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SUMMARY

A complete evaluation of the tribological characteristics of a given material/mechanical system is a time-consuming operation since the friction and wear process is extremely systems sensitive. As a result, experimental designs (i.e., Latin Square, Taguchi) have been implemented in an attempt to not only reduce the total number of experimental combinations needed to fully characterize a material/mechanical system, but also to acquire life data for a system without having to perform an actual life test. Unfortunately, these experimental designs still require a great deal of experimental testing and the output does not always produce meaningful information. In order to further reduce the amount of experimental testing required, this study employs a computer neural network model to investigate different material/mechanical systems. The work focuses on the modeling of the wear behavior, while showing the feasibility of using neural networks to predict life data. The model is capable of defining which input variables will influence the tribological behavior of the particular material/mechanical system being studied based on the specifications of the overall system.

INTRODUCTION

Recent advances in computer and electronics technology have greatly increased the reliability and longevity of electronic systems, which have long been considered to be the limiting life factor for satellites. As a result of these improvements, mechanical systems have now become a major life-limiting factor in current satellite systems (refs. 1 to 7). Recently, a number of significant spacecraft anomalies have occurred from problems with mechanically moving mechanisms such as bearings, gimbals, latches, and hinges (refs. 4 to 8). It has become evident that as mission durations extend beyond 5 years, further advances in the reliability and longevity of mechanical space systems will be required.

Verification testing is an important aspect of the design process for mechanical mechanisms. Full scale, full length life testing is typically used to space qualify any new component. However, as the required life specification is increased, full length life tests become more costly and also lengthen the development time. In addition, this type of testing becomes prohibitive as the mission life exceeds 5 years, primarily because of the high cost and the slow turnaround time for new technology. As a result, accelerated testing techniques are needed to reduce the time required for testing mechanical components.

Current accelerated testing methods typically consist of increasing speeds, loads, or temperatures in order to simulate a high cycle life in a short period of time. However, two significant drawbacks exist with this technique. The first is that it is often not clear what the accelerated factor is when the operating conditions are modified. Second, if the conditions are changed by a large degree, on a scale of an order of magnitude or more, the mechanism is forced to operate out of its design regime. Operation in this condition can often exceed material/mechanical systems parameters and renders the test meaningless.

It is theorized that neural network systems may be able to model the operation of a mechanical mechanism. If so, these neural network models could then be used to simulate long term mechanical testing using data from a short term test. This combination of computer modeling and short term mechanical testing could then be used to verify the reliability of mechanical systems, thereby eliminating the costs associated with long term testing. Neural network models could also enable designers to predict performance of

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mechanisms at the conceptual design stage by entering the critical parameters as inputs and running the model to predict performance.

The purpose of this study was to assess the potential of using neural networks for predicting the performance and life of a mechanical system. To accomplish this, a neural network system was generated to model previously taken data from (1) pin-on-disk, (2) line contact rub shoe, and (3) four-ball tribometers. Critical parameters such as load, speed, oil viscosity, temperature, sliding distance, friction coefficient, wear, and material properties were used to produce models for each tribometer. A methodology was then developed in order to use each model to predict the results of tests under conditions which were different that those used to predict the model.

BACKGROUND ON NEURAL NETWORKS

Neural Network Overview

Artificial neural networks are not new to the scientific community. They have been utilized in many applications since the late 1940's, when D.O. Hebb proposed a learning law that became the starting point of artificial neural network training algorithms (ref. 9). Only recently, though, has the power of the neural network model been realized and research into new application areas been started. Generally speaking, the artificial neural network is a powerful computing algorithm that mimics the functionality (i.e., neuron cells) of the human brain. They learn by trial and error directly from data in a manner analogous to the way a biological brain learns from sensory input. Thus, neural networks can be taught to analyze and model complex, nonlinear processes that are not well understood. Once these networks have "learned" the processes involved in the application, they are able to identify, extract, and characterize hidden patterns within the data that are difficult to observe by other analytical techniques. From this initial data, the network can then predict the output of a trial based on a limited amount of input.

It should also be noted that one of the advantages to a neural network model is its insensitivity to minor variations in its input. Essentially, the network is able to ignore noise and slight scatter in the data and focus on the underlying relationships between variables. However, it should be noted that neural networks are only as good as the input/output data used to train the model.

Basic Structure and Operation

Although many types of neural networks exist, they all have three things in common. The network can be described in terms of its individual neurons, the connections between them (topology), and its learning rule (ref. 10). The following section discusses the fundamental structure and operation of neural networks.

The Artificial Neuron

As the concept of neural networks was evolving, the artificial neuron was designed to mimic the first order characteristics of the biological neuron. Each input to a neuron represents the output of a neuron from a previous layer. The initial input values must be scaled from their numeric range into a range that the neural network deals with efficiently. Two ranges are commonly used in network design—[0,1] and [-1,1]. Generally, linear, logistic, and hyperbolic tangent functions are used to scale the input data. The input is then multiplied by a weight factor (analogous to a synaptic strength in biology), and the weights are then summed to determine an activation level of the neuron. The activation levels are then further manipulated by an activation, or transfer, function to obtain the neuron's output signal. In many instances, this transfer function is the logistic, or sigmoid, function, which has the form $f_{(x)} = 1/(1+e^{-x})$, although the transfer function can be any function simulating the nonlinear characteristics of the system. A schematic of this process is shown in figure 1. By utilizing multiple layers of neurons, with multiple neurons in each layer, more complex relationships can be modeled.

With this type of architecture, though, the output is solely dependent on the current input variables and the values of their weights. However, recurrent architectures, which are also investigated in this study, recirculate previous outputs back to neurons in the same or previous layer. Hence, their output is generated from current inputs/weights, as well as from previous outputs. For this reason, recurrent networks are said to have characteristics very similar to short-term memory in humans.

Even with the organization of neurons into various architectures, the network cannot function unless it has the ability to learn from the given inputs and outputs. This concept is the premise behind the training algorithms used in neural network development. Training is accomplished by sequentially applying inputs and adjusting the corresponding weights according to a specified procedure until the desired output value is obtained. During the course of training, the network weights for each input will converge to a specific value, such that values approximately equal to the desired output are obtained. Network training is completed when further modifications of the input weights do not produce closer approximations of the output values (i.e., the error between actual and approximate output values is minimized). The weights for each input can then be analyzed to determine the impact that variable has on producing the correct output. Larger weights on specific input variables mean that those variables have a stronger influence on the output parameter. This is referred to as determining the contribution strength of the input variable.

The training algorithm used in the designs studied in this work is known as backpropagation. Backpropagation, which had its beginning in 1974 with the work of Werbos (ref. 11), is a systematic method for training multilayer networks. The development of this training algorithm is directly responsible for the advancement of the field of artificial neural networks over the last 20 years. However, the topic of backpropagation is too complex for this paper, so the reader is referred elsewhere (ref. 12).

EXPERIMENTAL PROCEDURE

Data Sets Used

The data sets used in the three models developed in this work were obtained from various researchers, projects, and test rigs at the NASA Lewis Research Center. Each model was developed according to the material systems and test variables associated with the individual test rigs. The following sections will define the data sets and test variables used for each model developed in this work. The data for each model is given in Appendixes A to F.

The first network developed modeled data from a line contact rub shoe rig. A schematic diagram of this rig is shown in figure 2(a). The data set used for the training and testing of this model was accumulated from unpublished NASA data. All of the tests used in this data set were run using 440C stainless steel specimens at a constant speed of 100 rpm (0.1833 m/s). Table I lists the parameters that were varied in these tests as well as their ranges. The output variable for this model was the cumulative wear volume. This was used instead of a calculated wear rate parameter, since the calculation of accurate wear rates from the available data would have significantly reduced the number of data points available to train the model. By using this output variable, however, the amount of scatter in the model is increased, because wear volume is not constant from sample to sample.

The second model generated in this work utilized data from several early NASA Technical Memorandums (refs. 13 to 17), which investigated the tribological properties of various materials using a pin-on-disk apparatus, shown schematically in figure 2(b). Table I defines the parameters, materials, and ranges used in this model. Various materials, including polymers and steel, were used for the pins, while M50 steel was used as the disk material.

The final model generated in this work used published and unpublished NASA data which utilized a four-ball test rig, shown schematically in figure 2(c) (ref. 18). The specimen material for the balls was 440C stainless steel, and three perfluoropolyether (PFPE) fluids (Type K, Type F, and Type D) were used as lubricants. All specimens were run at a uniform speed of 0.0288 m/s. Since there was little variation in the ranges of the test variables, the focus of the model was on determining the tribological properties of various lubricants from extensive materials properties and limited test properties. Table I lists the properties and variables used for this model. Several of the material properties, the transient friction and initial λ ratio, were utilized in this work to provide general information on the lubricants behavior under the test rig conditions (i.e., sliding conditions). This information was acquired from previous researchers (ref. 19) who investigated the tribological behavior of these three lubricants. The transient friction (high initial friction sometimes observed in these materials) was listed as high, medium, and low for the three lubricants. These "levels" were given arbitrary numerical values of (2) for high, (1) for medium, and (0) for low. Also, the initial λ ratio, the film thickness to composite surface roughness ratio, was calculated for these materials using average values for each parameter. These ratios ranged between 1 and 2 for the three lubricant materials. The output variable for this model was the wear rate, which was determined from a linear regression analysis of wear volume versus sliding distance. It should be noted that all of the data sets used in this work were sorted numerically according to the output variable. This was done in an attempt to minimize the effects of scatter in the data.

Software Program

The neural network models developed in this work were created using a commercially available software package. This package, allows for modification of the network design architecture (i.e., back-propagation, kohonen, probabilistic, and general regression, etc.), as well as some of the design parameters (i.e., number of neurons per layer, scaling functions, activation (transfer) functions, learning rate, momentum, and initial weights, etc.). Although this package did offer a comprehensive assortment of possible modifications to network design, every modification was not investigated. Thus, this work mainly shows the feasibility of developing neural network models for wear data, rather than addressing optimum network designs.

Determination of the Optimum Architecture

The commercial software package used allows for a total of 15 different architectures to be investigated. Thus, the first step was to see which architecture design approximated the prescribed data with the highest degree of accuracy. The criteria for selection was the statistical indicator R^2 obtained from a multiple regression analysis. This coefficient describes the fit of the network's output variable approximation curve with the actual training data output variable curve. Higher R^2 coefficients indicate a model with better output approximation capabilities. The default settings in terms of weights, bias, momentum, scaling functions, and activation functions were used in these initial trials. Several of the architectures were not investigated, namely the kohonen and probabilistic architectures, since they do not work well with valued outputs. Once the proper architecture was determined, the various network parameters were systematically modified to determine the optimum parameters for each layer, as well as each link between layers.

RESULTS AND DISCUSSION

Rub Shoe Model

The first model investigated was the rub shoe model. The input variables used in the network included the following: load (lb), test time (min), sliding distance (m), viscosity (cSt), friction coefficient, and temperature (°C). The defined output variable was the cumulative wear volume ($mm^3 \times 10^{-5}$). The values for wear volume were reduced from their actual values to make them more manageable. By using only these input and output variables, a data set containing 55 data points was accumulated. Also, a separate data set, with 26 data points, was developed and used as an unknown test set for the trained model.

By means of the neural network software, the training data set was broken up further into a training set (43 points) and a test set (12 points). This was done because the software trains the network on the training set, and, after each iteration through the data, tests itself on the test set. Thus, the network is exposed to all 55 data points during the training procedure. When the errors (actual output value—network approximation output value) from the test set were minimized, the network was instructed to stop training.

The default settings for the network design parameters were used, and the various architecture designs were studied to determine which design best suited this tribological data. The results from this analysis are shown in table II. The architectural design column represents the different designs available in the commercial software package. The R^2-coefficient values presented illustrate each model's ability to approximate the outputs using only the default parameters.

The general regression architecture led to a model with the least amount of error in the training data, but the network did not have adequate generalized approximation abilities. This was due to the fact that this particular architecture (given the small number of data points available) may have been memorizing the data rather than learning it. This occurred with each of the three models developed in this study. Thus, unless large data sets can be developed, the general regression architecture does not appear to be a viable model. As a result, the input layer dampened recurrent network architectural design was selected as the architecture that best approximated the rub shoe data. Figure 3 schematically illustrates this architecture.

By using this architecture, with the default design parameters as a baseline, variations to the design parameters were investigated. These variations included the scaling function, the activation function, and the link parameters. Each parameter was systematically modified and the effect of each modification was again determined from the R^2-coefficient of the networks approximation of the actual data. When all of the possible modifications were made to the architecture, the R^2-coefficients were reviewed and the parameters yielding the highest R^2 values were deemed "optimum."

For the rub shoe model, an "optimum" design consisting of a linear [0,1] scaling function, 10 neurons in the hidden layer, and a hyperbolic tangent activation (transfer) function for both the hidden layer and the output layer was determined. Modifications to learning rate, momentum, and initial weights did not significantly impact the ability of the model to approximate data. Thus, these variables were kept at their default levels. The parameters for the "optimum" architecture were used to train the network on the given input data. By going through an iteration process (backpropagation training algorithm), the weight of each neuron was modified until the network approximation error of the output value was minimized.

The result of training the network is shown graphically in figure 4, which illustrates the ability of the network to predict an output value when that value is included in the data set. Once the "optimum" design was trained, the model was applied to the unknown data set and told to approximate the output value. This analysis is shown graphically in figure 5, which illustrates the ability of the network to approximate the output when no output values were given in the data set and when the model had never seen the input values. The x-axis in these figures represents the number of the data point from the data set used to approximate the wear volume (y-axis). In other words, the range of the x-axis is the size of the data set used to test or train the model. The scatter observed in this model is indicative of the problems associated with using wear volume as the output parameter, namely the lack of repeatability from sample to sample. However, further nonlinear curve-fitting of the network approximation curve will generate a better approximation of the data being modeled.

Pin-on-Disk Model

The next data set investigated was that taken from pin-on-disk testing. These tests used several fluids as lubricants and various materials as pin/disk specimens. The inputs used for this model were similar to those in the previous model (i.e., load (N), speed (m/s), viscosity (cSt), sliding distance (m), friction coefficient, and temperature (°C)), but the output variable was the wear rate (in units of m^3/m ($\times 10^9$)). The wear rate values were increased to a value greater than 1 was so that accurate R^2-coefficients could be obtained to classify the architecture designs.

A similar procedure to the one discussed earlier in determining the proper design was followed for the pin-on-disk data. Table II presents the results from this analysis. As was the case with model 1, the input layer dampened feedback network resulted in the best approximation of the training and test data. Using this basic design, the various design parameters were systematically modified to fully "optimize" the model. This optimum network consisted of a linear [-1,1] scaling function, 10 neurons in the hidden layer, and a logistical activation (transfer) function for the hidden and output layers. The default settings for learning rate (0.1), momentum (0.1), and initial weight (0.3) were used since modifications to these parameters tended to deteriorate the models ability to approximate outputs. Figures 6 and 7 illustrate graphically the networks ability to approximate wear rate for the training data set and test data set, respectively. An explanation for these figures is similar to that given for the rub shoe model.

As mentioned previously, this commercial software package allows the contribution strengths for each input variable to be determined. Table III lists the contribution strengths for the input variables used in the pin-on-disk model. This indicates that of the six input variables used to develop this model, the sliding speed and the sliding distance are the most important inputs, while the friction coefficient and the temperature of the system are the least influential. The remaining variables, load and viscosity, are intermediate in value. For the sake of this study, though, these variables will be considered to be important.

Since it was known which variables were influential in predicting the desired output, the pin-on-disk model was then used to study the feasibility of using neural networks to extrapolate variables and determine their overall impact on wear rate. For this work, a new data set was generated "hypothetically." Constant values were used for the least influential variables, while the other input variables were allowed to vary over a large range of potential values. This means that the model has to interpolate or extrapolate between known inputs in order to obtain an approximated wear rate. The test matrix for this data set is shown in Table IV. No output variable was associated with these input values. The data set was then exposed to the network model so that wear rates could be approximated. The results of this analysis, shown in terms of three-dimensional surface plots in figures 8 and 9, illustrate the power of the neural network. As can be seen, the impact of each variable on the wear rate is clearly evident. As the sliding distance and load increase, the expected wear rate also increases. *Simultaneously*, as the speed of the system decreases, the expected wear rate will increase. This type of information would be extremely beneficial to the design engineer developing new bearing systems. Knowing what the needed specifications are, the design engineer could customize the materials, and so forth to fit the system. This type of analysis could also steer the research engineer away from testing conditions which would be expected to lead to results outside of design specifications.

Four-Ball Data Model

A similar procedure to the one discussed earlier for the rub shoe data (for determining the proper design) was followed for the four-ball data. Table II presents the results from this analysis. Again, the input dampened feedback layer led to the most accurate model for this data set. The design specifications used to optimize the model included a linear [-1,1] scaling function, 20 neurons in the hidden layer, and a hyperbolic tangent activation (transfer) function in the hidden and output layers. Default values for learning rate, momentum, and initial weight were used. Figures 10 and 11 illustrate graphically the networks ability to approximate wear rates for the four-ball training data set and the test data set, respectively. Again it is seen that the neural network generated data can be made to very closely approximate the training data set, and then once trained the network can be used to predict data that it had not previously seen (the unknown test data). It is believed that an even better data fit could have been obtained if more data had been available to train the network.

CONCLUSIONS

The following results were obtained from this study:

1. Neural networks have been shown to model simple mechanical systems illustrating the feasibility of using neural networks to perform accelerated life testing on more complicated mechanical systems (i.e., bearings, etc.).

2. Although at an early stage of research, models have been successfully developed for three different test rigs (1) a rub shoe rig, (2) a pin-on-disk rig, and (3) a four-ball rig.

3. The models discussed have been shown to be capable of predicting wear rates regardless of the lubricants (materials) used in the system. This indicates that these models are able to generalize over a large range of variables.

4. The models have been shown to extrapolate/interpolate input variables to approximate wear rate values for conditions that have not been run experimentally.

5. An input layer dampened recurrent network architecture appeared to be the best architecture available (of those studied) to model wear data. Linear scaling functions and either hyperbolic tangent or logistic activation functions were beneficial.

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TABLE I.—DESIGN PARAMETERS AND VALUES USED IN NEURAL NETWORK MODELS

Rub shoe rig		Pin-on-disk rig		Four-ball rig	
Variable	Value	Variable	Value	Variable	Value
Lubricants					
PFPE (Type K)	-------	Super-refined mineral oil	-------	PFPE (Type K)	-------
PFPE (Type F)	-------	Ester-based fluids	-------	PFPE (Type F)	-------
		n-Hexadecane	-------	PFPE (Type D)	-------
		Synthetic paraffinic oil	-------		
		Glycol derivative	-------		
		Modified polyphenyl ether	-------		
Inputs					
Load, lb	50 to 100	Load, kg	0.5 to 1.5	Pressure-viscosity coefficient	-------
Viscosity, cSt	50 to 800	Speed, m/min	2.6 to 18.2	Transient friction	-------
Sliding distance, m	50 to 25 000	Sliding distance, m	100 to 1200	Initial λ ratio	-------
Friction coefficient	0.05 to 0.20	Temperature, °C	25 to 400	Kinematic viscosity, cSt	250 to 800
Temperature, °C	25 to 115	Friction coefficient	–0.1 to 0.2	Molecular weight	5600 to 10 000
		Kinematic viscosity, cSt	0.5 to 40	Vapor pressure, torr	3 to 500 000×10^{-12}
				Surface tension, dynes/cm	18 to 25
				Viscosity index	134 to 355
				Load, N	200 to 600
				Sliding distance, m	350 to 525
Output					
Wear volume	-------	Wear rate	-------	Wear rate	-------

TABLE II.—R^2 COEFFICIENTS FOR VARIOUS DESIGN ARCHITECTURES FOR VARIOUS MODELS DEVELOPED

Architectural design	Rub shoe model	Pin-on-disk model	Four-ball model
3 Layer backpropagation	0.76	0.89	0.67
4 Layer backpropagation	0.78	0.89	0.69
5 Layer backpropagation	N/A	0.88	0.66
Input layer dampened recurrent network	0.84	0.93	0.92
Hidden layer dampened recurrent network	0.82	0.91	0.82
Output layer dampened recurrent network	0.77	0.89	0.60
2 Hidden layers with different activation function	0.63	0.90	0.69
3 Hidden layers with different activation function	0.74	0.89	0.67
2 Hidden layers with different activation function and jump connection	0.76	0.90	0.67
3 Layers with jump connections	0.77	0.84	0.61
4 Layers with jump connections	0.76	0.84	0.54
5 Layers with jump connections	0.77	0.84	0.54
General regression	0.97	0.90	0.71

TABLE III.—CONTRIBUTION STRENGTHS FOR INPUT VARIABLES IN PIN-ON-DISK MODEL

Input variable	Contribution strength
Load	5.4
Speed	7.1
Viscosity	5.3
Sliding distance	6.0
Friction coefficient	5.0
Temperature	4.3

TABLE IV.—TEST MATRIX USED FOR VARIABLE EXTRAPOLATION STUDY

Input variable	Values
Speed, m/s	0.07, 0.11, 0.16, 0.21, 0.27
Sliding distance, m	130, 380, 630, 880, 1100, 1215
Viscosity, cSt	0.6, 10, 20, 30, 40, 55
Load, N	4.9, 7.5, 10, 12.4, 14.7
Friction coefficient	0.10
Temperature, °C	25

APPENDIX A

DATA SET FOR THE FALEX RUB SHOE MODEL

Test	Load, lb	Speed, rpm	Viscosity, cSt	Sliding distance, m	Friction coefficient	Temperature, °C	Wear Volume, μm^3
SM-5	50	100	800	330	0.056	30	2.9×10^{-5}
SM-5				660	.059	30	3.32
SM-5				1 320	.057	33	3.5
SM-4				110	.044	26	3.54
SM-4				330	.047	29	3.56
SM-3				330	.062	30	5.94
SM-13	100			440	.117	34	6.74
SM-11	100			550	.11	33	8
SM-4	50			660	.047	31	8.02
SM-12	100			110	.11	27	8.16
SM-11	100			11 768	.1	36	9.46
SM-11	100			40 583	.11	36	10
SM-6	50			330	.076	30	10.3
SM-5				3 299	.059	34	10.6
SM-6				660	.079	32	13.7
SM-4				1 320	.05	33	13.8
SM-6				1 320	.058	32	15.1
SM-3				660	.063	32	15.4
SM-13	100			880	.119	38	16.1
D2	100		50	220	.047	114	16.7
SM-5	50		800	47 841	.129	31	18.2
SM-12	100			330	.12	31	18.4
SM-4	50			1 980	.055	33	19.5
SM-6	50			1 980	.072	31	23.6
SM-4	50			5 279	.05	34	34.5
SM-12	100			660	.12	33	36.1
D5	100		255	330	.039	29	37.1
SM4	50		800	21 886	.044	34	47
D5	100		255	1 320	.026	29	113
SM-12			800	1 980	.11	34	124
D2			50	3 189	.043	112	139
SM-12			800	2 640	.1	33	140
D5			255	1 980	.022	29	143
D3			50	1 210	.094	114	146
D2			50	6 709	.033	111	242
D3			50	2 420	.084	113	248
SM-12			800	6 379	.07	32	302
D3			50	4 619	.075	113	318
SM-12			800	7 809	.08	34	328
SM-12				9 238	.075	34	343
SM-12				11 218	.085	34	348
SM-12				12 978	.075	35	350
SM-12				23 756	.06	33	437
SM-12				25 625	.085	35	439
SM-12				42 012	.065	36	449
SM-12				100 852	.07	32	451
D2			50	17 047	.06	112	507
D3			50	8 798	.063	113	533
D5			255	58 509	.006	28	579
D3			50	19 247	.015	108	754
D3				22 436	.034	111	849
D3				86	.028	113	1690
D3				83	.009	109	1720
D3				114	0	110	1740
D3				97	.012	111	1760

APPENDIX B

DATA SET FOR THE PIN-ON-DISK MODEL

Test	Load, N	Speed, m/s	Viscosity, cSt	Sliding distance, m	Friction coefficient	Temperature, °C	Wear rate, m^3/m
NASA TN D-6251	9.8	0.272	0.685	980	0.12	300	1.02×10^9
NASA TN D-6251			6		.12	200	1.02
NASA TN D-6251			6		.12	200	2.04
NASA TN D-6251			.94		.13	250	3.07
NASA TN D-6251			1.75		.1	250	3.07
NASA TN D-6251			1.38		.14	400	3.07
NASA TN D-6251			1.7		.14	350	4.09
NASA TN D-6251			1.225		.08	300	4.09
NASA TN D-6915		.2702	40	425	.12	25	4.4
NASA TN D-6251		.272	.935	980	.07	350	5.11
NASA TN D-6251			.73		.06	400	6.13
NASA TN D-6251			1.38		.14	400	6.13
NASA TN D-6251			3.5		.12	250	9.2
NASA TN D-6915		.2702	.69	425	.12	300	9.41
NASA TN D-6353	14.7	.17	.56	250	.16	260	10
NASA TN D-6251	9.8	.272	1.38	980	.14	200	10.2
NASA TN D-6251		.272	4.9	980	.1		12
NASA TN D-6915		.2702	1.27	425	.2		12.3
NASA TN D-6915		.2702	1.27	425	.18		14.7
NASA TN D-6915		.2702	4.5	425	.16	100	18.2
NASA TN D-6251		.272	1.7	980	.14	350	20.5
NASA TN D-6915		.2702	4.5	425	.14	100	21.2
NASA TN D-6915			4.5		.16	100	22.4
NASA TN D-6915			4.5		.15	100	22.9
NASA TN D-6915			40		.1	25	29.4
NASA TN D-6251		.272	2.8	980	.11	250	30.6
NASA TN D-6915		.2702	40	425	.1	25	32.3
NASA TN D-6915		.2702	40	425	.09	25	35.3
NASA TM-82839	4.9	.075	4.31	145	.15	20	37
NASA TN D-6915	9.8	.2702	.69	425	.16	300	37
NASA TM-82839	4.9	.073	4.31	142	.15	20	40
NASA TM-82839		.069		144			44
NASA TM-82839		.073		141			49
NASA TM-82839		.075		155			50
NASA TN D-6251	9.8	.272	3.5	980	.12	250	51.1
NASA TM-82839	4.9	.071	4.31	138	.15	20	53
NASA TM-82839	4.9	.078	4.31	149	.16	20	57
NASA TN D-6251	9.8	.272	1.3	980	.12	350	61.3
NASA TM-82839	4.9	.07	4.31	138	.15	20	62
NASA TN D-6915	9.8	.2702	.69	425	.2	300	64.7
NASA TM-82839	4.9	.074	4.31	143	.15	20	66
NASA TN D-6251	9.8	.272	2.38	980	.13	300	71.6
NASA TM-82839	4.9	.071	4.31	134	.14	20	75
NASA TM-82839	4.9	.067	4.31	134	.15	20	80
NASA TN D-6915	9.8	.2702	55	425	.1	25	82.4
NASA TN D-6915	9.8	.2702	.68	425	.12	300	82.4
NASA TN D-6915	9.8	.2702	1.33	425	.16	200	82.4
NASA TN D-6353	14.7	.17	.56	250	.13	260	100
NASA TM-82839	4.9	.071	4.31	141	.15	20	110
NASA TM-82839		.078	4.3097	152	.15	25	137.2
NASA TM-82839		.075	4.3097	146	.16	25	367.5
NASA TP-1658		.2702	39.6	1125	.09	20	453
NASA TM-82839		.072	4.3097	151	.14	25	485.1
NASA TM-82839		.077	4.3097	154	.14	25	490
NASA TP-1658		.2027	39.6	1100	.09	20	597
NASA TP-1658		.1352		920			927
NASA TP-1658	9.8	.2702		1125			964
NASA TP-1658	9.8	.2027		1215			1421

APPENDIX C

DATA SET FOR THE FOUR-BALL MODEL

Test	Lubricant	Pressure-viscosity coefficient, α	Transient friction	Initial λ ratios	Kinetic viscosity, cSt	Molecular weight	Vapor pressure, torr	Surface tension, dynes/cm	Viscosity index	Load, N	Sliding speed, m/s	Sliding distance, mm	Wear rate, mm^3/mm
1	Krytox 143 AC	4.50E-08	0	2	800	6 250	8.00E-08	18	134	200	0.0288	475 200	9×10^{11}
2	Krytox 143 AC	4.50E-08	0	2	800	6 250	8.00E-08	18	134	200	↓	501 120	26
3	Krytox 143 AC	4.50E-08	0	2	800	6 250	8.00E-08	18	134	200	↓	528 768	66
4	Fomblin Z25	1.50E-08	1	1	255	10 000	2.90E-12	25	355	600	↓	466 560	67
5	Fomblin Z25	1.50E-08	1	1	255	10 000	2.90E-12	25	355	600	↓	466 560	69
6	Krytox 143 AC	4.50E-08	0	2	800	6 250	8.00E-08	18	134	200	↓	451 008	71
7	Krytox 143 AC	4.50E-08	0	2	800	6 250	8.00E-08	18	134	↓	↓	473 472	88
8	Demnum	2.60E-08	2	1.5	250	5 600	5.00E-07	18.5	200	↓	↓	362 880	96
9	Fomblin Z25	1.50E-08	1	↓	255	10 000	2.90E-12	25	355	↓	↓	362 880	98
10	↓	↓	↓	↓	↓	↓	↓	↓	↓	600	↓	466 560	106
11	↓	↓	↓	↓	↓	↓	↓	↓	↓	200	↓	362 880	111
12	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	466 560	142
13	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	466 560	160
14	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	366 336	179
15	Demnum	2.60E-08	2	1.5	250	5 600	5.00E-07	18.5	200	600	↓	362 880	197
16	Demnum	2.60E-08	2	1.5	250	5 600	5.00E-07	18.5	200	↓	↓	371 520	216
17	Demnum	2.60E-08	2	1.5	250	5 600	5.00E-07	18.5	200	↓	↓	466 560	221
18	Krytox 143 AC	4.50E-08	0	2	800	6 250	8.00E-08	18	134	↓	↓	435 456	521
19	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	468 288	740
20	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	470 016	742
21	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	↓	468 288	770
22	Fomblin Z25	1.50E-08	1	1	255	10 000	2.90E-12	25	355	200	↓	499 392	1 049
23	Fomblin Z25	1.50E-08	1	1	255	10 000	2.90E-12	25	355	200	↓	475 200	1 290

APPENDIX D

UNKNOWN DATA SET FOR TESTING THE FALEX RUB SHOE MODEL

Test	Load, lb	Speed, rpm	Viscosity, cSt	Sliding distance, m	Friction coefficient	Tempera-ture, °C	Wear volume, μm^3
SM7	50	100	800	330	0.063	31	2.32×10^{-5}
SM7	50			660	.062	31	3.28
SM11	100			110	.1	28	3.88
SM13	100			110	.115	28	4.46
SM7	50			1 320	.061	33	5.12
SM5				1 980	.06	34	5.14
SM3				110	.063	27	5.28
SM7				1 980	.064	32	5.84
SM7				3 299	.066	33	9.60
SM7				16 717	.069	29	14.50
SM3				1 980	.065	30	27.10
SM3				3 299	.063	31	28.10
SM3				3 959	.063	31	30.30
D2	100		50	1 430	.062	113	57.60
D5			255	660	.037	30	63.40
SM12			800	1 320	.11	34	85.10
SM13			800	12 758	.082	34	173.00
D2			50	4 839	.028	113	191.00
SM12			800	3 959	.1	35	222.00
D5			255	13 528	.009	29	408.00
SM12			800	27 275	.078	34	442.00
SM12			800	38 163	.08	33	443.00
D3			50	68 518	.04	111	1600.00
D3			50	110 530	.004	111	1790.00
D3			50	156 392	.003	110	1830.00

APPENDIX E

UNKNOWN DATA SET FOR TESTING THE PIN-ON-DISK MODEL

Test	Load, N	Speed, m/s	Viscosity, cSt	Sliding distance, m	Friction coefficient	Temperature, °C	Wear rate, m^3/m
NASA TN D-6251	9.8	0.272	2.75	980	0.12	200	2.04×10^{9}
NASA TN D-6251		.272	2.38	980	.13	300	6.13
NASA TN D-6251		.272	.99	980	.13	400	10.2
NASA TN D-6915		.2702	1.27	425	.18	200	12.4
NASA TN D-6915		.2702	.69	425	.16	300	23.5
NASA TN D-6915		.2702	1.27	425	.18	200	29.4
NASA TM-82839	4.9	.078	4.31	153	.14	20	47
NASA TN D-6251	9.8	.272	1.8	980	.12	300	61.3
NASA TN D-6915	9.8	.2702	5.1	425	.16	100	82.4
NASA TM-82839	4.9	.078	4.3097	150	.16	25	264.6
NASA TP-1658	9.8	.2702	39.6	1125	.09	20	964

APPENDIX F

UNKNOWN DATA SET FOR TESTING THE FOUR-BALL MODEL

Test	Lubricant	Pressure-viscosity coefficient, α	Transient friction	Initial λ ratios	Kinetic viscosity, cSt	Molecular weight
1	Krytox 143 AC	4.50E-08	0	2	800	6250
2	Krytox 143 AC	4.50E-08	0	2	800	6250
3	Krytox 143 AC	4.50E-08	0	2	800	6250

Test	Vapor pressure, torr	Surface tension, dynes/cm	Viscosity index	Load, N	Sliding speed, m/s	Sliding distance, mm	Wear rate, mm^3/mm
1	8.00E-08	18	134	200	0.0288	489 024	57×10^{11}
2	8.00E-08	18	134	200	0.0288	468 288	67
3	8.00E-08	18	134	600	0.0288	483 840	737

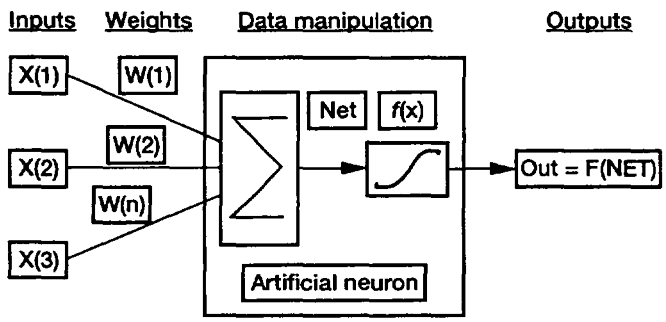

Figure 1.—Artificial neuron with activation function (Ref.5).

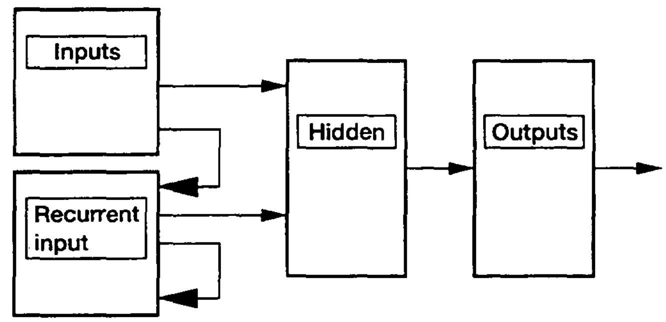

Figure 3.—Schematic illustration of the input layer dampened recurrent feedback design architecture.

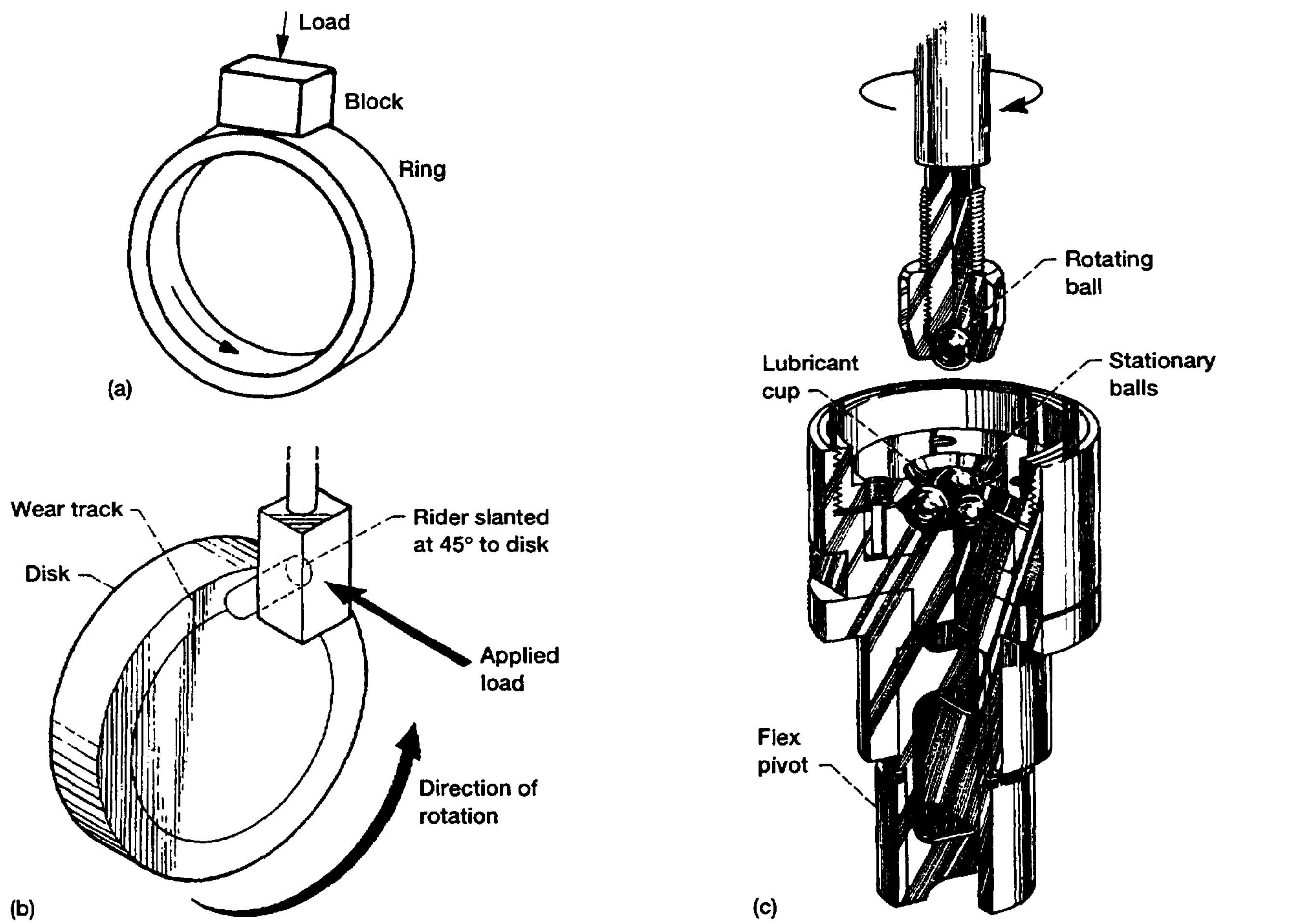

Figure 2.—Schematic diagrams of rub shoe sliding specimens, pin-on-disk sliding specimens, four-ball sliding specimens. (a) Rub shoe. (b) Pin-on-disk. (c) Four-ball.

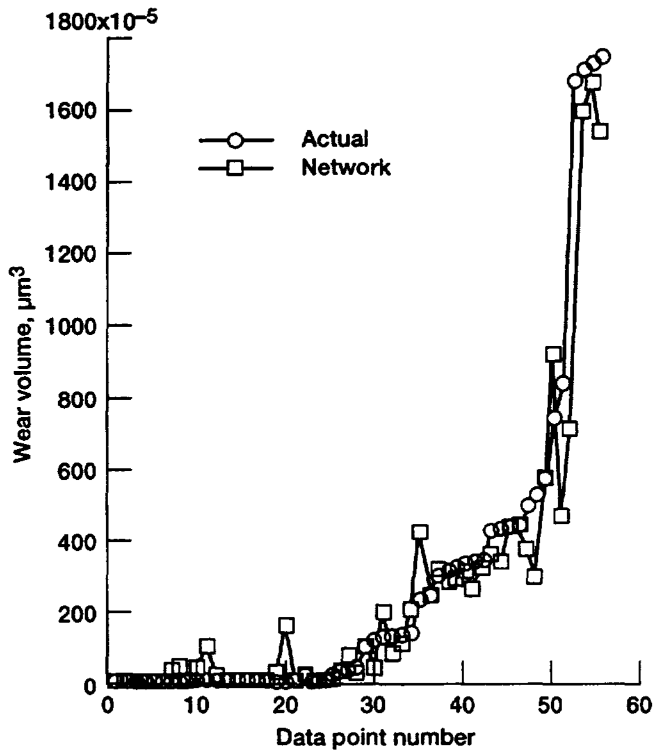

Figure 4.—Comparison of actual rub shoe data (used for training network) to that of network approximation data.

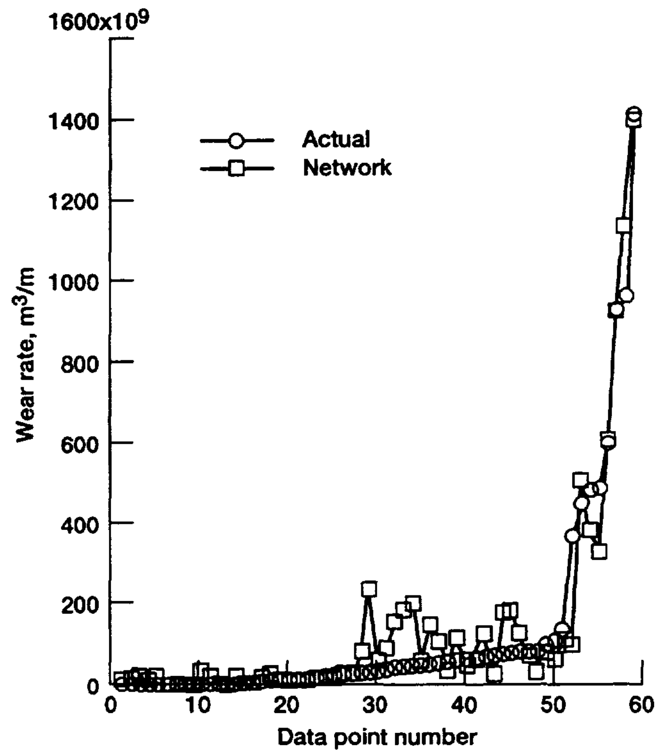

Figure 6.—Comparison of actual pin-on-disk data (used for training network) to that of network approximation data.

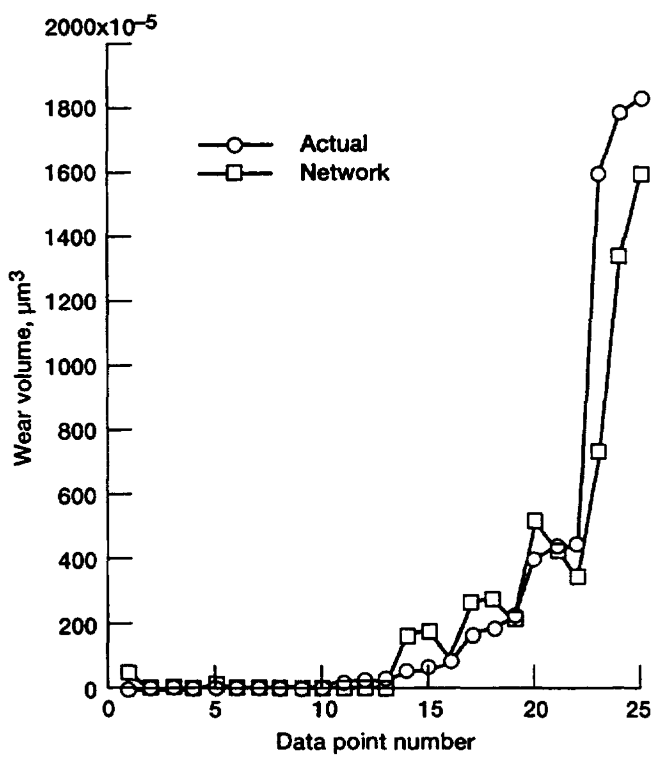

Figure 5.—Comparison of previously unknown rub shoe data (actual data) to that of network approximation data.

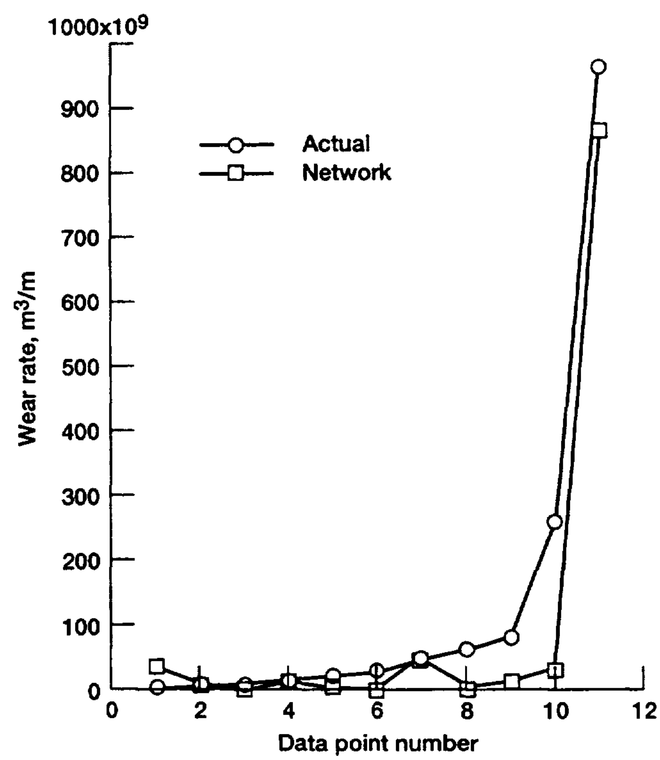

Figure 7.—Comparison of previously unknown pin-on-disk data (actual data) to that of network approximation data.

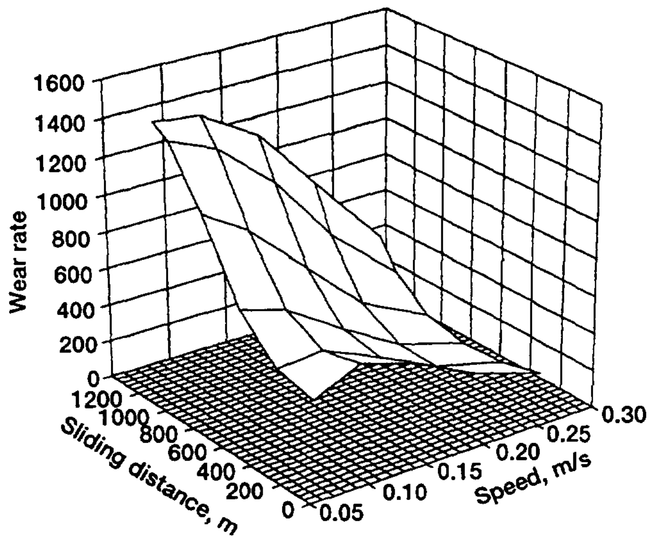

Figure 8.—Three-dimensional plots illustrating relationship between speed, sliding distance, and wear rate using pin-on-disk neural network model.

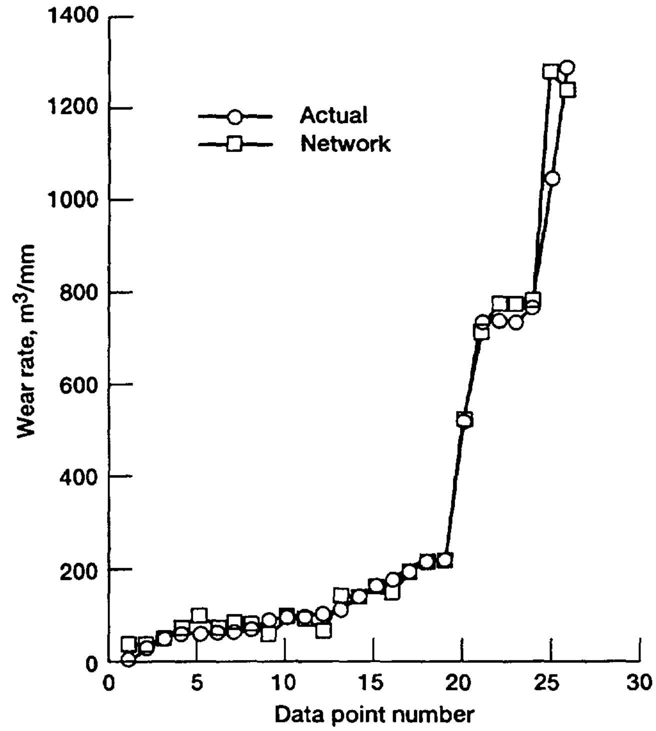

Figure 10.—Comparison of actual four-ball data (used for training network) to that of network approximation data.

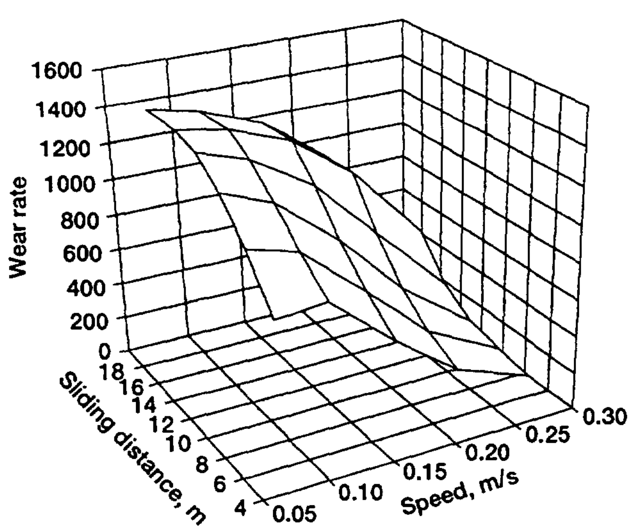

Figure 9.—Three-dimensional plots illustrating relationship between speed, load, and wear rate using pin-on-disk neural network model.

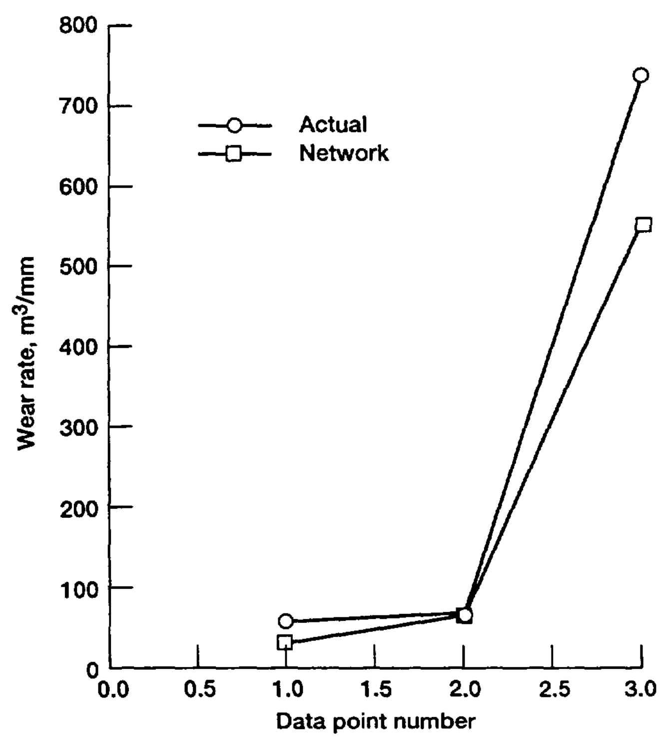

Figure 11.—Comparison of previously unknown four-ball data (actual data) to that of network approximation data.

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13. ABSTRACT ***(Maximum 200 words)***
A complete evaluation of the tribological characteristics of a given material/mechanical system is a time-consuming operation since the friction and wear process is extremely systems sensitive. As a result, experimental designs (i.e., Latin Square, Taguchi) have been implemented in an attempt to not only reduce the total number of experimental combinations needed to fully characterize a material/mechanical system, but also to acquire life data for a system without having to perform an actual life test. Unfortunately, these experimental designs still require a great deal of experimental testing and the output does not always produce meaningful information. In order to further reduce the amount of experimental testing required, this study employs a computer neural network model to investigate different material/mechanical systems. The work focuses on the modeling of the wear behavior, while showing the feasibility of using neural networks to predict life data. The model is capable of defining which input variables will influence the tribological behavior of the particular material/mechanical system being studied based on the specifications of the overall system.

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