represented by 128 points (256 divided by 2)[5,6,7]. The main reasons dictating the choice of these specific time intervals are summarized as follows.

Points close to the very beginning and end of the signal are subject to external influence (i.e., not absolute stability of the accelerometer) which is not related to the physical problem under investigation. Thus, these points were excluded from the monitoring process. In addition, sufficient time is required for every physical disturbance detected in parts of the signal to be developed and detected in subsequent signal intervals, but not enough for the disturbance to die out before appearing in a second signal part. Finally, the time intervals should give an overall coverage of the complete signal time span.

SET II

In order to further explore the applicability of the proposed methodology, a second set (Set II) of identical check valves was also used. This time the set consists of three 6" swing check valves, model P3-5500-N-13 constructed by Velan. The valves chosen for examination were: (1) A HVK*CHL1A Service Water Outlet (SWP) Check valve, (mark number **1SWP*V153**) for which the acoustic signature has been characterized as "unsatisfactory". The acoustic emission indicates minor impacting. (2) A HVK*CHL1C Service Water Outlet (SWP) Check valve, (mark number **1SWP*V154**) for which the acoustic signature has also been characterized as "unsatisfactory." The acoustic emission indicates that impacting occurs in the valve and it could be attributed to some minor wear at the hinge pin or stud nut area; and (3) a HVK*CHL1B Service Water Outlet (SWP) Check valve, (mark number **1SWP*V155**), for which the acoustic signature has been characterized as "satisfactory."

All three valves, apart from sharing exactly the shame physical characteristics, are located at symmetrical system locations, and perform the same task in the same physical environment. The maximum flow rate is 375 gpm, the fluid type is raw service water, the fluid temperature is 95 ^{0}F, and the normal position of the valves is open when the corresponding chiller is in service. The process described previously has been repeated for this set of valves using exactly the same network architecture as before. The signal intervals which were extracted for this study case are listed in Table 2, below.

Table 2: Extracted Signal Intervals for Set II

TIME STEP NUMBERING	ACTUAL TIME INTERVALS (sec)
300,000 - 399,999	12 - 16
600,000 - 699,999	24 - 28
900,000 - 999,999	36 - 40
1,200,000 - 1,299,999	*48 - 52*
1,500,000 - 1,599,999	60 - 64
1,800,000 - 1,899,999	72 - 76
2,100,000 - 2,199,999	84 - 88

It may be concluded from inspecting Table 2, that a 4 sec time interval has been extracted every 12 seconds of signal time. The 48 - 52 sec time interval from the **1SWP*V155** valve (which was characterized as "satisfactory"), has been used for training the neural network described previously. The rest of the time intervals from the **1SWP*V155** valve, as well as the equivalent intervals from the **1SWP*V153**, **1SWP*V154** valves have been used for network recall.

ANN TESTING AND RESULTS

In order to test the trained network, three different techniques were applied. Initially the pretrained network was supplied with the Hinge Pin APSDs of the six remaining signal intervals of the trouble-free valve (**1SWP*V326** and **1SWP*V155**). These APSDs had not been supplied to the network during the training process. The average square error between the network predicted Back Stop APSD and the actual Back Stop APSD, was calculated for each individual time interval. The results are shown for Set I in Figure 2 and for Set II in Figure 3. In Figure 2 the average square error between the network predicted APSD and the actual Back Stop APSD is shown to be in the order of $(6 - 8)*10^{-2}$ for the **1SWP*V326** valve. In Figure 3 the average square error for the **1SWP*V155** valve is shown to be in the order of $(2 - 4)*10^{-2}$. It is significant to notice the consistency exhibited in the ANN response in both "satisfactory" cases. The ANN prediction came very close to the expected pattern and furthermore all the test cases exhibited very comparable results. The latter is in accordance to the time stationarity nature of the acoustic signatures analyzed.

The above process is repeated for the "unsatisfactory" valves (**1SWP*V327** and **1SWP*V153**, **1SWP*V154**), and the ANN used has been trained for the corresponding "satisfactory" valves only. Hence, it is expected the average square error between the target and the predicted values to be higher than in the previous cases. The results are shown in Figure 2 for the **1SWP*V327** valve and in Figure 3 for **1SWP*V153** and **1SWP*V154** valves respectively. Indeed the results obtained exhibit that the network response to "unknown" "unsatisfactory" valve frequency signatures is of less accuracy than the previous case. The average square error between the predicted and actual Back Stop APSDs has been increased by 2 to 4 times with respect to the previous tests. It is worth mentioning that the increase is in a consistent manner and the network responses for different signal samples of the same signal exhibit comparable magnitudes, preserving the pattern detected in the previous tests. Furthermore it seems logical to assume that since valves **1SWP*V153** and **1SWP*V154** have different types of valve wearing and failure modes, the network should give different responses for the two test cases. Indeed the average square error between the predicted and the target values for the two "unsatisfactory" valves is different for each valve. This difference makes feasible a classification of valve damage/degradation, according to the magnitude of the average square error between the predicted by the network Back Stop APSD and the target Back Stop APSD.

Finally, in order to make sure that the network has not "memorized" the particular pattern on which it was trained, the average square error between the actual output vector and the vector the network was trained on, was calculated. The magnitude of the average square error between actual output vector and training vector, along with the consistency of the error level, support the argument that the network in neither of the test sets "memorized" the pattern on which it was trained.

DISCUSSION AND CONCLUSIONS

A new methodology for check valve NDE has been presented. ANNs are used as classifiers of frequency signatures corresponding to acoustic time series from NPP check valves. Acoustic signatures from valves classified as having "satisfactory" performance were used for neural network training. The APSDs of two acoustic signatures from different valve locations were inter-related as input and desired output of a neural network. In this way the network learned to recognize in the frequency domain the characteristics of a properly operating valve. This configuration rendered the pattern recognition system a "simulator" of the internal behavior of the valve. Possible mismatches between the actual and predicted APSDs are used as classification factors based on the magnitude of the average square error between predicted and actual values.

The real usefulness of this methodology is for the periodic monitoring of individual check valves. The ANN can be trained on data from the check valve when it is known to be operating properly. Then this ANN for that particular valve is saved for use when the valve is checked again (perhaps 6 months or a year later). At the later time, the HP spectrum is used as the input to the trained ANN, and the BS spectrum predicted by the trained ANN is compared with the actual BS spectrum. Significant differences, measured by the average square error, indicate that the internal relationship between the HP and BS spectra have changed since the last measurement. Correlation of the pattern of average square error measurements over a series of measurements with the actual physical condition of the valve should make it possible to use this methodology to predict specific faults.

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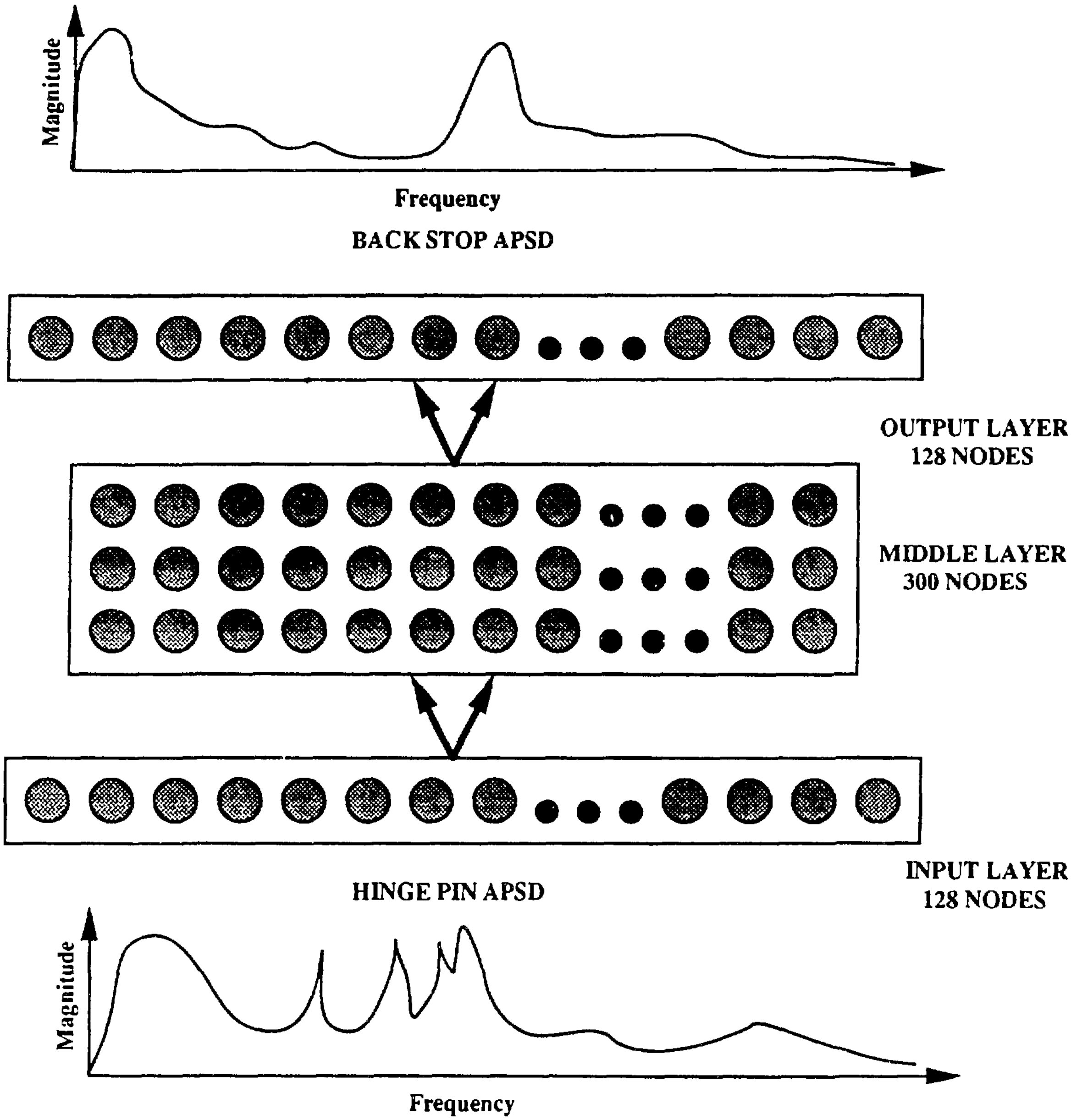

Figure 1: Neural Network Architecture

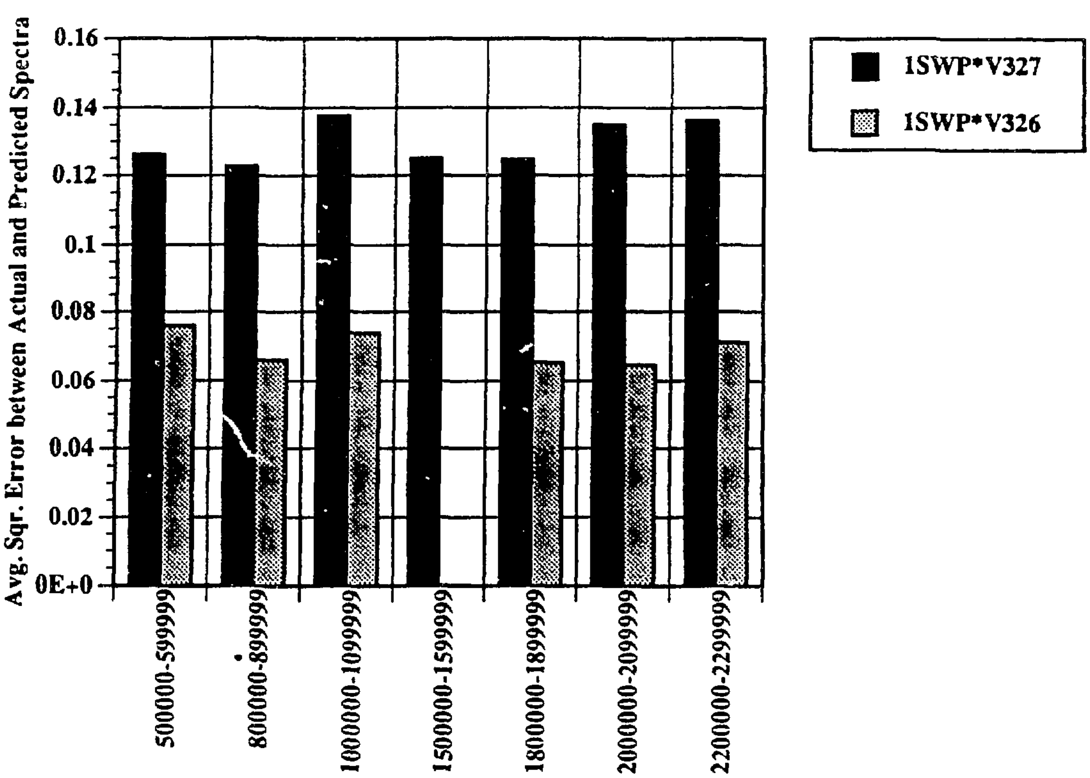

Figure 2: Average Square Error between Actual and Predicted Values for Valves 1SWP*V326 and 1SWP*V327

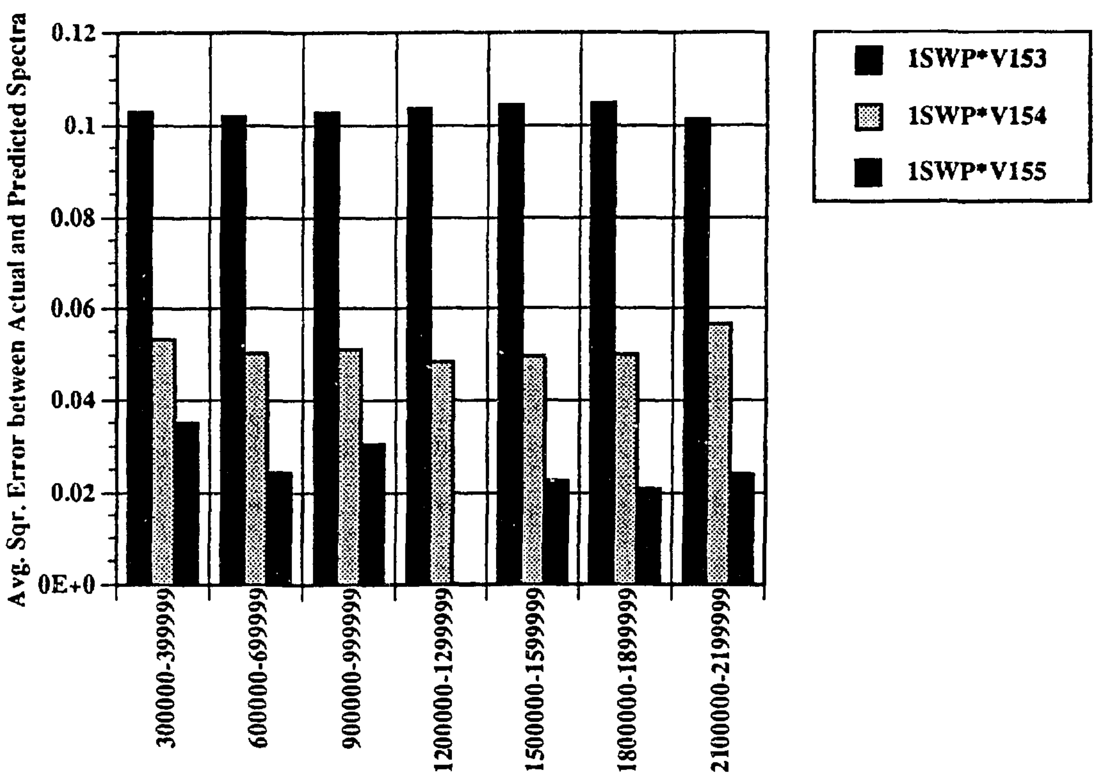

Figure 3: Average Square Error between Actual and Predicted Values for Valves 1SWP*V153, 1SWP*V154, and 1SWP*V155