1992 81

Space Time Neural Networks for Tether Operations in Space

S19-63
N93-22370
153387
p. 42

Robert N. Lea and James A. Villarreal
National Aeronautics and Space Administration
Lyndon B. Johnson Space Center
Houston, Texas 77058

Yashvant Jani
Togai InfraLogic Inc.
Houston, Texas 77058

Charles Copeland
Loral Space Information Systems
Houston, Texas 77058

Abstract

A space shuttle flight scheduled for 1992 will attempt to prove the feasibility of operating tethered payloads in earth orbit. Due to the interaction between the Earth's magnetic field and current pulsing through the tether, the tethered system may exhibit a circular transverse oscillation referred to as the "skiprope" phenomenon. Effective damping of skiprope motion depends on rapid and accurate detection of skiprope magnitude and phase. Because of non-linear dynamic coupling, the satellite attitude behavior has characteristic oscillations during the skiprope motion. Since the satellite attitude motion has many other perturbations, the relationship between the skiprope parameters and attitude time history is very involved and non-linear. We propose a Space-Time Neural Network implementation for filtering satellite rate gyro data to rapidly detect and predict skiprope magnitude and phase. Training and testing of the skiprope detection system will be performed using a validated Orbital Operations Simulator and Space-Time Neural Network software developed in the Software Technology Branch at NASA's Lyndon B. Johnson Space Center.

1.0 Introduction

NASA and the Italian Space Agency plan to fly the Tethered Satellite System (TSS) aboard the Space Shuttle Atlantis in July, 1992. The mission, lasting approximately 40 hours, will deploy a 500 kg satellite upward (away from the earth) [1,2] to a length of 20 km, perform scientific experiments while on-station, and retrieve the satellite safely. Throughout the deployment, experimentation, and retrieval, the satellite will remain attached to Atlantis by a thin tether through which current passes, providing power to experiments on-board the satellite. In addition to the scientific experiments on-board the satellite, the dynamics of the tethered satellite will be studied. The TSS dynamics are complex and non-linear due to the mass of the tethered system and the spring-like characteristics of the tether. A high fidelity finite element model of the TSS, in which the tether is modelled as a series of beads connected via springs (Fig. 1), realistically represents the dynamics of the TSS, including the longitudinal, librational, and transverse circular oscillations referred to as "skiprope" motion. Since the satellite is a 6 degree of freedom vehicle, it also properly exhibits the satellite attitude oscillations. The skiprope motion is generally induced when current pulsing through the tether interacts with the Earth's magnetic field [3, 4]. The center bead

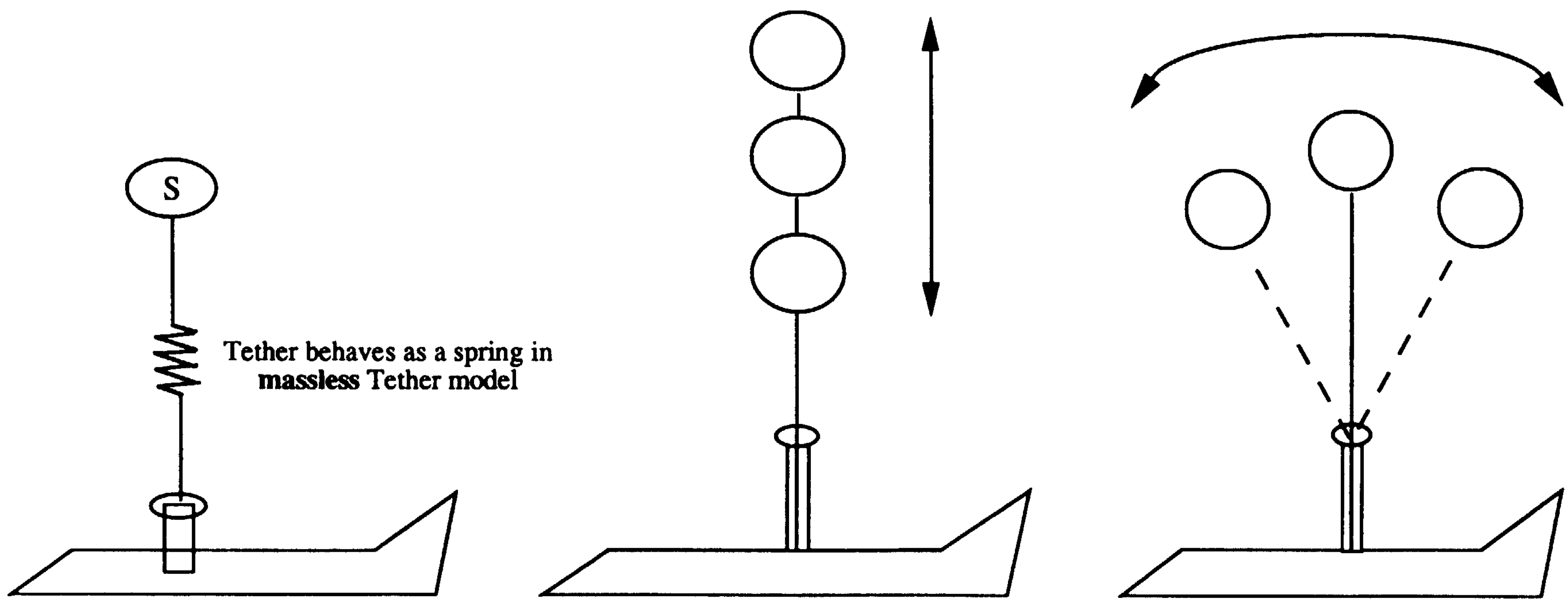


Fig. 1-a Longitudinal and Librational Oscillations in a Tethered Satellite System using Massless Tether Model

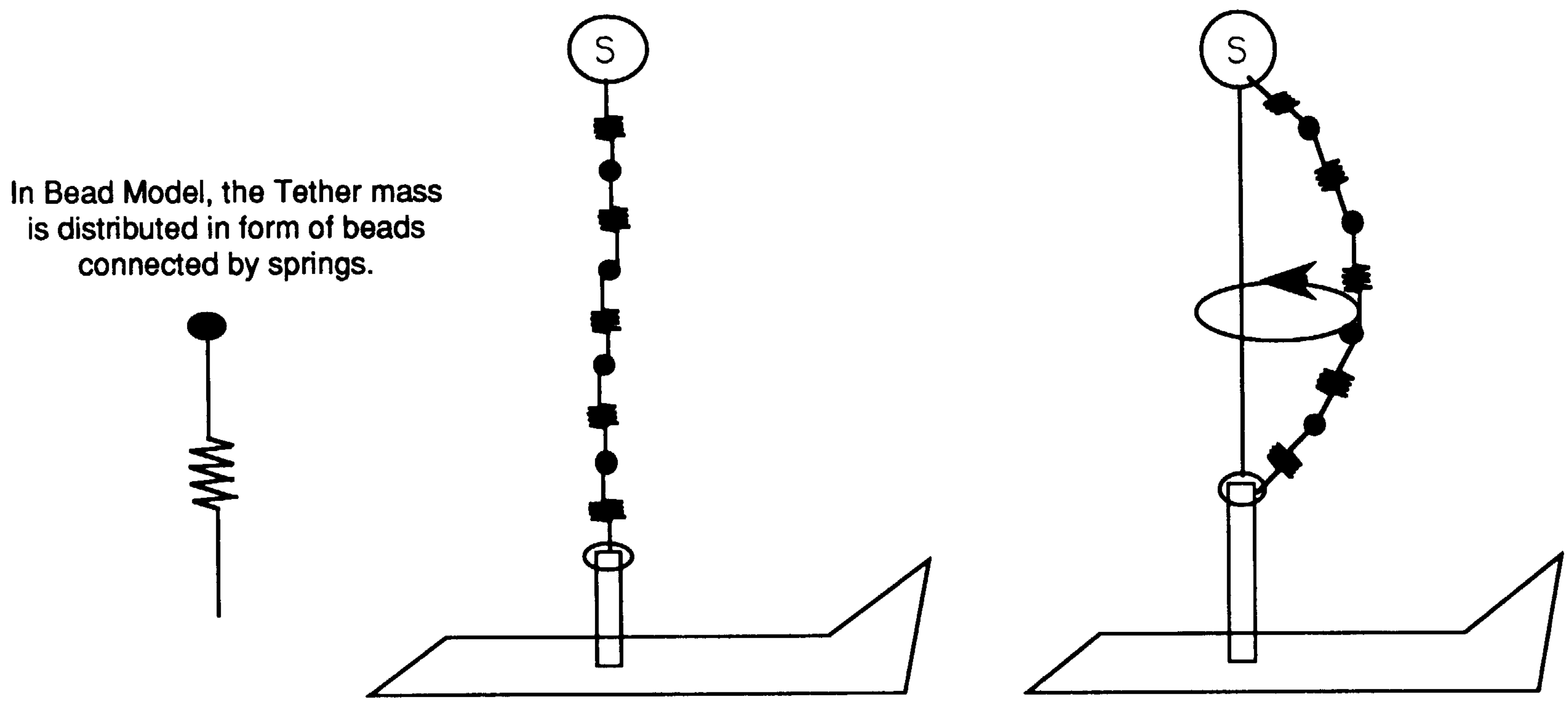


Fig. 1-b In Tether Bead Model, Skiprope Effect or Transverse Oscillations are created when Current interacts with Geomagnetic Field

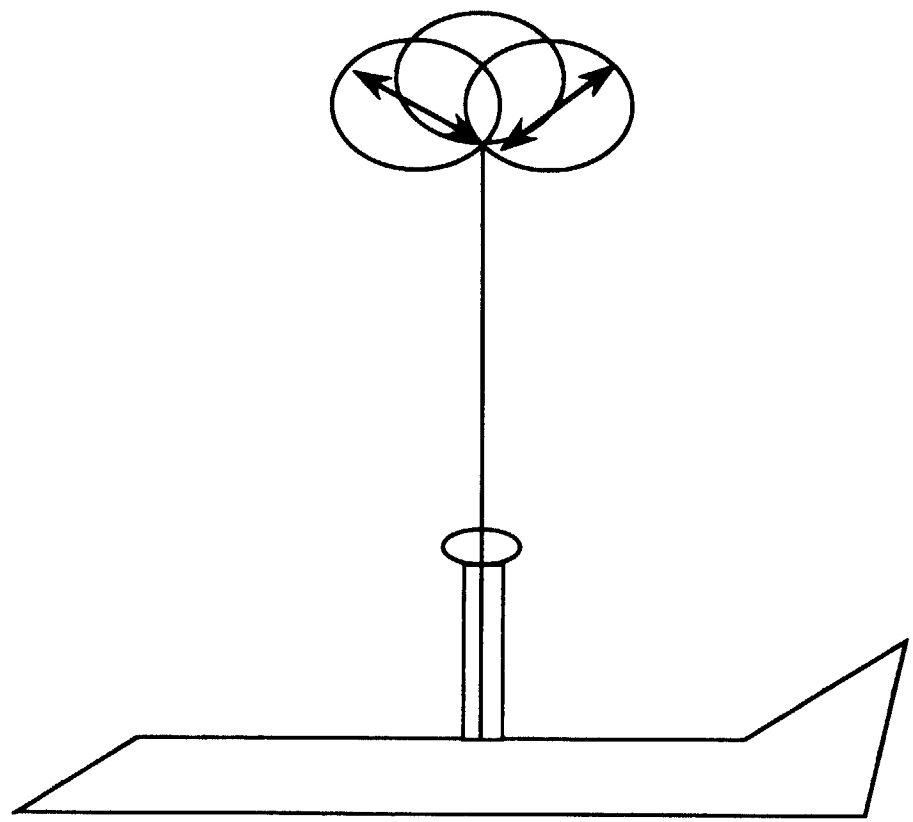


Fig. 1-c Since Satellite is a 6 Degree Of Freedom vehicle, it exhibits Attitude Oscillations which are coupled with the Skiprope Effect

typically displaces the most from the center line. Thus, the "skiprope" can be viewed by plotting a trajectory of the mid-point of the tether as it is retrieved slowly from the on-station-2 phase in high fidelity simulation test cases. As shown in Fig. 2-a, the circular skiprope motion is very simple when there are no perturbing forces. However, when the current is partially flowing, or the current is pulsing with the satellite spin, the skiprope motion is very non-linear as shown in Fig. 2-b and 2-c. Detection and control of the various tether modes, including the "skiprope" effect, is essential for a successful mission. Since there are no sensors that can directly provide a measure of skiprope oscillations, indirect methods such as the Time Domain Skiprope Observer [4] and Frequency Domain Skiprope Observer [3] are being developed for the TSS-1 mission. We are investigating a Space-Time Neural Network (STNN) based skiprope observer.

The Software Technology Branch (STB) is evaluating technologies such as fuzzy logic [5], neural networks [6,7], and genetic algorithms for possible application to various control and decision making processes [8,9,10] for use in NASA's engineering environments. This paper describes the feasibility of applying neural networks, in particular Space Time Neural Network (STNN), to detect and possibly control the skiprope phenomenon using training data from real–time man–in–the–loop simulations. The first phase, detection of skiprope effect (in terms of magnitude and phase angle with respect to the tether line), is vital for tether dynamics control. An STNN architecture has been developed which provides the capability to correlate the time behavior and generate the appropriate output parameters to identify and control skip rope behavior. In this paper, a brief description of the STNN architecture is provided (section 2) along with a scenario of the TSS mission with a focus on the 'skiprope' effect (section 3). The STNN configuration used in our initial test cases and preliminary results are described in section 4. Advantages of utilizing STNN over conventional methods for the detection of skiprope parameters are discussed in section 5. A summary including future activities is provided in section 6.

2.0 Space Time Neural Networks

The Space-Time Neural Network [11] is basically an extension to a standard backpropagation network in which the single interconnection weight between two processing elements is replaced with a number of Finite Impulse Response (FIR) filters. The use of adaptable, adjustable filters as interconnection weights provides a distributed temporal memory that facilitates the recognition of temporal sequences inherent in a complex dynamic system such as the TSS. As shown in Fig. 3a, the inputs are processed through the filters before they are summed at the summing junction.

Instead of a single synaptic weight with which the standard backpropagation neural network represents the association between two individual processing elements, there are now several weights representing not only spatial association, but also temporal dependencies. In this case, the synaptic weights are the coefficients to adaptable digital filters:

$$y(n) = \sum_{k=0}^{N} b_k x(n-k) + \sum_{m=1}^{M} a_m y(n-m) \tag{1}$$

Here the x and y sequences are the input and output of the filter and the a_m's and b_k's are the coefficients of the filter.

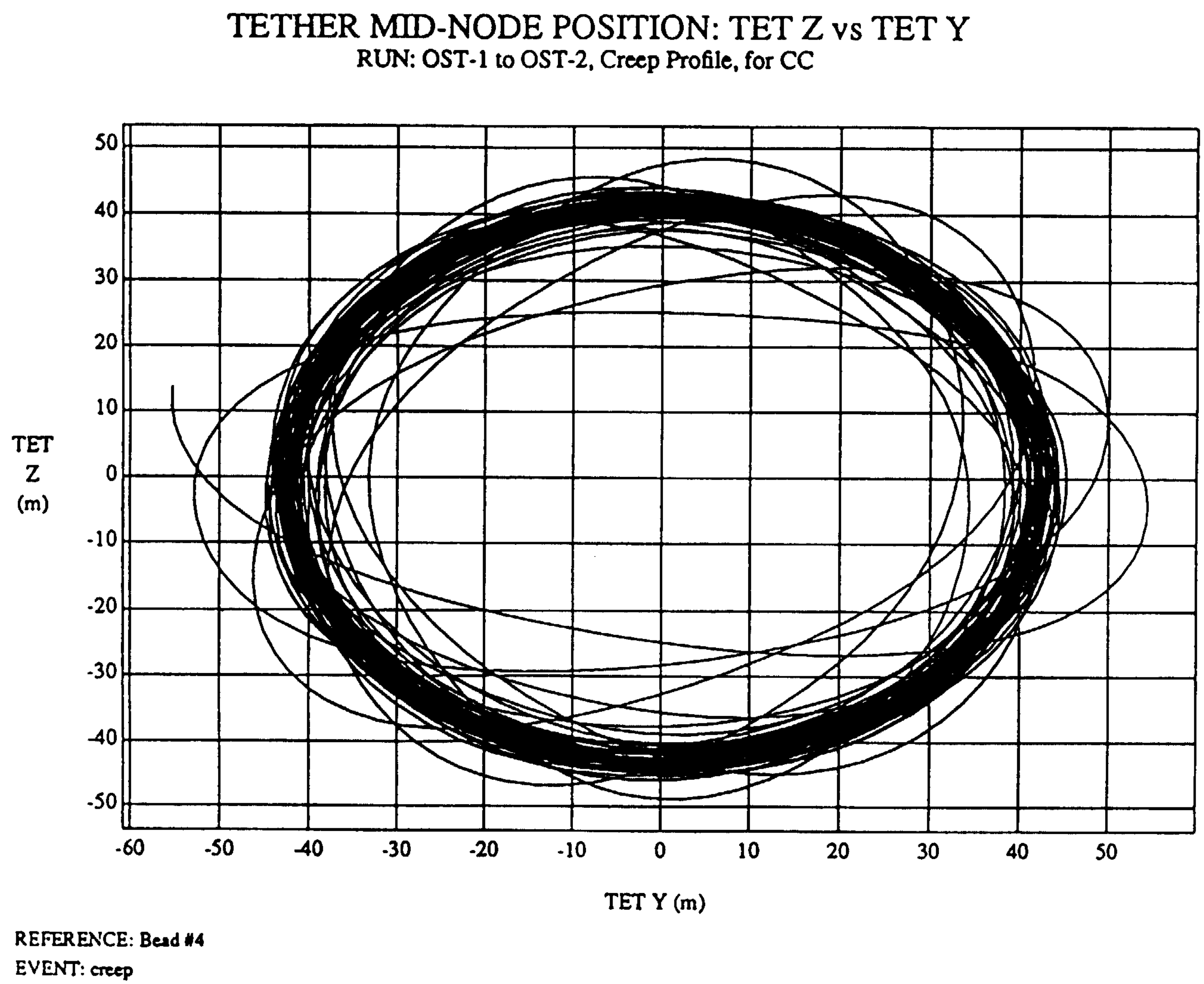


Fig. 2-a Circular Skiprope Motion

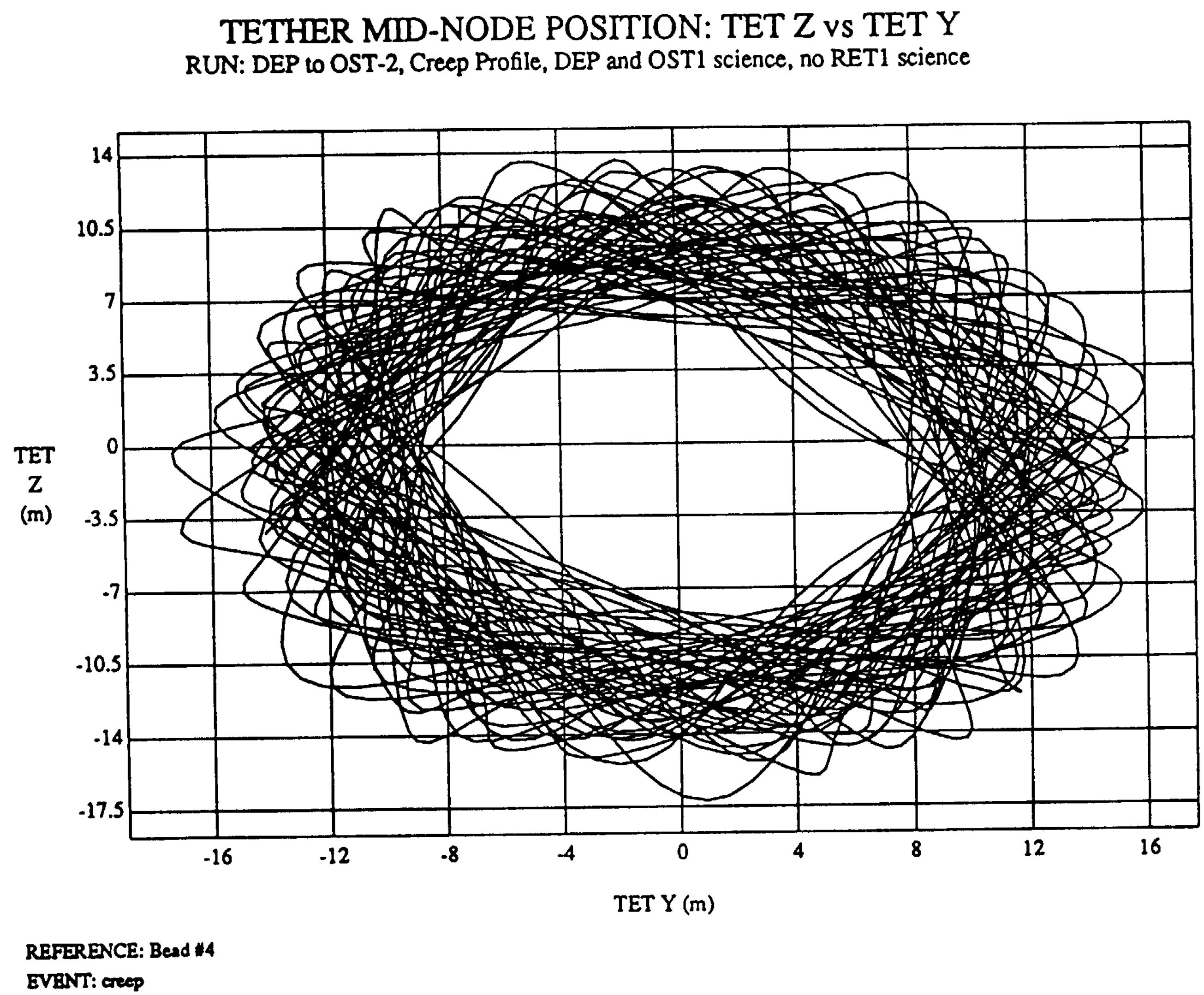


Fig. 2-b Skiprope Motion Resulting from Partial Current Flow

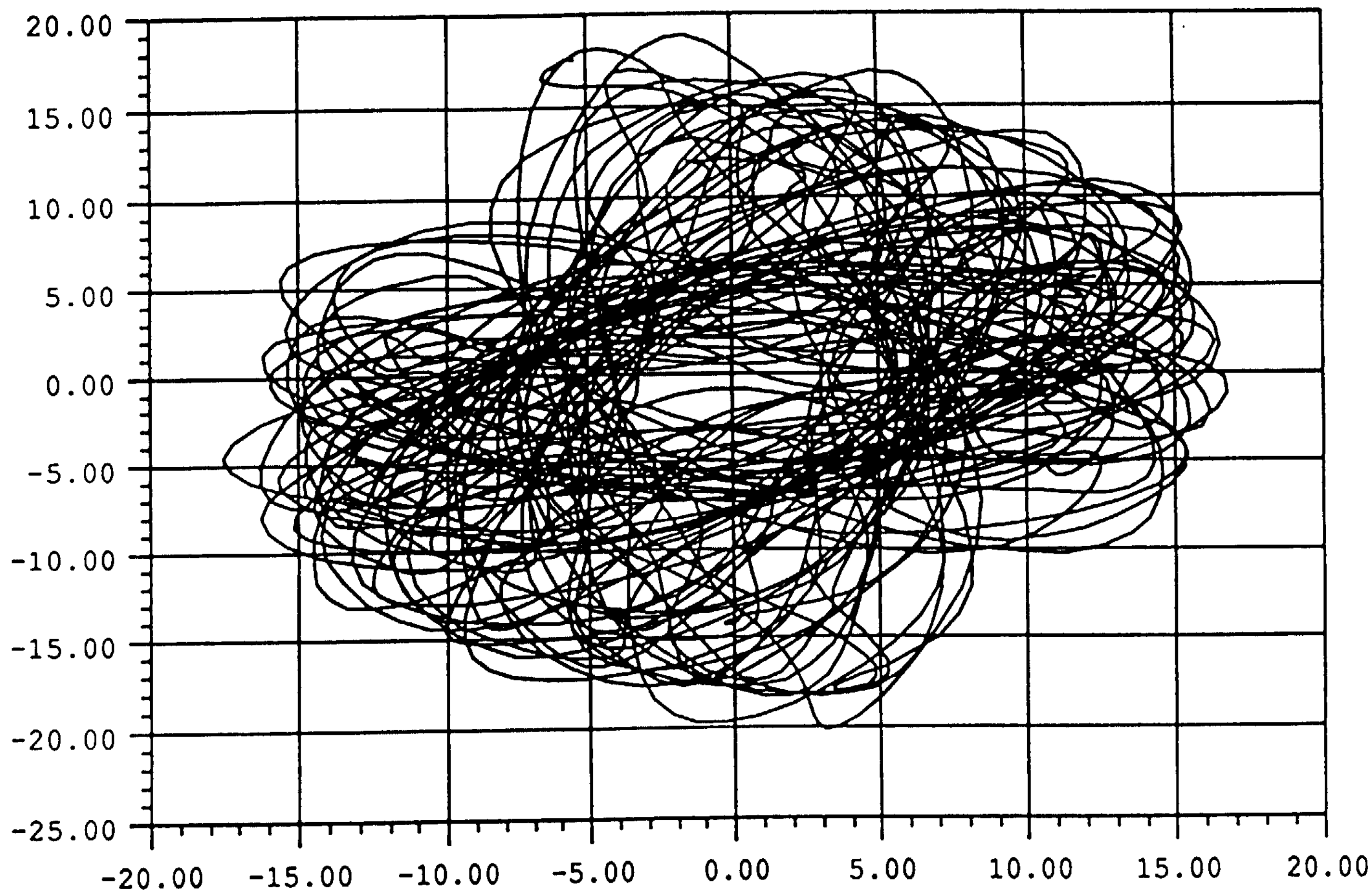


Fig. 2-c Skiprope Motion Resulting from Current Pulsing and Satellite Spin

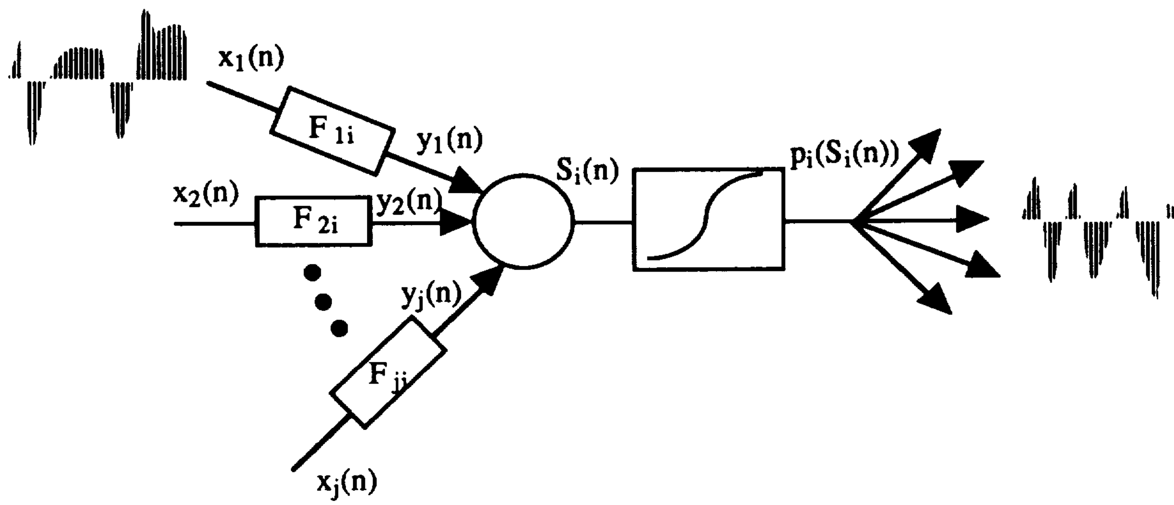


Figure 3 a.... A pictorial representation of the Space-Time processing element.

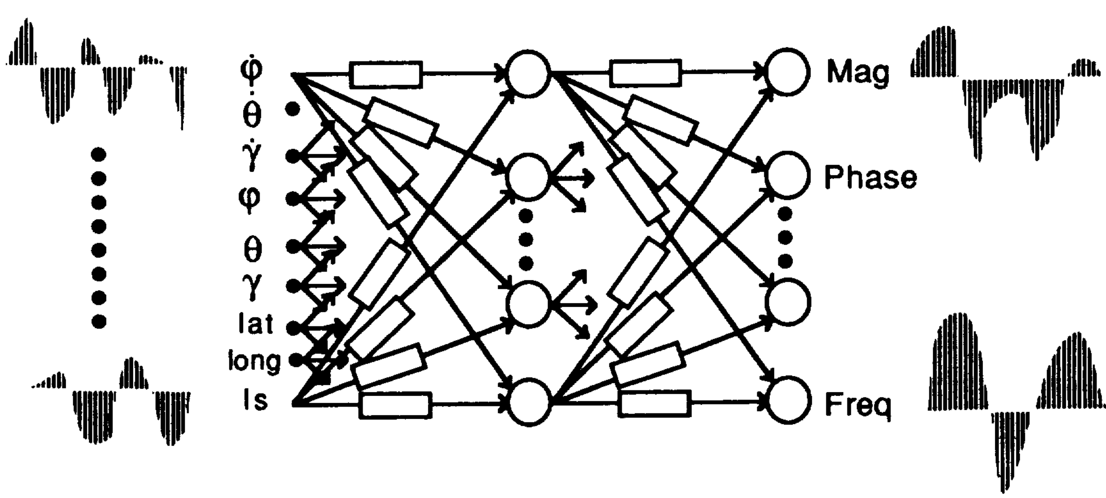


Figure 3b - A depiction of a STNN architecture showing the distribution of complex signals in the input space.

A space-time neural network includes at least two layers of filter elements fully interconnected and buffered by sigmoid transfer nodes at the intermediate and output layers. A sigmoid transfer function is not used at the input. Forward propagation involves presenting a separate sequence dependent vector to each input, and propagating those signals throughout the intermediate layers until the signal reaches the output processing elements. In adjusting the weighting structure to minimize the error for static networks, such as the standard backpropagation, the solution is straightforward. However, adjusting the weighting structure in a recurrent network is more complex because not only must present contributions be accounted for but contributions from past history must also be considered. Therefore, the problem is that of specifying the appropriate error signal at each time and thereby the appropriate weight adjustment of each coefficient governing past histories to influence the present set of responses. A detailed discussion of the algorithm can be found in the provided reference [11]. For the tether skiprope detection, the parameters like satellite spin in terms of roll, pitch and yaw body rates, angles which are derived from these rates, and length and tension will be input, while, the skiprope magnitude and phase will be the output of the net as shown in Fig. 3b.

3.0 Tether Skiprope Phenomenon in Space Operations

The TSS mission is divided into five phases: Deployment, On-station 1 (OST1), Retrieval to a 2.4 km. length, On-station 2 (OST2), and Final Retrieval. The tether motion exhibits longitudinal as well as librational modes as shown in Fig. 1 due to the interaction between gravity gradient forces and spring like characteristics of the tether. These natural modes are damped by controlling the deployed length and length rate using the reel motor drive. A conventional controller is baselined to utilize the sensed length and length rate measurements from sensors. Performance of this baseline controller is adequate in controlling these modes during all phases.

During the OST1 phase, scientific experiments planned include pulsing large electric currents through the conducting tether. Because of interaction between the Earth's geomagnetic field and the pulsing current, transverse circular oscillations known as the 'skiprope' effect as shown in Fig.2 are induced in the tether motion. Simulation results with a 19 bead model of the tether showed the skiprope magnitude between 20 and 70 meters at 20 km. tether length during the OST1 phase of the mission. The skiprope motion is slightly elliptical, i.e. asymmetric around the axis defined by orbiter-satellite line and thus the determination of phase angle becomes involved. To visualize the skiprope motion, we have plotted the z-y motion of the central bead as shown in Fig. 2-a. This motion is the departure from the line that connects the satellite and orbiter. The skiprope motion is very regular for a simple case with no satellite spin, and no current pulsing. When the satellite has spinning motion and the scientific experiments pulse the current through the tether, the skiprope motion is very non-linear as shown in Fig. 2-c. Various combinations of current flow and satellite spin can result in a motion similar to Fig. 2-b. For our initial study, we have utilized the skiprope motion from a simple case. In later test we progressed to more complicated skiprope motions.

Simulation results have shown that the librational amplitude increases about 6 times if there is a skiprope motion present during the retrieval. If librational amplitude is above a critical value, then, the librational oscillations must be damped to a safe value using the Orbiter pitch jets before any further retrieval can be performed. The skiprope amplitude remains between 10-20 meters during the OST2 phase. If the skiprope motion is not properly damped at 2.4 km. then two issues arise during the final retrieval: 1) The satellite pendulus motion increases significantly (about 6 degrees per meter of skiprope amplitude) such that the attitude control for the satellite fails. 2) The departure angle of the tether from the boom tip may go beyond 60 degrees, thus causing concerns about the tether hitting the Orbiter tail and getting tangled. This may result in a mission failure due to a situation known as "wrap-around" where the safety of the crew and the orbiter is questionable. Therefore the control of skiprope magnitude is very important during the final retrieval phase.

The satellite attitude motion depends on the orbital environment (e.g. perturbations from aero torques) as well as the tension resulting from tether modes. The longitudinal and librational modes affect the satellite rates because of tension coupling at the attach point. However, simulation results indicated that the skiprope effect induces highly characteristic oscillations in the satellite attitude motion (Fig. 1). Due to the dynamical coupling, the skiprope energy seems to be transferred to satellite attitude oscillations. Currently there is no direct measurement available that can provide information regarding the skiprope motion, particularly, the magnitude and phase of the skiprope. Since the satellite attitude behavior is coupled with skiprope, it is possible to utilize the satellite rate (and angles derived from them) information to detect the skiprope parameters.

Controlling the skiprope effect requires knowledge of the magnitude and phase angle of the tether. The amount of pitch torque applied using the Orbiter pitch jets is proportional to the skip rope magnitude. To decrease the skiprope magnitude, the pitch jets are used when the phase angle is 0 or 180 degrees. A pitch pulse increases the skiprope magnitude, if the phase is 90 or 270 degrees. Thus, the phase angle provides the timing of pitch pulse, while the magnitude establishes the amount of pitch torque to be applied.

Performance of the Neural Network Skiprope Observer (NNSO) will be evaluated in terms of the following top level requirements for the Time Domain Skiprope Observer (TDSO).

1.) Operate during all mission phases, where length < 1000 m.
2.) Operate during satellite spin.
3.) Operate during current flow.
4.) Operate during satellite spin and current flow.

In addition to these general requirements, the following goals should be met.

1.) During periods in which the skiprope motion is circular, and there exists no current flow and no satellite spin, the observer must predict skiprope amplitude to within 10% of actual amplitude or 5.0 m, whichever is greater, and predict phase to within 10 degrees

2.) During periods in which the skiprope is circular or non-circular, and there exists current flow and satellite spin, and after 20 minutes settling time, the observer must predict amplitude to within 20%, and phase to within 45 degrees.

3.) The observer must predict in-plane and out-of-plane libration to within 1 degree of actual values.

4.0 STNN configurations and Test Results

To provide data for the STNN training and testing, we have logged data from a high fidelity simulation of the TSS-1 mission, including the OST2 phase. The purpose of OST2 is to halt the retrieval phase at 2.4 kilometers so that skiprope motions and librational oscillations can be reduced to safe magnitudes to allow for final retrieval. Several different simulation runs were used to gather data for STNN training. The simulation runs are consistent with the requirement that the skiprope observer must be capable of performing during various combinations of current flow through the tether, and satellite spin. For example, our first set of test cases are based on data from a simulation in which there is no current flow or satellite spin which results in a circular skiprope motion. Another simulation represents the case in which current flows through the tether only during the on-station phase, and the satellite is in yaw-hold. A third simulation represents continuous current flow, and satellite spin at 4.2 degrees/second. These three scenarios will form the basis for STNN skiprope observer training and testing, and are consistent with simulations used for testing the Time-Domain Skiprope Observer (TDSO)[4] which will be used for skiprope recognition during TSS-1.

In each simulation run, we have logged 3,000 to 4,000 data points just prior to and during OST2 phase for neural network training. In our initial test cases we use roll rate, pitch rate, roll and pitch position, tether tension, and tether length as inputs to the neural network. Based on these inputs, we hope to find a neural network configuration which will predict skiprope amplitude and phase. The assumption that satellite rates are coupled with skiprope motion is consistent with the baseline Time Domain Skiprope Observer (TDSO) which will be utilized during the TSS-1 mission. The following sections discuss the results of four major test cases.

4.1 Identifying Skiprope Amplitude

To determine the feasibility of using STNN for skiprope detection, we initially trained on data from a simple, circular skiprope case with no satellite spin or current flow through the tether, which is consistent with the first requirement listed above. The data used for training and testing in preliminary tests reflect a near circular skiprope , as depicted in Fig. 2-a. Future test cases will concentrate on more difficult skiprope conditions, such as that pictured in Fig. 2-c, which results from satellite spin and current flow through the tether. The test cases described in this section attempt to evaluate the STNN's ability to identify skiprope amplitude only. We will present the results of test cases involving other skiprope parameters in subsequent sections.

The STNN configuration used in our initial test cases has six inputs, one output, 30 hidden units and 40 zeros for the filters. The choice of the inputs is based on the coupling between the satellite attitude and rates. We have used the roll and pitch angles, roll and pitch rates, tension and deployed length as input to the STNN, and skiprope amplitude as the output. Yaw angles and rates were not used on the inputs in this case because the satellite remains in yaw hold throughout the simulation. To determine if the network is capable of learning the training data, we first train and test on all available (4,001 in this run) I/O pairs. Fig. 4-a shows that the STNN reaches a MAX error of 0.07, and an RMS error of 0.02 within 150 cycles of training. As shown in Fig. 4-b, the STNN predicts skiprope amplitude to within about 3 meters of actual amplitude. For clarity, we have shown STNN performance on I/O pairs 1501-2000. This is fairly representative of the STNN's performance on all 4,001 I/O pairs.

In the next test case, in order to evaluate the network's ability to recognize previously unseen data based on limited exposure to training data, we train on only the first and last 200 I/O pairs, and test on the middle 3,600. Neural network practitioners typically test a network by training until the network reaches some minimum error, and then presenting the test data to the network. In our tests we alternate training and testing throughout a number of training cycles so we can see the correlation between training cycles and test errors. For this reason, our test error plots indicate errors over several presentations of the test data, rather a single presentation. Fig. 4-c shows the errors produced upon presentation of the

Fig. 4-a, MAX vs RMS Error

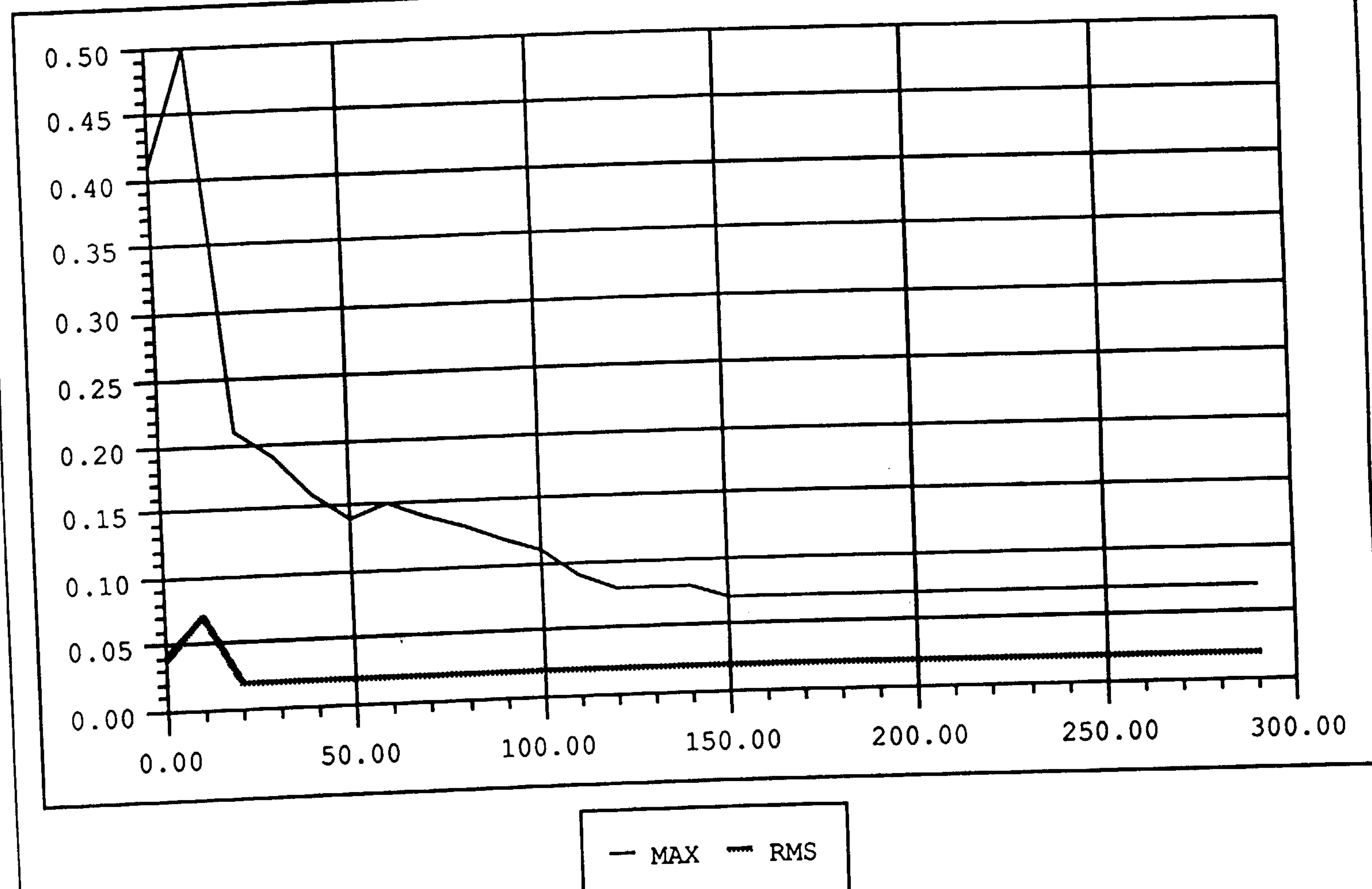


Fig. 4-b, Target vs STNN output.

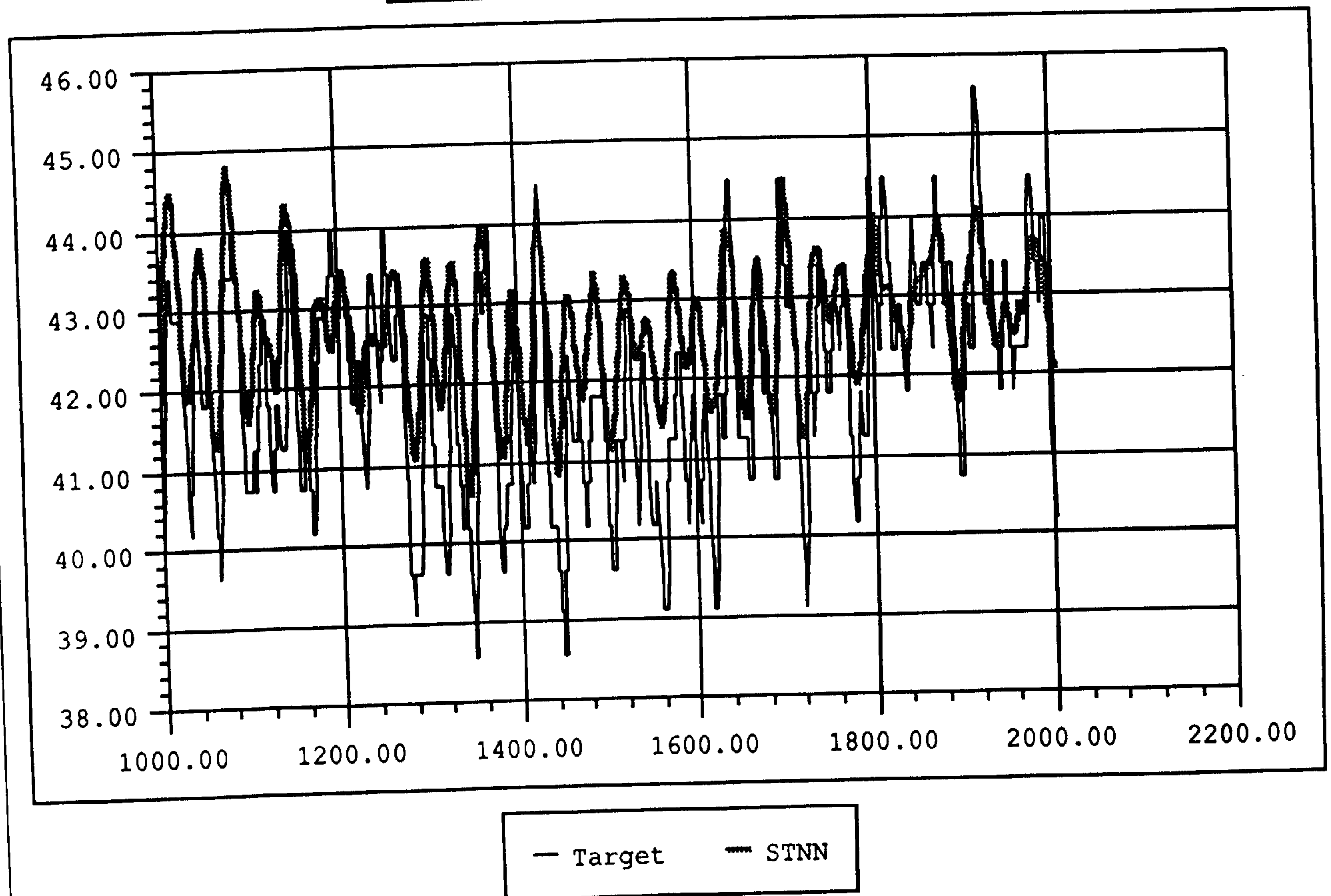
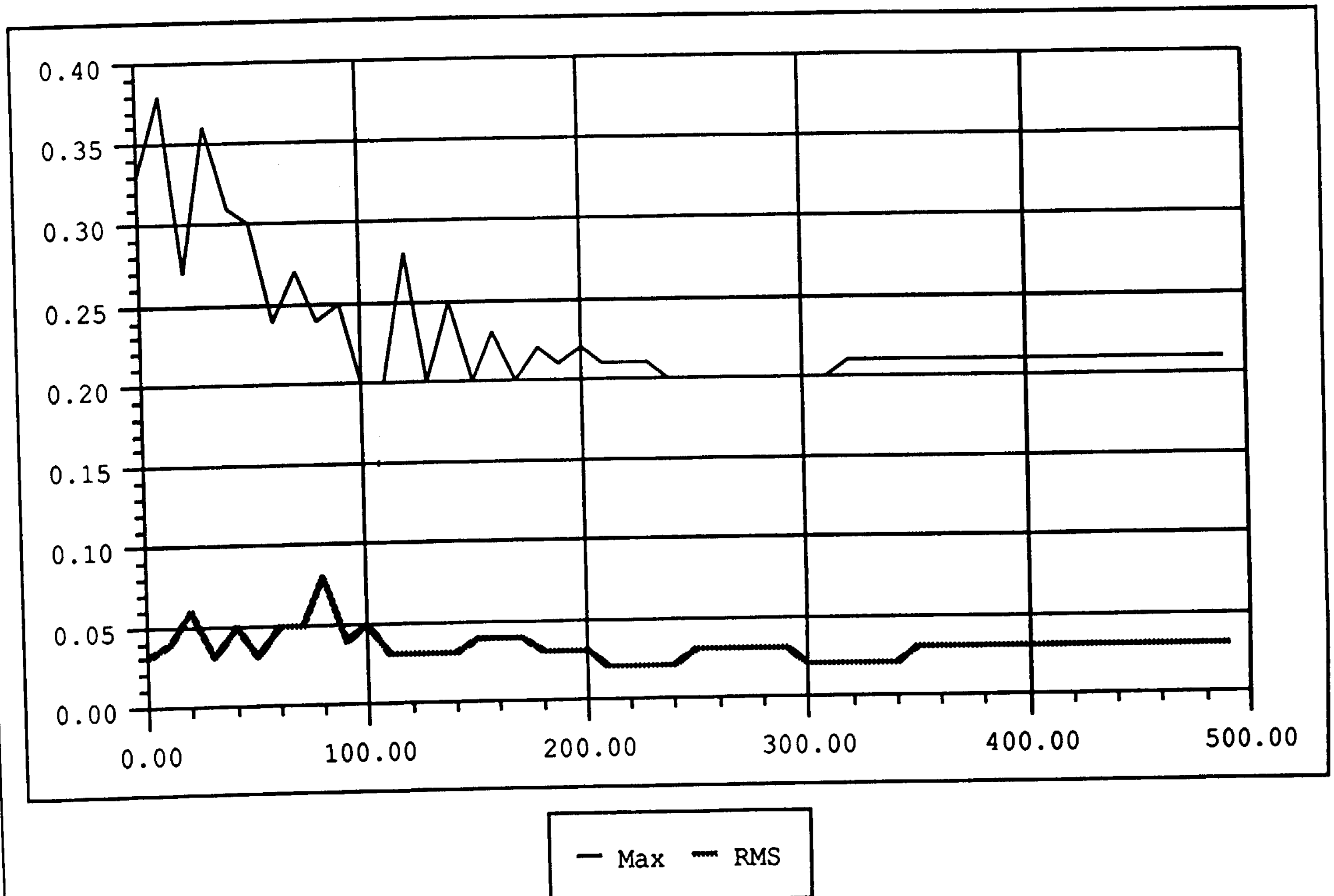


Fig. 4-c, MAX vs RMS Error.



test data. The lowest errors were reached after 240 cycles when the maximum error reached 0.2 and the RMS error reached 0.02. Fig. 4-d shows the STNN prediction of skiprope amplitude compared to actual amplitude. Again, performance seems to be within 2-to-3 meters of actual skiprope amplitude. The previous two test cases indicate that the STNN identifies circular skiprope motion within the required 5.0 meters or 10% of actual amplitude, as specified in the Skiprope Observer requirements.

Next, we train and test the STNN on skiprope data corresponding to the motion shown in Fig. 2-b. This motion results from current flowing through the tether during the On-Station-1 portion of the mission. In this test case, we use roll, pitch, and yaw rates, roll, pitch, and yaw angles, sensed length, and sensed tension as inputs, and skiprope amplitude as output. Fig. 4-e shows the MAX and RMS errors reached during training and testing on all 3501 I/O pairs. After 360 cycles, the STNN reached a MAX error of 0.17, and an RMS error of 0.04. Fig. 4-f shows that the STNN seems to have learned the training data after 360 cycles of training.

In our next experiment, we split the data into a training set and a test set by training on the first and last 200 I/O pairs and testing on the middle 2000. Fig. 4-g shows that the errors decrease for only about 50 cycles, and then begin to increase. Fig. 4-h shows that performance after 100 cycles of training is not as good as what was achieved above on circular skiprope data.

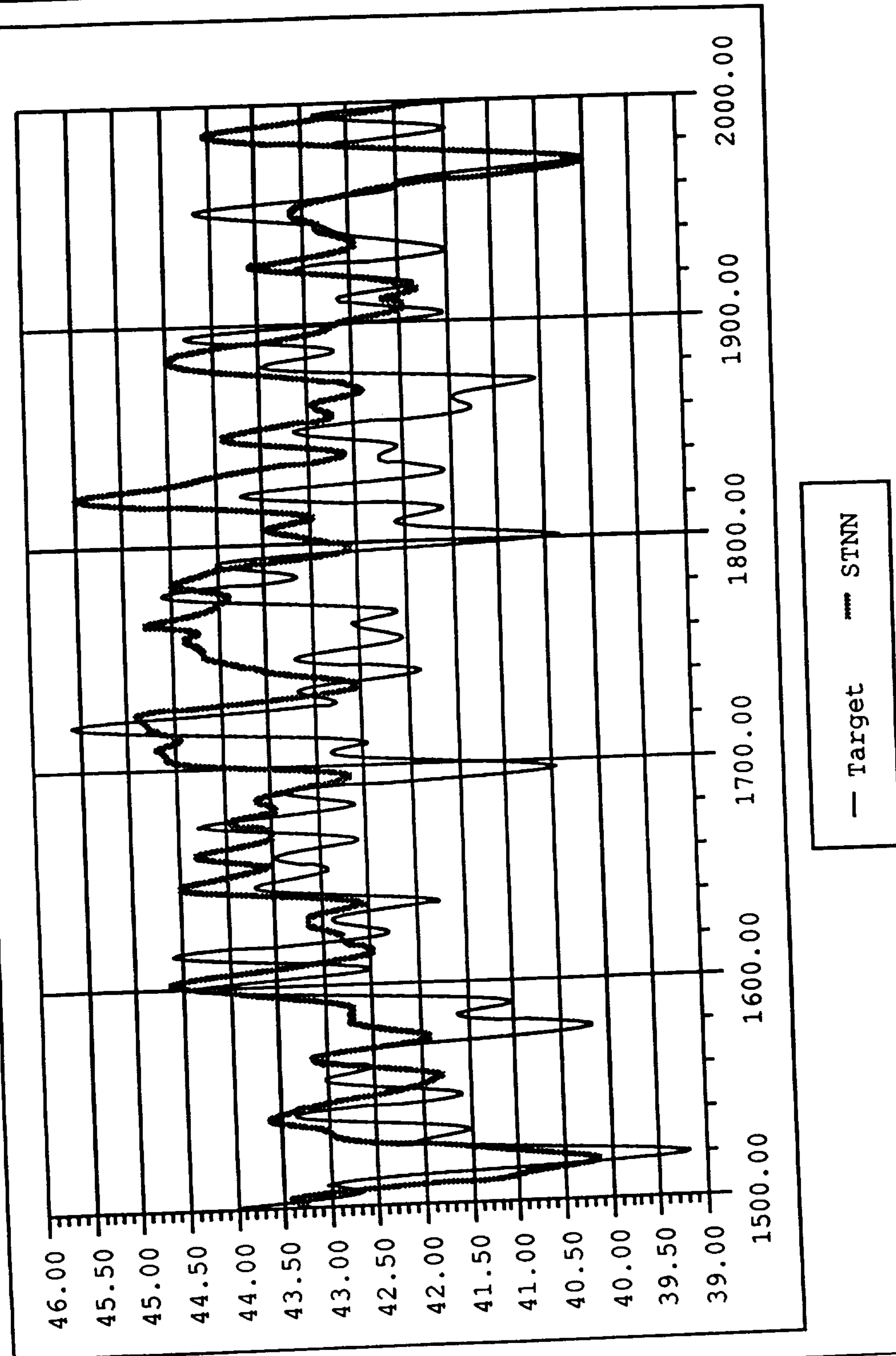
In our next experiment, we train and test on data corresponding to the skiprope motion depicted in figure 2-c. This very complex motion results from combinations of current flow and satellite spin throughout satellite deployment and retrieval. In this experiment, we train and test on all I/O pairs (3,502). Fig. 4-i shows that after 40 cycles, the network reached a MAX error of 0.29, and RMS error of 0.05. Fig. 4-j reveals that the network identifies the skiprope amplitude to within 2 meters. Again, for clarity, we only show a portion of the mapping of the entire data set. A plot of the entire data set reveals that the network can be off by as much as 6 meters in some areas.

4.2 Identifying Phase

In this section we examine test cases in which the STNN has been asked to identify skiprope phase in addition to amplitude. As in the previous section, we start with a circular skiprope motion and progress to more difficult situations. In our first experiment, we use roll and pitch rates, roll and pitch angles, sensed length, and sensed tension as input, and produce amplitude and phase on the outputs. In addition to the 6 inputs, and two outputs, the network consists of thirty hidden units, and forty filters between input and hidden, and hidden and output layers. Fig. 5-a shows the MAX and RMS errors achieved as the network trained on the first and last 200 I/O pairs, and tested on the middle 3,600 I/O pairs from the full set of 4,001 I/O pairs. Fig. 5-b shows a portion of the network's estimation of skiprope amplitude. The performance of the network is generally within 6 meters over the entire test data set. Fig. 5-c shows that the network identifies skiprope phase to within 50 degrees, which is not within the required 10 degrees.

Subsequent efforts to identify skiprope phase also fall short of the requirements. Fig. 5-d shows the training errors resulting from an attempt to train on data corresponding to a skiprope motion resulting from satellite spin and current flow through the tether. In this test case, the network trained and tested on a complete set of 3,501 I/O pairs. Although Fig. 5-e shows that the network identifies amplitude to within 4 meters, the network may incorrectly identify amplitude by as much as 8 meters. Fig. 5-f shows that the network performs poorly in identifying skiprope phase.

Fig. 4-d, Target vs STNN output.



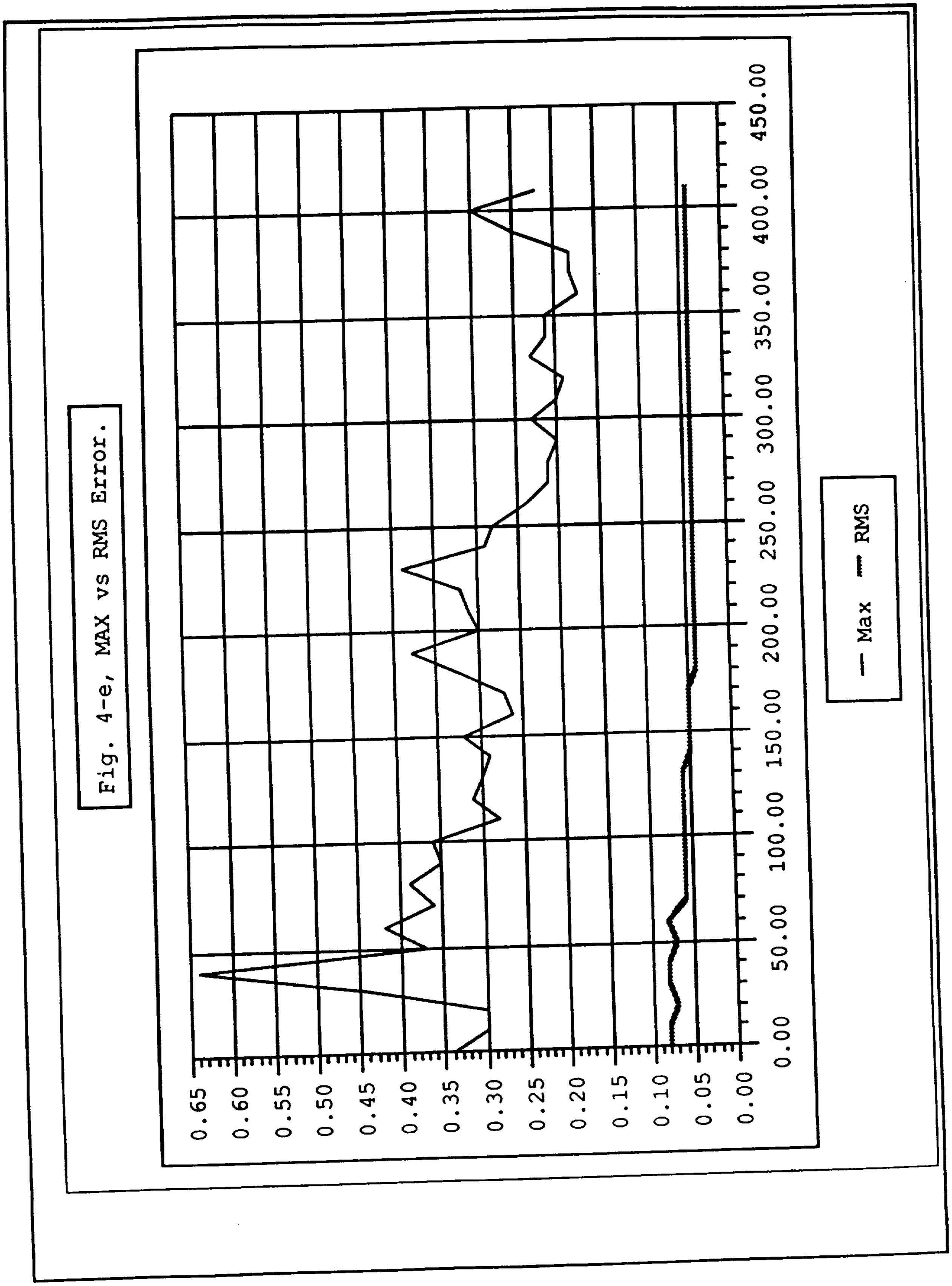


Fig. 4-e, MAX vs RMS Error.
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0.00
50.00
100.00
150.00
200.00
250.00
300.00
350.00
400.00
450.00
Max
RMS

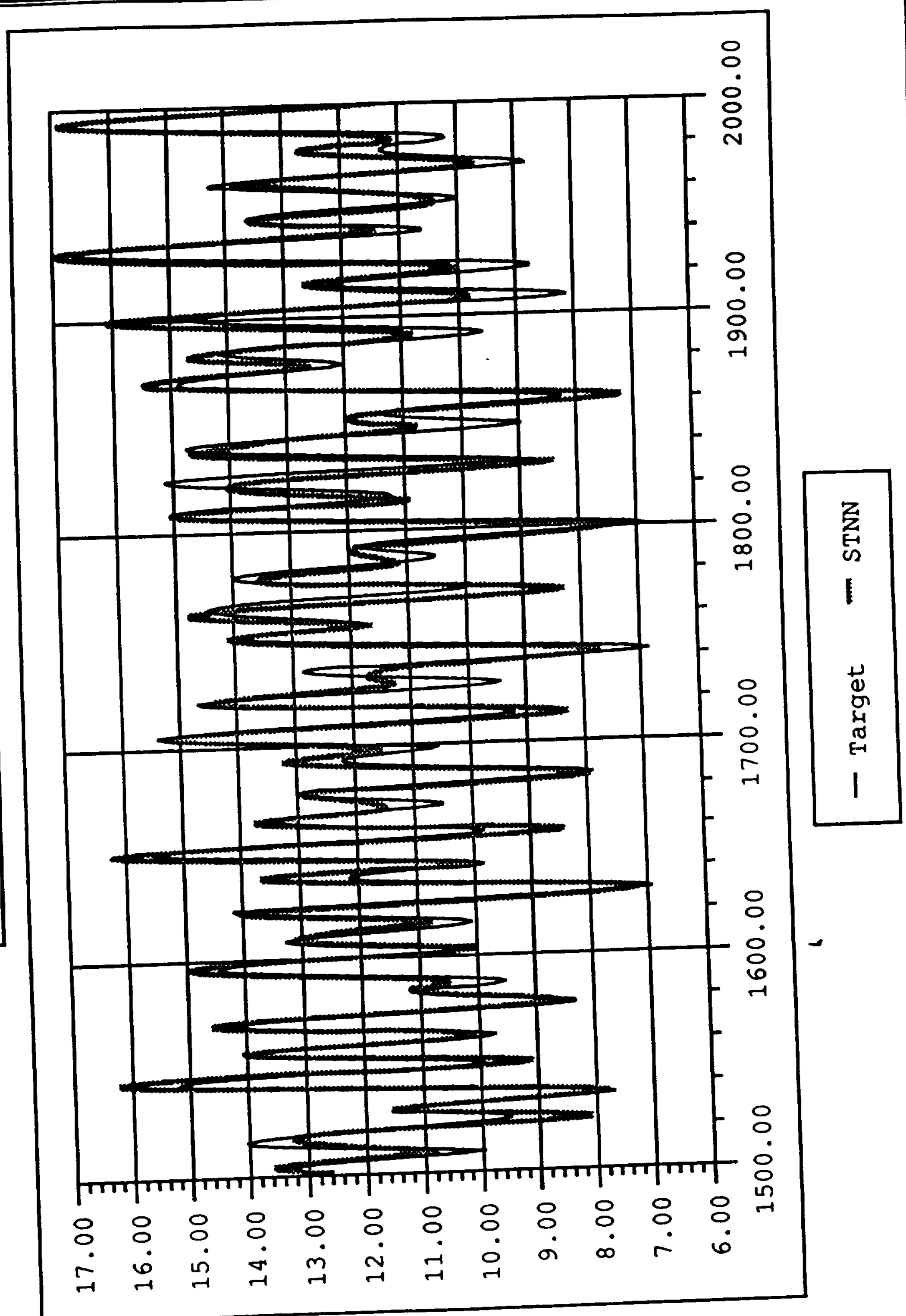


Fig. 4-f, Target vs STNN output.

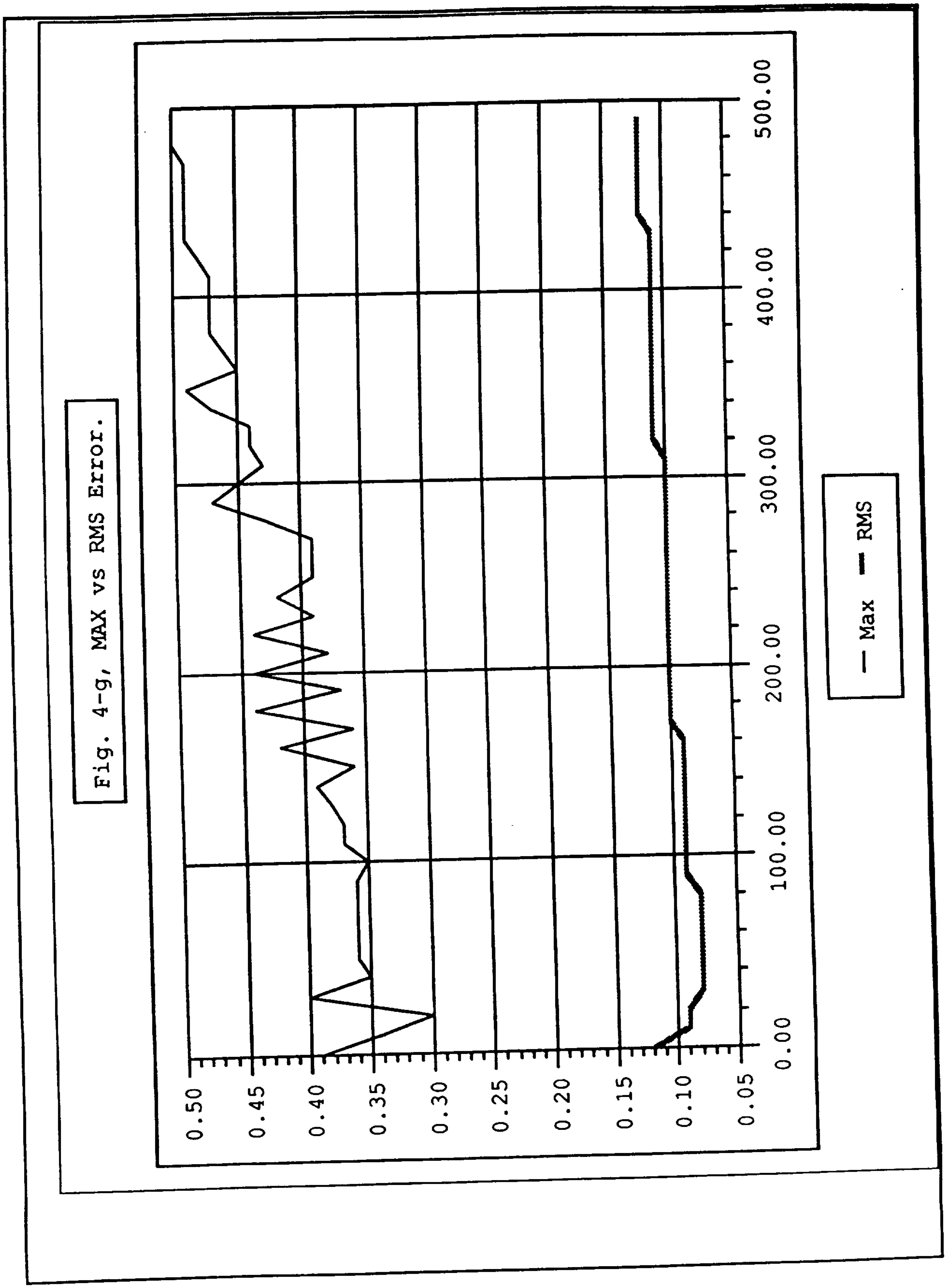


Fig. 4-g, MAX vs RMS Error.

Fig. 4-h, Target vs STNN output.

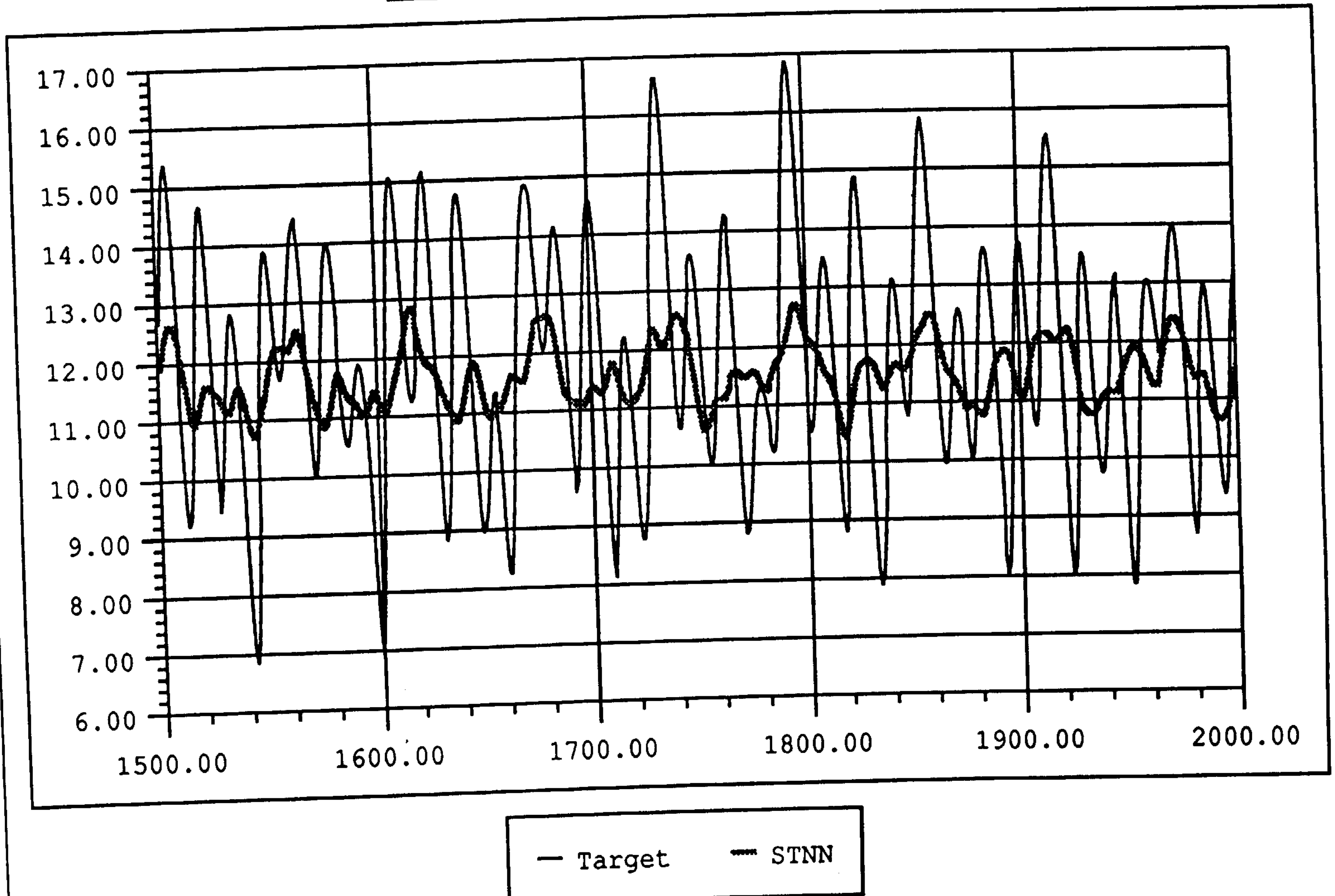


Fig. 4-i, MAX vs RMS Error.

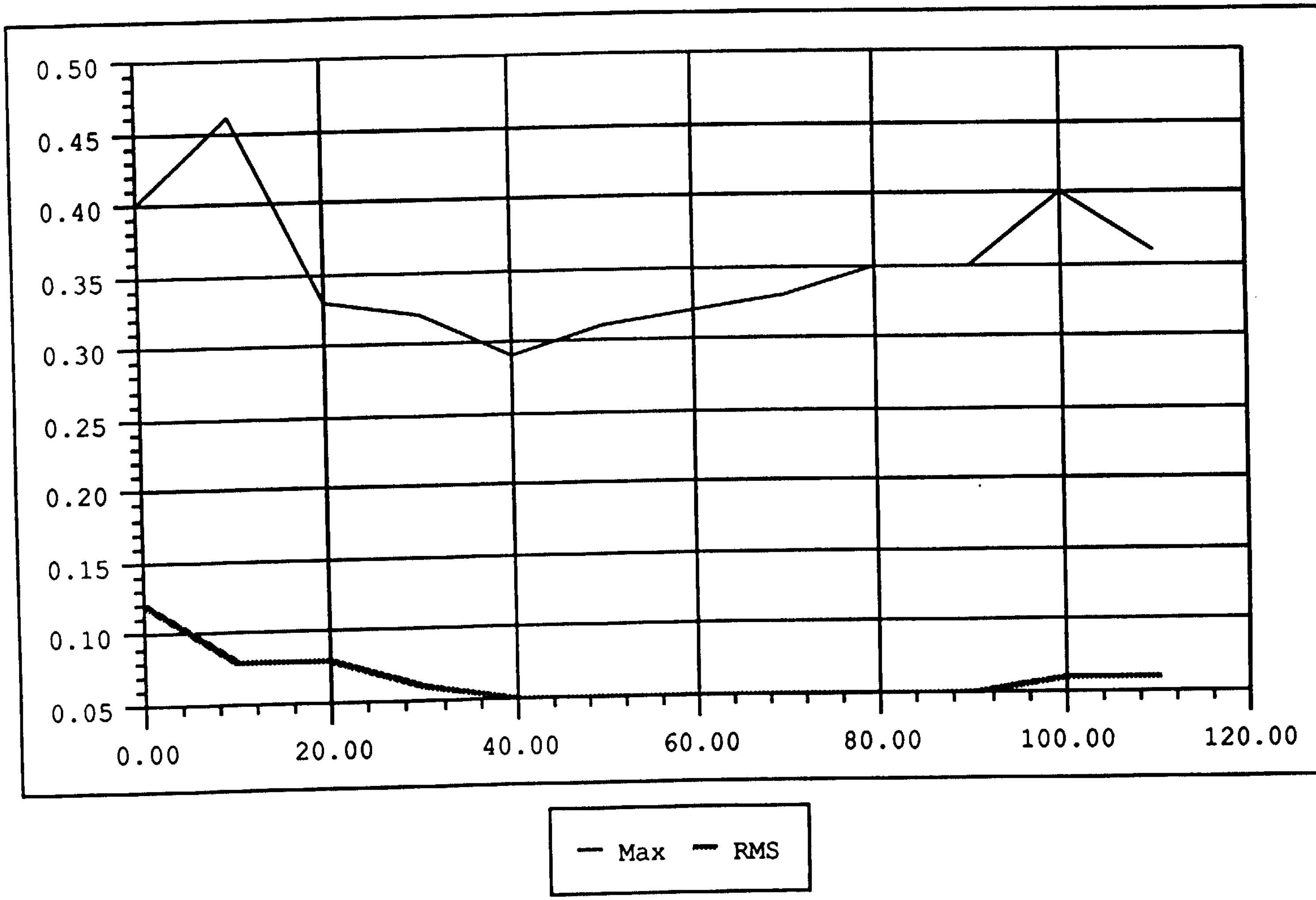
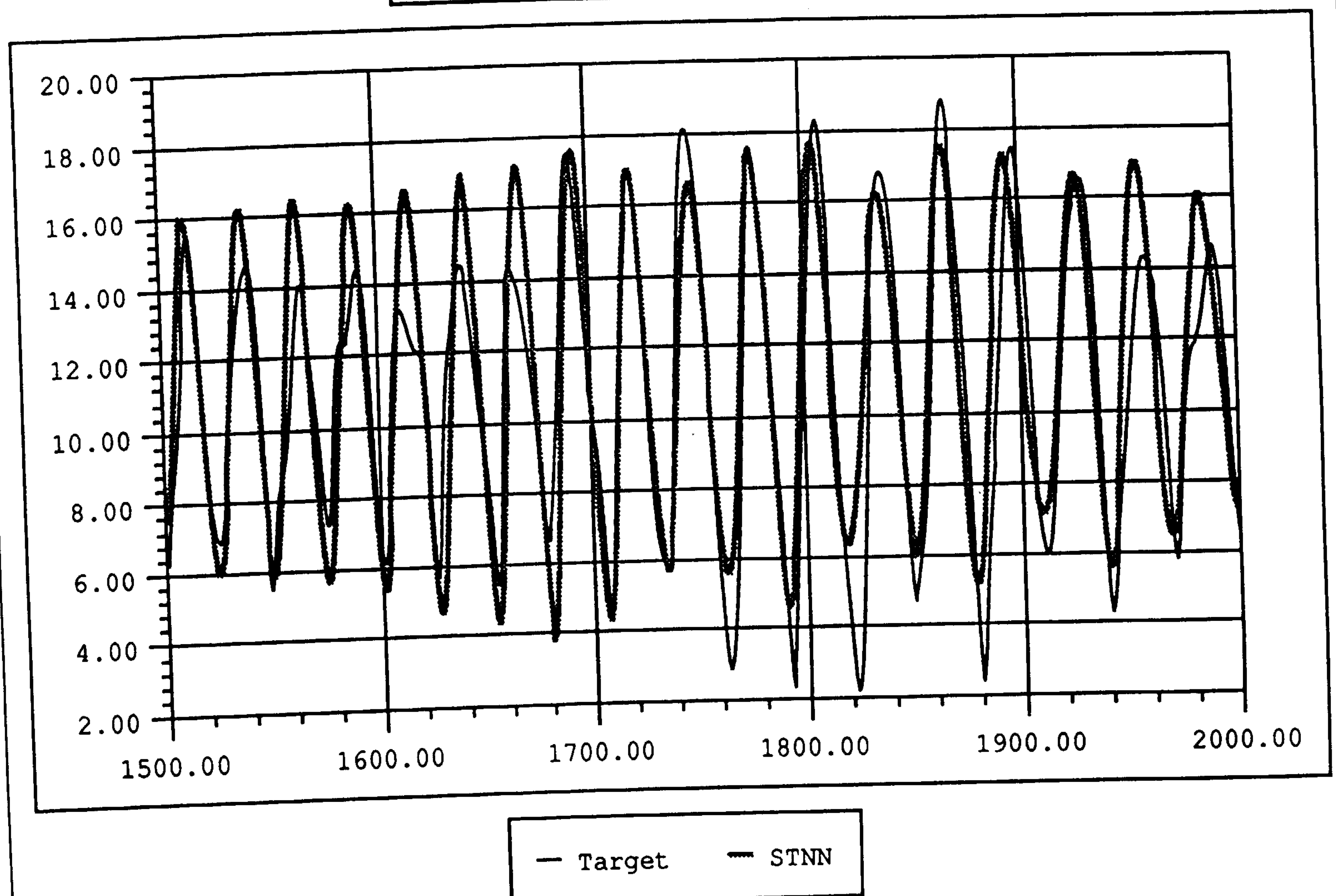


Fig. 4-j, Target vs STNN output.



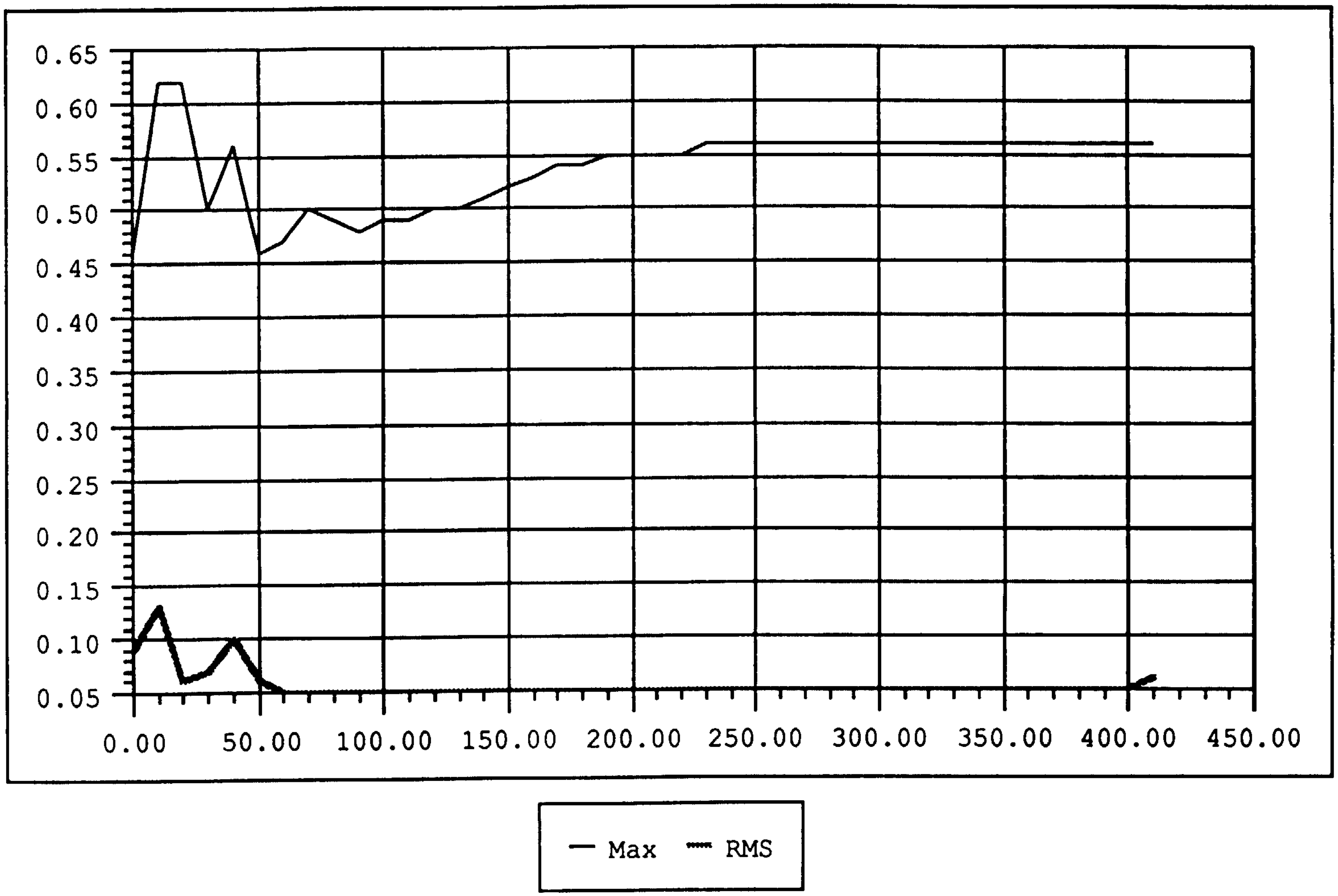


Fig. 5-a, MAX vs RMS Error.

Fig. 5-b, Target Amplitude vs STNN Amplitude.

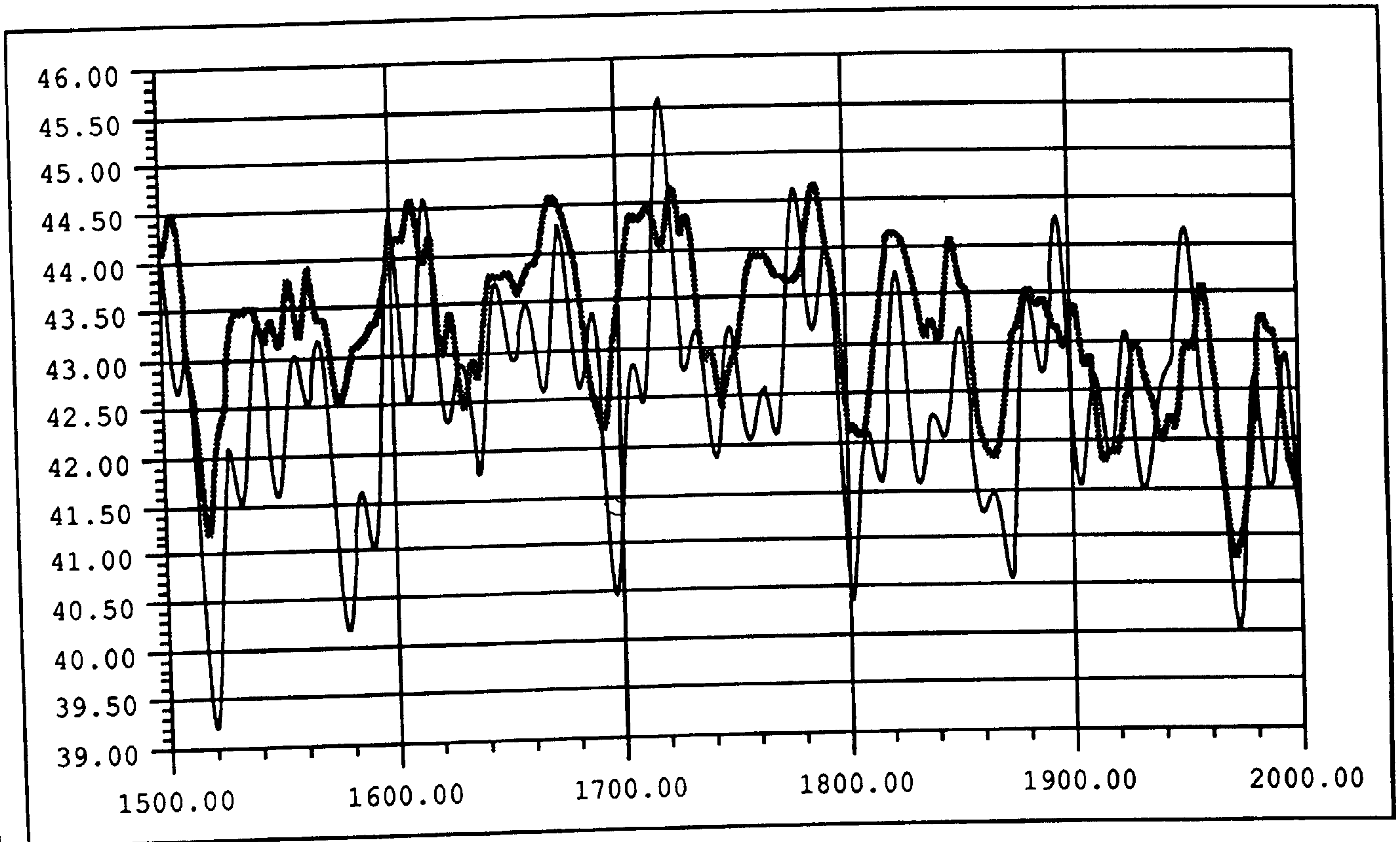
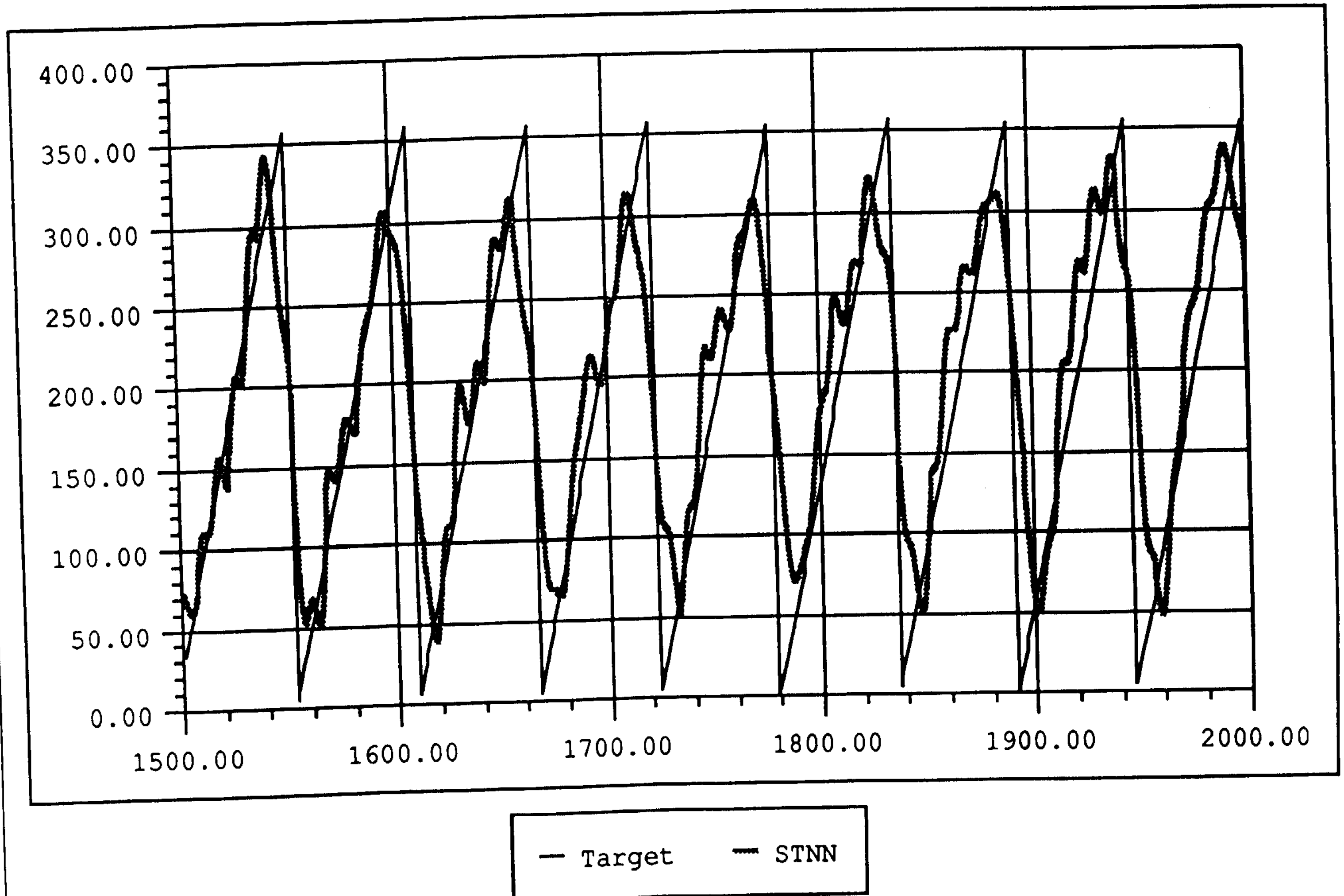


Fig. 5-c, Target Phase vs STNN Phase.



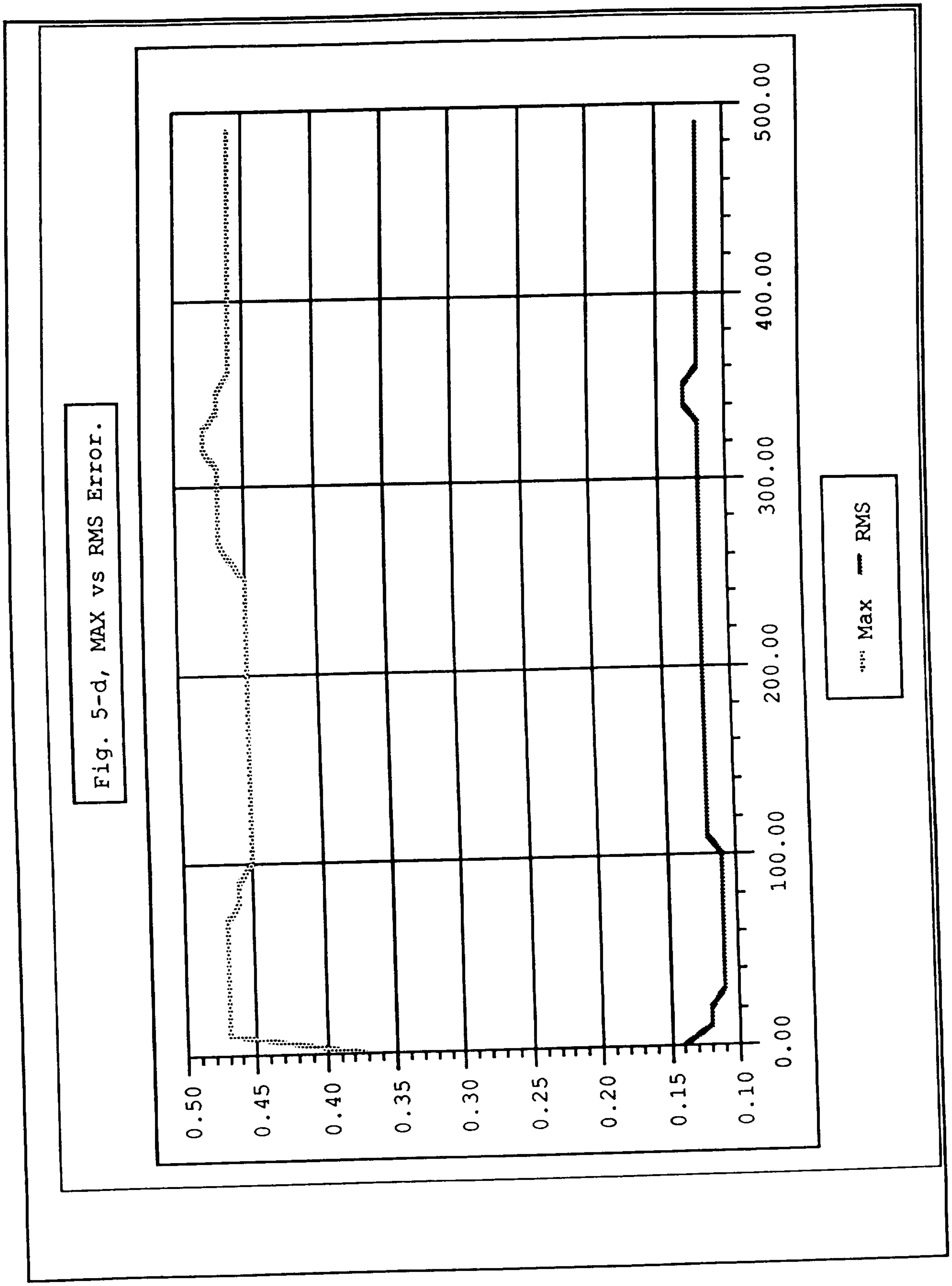


Fig. 5-d, MAX vs RMS Error.

Fig. 5-e, Target Amplitude vs STNN Amplitude.

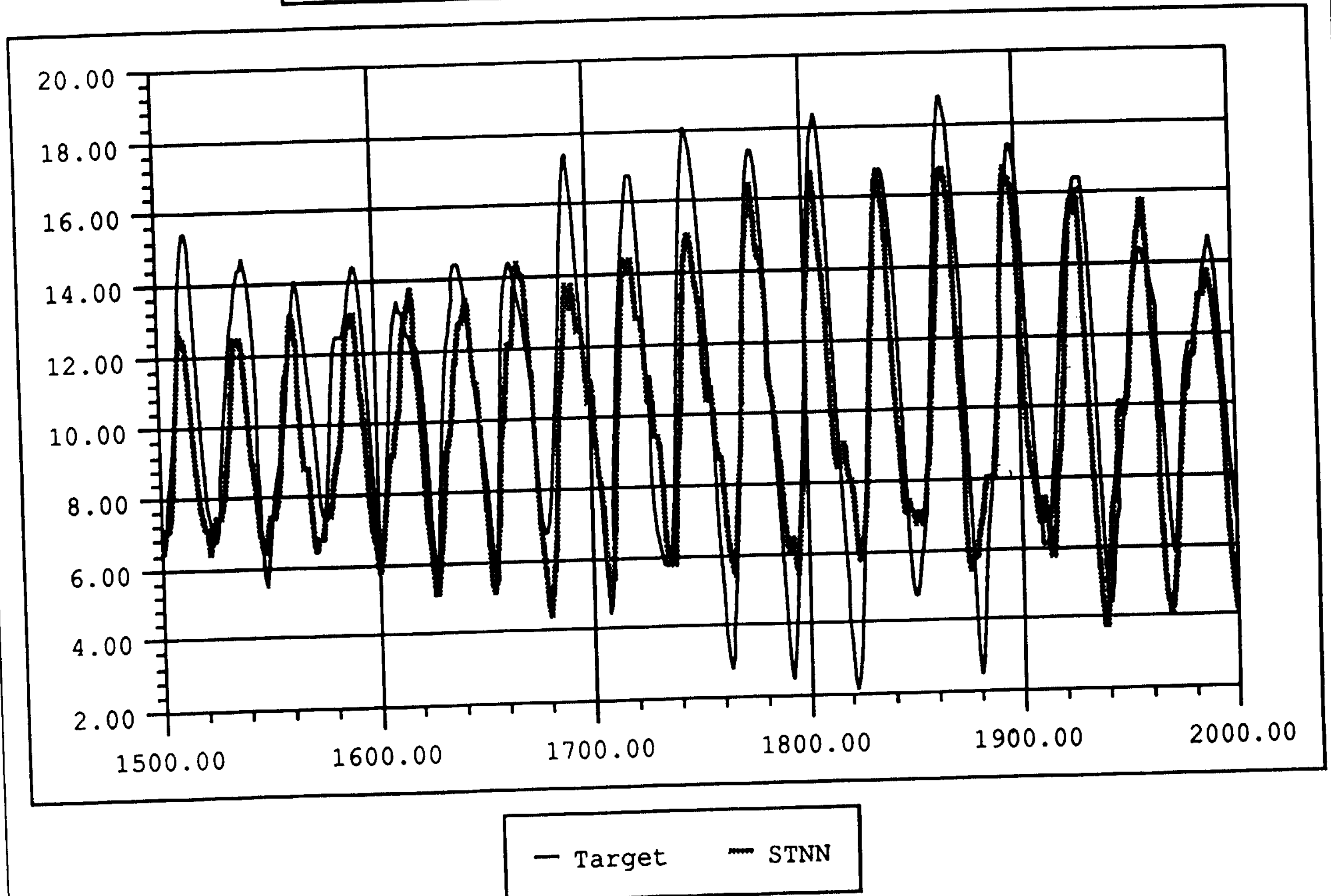
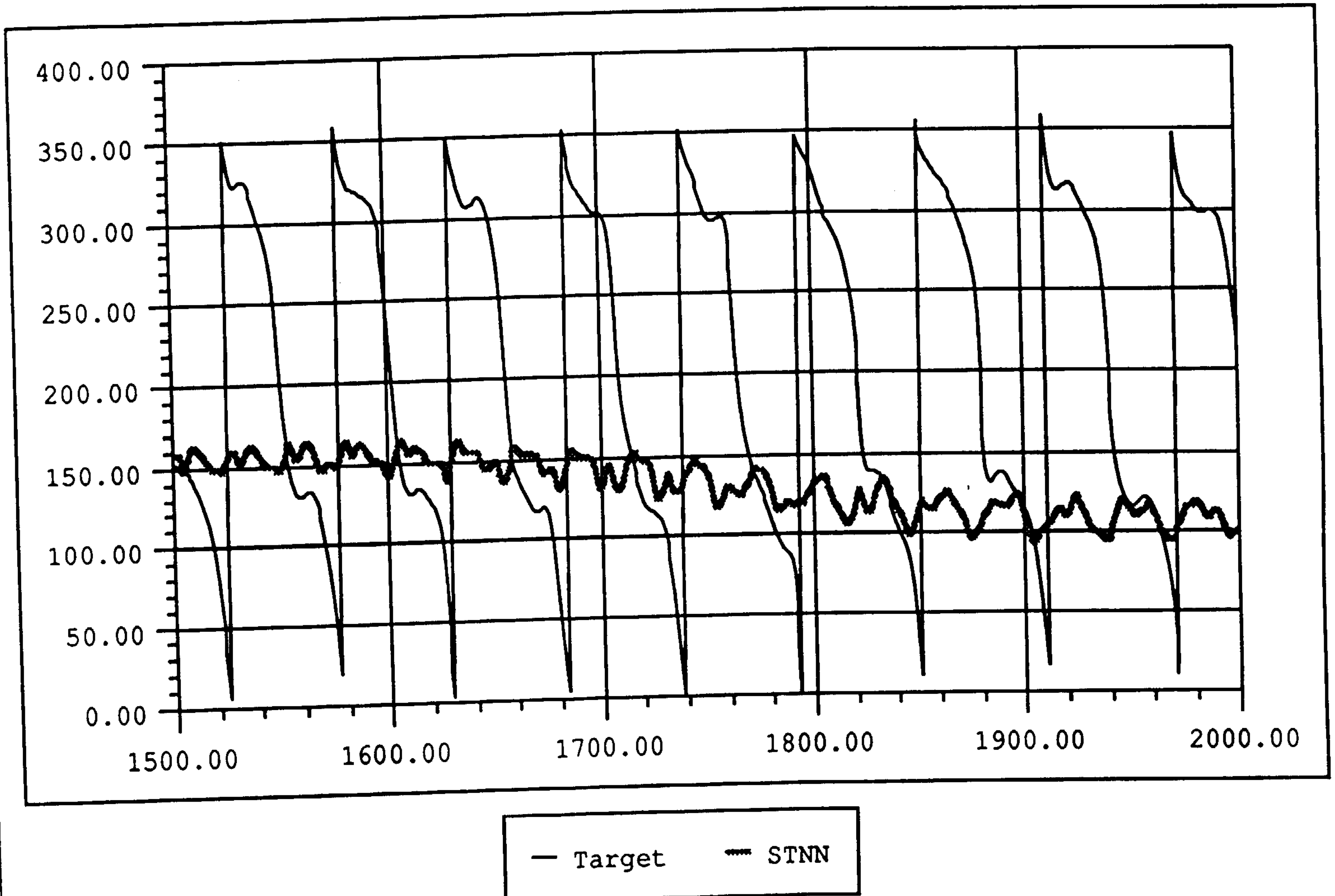


Fig. 5-f, Target Phase vs STNN Phase.



4.3 Identifying X, Y Components of Skiprope Amplitude

The biggest challenge to network training so far has been to learn the phase mapping. Several different network configurations have yielded good results in predicting skiprope amplitude, but we have not been as lucky with skiprope phase. Since the ultimate goal is to provide the crew with a reasonable estimate of skiprope amplitude and phase to support the yaw maneuver, the skiprope observer should learn not only to identify but also to predict amplitude and phase based on the available inputs. For predicting the skiprope motion, one can use the past estimates of the amplitude and phase and thus the network will have a feedback of its output as shown in Fig. 6-a. In other words, the characteristics of the skiprope motion can be identified based on several parameters that include the past x and y coordinates of the mid-point of the tether during skiprope motion.

The networks in the following test cases use satellite rates (roll, pitch, and yaw), sensed tension, and current x and y coordinates of the mid-point of the tether as inputs, and produce the next x and y position, $x(t + 1)$, $y(t + 1)$. Fig. 6-b shows the MAX and RMS errors achieved while training and testing on all 3,500 I/O pairs. As Fig. 6-b shows, the network reaches a low RMS error of 0.01, and a low MAX error of 0.05 within 500 training cycles. Figs. 6-c, and 6-d show that the network produces an accurate estimation of x and y components of the skiprope motion. Next, we divide the data into a training set and a test set and test for network generalization. Fig. 6-e shows the MAX and RMS test errors achieved after training on the first and last 400 I/O pairs, and testing on the middle 2,700 I/O pairs. Figs. 6-f and 6-g show that the network performed well on the test set. In reality, it may be impractical to use current x and y on the inputs to the network, so in subsequent test cases, we have used only satellite rates (roll, pitch, and yaw), satellite angles (roll, pitch, and yaw), sensed length, and sensed tension as inputs and trained the network to output x and y.

4.4 Combined Test Cases

So far we have focussed our efforts on training an STNN based skiprope observer to perform based on inputs representing one type of skiprope motion at a time. However, in order to place a neural network based skiprope observer in an operational environment, we must ensure that the network can be trained on data representing many different scenarios and perform adequately on conditions that it may have never seen. In the test cases described above we divided data sets into training sets and test sets to test for generalization. However, these experiments only tested the networks ability to generalize on data that was consistent with the training data. In the following test case, we train on part of the data from a simulation containing current flow and satellite spin, and data from a simulation with partial current flow and no satellite spin. The network is then tested on data that it has not seen from a simulation containing satellite spin and current flow. This method of testing ensures that the test data is consistent with some, but not all of the training data. As Fig. 7-a shows, the network reaches a low test set MAX error of 0.48 and RMS error of 0.12 after 150 cycles. Figs. 7-b and 7-c show that the network performs poorly in identifying skiprope X and Y components in this experiment.

5.0 Advantages and disadvantages of STNN over other methods

The primary skiprope detection system developed for the TSS-1 flight uses a ground-based Kalman filter coupled with a one-bead finite element model of the tethered system. The filter estimates amplitude, phase, and frequency of the skiprope motion based on the downlinked telemetry data. The simulation uses the downlinked satellite rate gyro data to

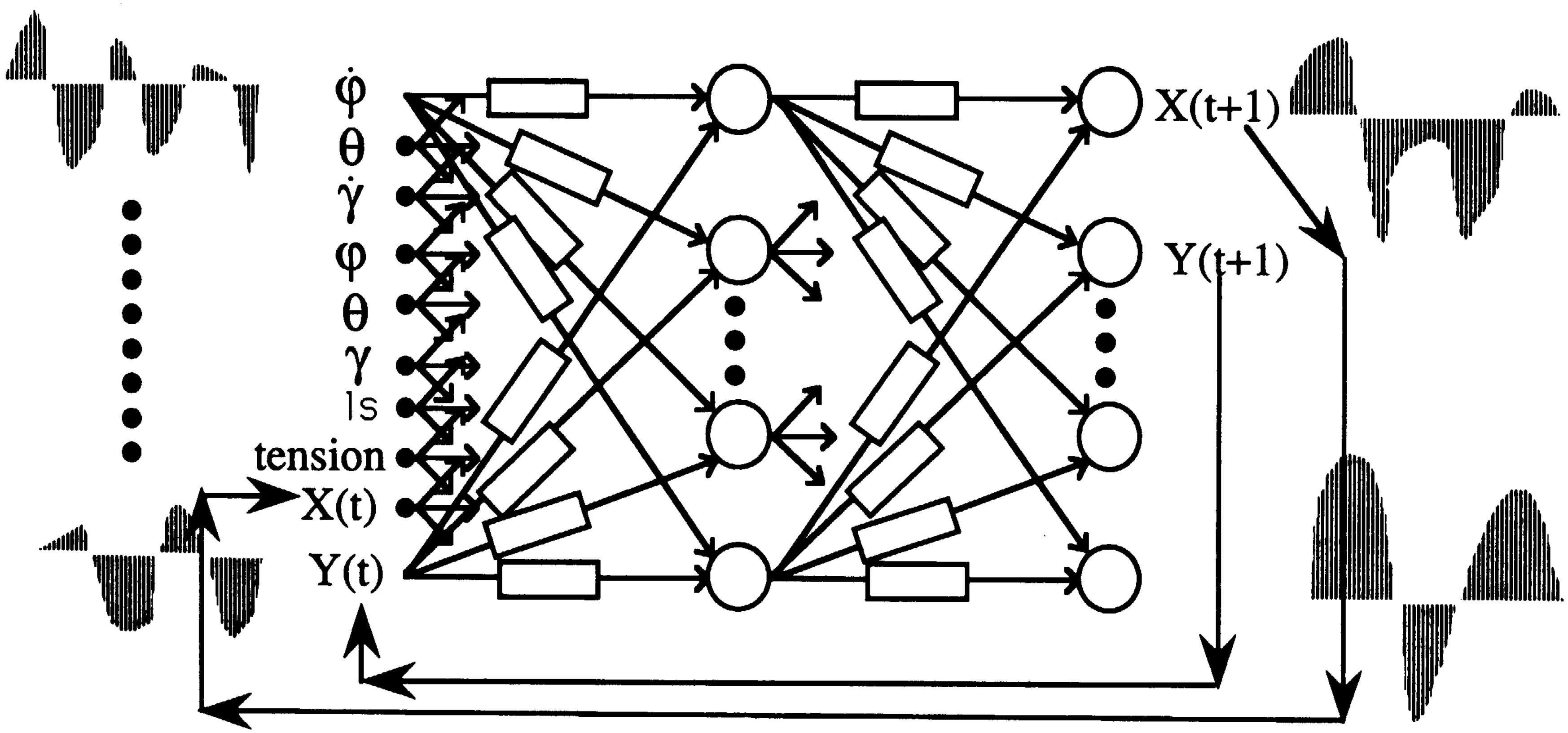


Fig. 6-a STNN Configuration with X(t) and Y(t) as feedback parameters

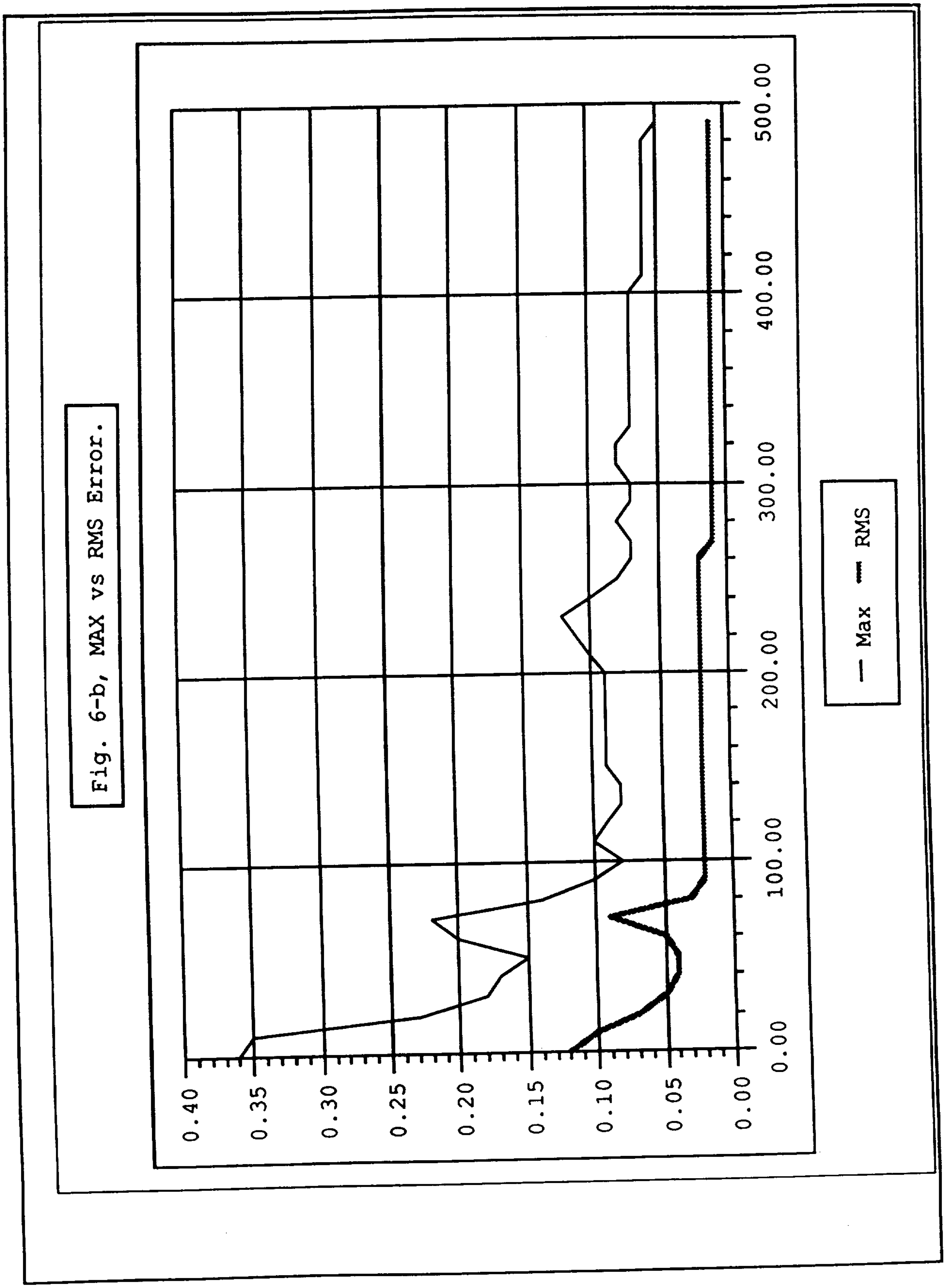


Fig. 6-b, MAX vs RMS Error.

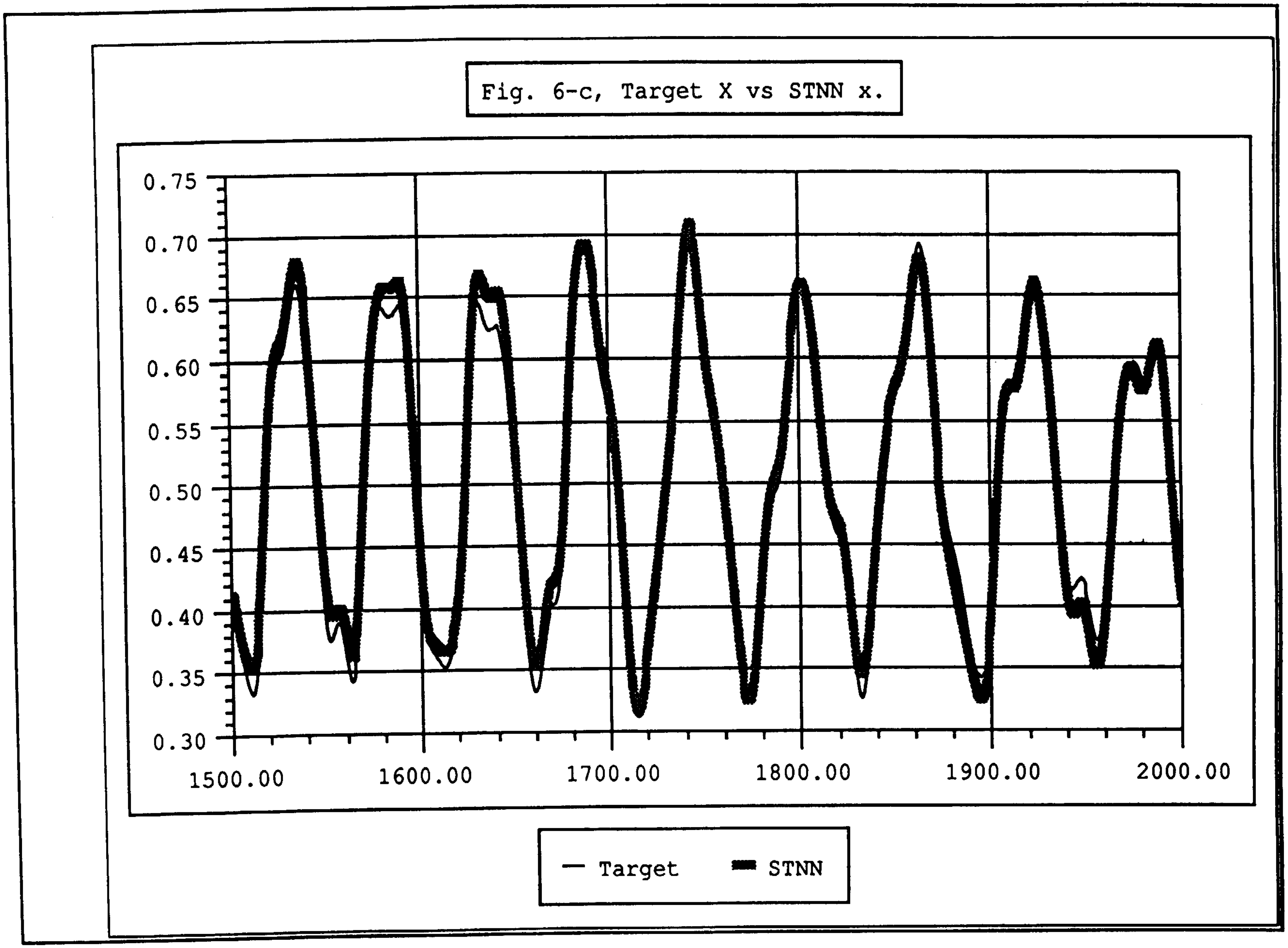
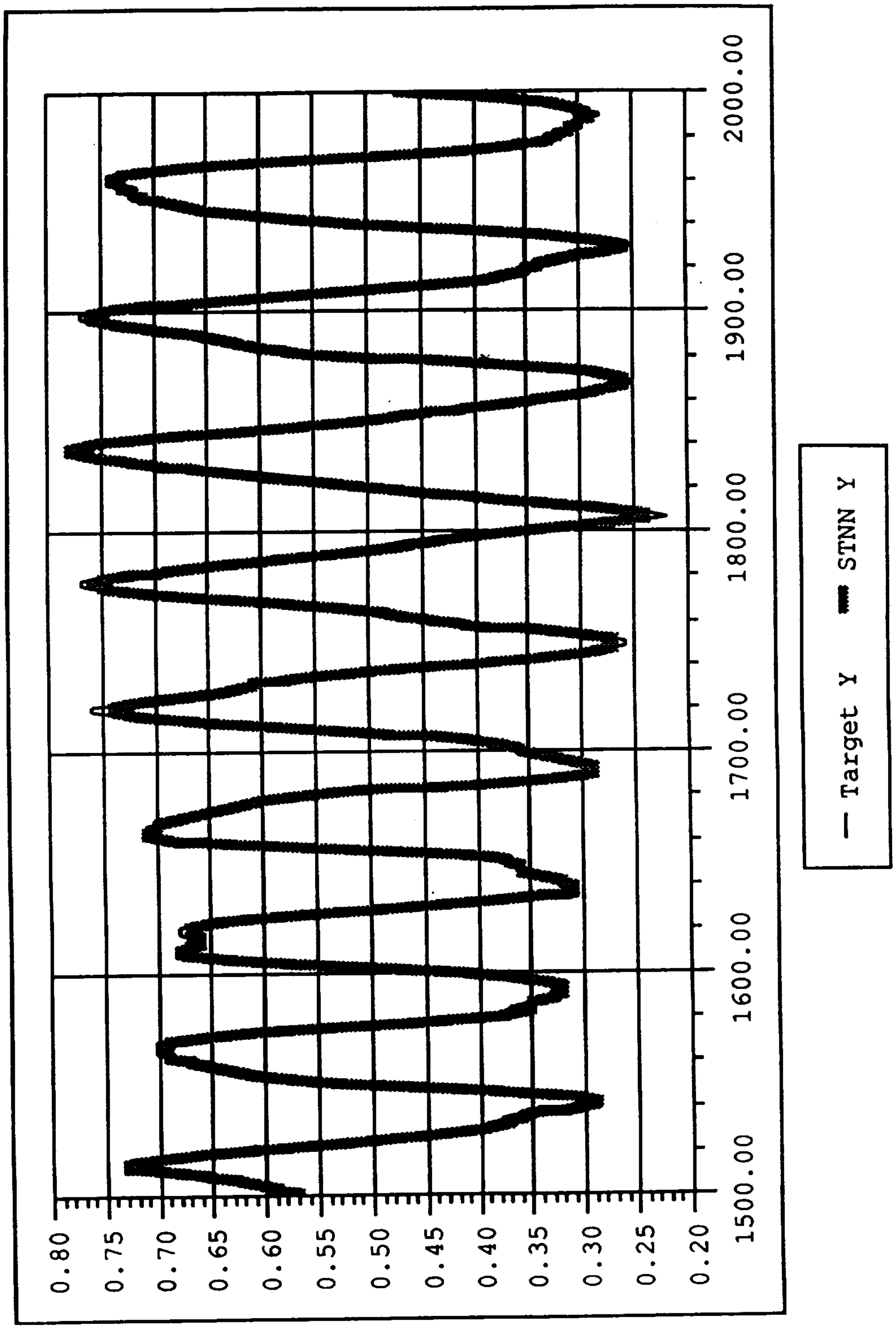


Fig. 6-c, Target X vs STNN x.
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
0.30
1500.00
1600.00
1700.00
1800.00
1900.00
2000.00
Target
STNN

Fig. 6-d, Target Y vs STNN Y.



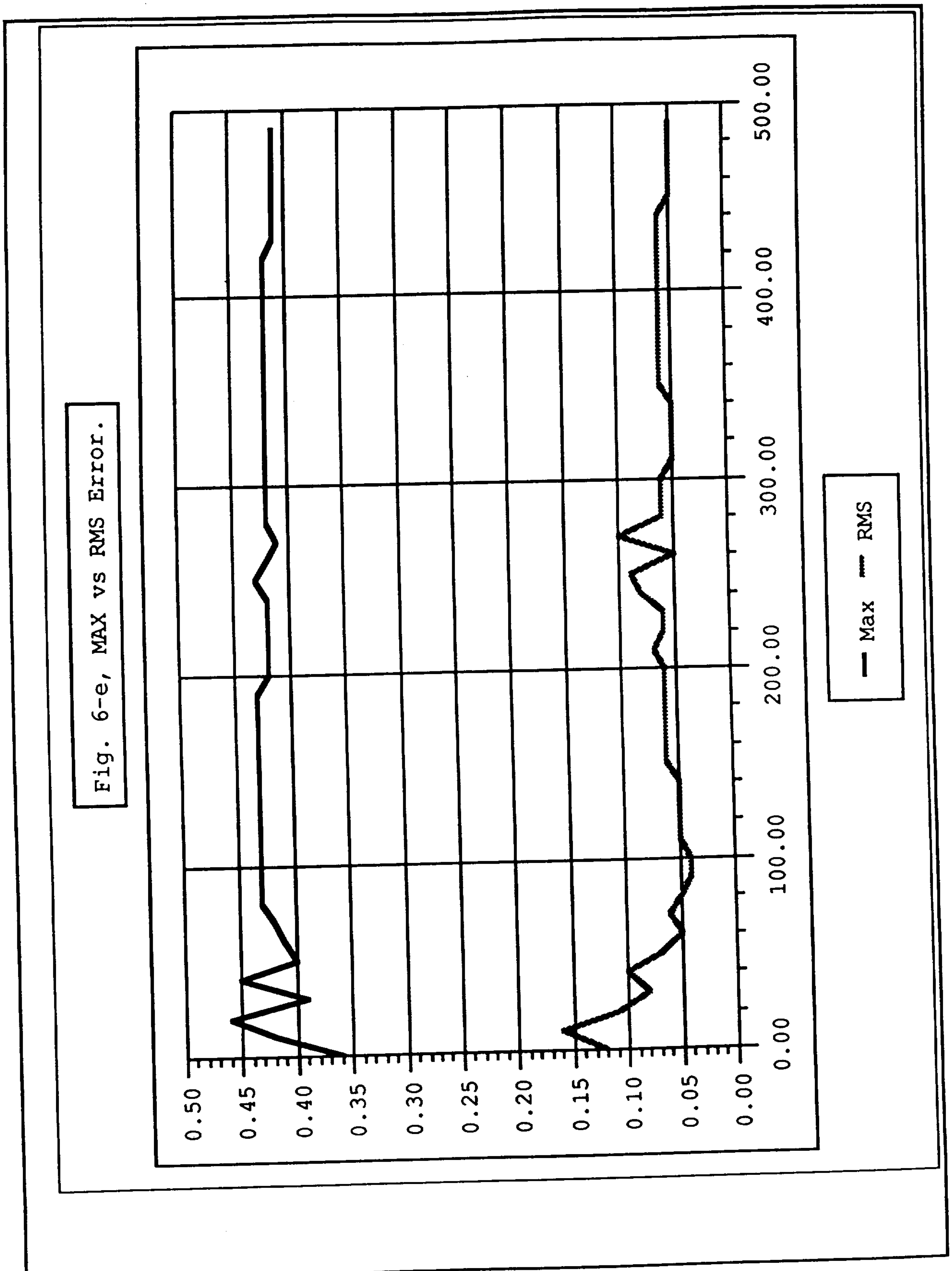


Fig. 6-e, MAX vs RMS Error.

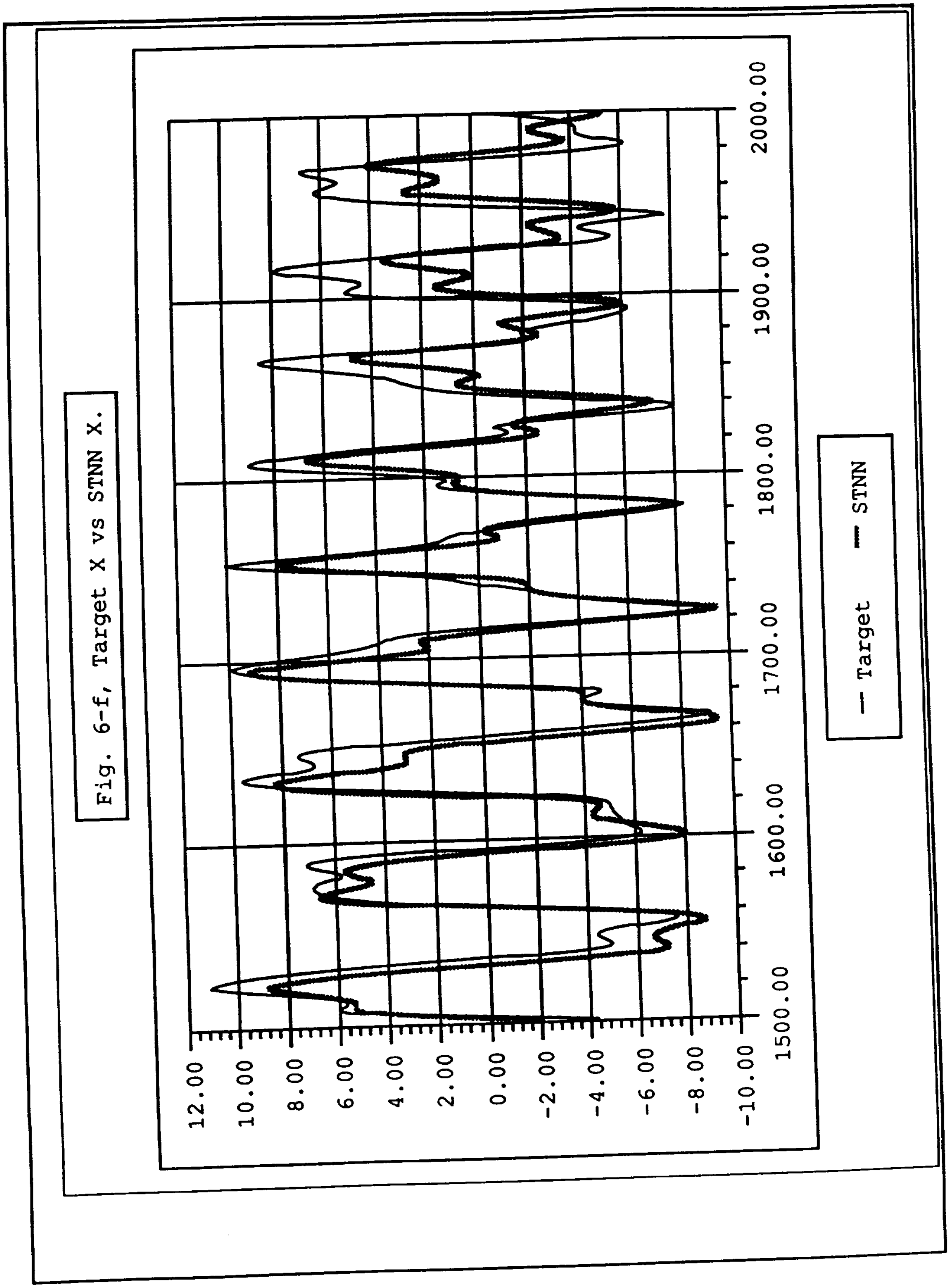
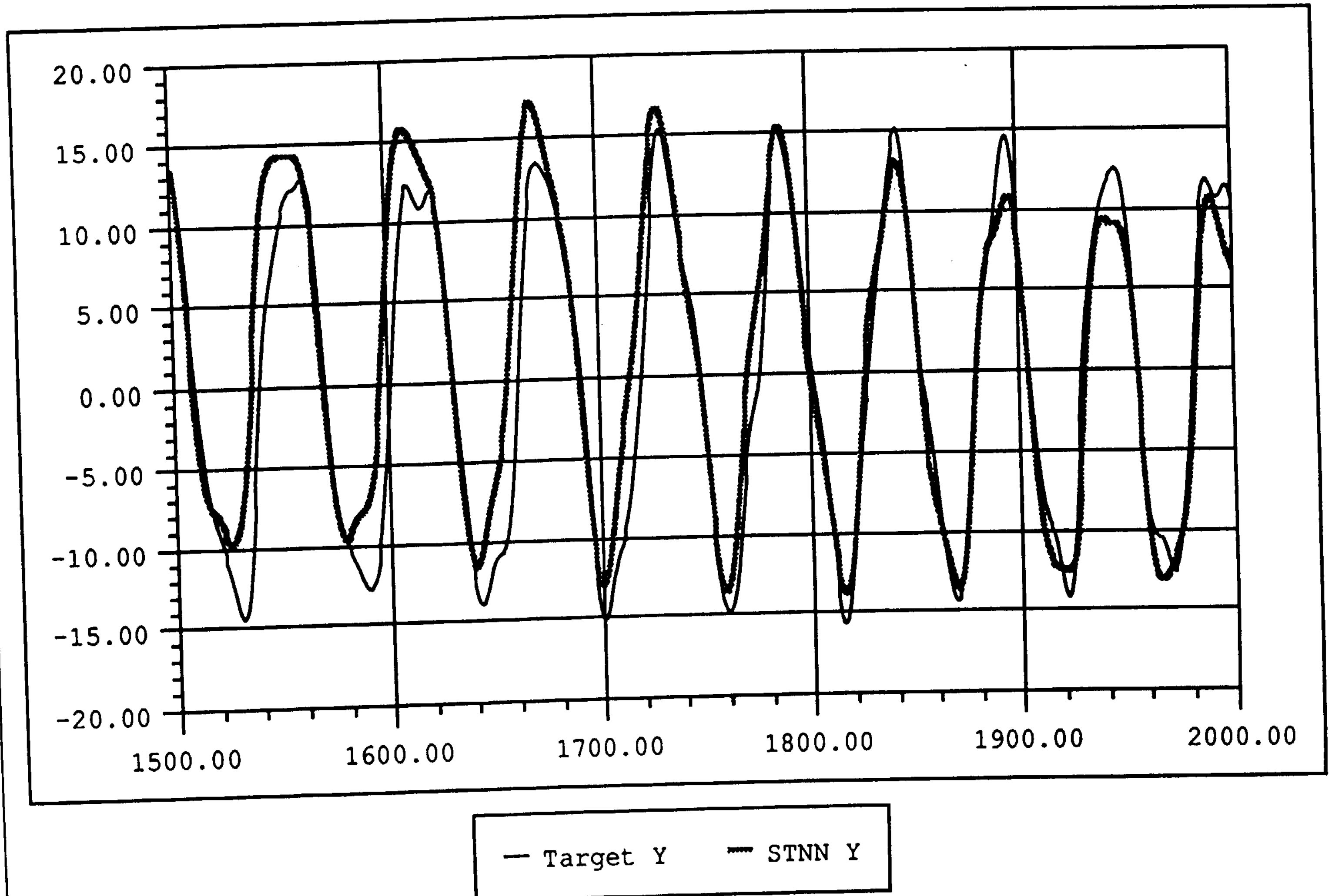


Fig. 6-f, Target X vs STNN X.

Fig. 6-g, Target Y vs STNN Y.



C-3

Fig. 7-a, MAX vs RMS Error.

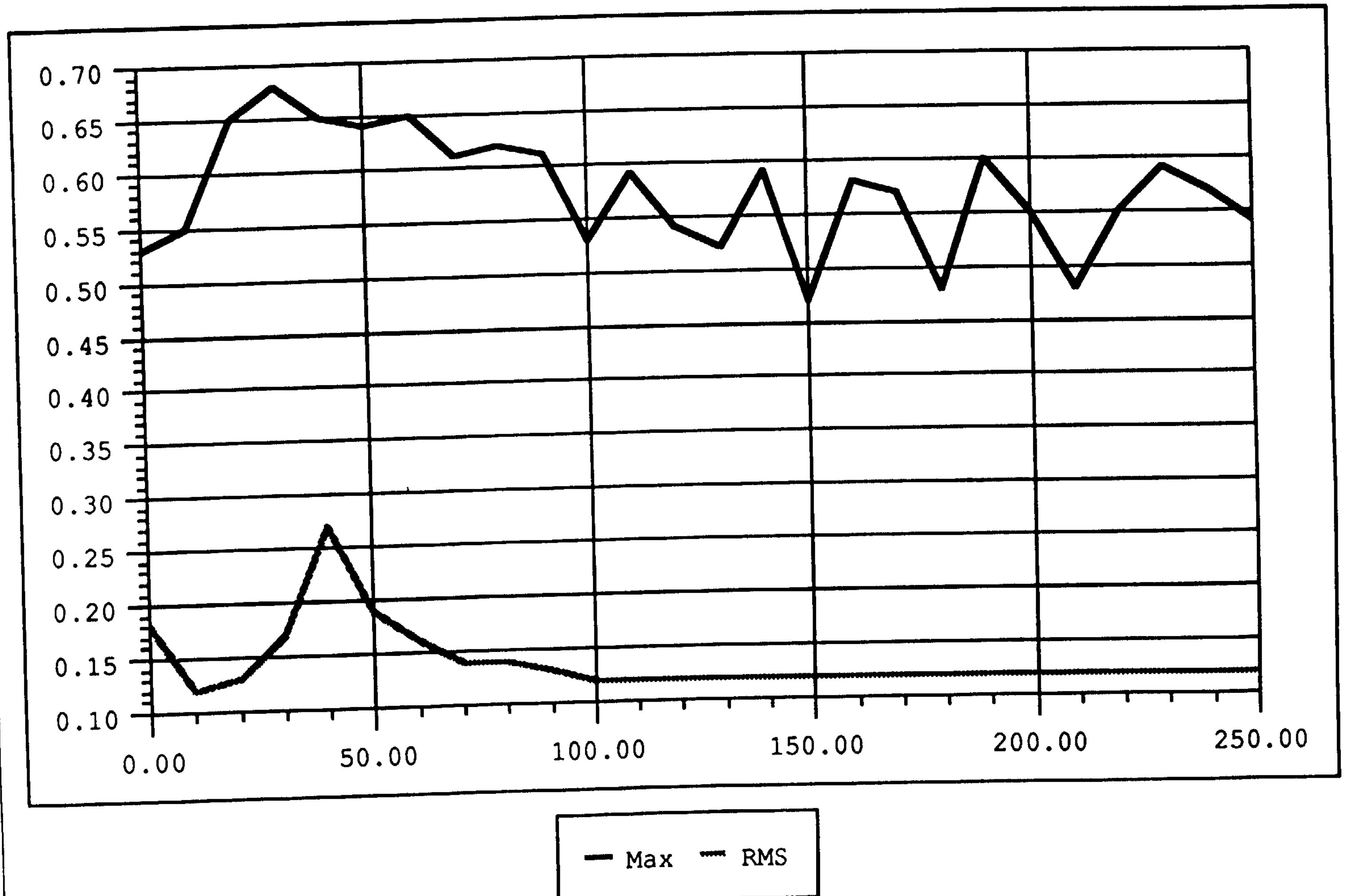


Fig. 7-b, Target X vs STNN X.

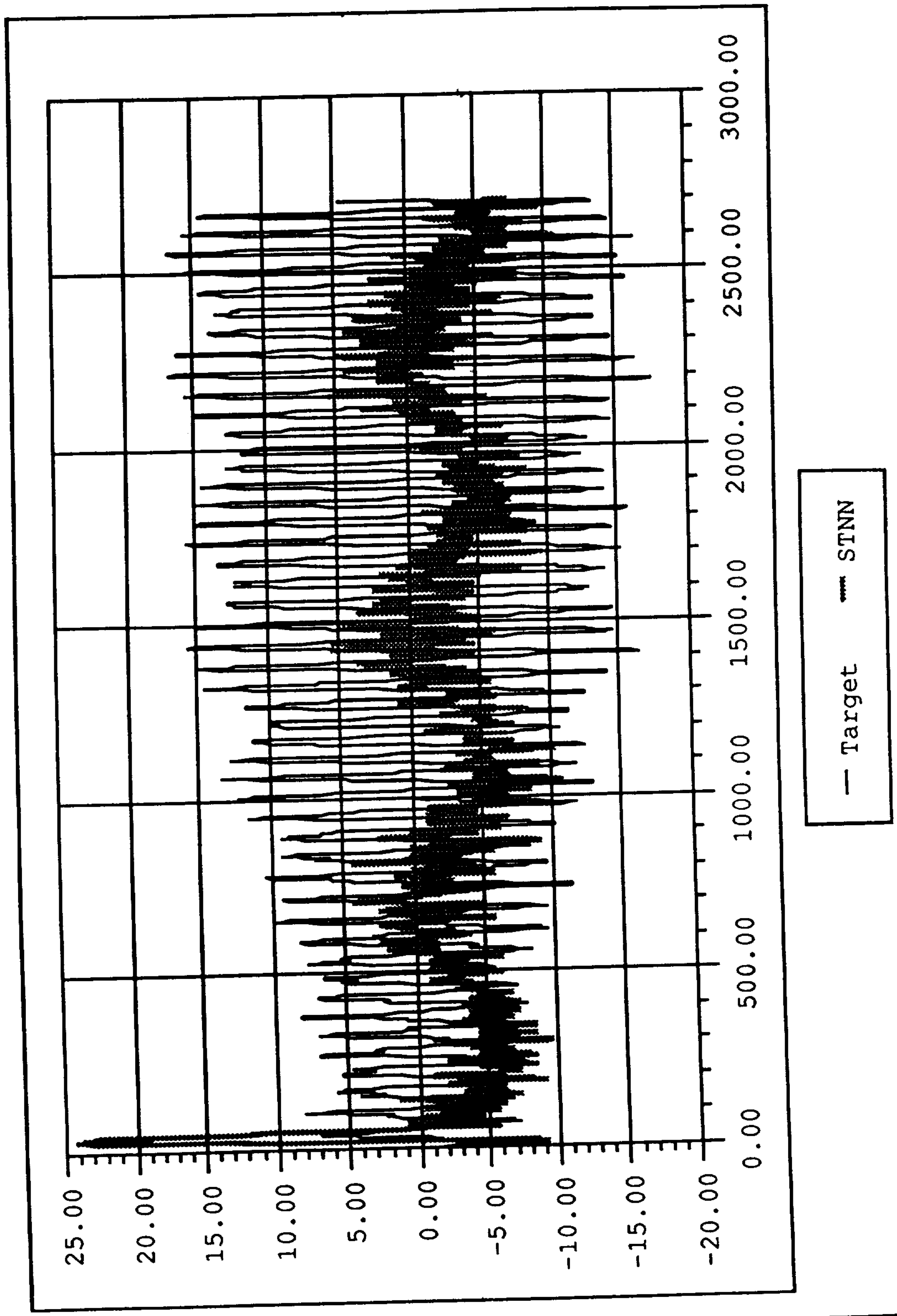
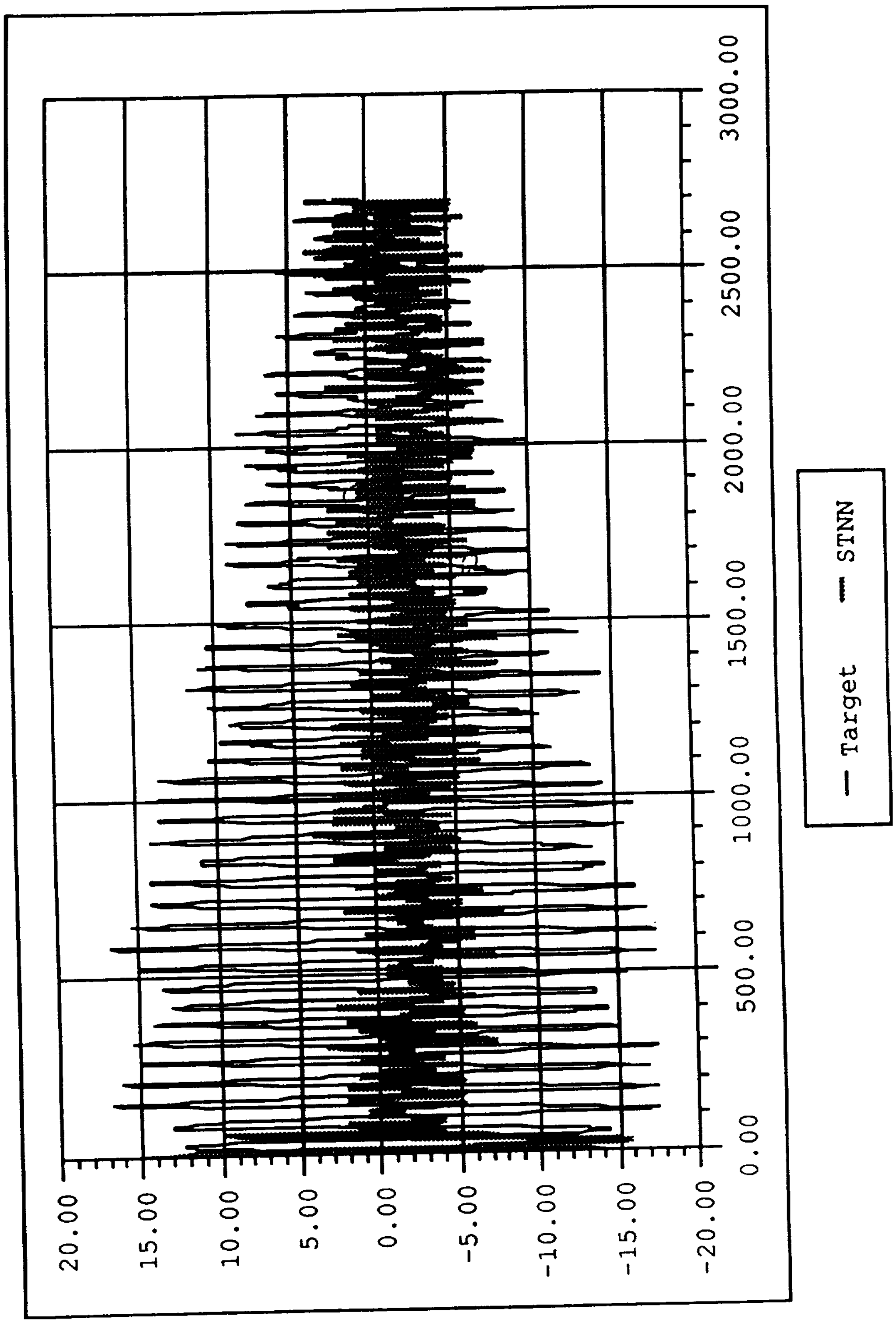


Fig. 7-c, Target Y vs STNN Y.



compare its predictions based on one bead model. The filter's gains are adjusted until the difference between simulated and actual rate gyro data is minimized. At this time the filter can be used to provide the crew with an estimation of skiprope motion parameters so that appropriate orbital maneuvers can be carried out to damp the skiprope motion.

The time-domain Kalman filter technique runs at real time on an HP 9000 computer and is expected to run faster than real time on the "back-room" computers at the Johnson Space Center. However, depending on the tether length, skiprope frequency, and actual phase angle during the mission, this single bead simulation could take from several seconds to several minutes to reasonably estimate the skiprope motion. During various phases of the mission, including satellite spin and current pulsing activities, the filter requires the maximum amount of time synchronized data to arrive at a prediction. In addition, the filter uses only a one bead simulation of the tethered system, and therefore, the predictions may not be as accurate as a multi bead simulation. Verification of the time-domain skiprope observer must be performed on Multi Purpose Support Room (MPSR) hardware to verify that the observer will perform within the required limits. As of this writing, the overall level of confidence that the time-domain skiprope observer will perform adequately in real time situations is not high. However, the technique is very well-known, well-studied and frequently used in space operations and thus there are no questions about the validity of the technique.

A frequency based method for skiprope observation has also been studied. This technique requires three full cycles, or up to 1500 seconds, of downlinked data that relates skiprope activity to arrive at a prediction. This method works well during steady state conditions but is less effective with perturbations such as satellite spinning or current pulsing. The frequency based method is also susceptible to data dropout and rate gyro saturation. The frequency domain filter is designed specifically to support the yaw maneuver scheduled during On-station 2 and does not perform well at On-station1. Results indicate that the frequency domain filter performs well for a 50 m skiprope, but not for skiprope in the 10 m to 15 m range. Again, the method is well-known, well-studied and has a history of utilization in many applications.

The STNN method that we have proposed offers the advantage that it is trained using a high fidelity simulation where from 10 to 50 beads are modelled, and the orbital environment is also modelled with high fidelity and accuracy. In addition, the network can be trained to account for a changing orbital environment due to crew inputs. The Orbital Operations Simulator (OOS) used to evaluate the STNN skiprope observer is also used for actual crew training during tethered satellite deployment and retrieval. Crew inputs to maintain attitude and damp skiprope motion may be logged and included in STNN training data. STNN is based on the promise that it can be trained for nonlinear behavior and it will perform proper interpolation for this non-linearity. Our objective is to demonstrate that the STNN skiprope observer can accurately predict skiprope parameters more accurately and with fewer data cycles than either the time-domain or frequency-domain methods.

Disadvantages of STNN based skiprope observer are many, especially in light of well-known methods. First of all, this a new method, and therefore, is not well-known. It has not been applied earlier in any other application and therefore it does not have a history like frequency domain method. There is no rigorous mathematical proof that neural networks map one set of parameters to another set of parameters uniquely. Thus, the method may not provide a confidence required for space operations. Further, the verification and validation of this method has to be carried out in detail. This task will be resource consuming and may prohibit the application of the method to real operations.

6.0 Future Work

Since the time-domain method has been baselined as the skiprope observer for TSS-1, the STNN skiprope observer will probably not be used operationally during the mission. However, we plan to utilize the STL's capability to receive telemetry data to test the STNN skiprope observer during the TSS-1 mission to evaluate it's performance. If the STNN observer meets the requirements, then it may be used on follow-up missions that are currently being proposed.

We plan to generate training data sets using the OOS that has a very high fidelity bead model for the tether dynamics and high fidelity space shuttle and Italian Satellite models with respective control systems. We can simulate up to 50 beads for the tether behavior and generate required data for the satellite attitude and skiprope parameters. Training and test data sets have already been prepared using the OST2 segment simulation.

Our next step is to configure STNN and train it using the data set. Once the training is completed, we will test the performance of the STNN using part of the data. Based on the results we will enhance the STNN configuration and perform retraining if necessary. Using the TSS-1 mission profile, we will generate the skip rope data for the On station 1, retrieval up to 2.4 km. and Onstation-2 and final retrieval phases so that we can train the STNN for full retrieval phase. We will test the performance of STNN using simulated telemetry data (while connecting the simulation with STNN) and see if the STNN can perform real time.

References

1. Coledan, S. : "Tethered Satellite Advances", Space News, vol. 2, no. 15, p. 8, 1991.
2. Powers, C.B., Shea, C., and McMahan, T. : "The First Mission of the Tethered Satellite System", A special brochure developed by the Tethered Satellite System Project Office, NASA/Marshall Space Flight Center, Huntsville, Alabama, U.S. GPO 1992-324-999, 1992.
3. Ioup, G.E., Ioup, J.W., Rodrique, S.M., Amini, A.M., Rayborn, G.H., and Carroll, S. : "Frequency Domain Skiprope Observer", Skiprope Containment Status Meeting held at Denver, Sep. 10-11, 1991. (Research supported by NASA Contract NA8-38841)
4. Glowczwski, R. : "Time Domain Skiprope Observer Overview", Skiprope Containment Status Meeting held at Martin Marietta, Denver, Sep. 10-11, 1991.
5. Klir, G.J., and Folger, T.A. : "Fuzzy Sets, Uncertainty, and Information", Prentice-Hall, New Jersey, 1988.
6. Kosko, B. : "Neural Networks and Fuzzy Systems", Prentice-Hall, New Jersey, 1992.
7. Freeman, J.A., and Skapura, D.M. : "Neural Networks, Algorithms, Applications, and Programming Techniques", Addition-Wesley, 1991.
8. Lea, R.N., and Jani, Y. : " Applications of Fuzzy Logic to Control and Decision Making", Technology 2000 Proceedings, NASA Conference Publication 3109, Vol. 2, p. 67, 1990.
9. Lea, R.N., Hoblit, J., and Jani, Y. : "Performance Comparison of a Fuzzy Logic based Attitude Controller with the Shuttle On-orbit Digital Auto Pilot", North American Fuzzy Information Processing Society 1991 Workshop Proceedings, pp 291-295, 1991.
10. Lea, R.N., Villarreal, J., Jani, Y., and Copeland, C. : "Fuzzy Logic Based Tether Control", North American Fuzzy Information Processing Society 1991 Workshop Proceedings, pp 398-402, 1991.
11. Villarreal, J.A., and Shelton, R.O. : "A Space-Time Neural Network", International Journal of Approximate Reasoning, vol. 6, number 2, February 1992.