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THERMAL ERROR COMPENSATION FEASIBILITY STUDY USING ARTIFICIAL INTELLIGENCE

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One of the major unresolved sources of machine tool errors is thermal effects. Neural networks potentially offer a means of predicting errors in machine tool positioning due to thermal effects. These can then be used for compensation resulting in more accurate machining. This study demonstrates the feasibility of using artificial neural networks to predict thermally induced positioning errors on a turning center. The potential for application to other types of machine tools and implementation issues leading to commercialization are also discussed.

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Feasibility of Neural Networks for Predicting Machine Tool Thermal Errors

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Feasibility of Neural Networks for Predicting Machine Tool Thermal Errors

Executive Summary

The Institute of Advanced Manufacturing Sciences has conducted a Mantech-sponsored program to determine the feasibility of using Artificial Neural Networks to predict thermally-induced position errors in machine tools. The network uses temperature data from thermocouples integrated into the machine tool to predict relative tool/part position errors due to thermal growth of the structure. These predictions could then be fed to the controller for real-time compensation to improve workpiece accuracy. If commercialized, this approach could provide thermal error prediction with accuracies similar to other modeling approaches, but at substantially reduced cost and development time. Specific program goals are: to determine whether neural networks can be used to predict thermally-induced motions, to define an appropriate class of network, to evaluate predictive performance on a turning center, and to summarize strengths and constraints of the approach with respect to general application to machine tools.

Artificial neural networks are a class of computing techniques modeled after the biological brain. In practice they are implemented on standard personal computers or workstations. The key difference between traditional analysis and the use of neural networks is that, in the former, the programmer must create the algorithms that predict deflection, while neural networks generate this logic through a "learning" process. During the training period the network is presented data that includes temperature readings and the measured positional error for a range of operating and environmental conditions. After training to an acceptable level of performance, it can be used to predict the positional error, based on thermal data. Once trained, the network could be copied and installed on subsequent machines, provided their thermal characteristics are consistent.

The first program phase showed that neural networks can be used to predict thermal phenomenon and what type of network is suitable. Initial testing was performed on an apparatus with simple thermal characteristics to facilitate development of an appropriate network. The results indicate that a fairly simple back-propagation network is capable of predicting thermally-induced deflections. This is one of a number of commercially available neural network software applications. In the second phase of the program, the network was applied to the much more complex case of a turning center. Predictions showed good correlation to measured deflections over a wide range of thermal conditions. The network was successfully able to predict the trend and pattern of the thermal error to within 2%. The study also evaluates the potential for application to other types of machines and identifies issues relating to commercialization.

This project has successfully demonstrated the error compensation philosophy (totally empirical using neural network methods) and approach (predicting offsets for each machine control axis). Modern machine controls should be capable of processing periodic offsets with only limited additional engineering, temperature sensing technology is established, and the computer requirements for data processing are reasonable. The control loop remains to be closed and the machining of simple parts must be demonstrated. Data should be collected to clearly document accuracy improvement, variability reduction, and reliability of operation.

Section 1. Objective and Scope

1.1 Program Objective

The demand for products with higher performance, better efficiency, and longer service life is driving designers to specify machined components with increasingly tighter tolerances. Not only is the geometrical accuracy of the individual components important, but the parts must be consistent from one to the next over long production runs. These factors are driving the need to improve the consistency of all production processes and machine tools in particular.

Since 1982, the severe economic recession in capital goods and increased foreign competition has resulted in an extended period of downturn and cutbacks for the U.S. machine tool industry. With foreign suppliers controlling a significant percentage of the U.S. machine tool market, domestic companies must exploit opportunities to recapture their market segments. Utilizing advanced technology to enhance machine tool accuracy and precision is one such opportunity.

There are a number of factors that affect the accuracy of a machine tool. Although the scope of this program deals exclusively with thermal errors, artificial neural networks might also be applied to many of the other errors typical of a machine tool. Major machine tool errors include:

- *Tolerances in the machine structure and drive system*. Except for wear, these errors do not change over time and straight-forward compensation techniques are available.

- *Structural stiffness and dynamics of the machine*. If the structure of the machine is weak, the cutting forces may be large enough to "spring" the machine open, causing geometry errors. Machines (or tools) with low stiffness can also be susceptible to unwanted vibrations (chatter) which affect part quality. Although the rigidity of the system can be modelled and compensation applied, more common approaches are to reduce the applied forces by changing the operating conditions or to allow time for the system to relax on the final cut (e.g. "sparkout").

- *Controller Following Errors*. At very high speeds positional errors can arise due to limitations in the controller feedback loop.

- *Tool wear*. Compensation strategies based on historical wear data or on-line gaging can be employed to compensate for tool wear.

- *Thermal effects*. The materials that make up the machine tool expand as their temperature increases, resulting in relative displacement between the tool tip and the workpiece. It is important to note that both the tool tip and the workpiece move with respect to a hypothetical fixed point in space, and that these motions can be both translational and angular. The techniques investigated in this program address these thermally-induced geometrical errors.

1.1.1 Traditional Solutions to Thermal Distortion

Machine tool builders generally address thermal problems by designing critical components in more thermally stable materials, designing symmetrical structures to reduce angular deflections, and isolating critical areas from sources of heat. More exotic solutions include running temperature-controlled fluids through the structure. The traditional solution for users has been to run a machine for a significant "warmup" period before producing parts to avoid the most severe thermal growth period. More effective user solutions include control of the ambient environment and metalworking fluid temperature.

Thermally-induced geometrical effects can also be predicted with traditional modelling approaches, using basic engineering principles such as thermal dynamics, heat transfer, and structural modelling to develop a mechanistic model of the machine tool and its thermal response. This is typically a time-consuming task for skilled engineers because of the complexity of the structure and of the temperature distribution (which is a function of the operating conditions and is typically non-linear). A new model must also be designed for each new machine to be analyzed.

1.1.2 Active Control Through Thermal Feedback

A proposed approach is to actively cancel thermal errors by including a corrective tool offset in the program that controls the tool position as it creates the part geometry.

This is similar to "error mapping" where the machine positioning errors are measured as the machine is commanded to move to a selection of points throughout the work volume. The measured errors are then stored (mapped) in the controller memory which uses them to calculate compensating offsets as the part is machined. However, in order to simply error map for thermal errors it would be necessary to measure tool tip errors throughout the work envelope under all thermal conditions including the transient response of the tool to even fairly simple temperature inputs. Therefore, error mapping is not a practical solution.

Another approach is to create a thermal model of the machine and store it in the machine controller or auxiliary computer. The model would calculate the tool tip error under any given temperature profile. A number of thermocouples would be placed on the machine to provide information on the instantaneous temperature distribution to the model. A finite-element analysis is one example of the type of model that might be used. The difficulty is in economically and accurately creating such a model for an assembly with such a large variety of components and materials.

1.1.3 Artificial Neural Networks for Thermal Error Compensation

The objective of this program is to demonstrate the feasibility of using a neural network to predict the dimensional correction required to compensate for thermally induced errors on a CNC turning center. Once this feasibility is demonstrated, additional research would be required to formulate, engineer and demonstrate thermal error compensation strategies to improve the accuracy and precision of machining.

Two factors make this a non-trivial question but at the same time make an artificial neural network approach more attractive than traditional mechanistic modelling. First, the dynamic nature of heat transfer requires constant updating of the deflection prediction as heat is transferred through a structure. This is especially true of structures with relatively long time constants, such as machine tools. In contrast to neural network applications for character recognition for example, where each input/output set is discrete, the temperature profile at any given time is related to the previous condition. Second, the number of components, materials, and heat sources in a typical machine tool present a complex thermal dynamic situation. The complexity of the problem makes the potential of a simple, real-time analysis tool very attractive and also defines the fundamental questions to be addressed by this study:

> Can neural networks predict thermal behavior and, if so, how complex a neural network is required to handle the thermal dynamic complexity of a typical machine tool?

If neural networks are an appropriate tool, the empirical, data-driven approach is expected to provide a more robust, flexible, and economical solution to the challenge of thermal deflection prediction than the mechanistic approach. This is expected to benefit both the machine tool builders who can enhance the precision of their products, and industrial users who will benefit from more accurate parts.

1.2 Scope of the Program

The scope of this project is limited to the investigation of neural network feasibility in addressing thermally-induced dimensional errors found in machining. A key issue is the definition of "dimensional error". It is recognized that much research and engineering has been devoted to 1) identifying and measuring absolute errors, 2) reducing and isolating the causes of these errors, and 3) dealing with the underlying science of precision engineering (in some cases to the molecular level) as applied to machine tools. This project is not intended to research these issues. Indeed, the attraction of the neural network approach is the potential for compensation based on empirical data rather than on a theoretical understanding of the error source. In the context of this report, the "error" predicted by the neural network is more accurately the "corrective offset" required along each of the measurement axes.

The program is divided into three distinct phases designed to sequentially increase the complexity of the predictive task.

1.2.1 Phase I : Predicting Thermally-Induced Motion

The first phase of the program is designed to develop a neural network appropriate for thermal modelling in a simple thermal-mechanical environment. The test vehicle is a copper tube instrumented to measure temperature profile and deflection. The goal of Phase I is to answer several specific questions:

- Can neural networks predict thermally-induced motion based on the temperature profile of the structure?
- What type of neural network (and computer resource) is required?
- What type of training (data sets, data presentation, training cycles) is required?
- What levels of predictive performance are attainable and are there any constraints?

The bench-test apparatus serves to develop data acquisition, training, and presentation strategies which will also be used in Phase II on the machine tool test bed. It is not the intent of the Phase I investigation to optimize the performance of a network on the bench-test apparatus. Satisfactory performance on the simple bench-test apparatus is required to justify Phase II.

1.2.2 Phase II: Predicting Machine Tool Thermal Errors

The second phase of the program takes the neural network, data acquisition, and training schemes developed in Phase I and applies them to the more thermally complex environment of a machine tool. The test bed is a Cincinnati Milacron turning center. The relative distance between a reference part mounted in the chuck and a tool position on the turret is measured by a series of non-contact gages. A number of thermocouples mounted near heat sources and on critical structural members provide the temperature profile to the network. The thermocouples and sensors are sampled periodically while the machine undergoes thermal cycling to provide training data for the network. After training is complete the performance of the network is tested by comparing the prediction of the neural network to the measured deflection while thermally cycling the lathe.

To simplify the investigation, the original program scope specified that the offset between the "tool" and "workpiece" would be measured at a single point in the machine workspace. This approach would capture errors due to headstock, spindle or structure growth but would not include position-dependent errors due to thermal effects on the axes or the ballscrews, or to velocity and acceleration effects. Prior experience indicated that several thousandths offset between the tool and workpiece could be expected on this machine due to headstock and spindle growth alone. Due to the success in predicting the thermal deflection at the single test point, the scope was later expanded to include measurement of x and z offsets at several points in the workspace.

The scope of the program is to investigate the feasibility of a neural network approach. Implementation of a compensation scheme, including a controller interface, is outside the scope of this project. The final section of this report discusses this and other implementation issues.

1.2.3 Phase III : Observations and Implementation Issues

The third phase of the program draws general conclusions from the Phase I and Phase II results as to the applicability of neural networks for thermal compensation in the machine tool industry. Opportunities and questions raised by the test results are detailed, and issues concerning industrial implementation are discussed.

A critical component of this phase is the promotion of industrial awareness. One aspect of that effort was an industry briefing, added to the original scope of the project based on the technical success of the work. The presentation included technical results, implementation issues, and several demonstrations of real-time deflection prediction using artificial neural networks. Some of the early industrial feedback from that meeting is incorporated in this report.

Section 2. Predicting Thermally-Induced Motion

Initial investigations using neural networks were performed off the machine tool on a bench-test apparatus (the "thermal tube") which was designed to have a simple thermal mechanical behavior and serve as a proof-of-concept. Testing could proceed more quickly because relatively small heat inputs produced significant deflections of the thermal tube in much shorter periods of time than were required on the turning center. The thermal tube also provided a simple geometry for traditional analysis (if required to correlate the predictions of the network) and had a short time constant that would challenge the network to produce very dynamic predictions.

The intent of the thermal tube tests was to demonstrate predictive capability of the neural network approach and to select a suitable network and training scheme. Because the eventual goal is industrial implementation, simpler neural networks and efficient training schemes are emphasized. There are many neural network configurations and data processing procedures that were not evaluated and which might provide enhanced predictive performance or efficiency. However, the objective of identifying a suitable network and training procedures that could then be transferred to a machine tool for further evaluation was met by the thermal tube testing described here.

2.1 Description of the Bench-Test Apparatus

The "thermal tube" (Figure 1) consists of a 1.625 inch (4.12 cm) diameter thin wall copper tube 24 inches (61 cm) long, mounted to a base so that the tube stands vertically. Copper was chosen because it has a high coefficient of thermal expansion (producing relatively large motions with small heat inputs) and high thermal conductivity (producing a structure with a short thermal time constant and dynamic behavior). Thirty-six thermocouples are welded to the tube at eight levels along the length of the tube. Each level has four thermocouples mounted at 90° intervals around the circumference. The spacing of the levels is slightly wider towards the top of the tube. There is also one thermocouple that measures air temperature near the tube and can be positioned in a heat stream. J-type thermocouples were used and adequately cover the thermal test conditions.

Figure 1. The Thermal Tube Bench-Test Apparatus

A .75 inch (1.9 cm) diameter Invar rod (selected for its thermal stability) is mounted coaxially down the center of the tube. The rod has two flats machined at the top 90° apart. The flats serve as reference surfaces for two displacement gages mounted to a collar attached to the top of the copper tube (Figure 2). LVDTs were originally used for displacement measurement. As the predictive accuracy of the neural network improved it became necessary to replace the LVDTs with non-contact gages due to a .0002" mechanical hysteresis attributed to the tips of the LVDTs dragging across the flats on the Invar rod for motion orthogonal to their individual measurement axes.

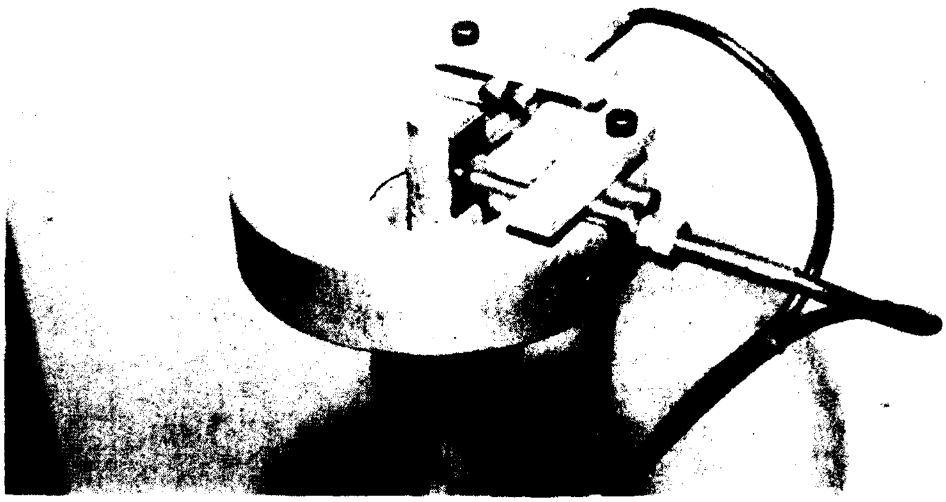


Figure 2. Displacement Sensors on the Top of the Thermal Tube

When heat is applied to the tube the copper material expands locally causing the tube to bend away from the heat source(s) (the tube will also get longer but this is not measured in this experiment). This causes the top of the tube to move with respect to the fixed invar rod and the movement is measured as a combination of x and y offsets by the displacement gages.

2.2 Development Path of the Neural Network

2.2.1 Neural Networks

Artificial Neural Networks are a class of computing methodologies inspired by the biological brain. In "traditional" computers, input information is decomposed into a huge series of +/– operations (decisions) which are performed one at a time, albeit very quickly. The way in which the information is to be decomposed and then recomposed must be specified by the programmer. In writing the algorithms, the programmer specifies each individual "decision" that transforms the input information into the output information.

The biological brain is structured differently. It is a massively interconnected system (network) of decision nodes - each with a number of inputs and outputs. The state of the output signal depends on the composite of the inputs to that node and on a weighting function associated with each input.

This type of decision structure can be modeled on a personal computer. While the initial characteristics of the network (number of nodes, initial weightings, etc.) are specified by the user, an artificial neural network is not programmed, it is "trained". Training a network consists of providing many sets of input information and the corresponding known "answers" to the network. The network then automatically goes through many cycles of adjusting internal weights to develop a structure that will generate the desired "answer" for each set of input data. Networks are typically trained for tens of thousands of cycles (up to several days of PC time) until some target level of performance is achieved. In contrast, most of the networks used in this study required training to only 1000 cycles. However, once the network is trained (the algorithm is set) the network can calculate an "answer" to a new set of inputs in fractions of a second.

There are many different types of artificial neural networks being studied or applied in industry today. One of the most popular for predicting a set of output conditions where there is a causal relationship between input and output conditions is the "Multi-layer Feed-forward Back Propagation" network. A schematic of a simple version of this network is shown in Figure 3. This type of network has been successfully applied to a number of "real world" problems including optical character recognition, analysis of sonar signals, curve fitting for arbitrary waveforms, and digital compression.

The network shown in Figure 3 has a single "hidden" layer as well as an "input" layer where the network interfaces to the process to be monitored, and an "output" layer where the network's decisions are presented. Networks can have several hidden layers but a single layer should be sufficient to model any arbitrary function as long as that layer has sufficient nodes ("hidden nodes"). If a very large number of hidden nodes is required it may be more efficient to go to multiple hidden layers with fewer nodes in each. In theory, 2n+1 hidden nodes (where n = the number of inputs) should exactly model any arbitrary function, but in practice far fewer hidden nodes generally suffice. Hidden nodes apply a function to the weighted sum of their inputs and the result of that operation is applied to each of the output connections for the node. The type of "activation function" is specified by the network designer. A simple activation function might state that if the sum of all the weighted inputs is greater than two, then output of the node will be "one".

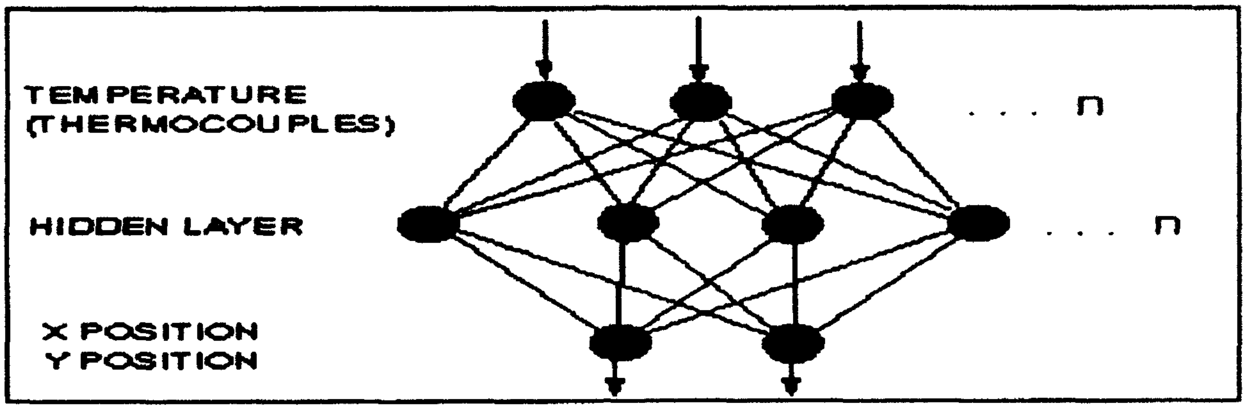


Figure 3. Artificial Neural Network Structure

Once the structure of a network is set, the network learns a specific input-output relationship during the training process. "Learning" consists of modifying the weights that act between the output of one node and the input of the next. The following example represents the training cycle for a simple feed-forward back propagation network with a single hidden layer.

> One vector of information from the training data set is applied to the input and output nodes of the network (during training both the data (inputs) and the desired solution (outputs) are supplied). The input nodes pass a value along each of their output connections and each of those values is modified by a weighting factor which has been arbitrarily set. The weighted values are received as inputs by the nodes in the hidden layer and acted on by the activation function. The resulting outputs of the hidden layer are similarly passed to the output layer where the output of those nodes is compared to the desired output from the data vector. The errors, or differences between the desired and calculated outputs are then fed back through the network and the weights are adjusted to reduce the errors. Each vector in the training set is processed in the same way except the weights are no longer arbitrary, but are the result of the previous vector's back propagation. When the complete data set has been processed this represents one training cycle ("epoch"). The entire process is then repeated using the last weights of the n^{th} cycle as the starting weights for cycle n+1. Networks may be trained for tens of thousands of cycles.

Another variable in the training process is the selection of parameters that control the learning process. "Learning rate" and "momentum" for example, determine how the network reacts to the back propagated errors. Globally, the type of network and selection of training parameters determine how the network behaves on a multi-dimensional solution space. The network chosen in this study for example, is designed to learn quickly by changing weights more radically in a flat area of the solution space and more slowly in highly sloped regions. Slower learning networks are more likely to become trapped in local minima, while larger weight changes can lead to instability.

2.2.2 Description of the Experimental Procedure

Heat is applied to the thermal tube using one or two heat guns which are computer controlled to turn on and off pseudo-randomly. Four heat gun configurations were used during testing, in increasing order of thermal complexity (Figure 4):

- Two heat guns aligned with a single measurement axis . ("On-axis")
- Two heat guns, one aligned with each of the measurement axes. ("Orthogonal")
- Two heat guns, rotated 30° off each measurement axis. ("Off axis")
- One heat gun applied in a slow random motion. (The uninsulated thermocouples can respond to a transient temperature so short that insufficient heat is transmitted to the copper material to cause deflection. For this reason there is a limit to the speed of the random motion of the heat source.)

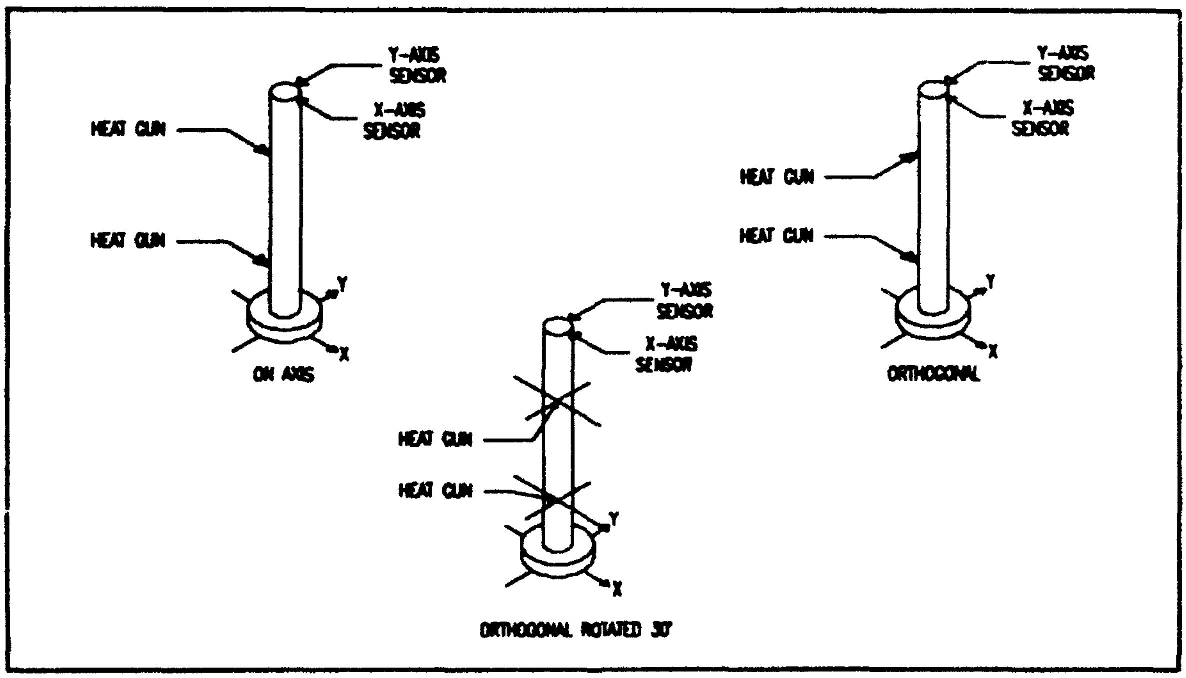


Figure 4. Orientations of the Heat Sources for Thermal Tube Experiments

Data is collected for ten minutes at one second intervals. Each data vector consists of 37 temperature readings and two displacement readings. The data is archived in a file for convenience. This method decouples data collection and network training, allowing a number of physical tests to be run sequentially to make efficient use of the testing resources (e.g. a test-bed machine tool). Once archived, the data can be manipulated to enhance network training and performance without having to collect new data sets.

For each physical test condition at least three sets of data were collected. One set (or a portion of one set) was used for training, a second for testing during the process of developing training techniques, and a third held back for independent verification at a later time.

2.2.3 Training Variations

The first attempt at network training used the first half of a data set for a single heat gun orientation (data from the first 5 minutes of the ten minute test). The first and easiest test for a trained network is to check the predictive performance on the same data that was used for training. At a minimum the network should be able to accurately predict the output for input data which it has "seen" during training. This baseline test, using a data set that represented only a single heating orientation, was used to evaluate various network configurations. After significant experimentation, a network with one hidden layer, 11 nodes in the hidden layer, and a sigmoidal activation function was the simplest found that could model one of these data sets. At this time the network could, on the average, predict the position of the tube to within about $\pm$ 0.001" (0.025 mm). The full range of motion was about $\pm$ 0.020" (0.5 mm).

To minimize the amount of training data that will be required in a machine tool application, the network should be able to predict deflections caused by temperature profiles that are not specifically part of the training set. During the thermal tube development work the network was also tested on the second half of the training data set (the second 5 minutes), and also on data from the other heating orientations. As might be expected, the network was able to predict the tube's motion during the second half of the set used for training roughly as well as it did for the first half. It was able to do this even though it had never been exposed to this data because the data was from the same orientation and time period; it was of very similar character to the data the network was trained on. When tested on data from other heating orientations however, the network's predictive performance fell dramatically. In effect, the network was not able to learn the systems response to a wide range of heating conditions from a single, narrow example.

It was clear that before the network would be able to predict motion caused by heating conditions it had never seen, it would need to be exposed to a broader set of information (input - output vectors) during its training period. To provide a richer training set, subsets of data from each of the four heating orientations were combined into one new training set (note that no new data had to be collected). The network was retrained on this combined set which contained roughly the same number of data vectors (due to system memory limitations) but represented a much broader variety of data.

The network performed better overall on the range of test conditions (heat gun orientations) but did not perform as well on any given test orientation as a network trained exclusively on that orientation. In general the predictive capability was similar for the various test orientations.

A collection of 600-1500 data vectors comprises a data set, and the entire set is fed into the network repeatedly, one vector at a time, until a predetermined number of training cycles has been exhausted. The thermal and displacement data was fed to the network in the same sequence that it was collected. That is, from one data vector to the next, the network was seeing differences in the tube's state that were separated by one second in time. Neither the thermal profile nor the tube's deflection changed significantly during one second, so the network tended to follow the trend of the data, and not train as well as expected. Once this shortcoming was suspected, the training program was modified so that all of the individual data vectors in a data set were fed to the network at random. This is a fairly common data pre-processing technique. One training cycle still included all of the vectors of a given set, but the vectors were given to the network in a different order from one epoch to the next. This enhancement improved the predictive ability of the network from errors of 1.5% RMS to errors of under 0.75% RMS.

Though the network performed adequately on data from which the training data was drawn, there were still significant errors when it made predictions about other data sets. Since all of the data was collected during a relatively short time frame, and the tube was not disturbed during this period, data sets of the same heat gun orientation should have had the same character, and the network should have been able to generalize better. It was suspected that the friction of the LVDTs as they slid across the Invar rod could induce enough hysteresis in the tube's motion to prevent the network from properly generalizing using only thermal data. In effect, deflection was due to both thermal and mechanical sources and the network was only provided information on the thermal profile of the tube from which to make deflection predictions. The LVDTs were replaced with non-contact fiber optic gages, and new data was collected. When trained with this new data, the network was able to produce errors of less than 1%, not only on the training data set, but also on several other test data sets that it never encountered during its training.

2.2.4 Network Variations

Most of the early network development performed at the University of Cincinnati centered on defining the structure of the network that would be needed to predict thermally-induced deflections. The early networks were run using an ANZA-plus neural network co-processor and software by Hecht-Neilsen Neurocomputing Corporation (a plug-in board for IBM PCs). Various numbers of hidden layers, nodes in the hidden layers, and various activation functions were evaluated with this board. Due to memory limitations on this particular version of the ANZA board, only very small data sets (about 300-600 vectors; 5-10 minutes of continuous data) could be used for the network training process. Even restricted to small data sets, these tests indicated that a relatively simple, single-layer, back-propagation type network might be sufficient to predict deflections of the thermal tube to the required accuracies. However, as described in the previous section, it quickly became apparent that capacity for much larger data sets would be required.

Feasibility of Neural Networks for Predicting Machine Tool Thermal Errors

A single hidden layer delta-bar-delta back-propagation network implemented in UNIX by Dr. Timothy Grogan was selected as the next test vehicle. It was subsequently ported to the DOS environment and run on a 486 personal computer. The delta-bar-delta configuration is designed to speed learning by increasing the rate where the slope of the solution space is relatively flat and avoid instability by slowing network changes in highly sloped regions. This basic configuration was used for the remainder of the network development tests. When this network was shown to be successful, it was also implemented and tested on a commercial piece of neural network software (NeuroShell) to ensure that performance was not code dependent.

There is a strong intuitive argument that prediction of thermal deflection should be enhanced by knowledge of the rate of temperature change because heat is dynamically transferred through the structure. This can be implemented in the neural network training by expanding the data vector (and typically increasing the number of hidden nodes) to include not only the current temperature distribution but also some previous distribution(s). (Note that the network itself does not know which is current or historical data, only that it sees a larger data vector.) Several cursory tests were run using one or two of the immediately preceding temperature distributions both on the thermal tube and later on the lathe. The results were mixed, with some improvement in predictive accuracy for some data sets and performance degradation for others. Because significant improvement was not noted, and a simpler implementation with satisfactory performance had been identified, this development path was not pursued further and may represent a technique of opportunity for some applications.

As noted above, the performance of the network at the end of the Phase I thermal tube studies depended on a combination of network structure and data presentation. Several sample plots showing both the actual tube displacement and the displacement predicted by the network are included in Appendix F. The bottom line on each chart is a calculated "error", the difference between actual and predicted deflection over time. Several plots are included where the network was trained without randomizing the vectors between epochs as well as plots typical of the performance with randomized vectors

The following network resulted from the Phase I investigations and was used as a starting configuration for the Phase II studies on the turning center:

- Delta-Bar-Delta Back Propagation Network.

- Sigmoidal activation function (clamps the output of a node between 0 and 1 for inputs ranging over $\pm$ infinity).

- One hidden layer with eleven hidden nodes, weights initially randomized between 0 and 1.

- Normalized data with vectors randomized between epochs.

2.2.5 Key Findings

The key findings of the Phase I study are:

- Neural networks are capable of predicting thermally-induced deflections in mechanical structures. The precision of those predictions on the thermal tube bench-test apparatus was judged to justify moving into Phase II investigations on the machine tool.

- Relatively simple neural networks that run on inexpensive computer platforms are sufficient.

- The training set should be inclusive of the test (expected operating) conditions.

- Data pre-processing can enhance the predictive performance of the network.

- No constraints in the application or predictive performance of the network were identified.

2.3 Demonstration of Predictive Capability

In order to more clearly demonstrate the predictive function of the neural networks, a demonstration was created using the thermal tube bench-test apparatus. Presentation software was written that displays the actual deflection of the tube as measured by the non-contact gages against the real-time prediction of the neural network based on the thermocouple readings. A rolling historical graph similar to those in Appendix F is also presented for each axis. The demonstration uses a previously trained network and is similar to testing the network, except that "live" data is used. In practice the heat guns (randomly actuated by the computer) provide thermal input to the tube and the viewers watch the network prediction track the actual motion of the tube. Based on the success of this demonstration in conveying the key concepts of the program to both technical and non-technical viewers, a similar demonstration was later created for the machine tool (although the dynamics are far slower on the turning center).

2.4 Optimization of the Neural Network

The Phase I effort was designed to provide a capable network for use on machine tools and to develop a baseline understanding of the use and potential constraints of artificial neural networks for predicting thermally-induced deflections. There was no significant effort to identify the optimal neural network for this class of problem, or to finely tune the selected network for peak performance. Several variations were investigated however, to identify general behaviors as they apply to future optimization in a commercial environment.

A key concern with respect to the practicality of an industrial application is the number of input sensors required. The design intent of the thermal tube apparatus was to overpopulate the surface with sensors. Evaluating the performance of the network with fewer inputs requires no physical modification of the system, but does require that some of the data be stripped form the training set. Various numbers and combinations of thermocouples were evaluated on the thermal tube. For a well distributed selection of thermocouples, predictive performance was maintained down to about eight thermocouples after which significant degradation was noted. The number of required thermocouples is obviously directly related to the structure and thermal profile so general conclusions can not be drawn from this data.

Much research is currently underway to develop ways of identifying the significant input nodes based on the results of the network training. The commercial NeuroShell package has a utility designed to assist in this type of analysis. This would allow a machine builder to overpopulate a prototype or first production machine with sensors, train the network, and then retain only those sensors indicated as significant. This strategy is practical even without a network shell utility by using Monte Carlo methods. The network would be trained (probably to a small number of cycles) using various subsets of inputs from the complete data set and the smallest subset that resulted in a target level of performance would be selected. Only the corresponding sensors would be retained. On modern workstations this type of analysis could run unattended in a reasonable time frame.

Greater and lesser numbers of hidden nodes were also evaluated. Significant changes were not noted by adding or subtracting a few nodes. Performance degradation was noted when more than a few nodes were added or deleted. Networks with as few as a single hidden node were able to provide some prediction but the accuracy suffered significantly. Because addition of a node does not require significant resource (like the addition of a sensor), fine optimization of the number of hidden nodes is not a priority of this program, though it might be for a commercial implementation.

Section 3. Evaluation of the Artificial Neural Network on a Turning Center

3.1 Scope of Experiment

The feasibility of artificial neural networks for thermal error compensation of mechanical systems was proven with the bench test described above. The next step was to apply this approach to a machine tool.

The machine tool chosen for this investigation was a Cincinnati Milacron CINTURN 10 turning center. The tests were configured to consider only thermal effects, thus other factors such as servo error, load deflection, inertia and so forth were not included.

Measurements included temperature at various locations on the lathe, and displacement between the tool and workpiece locations. Changes in this displacement value provide a measure of the error in machine positioning. The non-contact laser gages from the thermal tube were used to measure the relative displacement between the reference part and a tool position. The experimental setup was used to investigate several different thermal states of the machine. Initially, measurement of displacement was done at only one X/Z coordinate in the workspace. However, results were so encouraging that it was decided to include position of the tool as a variable. For the rest of the investigations this additional variable was incorporated into the experiments by using a fixture that allowed measurement of displacement at three positions.

The base neural network used was also the one found to be best in the bench test evaluations. In addition, several variations of network and network input structure were investigated. The comparison of results from network predictions with experimental results then gave a measure of the capabilities of neural networks for prediction of thermally induced errors in machine tools.

3.2 Experimental Approach

The machine used for this portion of the investigation was a Cincinnati Milacron CINTURN Series C Universal Turning Center (Figure 5). It has a Cincinnati Acramatic 900TC CNC Control. This controller contains no provision for thermal compensation. Slide repeatability (X and Z axis) is ± .0002 inches

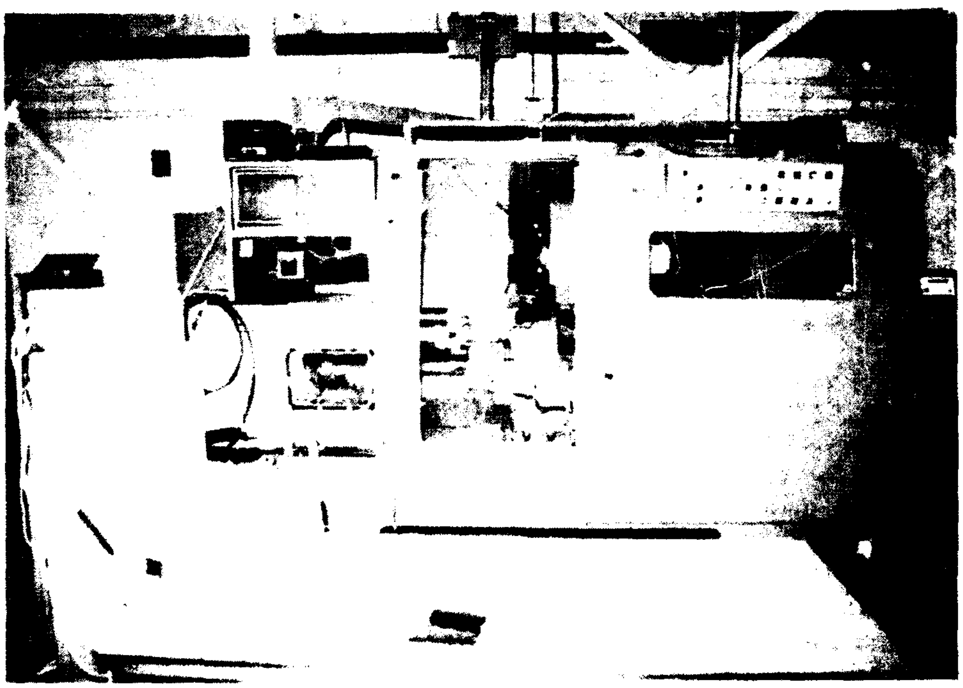


Figure 5. Turning Center Test-Bed

Temperature was measured with the same Type J thermocouples used for the bench test. They were spot welded to the surface. The philosophy behind thermocouple positioning was to "over-populate" the machine to make sure all "hot spots" had been covered. During the investigation networks with fewer inputs were evaluated to gain insight into the actual number and position of temperature measurement locations required to adequately define the thermal state of the machine. Table 1 lists the locations of the 23 thermocouples installed on the turning center.

To measure the displacement that would occur between the part and workpiece during a machining operation, a reference part was made to simulate a part, and a fixture was made to position the optical sensors. The first reference part was a 6-inch diameter tube. The fixture to position the optical sensors is shown in Figure 6. The sensors were aligned against the end of the reference part to measure relative motion in the X (radial) and Z (axial) directions. Figure 7 shows the second reference part, used to measure displacement at three positions. Position 1 is at the extreme right end of the part at the furthest radial location. The dimensions here are X = 2.25 inches and Z = 9 inches where X is measured from the centerline and Z is measured from the chuck face. Position 2 is at the corner between the long shaft and the larger diameter disc next to the chuck. Its dimensions are X = 2.25 inches and Z = 2 inches. Position 3 is at the extreme of the disc nearest to the chuck. Its dimensions are X = 3.875 inches and Z = 1 inch.

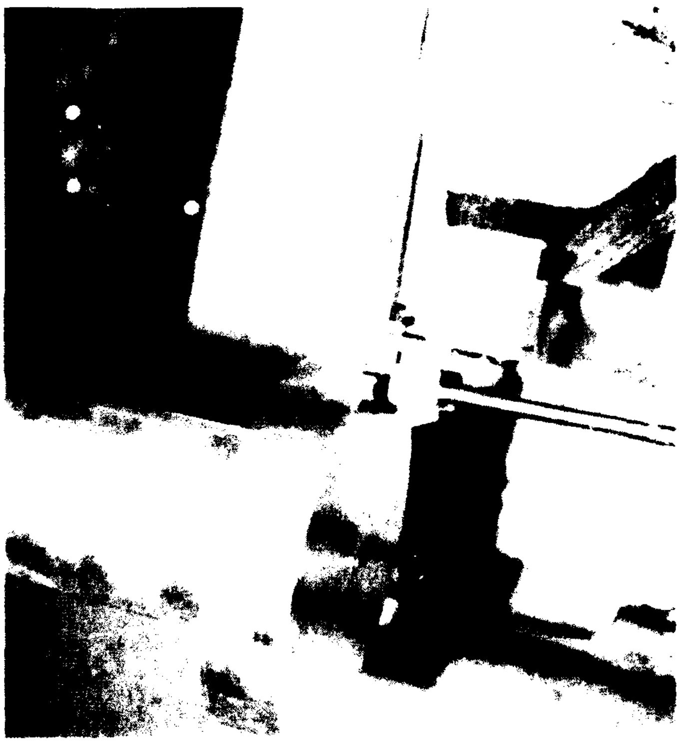


Figure 6. Fixture for Displacement Measurement

Table 1. Thermocouple Locations on the Turning Center

I.D.	Description
Z-axis Drive	Outer Casing of Z-axis Drive Motor
Drive Motor	Outer Casing of Spindle Drive Motor
Drive plate	Plate Supporting Spindle Drive Motor
Bed Top 1	Top of Bed at Right Rear
Bed Top 2	Top of Bed at Center Right Rear
Bed Top 3	Top of Bed at Center Left Rear
Bed Low 1	Low on Bed at Center Right Rear
Bed Low 2	Low on Bed at Center Left Rear
Bed Top 4	Top of Bed at Left Rear
Turret Side	Side of Turret Way Support
Turret Left	Lower Bed of Left Turret Way
Turret Right	Lower End of Right Turret Way
Z-way Spindle	At Z-way at Left
Z-way Middle	At Z-way in Middle
Z-way Turret	At Z-way at Right
HYD Line	Hydraulic Line
Hydraulic Ret. Pipe	Hydraulic Return Pipe
Spindle Top	Headstock at Top of Spindle
Oil	Oil in Headstock
Oil	Oil in Headstock
Spindle Side	Headstock at Side of Spindle
Plate Wear Sp	Plate on Headstock on Side Opposite Spindle
Ambient	Ambient

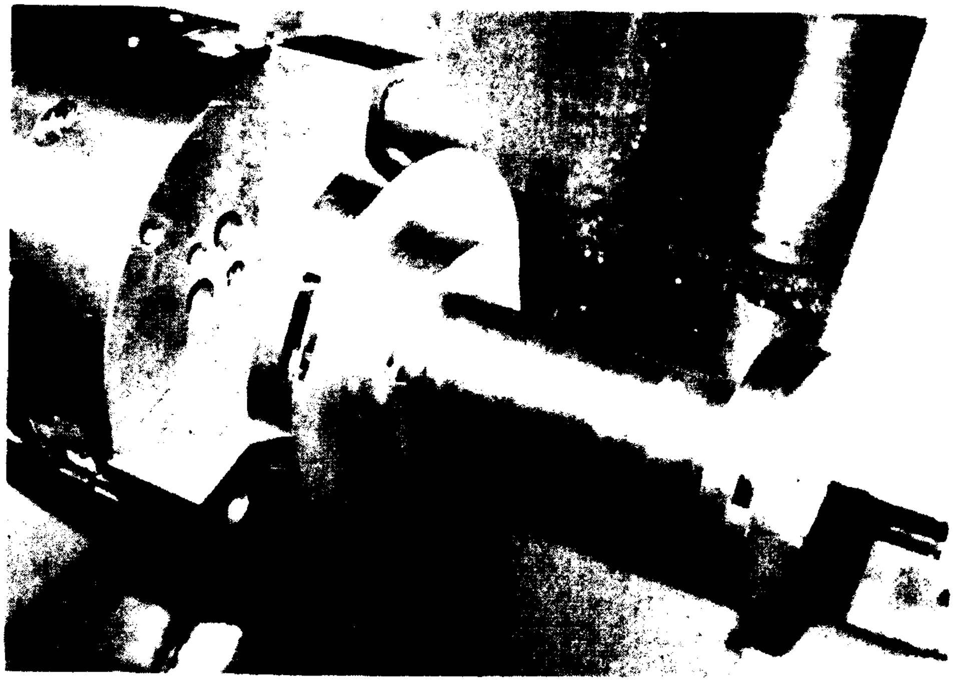


Figure 7. Reference Part for Measuring 3 Positions

Displacement measurements were taken using the same fiber optic gages used for the final bench tests. These were manufactured by Philtec, Inc. and are capable of an accuracy of $\pm$.0001 inch. The application of these sensors to the turning center was more difficult than for the bench test because the part was rotating. For this situation, if measurement takes place at random positions around the periphery of the part, an error will be introduced in displacement measurement by part and/or spindle runout. In order to prevent this, a piece of highly reflective tape was attached to the reference part (Figure 7). With proper setting of the sensitivity of the sensor, displacement measurement only occurred on this tape, assuring that runout was not a factor.

Using reflective tape (or the surface of the reference part) presented another increase in difficulty over the bench test setup. The bench test utilized a mirror as a target for the displacement measurement. This very flat surface assured repeatability for measurements at slightly different positions on the mirror. However with the reflective tape, measurements at slightly different positions would produce different values because the surface of the tape was not perfectly flat, and because the reflectivity of the tape was also slightly variable. In order to prevent this from introducing errors into the experiment, a series of measurements was taken as the tape passed under the sensor and were then averaged.

An NC program was written to enable measurement of error at the three positions repetitively. It included the following features:

1. Advance sensors to X and Z coordinates at position 1.

2. Acquire temperatures and X and Z displacements at position 1.

3. Move to positions 2 and then 3 and repeat data acquisition.

4. Dwell away from the part with the spindle rotating at a higher RPM to warm up the machine.

5. Repeat this sequence for the duration of the test (4 hours).

After measurement at each location, the displacement values along with the thermocouple measurements and X and Z coordinates at the position were stored. An example of the form of the data is given in Appendix A.

A test plan was developed to establish the validity of neural networks in predicting thermal distortion of a machine tool. The first step was to check the consistency of the experiment with repeatability tests. Additional tests then involved changes in the thermal inputs to the machine to permit evaluation of the network under taxing conditions. The following inputs were used:

1. Different ambient temperatures.

2. Different settings of the hydraulic oil chiller.

3. External thermal input to the headstock.

4. External thermal input to the rear of the bed of the machine.

3.3 Neural Network Features and Application

In the initial phases of the program it was determined that a modified back propagation network performed very well in predicting distortion of a mechanical system due to thermal input. This same type of network was used for the machine tool evaluations. The following features were included in the base network used for this:

1. Delta-Bar-Delta Back Propagation Network.

2. One hidden layer with 13 nodes.

3. 25 inputs (23 thermocouples and 2-position coordinates) and two outputs. The outputs were the predicted errors in the X and Z directions.

4. Normalized data vectors which were randomized.

5. Data set included data vectors from 1 test (153 data vectors) for the 1-point reference part and data vectors from 3 tests (123 data vectors) for the 3-point reference part.

The back propagation neural network must first "learn" from example data before it can be used to predict results. This implies two distinct requirements. A procedure must be used to "train" a network with a data set having the same characteristics (inputs, outputs) as the test data. In addition, the data used for training must incorporate information about the condition to be tested. For example, if the network is to be used to predict error caused by a difference in the ambient temperature, the data set must include data acquired over a range of ambient temperatures that include the ambient requiring prediction.

The network training procedure used during the bench test portion of the program was also used here. It included the following steps:

1. *Give the network a vector of data from one instant of time.*

2. The network makes a prediction about the error and uses the actual error to determine the accuracy of the prediction.

3. The network then adjusts the weights in an attempt to improve the accuracy.

4. The network is given the rest of the data vectors in random order and goes through this adjustment for each. One "training cycle" consists of presenting the full data set to the network.

5. The network is trained over succeeding cycles using the same data in different random order until the desired accuracy is achieved. There is a trade-off in this procedure between accuracy and training time.

For the analyses performed on the turning center data it was found that 1000 training cycles produced very good accuracy within a minimum training time. As an example of training time required, it took about 2.5 hours on a 486 33MHz PC to train the network with 123 data vectors.

3.4 Results of Experimental Studies

3.4.1 Description of Typical Data

The data plotted in Figure 8 shows the typical form of the displacement in the X direction for the turning center tests. The sample number is plotted on the horizontal axis, thus this axis basically represents time where each increment is the amount of time between samples (about 6 minutes). The vertical axis represents displacement, given in thousandths of an inch.

The tests all began with the machine cold and progressed through warmup to a steady state warmed-up condition. This is shown in Figure 9 which gives temperature at the spindle nose as a function of sample. From the data in Figure 8 it can be seen that the displacement increases rapidly during initial machine warmup, then levels off until there is no overall change with time as machine temperature stabilizes. The small perturbations in displacement are primarily due to temperature cycling caused by on/off cycling of the oil chiller.

The data plotted in Figure 10 shows the typical form of the displacement in the Z direction. As with the X direction the scales are sample number (proportional to time) and displacement. The form of the displacement curve with time is somewhat different from the X direction. Here the displacement increases to a maximum value then begins to decrease. The rate of decrease slows until the displacement reaches a steady state level as the machine temperature stabilizes. Apparently, there are two contradictory influences causing error as the machine warms up. The portion of the machine which is closest to the heat sources (probably the spindle) responds in such a way that the displacement becomes negative. Portions of the machine further from the heat sources (such as the bed for example), which will be influenced later, respond by causing the displacement to go positive.

Measurements from positions 2 and 3 follow exactly the same trends as position 1. The only difference is a shift of the entire curve caused by different initial settings for the optical sensors. Typical data from these positions are given in Appendix B.

In order to provide a better understanding of the response of the machine to the test inputs and the ability of the network to predict these, the data from all three positions were merged into one file. Figures 11 and 12 show typical data displayed in this manner. The X axis is broken into 3 segments with sample number starting at 1 for each segment. However, in this case, the scale restarts at the value one for each tool position. It can be seen very clearly that displacement at each position follows the same trend with temperature.

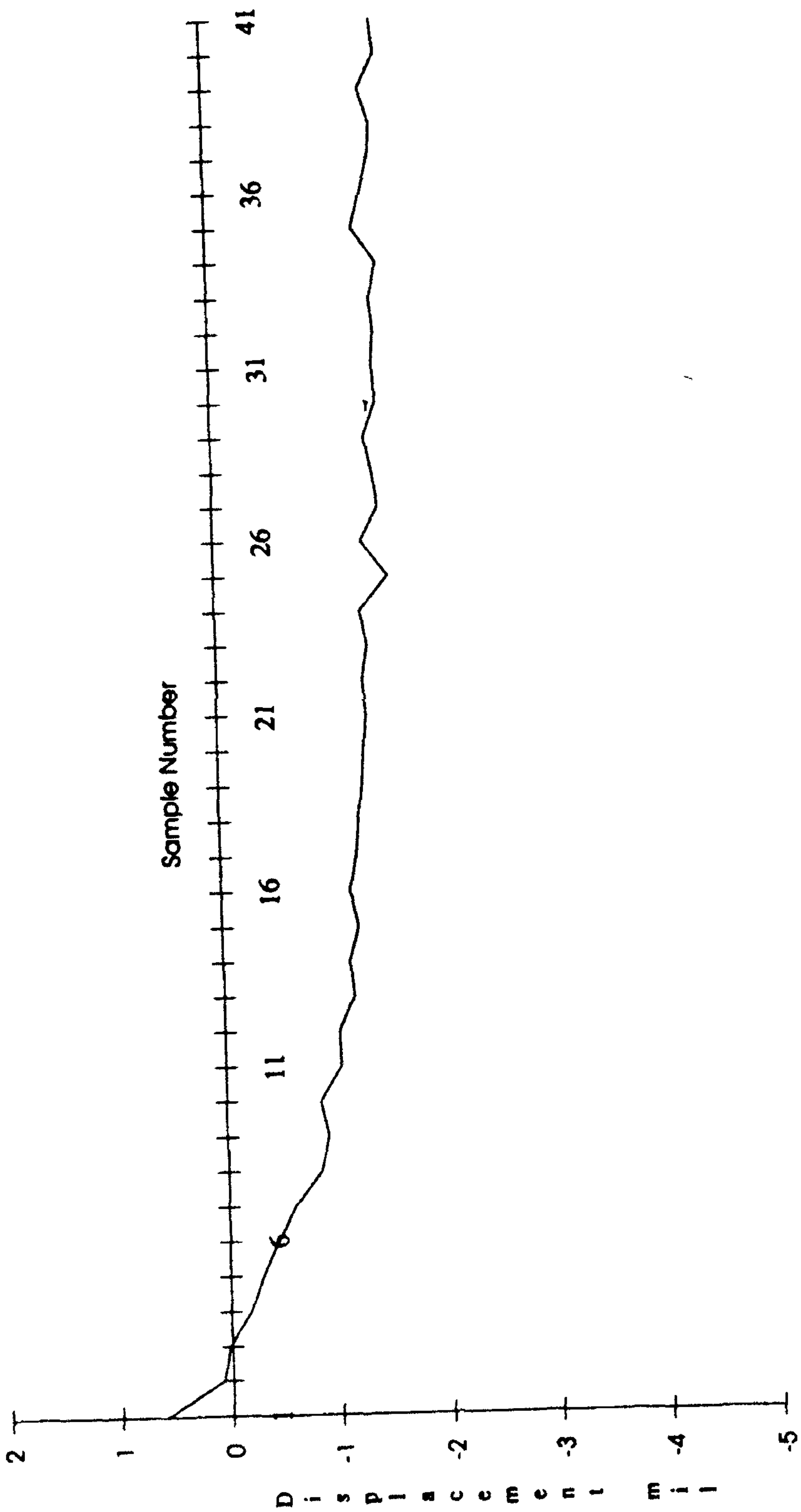


Figure 8. Displacement in X Direction at Position 1

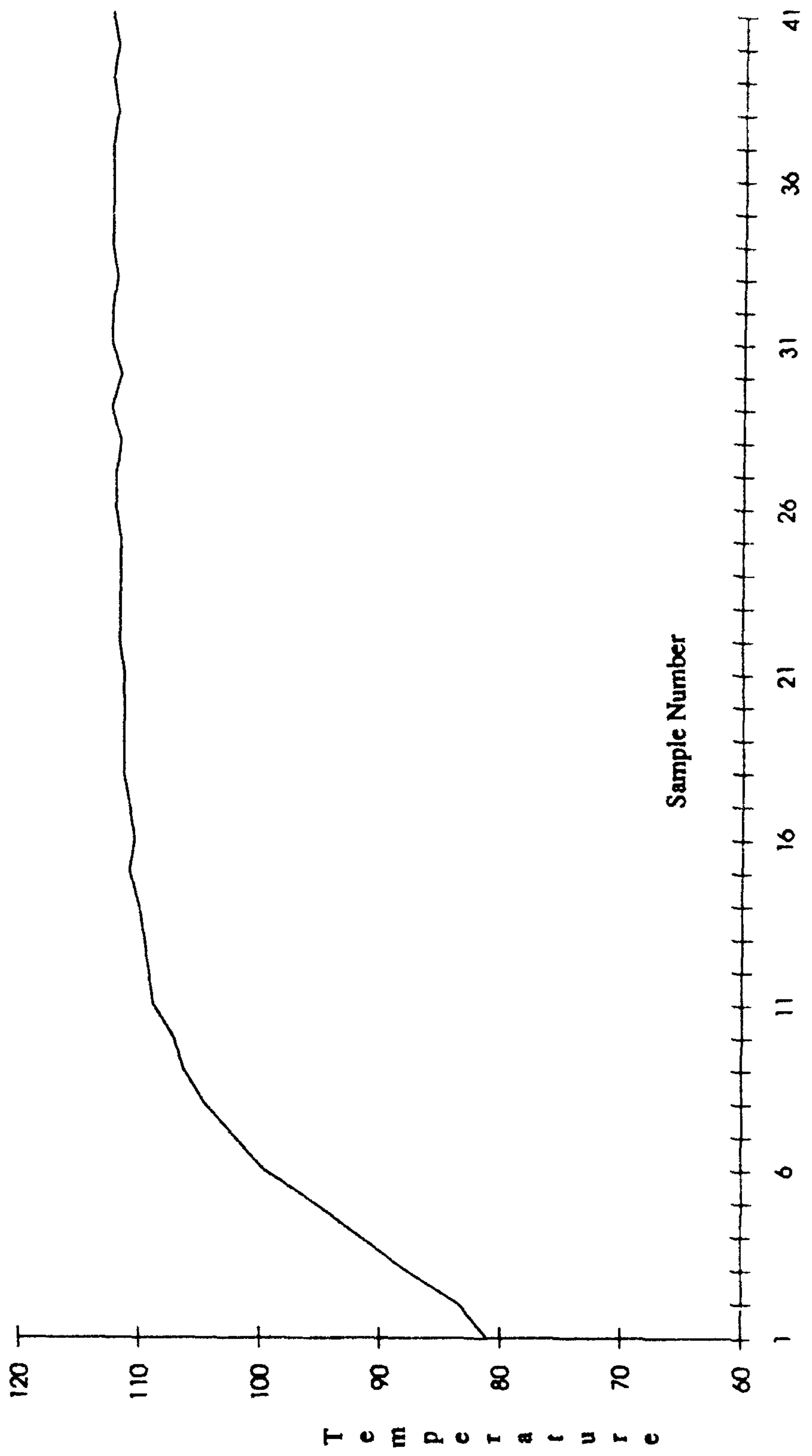


Figure 9. Temperature at Spindle Nose

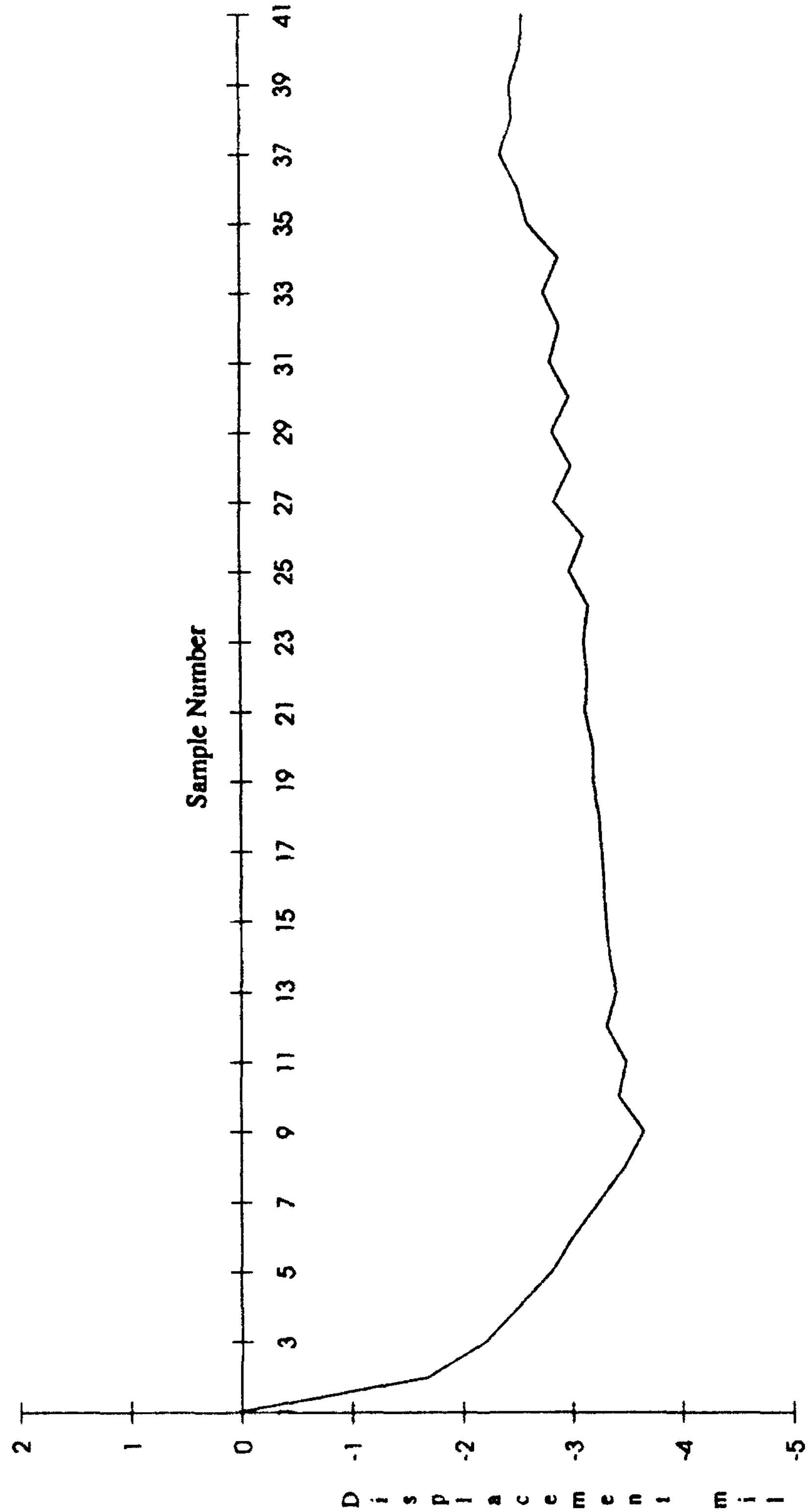


Figure 10. Displacement in Z Direction at Position 1

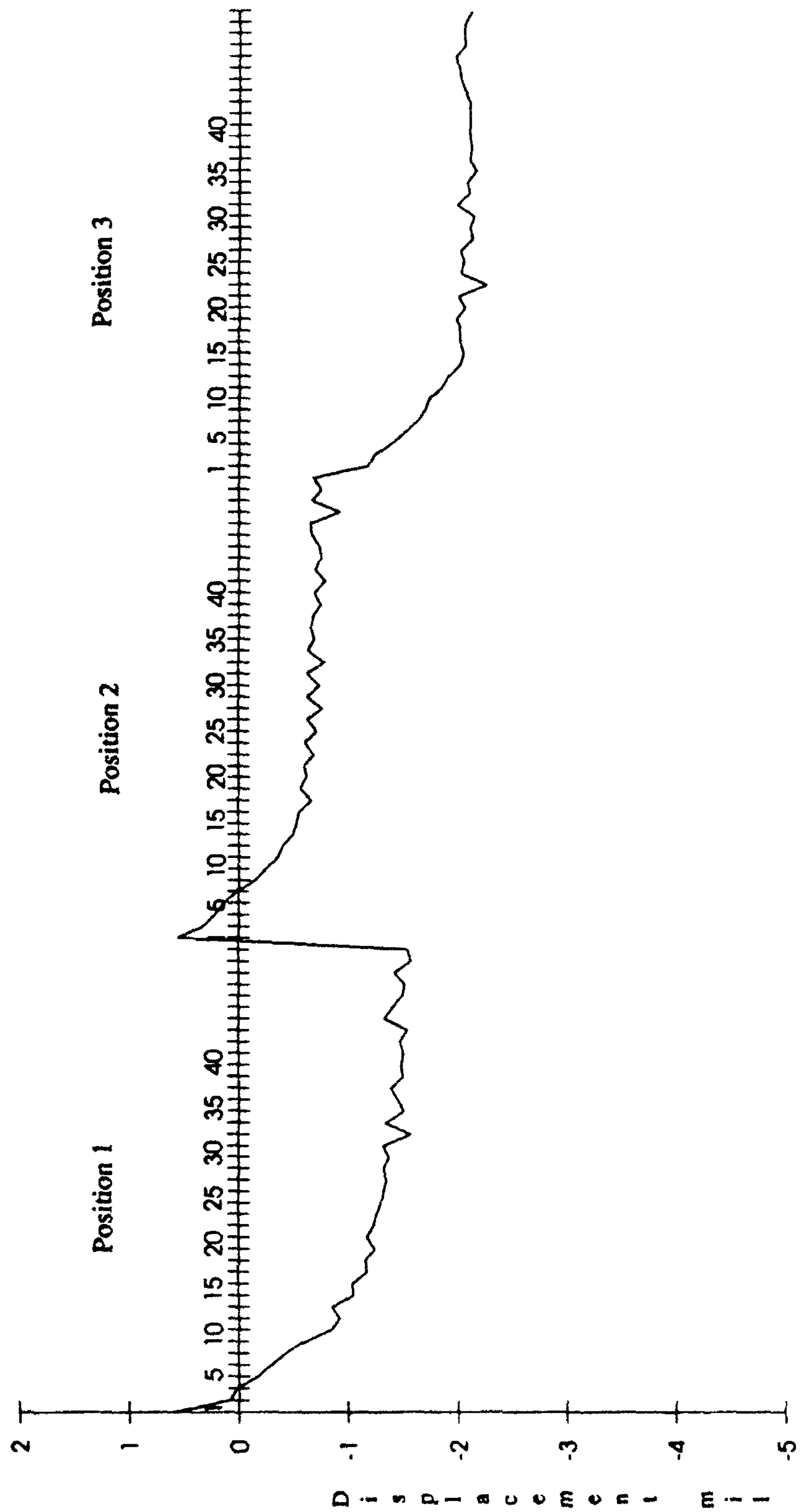


Figure 11. Displacement in X Direction at All Positions

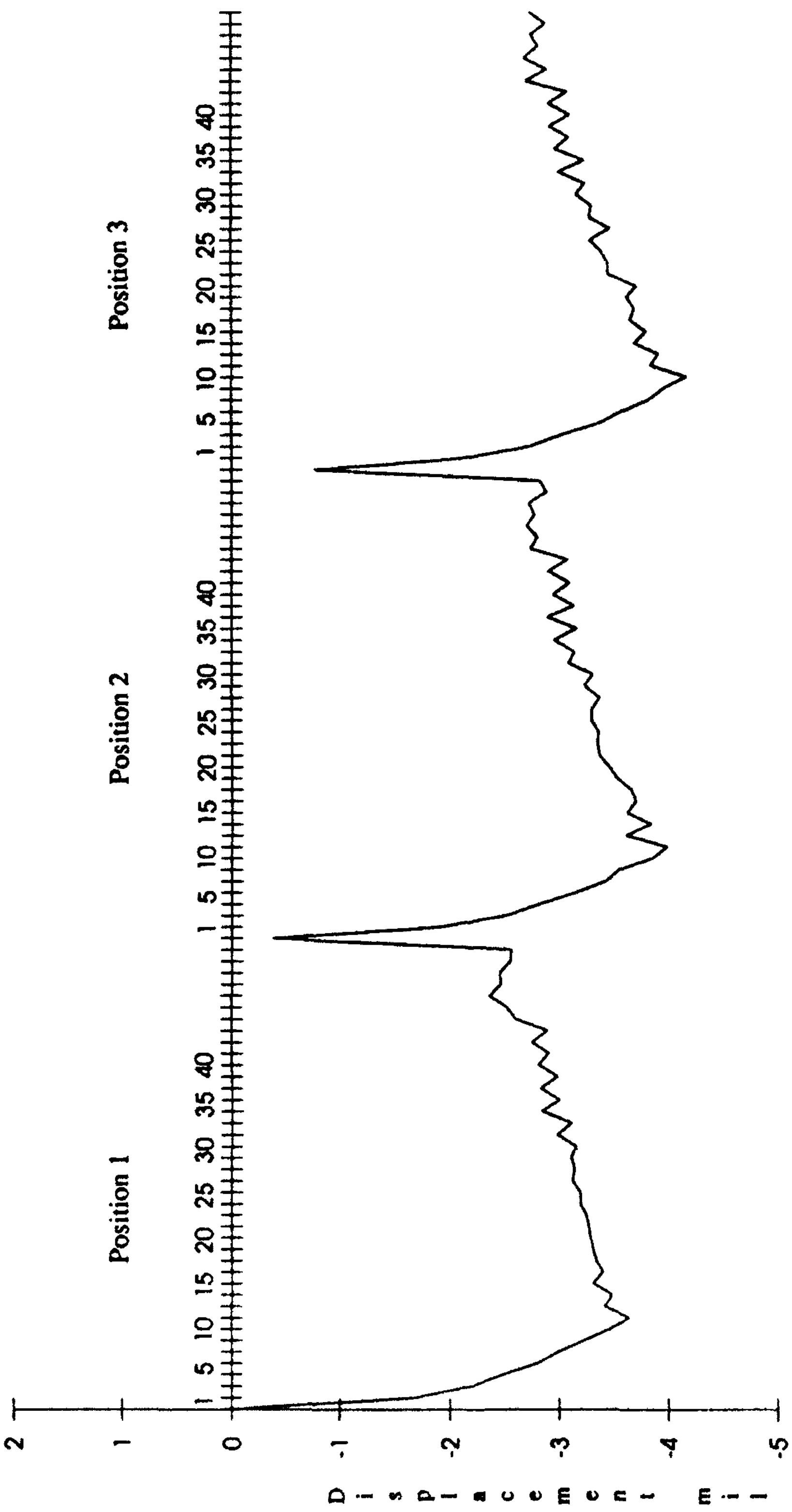


Figure 12. Displacement in Z Direction at All Positions

3.4.2 Variables Evaluated

The experimental setup described above was used to investigate several thermal variables. The intent was to establish the feasibility of the network as a means of providing compensation for various types of inputs. Some of these inputs were deliberately chosen to severely test this approach by requiring the network to perform on thermal conditions that it had not been specifically trained on. Specific conditions for these are given in Table 2. The following is a brief description of each.

a. *Repeatability*. In any experimental investigation, it is necessary to verify that only the variables of interest are affecting the outcome. Thus a "baseline" condition is repeated periodically to make sure that an uncontrolled variable is not changing the output (in this case, the X and Z displacement). Comparison of the output of a baseline repeat with the original baseline will establish the consistency of the experiment.

b. *Ambient Temperature*. An important thermal variable in a machine shop is the temperature of the environment surrounding the machine. This was included in these investigations by running experiments at various ambient temperatures.

c. *Different Chiller Setting*. The temperature of the machine tool used for these investigations was stabilized somewhat through the use of a thermostatically controlled heat exchanger to maintain the temperature of the hydraulic oil within a certain range. The setting of the thermostat was increased from 120 degrees to 135 degrees for this experiment.

d. *Thermal Input to Headstock*. An artificial thermal input to the headstock was created by directing two heat guns totaling 3500 watts against the headstock. This was done to simulate a condition wherein the spindle and/or gear train generate excessive thermal energy.

e. *Thermal Input to Bed of Lathe*. For this experiment 7 infrared lamps totaling 1750 watts were directed against the bed at the rear of the machine. This was done to simulate an external heat source such as the sun.

Table 2. Conditions for Experimental Tests

		Ambient Temperature	
Date	Condition	Start	End
12/17	Baseline	71	72
12/18	Different Ambient	67	70
12/19	Different Ambient	68	72
12/21	Different Ambient	63	68
12/23	Increased Chiller Temp. from 120 to 135 Degrees	70	72
12/28	Heat Guns on Headstock at Start of Test	71	73
12/29	Repeat Baseline	71	72
12/30	Infrared Lamps Input to Back of Lathe Base at Start of Test	70	75
1/6	Repeat Baseline	71	71

General testing conditions summary:

a. *Different Ambient.* Decreasing the ambient temperature results in a more negative displacement and increasing the ambient temperature results in less negative displacement when compared to the baseline.

b. *Chiller Effect.* Increasing the chiller thermostat limit from 120 degrees (standard) to 135 degrees, resulted in a significant increase in both the X and Z displacement.

c. *Heat Guns on Headstock.* In the X direction, the displacement was more negative. The Z direction displacement was significantly less negative.

Note: After December 29 testing, an "offset" shift in amplitude occurred in the +X direction for position 1 and the -X direction for position 3. However, the form of the displacement change with temperature remains the same. The change in displacement most likely resulted from the reference part moving in the chuck.

d. *Infrared Lamps.* Compared to the baseline test, the X direction deflection was more negative. The Z direction displacement was less negative. The changes in displacement might have been caused by adding infrared lamps as an additional thermal input to the back of the lathe and/or the unknown change in test conditions after December 29.

e. *Repeat Baseline.* The repeat baseline on December 29 demonstrated that the experiment repeated very well. However, with the change in testing conditions, January 6 displacement in the X direction for position 1 became less negative and more negative for position 3.

3.4.3 Base Network Initial Evaluation

The initial step in establishing the feasibility of neural networks for thermal compensation is to use data from the baseline experiment to train the network and to then use this trained network to make a prediction from the same data. The step involving the use of a network to make a prediction is termed "testing" the network.

When the basic network was trained and tested on the baseline data, the results were as given in Figures 13 and 14 where the individual curves represent measured displacement (actual) and displacement (network) predicted by the network. The following important conclusions can be drawn from these results:

- Since testing on training data gave a prediction by the network which is very close to the actual, the procedure and computer program being used are functioning properly.

- This type of artificial neural network will work on typical turning center data. It had no difficulty in processing the data and producing the appropriate weights in a reasonable amount of time (1000 training cycles were more than adequate).

- The network very accurately predicts the change in displacement (error) as the machine warms up.

Since the basic network worked so well on the type of data obtained from the turning center tests, the project was broadened to include the position of the tool as a variable. The rest of the experiments thus incorporated the reference part described above which contained provision for measurement at three locations. The basic network was also initially evaluated by training and testing on baseline data taken at these three positions. Results are given in Figures 15 and 16 and Table 3. A very small percentage of error confirms that visually, the curves show a good fit. An additional conclusion that can be reached from these results is that the network will predict displacement at separate positions in the workspace when trained on them.

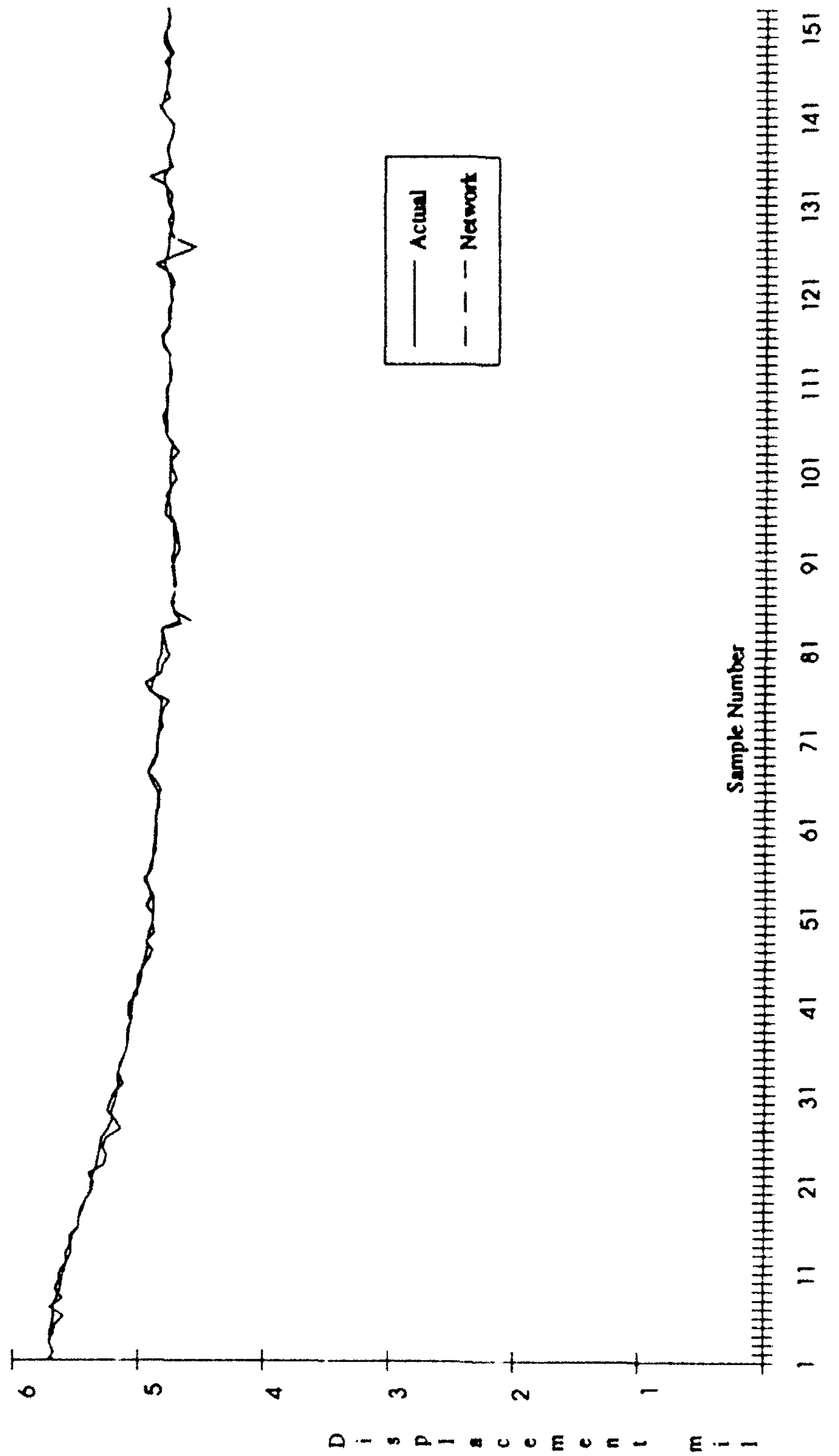


Figure 13. Network Result for Training Data at One Position - X Direction

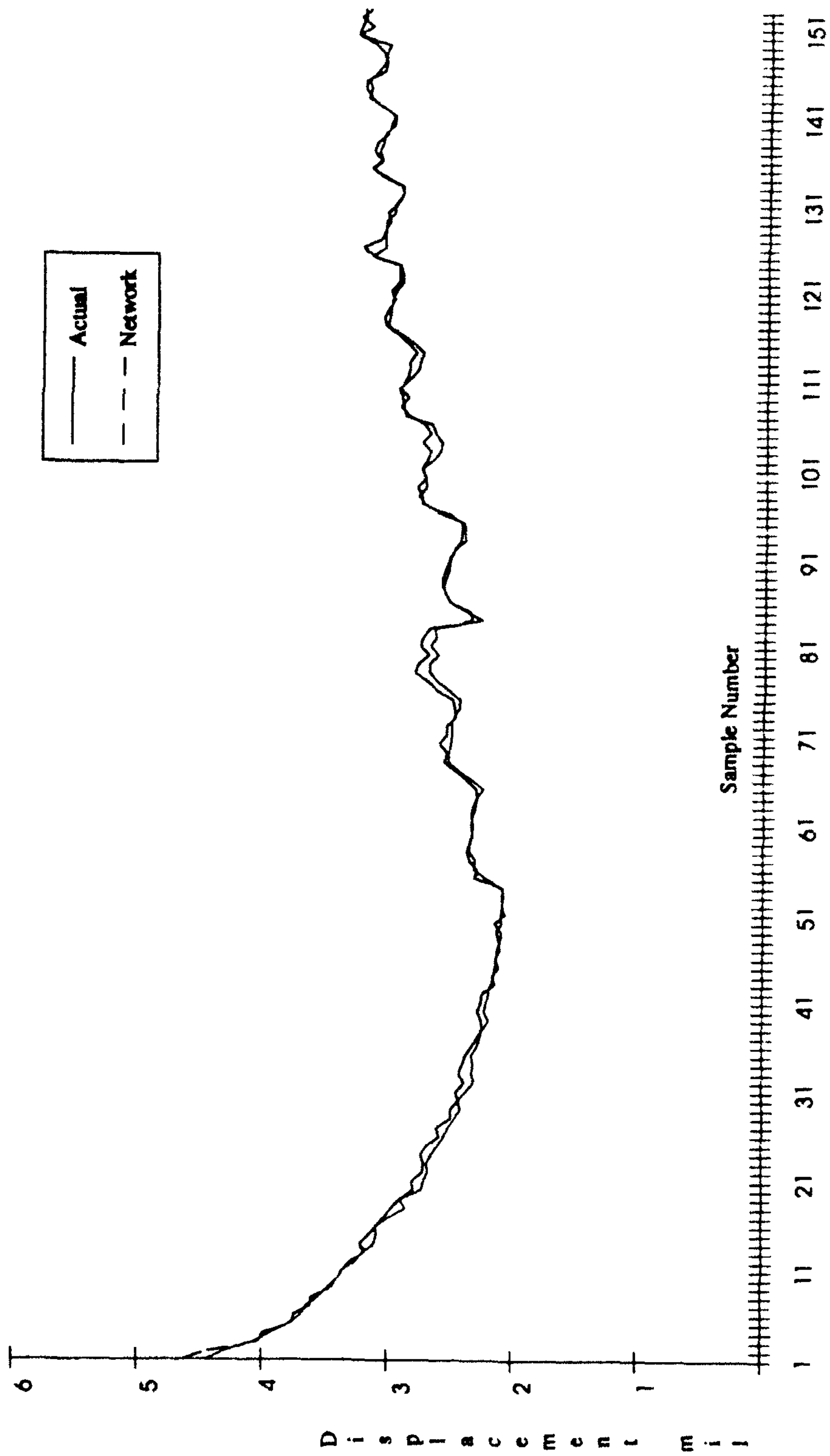


Figure 14. Network Results for Training Data at One Position - Z Direction

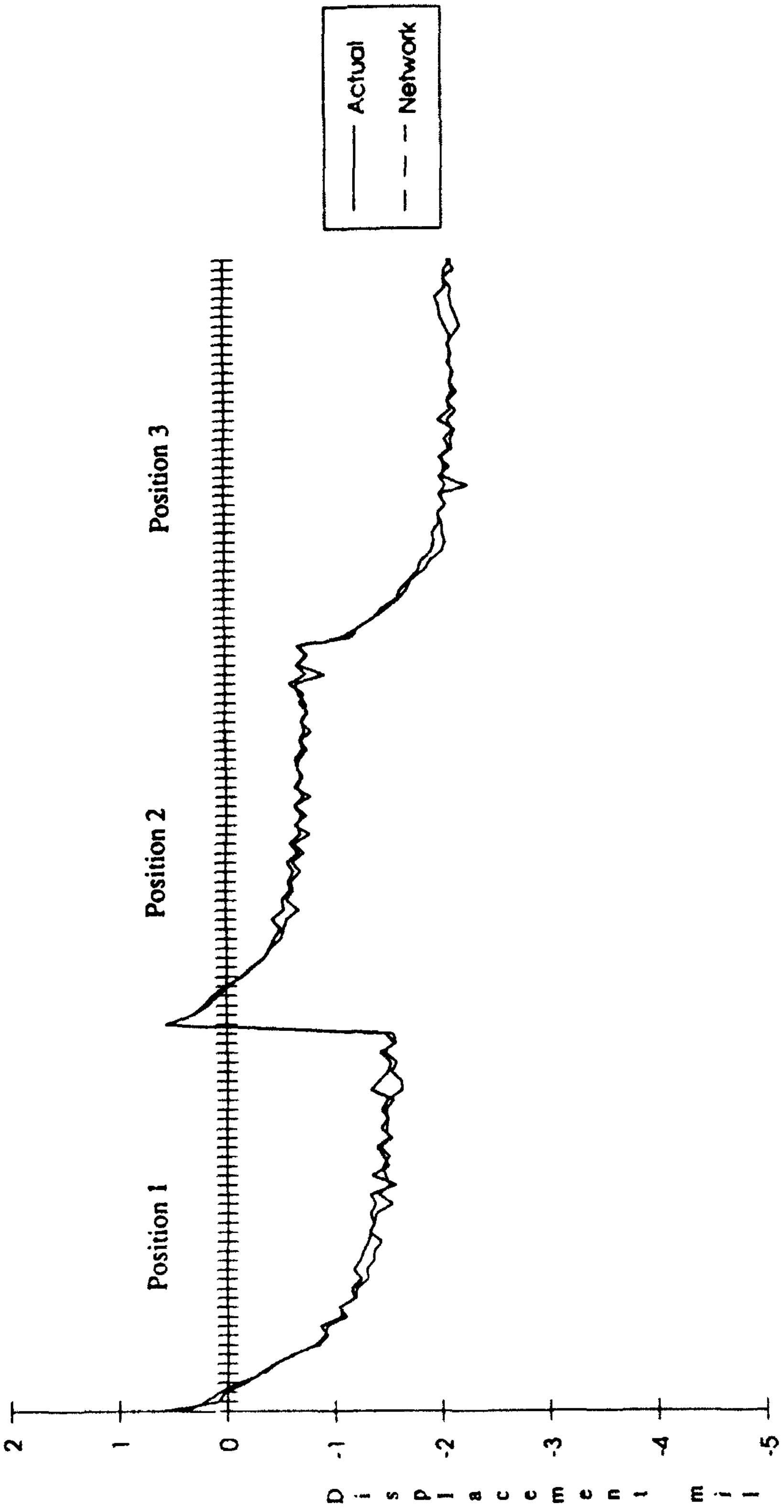


Figure 15. Network One Position Result for Training Data at 3-Position - X Direction

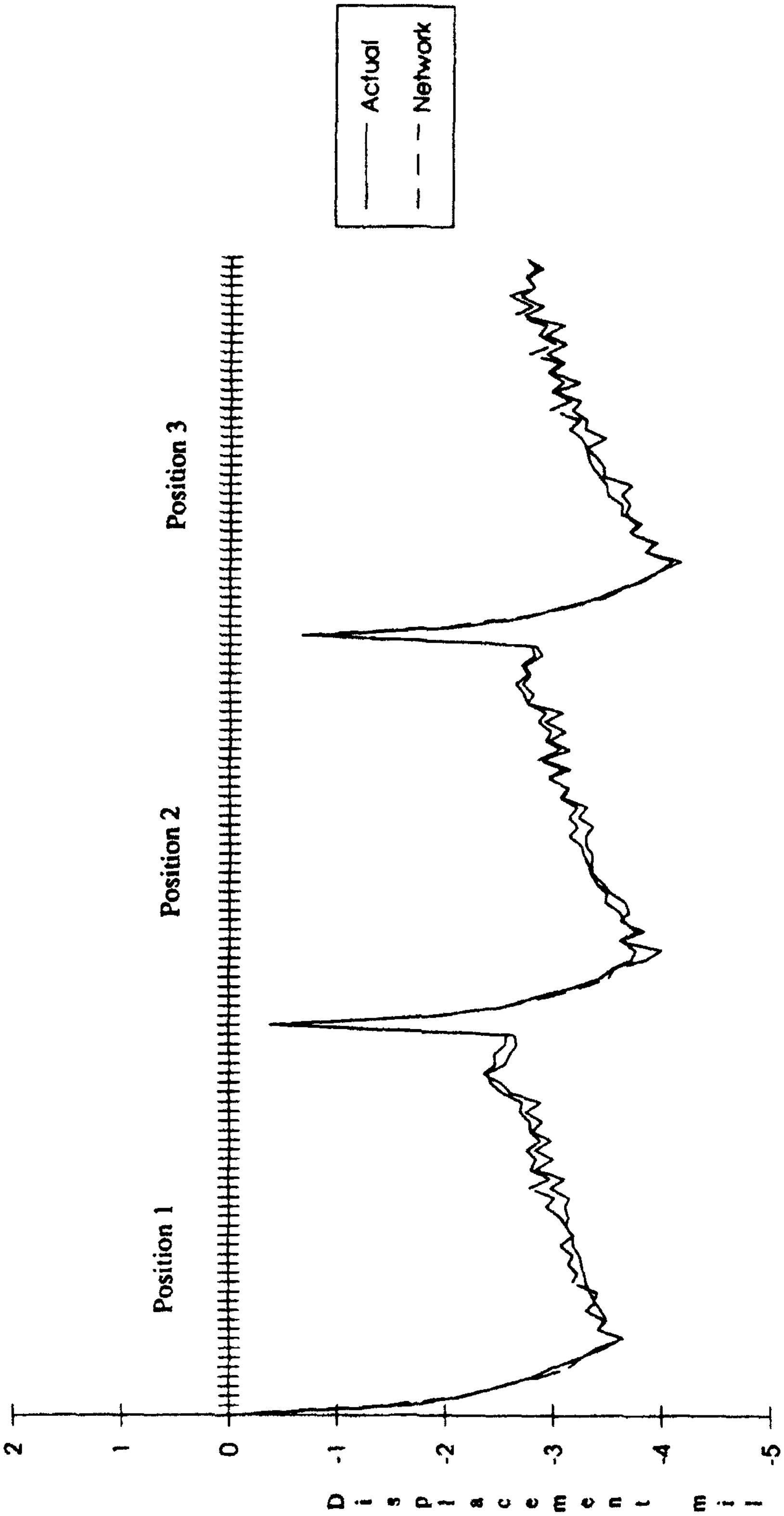


Figure 16. Network Result for Training Data at 3-Position - Z Direction

Table 3a. Results of Network Evaluations

	Condition	Base Network 25 Inputs, 13 Nodes			13 Inputs, 13 Nodes			5 Inputs, 13 Nodes			Time Delay 50 Inputs, 13 Nodes		
Date		Avg. Abs. Error (%)	RMS Error (%)	Max Abs. Error	Avg Abs. Error (%)	RMS Error (%)	Max. Abs. Error	Avg. Abs. Error (%)	RMS Error (%)	Max Abs. Error	Avg Abs. Error (%)	RMS Error (%)	Max Abs. Error
12/17	Baseline	.53	.97	.29	.66	1.2	.36	2.0	3.7	.96	.50	.92	.34
12/18	Different Ambient	.66	1.5	.66	.76	1.5	.74	1.6	3.2	1.44	.66	1.3	.52
12/19	Different Ambient	.47	.88		.70	1.3		1.4	2.8		.50	.92	
12/21	Different Ambient	.50	.94		.50	.92		1.4	2.8		.53	.97	
12/23	Increase Chiller Temp from 120 to 135 degrees	1.51	2.5	.64	1.2	2.0	.36	6.1	10	1.97	1.6	2.6	.48
12/28	Heat Guns on Headstock at Start of Test	3.5	5.9	1.07	2.5	4.3	.88	2.2	3.8		4.1	7.0	1.06
12/29	Repeat Baseline	1.1	1.8	.37	1.1	1.8	.42	2.3	4.2	1.16	1.0	1.8	.34
12/30	Infrared Lamps	2.4	4.0		2.5	4.1		2.0	3.3		2.2	3.5	
1/6	Repeat Baseline	2.2	4.1		2.2	3.9		2.8	4.9		2.5	4.8	

All errors except RMS are absolute.

Table 3b. RMS Error (%)

Nodes	12/17	12/18	12/30
7	1.6	1.6	5.6
9	1.2	1.4	5.2
11	1.5	1.8	5.1
13	1.3	1.6	7.5
15	1.3	1.8	8.4

General Network Summary:

Conditions 1 (25 inputs, 13 nodes) and 4 (time delay inputs, 13 nodes) have similar predicted results. Reducing the number of inputs to 13 (condition 2 - 13 inputs, 13 nodes), produces mixed results – accuracy is sometimes improved and sometimes worsened. Decreasing the inputs to 5 (conditions 3 - 5 inputs, 13 nodes) results in a higher error between actual and predicted output in most cases.

The last step in the initial evaluation of the network was to apply it to data which was different from the data trained on. For this, the data from the first repeatability test on December 29 was used. Experimental results from this test, given in Figures 17 and 18, indicated that the test repeated very well, thus test conditions were very similar to the baseline.

The results of this testing of the network are given in Figures 19 and 20 and Table 3. Again, the network prediction agrees well with the actual displacement. The network thus is capable of processing data which is completely different from the data trained on and not only gives a valid result, but a result which is accurate in its representation of the machine's response to the test conditions.

3.4.4 Result of Repeatability Studies

The results shown in Figures 17 and 18 indicated that the experiment repeated very well. This provides a good level of confidence that the experimental conditions were consistent with no unwanted variables producing errors. The underlying conclusion is that the results for the tests run between the baseline test on December 17 and December 29 resulted only from the parameters set for the tests.

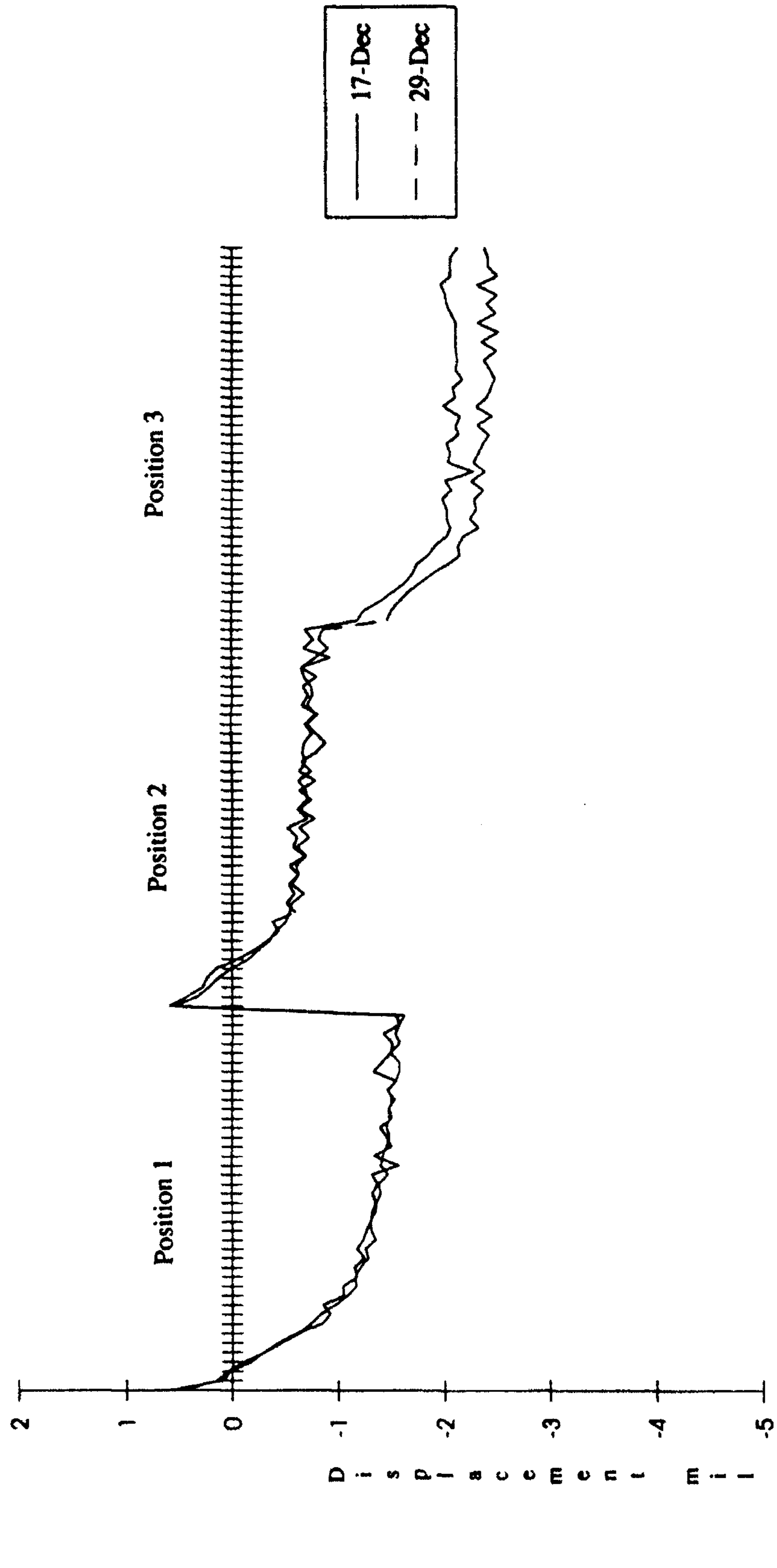


Figure 17. Displacement Result for December 29 Repeatability Experiment - X Direction

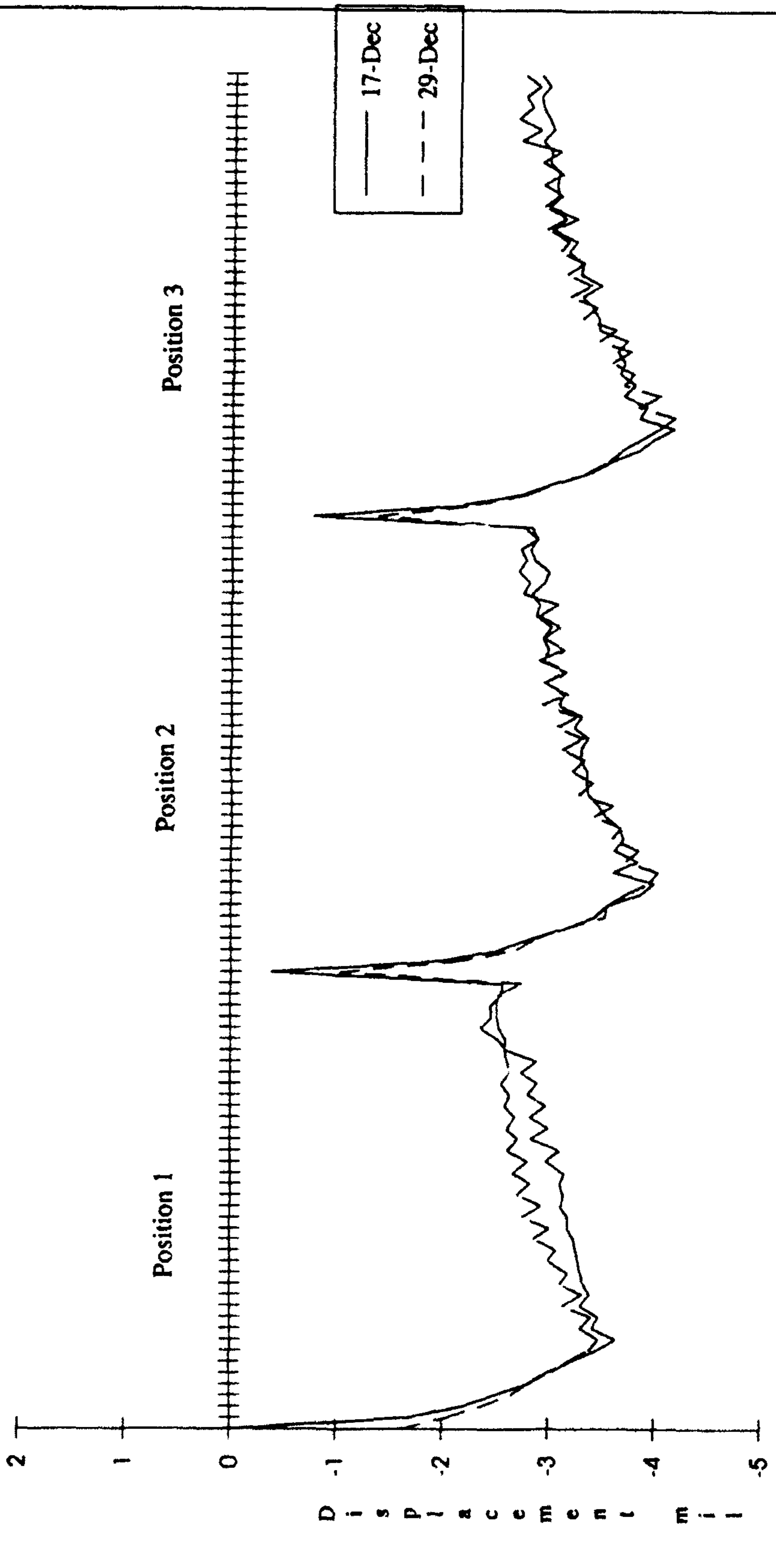


Figure 18. Displacement Result for December 29 Repeatability Experiment - Z Direction

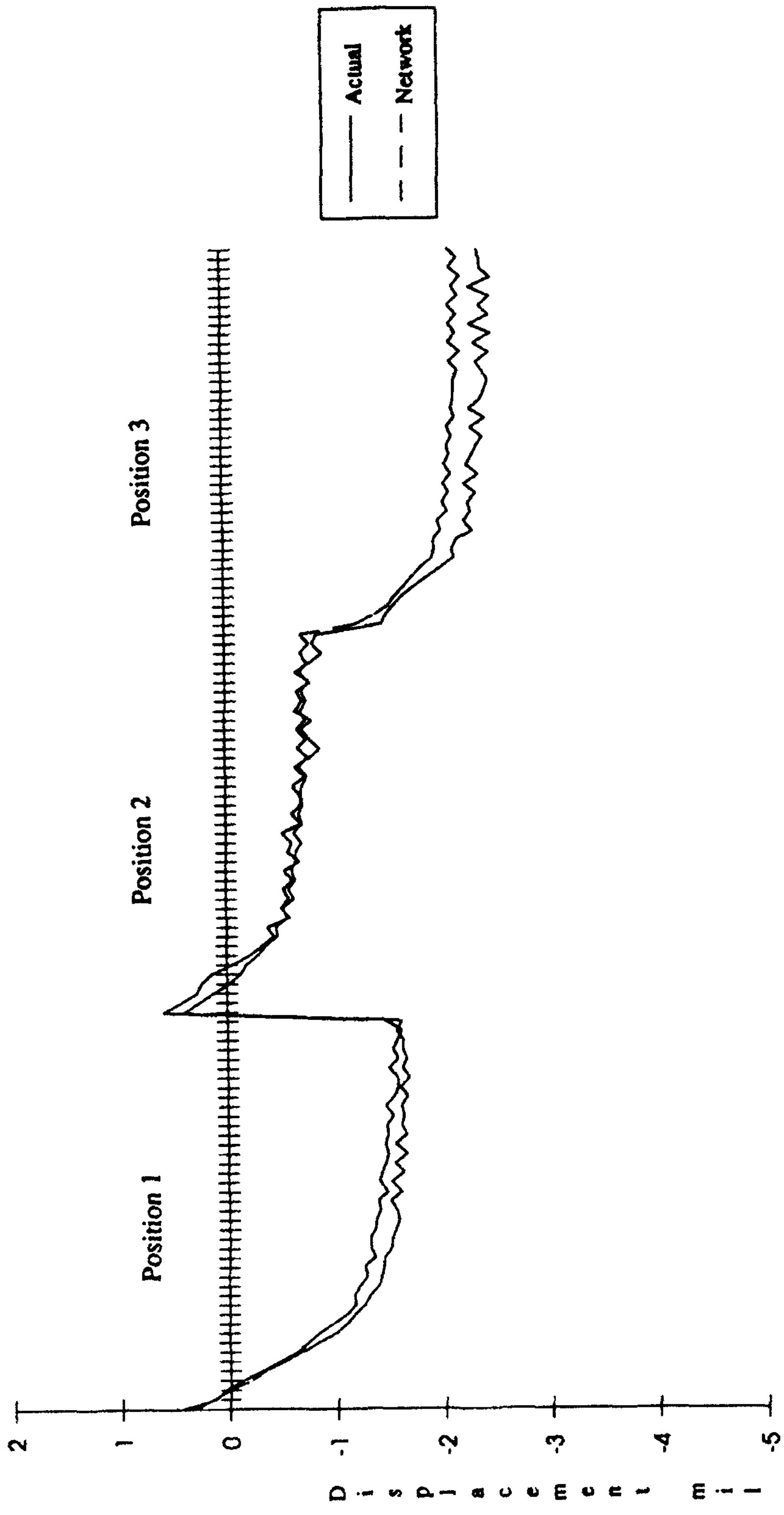


Figure 19. Network Result for December 29 Repeatability Experiment - X Direction

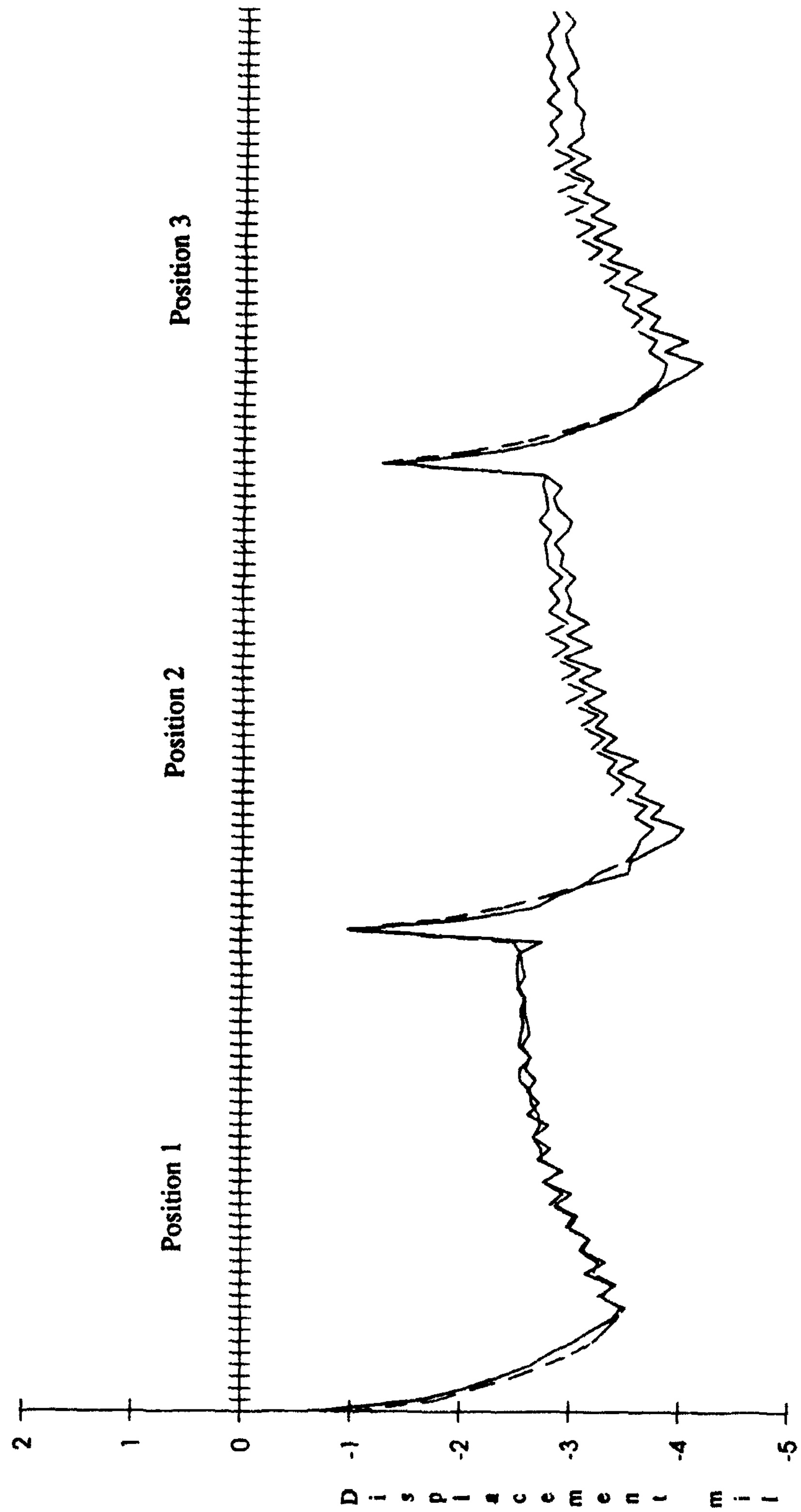


Figure 20. Network Result for December 29 Repeatability Experiment - Z Direction

An additional repeat test was run after the rest of the experiments. The results of this repeat (on January 6) are given in Figures 21 and 22 where it can be seen that displacement for the January 6 test is not the same as with the tests of December 17 or 29. The form of the displacement change with temperature is still the same and the displacement in the Z direction was about the same, but a shift in amplitude (termed an "offset") occurred in the +X direction for position 1 and the -X direction for position 3. A careful study of the temperature data uncovered no change that would indicate a reason for this difference in displacement. A study of other factors which could cause such a change in displacement resulted in only one probable cause; the reference part moved in the chuck. The chuck is actuated hydraulically, thus a momentary relaxation, such as an accidental "bump" of the actuation lever, would let the part become loose in the chuck and, when reclamped, would be in a slightly different position. It is important to keep in mind the result of this repeat test when evaluating the tests done after December 29. Offsets in the X direction could be caused by the (probable) affect of unclamping and clamping the chuck as well as the variable under study.

The network was then tested on the repeat data from January 6. The results of this, given in Figures 23 and 24, show that the network predicted displacement as if the part/chuck positioning error had not occurred. This is just as expected, because the network can only predict changes in outputs which are directly related to the information in its inputs.

3.4.5 Results of Ambient Studies

As emphasized in the results of the bench test portion of this project and the repeatability studies above, an artificial neural network can only predict results due to inputs it has been trained on. For this reason, two experiments were run on December 19 and December 21 with the turning center exposed to different ambient laboratory temperatures. The network was then trained on a combination of data from these tests and the baseline test (December 17, December 19 and December 21). This then supplied it with the knowledge to be able to predict changes in displacement due to ambient changes. The network, trained in this manner, then became the base network that was used for evaluation of all the other thermal input studies. (This was also the network used in the repeatability studies.)

The base network was then tested on data from another experiment (run on December 18) in which the ambient temperature was lower than the baseline, 67 degrees at the start as compared to 71 degrees at the start for the baseline experimental test. The results of this are given in Figures 25 and 26 and Table 3. Comparison of the actual data in these figures with the actual data from the baseline test, given in Figures 13 and 14, shows that the lower ambient temperature caused a difference in displacement of .0003 inch to .0005 inch. More detail on this is given in comparison plots shown in Appendix C. Figures 25 and 26 show that the network prediction agrees very well with the actual, indicating that the network did an excellent job of predicting change in displacement due to a change in ambient temperature.

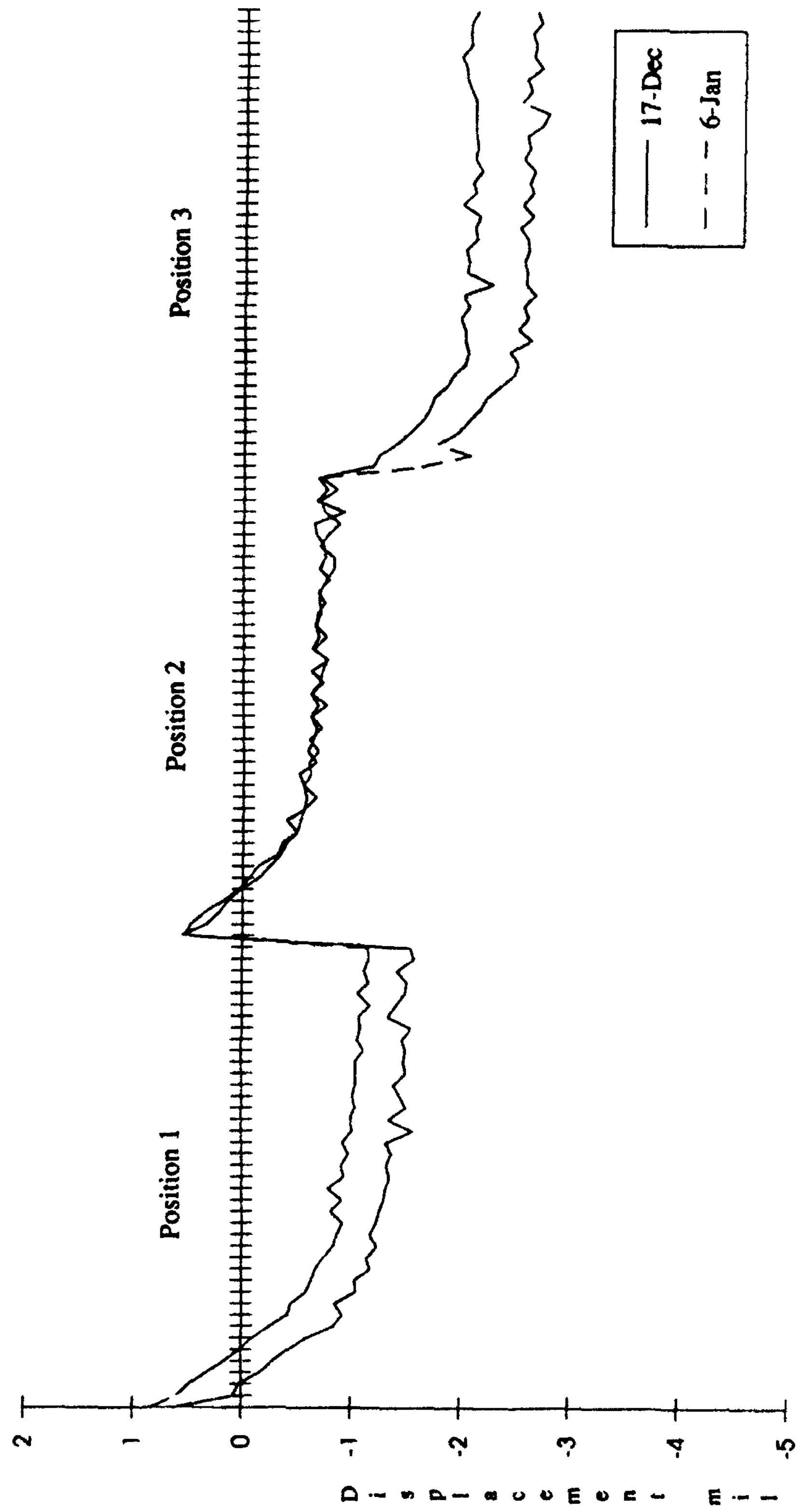


Figure 21. Displacement Result for January 6 Repeatability Experiment - X Direction

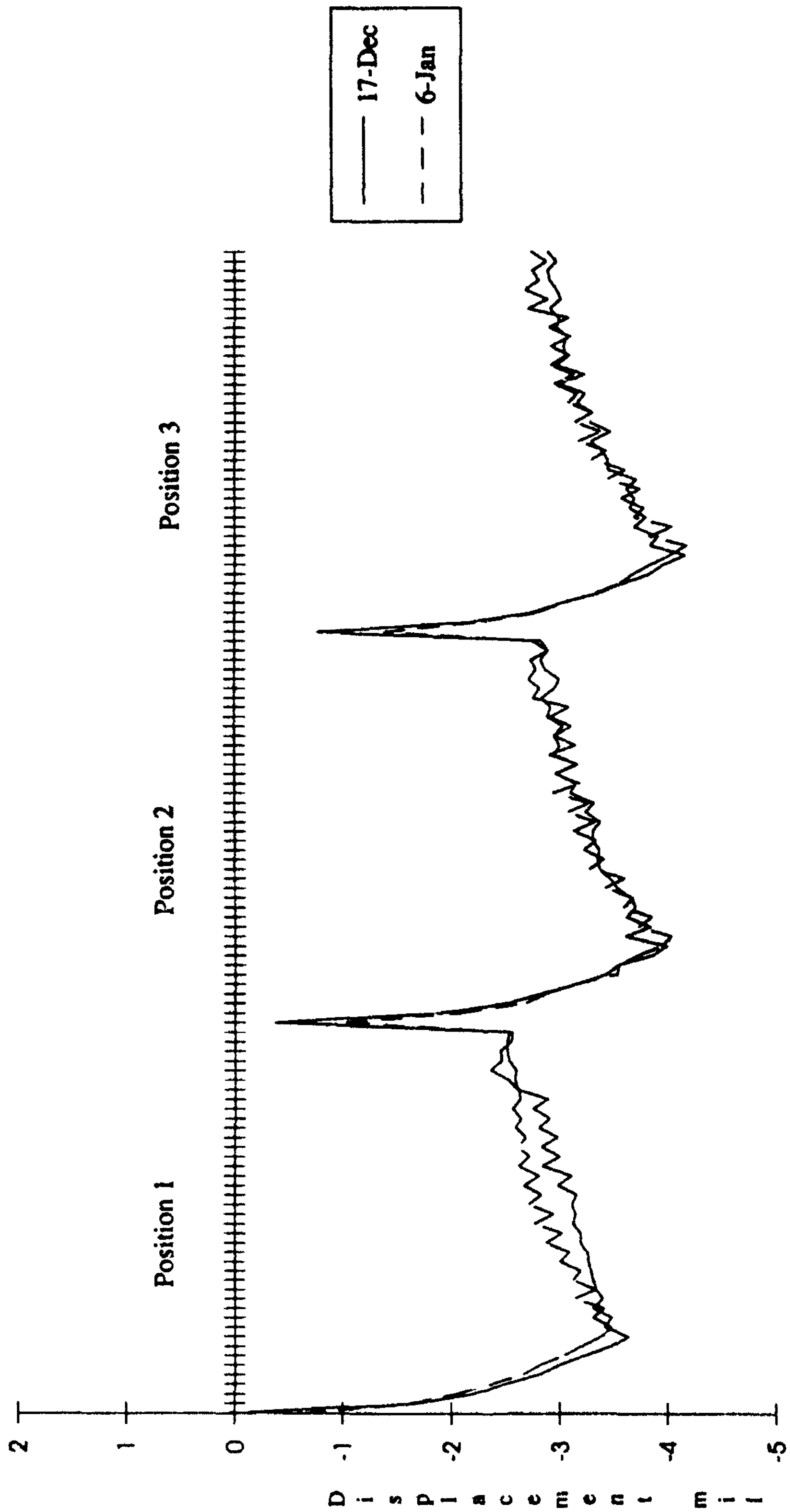


Figure 22. Displacement Result for January 6 Repeatability Experiment - Z Direction

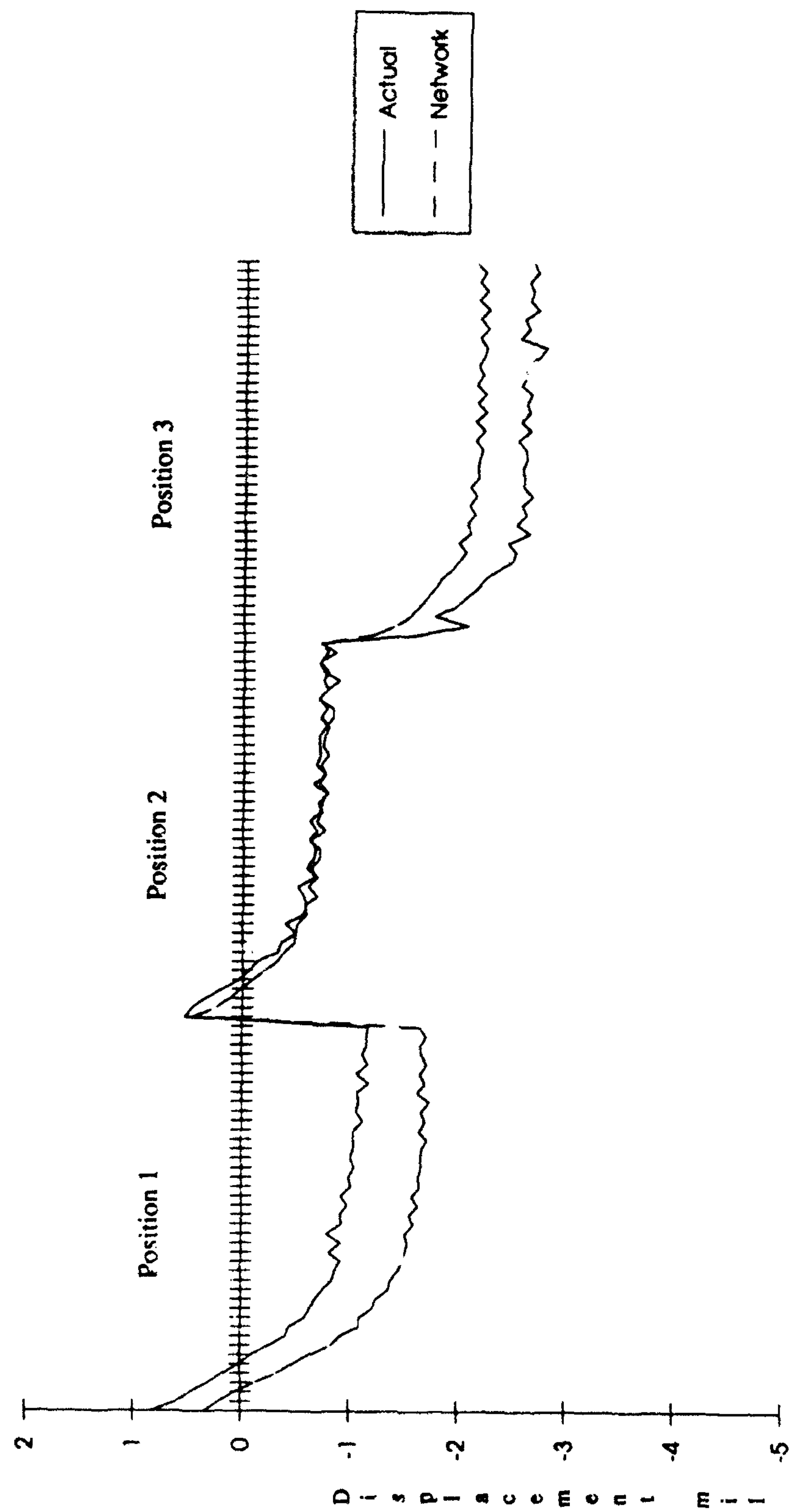


Figure 23. Network Result for January 6 Repeatability Experiment - X Direction

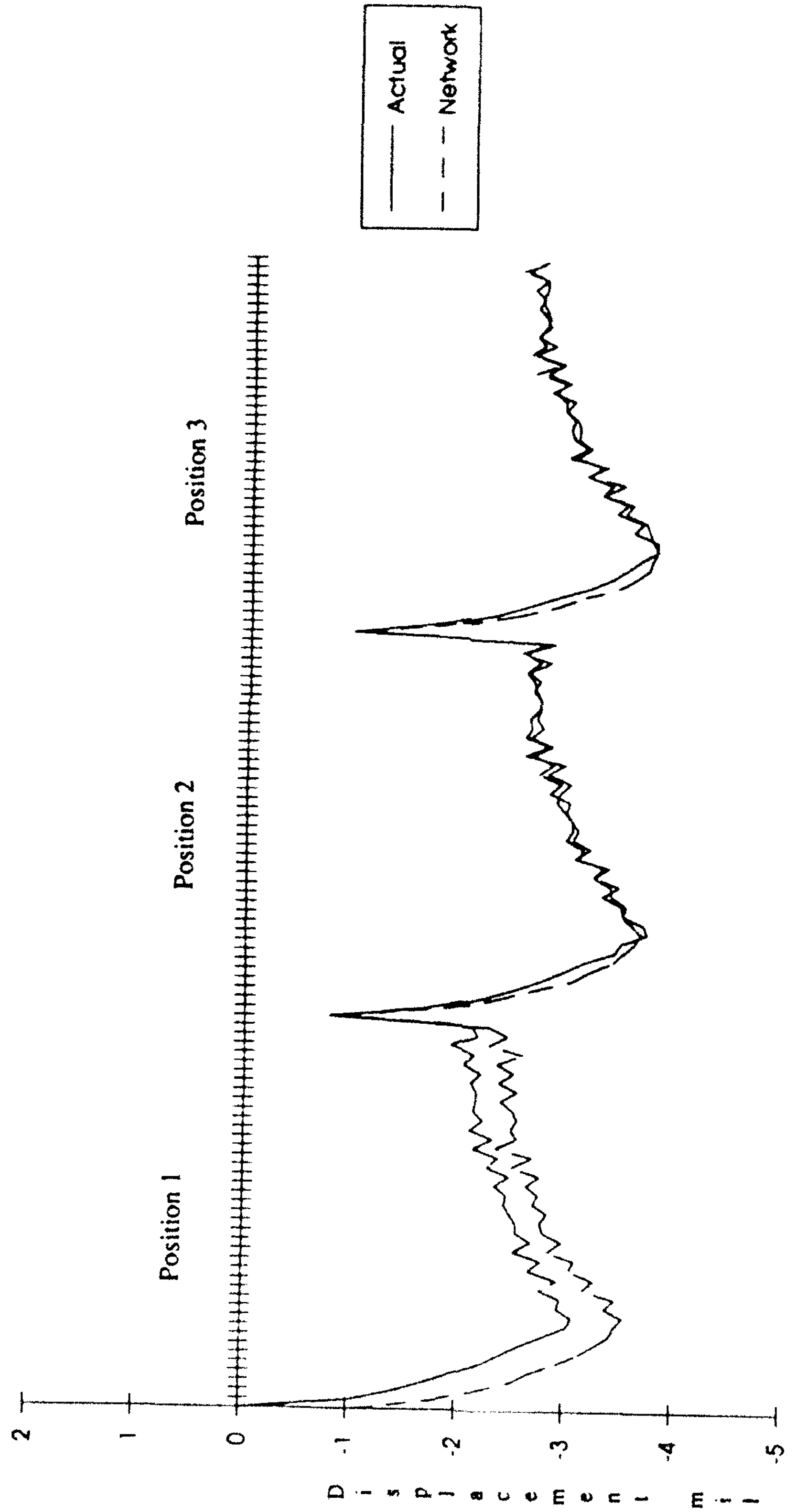


Figure 24. Network Result for January 6 Repeatability Experiment - Z Direction

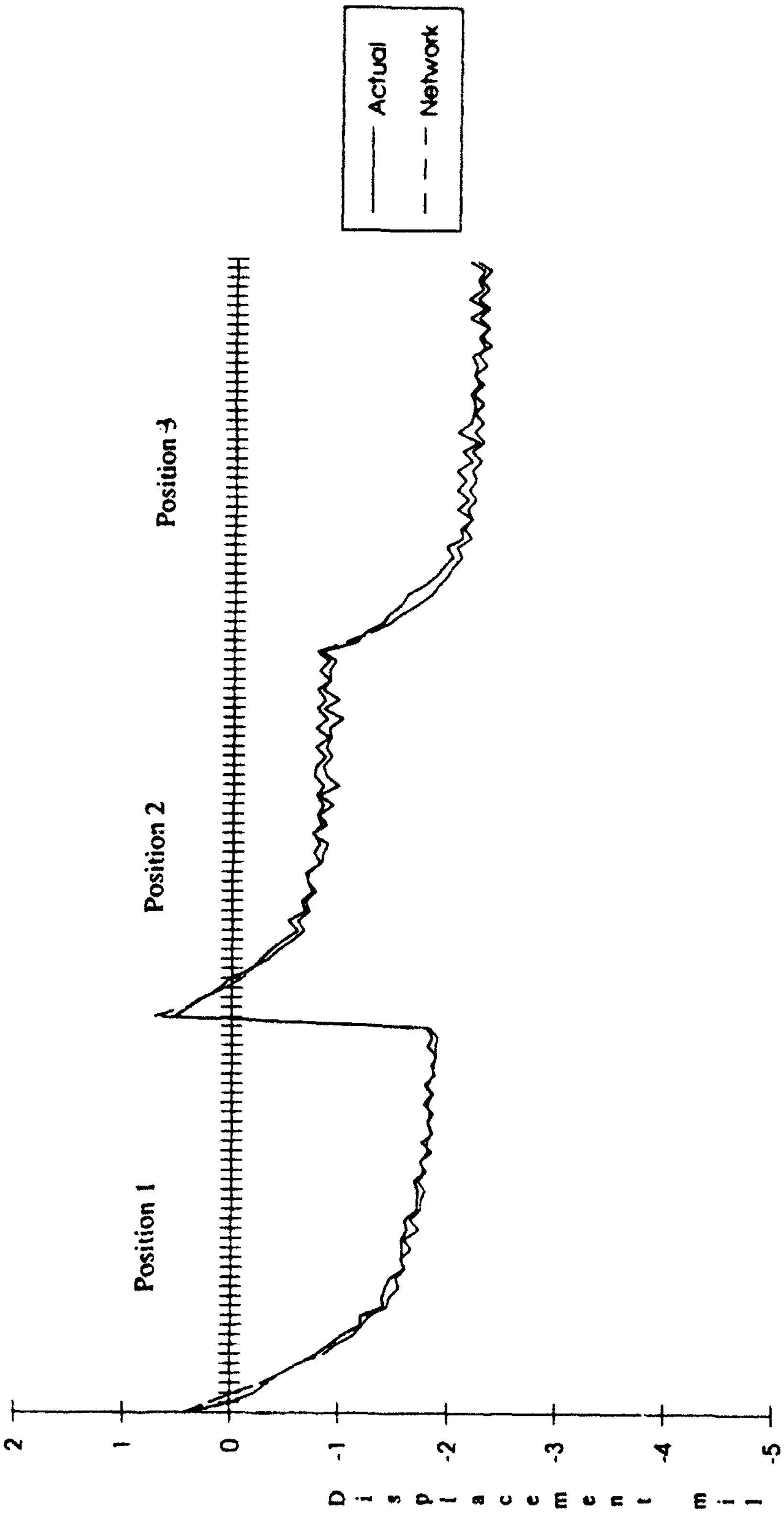


Figure 25. Network Result for Different Ambient - X Direction

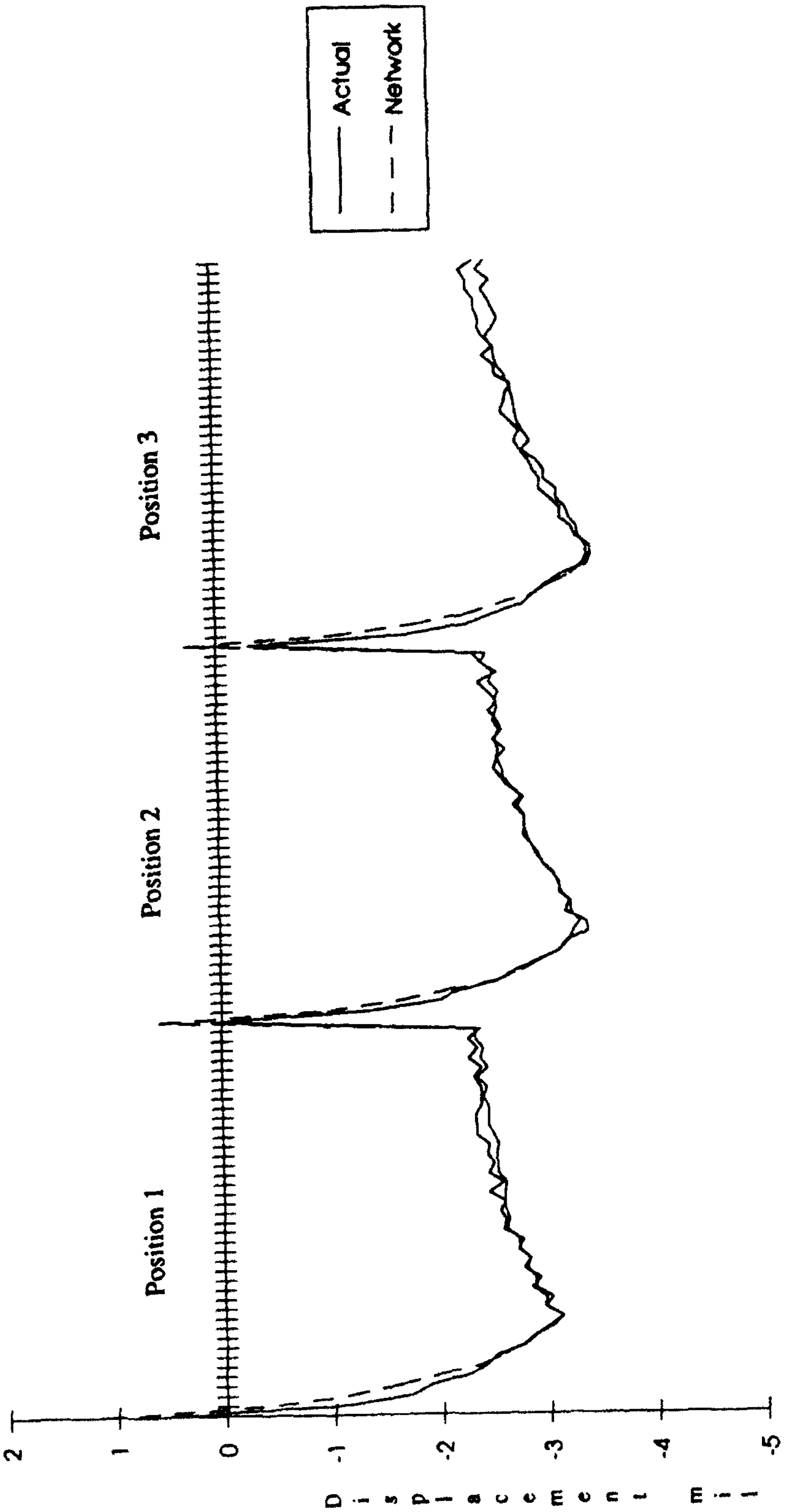


Figure 26. Network Result for Different Ambient - Z Direction

3.4.6 Results of Changing Hydraulic Oil Chiller Setting

The chiller thermostat was changed to a limit of 135 degrees compared to the standard limit of 120 degrees. The network was not specifically trained on this input, thus its ability to predict the changes in displacement will depend on the similarity of temperature response for this input as compared to the inputs trained on.

Comparison of the displacements measured with this input and the baseline test show a significant effect, with Z axis displacement increasing by up to about .0008 inch and X axis displacement increasing by up to about .0007 inch. Further information on this can be obtained from the results presented in Appendix C. Even though the network was not trained specifically on this type of input, it predicted most of this change as shown in Figures 27 and 28 where the degree of fit, although not perfect, is much better than if there were no correction for the chiller effect. Table 3 shows that the error, although greater, is still not large. Thus the network demonstrates that the thermal information contained in the baseline test, plus the addition of ambient effects, is sufficient to permit some prediction of other effects as well.

3.4.7 Results of Studies of Thermal Input to Headstock

Additional thermal energy was input to the headstock by directing heated air from two heat guns at it. These were positioned about 3 inches above the spindle centerline at distances of 16 inches and 27 inches from the face of the chuck. A total of 3500 watts was produced by the heat guns. The network was not trained specifically on this type of thermal energy either, thus its ability to predict the change in displacement will also depend on the similarity of response for this input as compared to the inputs trained on.

Comparison of the displacements measured with this input and the baseline, given in Appendix C, show a response very different from the type found with the other thermal inputs with the Z direction displacement <u>decreasing</u> in magnitude by up to .0008 inch. In the X direction the displacement followed the pattern set with the other thermal inputs and increased by up to .0008 inch. The network was not able to predict the deflection here nearly as well as with the other inputs. Figures 29 and 30 show that it did very poorly in the Z direction at all three positions and in the X direction it did poorly at position 3. The errors listed in Table 3 also indicate poor prediction accuracy.

The reason for these results is that the network did not have information on the affects of thermal energy input to the headstock. The network was not trained specifically with data collected using this type of thermal input and the basic information collected to provide training for the other inputs did not contain information adequate to predict displacement accurately.

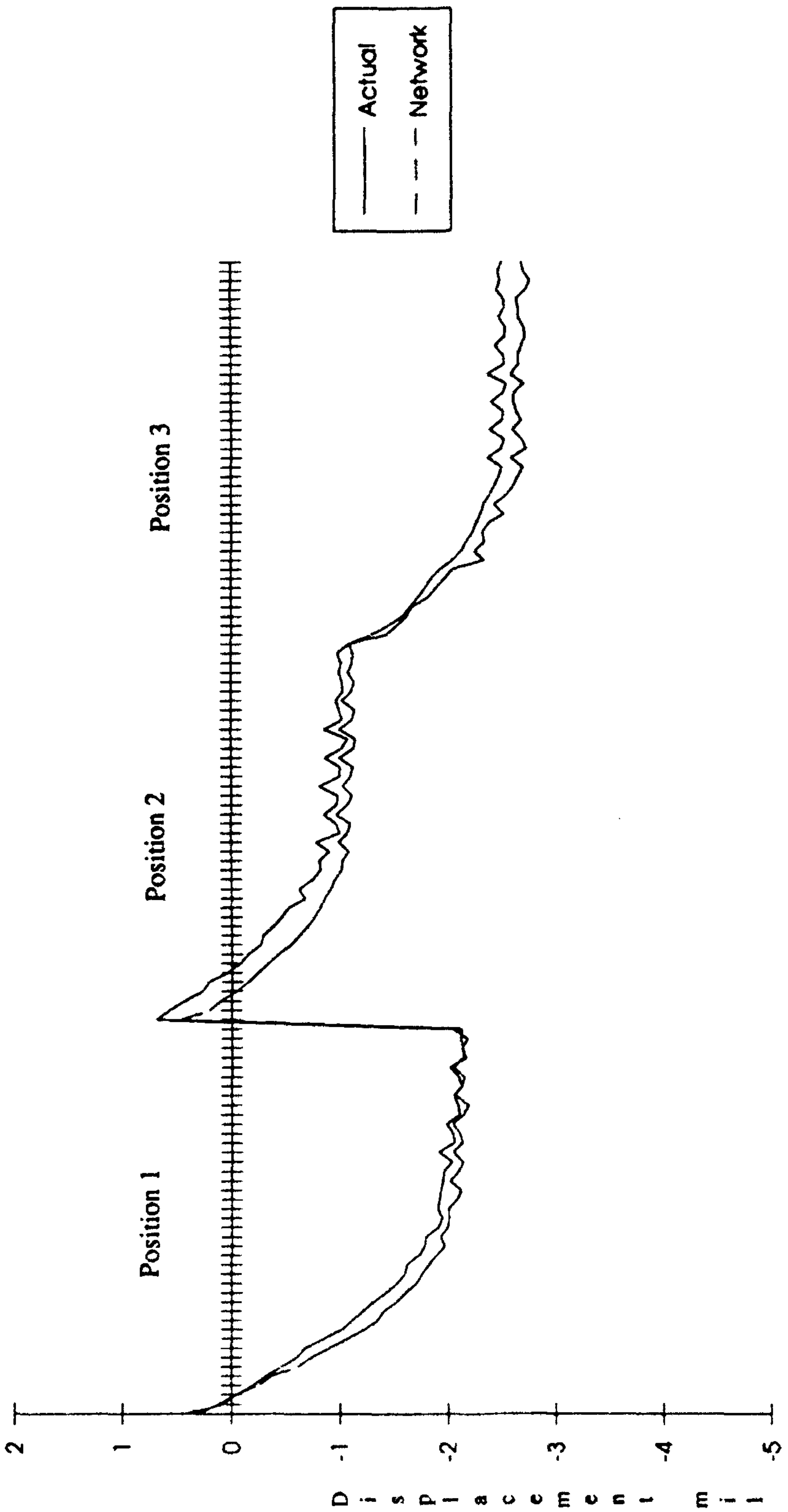


Figure 27. Network Result for Different Chiller Setting - X Direction

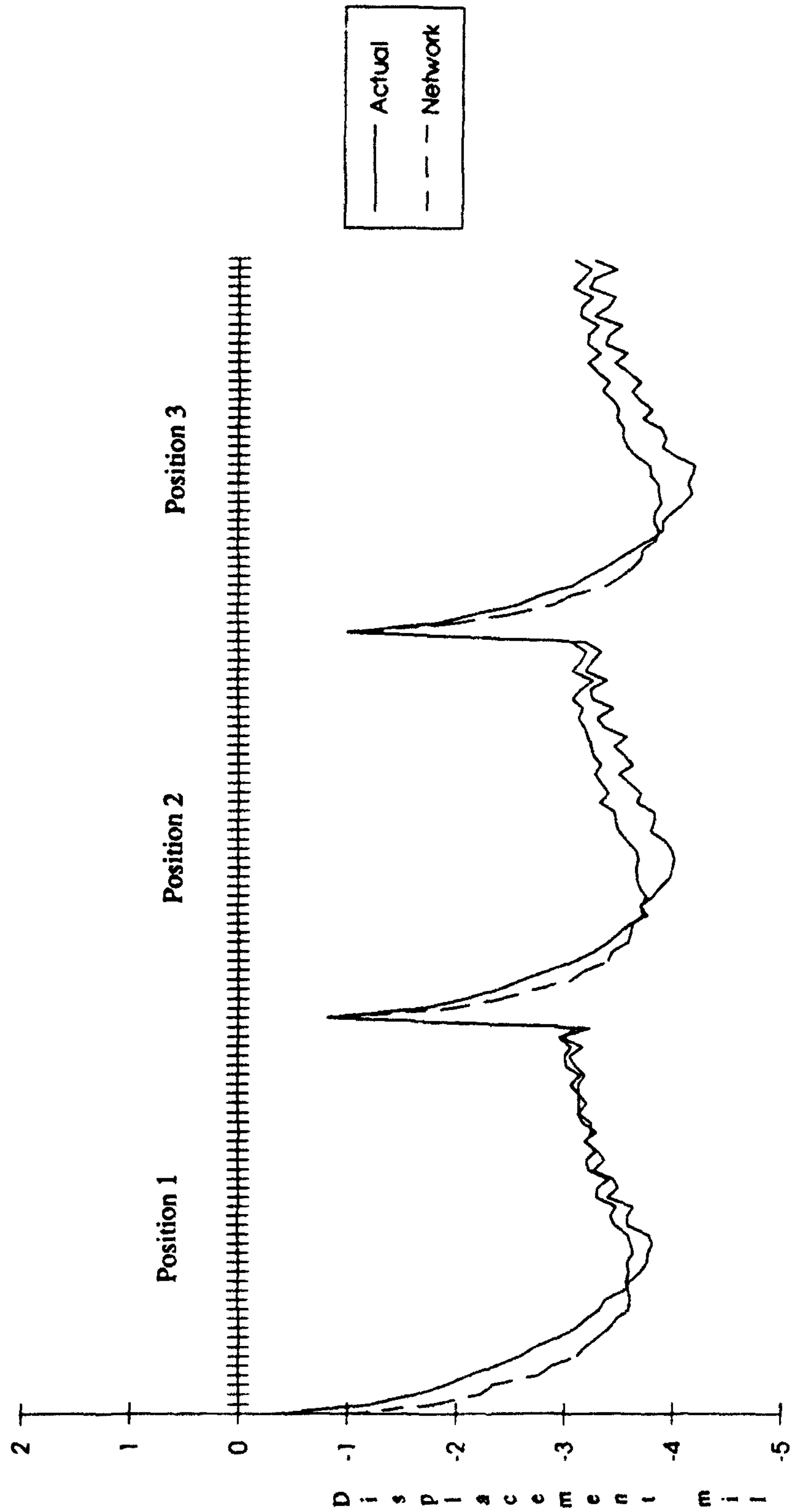


Figure 28. Network Result for Different Chiller Setting - Z Direction

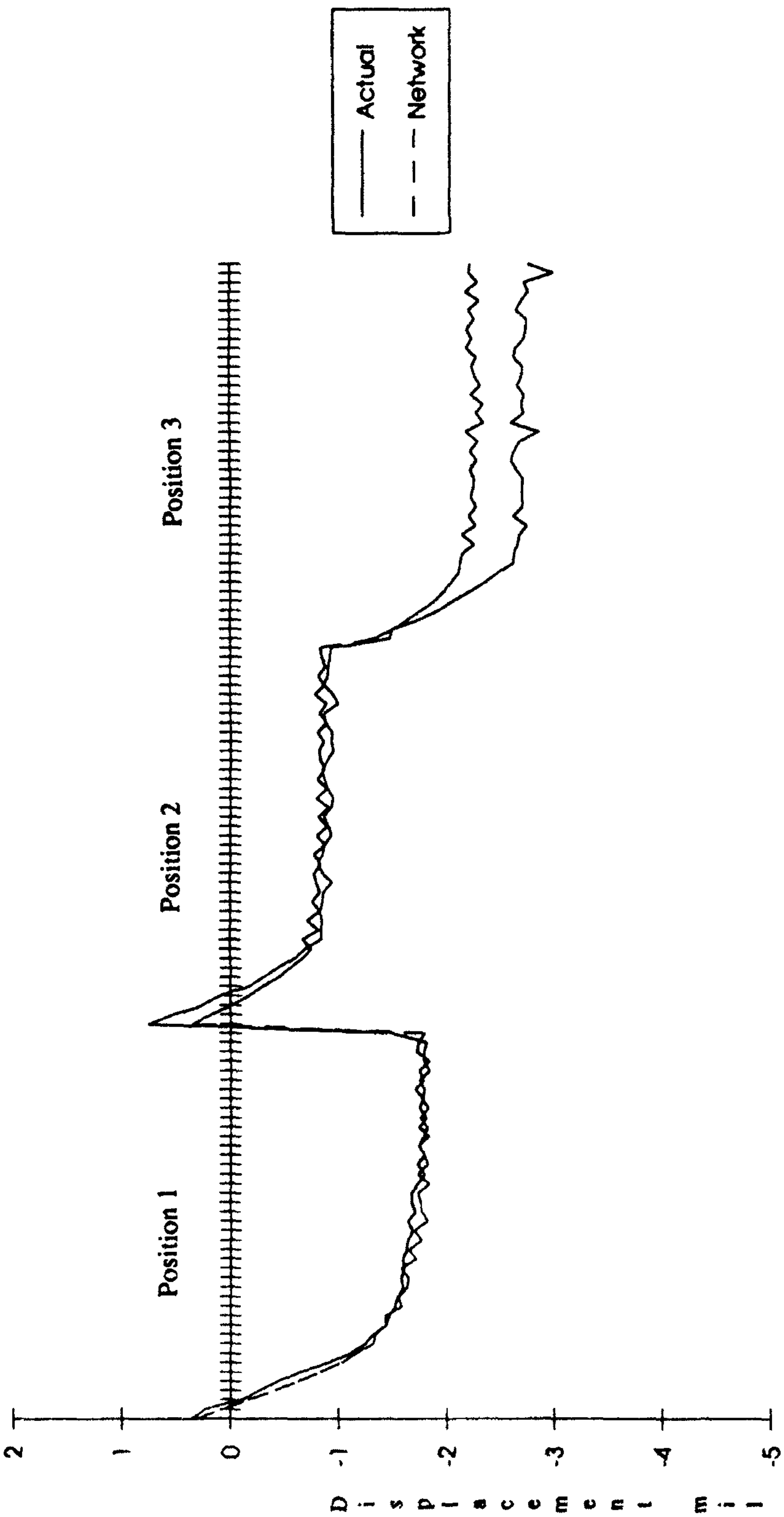


Figure 29. Network Result for Thermal Input to Headstock - X Direction

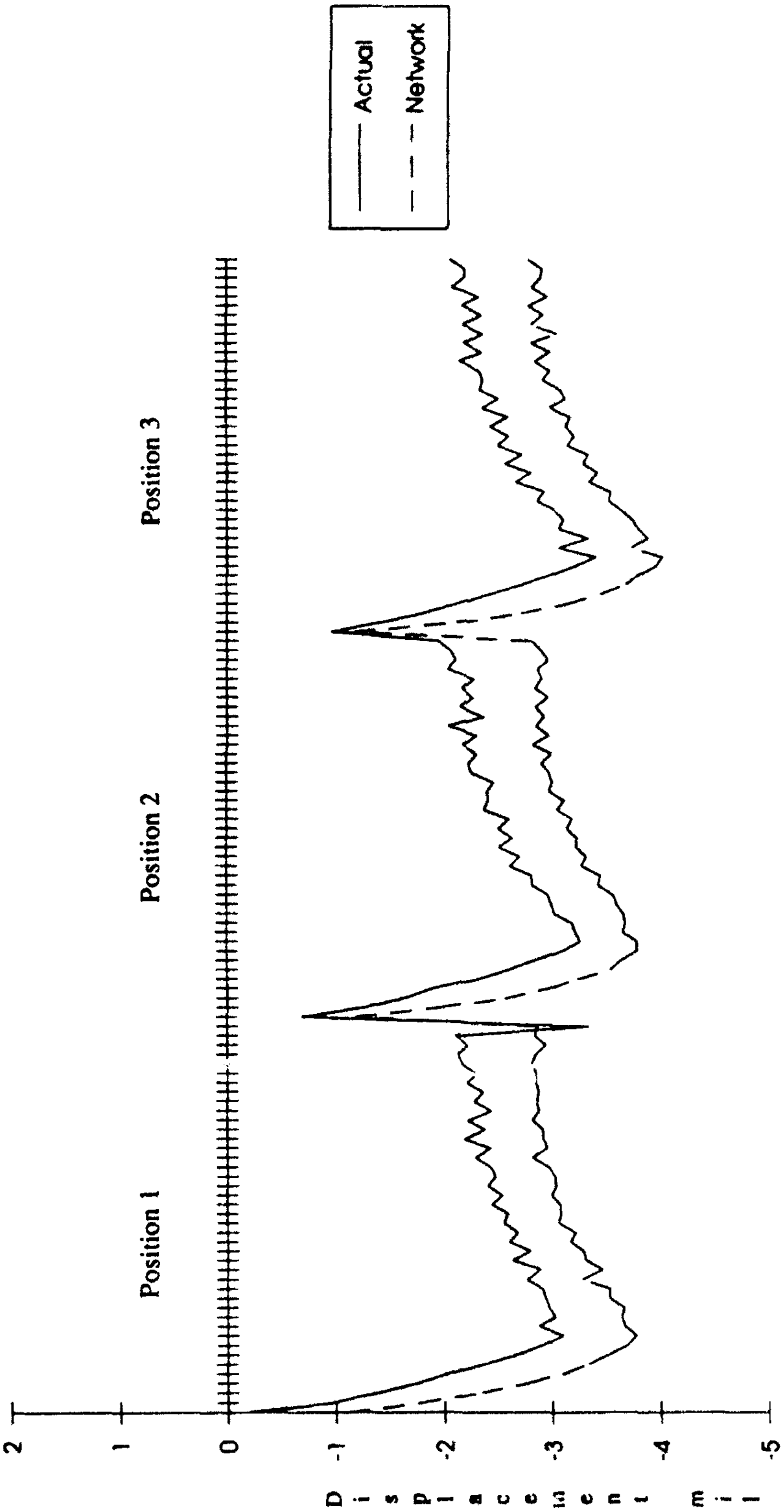


Figure 30. Network Result for Thermal Input to Headstock - Z Direction

3.4.8 Results of Studies of Thermal Input to Bed

An additional thermal input to the bed of the turning center was accomplished through the use of seven infrared lamps which were directed at the rear of the bed. The total energy input was 1700 watts. The network was not specifically trained on this input, thus its ability to predict the change in displacement will also depend on the similarity of response for this input as compared to the inputs trained on.

Comparison of displacements measured with this input and the baseline test also show a significant effect, with the Z axis response decreasing by up to about .0007 inch, and the X axis response decreasing by up to about .0005 inch. Refer to the results given in Appendix C for details. The network adjusted for part of the change on the Z direction, but did not adjust well for differences from baseline in the X direction. This is illustrated in Figures 31 and 32. Errors listed in Table 3 also indicate this. However, recall that the repeat test run on January 6 indicated a change in the displacement in the X direction that was due to an unknown change in test conditions which occurred after the December 29 repeatability test. Since the test with thermal input to the bed occurred after December 29, there is a question as to whether the change in displacement seen in the X direction is due to the thermal input or a result of the change in test conditions.

3.5 Results of Network Studies

During the initial phases of this program several different configurations of neural networks were evaluated. Many of these same configurations, all involving application of the modified back propagation network, were also tested as part of the studies involving the turning center. The following is a listing of the test variations.

1. The number of inputs was decreased from 25 to 13 and from 25 to 5.

2. The number of nodes in the hidden layer was varied from 7 to 15 (using only odd numbers).

3. Time delay was incorporated in the input data.

4. Data vectors were input in sequence now (randomized) as opposed to the base network where the data vectors were randomized.

5. A commercial network was evaluated.

6. Evaluation of the network's ability to predict displacement at positions not trained on.

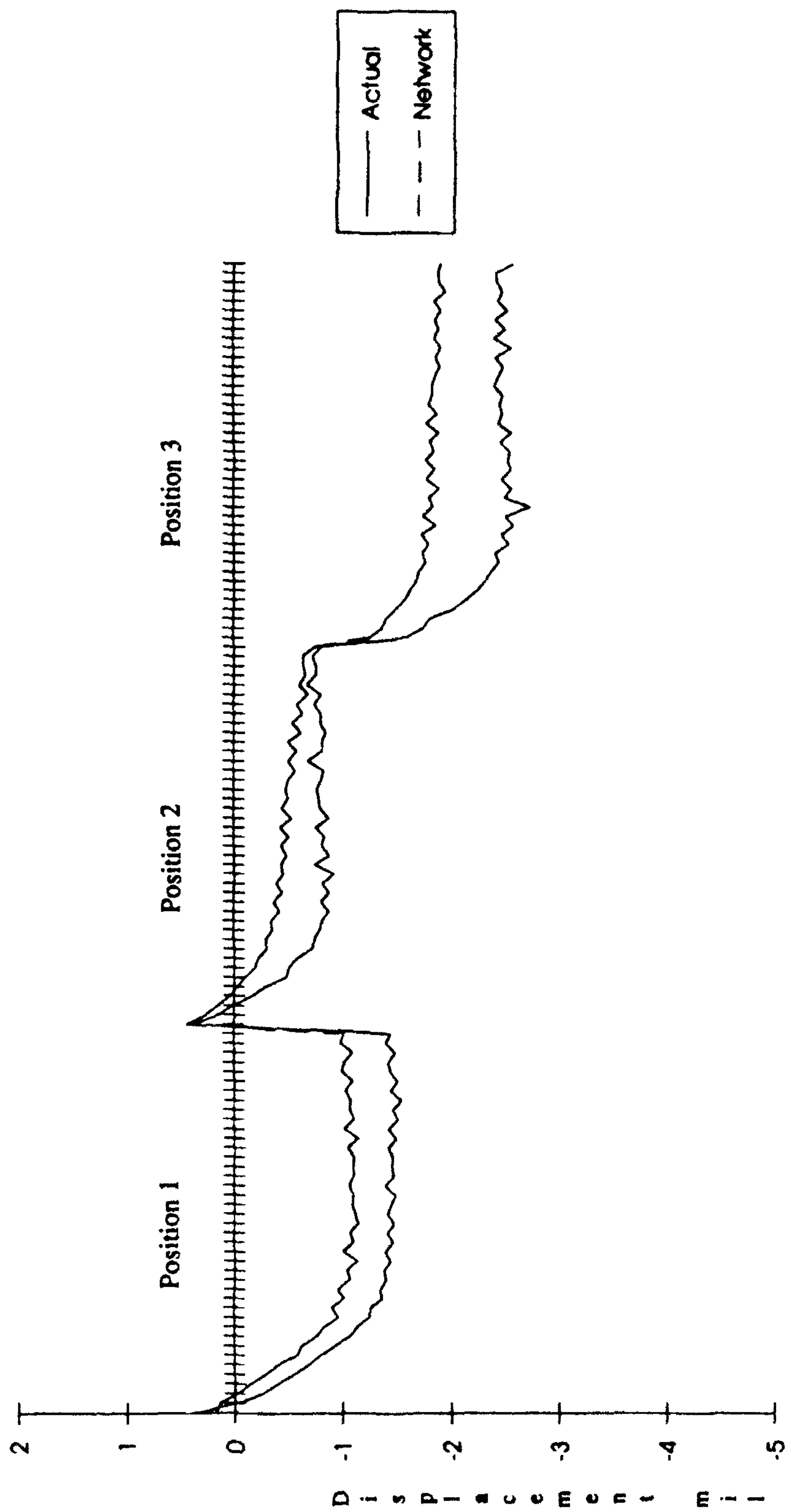


Figure 31. Network Result for Thermal Impact to Bed - X Direction

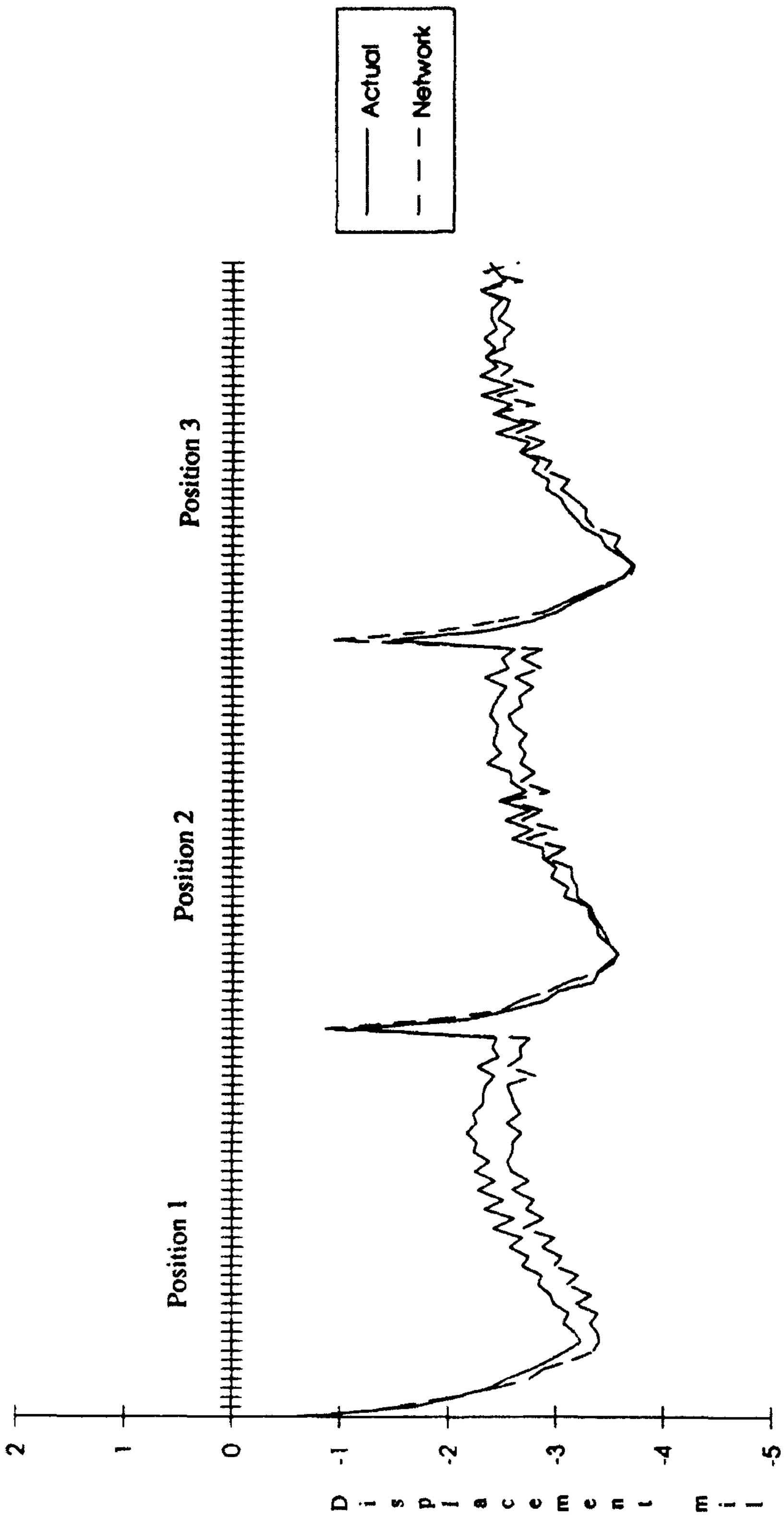


Figure 32. Network Result for Thermal Impact to Bed - Z Direction

In all cases, the modified network was trained on the same combined data (from the experiments on December 17, December 19 and December 21) used for the base network. It was then tested on one of the test cases used for the base network and the results compared to the results obtained from the base network.

3.5.1 Evaluation of Different Numbers of Inputs

For these experiments the number of inputs was reduced by removing some of the thermocouple inputs. The X and Z coordinates of the measurement positions were retained as inputs to the network in both cases. Listings of the thermocouples retained are given in Table 4. In order to decide which thermocouples to remove, the temperature data was evaluated. From this it was found that the temperature measurements fell into certain "families" (as far as overall level and trends with time were concerned) as can be seen in Appendix D. It was reasonable to assume that all thermocouples in these "families" would not be needed to assure adequate information on the temperature state of the turning center during the baseline and ambient tests. Other information bearing on which thermocouples to remove was obtained from the commercial network where a "contribution" factor was produced. Thermocouples providing small contributions to network training could more likely be removed without adversely affecting accuracy.

Table 4. Listing of Inputs for Reduced Input Network Evaluations

The following inputs were used for the network with 13 inputs:

Thermocouple at Z-way at left
Thermocouple at Z-way at middle
Thermocouple at Z-way at right
Hydraulic line
Hydraulic return pipe
Headstock at top of spindle
Oil in headstock
Oil in headstock
Headstock at side of spindle
Plate on headstock on side opposite spindle
Ambient
X coordinate
Z coordinate

Table 4. Listing of Inputs for Reduced Input Network Evaluations (Continued)

The following inputs were used for the network with 5 inputs:

Hydraulic line
Oil in headstock
Ambient
X coordinate
Z coordinate

The results obtained with these networks are given in Figures 33, 34, 35 and 36 (which are for the ambient test), in Appendix E and in Table 3. Graphically the network with 13 inputs appears to perform as well as the basic network. The error data indicates also that this network is roughly equivalent to the basic network, with errors that are in some cases lower and in some cases higher. The network with 5 inputs, on the other hand, is clearly not as accurate in most cases. However, there are two notable exceptions – with thermal inputs into the headstock and bed. For these cases the network containing 5 inputs has less average and absolute error. Both of these involve situations where the network was not specifically trained on the input. The results indicate that the carryover of information from the trained to untrained situations is beneficial for only some of the inputs. The overall conclusion from this is that to optimize the network, each potential thermal input must be studied for its effect on thermocouple number and positioning.

3.5.2 Evaluation of Different Numbers of Nodes

For these experiments the basic network was modified so that it contained from 7 to 15 nodes in the hidden layer (odd numbers only). Information on this is valuable because if a network can be reduced in size it will take less time to train and test resulting in faster operation. The essential results of this are shown in Figures 37 and 38 that cover 7 nodes. The results for the other networks are given in Table 3 and Appendix E. The network provided a fit which, in all cases, agreed with the shape of the data very well. The RMS error information given in Table 3 indicates that the best fit was obtained with 9 or 11 nodes. The overall conclusion here is that optimizing the size of the network can result in improvements in accuracy as well as in the amount of time it will take to train and test the network.

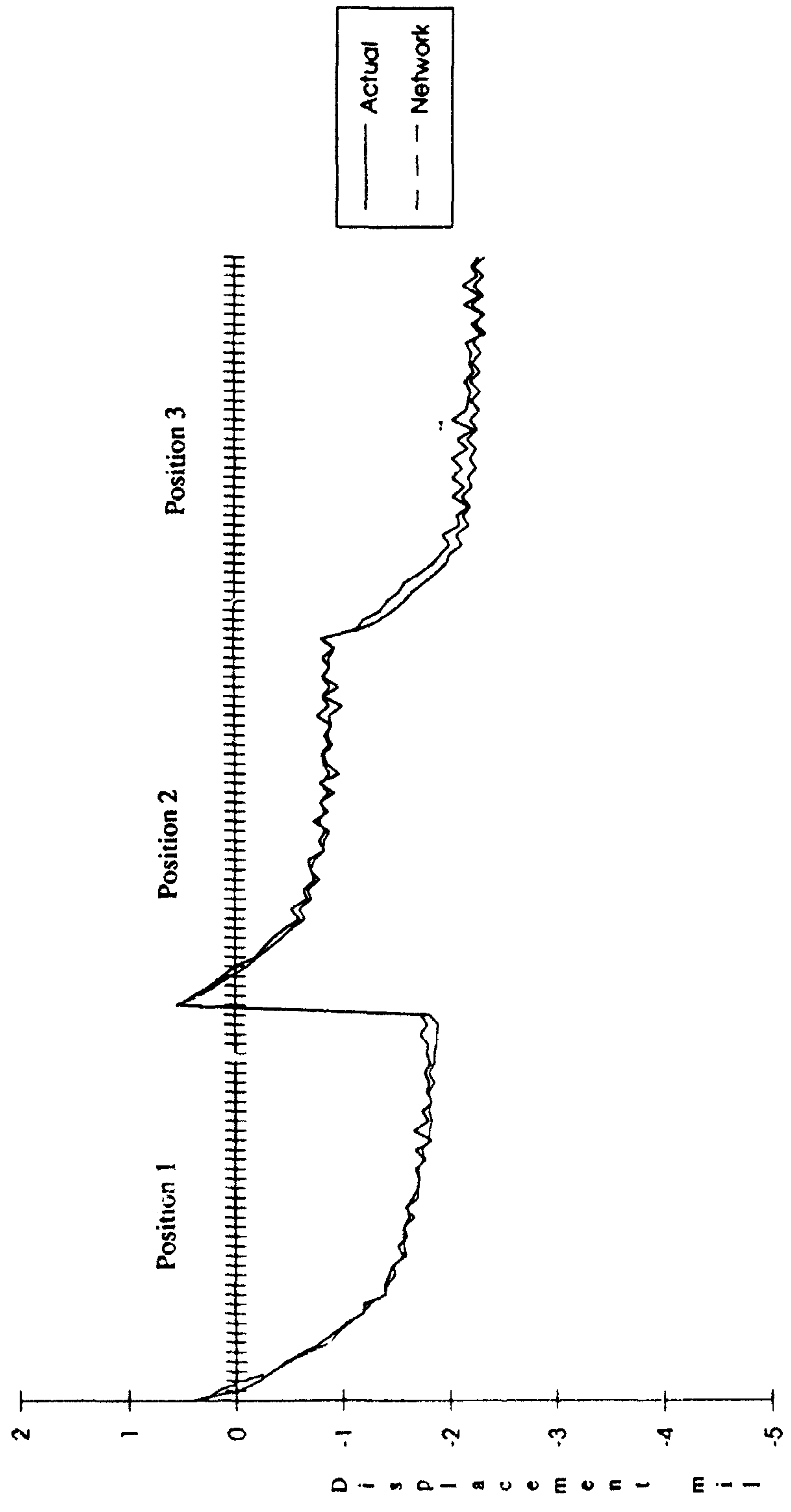


Figure 33. Network Result with 13 Inputs - X Direction

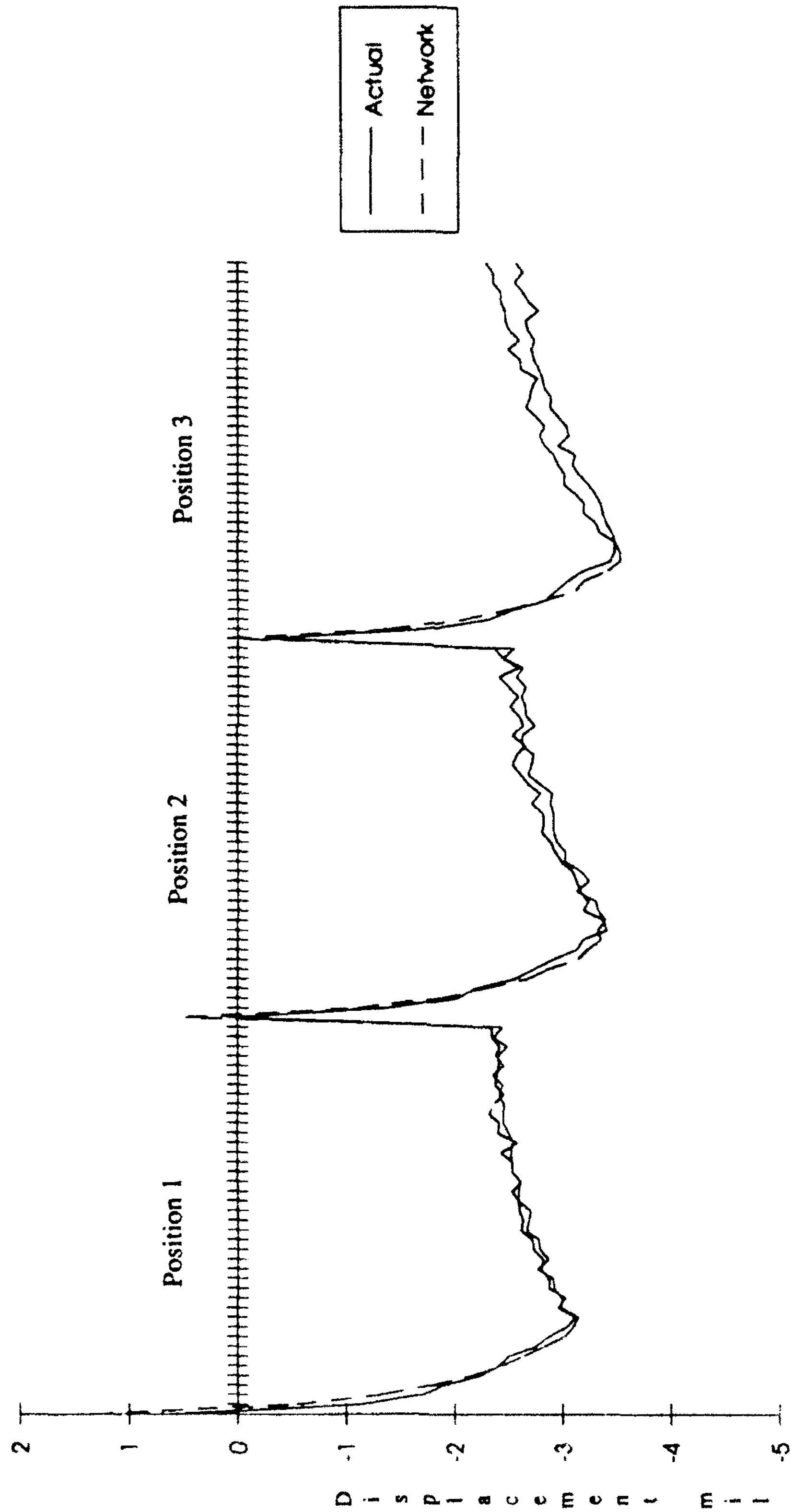


Figure 34. Network Result with 13 Inputs - Z Direction

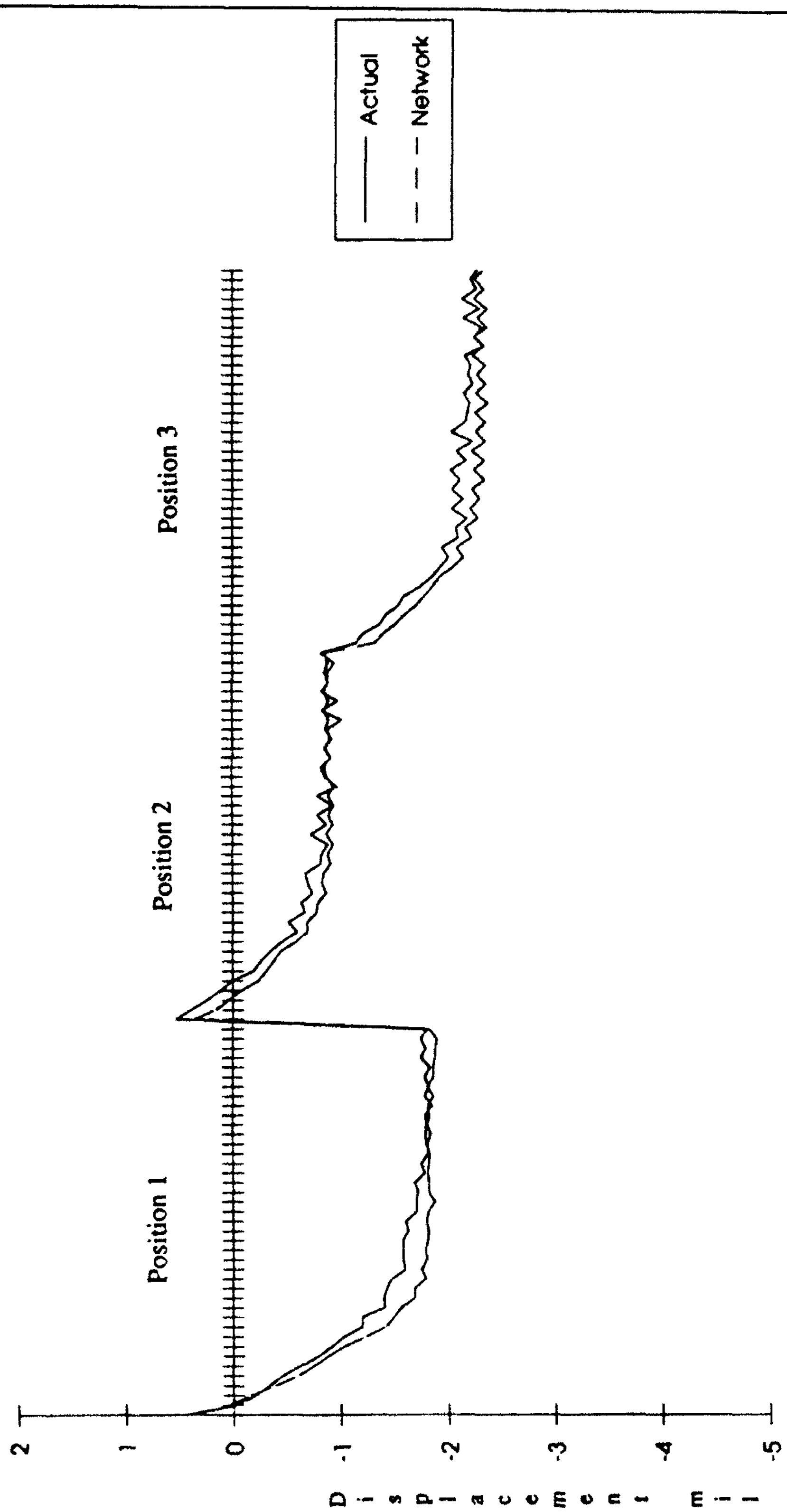


Figure 35. Network Result with 5 Inputs - X Direction

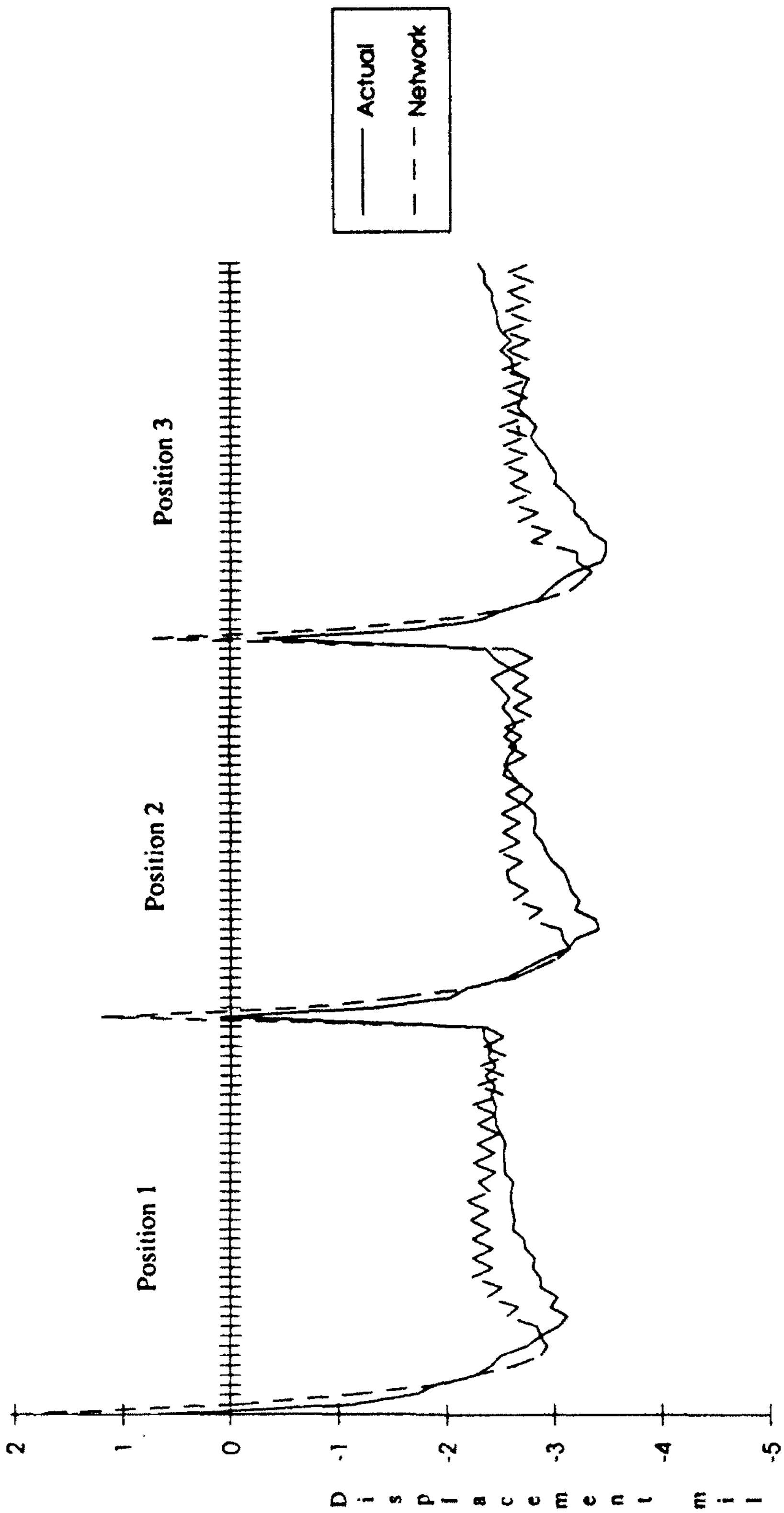


Figure 36. Network Result with 5 Inputs - Z Direction

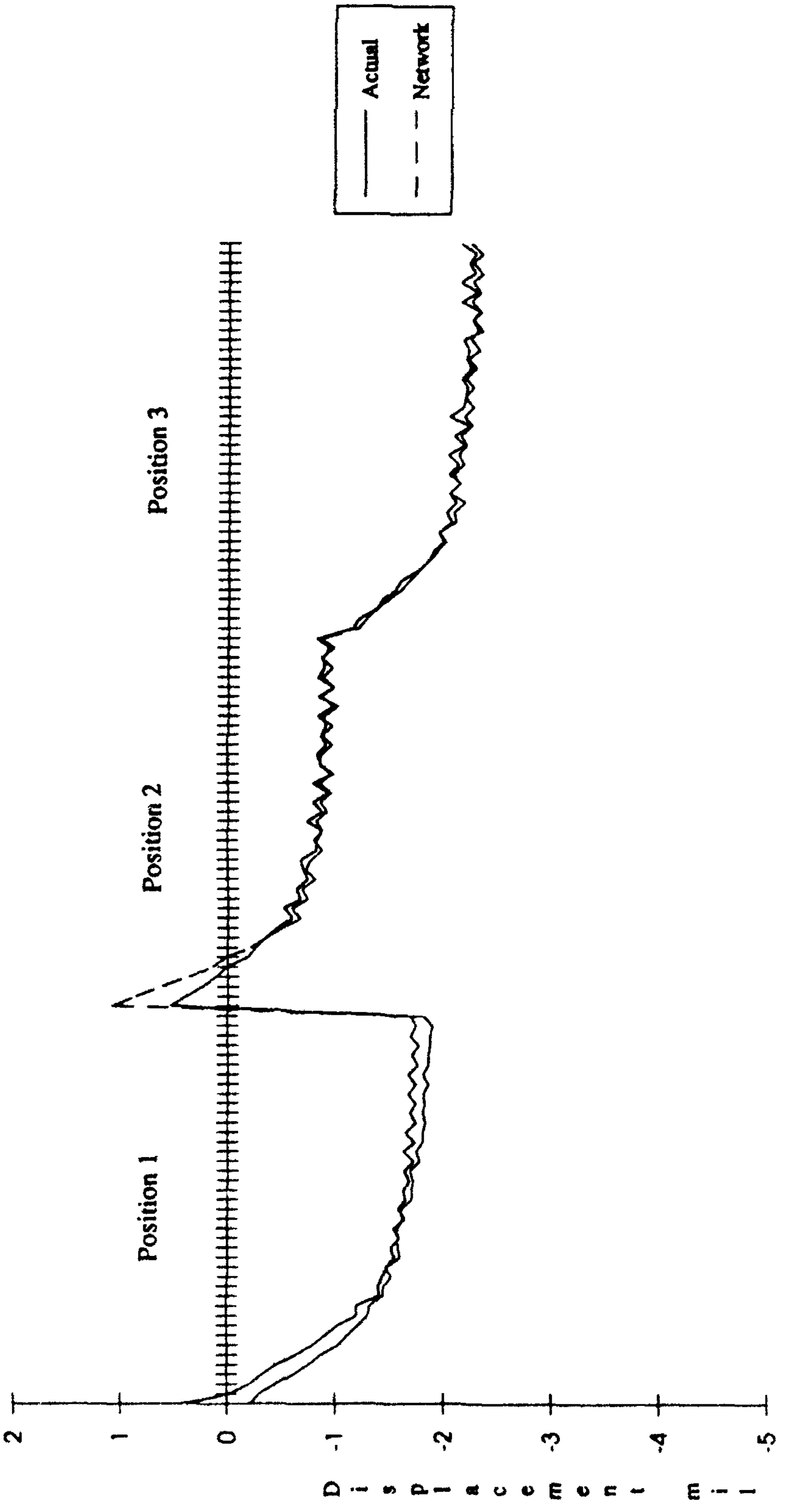


Figure 37. Network Result with 7 Hidden Nodes - X Direction

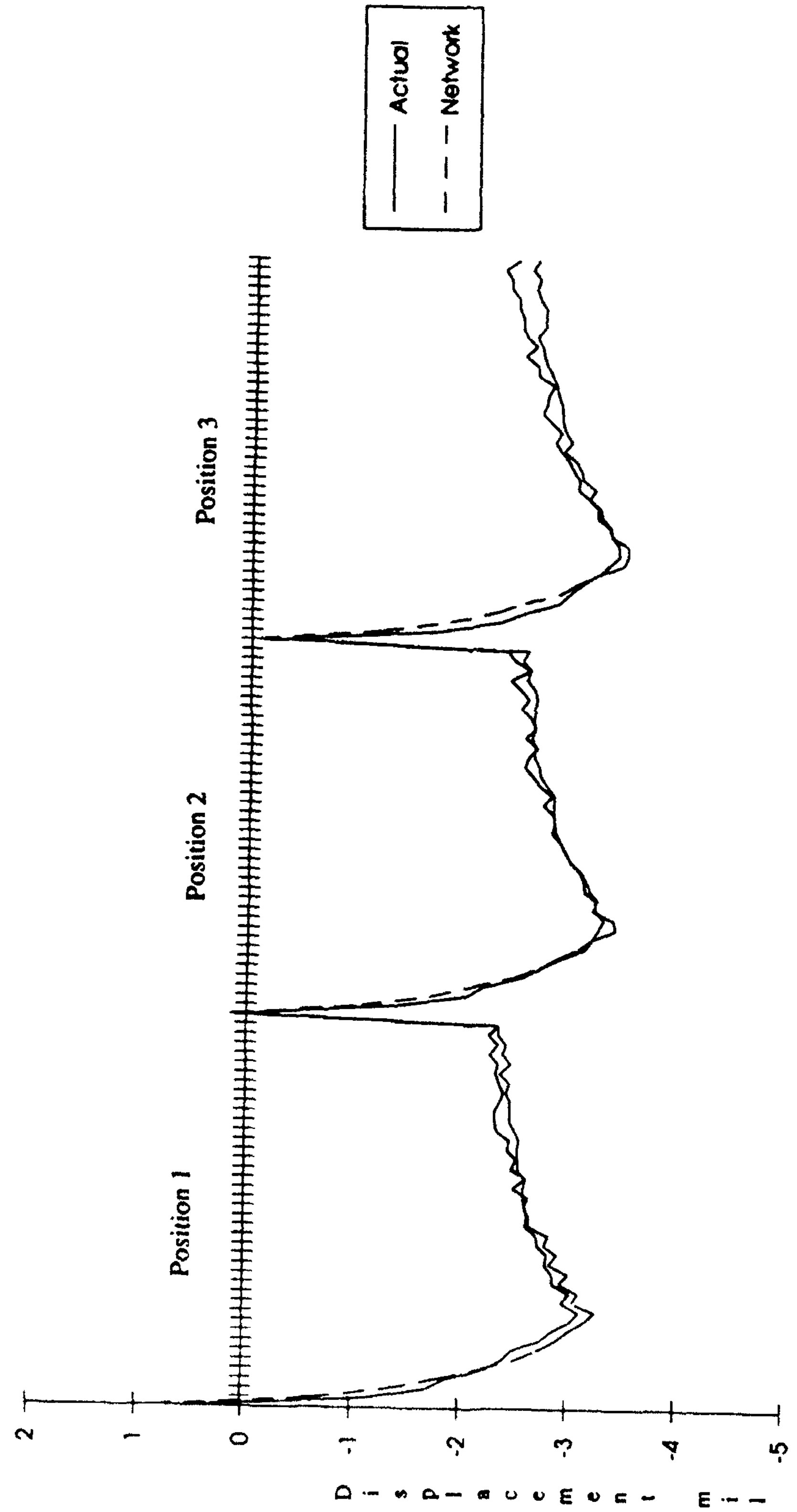


Figure 38. Network Result with 7 Hidden Nodes - Z Direction

3.5.3 Evaluation of Time Delay of Input Data

The input data file was modified to incorporate a time delay feature in the same manner as was done in the bench test portion of this project. This was done as a modification to the base network, resulting in a network with 50 inputs. Typical results of this are contained in Figures 39 and 40, with complete results given in Appendix E and Table 3. The conclusion is that the addition of time delay does not materially affect the performance of the network. Since the network is larger with twice as many inputs, it will take more time to train and use.

3.5.4 Evaluation of Input Data Randomization

For the basic network application the input vectors were randomized during training. This was done because it was found during the bench test studies that training time was much less than with input vectors ordered as when measured during data acquisition (nonrandomized). As a part of the studies involving the turning center, the network was trained with nonrandomized data in one example case. It was trained until the overall error was approximately the same as obtained with the basic network when trained for 1000 cycles. This occurred after about 10000 training cycles for the nonrandomized input. The results are given in Figures 41, 42, 43 and 44. Comparison of these results with the results from the basic network, given in Figures 13 and 14, show that the same type of fit was achieved. The information on percentage of error vs. training cycle, given in Figures 43 and 44, indicate that both networks achieve most of their fit in relatively few cycles. From this point on, the network with nonrandomized input smoothly improves in error at a slow rate, while the network with randomized data varies considerably in error over a small range with the overall trend being to reduce error. In practice the set of weights corresponding to the minimum error achieved during training is retained and used for the network. Thus the randomized approach, with its variability, results in a set of weights giving a specific level of error in a lot less training cycles than the nonrandomized approach.

3.5.5 Evaluation of Commercial Network

The network used for all the turning center investigations described above was programmed specifically for this project. Even though it uses standard neural network architecture, there was some question as to whether a standard off-the-shelf network of the same architecture would perform equivalently. To answer this question a commercial neural network shell program, NeuralShell, produced by Ward Systems Group, Inc. was purchased and applied to a sample test case.

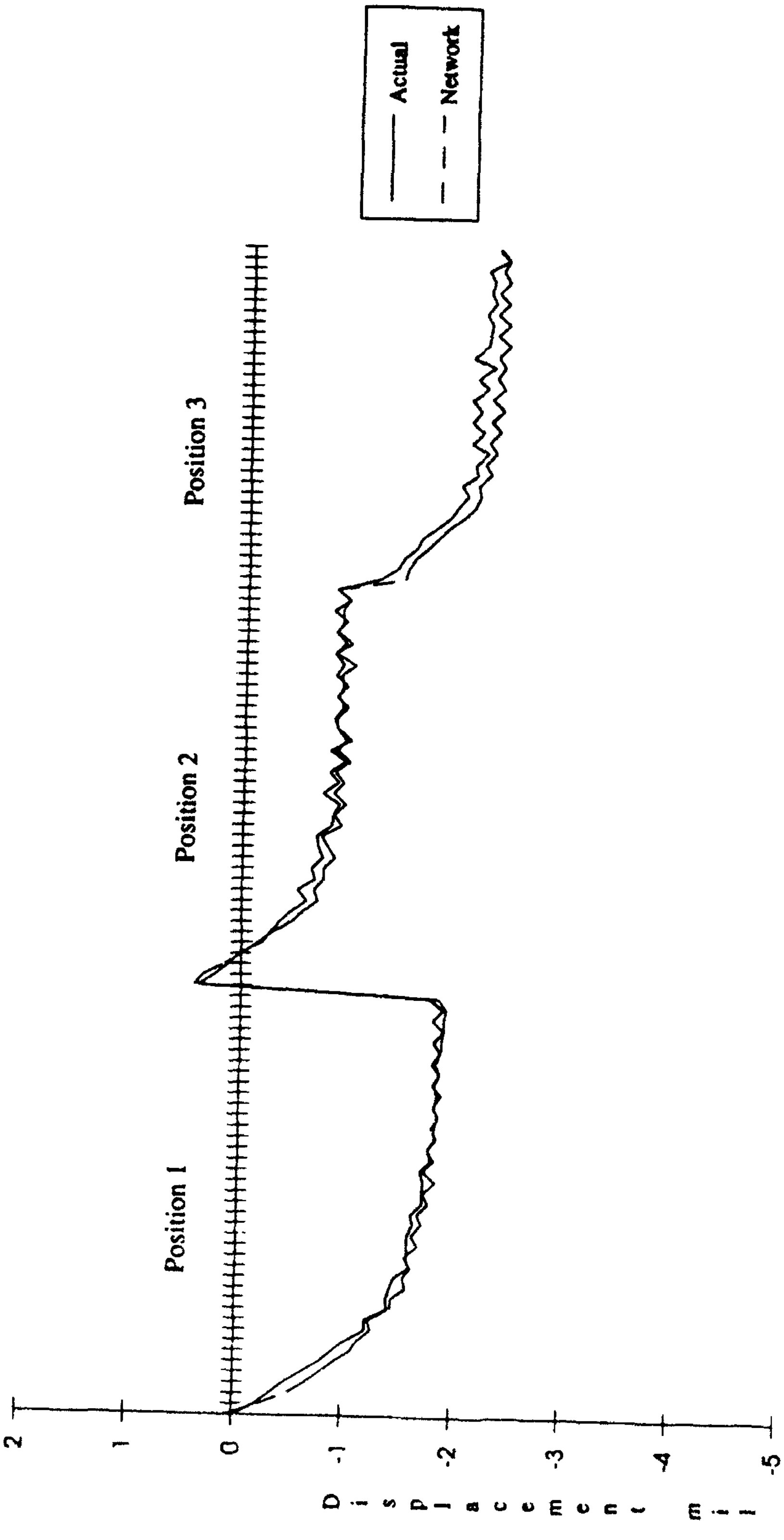


Figure 39. Network Result with Time Delay - X Direction

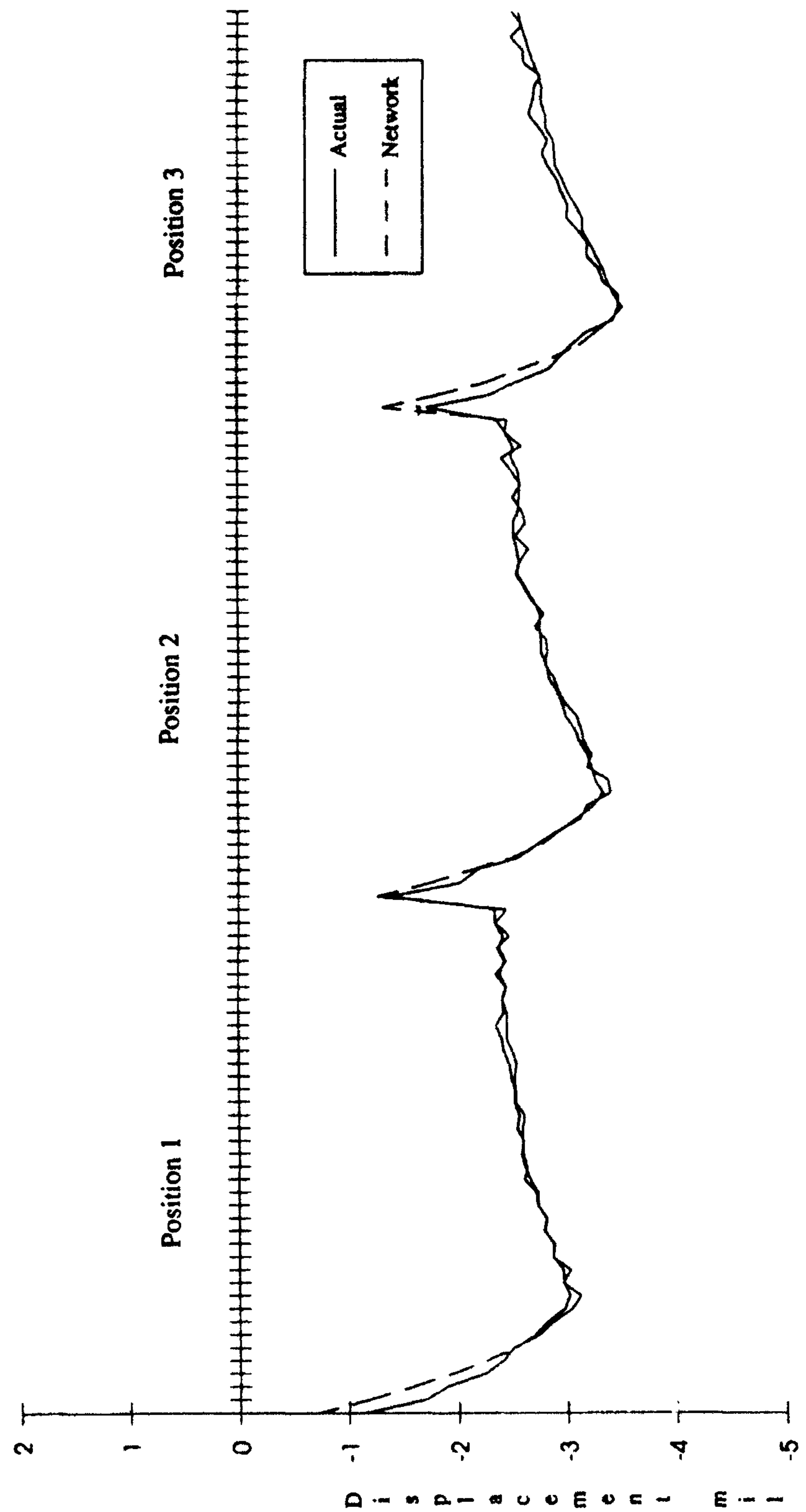


Figure 40. Network Result with Time Delay - Z Direction

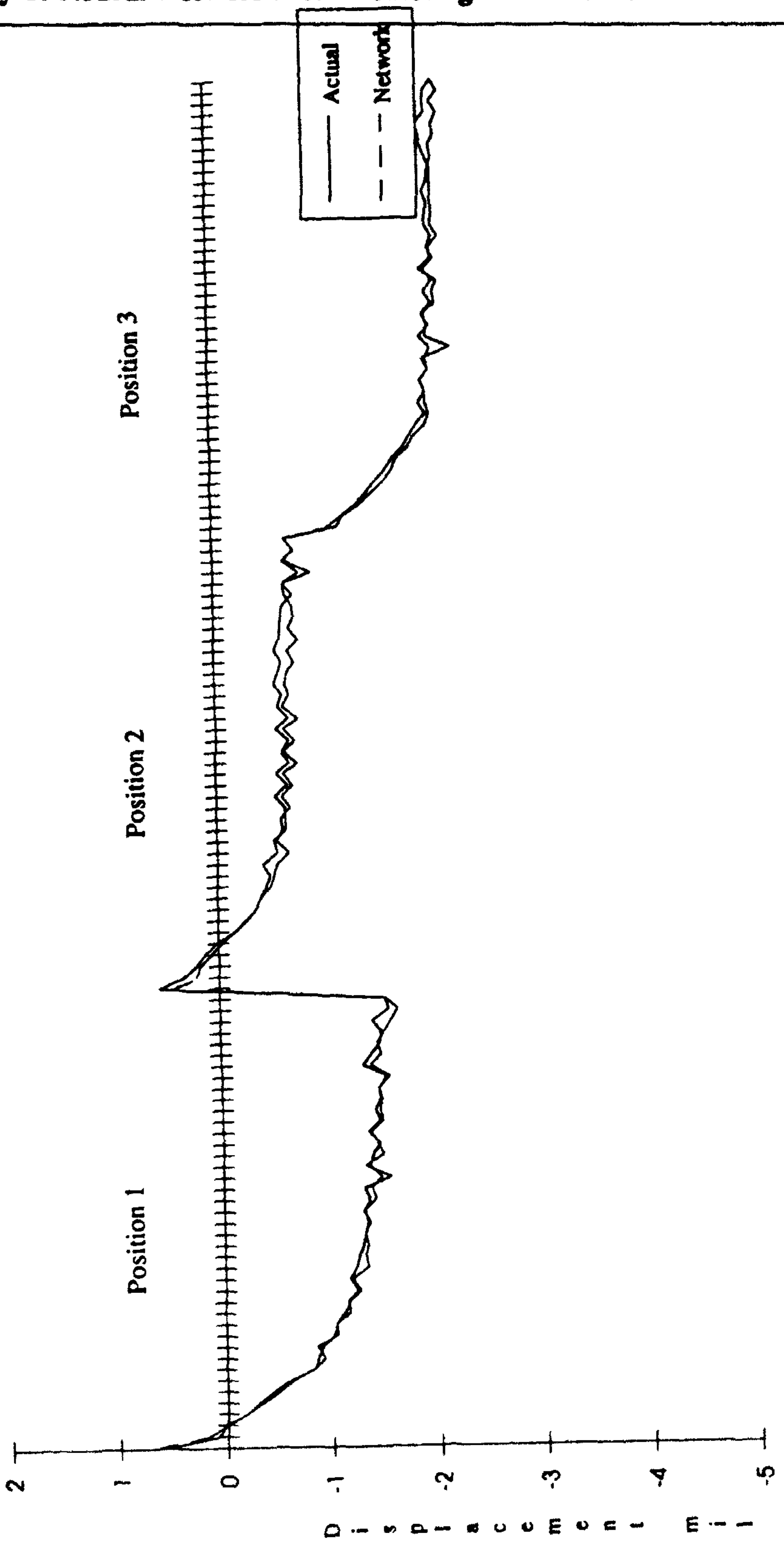


Figure 41. Network Result with Nonrandomized Input Using 10,000 Training Cycles - X Direction

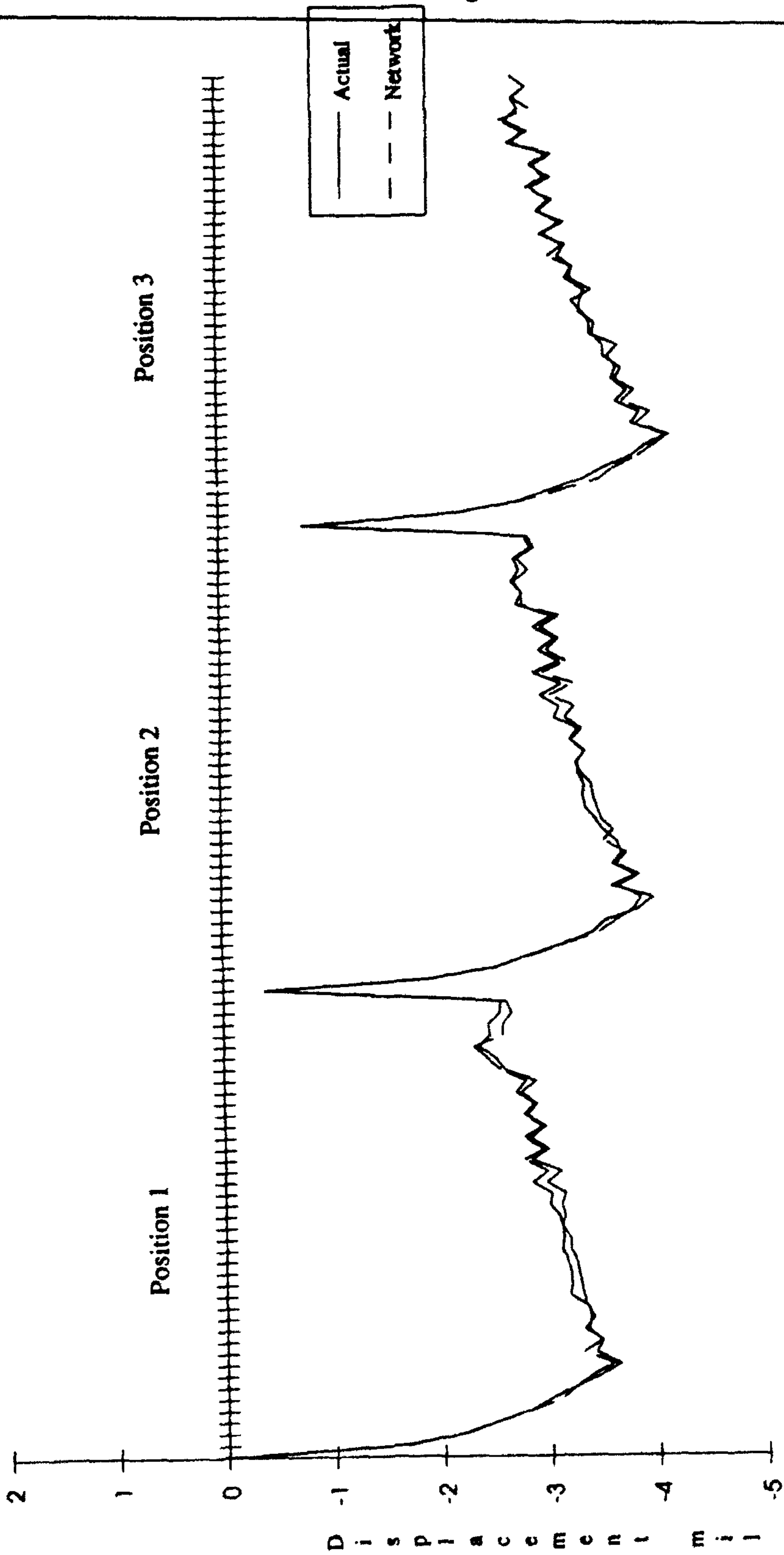


Figure 42. Network Result with Nonrandomized Input Using 10,000 Training Cycles - Z Direction

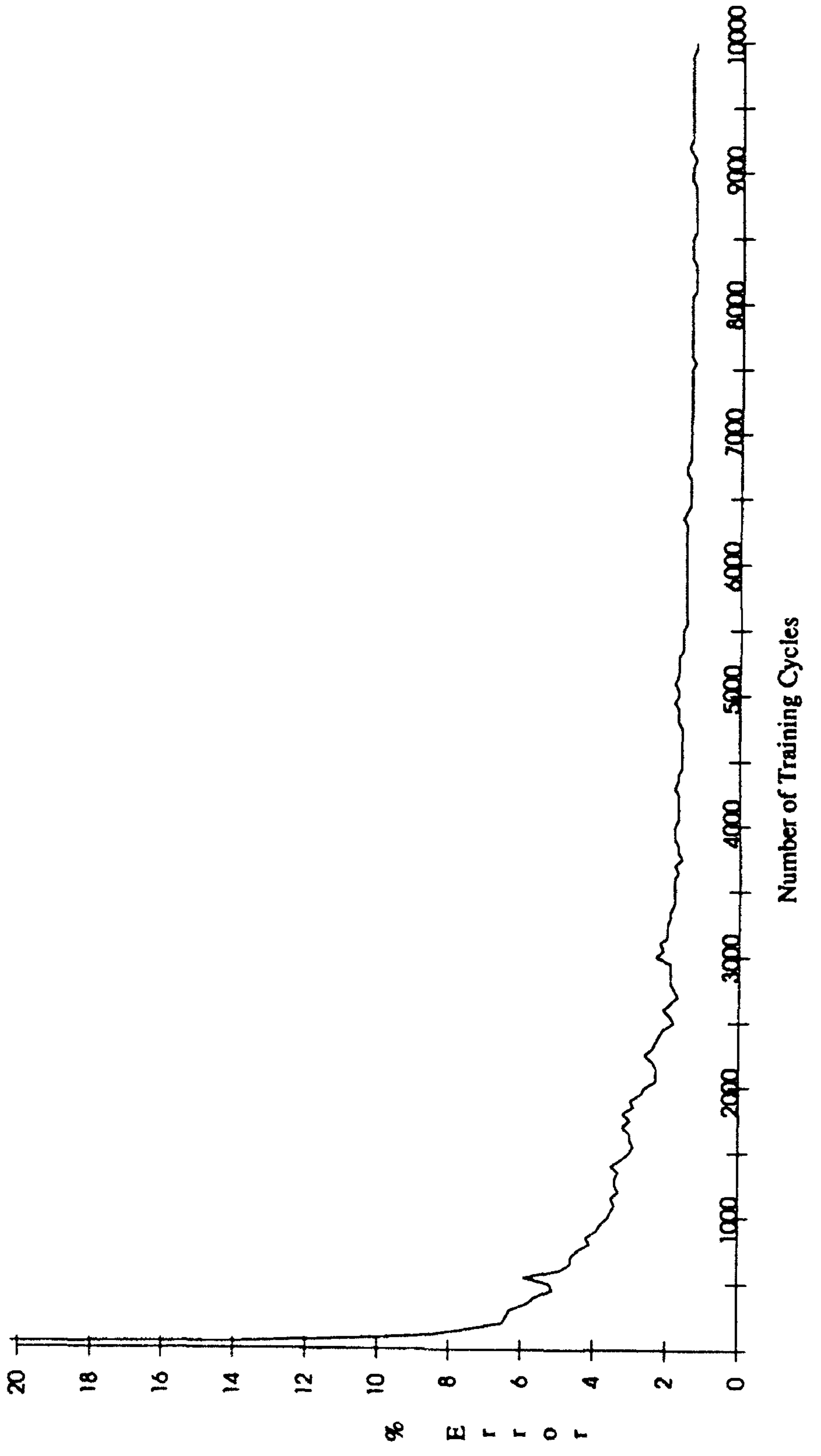


Figure 43. Error Versus Training Cycle - Nonrandomized Input

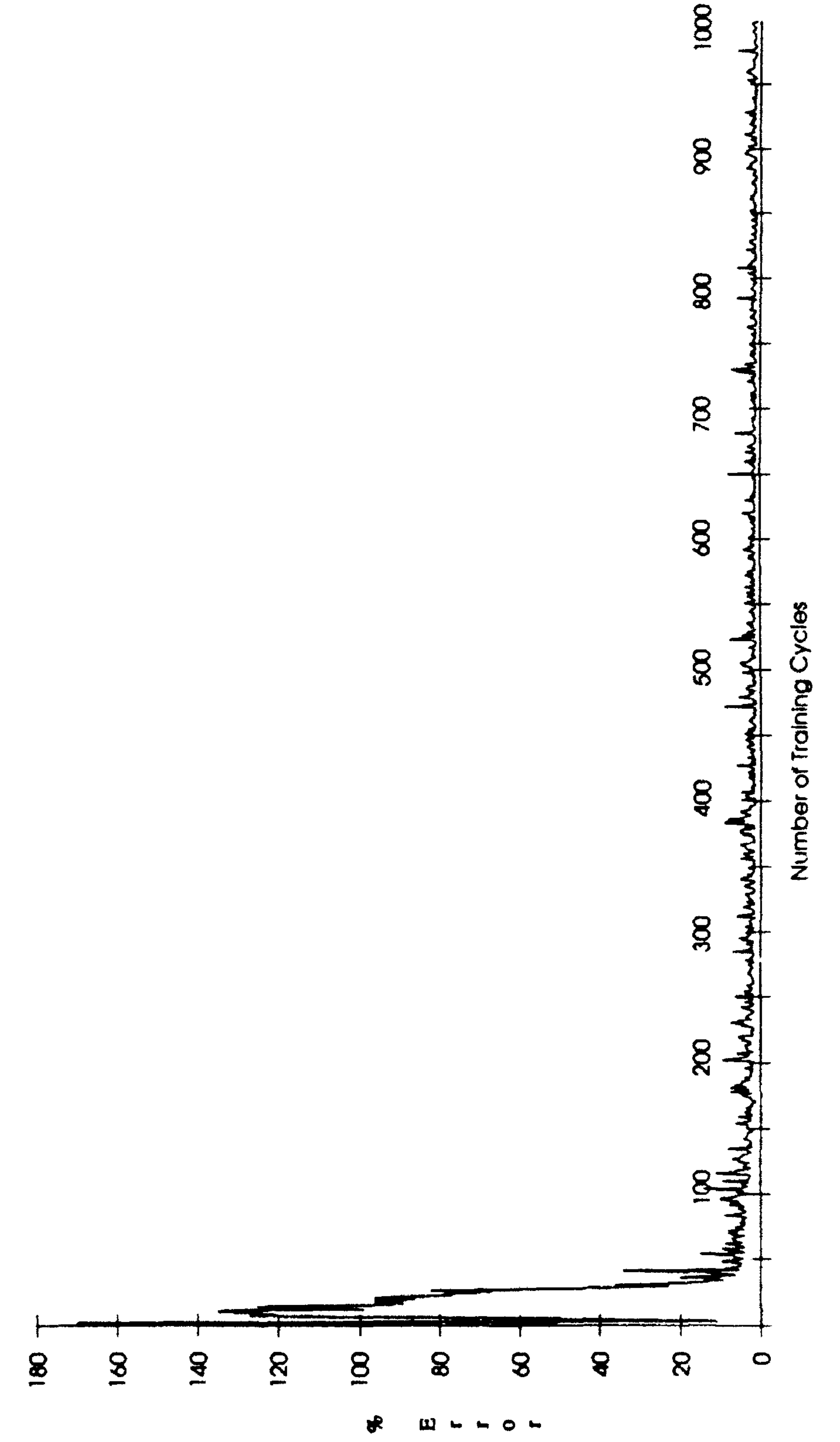


Figure 44. Error Versus Training Cycle - Randomized Input

The network configuration used for this comparison was the same as the basic network. It included 25 inputs, 2 outputs and an input set comprised of data from tests December 17, December 19, and December 21 with the input vectors randomized. Training time was about the same as for the base network. Results of this comparison, with testing on data from the ambient experiment are given in Figures 45 and 46. Comparison with results obtained from the basic network, given in Figures 25 and 26, indicates that the commercial network performed equivalently. The conclusion is that the network used for these investigations does not contain any special qualities, but rather is equivalent to what can be bought in a standard off-the-shelf package.

3.5.6 Evaluation of Ability to Predict at Positions Not Trained On

In all of the evaluations described above, the network was trained and tested on the same three positions in the workspace established by the design of the reference part. In a real world application, of course, the network would be required to predict displacement (equivalently error) anywhere in the workspace. In order to determine whether the network was capable of this, the input data was altered by substituting different values of the X and Z coordinates in place of the actual values for position 3.

Two cases were examined, one with the X and Z coordinates changed only a small amount from the actual, and a second where the X and Z coordinates were changed considerably. The following coordinates were used:

Case 1 $X = 4.5, Z = 5.0$

Case 2 $X = 10.0, Z = 20.0$

The results from case 1 are given in Figures 47 and 48. Comparison with results from the basic network, given in Figures 19 and 20, show that the predictions of displacement at positions 1 and 2 are the same as the basic network. In the portion of the graph where position 3 would normally be given, the prediction of displacement for the "new" position is presented. It can be seen that the network prediction is very believable, with the same shape of response vs. time and an overall position level which is reasonable.

From the results given in Figures 49 and 50 for case 2, however, it can be seen that the result is not as favorable. The predicted X displacement is larger than would be expected and the predicted Z displacement is opposite from what would be expected (positive). The shape of the predicted displacement curve, however, is as would be expected. In order to completely establish the accuracy of the prediction, it would be necessary to build a reference part with measurement positions at the coordinates used for case 1 and 2 and measure displacement there. Since this was not done, absolute conclusions cannot be reached. The data, however, suggests strongly that the network will work at positions not trained on, if the coordinates are not considerably different from the training values.

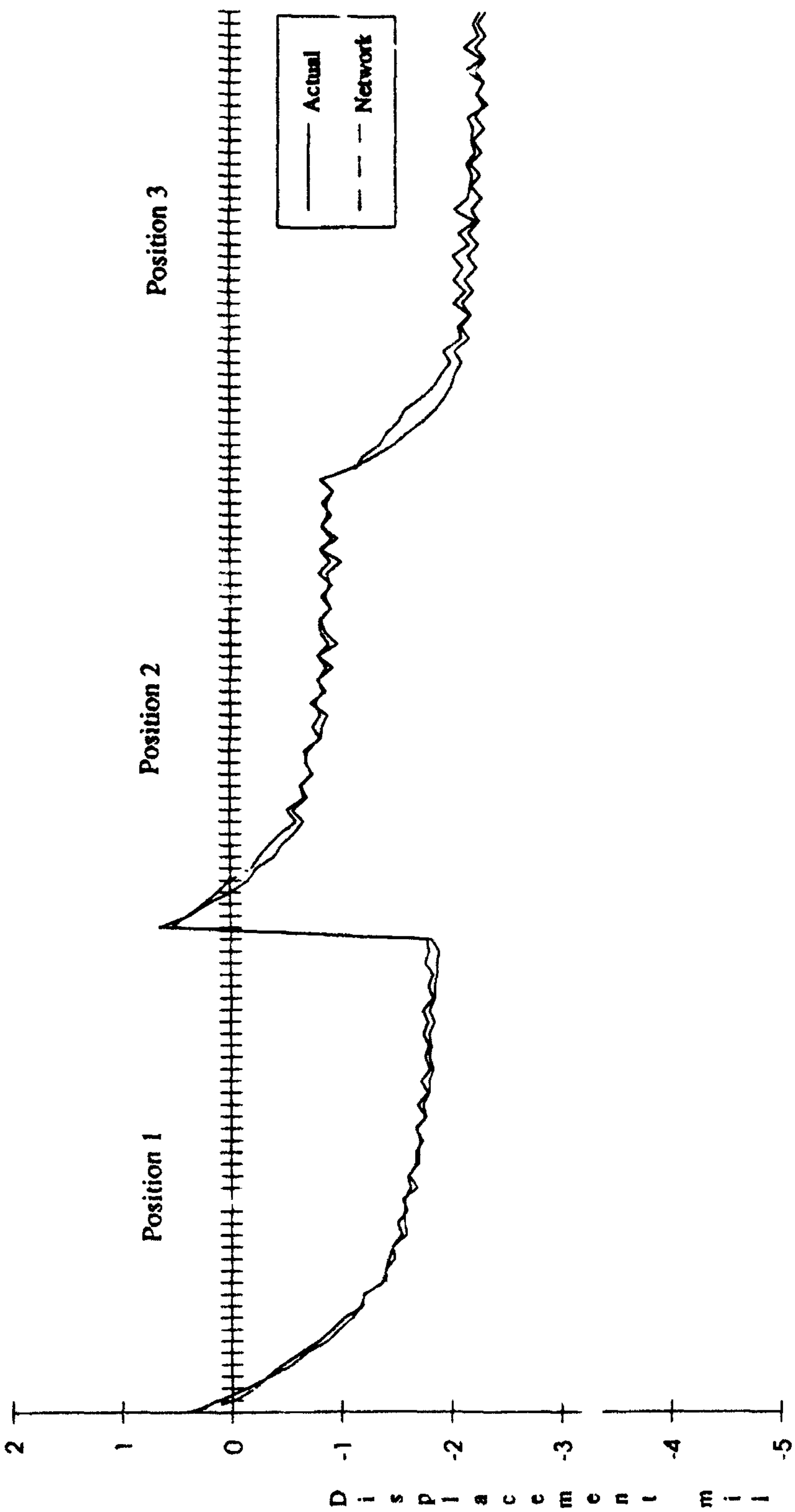


Figure 45 Result with Commercial Network - X Direction

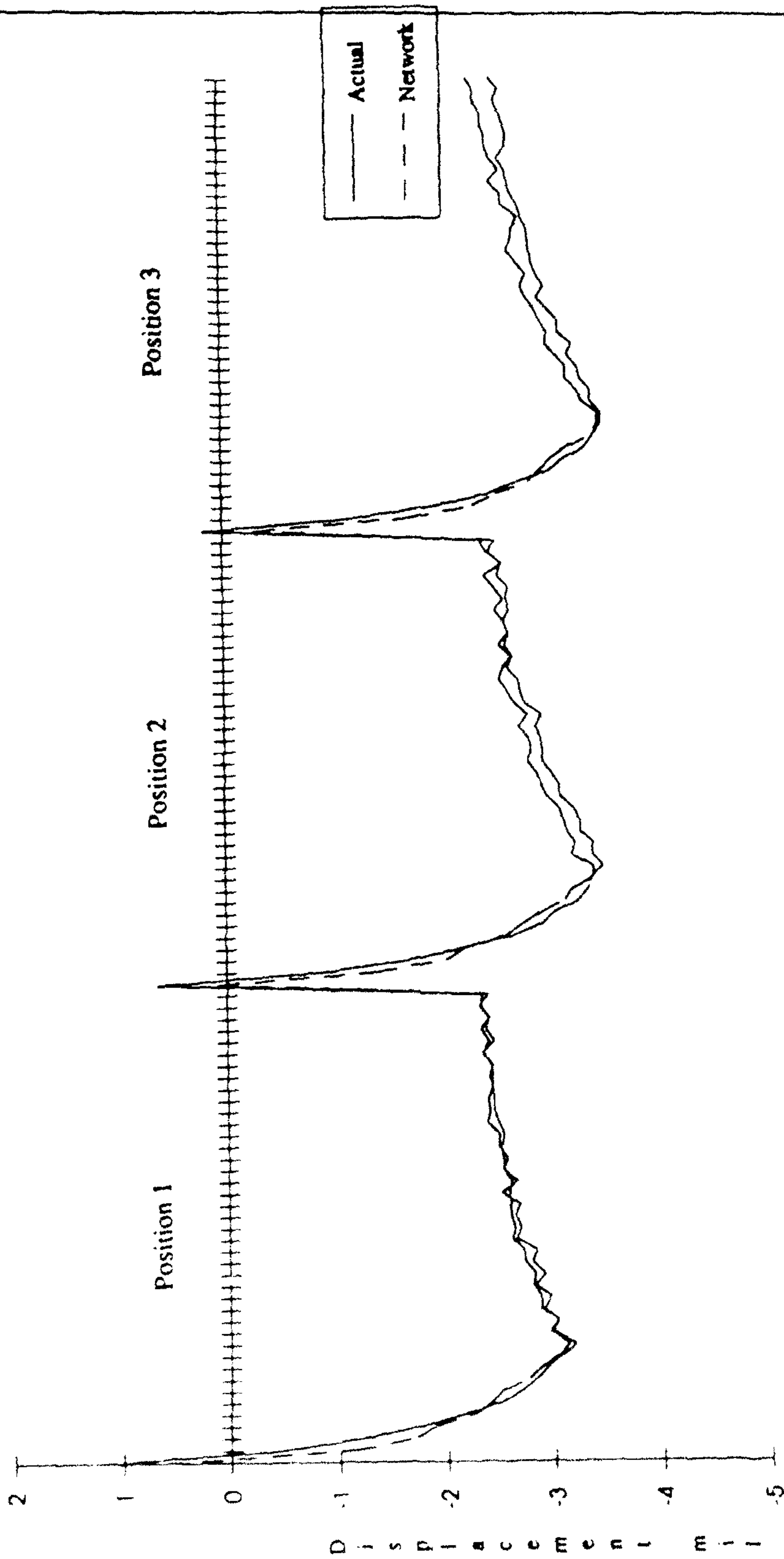


Figure 46 Result with Commercial Network - Z Direction

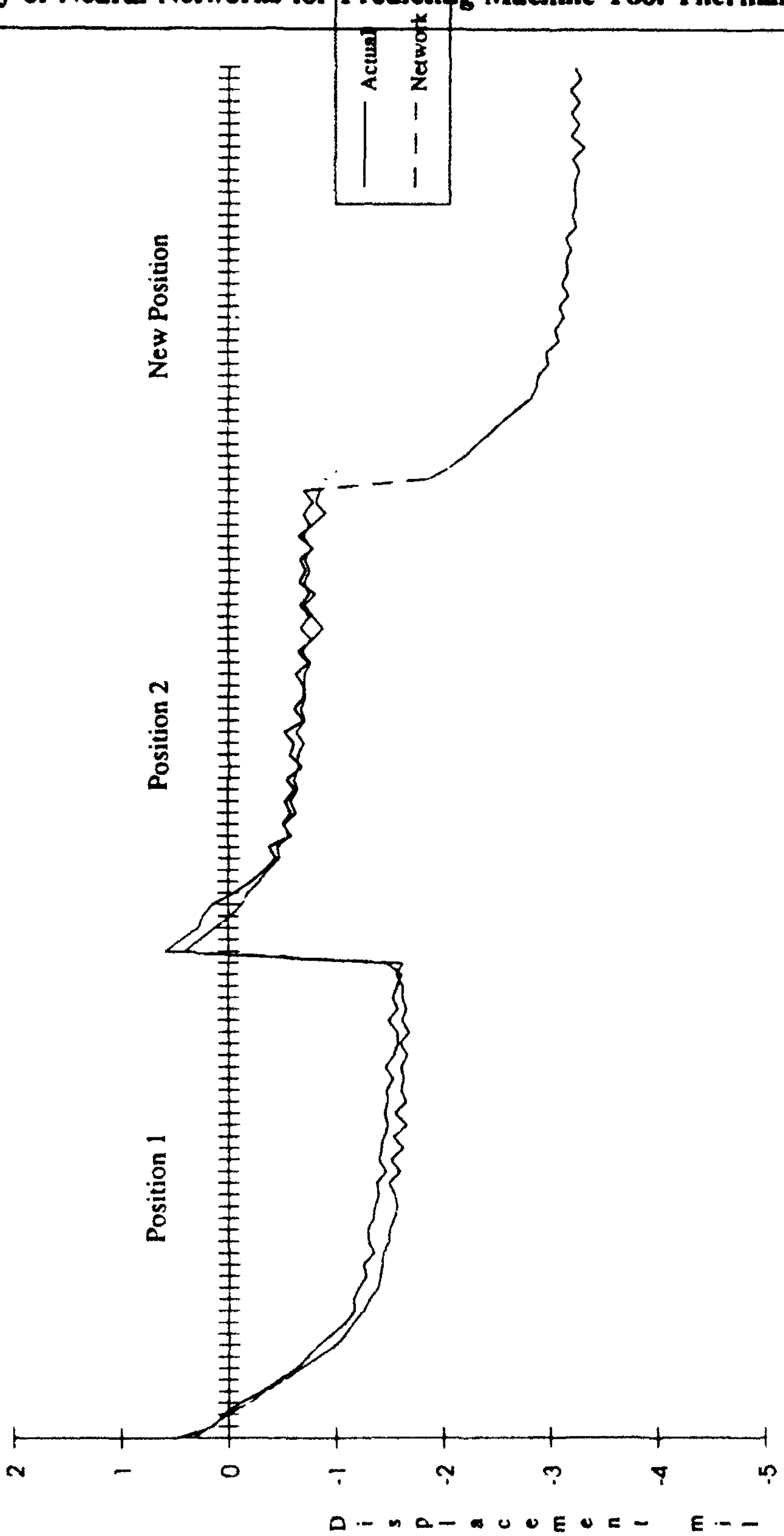


Figure 47 Result for Extra Training Position at Small Coordinate Change - X Direction

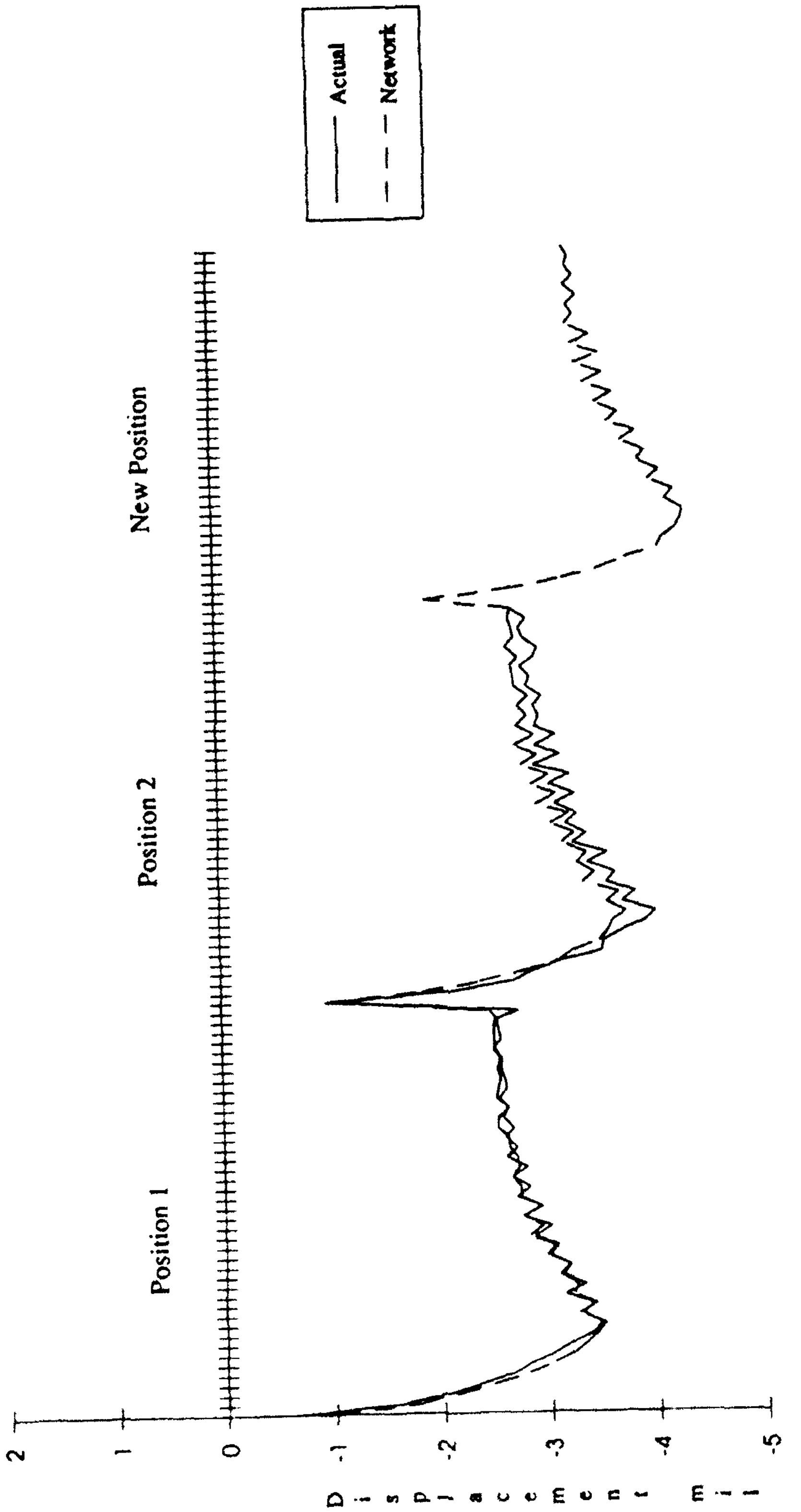


Figure 48. Result for Extra Training Position at Small Coordinate Change - Z Direction

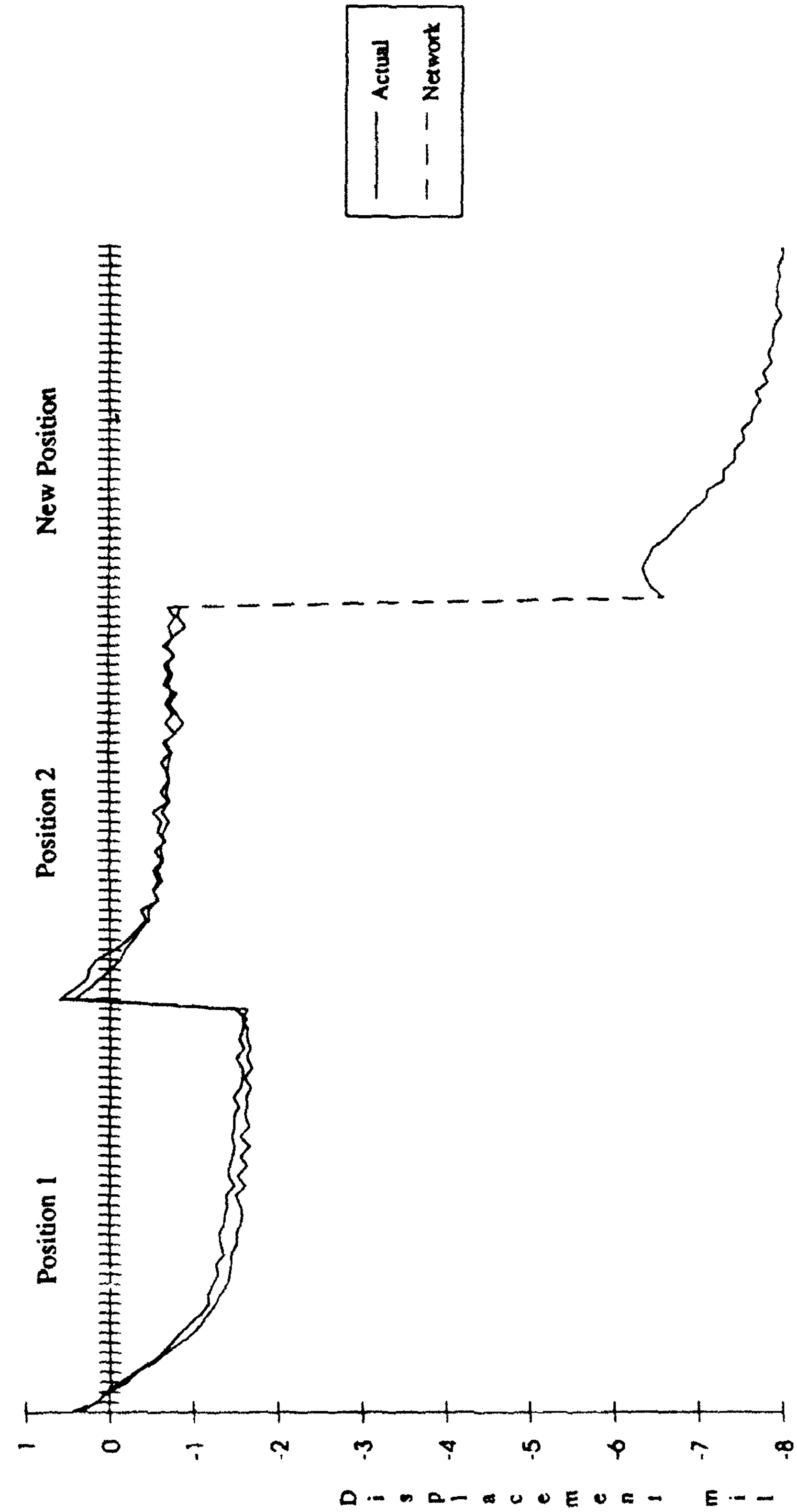


Figure 49. Result for Extra Training Position at Large Coordinate Change

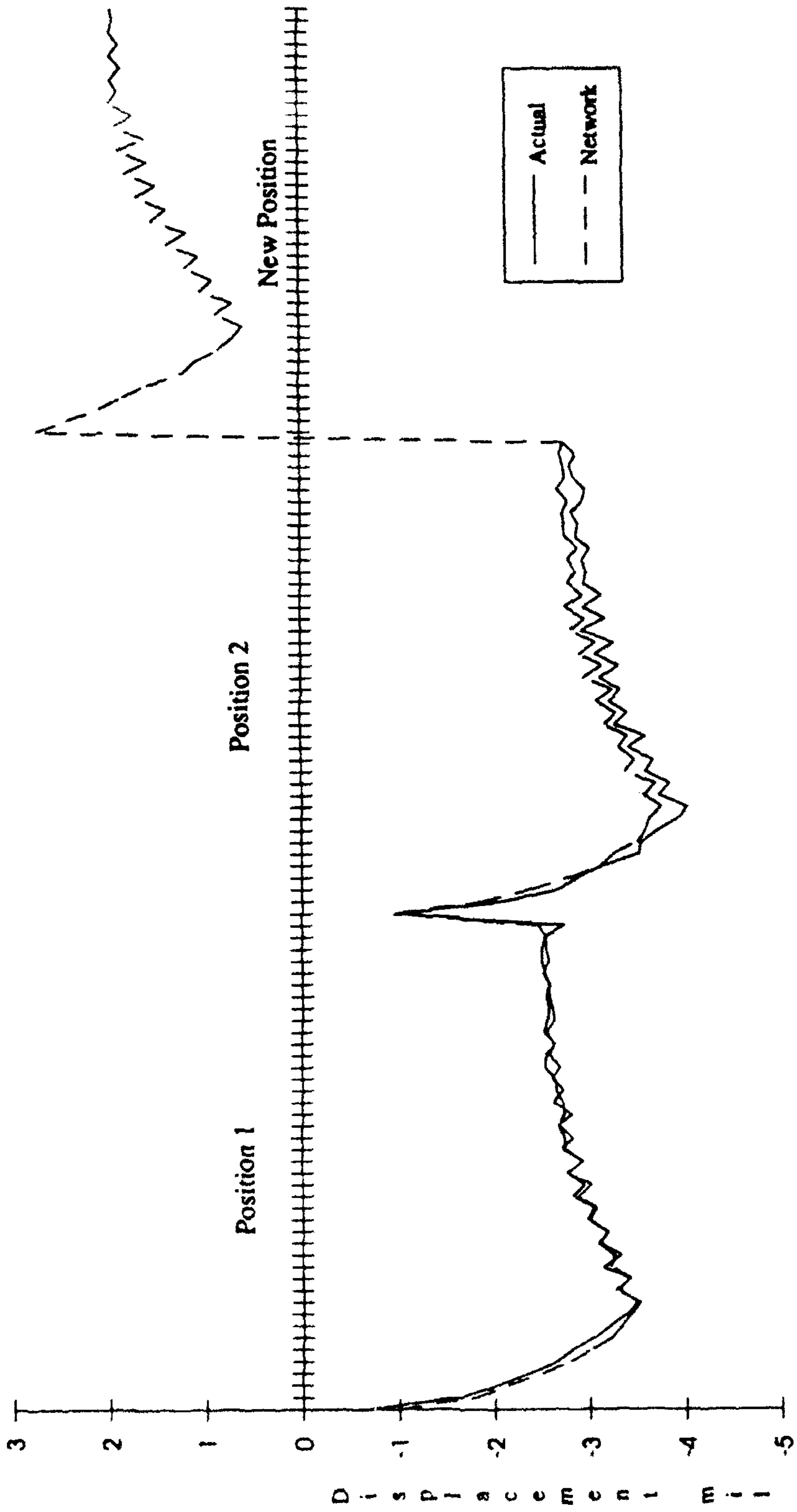


Figure 50. Result for Extra Training Position at Large Coordinate Change - Z Direction

3.6 Conclusions of Turning Center Studies

1. The neural network successfully predicted changes in displacement between the tool and workpiece as the turning center warmed up.

2. The neural network successfully predicted displacement at separate positions that it had been trained on in the work space.

3. The network predicted displacement at other positions not trained on. Accuracy was reduced considerably for coordinates much different from those trained on.

4. The neural network successfully predicted displacement with different ambient temperatures.

5. Prediction was less accurate for thermal inputs not trained on. However, specific training or more inputs would improve this.

6. Displacement due to other, non-thermal factors was not predicted, but this could be accomplished through measuring of other parameters or by introducing tool offset.

7. Displacement can be predicted with few inputs – accuracy depends on the thermal energy source.

8. Prediction error reached a minimum with about 9 hidden nodes.

9. Prediction was not consistently better or worse with time delay.

10. Randomization of input vectors improves training speed.

11. Commercial network worked very well.

Section 4. Findings and Recommendations

This section summarizes the projects' findings on the feasibility of using neural network technology to model machine tool thermal behavior emphasizing the viewpoint of machine tool builders. First, the advantages of using this technique on a typical CNC machine tool will be discussed. These include implementation, performance, and cost benefits. Second, the limitations of the technique will be discussed. Finally, recommendations will be provided for future developments, including 1) expanding the application to more complex machine tools with three or more axes of motion, 2) refinements of the neural network technique for this application, and 3) commercial viability issues.

In metal cutting and grinding, virtually all of the considerable power input to the machine is converted to heat. As cutting conditions vary the amount of heat produced tends to vary proportionally. Much of the heat is transmitted to the machine tool structure; therefore the thermal motion of the machine tool tends to respond to the level of cutting activity. Machine thermals remain one of the major uncontrolled and uncompensated error sources. In precision operations, machine thermals are often responsible for continuous changes in part size and shape. By using neural network methods it should be possible for machine builders to devise practical, automatic compensation schemes to minimize the effects of machine thermals on part quality.

For the purposes of this discussion, it is assumed that the machine tool builder makes CNC machine tools used to produce small batches of precision parts. In small batch production it is particularly difficult to achieve thermal stability. Typically, the machine operator must diligently monitor part size and continuously compensate for thermally induced errors. Even when the machine has been carefully warmed-up, variations in processing conditions (e.g. unscheduled process interruptions) can result in thermally induced workpiece errors of several thousandths of an inch. Comparable errors can also result from variations in ambient temperature if the production shop is not temperature controlled.

Neural network thermal compensation techniques will be most effective when used in conjunction with established machine design practices for minimizing thermal distortion. Consequently, it is assumed that the machine tool builder has already taken steps to reduce intense sources of frictional heating, attempted to isolate heat sources from the machine structure, and has designed the structure to minimize thermal asymmetry and Abbe errors.

4.1 Advantages of Neural Networks for Compensating Machine Thermals

It is likely that producers of quality CNC machine tools have all the hardware resources and engineering expertise required to quickly implement and evaluate neural network thermal compensation. Consequently, one advantage of the approach is that virtually any machine tool builder should be able to quickly evaluate the potential for neural networks to provide a competitive advantage. A second, related advantage of neural network technology is that it can be implemented incrementally. In fact, the results of this study suggest that a machine tool builder should start with a simple implementation. A third advantage, that should reduce the learning curve for neural network applications, is the strong parallel between the neural network approach for thermal problems and the common structural analysis approaches to resolve machine tool deflection and vibration problems.

4.1.1 Rapid In-House Implementation

The concept of error compensation is well accepted in the machine tool industry. Introducing position correction (offset) information into the control for each axis is common practice. This approach is developed during machine alignment to compensate for straightness errors and after tool restocking to compensate for tool variability. Thermal error compensation is conceptually an extension, although not trivial, of this approach.

Offsets are typically pre-taught and remain static during the machine's duty cycle. Look-up tables for tool and alignment offsets are refreshed only when required by tool restocking or machine maintenance. Thermal error compensation requires moving toward a dynamic offset concept. Due to the relatively sluggish thermal response typical of machine tools, a "periodic offset refresh" may be sufficient. Unless also compensating for other "faster" errors, real-time dynamic compensation should not be necessary.

Most modern CNC controls already have the capacity for simplified thermal compensation of one or more axes. The typical implementation involves attaching a single thermocouple at a thermally active location on the machine. A series of periodic measurements is taken while running the machine to determine the relationship between the thermocouple reading and the deflection of the machine axis in question. Assuming a straightforward relationship is obtained, a simple compensation algorithm can be implemented to compensate the axis position. Conceptually, moving to a multiple sensor, neural network thermal compensation approach should not represent a significant technological departure. Data to train the network is acquired by periodically recording the output of a number of thermocouples and the axis motion while the machine is exercised and/or thermally excited with external heat sources. Many machine builders would likely use existing laser interferometer hardware to track axis motion. When tool wear and cutting forces are small, as in machining aluminum, axis thermal error might be estimated by measuring a series of machined parts.

The fact that a number of thermocouples are used on the test machine with the neural network approach is not prohibitively expensive, especially if the machine tool builder already owns a multi-channel data acquisition system for logging the thermocouple and displacement data. Ideally, the data acquisition system should store the training data in a format suitable for subsequent processing. Although the test machine may be overpopulated with thermocouples it is anticipated that a few key sensors will be identified during training and only those sensors would be installed on production machines. If analysis shows the need for many sensors to obtain the required predictive accuracy for a given machine, the cost of installing and monitoring those sensors may become significant.

The training data should include cases representative of the thermal conditions likely to be encountered when the machine is run. In creating the training data, it may also be worthwhile to systematically excite the machine tool structure near each thermocouple with some sort of external heat source. The purpose of this training data is to try to improve the ability of the network to respond to unanticipated operating conditions.

4.1.2 Incremental Implementation

Reading the extensive technical literature on artificial neural networks, it is easy to lose sight of the fact that they are essentially a trial and error engineering tool, useful for creating practical control schemes for very complex control problems. These problems generally involve a very large number of process variables and process interactions. Neural network modeling enables the control engineer to simplify the control task without making far reaching, a priori, assumptions regarding the nature of the system.

As in most engineering situ..tions, it is good idea to start with simple neural network models and increment to higher levels of complexity as required. It is generally advantageous to collect more input and output training data than may be apparently required, since data subsets can be easily created for initial network development. This is particularly true for machine tool applications since the laboratory experimental costs of gathering data on the machine will be significantly greater than the iterative computer effort required for network development and training. A side benefit of starting simple is that this incremental approach to neural networks can help the personnel gradually develop reasonable expectations regarding the benefits and limitations.

The systematic escalation of the thermal error compensation challenge suggests that neural networks are appropriate to address an ever increasing range of errors. Expanding the scope to include additional machining errors is not only intuitive but reasonable. The robustness of this modeling tool should allow machine control engineers to develop creative, far reaching strategies to address overall machining errors in an integrated rather than separated fashion.

4.1.3 Parallels Between Thermal Modeling and Design

In the 1960's the US Air Force funded programs that ultimately led to the development of powerful tools for analysis of machine structures. As a result, high performance machine tools are designed with sophisticated finite element methods using test data gathered via user-friendly Fourier analysis techniques. The synergism resulting in co-development of computer-based design and new structural testing methods was quite important. Advances in one area tended to drive advances in the other.

A similar synergism would be highly desirable to drive improvements in machine tool thermal performance. There are a number of finite element tools for thermal design but very few user-friendly tools for thermal testing and empirical modeling. However, neural network methods could provide a viable user-friendly tool for characterizing machine thermals experimentally.

Fourier analysis and Modal test methods are invaluable in identifying dominant modes of vibration that can influence machining performance. These testing techniques are essential for rapid diagnosis and correction of machine tool structural problems in both the laboratory and the production shop. In the sense that a machine tool consists of many elements that function together as a mechanical system, these techniques help identify the contribution of each component to the overall structural performance.

Similar methods are needed to identify and quantify the contribution of each thermal element to the system's thermal performance. As with structural testing, this project involved careful (thermal) excitation of the machine tool structure to establish a mathematical correspondence between inputs and outputs. The neural network served as the modeling tool. Exploitation of the equivalencies between mechanical and neural network thermal testing is probably both feasible and highly desirable as a tool to drive improvements in machine design.

4.2 Limitations of Neural Networks for Machine Compensation

On the basis of the project results it is difficult to disparage neural networks as a promising technology for addressing machine tool thermal errors. However, machine tool builders who would like to utilize this technology must consider several implementation issues.

One current difficulty with artificial neural networks is that there is very little useful *application data* in the literature compared to the number of technical papers and journal articles describing complex, highly esoteric neural network *paradigms*. While some of the theory is helpful, much of it appears to be quite speculative. Most machine builders will likely find that working with knowledgeable neural network vendors and hands-on practitioners with application experience is more useful than trying to master the leading-edge technical literature.

A second challenge is how to interpret the final weights of the completed model in terms of the physical behavior of the machine tool. Understanding the relationship between the weights and the physical system is not critical for successful applications (in fact this is a key advantage of the approach). However, it would ease the curiosity of traditional engineers and managers and could provide feedback to the design process.

A third area of concern is the measurement of thermal distortion error. Sensor strategies and fixtures need to be developed which will permit measurement of parameters which will allow correction of thermally induced errors with adequate accuracy and reliability.

A final implementation issue concerns the sensitivity and response of a network to input data significantly outside the range of the training set. Robust neural networks are expected to be able to generalize and handle new, unfamiliar data and still perform adequately. However, the concepts of robustness and adequate performance are currently largely qualitative matters.

Due to the nature of neural network models it may be unreasonable to expect to quantitatively predict the performance of a model given atypical new data. Nonetheless, before entrusting the control of a machine to a neural network model, it will be necessary to identify the types of input that cause unacceptable behavior and to develop tools for recognizing strange input data. One potential solution is the use of cluster analysis. With cluster analysis, it should be possible to devise quantitative measures of the similarity between training, test, and operational input data sets.

Each application may have a number of special application issues. For example, it may not be possible to mount thermocouples close enough to heat sources such as ball screws and rotating spindle elements or the particular environment may be too hostile to reliably accommodate thermocouples distributed about the structure. Should these concerns prove to be problems, it may be possible to simply replace some or all of the thermocouples with less direct means of sensing temperature. For example, measurement of the power required to drive a ball screw could provide a measure of ball screw friction and, indirectly, temperature. As far as a neural network is concerned, an input is an input. Note that in the lathe tests measuring three positions, the x/z coordinates were in no way distinguished from temperature readings in the data vector. The network "learned" the relative importance of each input in the vector, regardless of its physical significance.

4.3 Recommendations for Future Work

The research showed the feasibility of neural network techniques to predict the thermal distortion error for a CNC turning center. Additional work is required to bring this technology into production use. Three areas of further research are identified with specific issues and focus areas discussed. These are:

- Issues related to machine tools, including the expansion to more complex multi-axis machines.
- Refinements in the Artificial Neural Net techniques as applied to the machine tool application.
- Issues related to commercial viability and production implementation.

These three areas are discussed in the following sections.

4.3.1 Expanding to New Machine Tool Applications

The scope of this research was focused on predicting two dimensional (X and Z directions), relative translation thermal errors between the tool and part in a CNC turning center. This scope simplified the generalized multi-dimensional machine tool thermal error problem.

Feasibility of Neural Networks for Predicting Machine Tool Thermal Errors

The following technical questions remain before the neural network technique is ready for *general* (any machine tool) application in the machine tool area.

1. What is the ability of neural networks to predict across the total working envelope of the machine tool rather than at just a few points. Will they effectively "model" and "interpolate" the error between a relatively few tested locations? How many locations are required to cover the envelope? What strategy should be used to identify the test locations to use in the training set of data?

2. How will the neural networks predict dimensional thermal errors while the machine is moving? Do the velocity and acceleration of motion need to be input to the net? Should the network predict offsets in real time or periodically update an offset table?

3. How can training data be collected efficiently, particularly with respect to the above two issues? How much data is needed? What is the sensor and/or measurement strategy to capture the thermal error?

4. How do neural networks behave as additional machining error sources are introduced during actual machining? (Data from this program indicates that a least single axis offsets are accepted gracefully by the network.) These errors include static and dynamic deflection, tool wear, control tracking and machine alignment. Is it possible the network can handle this "composite error" directly without necessarily decomposing and understanding the elements of this error? Can the composite error be measured by simply measuring part error?

5. Will the network performance change over time due to changes in the system? Will there need to be a long-term neural network maintenance strategy developed to "reteach" the network? Can tracking part error be used as long-term teaching data for the composite error?

These issues need to be addressed for general machine tool applications. This research program measured the error for a CNC turning center having only two dimensional control axes. As a result, the errors predicted by the neural network are essentially equal to the offset corrections sent to the control for each axis. As more control axes are introduced the problem becomes more complex. The following questions and issues need to be considered specifically for *expanded* (multi-axis) machine tool applications.

6. How will the complexity of the network grow as three, four or five axis machines are considered? How does the amount of training data required to "cover the working envelope" expand? Does the dimension of the problem (number of inputs and outputs) grow linearly or exponentially with each additional axis? How many thermocouples are needed and what are the real-time data analysis requirements?

7. How is thermal distortion error measured? Does the error measurement correspond to the part (x, y, and z translation) or machine axis (x, y, z, a and b offset) domain? What kind of test fixture and sensor strategy is required?

8. Does the source, nature and geometrical relationship of the thermal error need to be explicitly understood? For example, do spindle thermal error, lead screw thermal errors and alignment thermal errors need to be "decoupled"? Does the analogy of decoupling vibration modes using Modal Analysis apply to thermal errors?

9. Is it more appropriate for the network to predict the necessary "correction offset" rather than the thermal error? For example, when considering five-axis machines where there may be several methods to compensate for an error it may be more appropriate to teach the network the corrective action rather than the error. Specifically, an error may be corrected by a simple [x, y, z] translation offset or a combination translation offset with rotation involving the two angular axes.

These issues, particularly the last one, require a better understanding and agreement as to the use of artificial neural networks in the thermal error application. Understanding the "corrective action" expands the level of knowledge the network requires as to the context of the problem -- something that neural network technology is not specifically designed to undertake. For example, the requirements and attributes of the part being machined (prismatic, sculptured surface, etc.) may dictate the corrective action strategy, such as "remain normal to the surface" or "avoid collision in tight cavities". In this case should the network be burdened with "understanding" the context (i.e., part family issues) of the problem or be only taught a corrective action for the context? If so, how? Would a series of networks be required (one for each application context)?

Clearly these issues remain unanswered and frame the future research necessary to move this technology toward implementation. Fortunately, not all of these issues need to be resolved before implementation in simpler, limited applications can be attempted. Moving forward in the two-dimensional CNC turning center application is recommended. Addressing issues 1, 2 and 3 should be the priority.

4.3.2 Refinement of the Neural Network

The goal of the program was to identify and test the performance of a *suitable* neural network, not to develop the *optimal* network configuration. A more rigorous optimization would certainly be part of any commercial application.

The network utilized successfully during this program was of a size and complexity such that computer resources, training time, network complexity, and predictive speed would probably not be barriers to implementation even at their current levels. The two parameters that would be of paramount interest to a machine builder are predictive accuracy and the number of sensors required. To a large degree the two are interdependent and optimizing one negatively impacts the other.

Several techniques have been presented in this report to optimize (minimize) the number of input nodes and thus the number of sensors. Optimization involves two issues; ranking the input nodes based on their significance to the decision process, and determining how many of the most significant nodes are required to achieve a target level of performance. Continued development of diagnostic applications in the commercial network packages will enhance the ability to identify the most significant nodes. Fortunately, due to the relatively fast training time and reasonable data set sizes, brute force cut-and-try methods are also feasible.

A related implementation issue is the specification of sensors. It may, for example, be possible to get the same predictive performance from several thermocouple inputs or a single power monitor (or perhaps even from a control signal such as spindle speed). Likewise, one well-placed thermocouple may be more effective than three poorly placed sensors. Engineering intuition can be of significant importance in this regard, but creativity, overpopulation, and analysis can also be applied.

From a practical standpoint, a machine tool builder may approach optimization from another perspective. Given a specific limit to the number or placement of sensors, what network configuration gives the best performance? To evaluate the full scope of available networks would be a difficult task, however, from a business standpoint a builder would probably insist on a network that is commercially available from several vendors and is relatively simple to understand and apply. The decision might well hinge on non-network issues such as user interface, documentation, service, training, installed user base, and price. Within the class defined by these constraints there is still considerable investigation to be performed with respect to optimization issues such as:

- What activation function, learning rate, and momentum should be applied?
- Should historical data be included in the input vector? If so, how many historical periods should be included? What should the sampling rate be? Although cursory tests as part of this study did not clearly support this approach, there may be a different network configuration that would produce better results. For example, an expanded input vector implies a larger hidden layer and perhaps this was not increased sufficiently.
- Are there additional data preprocessing techniques (other than vector randomization) that might further enhance predictive performance?

- If the application is designed to allow re-calibration (re-training), a network that can be trained incrementally by simply adding data might be more appropriate. This would reduce the re-training time which would be critical for a system in the field.

There are a number of issues related to the application of the network in a machine tool environment that will also need to be quantified before commercialization. Some of these issues may be addressed by the selection of the network structure or nature of the training.

- The system must respond gracefully to the failure of one or more input signals.

- The system must respond gracefully to inputs outside of the range of the training set.

- The system must fail gracefully.

- The compensation must contribute to improvement in the accuracy or consistency of the machined components. For example, a network with a small maximum error would likely be more appropriate than a network with a smaller average error that had infrequent large error spikes.

- Any network that provides the network designer with intuitive feedback on the thermal performance of the machine tool will be more favorably received.

In machine tools, and most other commercial applications, consistent, predictable performance of the network (for the given application) will be more important than the average or best predictive performance.

4.3.3 Commercial Viability and Production Implementation

The project results were presented to industry during a formal briefing at the Institute. Several participants provided advice, both written and verbal, as to future directions this technology should be taken with respect to machine tool applications. The research team greatly appreciates their feedback which is included in the discussion that follows.

Clearly the most good and use from this research will come when an attempt, no matter how limited, is made in an actual production context to compensate for thermal errors while machining a part. Only when at least one user receives a benefit from the technology will commercial viability issues be able to be fully addressed.

This project has successfully demonstrated the error compensation philosophy (totally empirical using the artificial neural network methodology) and approach (predicting translational offsets for each machine control axis). The technology of today's machine controls should be capable of receiving periodic offsets with only a limited amount of additional engineering, temperature sensing technology is established, and the computer requirements for data processing are reasonable. The control loop needs to be closed and the machining of simple turned parts must be demonstrated. Data should be collected which clearly documents the accuracy improvement, variability reduction, and reliability of operation.

To be successful the technology must be desirable, affordable and available to the end user. Certainly accuracy and consistency improvements are desirable to users of machine tools; particularly during machine warm-up periods which are typically non-productive. Retrofit solutions to existing machine and controls should be the first and most logical step. The use of an external dedicated PC computer for trial purposes should not be a limiting factor.

The commercial scenario for this technology may take either or both of these directions:

1. The technology of artificial neural networks for thermal error compensations is incorporated into new machine and controller designs. The machine tool builder takes the lead in engineering thermocouple sensors deep into the machine structure (not just surface mounted), implements the network training methodology on the "first machine run-off", and packages the taught neural network as an integral component of the control system. Long term network maintenance strategies are developed and imbedded into the machine package and/or taught to the end user to execute as part of preventative maintenance procedures.

2. The artificial neural network thermal error compensation package is engineered as a retrofittable and/or add-on accessory component. Special engineering services are provided for field installation, data collection, network training, run-off and user training. The technology is packaged and sold as an "add-on", "as-requested" sub-system by either the machine tool builder, a third party or both.

There is nothing inherent in this technology which prevents nor encourages either scenario to be commercially developed. The incremental nature and robustness shown in this project encourages flexibility.

APPENDIX A. DATA FROM THE BASELINE EXPERIMENT

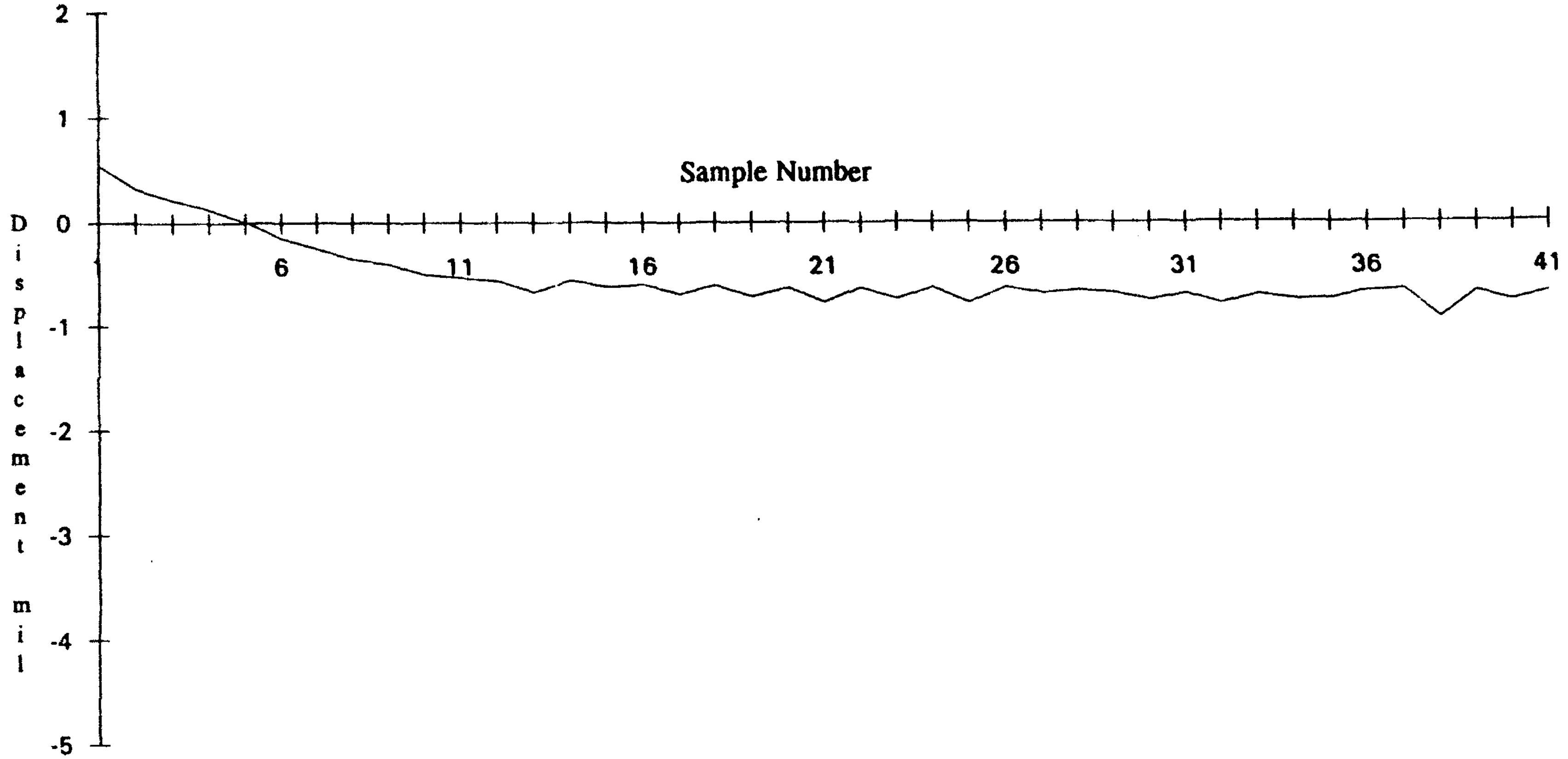
Time	Plate Near Sp.	Ambient	X-axis	Z-axis	X-Location	Z-Location
10:14:07	86.1	75	0.36	-0.52	2.25	9
10:19:57	93.7	74.6	-0.25	-2.3	2.25	9
10:25:47	99.2	74.2	-0.34	-2.75	2.25	9
10:31:37	103.4	73.8	-0.57	-3.06	2.25	9
10:37:26	107.6	74.2	-0.73	-3.34	2.25	9
10:43:16	111.4	74.2	-0.34	-3.47	2.25	9
10:49:05	114.7	75.1	-0.44	-3.68	2.25	9
10:54:55	114.7	74.6	-0.56	-3.83	2.25	9
11:00:45	112.6	74.6	-1.14	-3.74	2.25	9
11:06:34	116.4	74.6	-1.23	-3.94	2.25	9
11:12:24	113.5	75.5	-0.85	-3.59	2.25	9
11:18:13	116	75.1	-0.91	-3.66	2.25	9
11:24:03	114.3	75.1	-0.89	-3.64	2.25	9
11:29:52	115.5	75.9	-0.93	-3.54	2.25	9
11:35:42	114.7	75.5	-0.96	-3.58	2.25	9
11:41:32	113.9	75.1	-0.98	-3.39	2.25	9
11:47:21	115.5	75.1	-0.93	-3.55	2.25	9
11:53:11	113	75.5	-0.97	-3.34	2.25	9
11:59:00	116	75.5	-1.05	-3.46	2.25	9
12:04:50	114.3	75.9	-0.99	-3.32	2.25	9
12:10:39	116.4	75.9	-1.04	-3.38	2.25	9
12:16:29	114.3	75.9	-0.97	-3.24	2.25	9
12:22:18	114.3	75.9	-1.05	-3.17	2.25	9
12:28:08	116.4	75.5	-1.02	-3.35	2.25	9
12:33:58	114.3	76.4	-1.06	-3.23	2.25	9
12:39:47	117.2	76.4	-1.08	-3.21	2.25	9
12:45:37	115.1	76.8	-1.07	-3.14	2.25	9
12:51:26	116	75.9	-1.15	-3.14	2.25	9
12:57:16	116	76.8	-1.11	-3.15	2.25	9
13:03:06	113	75.5	-1.13	-3.01	2.25	9
13:08:55	117.2	77.2	-1.08	-3.12	2.25	9
13:14:45	114.7	76.8	-1.09	-3.03	2.25	9
13:20:34	115.6	76.4	-1.07	-3.03	2.25	9
13:26:24	115.6	76.8	-1.08	-3.12	2.25	9
13:32:13	114.3	76.8	-1.12	-2.96	2.25	9
13:38:03	116.8	76.4	-1.1	-3.07	2.25	9
13:43:52	114.7	76.4	-1.11	-3.02	2.25	9
13:49:42	113.9	76.8	-1.12	-2.9	2.25	9
13:55:32	116.8	76.8	-1.1	-3.03	2.25	9
14:01:21	114.3	76.8	-1.08	-2.87	2.25	9
14:07:11	116.8	77.2	-1.18	-3.02	2.25	9

Time	Z Axis Drive	Drive Motor	Drive Plate	Bed Top 1	Bed Top 2	Bed Top 3	Bed Low 1
10:14:07	81.4	115.1	105.1	78.9	77.2	75.9	77.6
10:19:57	81.9	110.5	103	78.9	77.2	75.9	77.2
10:25:47	81.8	106.3	100	78.4	76.3	75.9	77.2
10:31:37	82.7	103.8	98.3	78.9	77.2	75.9	77.6
10:37:26	83.1	101.3	97.1	78.9	77.2	76.3	77.6
10:43:16	83.6	98.8	95.4	78.9	76.8	75.5	77.6
10:49:05	84.4	97.1	94.1	80.2	77.2	76.3	78.5
10:54:55	85.3	95.4	92.9	80.6	77.6	75.9	78
11:00:45	86.1	94.1	91.6	81	77.2	76.3	78
11:06:34	87	92.4	90.3	81.4	77.2	76.3	78
11:12:24	87.8	91.6	89.5	82.3	77.2	76.3	78
11:18:13	87.8	90.8	88.6	82.7	77.6	75.9	78
11:24:03	88.7	90.3	88.7	83.6	78	76.3	78.5
11:29:52	89.1	89.5	87.4	84	78	76.3	78
11:35:42	89.5	89.1	87	84.4	78	76.8	78.5
11:41:32	90.3	89.1	87	85.3	78.9	76.8	78.9
11:47:21	90.8	88.7	86.5	85.7	78.9	76.8	78.5
11:53:11	91.6	88.7	86.1	86.5	78.9	77.2	78.9
11:59:00	91.6	88.2	85.7	87	78.9	77.2	78.5
12:04:50	92	88.2	85.7	87.4	79.3	77.6	78.9
12:10:39	92	87.8	85.7	87.8	79.3	77.6	78.9
12:16:29	92.5	88.2	85.7	88.2	79.8	77.2	79.3
12:22:18	92.9	87.8	85.3	88.7	79.8	77.6	78.9
12:28:08	93.7	88.2	85.7	89.1	80.2	78.1	79.3
12:33:58	93.7	88.2	85.7	89.5	80.2	78.5	80.2
12:39:47	93.7	87.8	85.3	89.5	80.6	78.1	79.3
12:45:37	94.2	88.2	85.3	89.9	80.6	78.1	79.3
12:51:26	94.2	88.2	85.3	90.4	81	78.5	79.8
12:57:16	94.6	88.2	85.3	90.8	81	78.5	79.8
13:03:06	94.6	87.8	85.7	90.8	81.5	78.5	79.8
13:08:55	95.4	88.7	86.1	91.6	82.3	79.8	80.6
13:14:45	95	87.8	85.3	91.2	81.9	78.9	79.8
13:20:34	95	87.8	85.3	91.2	81.9	79.3	79.8
13:26:24	95.9	88.2	85.7	92.1	82.3	79.3	80.6
13:32:13	95.9	88.7	85.3	92.1	82.3	79.8	80.6
13:38:03	95.8	87.8	85.3	92	82.3	79.3	80.2
13:43:52	96.3	88.2	86.1	92.5	82.7	79.8	80.6
13:49:42	96.3	88.2	85.7	92.5	82.7	80.2	81
13:55:32	96.3	88.2	85.7	92.5	82.7	79.8	80.6
14:01:21	96.3	87.8	86.1	92.9	83.2	79.8	80.6
14:07:11	97.1	89.1	86.1	93.3	83.2	80.6	81.1

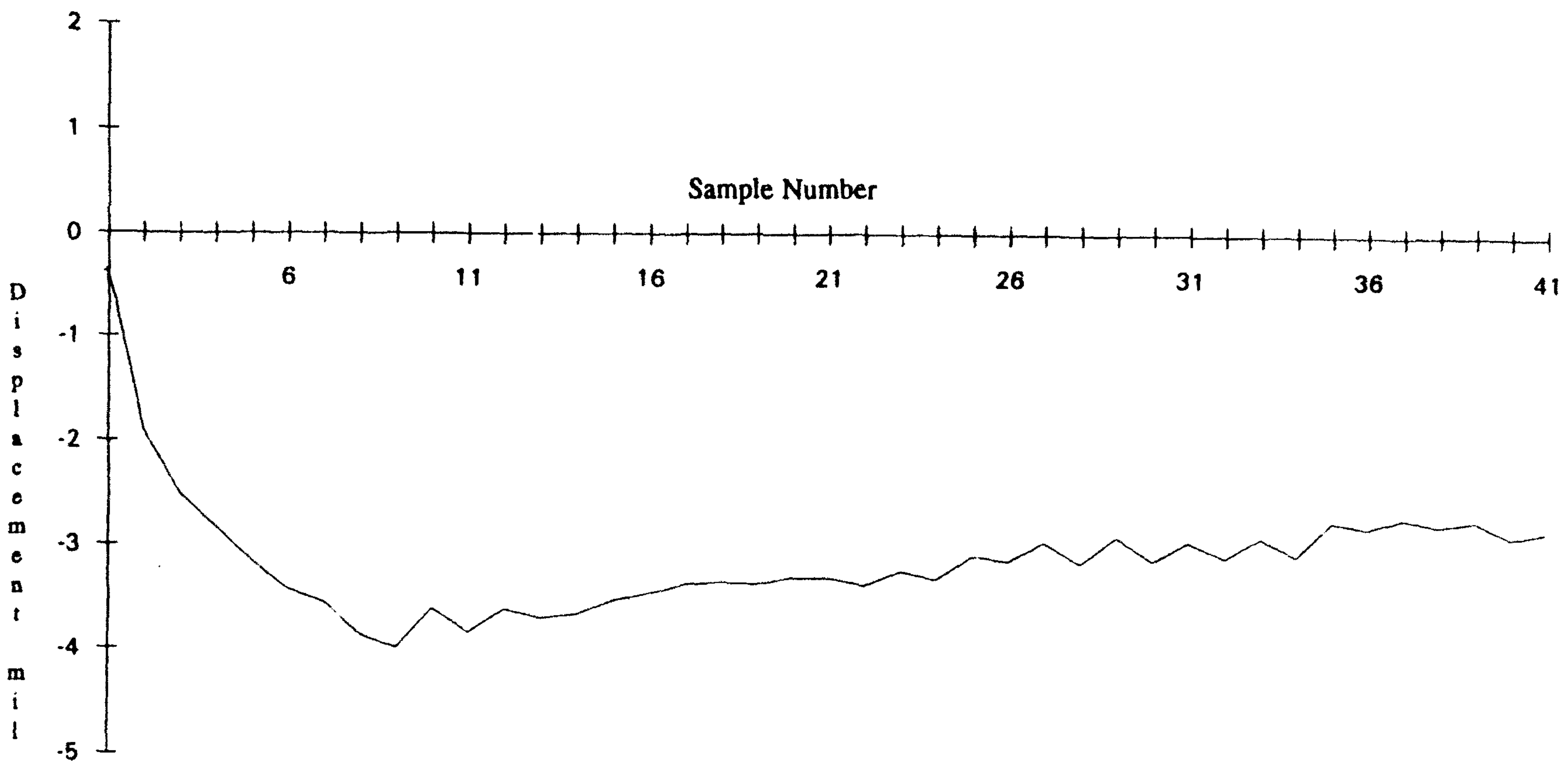
Time	Bed Low 2	Bed Top 4	Turret Side	Turret Left	Turret Right	Z-way Spindle	Z-way Spindle
10:14:07	75.9	75.5	76.8	75.9	75.9	78.9	76.3
10:19:57	75.9	75.5	76.3	75.9	75.9	78.9	76.8
10:25:47	75.9	75	76.3	75	75.5	78	76.3
10:31:37	75.9	75.5	76.3	75.9	75.9	78.5	76.8
10:37:26	76.3	75.5	76.8	75.9	75.9	78.9	76.8
10:43:16	75.9	75.1	76.8	75.5	75.5	79.3	76.8
10:49:05	76.3	75.9	76.8	76.3	75.9	79.3	76.8
10:54:55	76.3	75.5	77.2	75.9	75.9	79.8	77.2
11:00:45	76.3	75.9	76.8	76.8	76.3	79.8	77.6
11:06:34	76.3	75.5	77.2	76.3	75.9	79.7	77.2
11:12:24	76.3	75.5	77.2	76.3	76.3	80.2	77.2
11:18:13	75.9	75.9	77.6	76.8	75.9	80.6	77.6
11:24:03	76.8	75.9	78.5	76.8	76.8	81.4	78
11:29:52	76.3	75.5	78.5	77.2	76.3	81.4	77.6
11:35:42	76.3	75.9	78.5	76.8	76.3	82.3	77.6
11:41:32	76.8	76.3	78.9	77.6	77.2	82.7	78.5
11:47:21	76.8	75.9	78.9	77.6	76.8	82.7	78.5
11:53:11	77.2	76.3	79.3	77.6	76.8	83.1	78.5
11:59:00	76.8	76.3	79.3	78	76.8	83.1	78.9
12:04:50	77.2	76.8	79.8	78	77.2	83.6	78.5
12:10:39	77.2	76.3	80.2	78	77.2	84.4	78.5
12:16:29	77.2	76.3	80.2	78.5	77.5	84	79.3
12:22:18	77.2	76.8	80.2	78.5	77.6	85.3	79.3
12:28:08	78.1	76.4	80.6	78.9	77.6	85.3	79.8
12:33:58	77.6	77.2	80.6	78.9	77.6	85.7	79.8
12:39:47	77.6	76.8	80.6	78.9	77.6	85.7	79.8
12:45:37	77.6	77.2	81	78.9	78.1	86.1	80.2
12:51:26	77.6	77.2	81	79.3	78.1	86.1	79.8
12:57:16	78.1	77.2	81.5	79.3	78.1	86.5	80.2
13:03:06	78.1	76.8	81.9	78.9	78.1	87	80.2
13:08:55	78.9	77.7	82.3	80.6	79.4	87.8	81.1
13:14:45	78.1	77.2	81.9	79.3	78.5	87	80.2
13:20:34	78.1	76.8	81.9	79.3	78.5	87.4	80.6
13:26:24	78.5	77.6	82.3	79.8	78.9	87.8	81
13:32:13	78.5	77.6	82.7	80.2	78.9	87.8	81
13:38:03	78.1	77.6	82.3	80.2	78.9	87.4	81
13:43:52	78.5	78.1	82.7	80.6	79.3	87.8	81
13:49:42	78.5	78.1	82.7	80.6	79.3	88.7	81.5
13:55:32	78.5	78.1	82.7	80.6	79.3	88.2	81
14:01:21	78.5	78.1	82.7	80.6	79.3	88.2	81.5
14:07:11	78.9	78.5	83.2	81.1	79.4	89.1	81.9

Time	Z-way Turret	Hyd. Line	Hyd. Ret Pipe	Spindle Top	Oil	Oil	Spindle Side
10:14:07	75.9	90.7	89	80.6	80.6	83.5	81
10:19:57	75.9	93.7	96.6	86.1	85.7	92	83.5
10:25:47	75.5	97.5	101.3	91.6	90.3	96.2	87.8
10:31:37	75.5	101.7	105.1	96.2	94.1	100.4	91.6
10:37:26	75.5	105.1	108.4	100	98.3	104.2	95.4
10:43:16	75.5	108.9	111.8	103.4	101.7	107.6	99.6
10:49:05	76.3	111.8	114.3	106.3	105.1	111.4	102.1
10:54:55	76.8	109.3	116	108.4	107.6	113	104.6
11:00:45	76.8	108	114.3	109.7	110.1	113.4	106.3
11:06:34	75.9	112.6	117.2	110.5	111.8	116	107.2
11:12:24	75.9	106.3	115.5	111.4	113.5	115.1	108.9
11:18:13	76.3	112.2	117.2	111.8	114.7	117.6	109.3
11:24:03	76.8	107.2	116.4	112.6	115.1	116.8	109.7
11:29:52	76.3	111.8	117.6	112.6	115.5	118.1	110.1
11:35:42	76.3	108	117.2	113.5	116.4	118.1	110.9
11:41:32	76.8	110.1	116	113	116.8	117.6	110.5
11:47:21	76.8	109.3	117.6	113.5	116.8	119.3	110.9
11:53:11	76.8	106.3	116	113.9	117.2	118.1	111.4
11:59:00	76.8	112.2	117.6	113.5	116.8	118.9	111.4
12:04:50	77.2	107.6	116.8	114.3	118.1	118.9	111.4
12:10:39	76.8	112.2	118.1	114.3	118.1	119.7	111.4
12:16:29	77.2	107.2	117.2	114.3	118.1	118.9	111.8
12:22:18	77.2	110.1	116.8	114.3	118.1	118.5	111.8
12:28:08	77.6	110.1	118.1	114.3	118.5	120.1	111.8
12:33:58	77.6	107.2	116.8	114.3	118.9	118.5	111.8
12:39:47	77.2	112.6	118.1	114.7	118.5	119.3	112.2
12:45:37	77.6	108	117.7	115.1	119.3	119.3	112.2
12:51:26	78.1	111.4	117.7	114.7	118.5	119.3	111.8
12:57:16	77.6	108.9	118.5	114.7	118.9	120.2	112.6
13:03:06	78.1	106.3	116.4	114.3	118.5	118.5	111.8
13:08:55	78.5	113.5	118.9	115.2	119.3	120.2	112.6
13:14:45	77.6	108	117.7	114.7	119.3	119.7	112.6
13:20:34	77.6	111.4	117.7	114.3	118.5	119.3	112.2
13:26:24	78.1	109.3	118.5	115.6	119.3	120.2	112.6
13:32:13	78.5	107.6	117.2	114.7	119.3	119.3	112.6
13:38:03	78.1	113.1	118.9	115.2	118.9	120.2	112.6
13:43:52	78.5	108	117.7	115.2	119.3	119.7	112.6
13:49:42	78.9	109.3	117.2	114.7	118.9	118.5	112.2
13:55:32	78.5	109.7	118.5	115.2	118.9	120.2	112.6
14:01:21	78.5	107.2	117.2	114.7	119.3	119.3	112.2
14:07:11	78.9	113.1	118.5	115.2	119.3	120.2	112.7

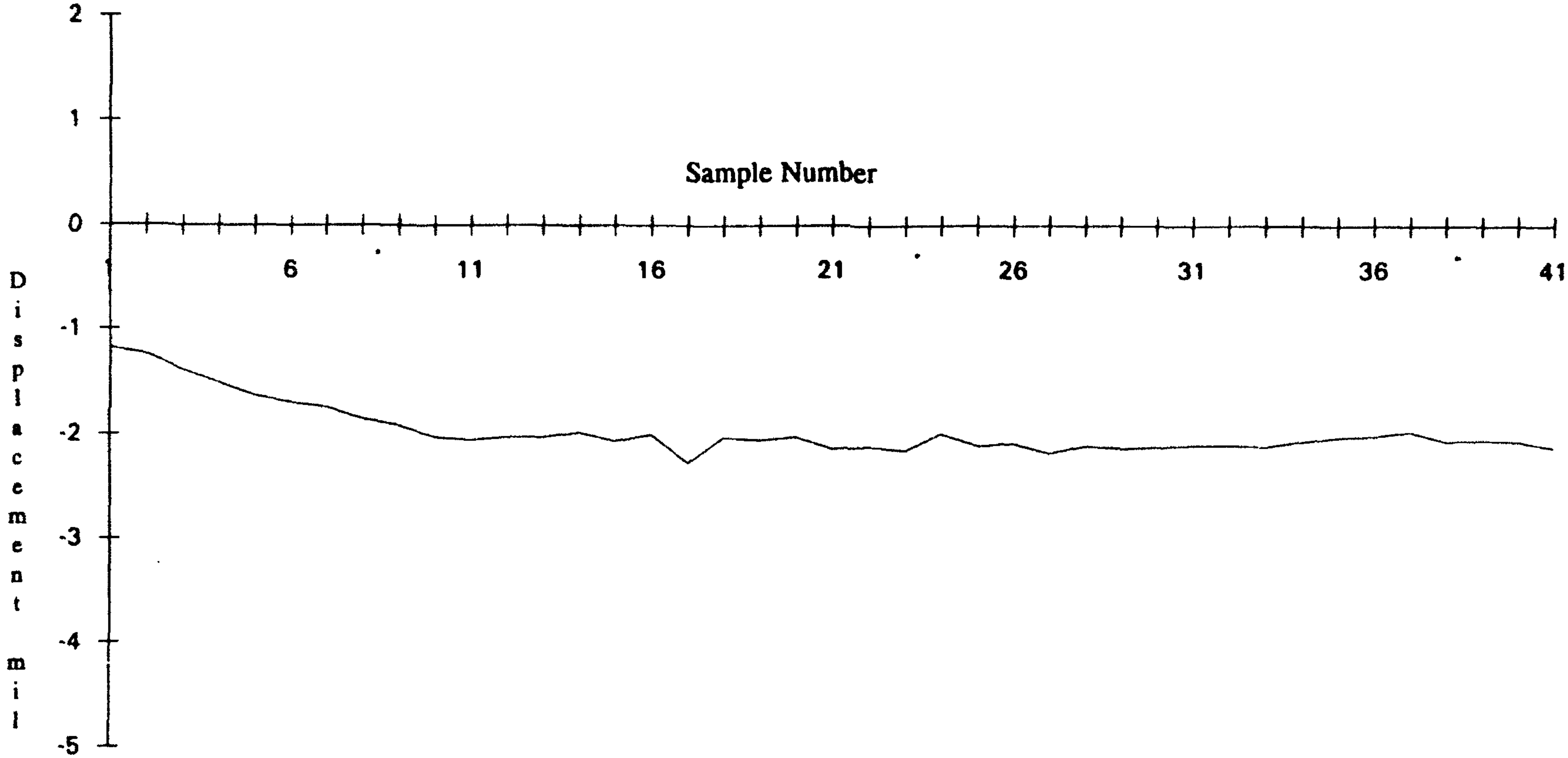
APPENDIX B. TYPICAL DISPLACEMENT DATA FOR POSITIONS 2 AND 3



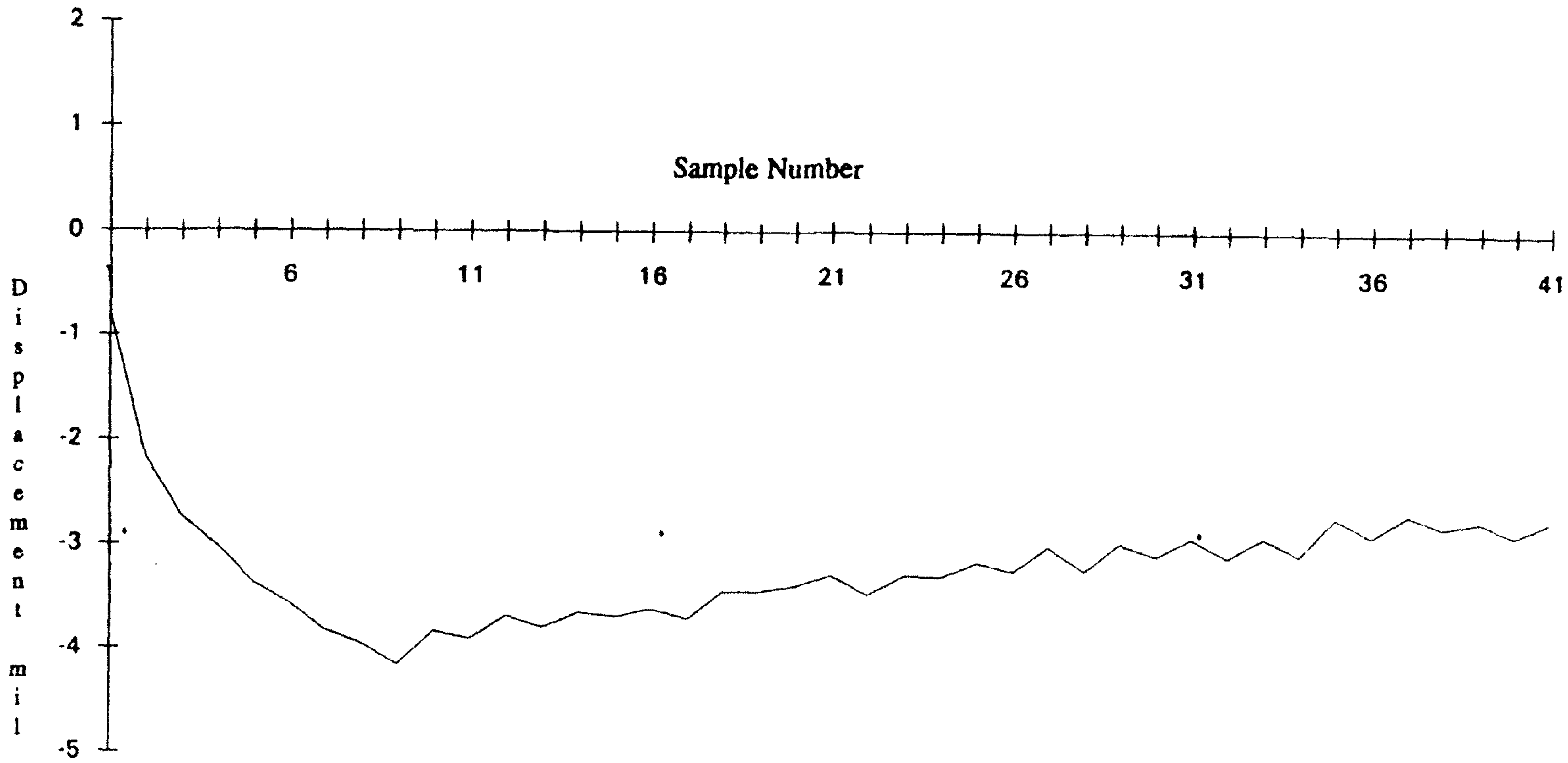
Appendix B1. Displacement in X Direction at Position 2



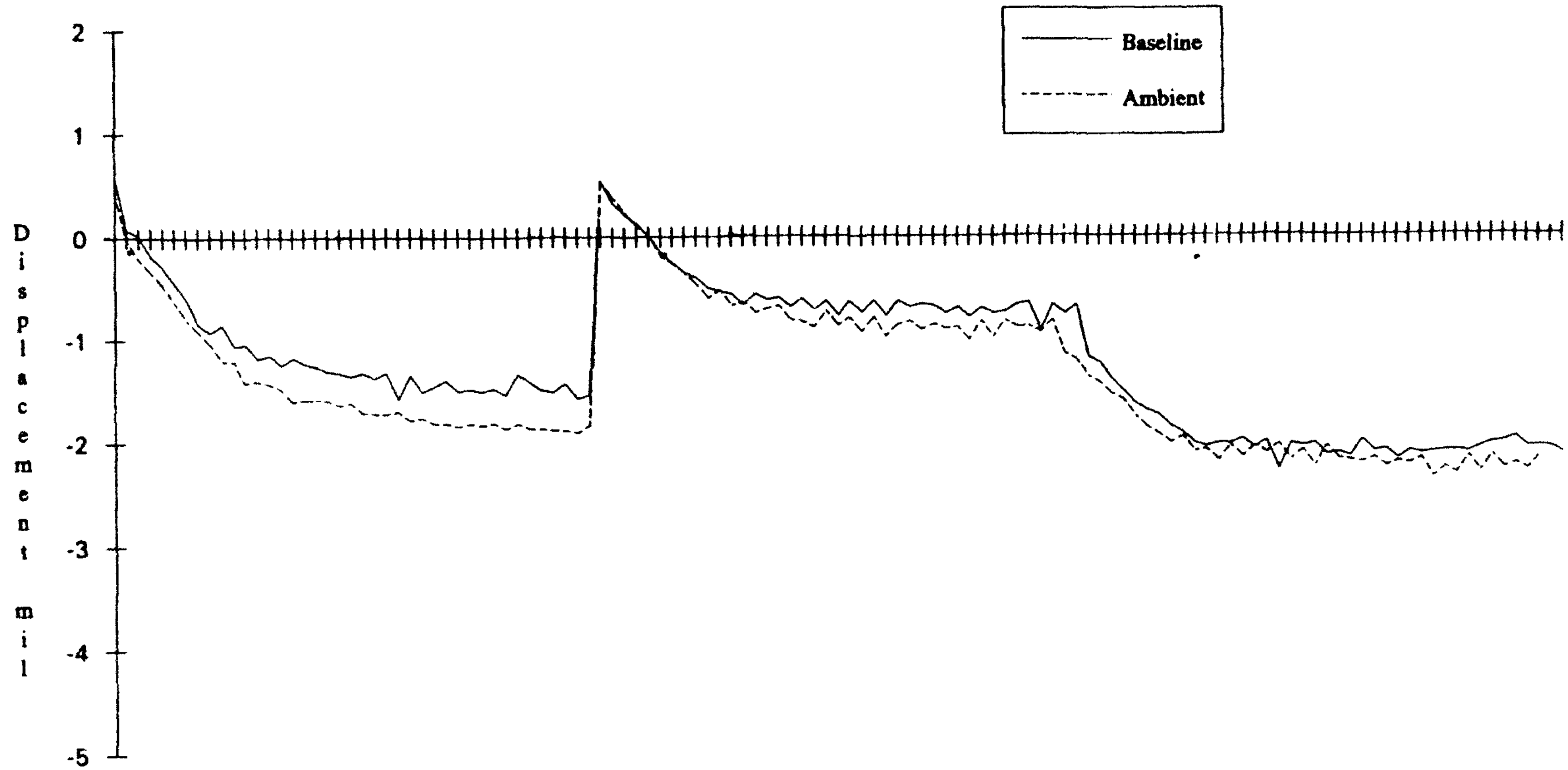
Appendix B2. Displacement in Z Direction at Position 2



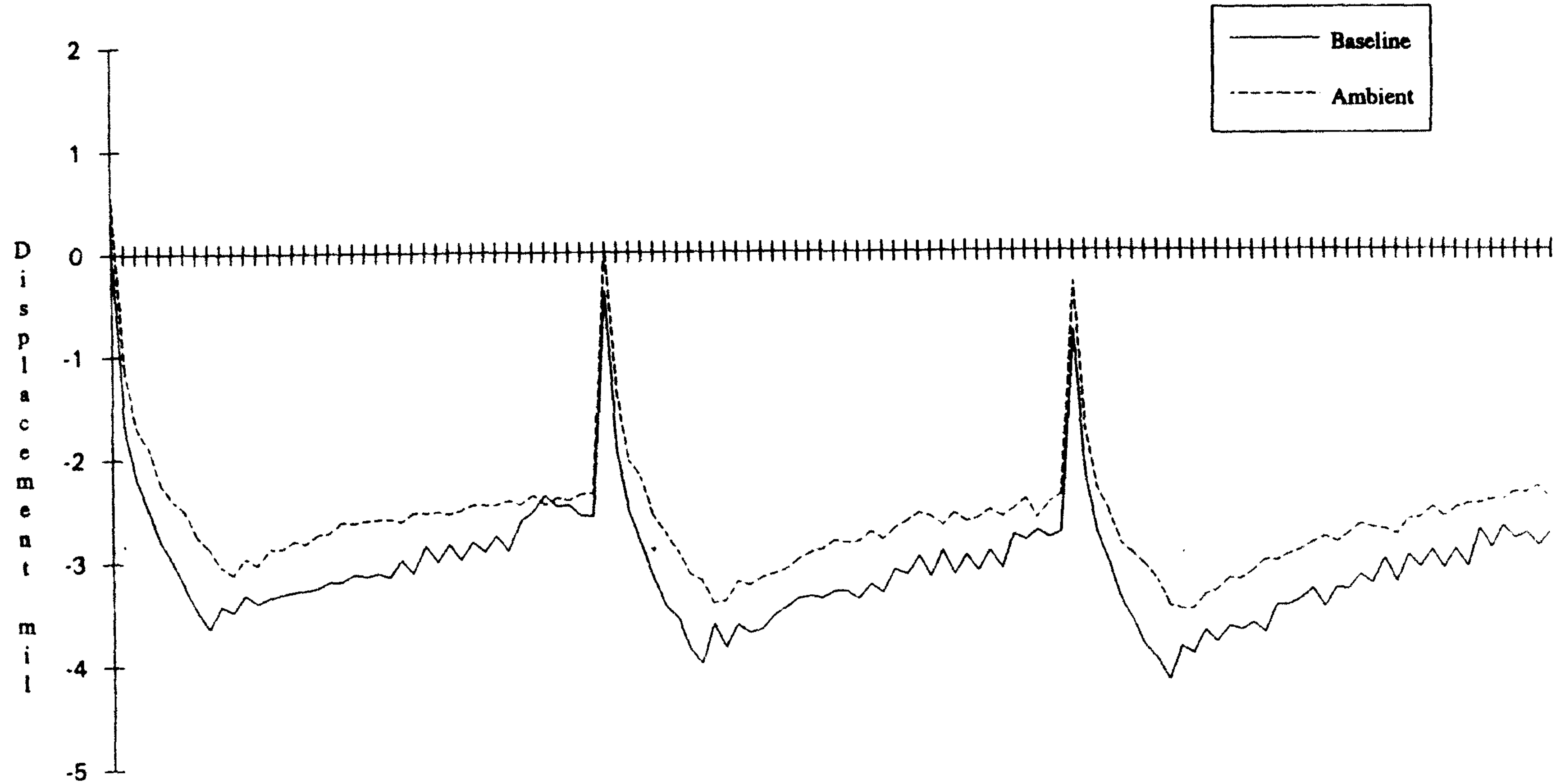
Appendix B3. Displacement in X Direction at Position 3



Appendix B4. Displacement in Z Direction at Position 3

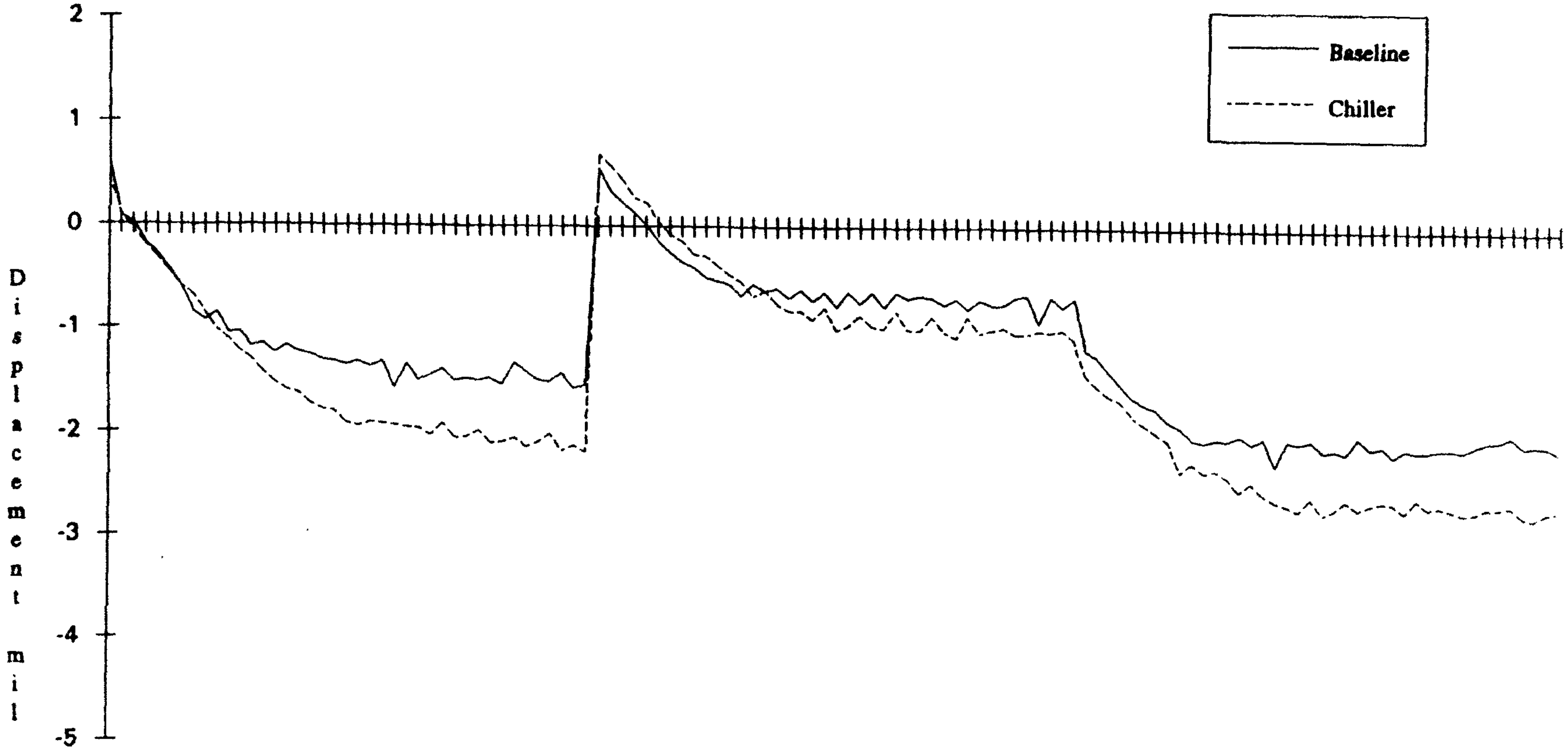


Appendix C1. Comparison of Ambient and Baseline Displacements -- X Direction

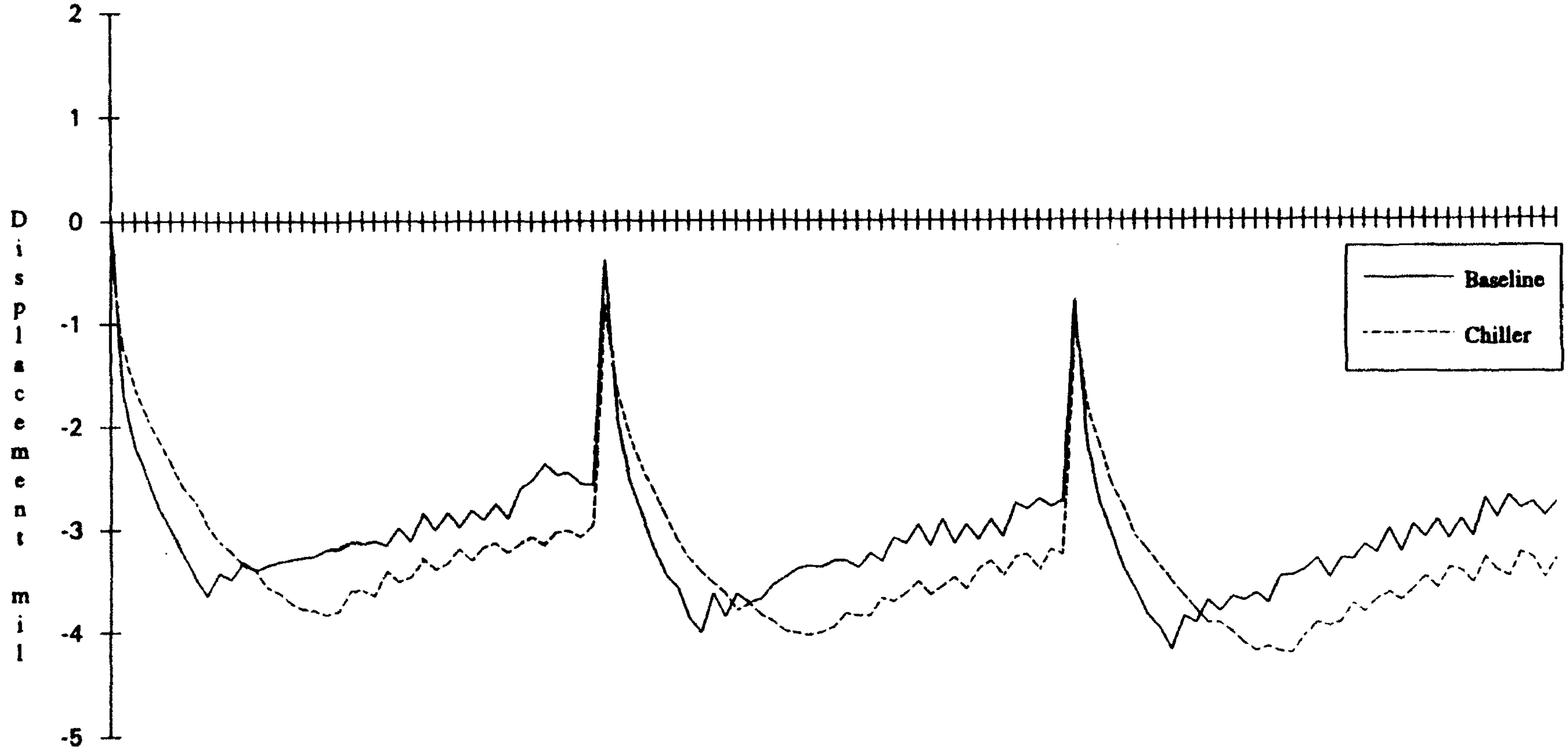


Appendix C2. Comparison of Ambient and Baseline Displacements – Z Direction

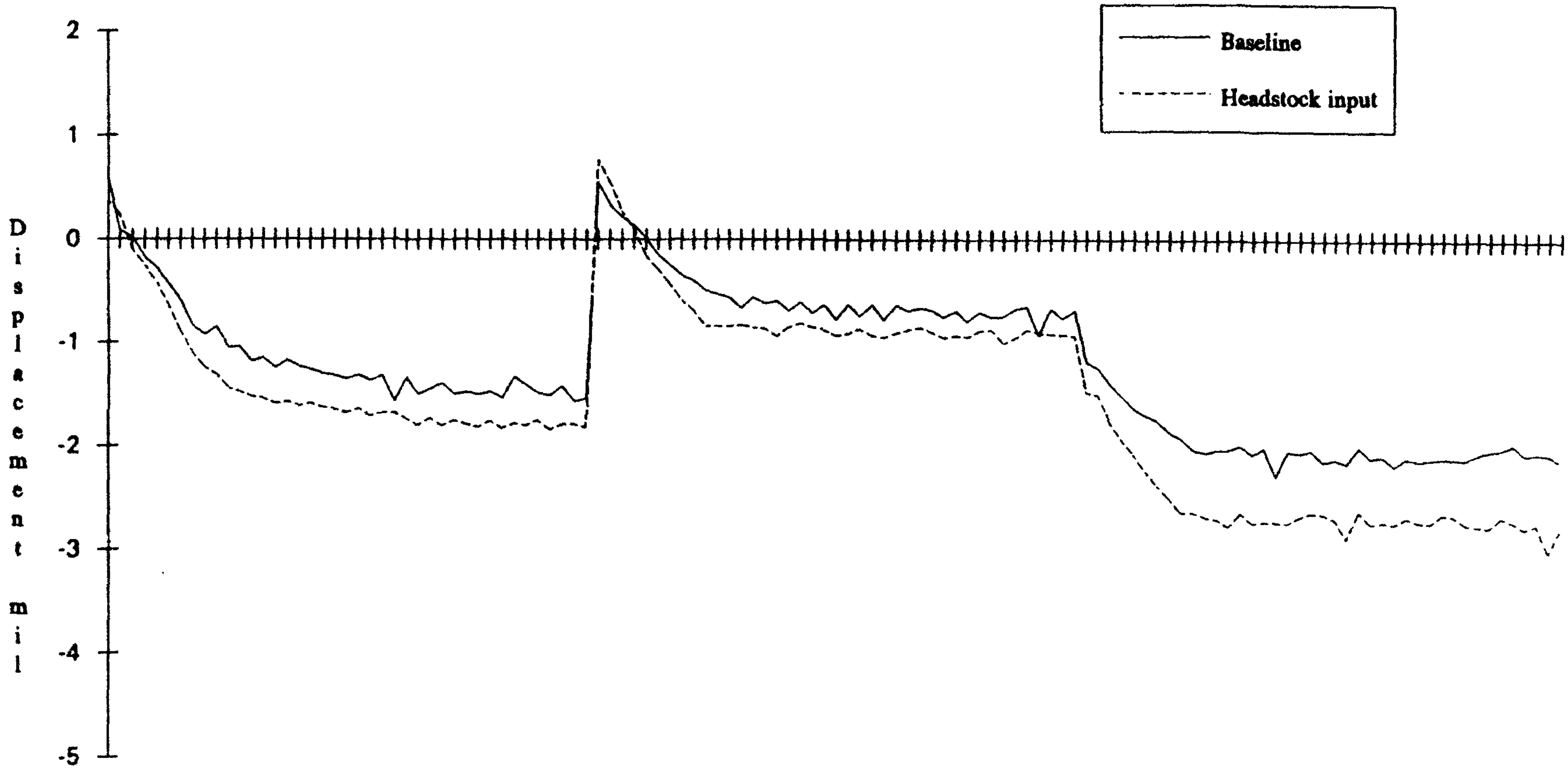
APPENDIX C. COMPARISON OF ACTUAL RESULTS OF TESTS WITH DIFFERENT THERMAL INPUTS



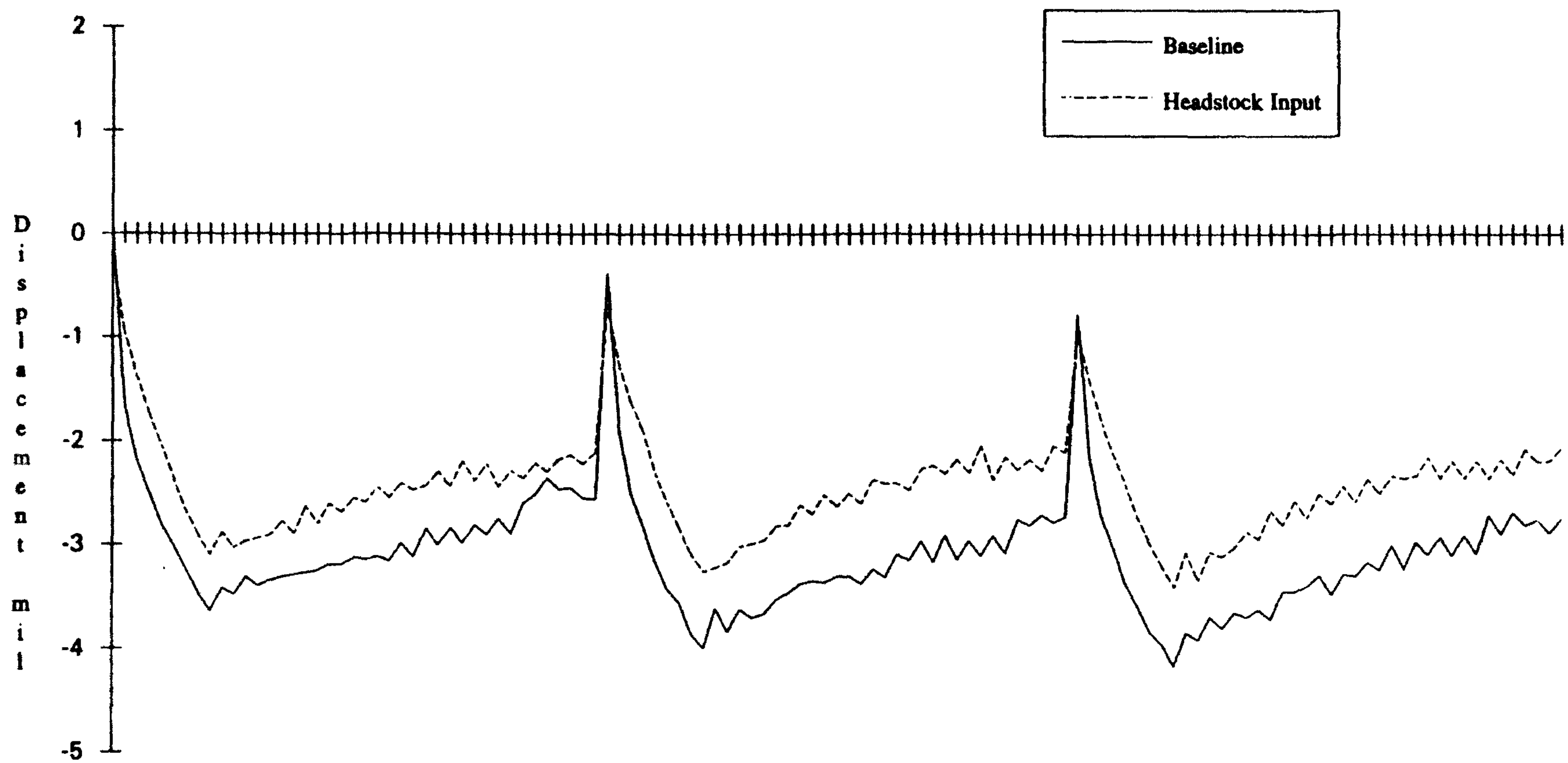
Appendix C3. Comparison of Displacements: Different Chiller Setting and Ambient – X Direction



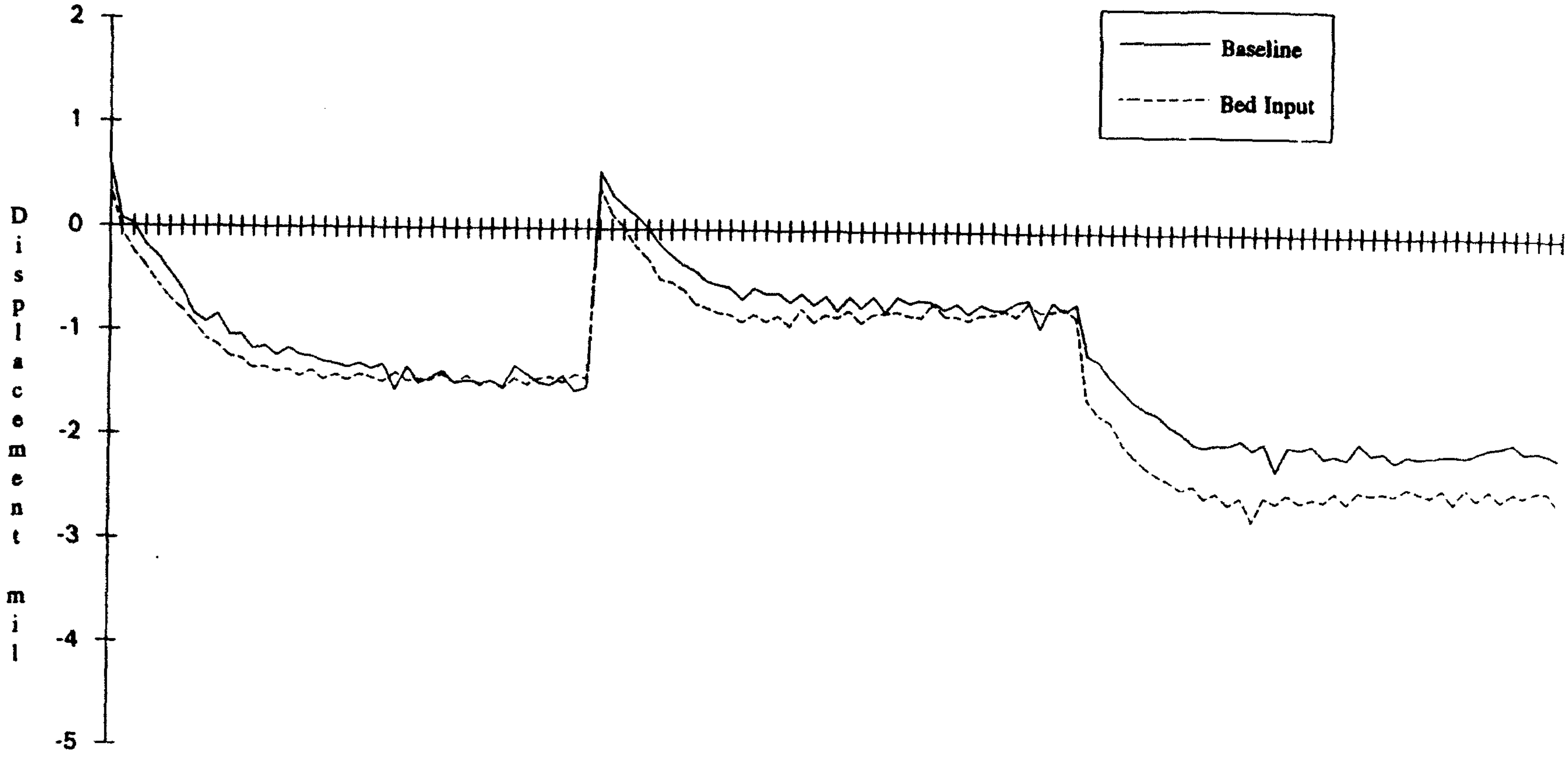
Appendix C4. Comparison of Displacements: Different Chiller Setting and Ambient -- Z Direction



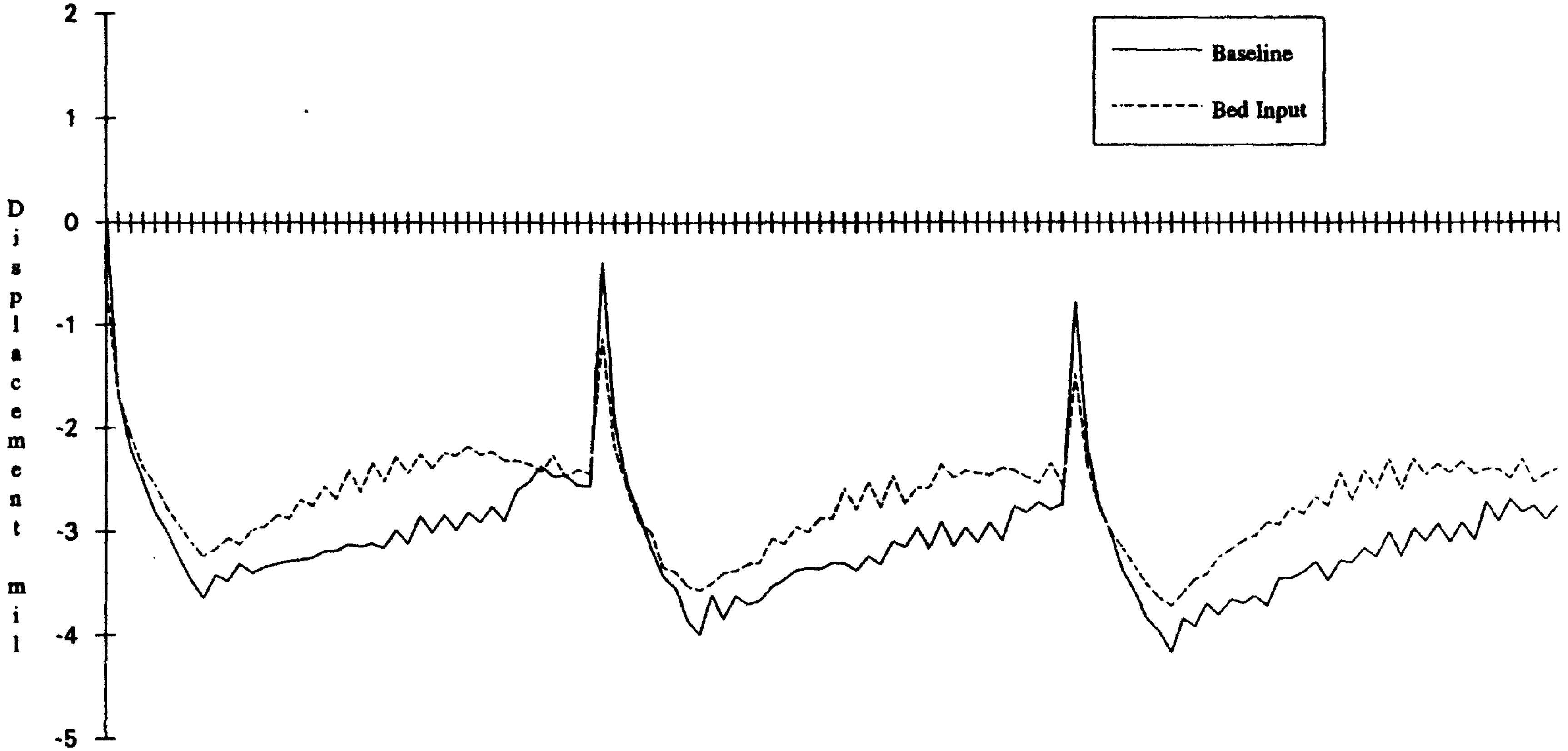
Appendix C5. Comparison of Displacements: Thermal Input to Headstock and Ambient – X Direction



Appendix C6. Comparison of Displacements: Thermal Input to Headstock and Ambient – Z Direction

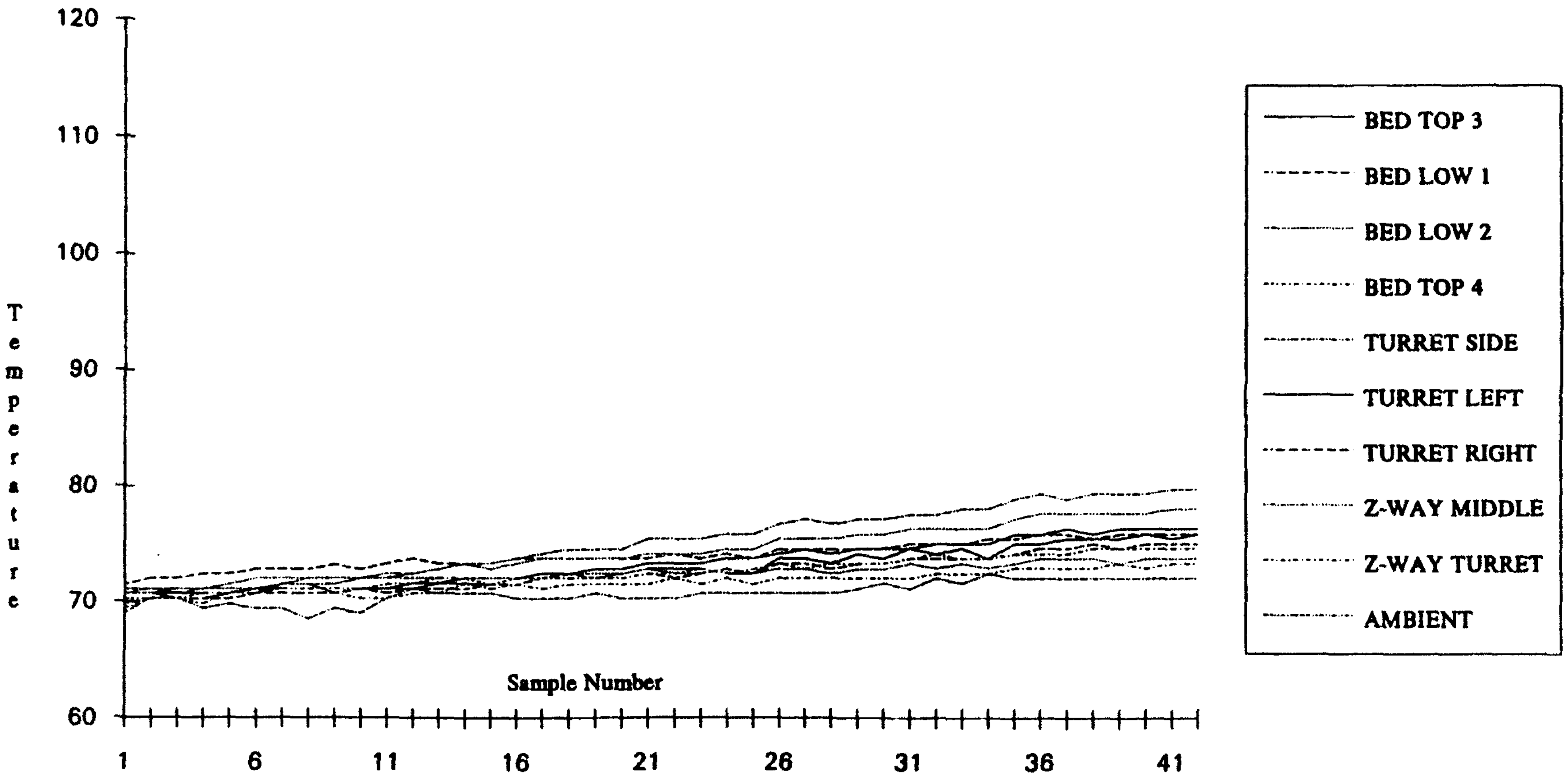


Appendix C7. Comparison of Displacements: Thermal Input to Bed and Ambient – X Direction

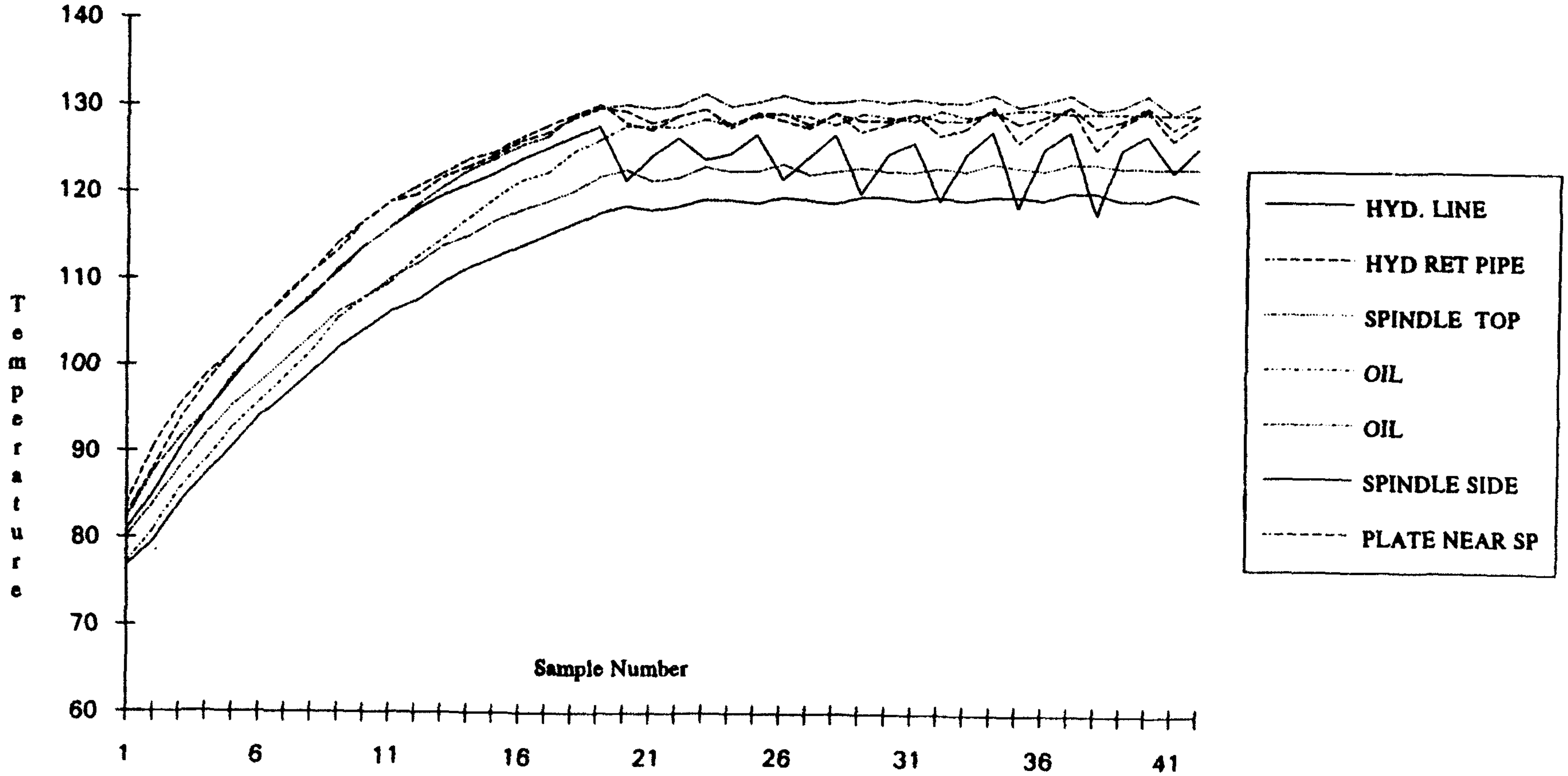


Appendix C8. Comparison of Displacements: Thermal Input to Bed and Ambient -- Z Direction

APPENDIX D. TEMPERATURES MEASURED DURING A TYPICAL EXPERIMENT

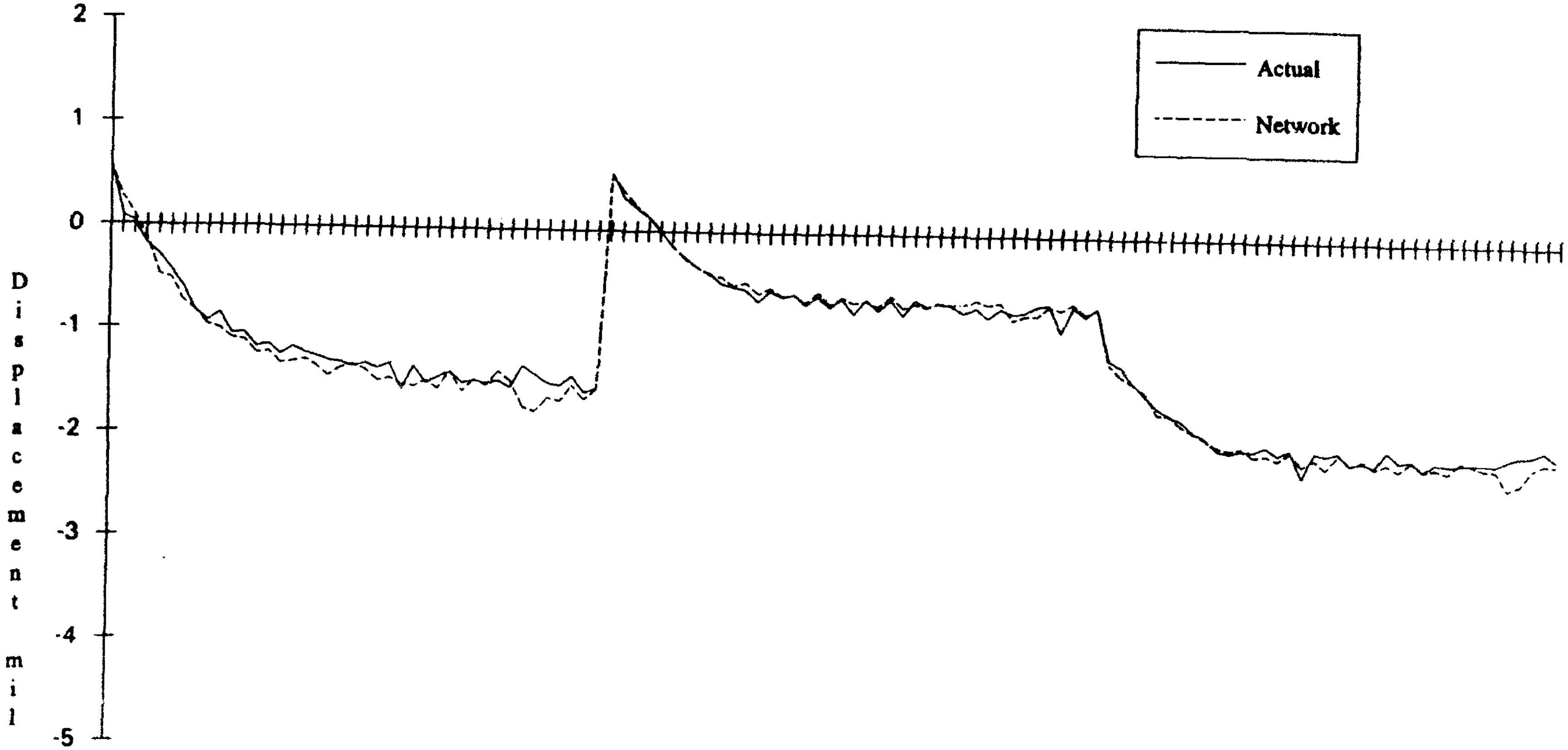


Appendix D1. Family of Curves from Bed, Turret and 2-way Measurements

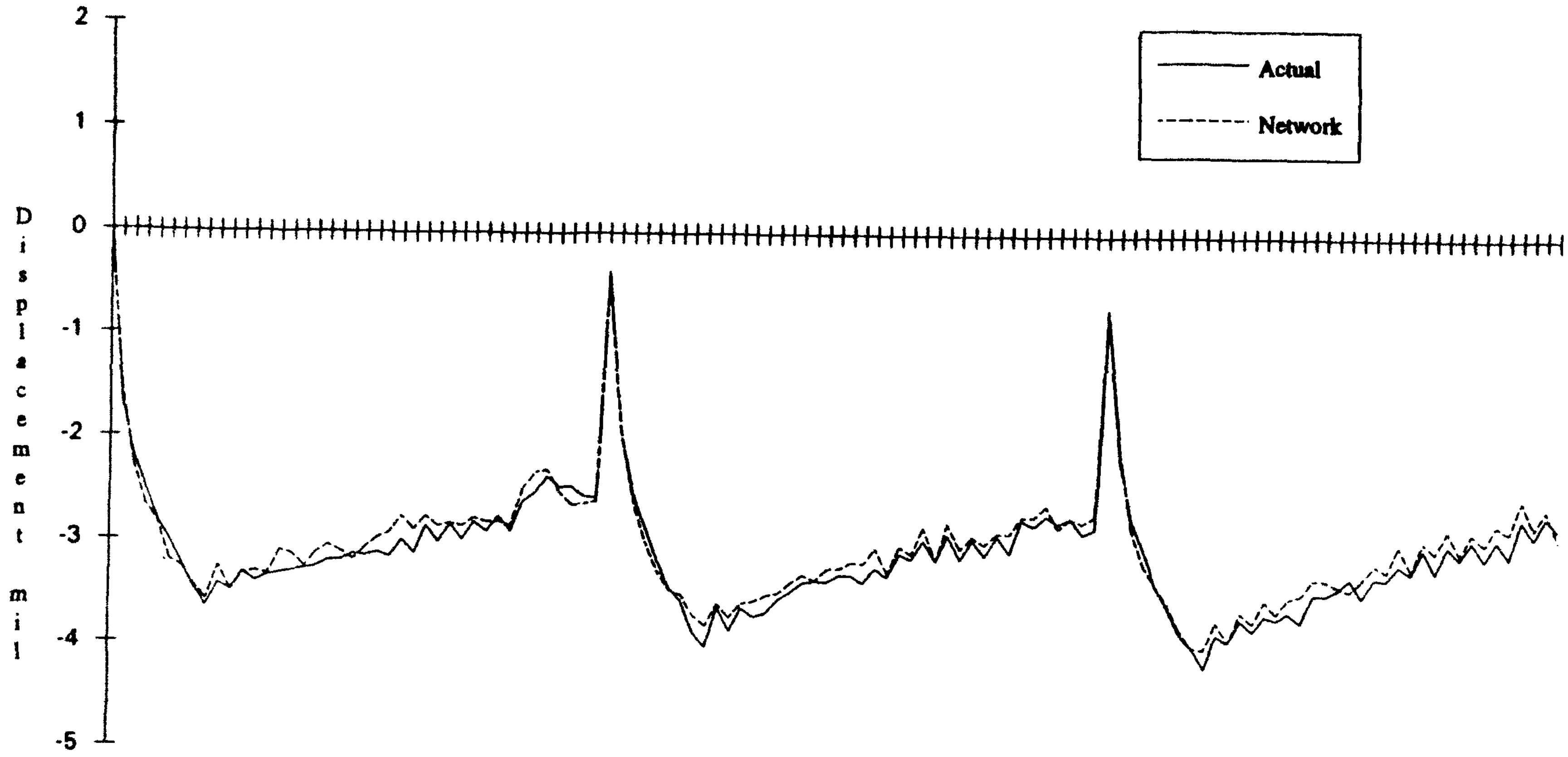


Appendix D2. Family of Curves from Hydraulic Lines and Headstock

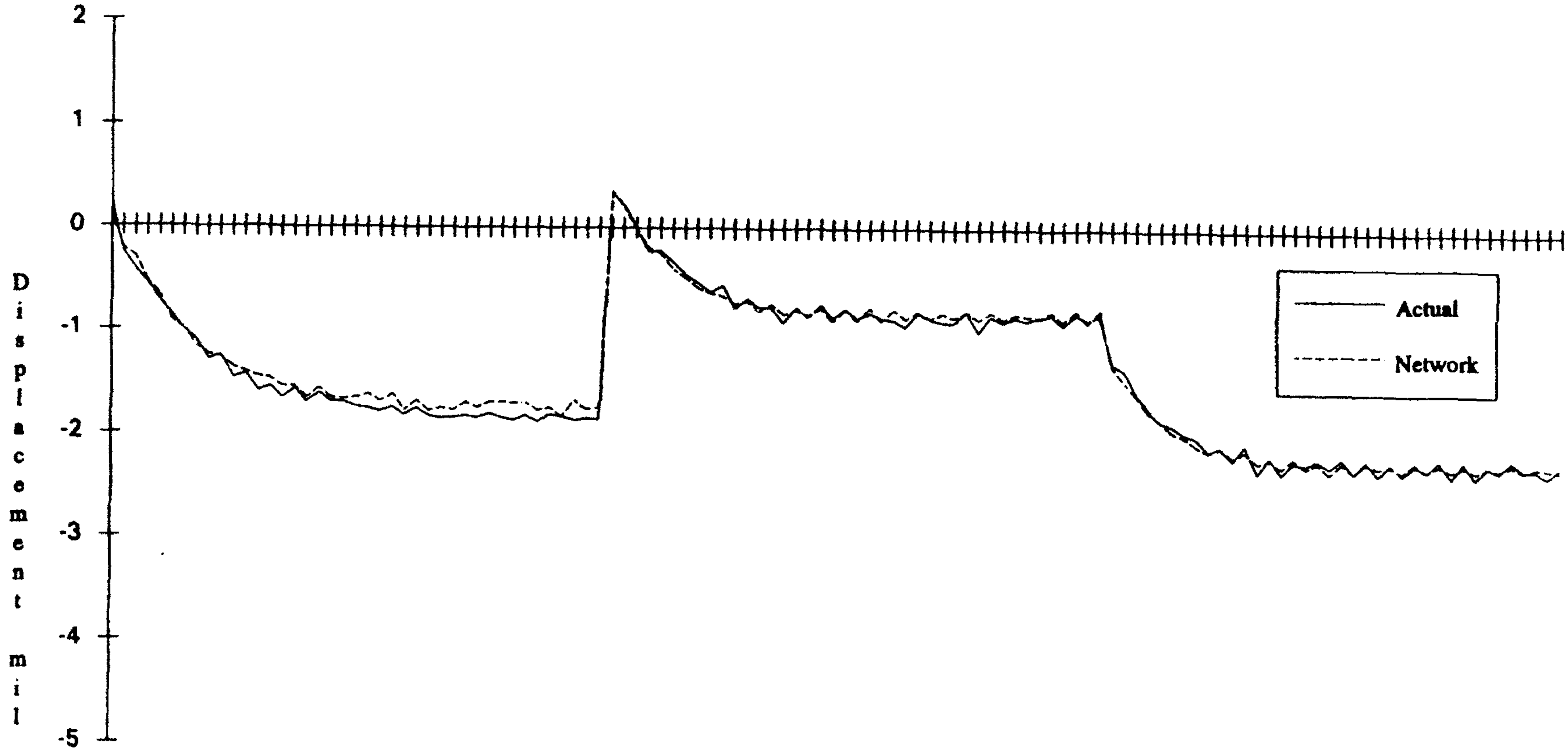
APPENDIX E. ADDITIONAL NETWORK COMPARISONS



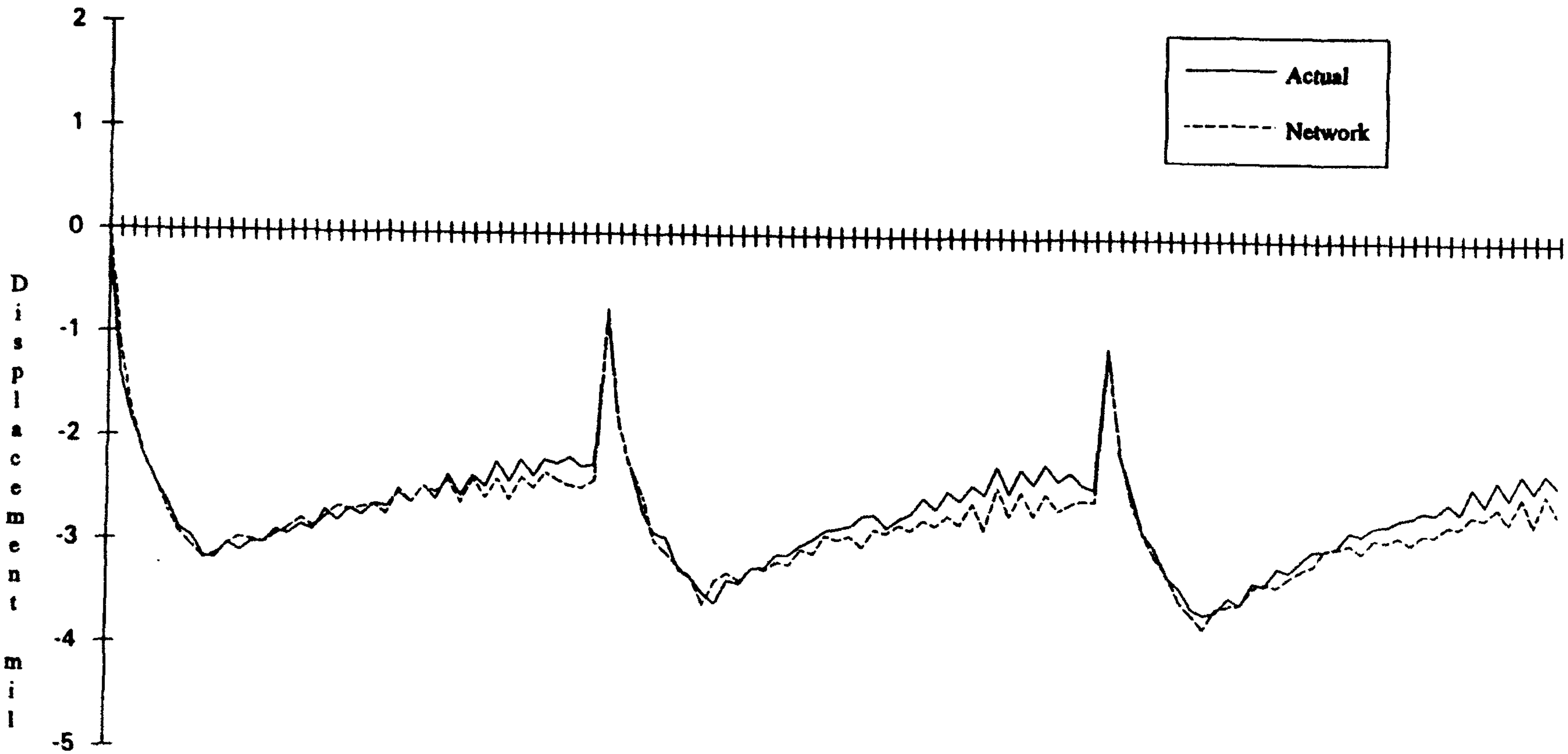
Appendix E1. Network Result for Baseline with 13 Inputs – X Direction



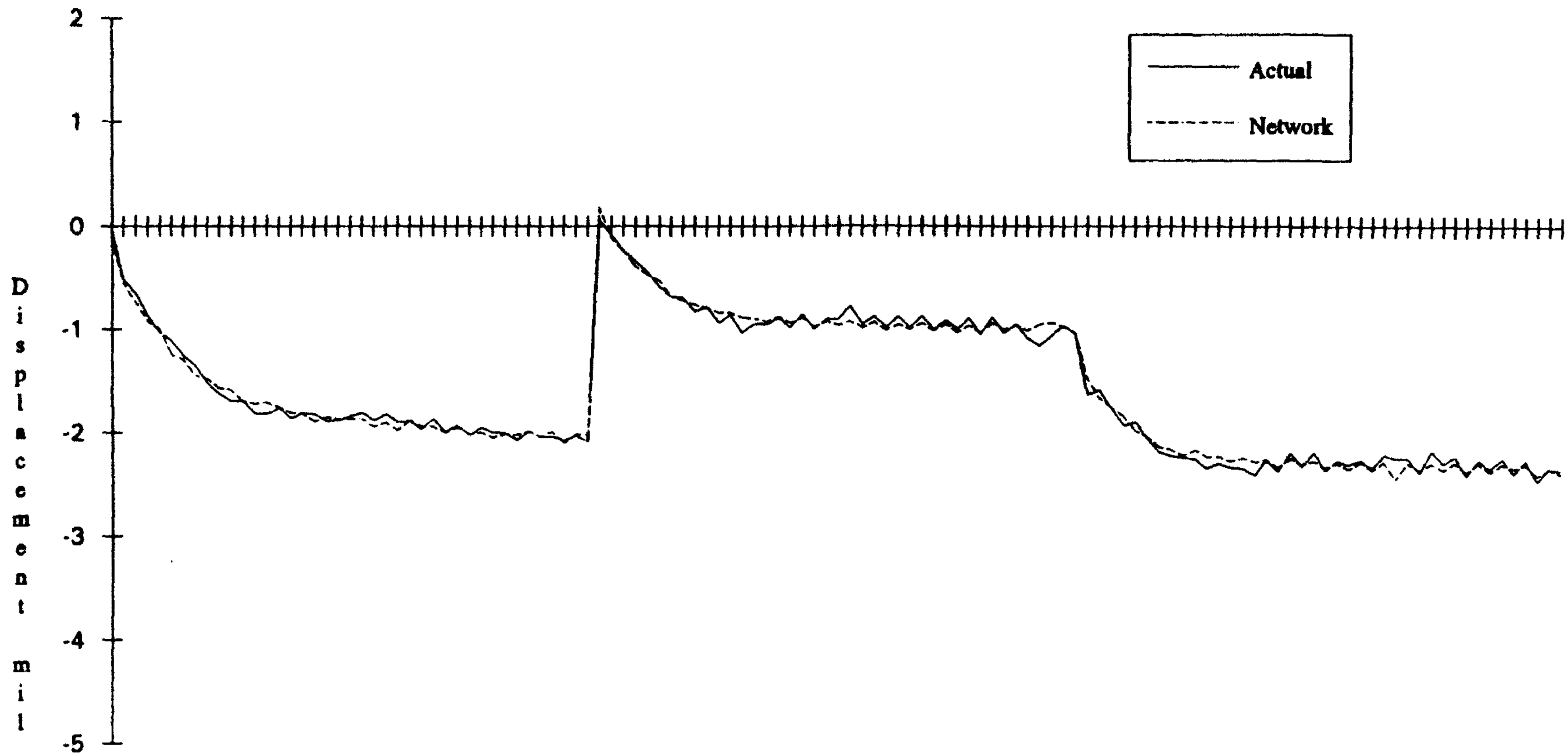
Appendix E2. Network Result for Baseline with 13 Inputs – Z Direction



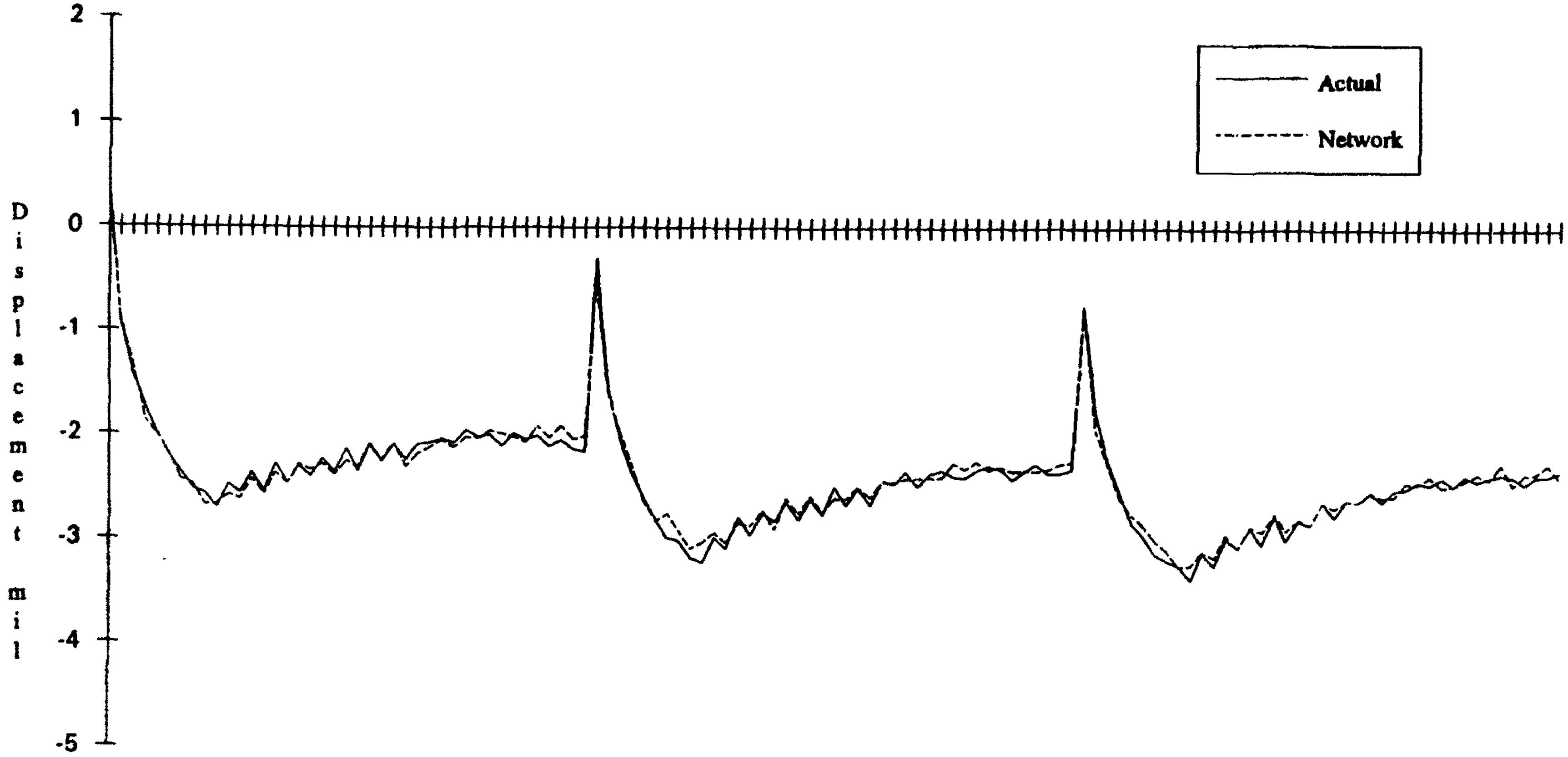
Appendix E3. Network Result for December 19 Ambient with 13 Inputs – X Direction



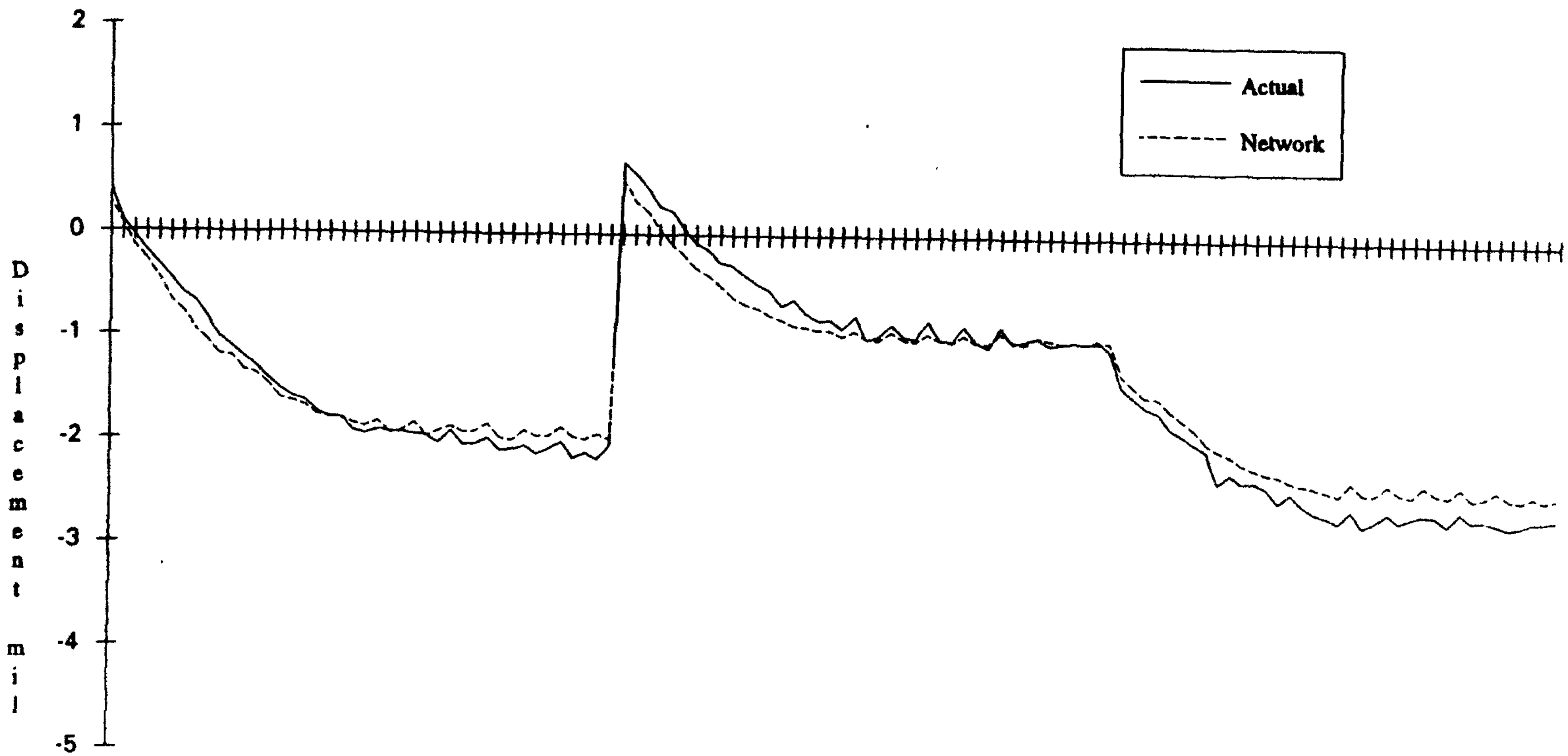
Appendix E4. Network Result for December 19 Ambient with 13 Inputs -- Z Direction



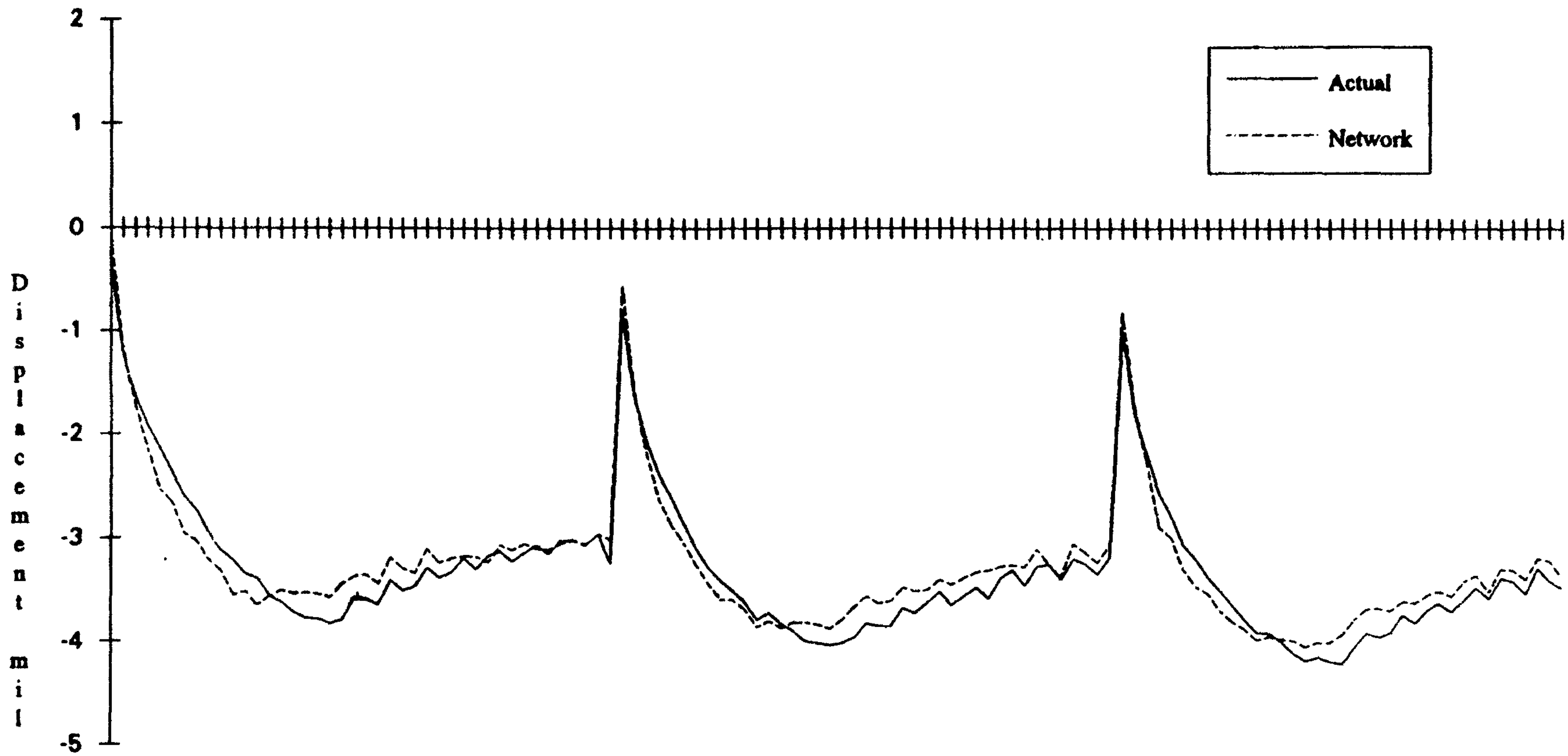
Appendix E5. Network Result for December 21 Ambient with 13 Inputs – X Direction



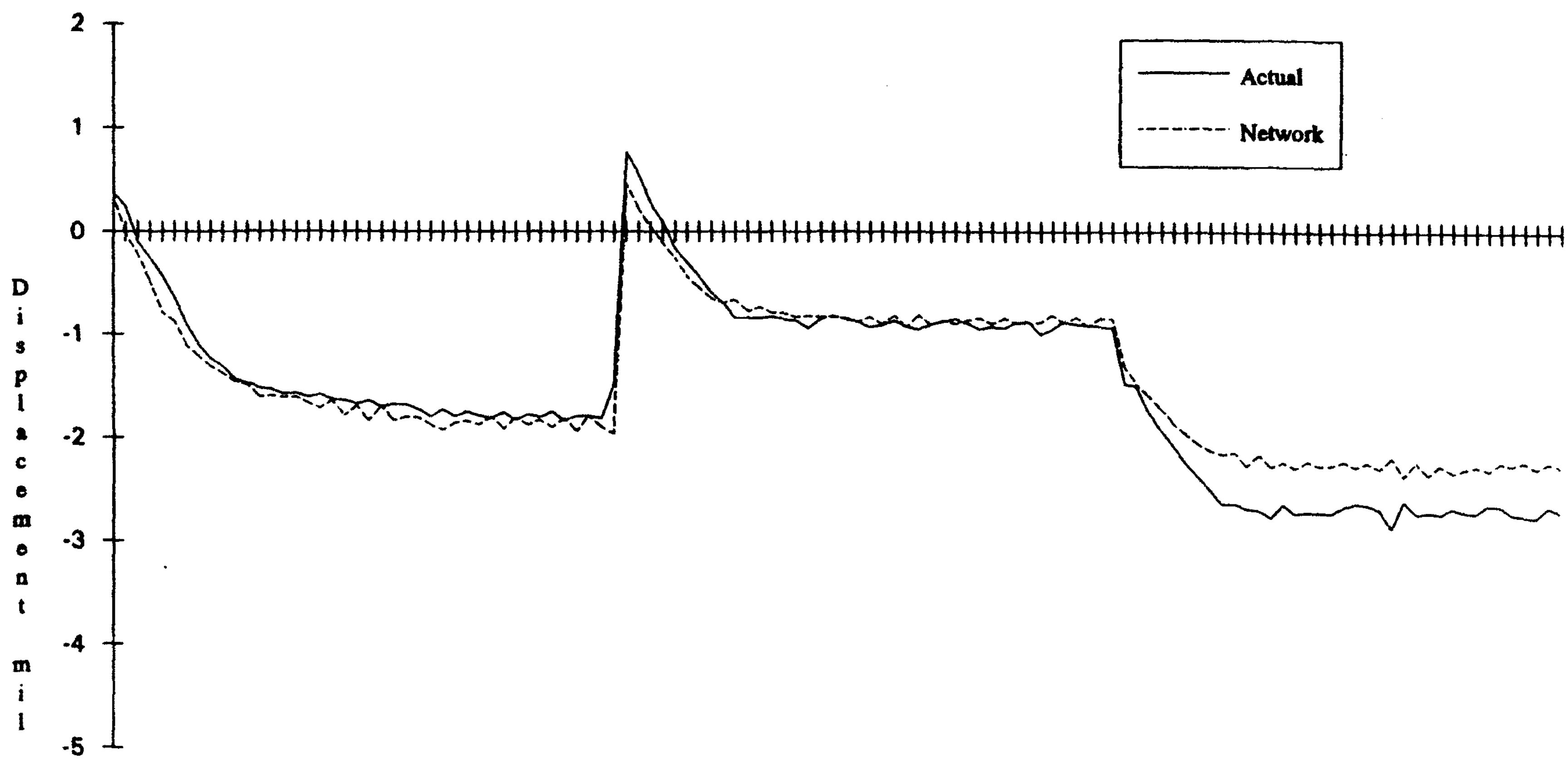
Appendix E6. Network Result for December 21 Ambient with 13 Inputs – Z Direction



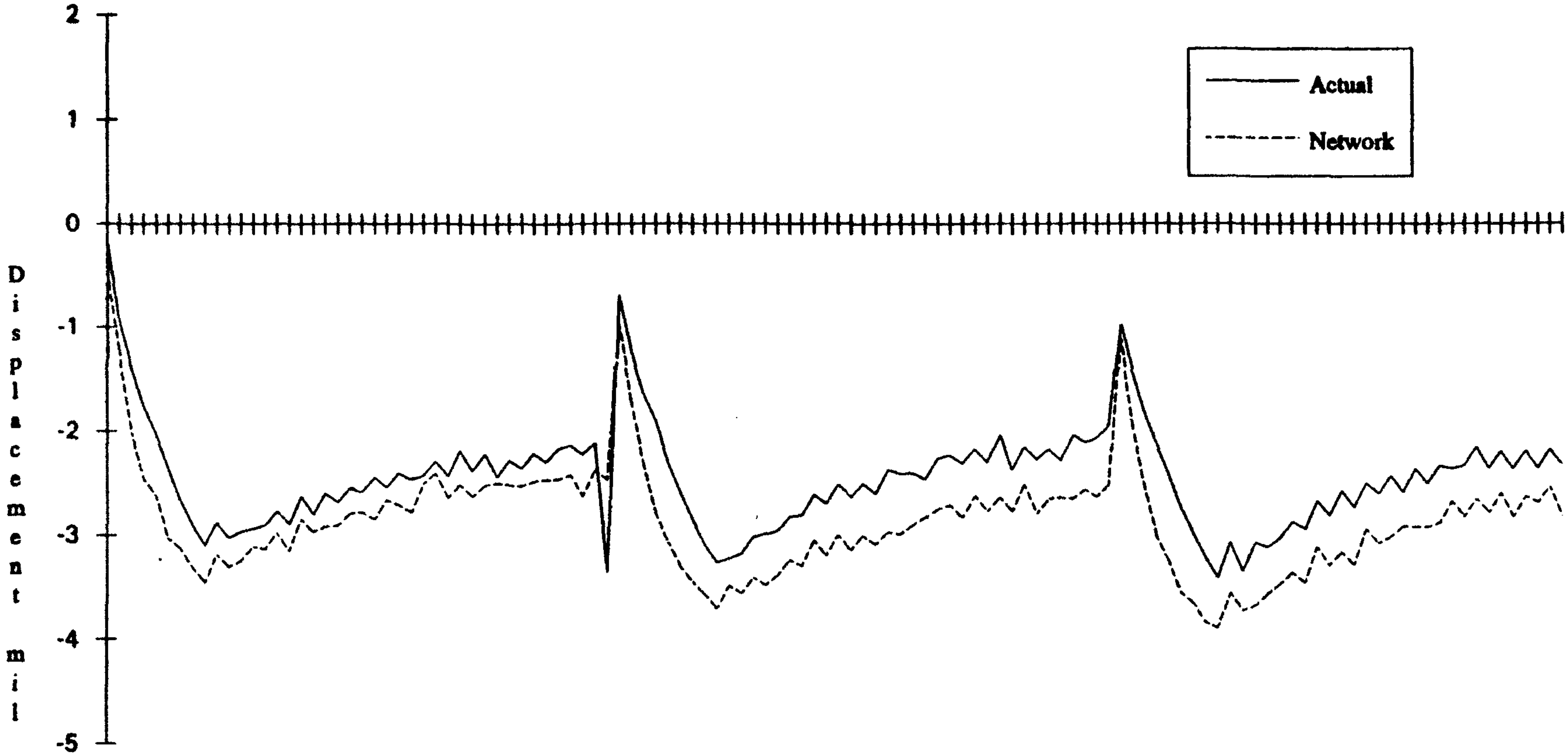
Appendix E7. Network Result for Different Chiller Setting with 13 Inputs – X Direction



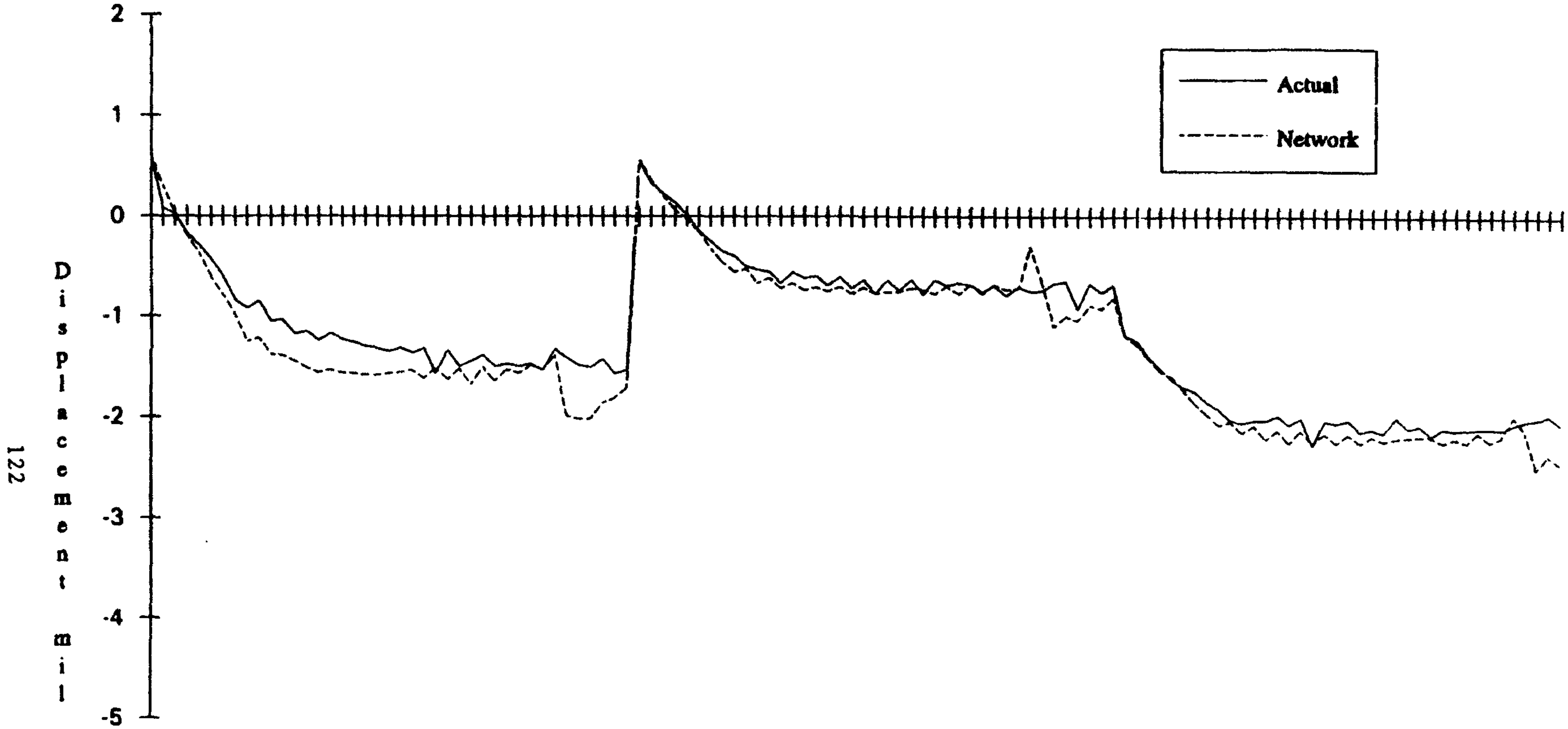
Appendix E8. Network Result for Different Chiller Setting with 13 Inputs – Z Direction



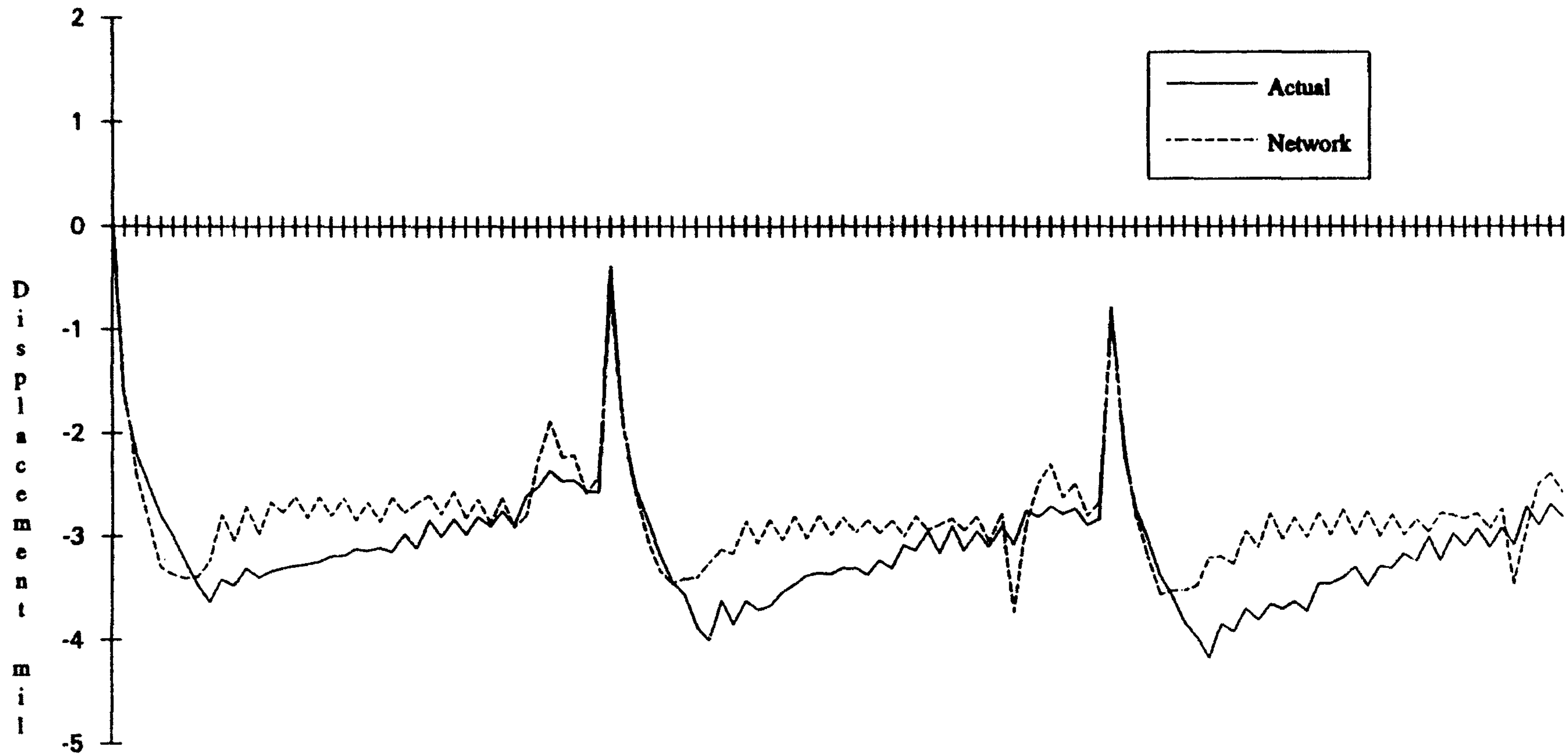
Appendix E9. Network Result for Thermal Input to Headstock with 13 Inputs -- X Direction



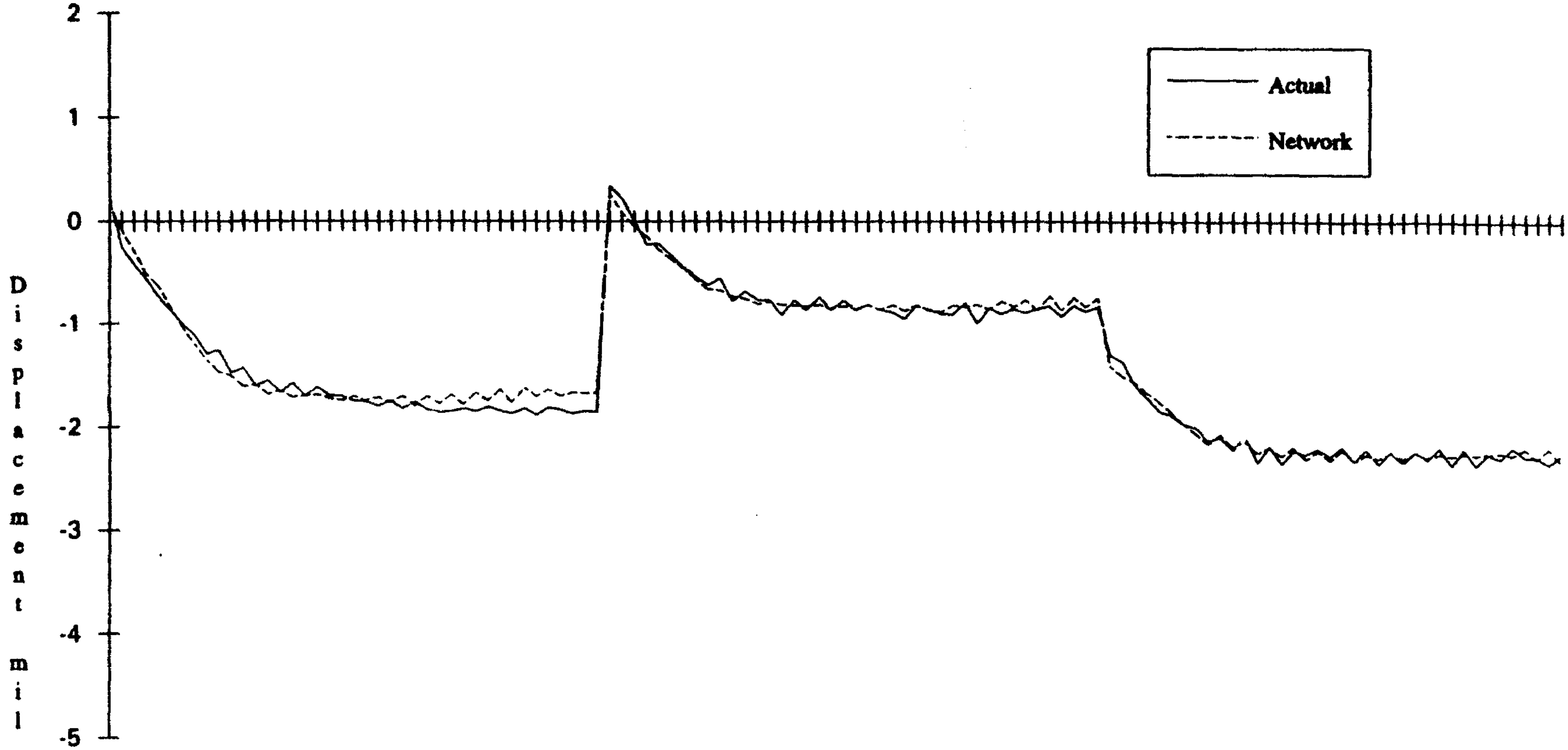
Appendix E10. Network Result for Thermal Input to Headstock with 13 Inputs – Z Direction



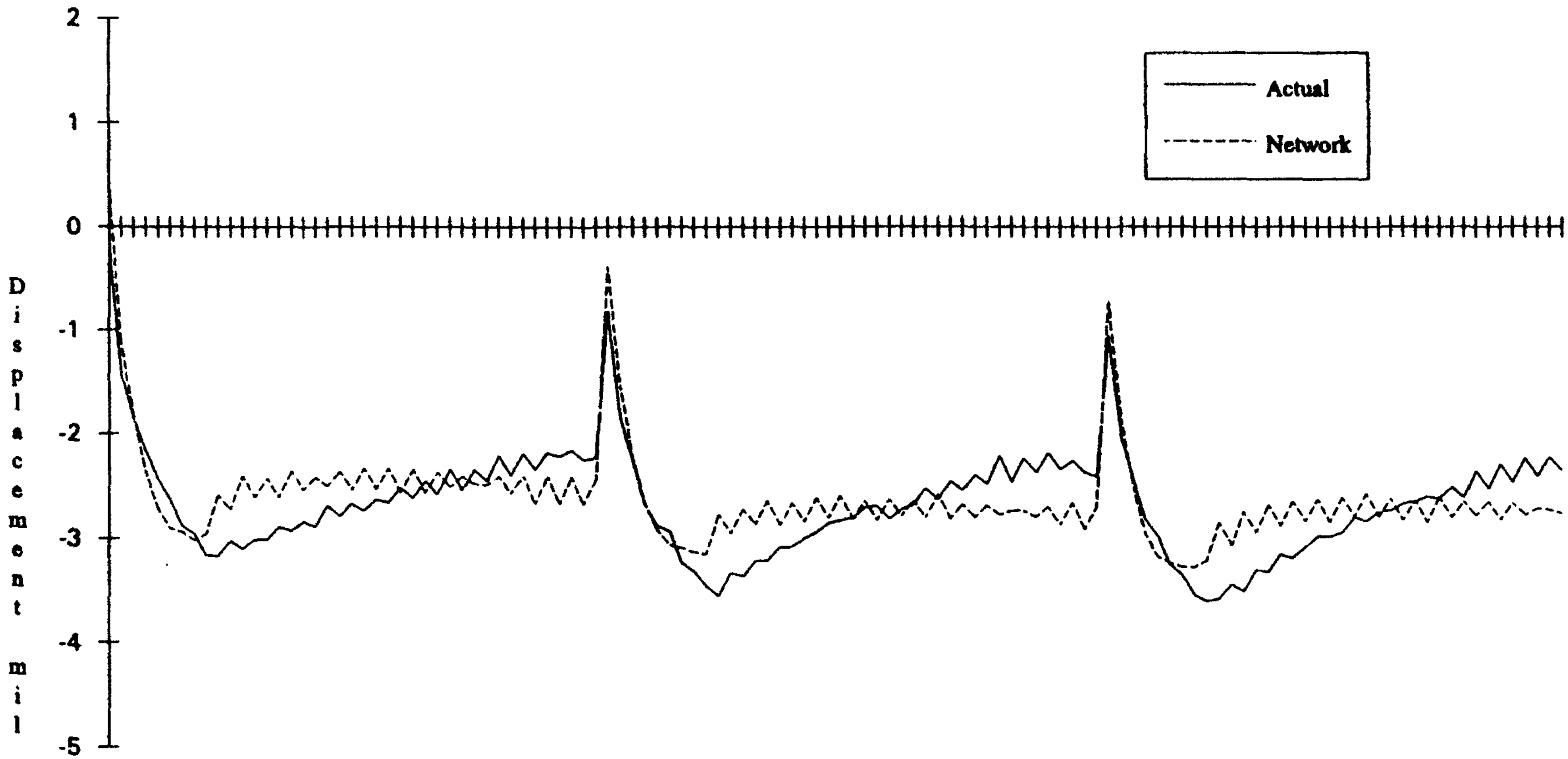
Appendix E11. Network Result for Baseline with 5 Inputs – X Direction



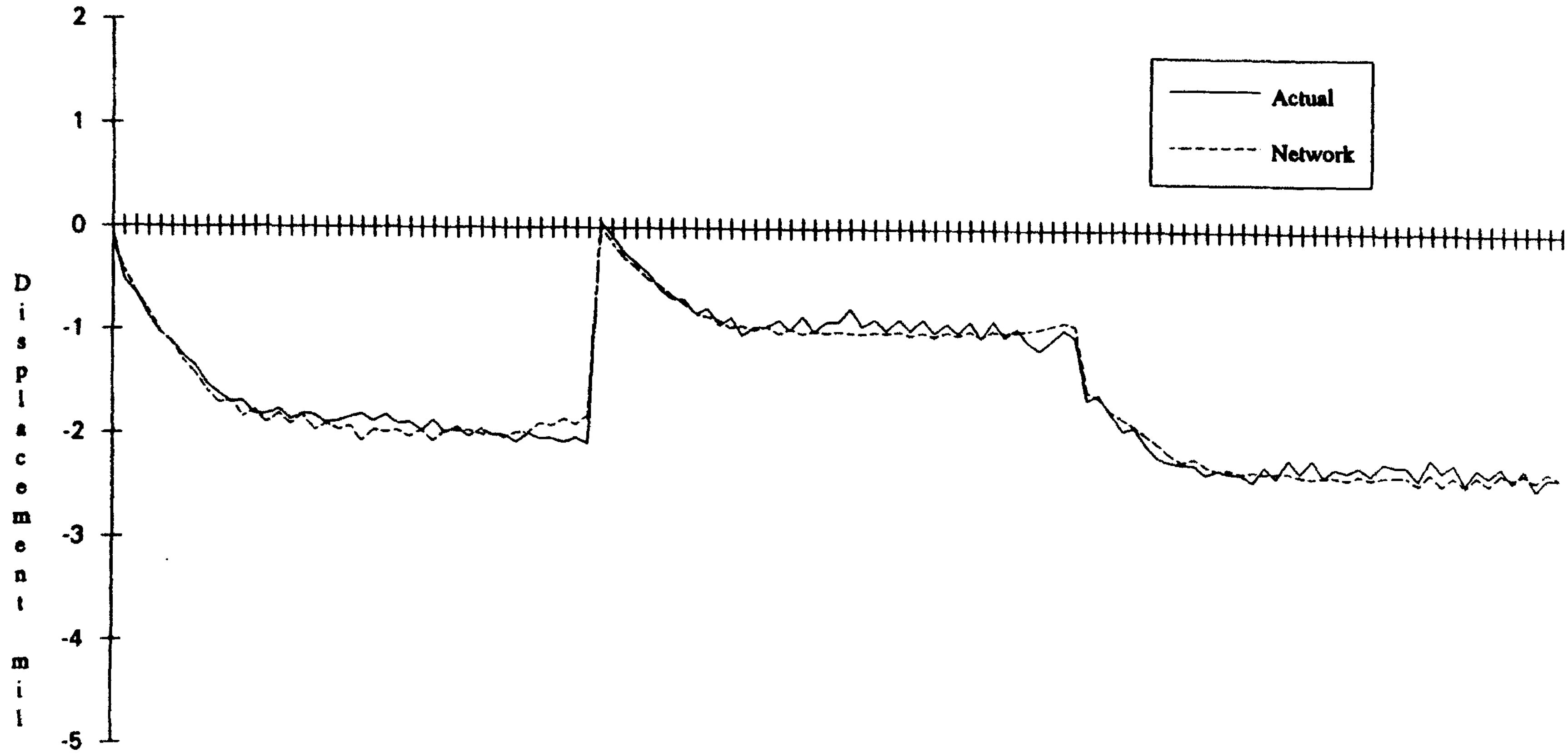
Appendix E12. Network Result for Baseline with 5 Inputs – Z Direction



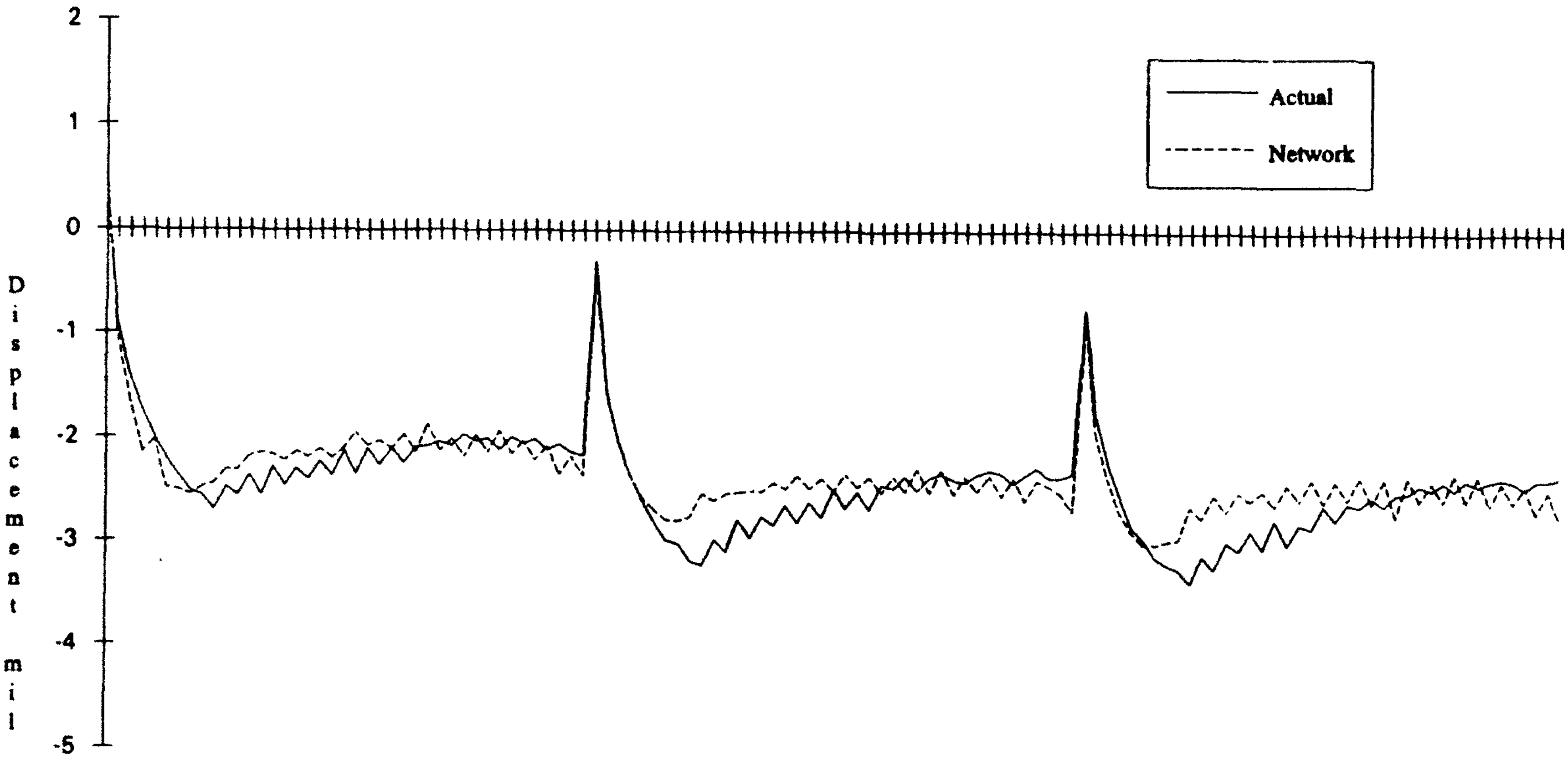
Appendix E13. Network Result for December 19 Ambient with 5 Inputs -- X Direction



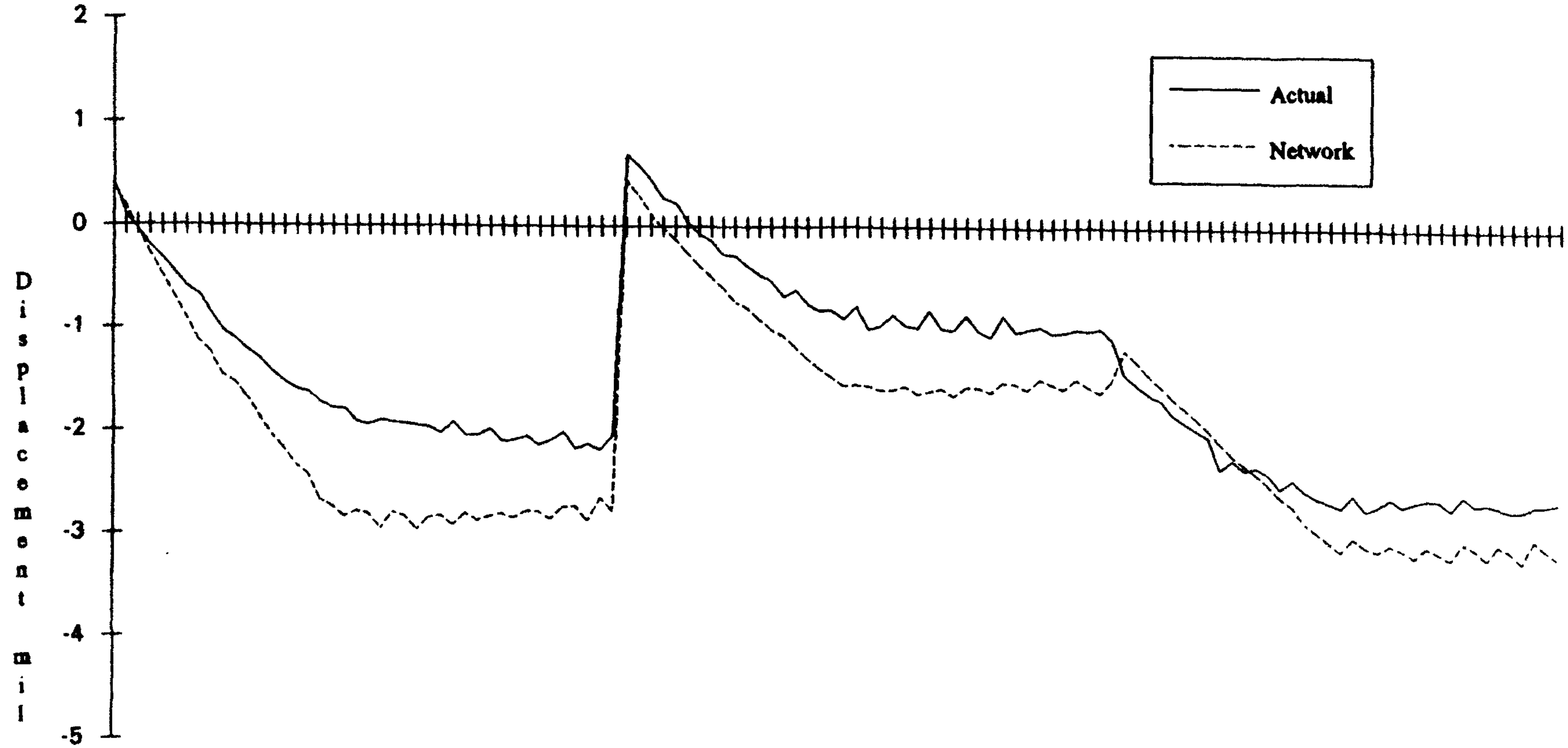
Appendix E14. Network Result for December 19 Ambient with 5 Inputs – Z Direction



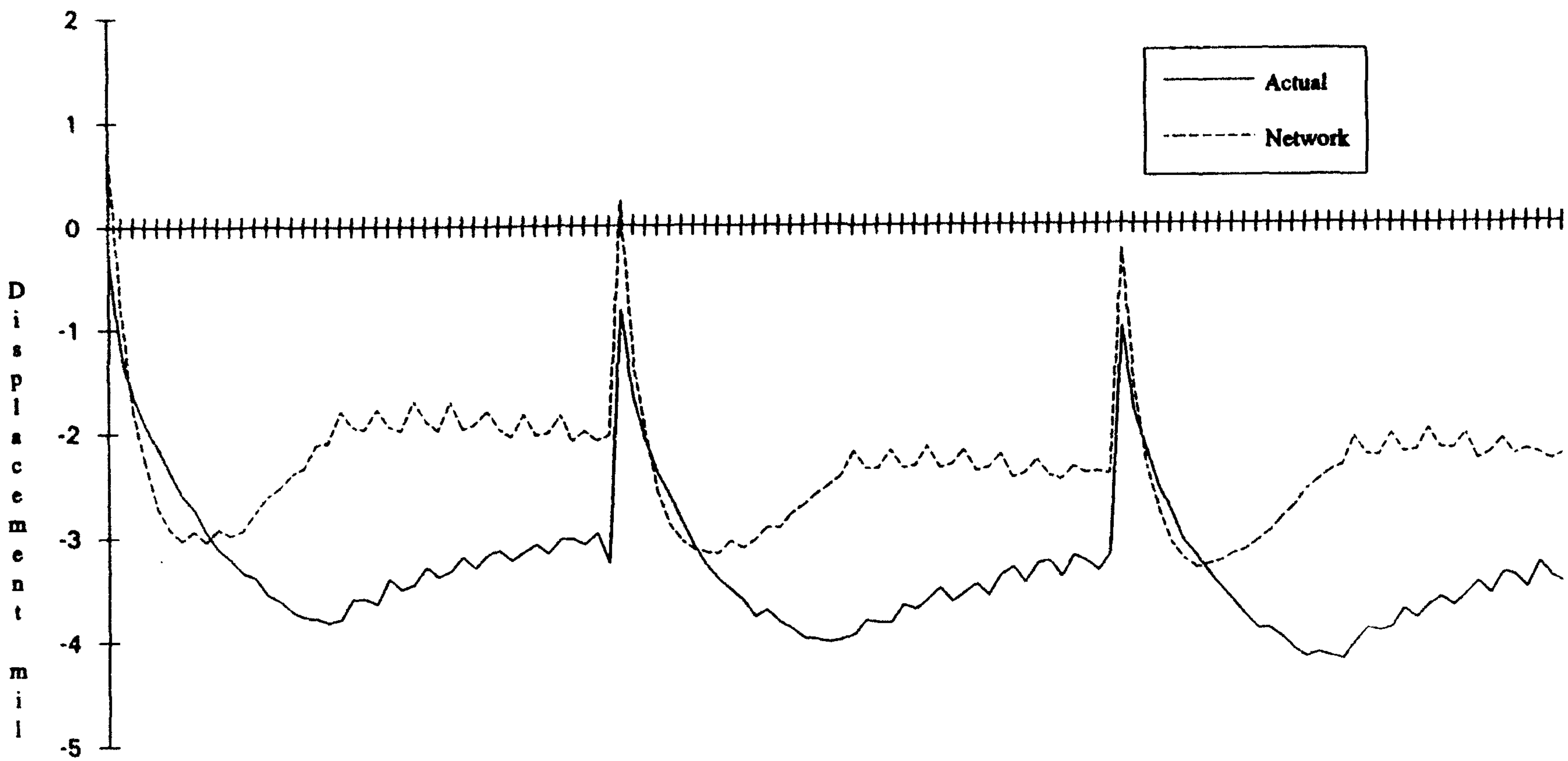
Appendix E15. Network Result for December 21 Ambient with 5 Inputs -- X Direction



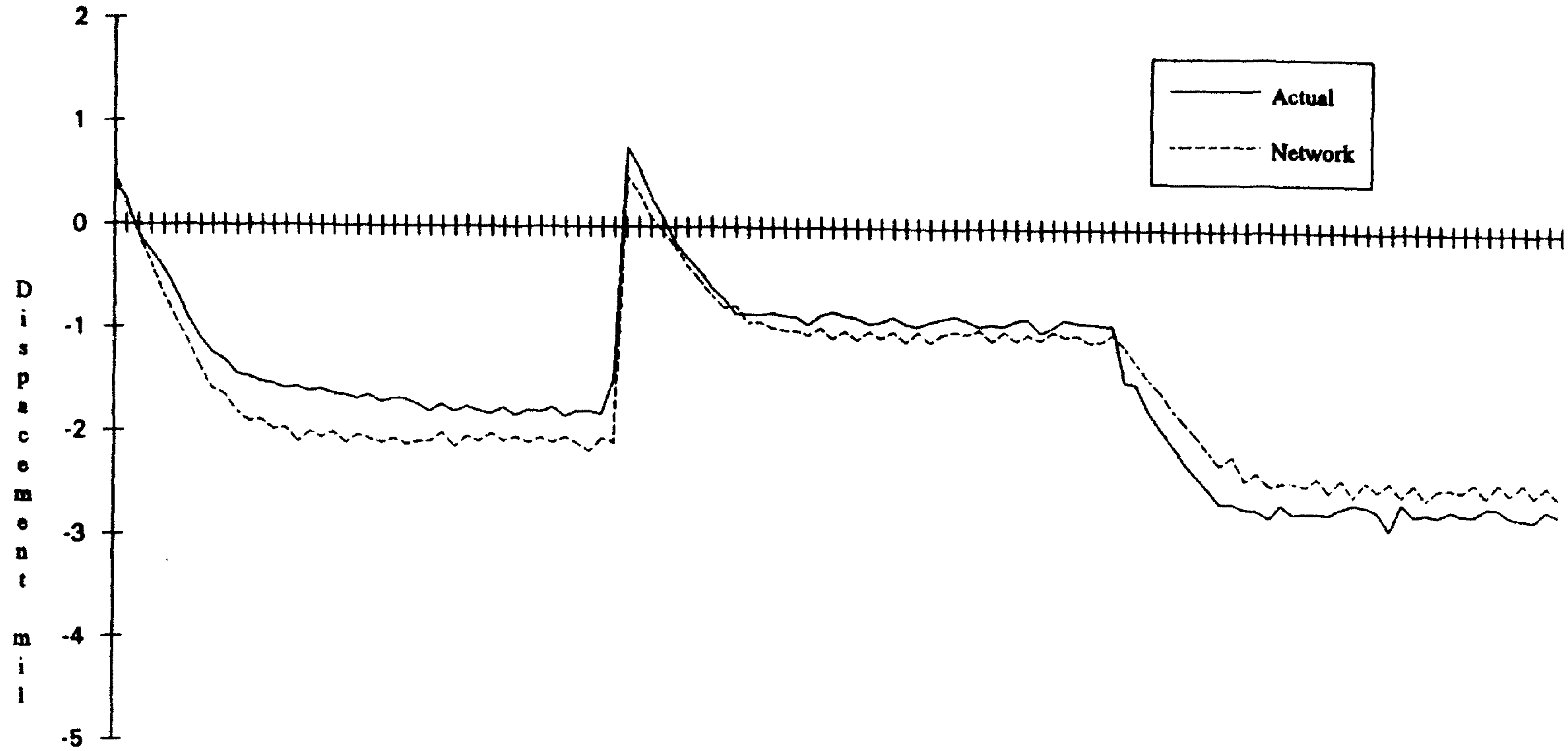
Appendix E16. Network Result for December 21 Ambient with 5 Inputs – Z Direction



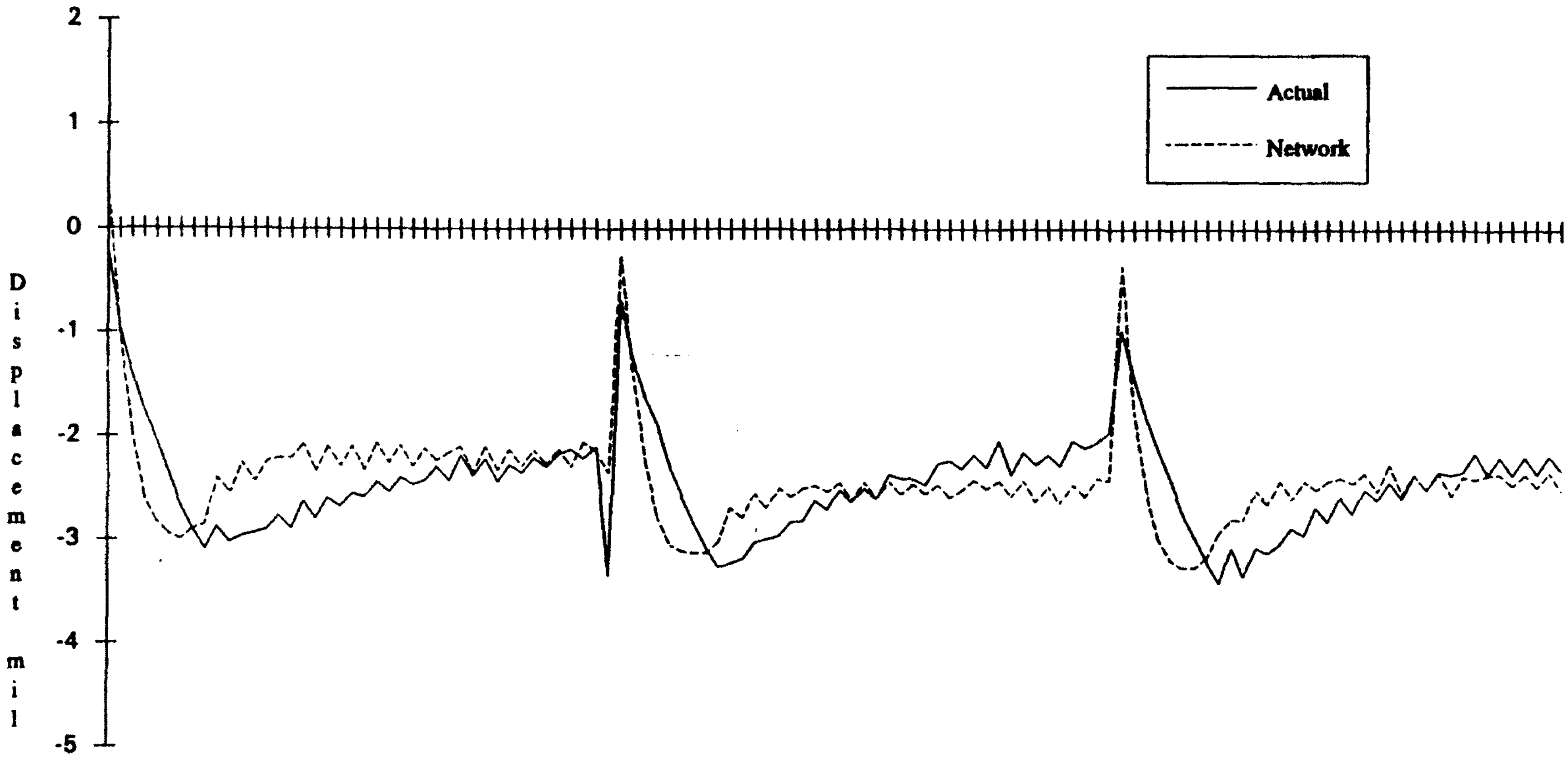
Appendix E17. Network Result for Different Chiller Setting with 5 Inputs -- X Direction



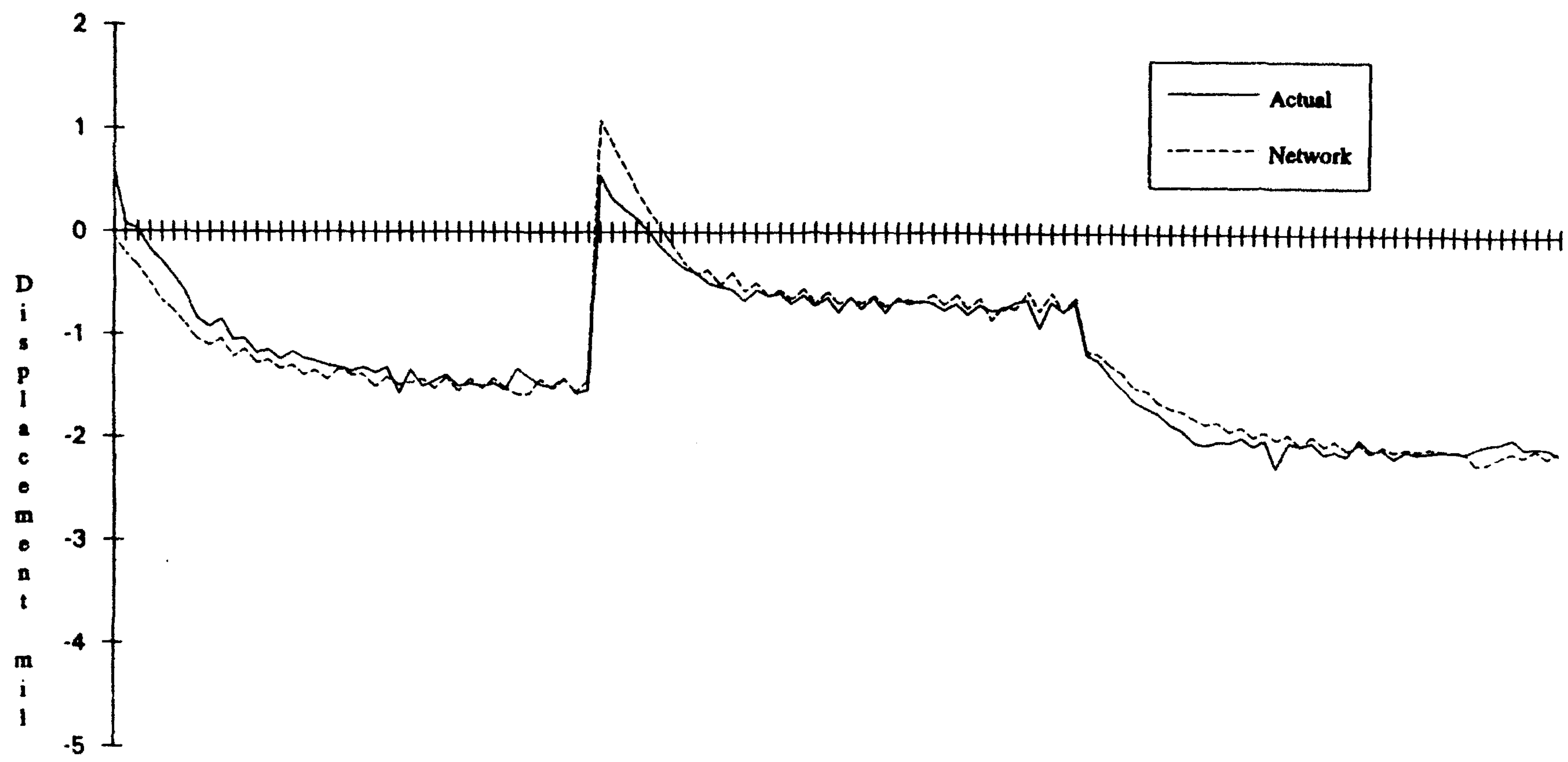
Appendix E18. Network Result for Different Chiller Setting with 5 Inputs -- Z Direction



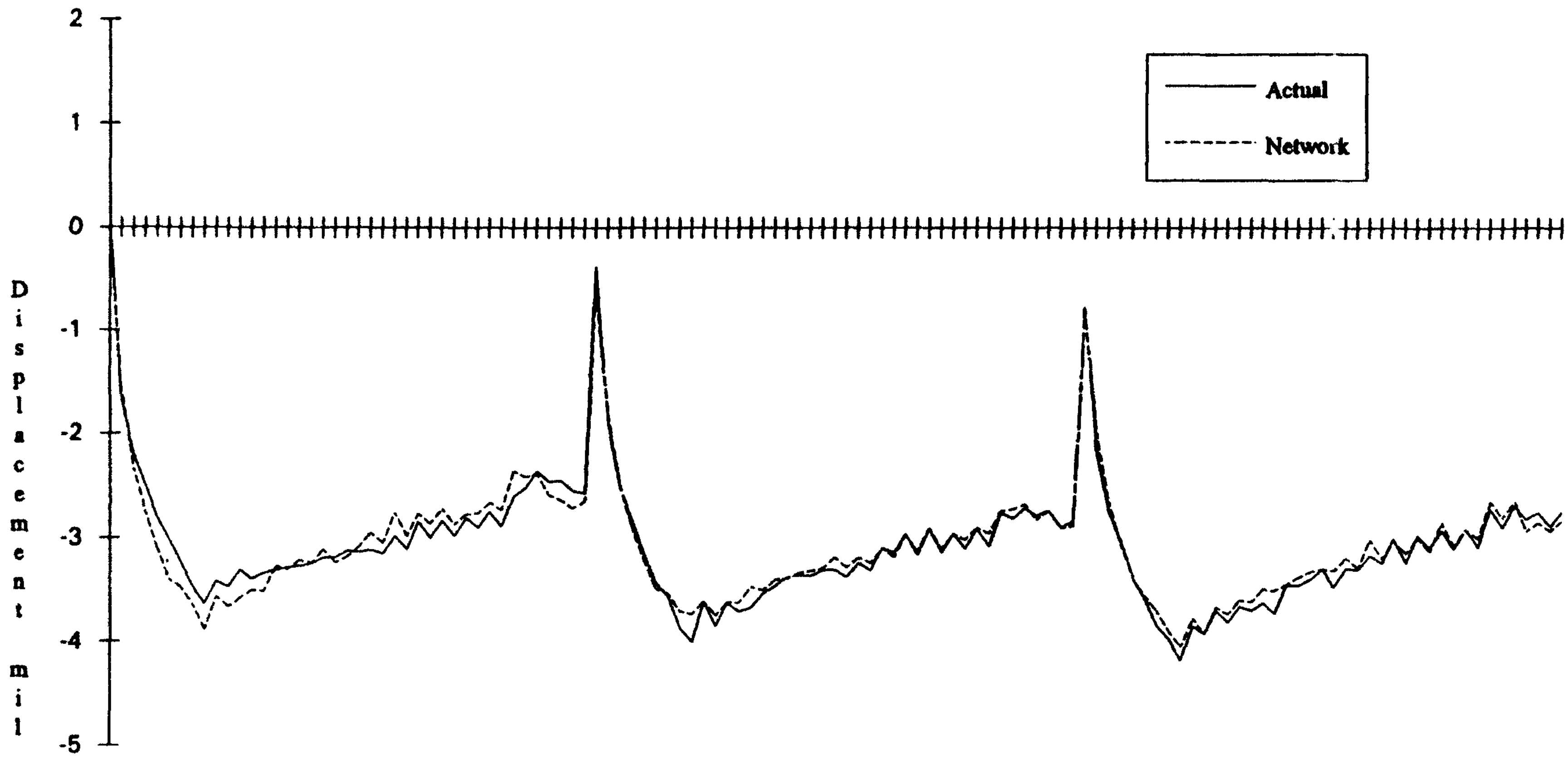
Appendix E19. Network Result for Thermal Input to Headstock with 5 Inputs – X Direction



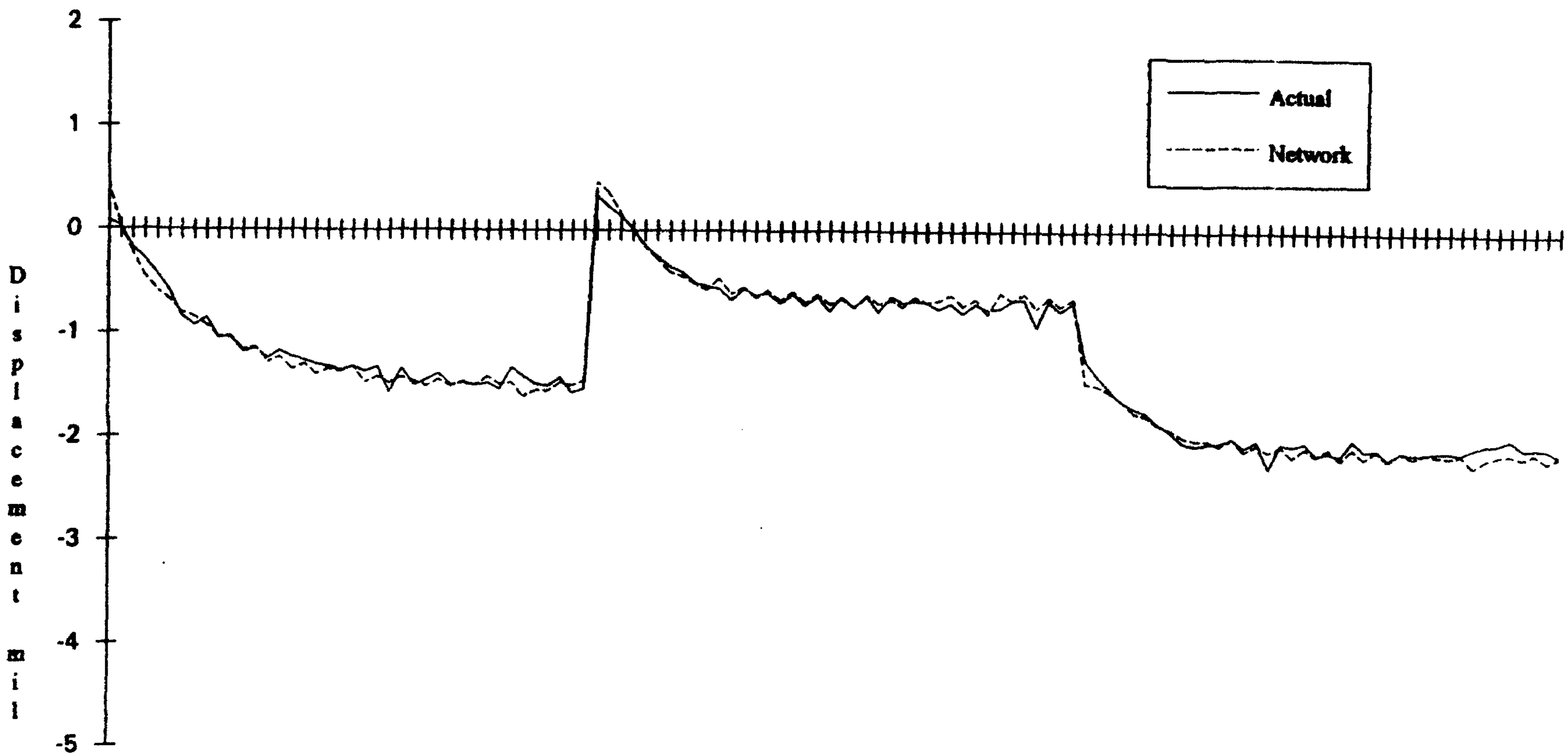
Appendix E20. Network Result for Thermal Input to Headstock with 5 Inputs – Z Direction



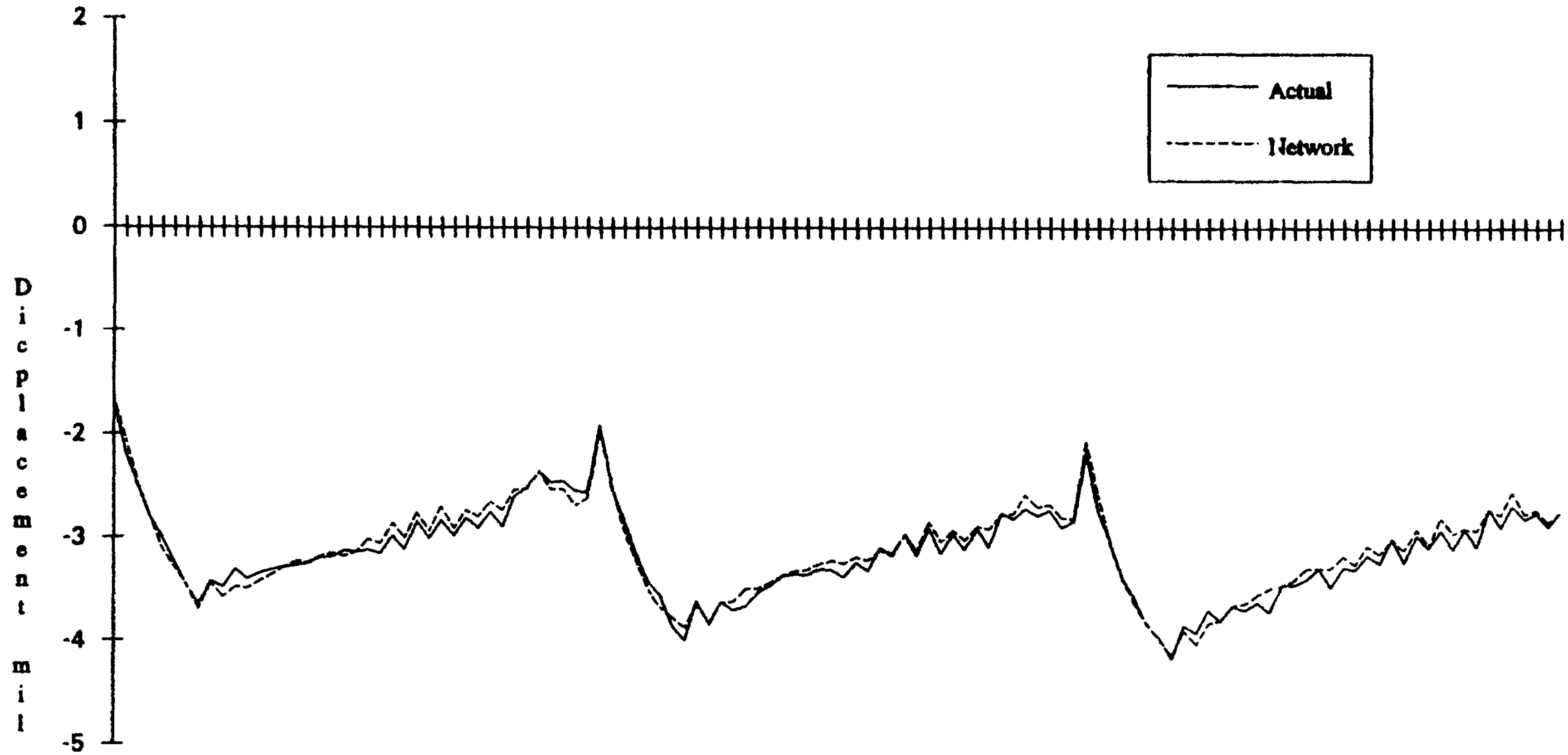
Appendix E21. Network Result for Baseline with 7 Nodes in Hidden Layer – Z Direction



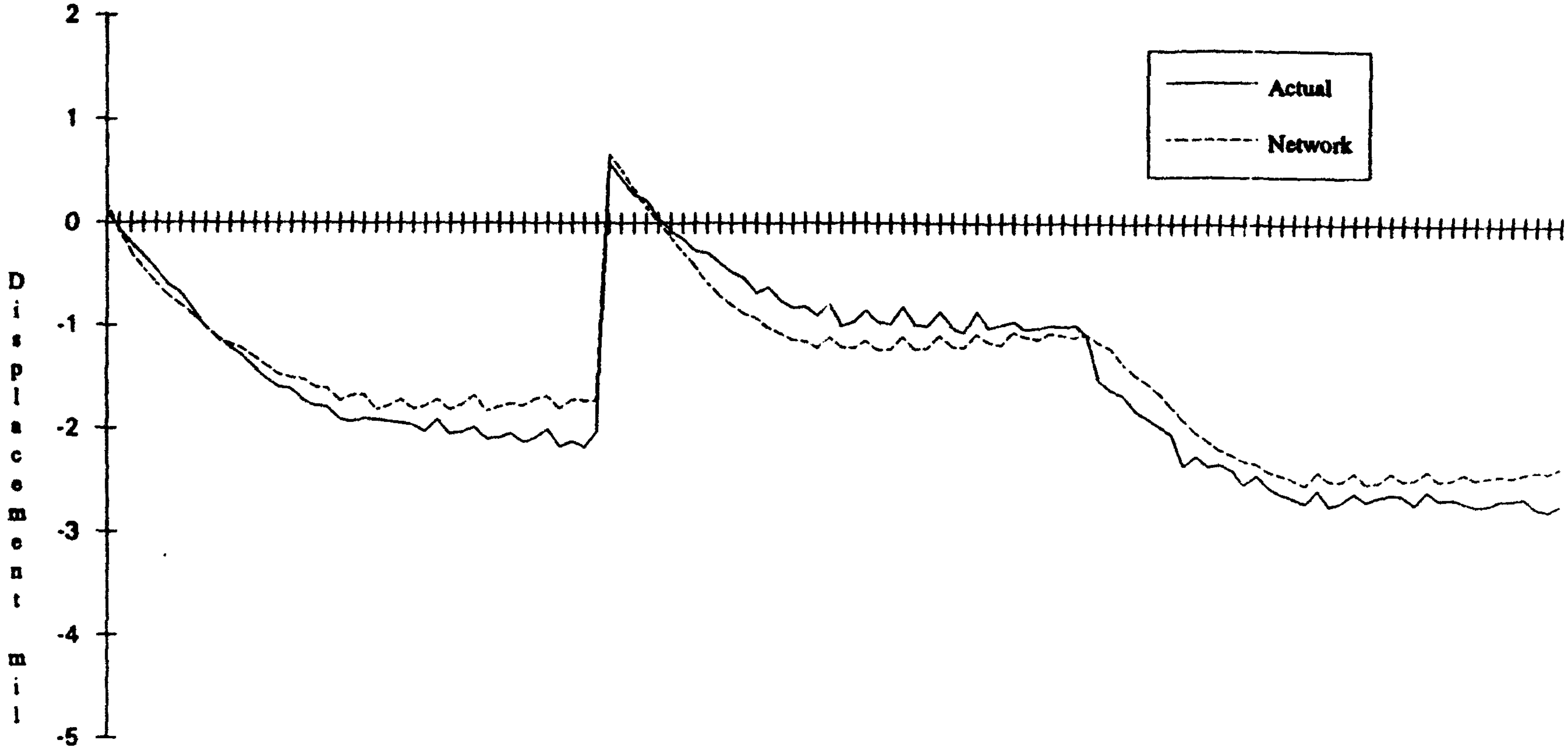
Appendix E22. Network Result for Baseline with 7 Nodes in Hidden Layer – Z Direction



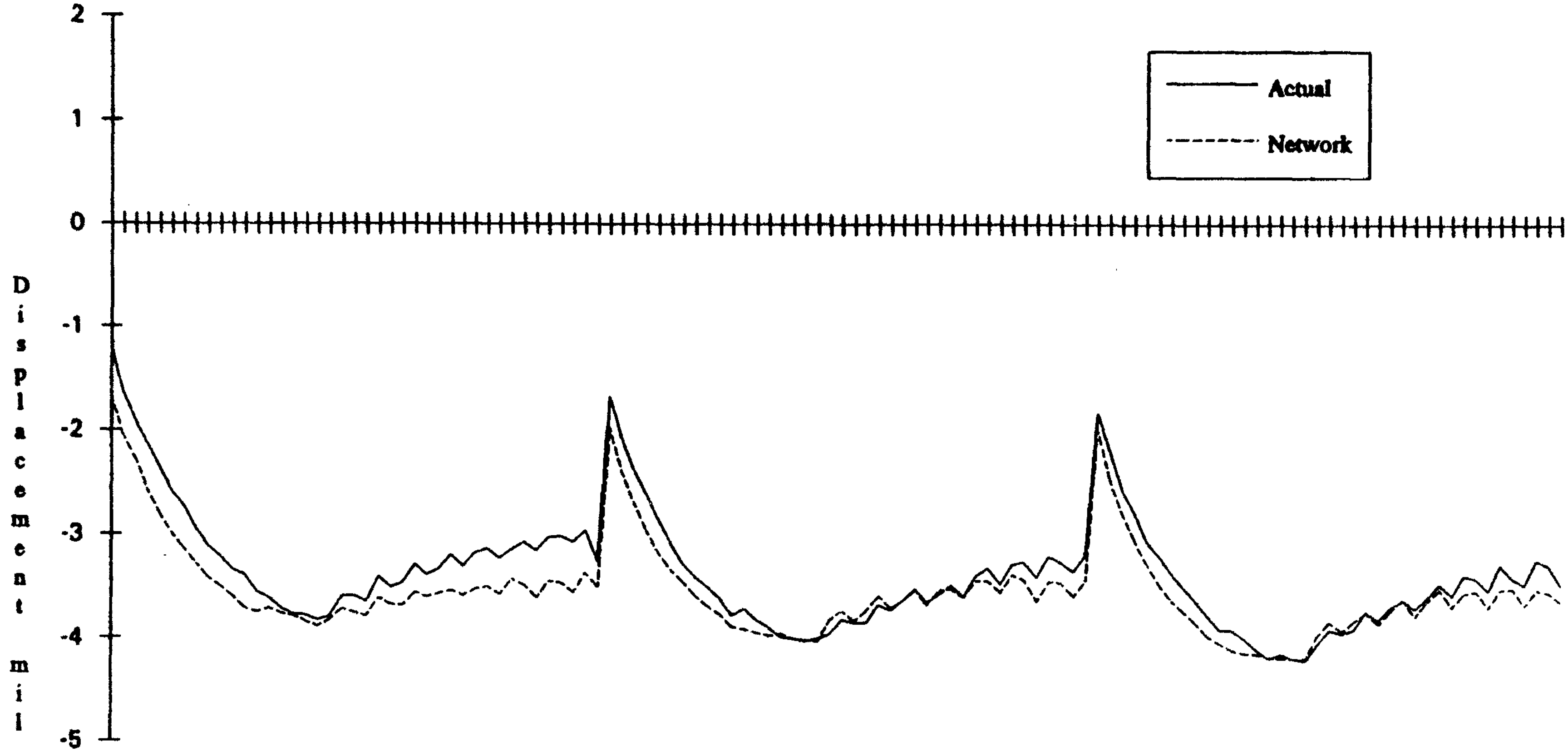
Appendix E23. Network Result for Baseline with Time Delay – X Direction



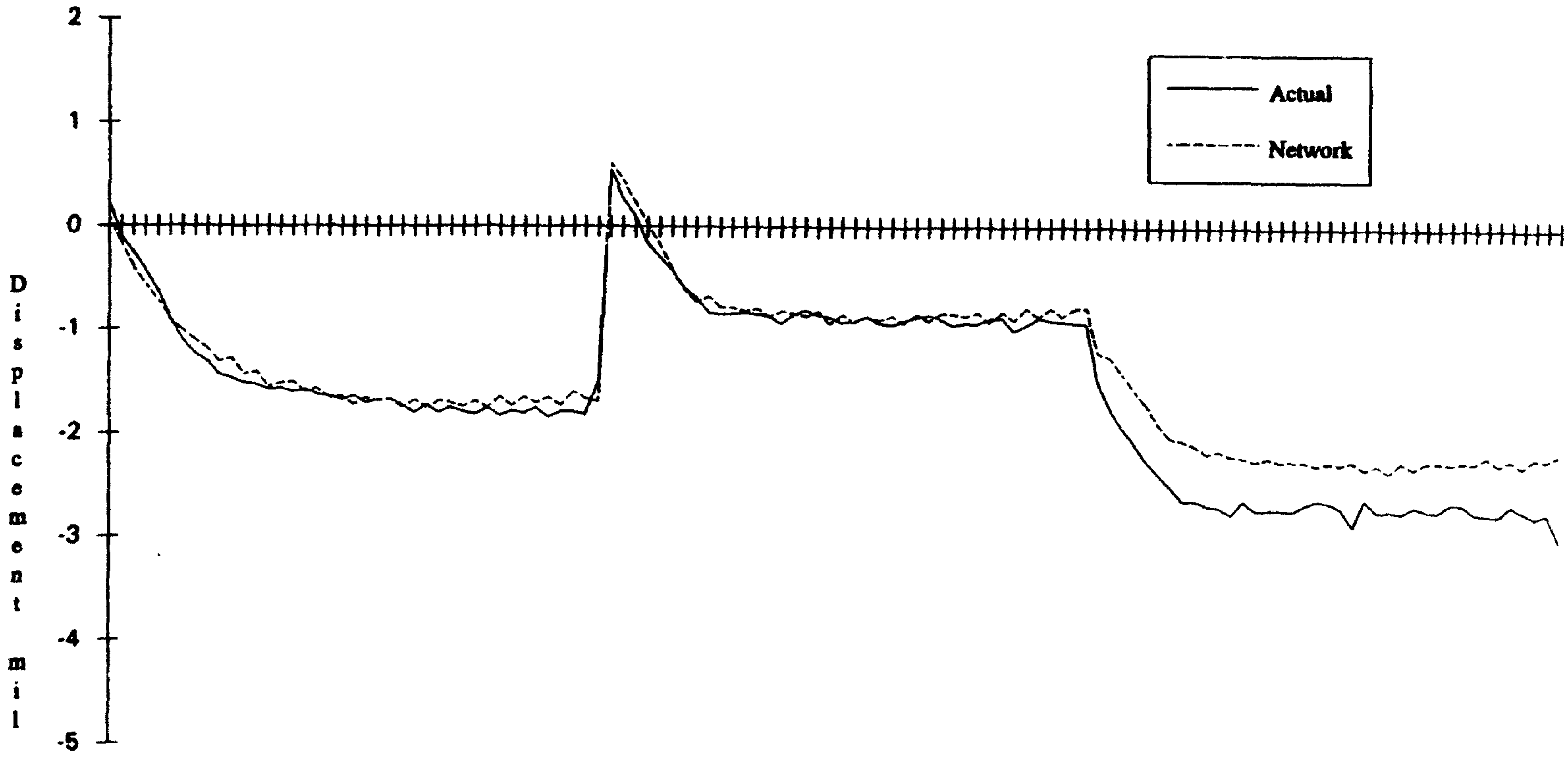
Appendix E24. Network Result for Baseline with Time Delay -- Z Direction



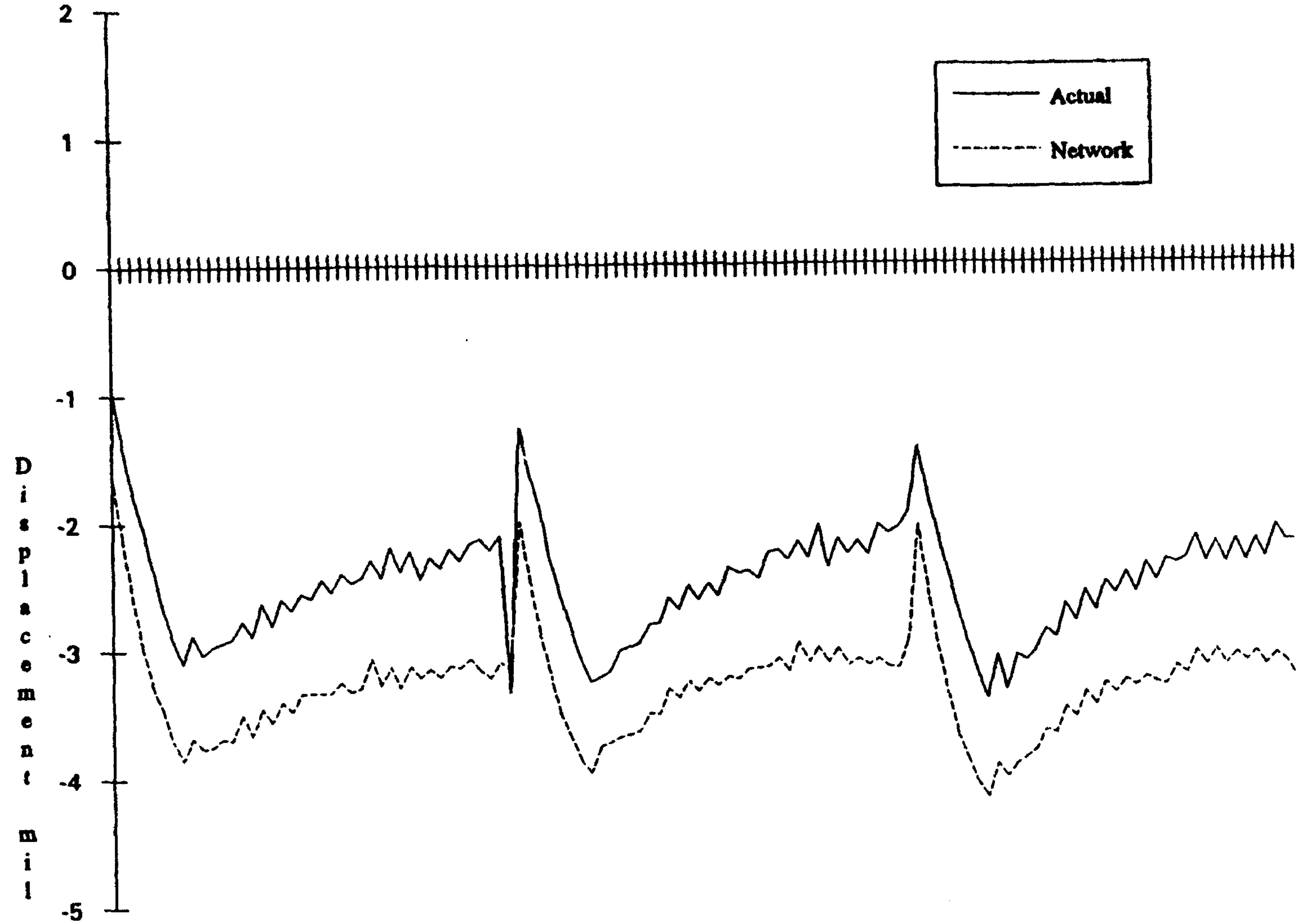
Appendix E25. Network Result for Different Chiller Setting – X Direction



Appendix E26. Network Result for Different Chiller Setting – Z Direction



Appendix E27. Network Result for Thermal Imput to Headstock -- X Direction



Appendix E28. Network Result for Thermal Input to Headstock – Z Direction

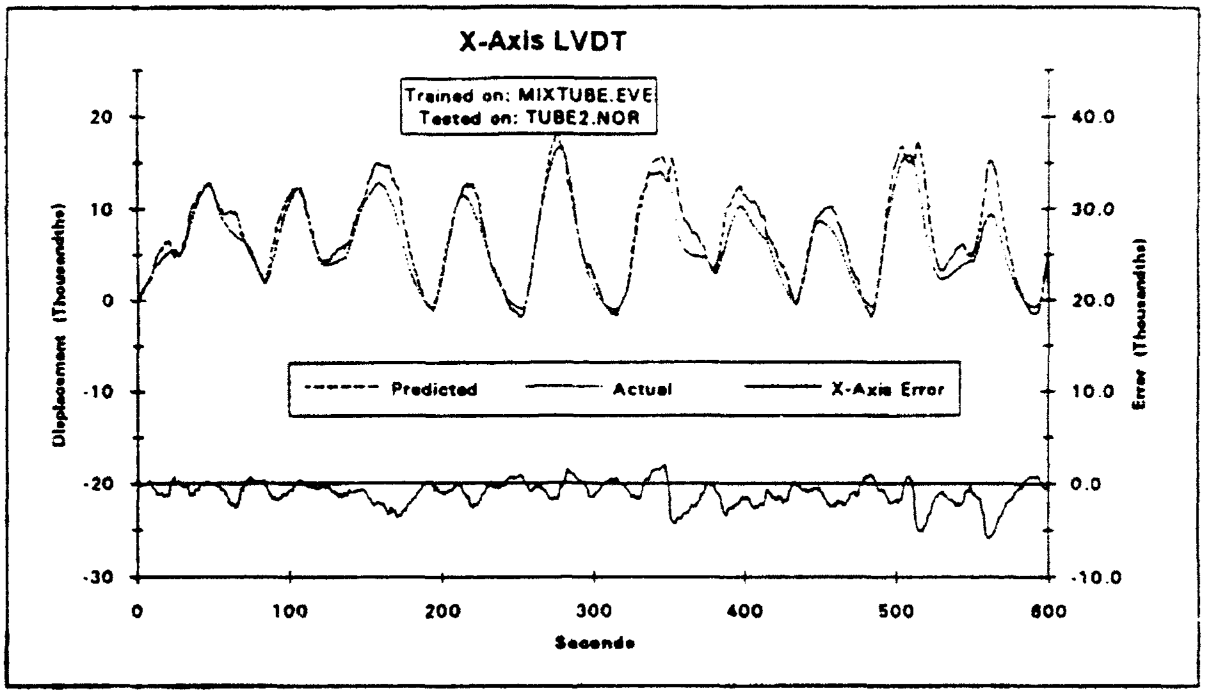
APPENDIX F. RESULTS OF THERMAL TUBE PREDICTION TESTING

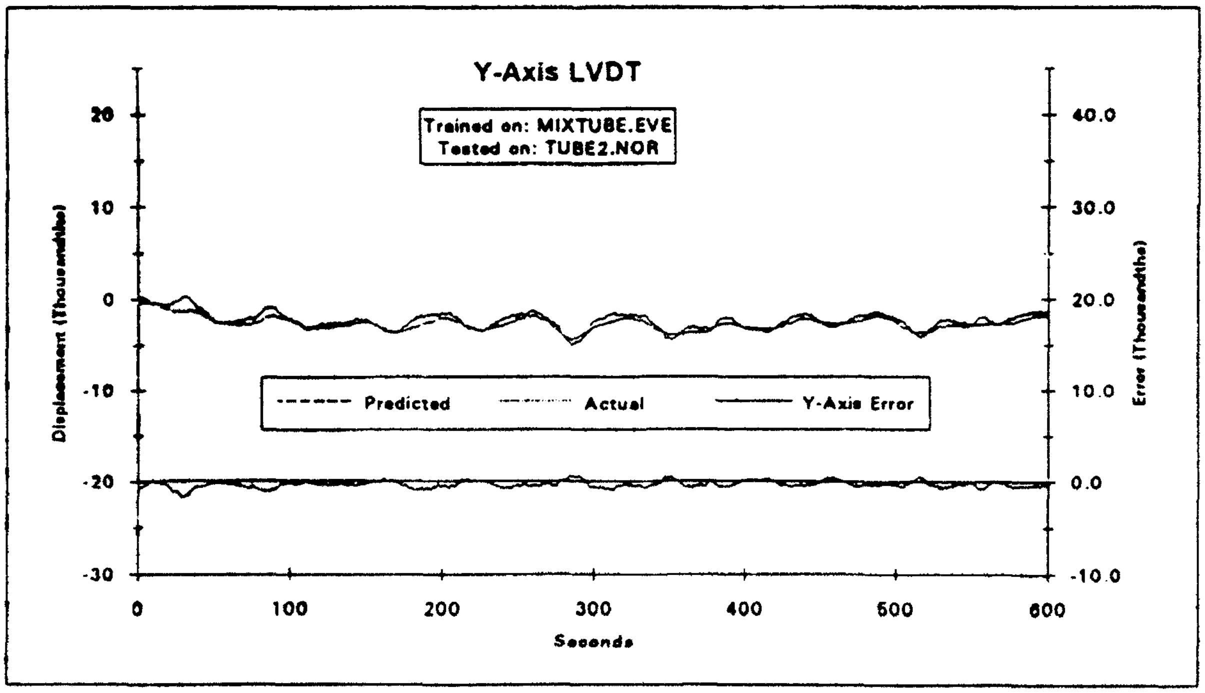
Back Propagation Neural Network

Enhanced with Delta-Bar-Delta adaptive learning constant.

Input nodes: 37
Hidden nodes: 11
Output nodes: 2

Trained for 20,000 Cycles on MIXTUBE.EVE
(A sampling of four different data sets.)





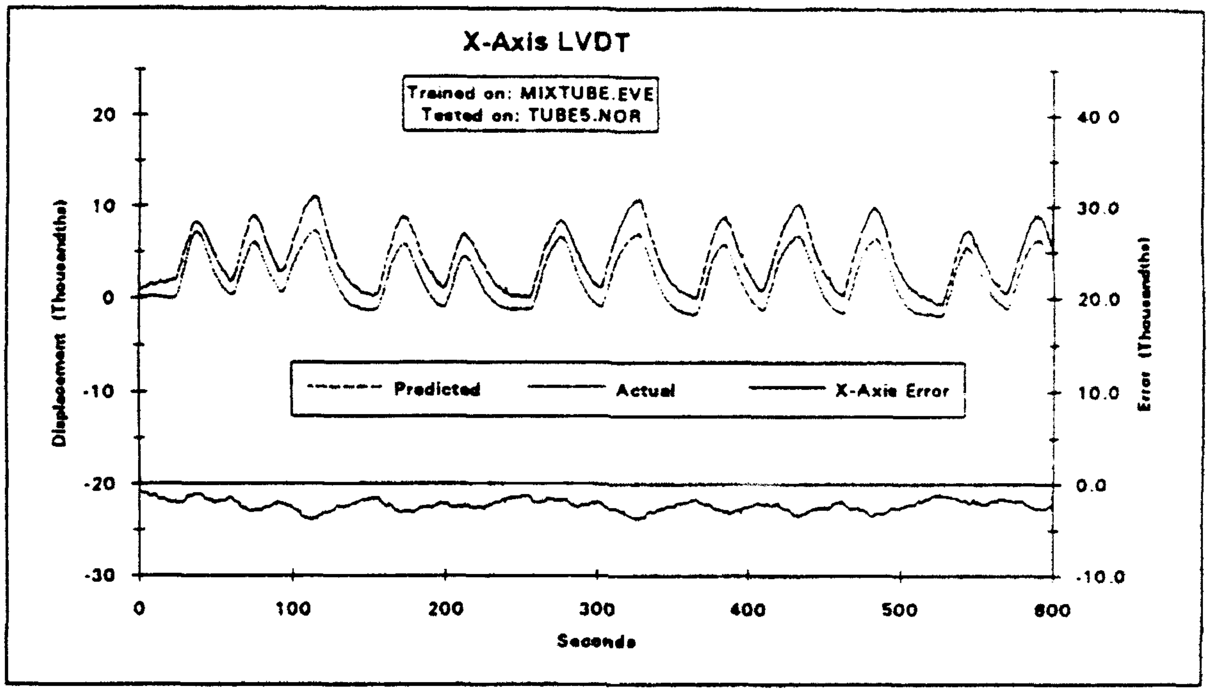
Appendix F1. Network Trained on a Composite Data Set and Tested on Data from Single Axis Heating

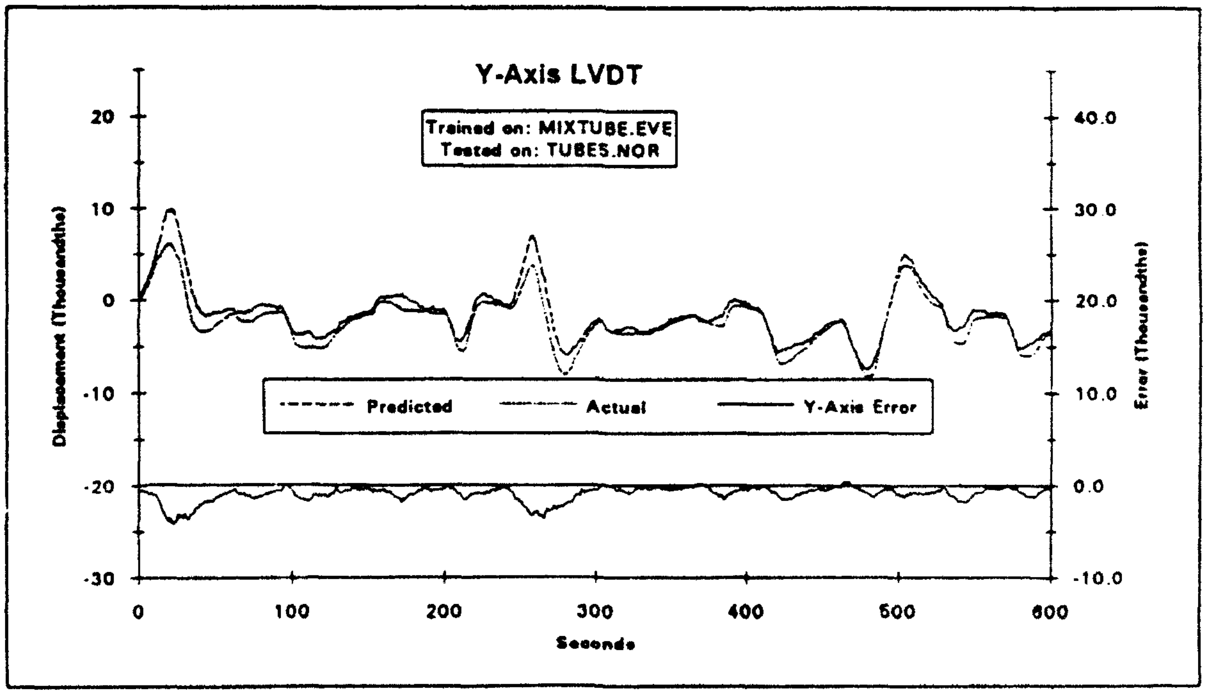
Back Propagation Neural Network

Enhanced with Delta-Bar-Delta adaptive learning constant.

Input nodes: 37
Hidden nodes: 11
Output nodes: 2

Trained for 20,000 Cycles on MIXTUBE.EVE
(A sampling of four different data sets.)





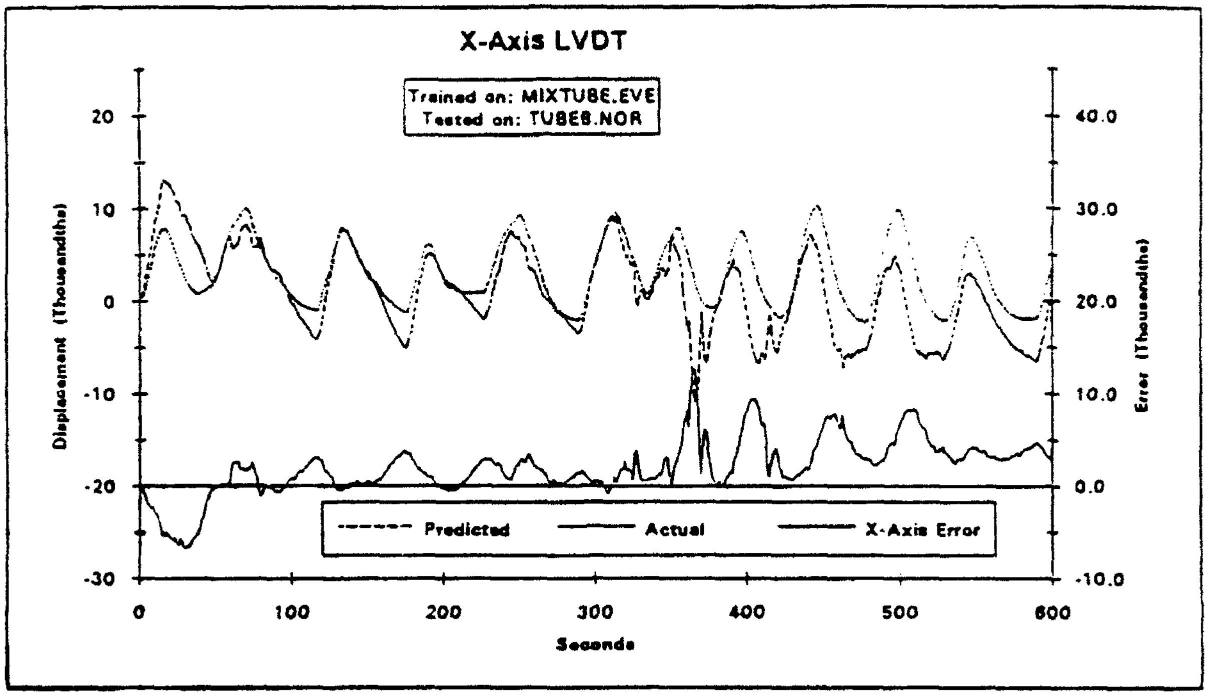
Appendix F2. Network Trained on a Composite Data Set and Tested on Data from Orthogonal On-Axis Heating

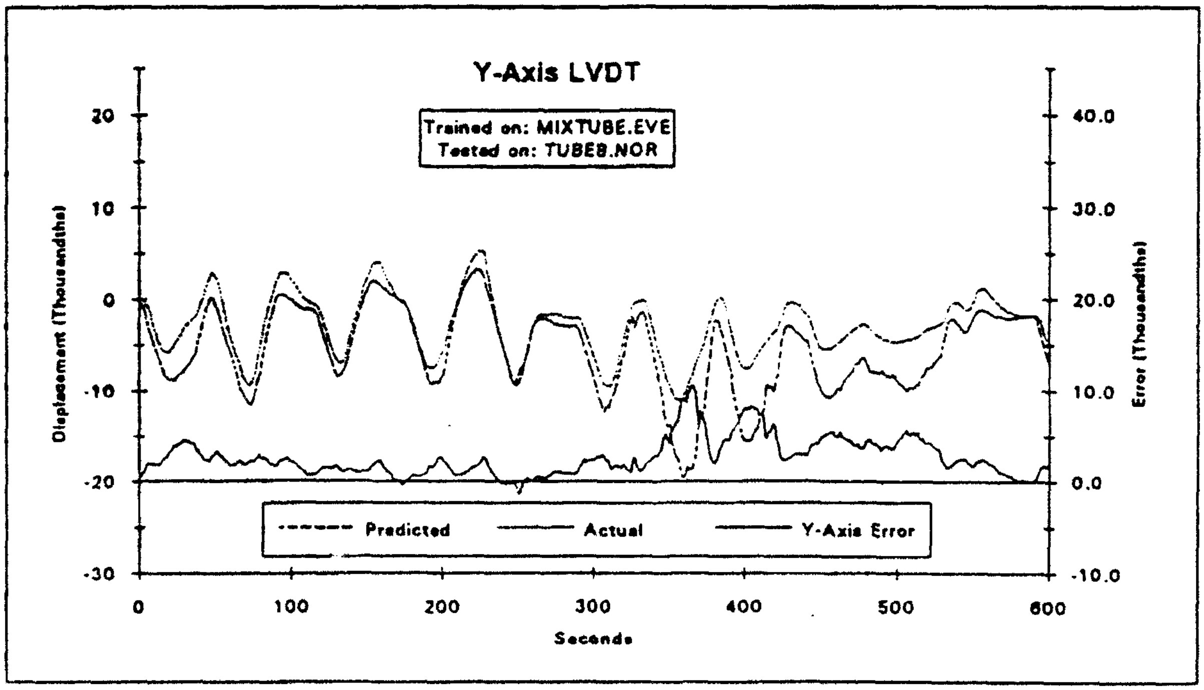
Back Propagation Neural Network

Enhanced with Delta-Bar-Delta adaptive learning constant.

. ıput nodes: 37
Hidden nodes: 11
Output nodes: 2

Trained for 2500 Cycles on MIXTUBE.EVE
(A sampling of four different data sets.)





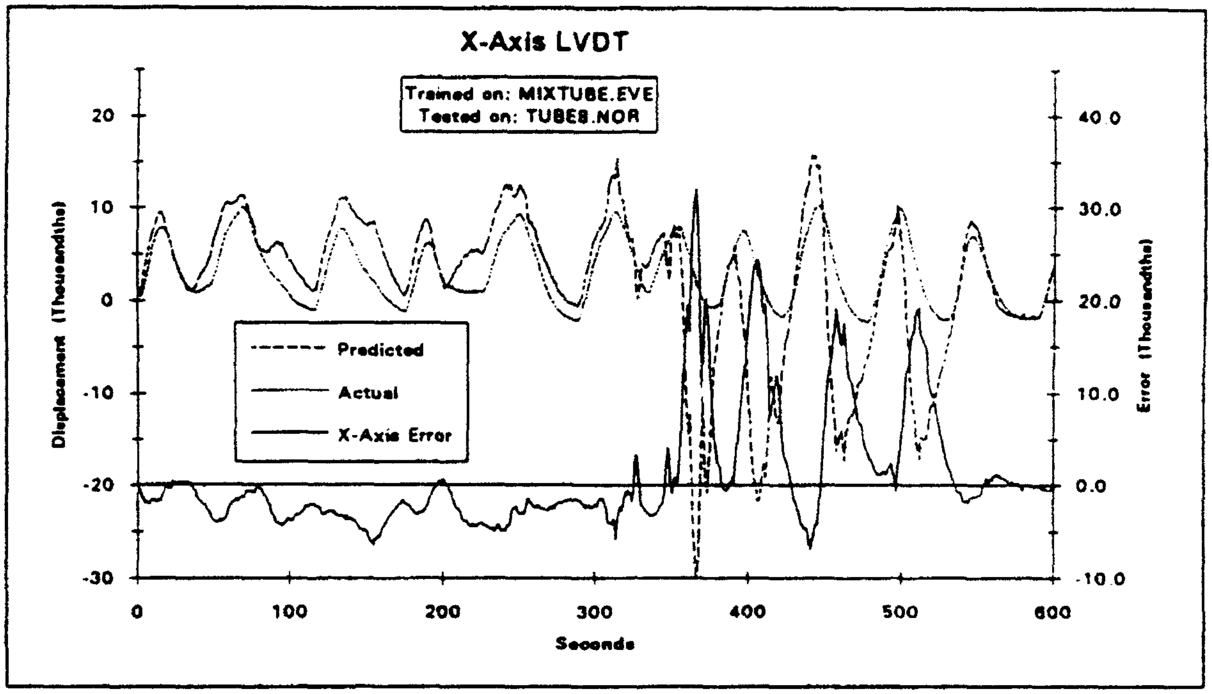
Appendix F3. Network Trained on a Composite Data Set and Tested on Data from Orthogonal Off-Axis Heating 2500 Training Cycles

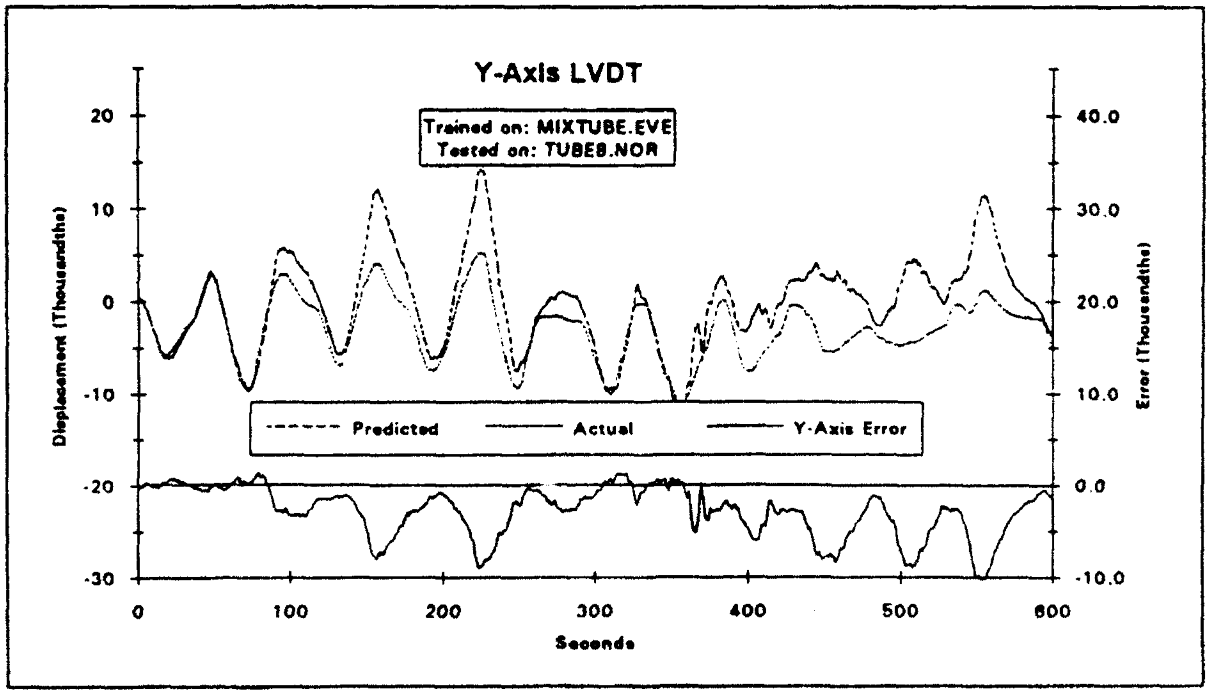
Back Propagation Neural Network

Enhanced with Delta-Bar-Delta adaptive learning constant.

Input nodes: 37
Hidden nodes: 11
Output nodes: 2

Trained for 20,000 Cycles on MIXTUBE.EVE
(A sampling of four different data sets.)



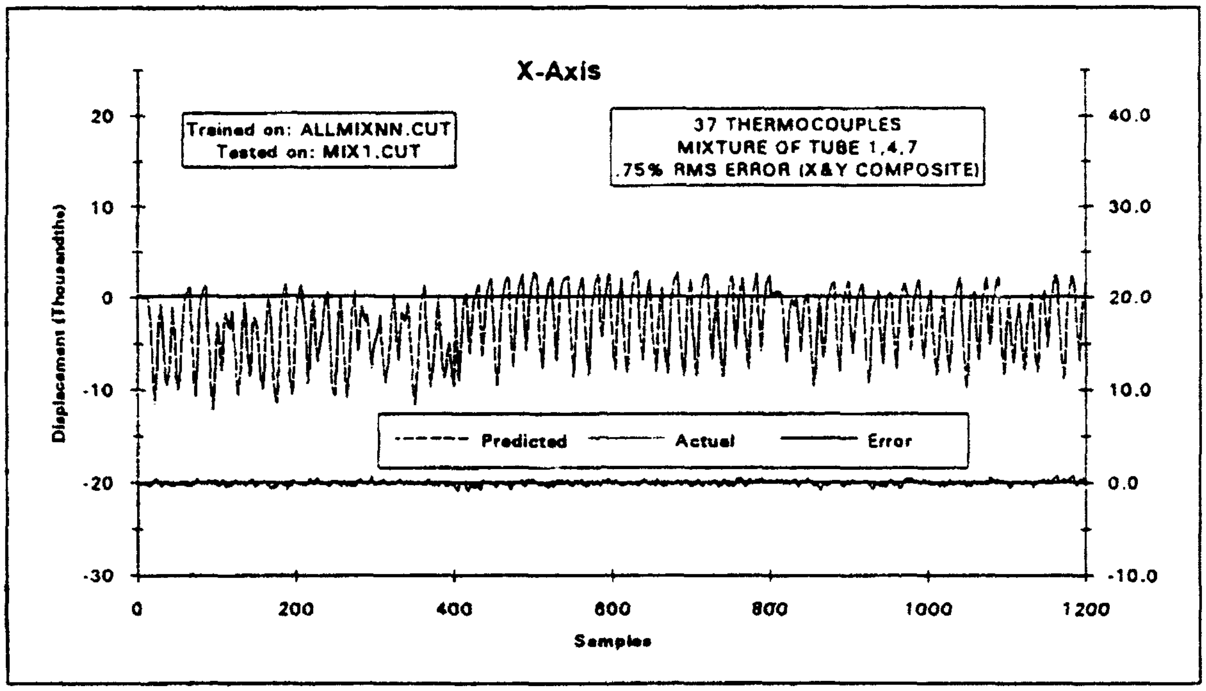


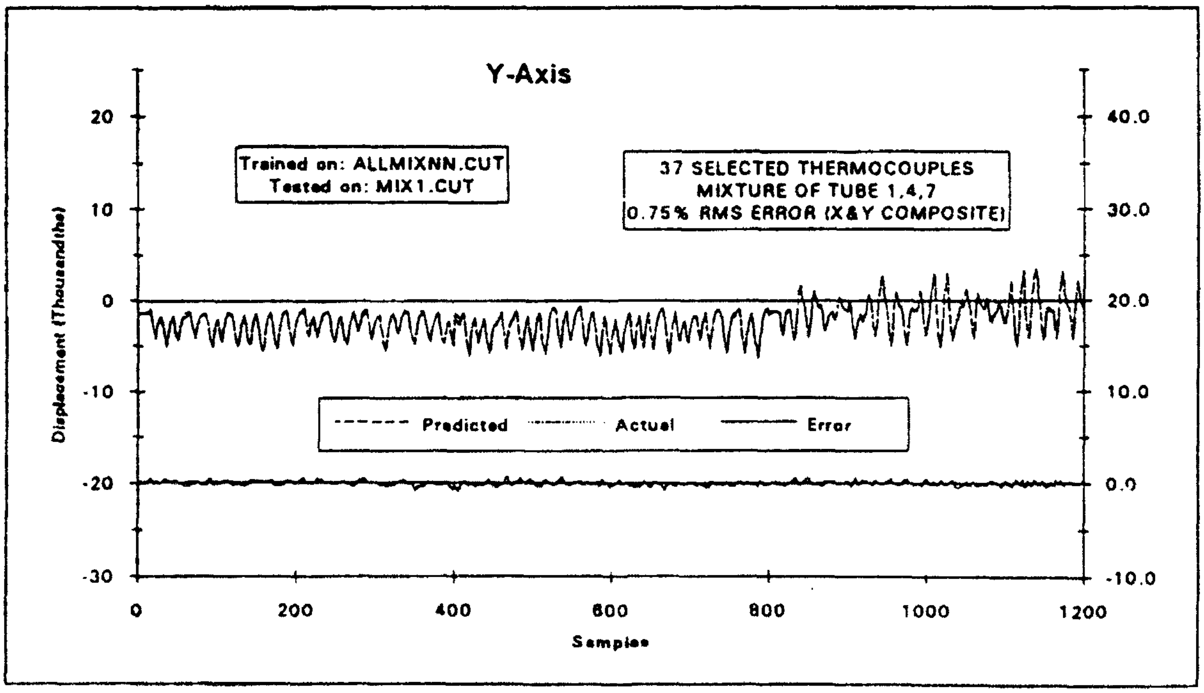
Appendix F4. Network Trained on a Composite Data Set and Tested on Data from Orthogonal Off-Axis Heating 20,000 Cycles

Back Propagation Neural Network

Enhanced with Delta-Bar-Delta adaptive learning constant
Data vectors randomly scrambled between epochs

Input nodes:	37	Trained for 20000 Cycles on ALLMIXNN.CUT
Hidden nodes:	11	(A sampling of three different data sets.)
Output nodes:	2	Non Contact Gaging used on benchtest





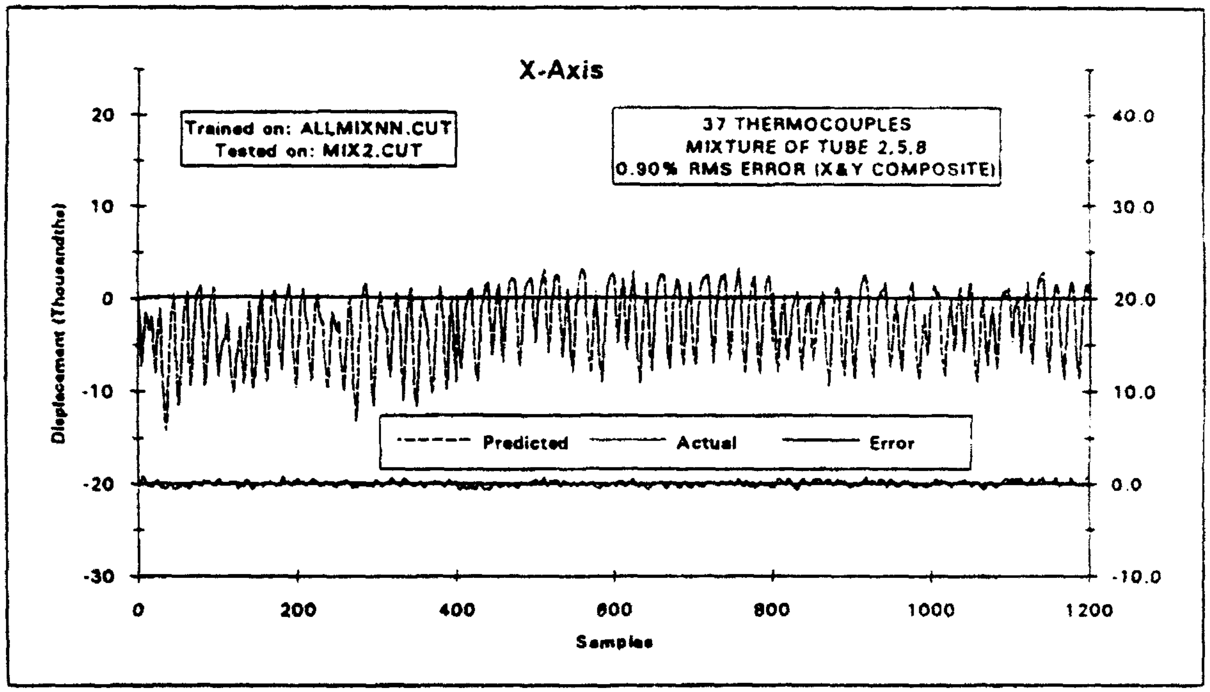
Appendix F5. Network Trained on a Composite Data Set and Tested on Data from Single Axis Heating. Vectors Randomized Between Training Cycles.

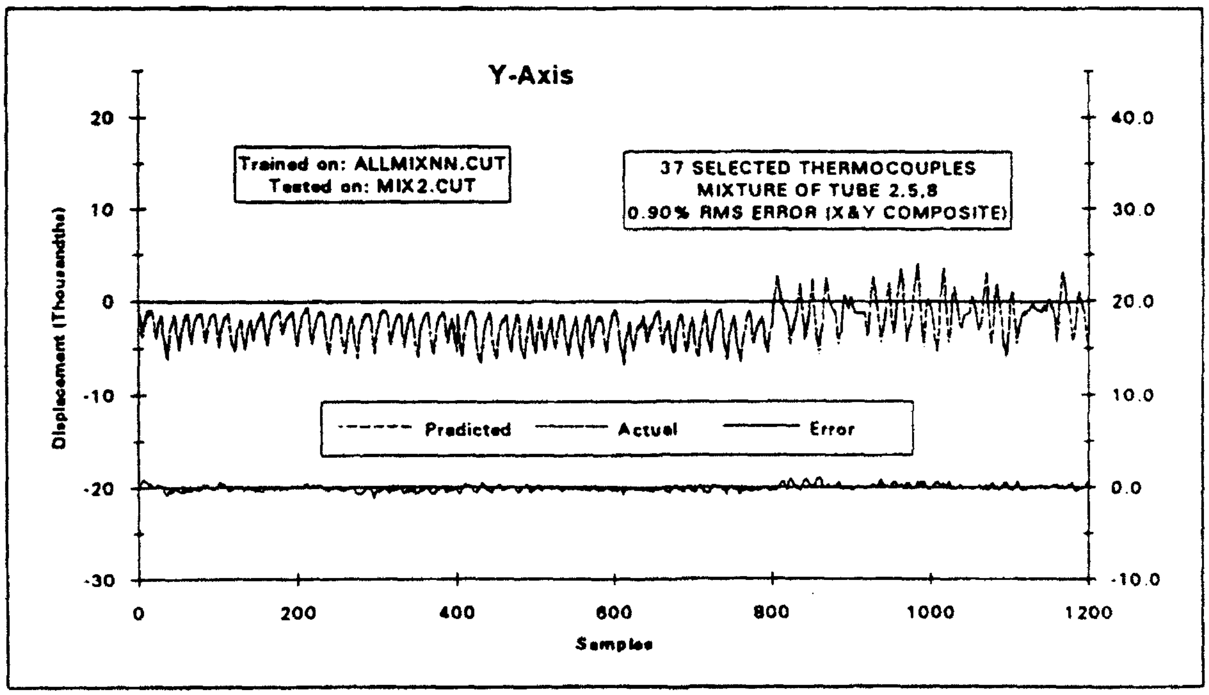
Back Propagation Neural Network

Enhanced with Delta-Bar-Delta adaptive learning constant
Data vectors randomly scrambled between epochs

Input nodes: 37
Hidden nodes: 11
Output nodes: 2

Trained for 20000 Cycles on ALLMIXNN.CUT
(A sampling of three different data sets.)
Non Contact Gaging used on benchtest





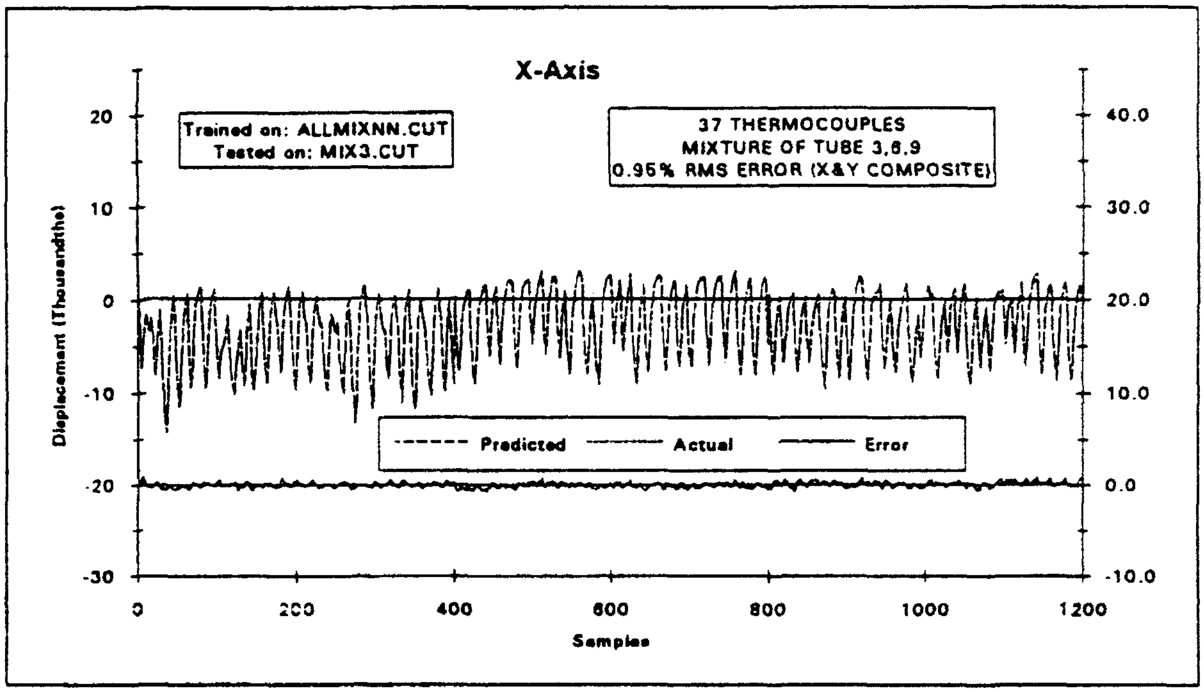
Appendix F6. Network Trained on a Composite Data Set and Tested on Data from Orthogonal On-Axis Heating. Vectors Randomized Between Training Cycles

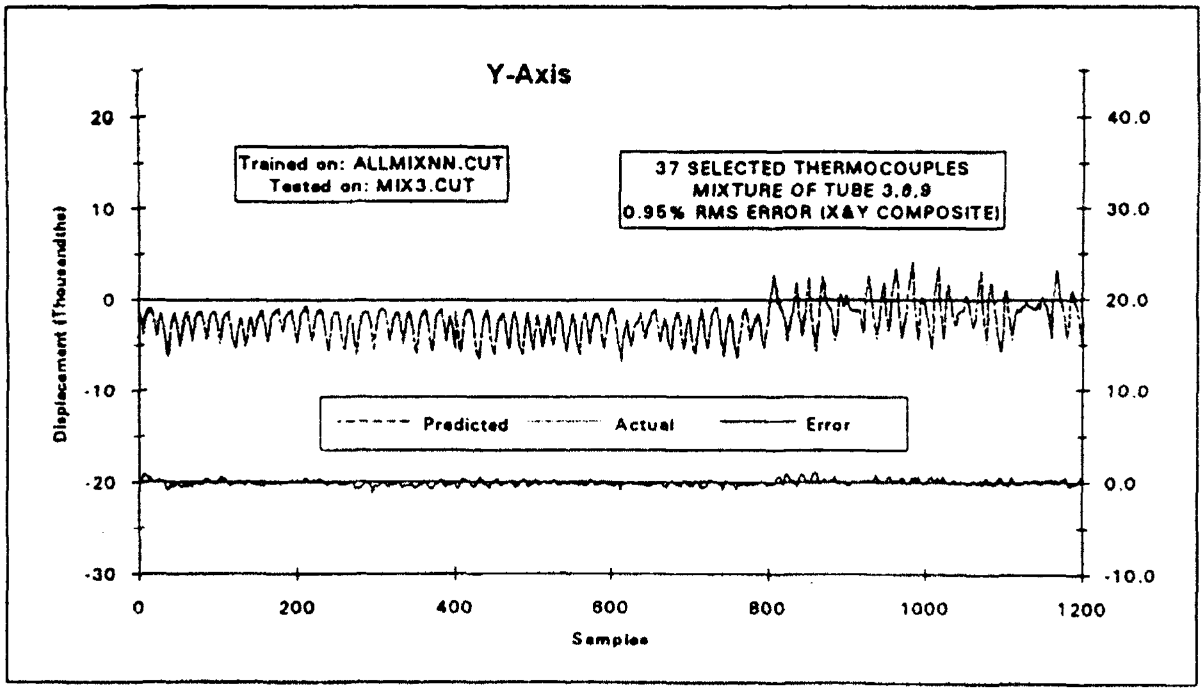
Back Propagation Neural Network

Enhanced with Delta-Bar-Delta adaptive learning constant
Data vectors randomly scrambled between epochs

Input nodes: 37
Hidden nodes: 11
Output nodes: 2

Trained for 20000 Cycles on ALLMIXNN.CUT
(A sampling of three different data sets.)
Non Contact Gaging used on benchtest





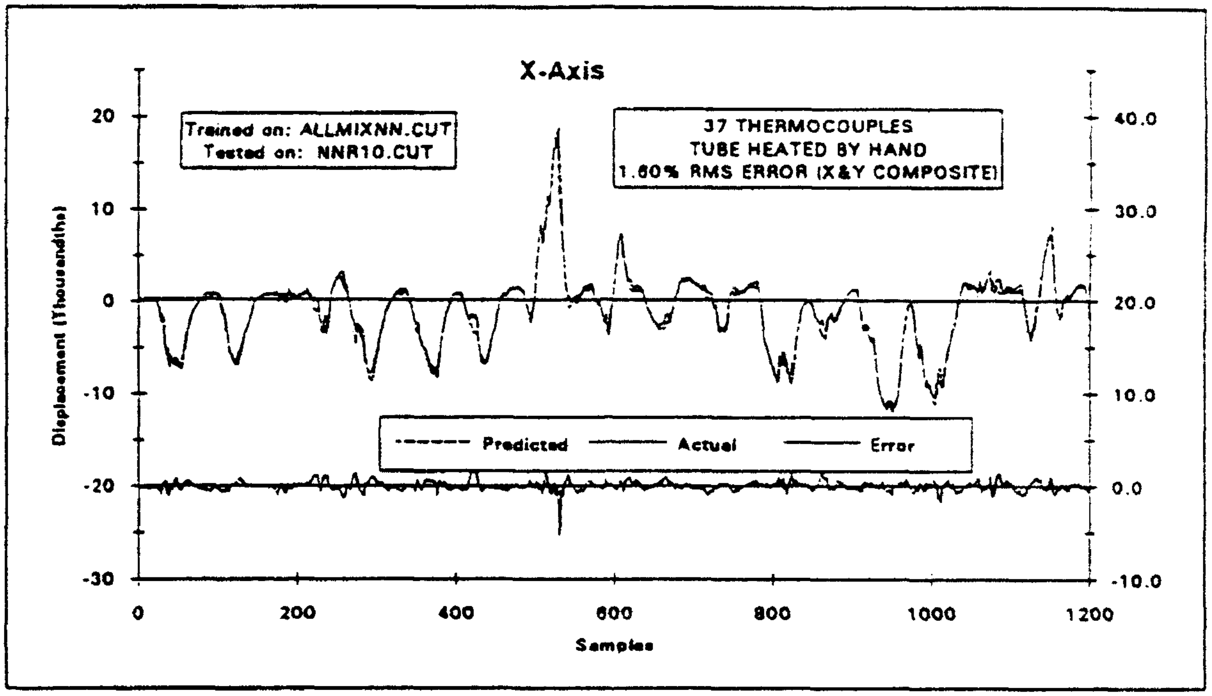
Appendix F7. Network Trained on a Composite Data Set and Tested on Data from Orthogonal Off-Axis Heating. Vectors Randomized Between Training Cycles

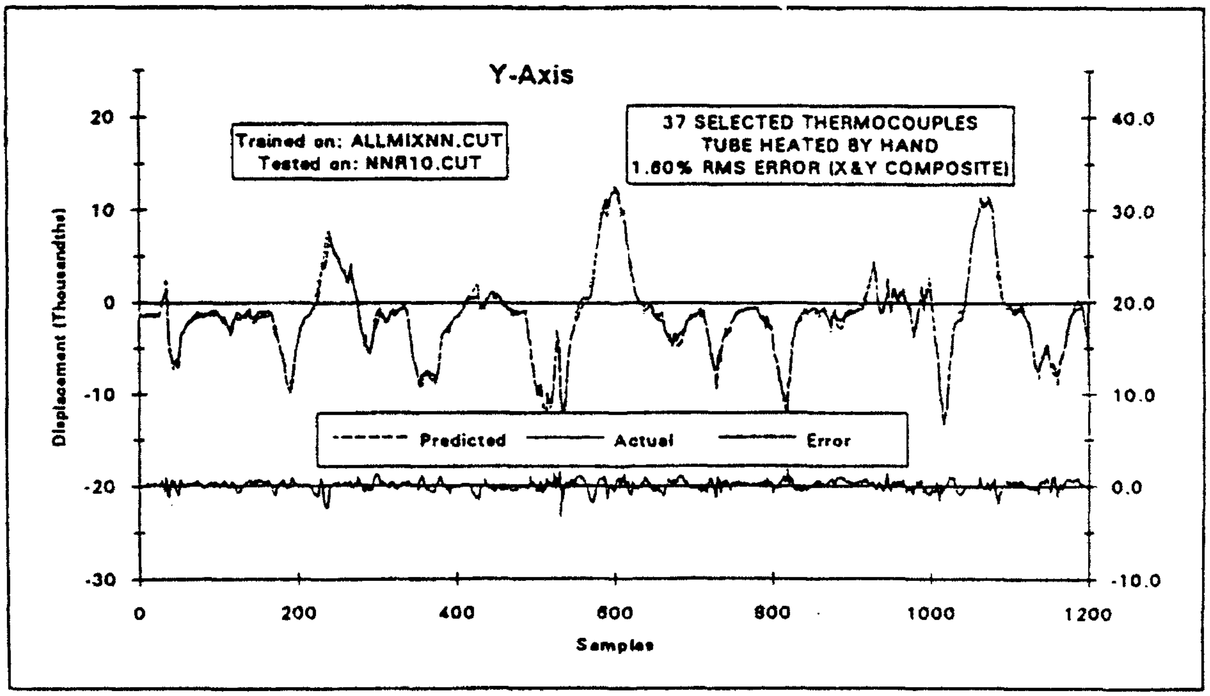
Back Propagation Neural Network

Enhanced with Delta-Bar-Delta adaptive learning constant
Data vectors randomly scrambled between epochs

Input nodes: 37
Hidden nodes: 11
Output nodes: 2

Trained for 20000 Cycles on ALLMIXNN.CUT
(A sampling of three different data sets.)
Non Contact Gaging used on benchtest





Appendix F8. Network Trained on a Composite Data Set and Tested on Data from Randomly Oriented Heating. Vectors Randomized Between Training Cycles.

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