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APPLICATION OF BACK PROPAGATION NEURAL NETWORK TO THE ANALYSIS OF AIRCRAFT WING LOADING

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ABSTRACT

Using the flying parameters to map strain on the aircraft by Neural Network is easier and more reliable than that of using the traditional method. Also, taking too many flying parameters will not only increase the complexity of the network structure, but also the difficulty of the learning scheme. Screening out the unwanted parameters is an important procedure to the strain measurement. In this paper, we use the TQEM (Taguchi Quality Engineering Method) is applied to chose the required flying parameters for better referencing. The demonstrated results show that the TQEM is a new and effective method to choose the required parameters for system identification.

1. INTRODUCTION

In traditionally, the method to measure strain value is to put a strain gage on the surface of the structure. Because of installing strain gages for the aircraft loading analysis needs a huge number of sampling points, it is a difficult job, and maintenance is difficult, too. Therefore, this method is not effective on the aircraft structure loading measurement. Many researchers mentioned that use the flying parameters to map strain on the structure and to get the load data on the aircraft by Neural Network [1-8] is an easy and reliable method. To handle high precision, we have to collect a lot of flying parameters. Taking too many sampled parameters will cause network not easy to converge on the learning scheme of the neural network. By the way, we can see that not every parameter is important to the analysis of the strain at each point. Therefore, we have to careful select the required flying parameters, focus on the different point, to reduce the calculation and to speed up the convergence of the neural network learning rules.

Bastian [9] proposed a method for screening the less weighted parameters, named TSI (Type 1 Structure Identification). The method needs to change input parameter instead of random variable one by one and to test the importance of the whole system at the selected parameter. After testing all the input parameters, we can find which one has the most or the least importance to the system. This method needs a lot of calculation works, and also not consider the cross correlation among all the parameters. Thus, some important clues are lost. In this paper, we use the TQEM (Taguchi Quality Engineering Method) [10-13] to try to find a better method for system identification.

The TQEM can increase the efficiency and productivity of new developed products and manufacturing techniques. The advantages of the TQEM are low cost, high efficiency and index digitalization. The usage of these features can help us easily manage the resources and improves the quality of industrial products. The purpose is for completing the design of new product and modifying product earlier than the other companies via the efficiency of development and design research. Hence, the research point is: while thoroughly examining product function in the market, using orthogonal array and variation cause of various noise sources to increase fault tolerance, reliability, reduce the cost, and also, adopt significant stability designing at the same time.

In our research, we use the parameter design method of TQEM and coordinate with the matrix experiment that constructed by orthogonal array to find the important parameters of the system. The flying data of this experiment is a real flying data provided by the Aeronautical System Research Division of Chung San Institute Science and Technology. There are 21 input parameters and 35 output parameters. The importance of each output parameter to each input parameter is different. To avoid the intersection cause by different requirement of each output parameter to input parameters, we focus on each output parameter to analyze the importance of input parameter. To do so, we isolate each output parameter, that is each output parameter forms an independent network. Because of the huge of whole data, we are randomly picked 100 data from database to instead of whole data set to participate in the experiment. It will save experiment time. In this paper, we just discuss the strain on opposite point of the left and right wing of aircraft. The conclusion of this research can approve the whole aircraft.

2. RSEARCH METHOD

The experimental example used in this research is the system identification of the loading of aircraft structure. That is to use every aspect of the flight parameters generated from its information center, such as height, flight speed, attack angle, etc, to evaluate the loading condition distributed overall the wing of the plane. Many researchers have discussed this topic before, such as: Hoffman [4-5], Raza and Ioannou and Youssef [6], Freitas and Stevens [7] and Napolitano and Windon [8].

We have to design a neural network to evaluate the loading condition for experiment. The proposed network structure is a fully connected BPNN (Back Propagation Neural Network) and adopted one hidden layer (Decided by the demand of experiment, let network can converge smoothly). In the example, there are 21 input nodes and one output node in total (table 1), and learning examples are randomly picked 100 data from the database which sampled 2700 data totally. The control factors of this experiment are 21 input parameters. There are two levels on control factors, chosen (1) or not (0). Therefore, we constructed matrix experiment by the $L_{32}(2^{31})$ orthogonal array, and use identification rate of network to be the evaluation condition. The row of the L_{32} orthogonal array is parameter set. There are 31 sets. Column is the experiment set. The actual parameter of this experiment are 21 sets, thus, other 10 sets can be deleted. We do not need to get the minimum error of network convergence, just to get preliminary identification rate for different compare usage. Therefore, for saving experiment time, we stop network convergence after 100 times network converge calculations, and compute identification rate for evaluation.

Because of the identification rate of network is the higher the better; this experiment is then belongs to the Larger-is-Better Parameter Design Method. The formula of the Signal-to-Noise Ratio, S/N (Appendix 1) is:

$$S/N = -10\log\sigma^2 \tag{1}$$

Where σ^2 is variation, and log is logarithm base on 10.

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n} y_i^2 \tag{2}$$

Where y is system output (network identification rate).

After experiment, we use result (Table3) to make the assistance chart (Table 4,5). Row of result is the input parameters that attend to experiment. The second row of the end of the table is identification rate of network that was passed by 100 times network convergence calculations. It is defined by the correlation coefficient function of target output and real output. The calculate formula is:

$$C_{xy} = \frac{N \times \sum (X \cdot Y) - (\sum X) \times (\sum Y)}{\{[N \times \sum (X^2) - (\sum X)^2] \times [N \times \sum (Y^2) - (\sum Y)^2]\}^{\frac{1}{2}}} \quad (3)$$

Where C_{xy} is correlation coefficient function of X, Y, N is the number of X, Y, and X is the target output; Y is the real output. The first row of the end of the table is S/N value that is calculated by the S/N formula of Larger-is-Better Parameter Design Method and represented by dB value.

We get the sum of each parameter's S/N value to form the assistance chart, where 0 represented the parameter did not attend experiment, 1 represented the parameter attend experiment. Then, we can get the importance of each input parameter to output parameters. The higher S/N value represented more important to the system. This result provides us how to choose the required parameters.

3. COMPARSTION

We now compare the previous result to the type 1 system (TSI) identification method. WE first divide the input/output data set into two groups: A and B. Train the neural network M_A using all n available inputs of data set A and network M_B using data set B. These are two reference networks. After training, the reference networks M_A and M_B are tested using data set B and A, respectively. Compute the regularity criterion (RC) as follows:

$$RC = \left[\sum_{i=1}^{k_A} \frac{(y_i^A - y_i^{AB})^2}{k_A} + \sum_{i=1}^{k_B} \frac{(y_i^B - y_i^{BA})^2}{k_B} \right] \times \frac{1}{2} \quad (4)$$

Where k_A and k_B are respectively the number of data in sets A and B, y^A and y^B are the output data in sets A and B, y^{AB} is the output obtained for the data set A using the network M_B, and y^{BA} is the output obtained for data set B using the network M_A. The calculated RC value would be used as a reference value.

Replace each input variable in the test sets A and B with a random variable and compute the RC according to Eq. (4). The input variables with a high RC value are considered to be the important variables, while the variables with a low RC are considered to be not important variables.

After this step, we can get the preliminary importance of input parameters to system. Next step, we choose two input parameters with low RC value to replace with random variables. Compute new RC value until all of the parameter's linear combinations are calculated. We got the common importance of two low RC value parameters to system. Recursive this routine, we will get the importance of all combinations of low RC value parameters to system. Generally, the preliminary result of first step will satisfy the requirement of system parameter condensed.

According to the result of experiment, we got the importance of input parameters to system at opposite point (LW56VZ, RW56VZ) of the wing. The result of TQEM is difference to TSI (Table 6). Therefore, we take the result (first 10, first 8, first 5, first 3) of this two method to participate in check experiment and compare the difference between. After 200 times convergence calculations, we got identification rates of TQEM and TSI method (Table 7).

According to check experiment, the identification rates of chosen result of the input parameter by TQEM are different form TSI. Because of the Parameter Design Method of TQEM will consider the intersection of input parameters, and the TSI method is not. It is considered that each parameter is independent and they do not have correlation each other.

Actuarially, each parameter must have the intersection because of network is a full connected in this experiment. It will get some error if we isolate input parameter and neglect the intersection for each other. It is the reason of the difference between the result of TQEM and TSI.

4. CONCLUISION

We have provided a new method, TQEM, to select the more suitable parameters for network training. Using

TQEM can find the importance of input parameters in one experiment, but TSI method can not. It must proceed several times to decide the importance of the input parameters. Comparing to the TSI method, We can see the advantages of using TQEM are fast, easy, and expedient.

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6. REFERENCE

[1] Mo-Chung Li, Chii-Maw Uang, and M. S. Young, "Neural Network-Based Simulation System for Monitoring and Tracking the Load of Aircraft Structure", The Fifth Military Symposium on Fundamental Science, Vol. 2, pp2.03-1~2.03-4 1998

[2] M.E Hoffman, "Neural Network Prototype for Individual Aircraft Tracking", Report from Neural Air Warface Center, Ciode6042, pp.802~819, 1992

[3] M.E. Hoffman, "A Neural Network Prototype for Predicting F-14Bstrains at B.L. 10 Longeron", Report from NAWCAD WAR-92042-60,1992

[4] H.Raza, P. Ioannou, H.M. Youssef, "Surface Failure Detecting for an F/A-18 Aircraft Using Neural Networks and Fuzzy Logic", IEEE ICNN, pp.3363-3368, 1994

[5] JFG de Freitas, AL. Stevens, "Identification of Vibrating Structures and Fault Detection Using Neural Network", IEEE ICNN, pp. 2044-2048, 1996

[6] Marcello R.Napolitano, Dale A. Windon, "Neural Network-Based Reconstruction of Flight Data for Aircraft Crash Investigations", IEEE ICNN, pp. 2084-2089, 1996

[7] "Neural Networks - A Comprehensive Foundation", Simon Haykin, Macmillan, 1994

[8] "Neural Networks - Algorithms, Applications, and Programming Techniques", James A. Freeman, David M. Skapura, Addison-Wesley, 1992

[9] Andres Bastian, and Jorge Gasos, "A type I Structure Identification Approach Using Feedforward Neural Networks", IEEE ICNN, pp. 3256~3260,1994

[10] "Quality Engineering Using Robust Design", Madhav S. Phadke, AT&T Bell Lab. 1989

[11] "Taguchi Methods", Glen Stuart Peace, Addison-Wesley, 1993

[12] "Taguchi Techniques for Quality Engineering", Phillip J. Ross, McGraw-Hill, 1996

[13] "Quality Engineering in Production Systems", Genichi Taguchi, Elsayed A. Elsayed and Thomas Hsiang, McGraw-Hill, 1989

Table 1. Input / Output Parameters

Input Parameters	
MACH	Mach Number
ALT	Altitude(FT)
WT	A/C Weight(LBS)
XCG	A/C Center of Gravity
NX,NY,NZ	Roll, Yaw, Pitch Load Factor
P,Q,R	Roll, Pitch, Yaw Rate(DEG/SEC)
PDOT,QDOT, RDOT	Roll, Pitch, Yaw Acceleration (RAD/SEC*SEC)
α	Angle of Attack
δ LEF	LEF Deflection (DEG)
δ TEF	TEF SYM. Deflection ((Right + Left)/2)(DEG)
δ HT	HT SYM. Deflection ((Right* + Left)/2)(DEG)
δ AIL	TEF Aileron Deflection ((Left - Right)/2)(DEG)
δ HA	HT Aileron Deflection ((Left - Right)/2)(DEG)
β	Angle of Yaw
δ R	Rudder Deflection(DEG)
Output Parameters	
RW56VZ	Right Wing BL=56 Shear(LB)
LW56VZ	Left Wing BL=56 Shear(LB)

Table 2. $L_{32}(2^{31})$ **Orthogonal Array**

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
4	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
5	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0
6	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1
7	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1
8	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0
9	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0
10	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1
11	1	0	0	1	1	0	0	0	0	1	1	0	0	1	1	1	1	0	0	1	1	0	0	0	0	1	1	0	0	1	1
12	1	0	0	1	1	0	0	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	1	1	0	0	1	1	0	0
13	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1
14	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0
15	1	0	0	0	0	1	1	0	0	1	1	1	1	0	0	1	1	0	0	0	0	1	1	0	0	1	1	1	1	0	0
16	1	0	0	0	0	1	1	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0	1	1	0	0	0	0	1	1
17	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
18	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
19	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1
20	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	1	0	1	0	1	0	1	0
21	0	1	0	0	1	0	1	1	0	1	0	0	1	0	1	1	0	1	0	0	1	0	1	1	0	1	0	0	1	0	1
22	0	1	0	0	1	0	1	1	0	1	0	0	1	0	1	0	1	0	1	1	0	1	0	0	1	0	1	1	0	1	0
23	0	1	0	0	1	0	1	0	1	0	1	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	1	0	1	0
24	0	1	0	0	1	0	1	0	1	0	1	1	0	1	0	0	1	0	1	1	0	1	0	1	0	1	0	0	1	0	1
25	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1
26	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0
27	0	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	0	0	1	1	0	0	1	0	1	1	0	0	1	1	0
28	0	0	1	1	0	0	1	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	1	0	0	1	1	0	0	1
29	0	0	1	0	1	1	0	1	0	0	1	0	1	1	0	1	0	0	1	0	1	1	0	1	0	0	1	0	1	1	0
30	0	0	1	0	1	1	0	1	0	0	1	0	1	1	0	0	1	1	0	1	0	0	1	0	1	1	0	1	0	0	1
31	0	0	1	0	1	1	0	0	1	1	0	1	0	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	0	0	1
32	0	0	1	0	1	1	0	0	1	1	0	1	0	0	1	0	1	1	0	1	0	0	1	1	0	0	1	0	1	1	0

Table 3. Experiment Result of RW56VZ, LW56VZ

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	RW56VZ		LW56VZ	
																						Id. Rate	S/N (dB)	Id. Rate	S/N (dB)
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.9167	-0.75546	0.8847	-1.06408
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0.8442	-1.47109	0.819	-1.73432
3	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0.7993	-1.9458	0.763	-2.34951
4	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.9531	-0.41723	0.9589	-0.36453
5	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0.5908	-4.57119	0.5113	-5.82648
6	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0.5732	-4.83388	0.5147	-5.76892
7	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0.0167	-35.5457	0.0337	-29.4474
8	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	1	1	0.5242	-5.61006	0.4652	-6.64721
9	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0.1063	-19.4693	0.1635	-15.7296
10	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	0	0	1	1	0	0	0.7089	-2.9883	0.6763	-3.39721
11	1	0	0	1	1	0	0	0	0	1	1	0	0	1	1	1	1	0	0	1	1	0.5905	-4.5756	0.5373	-5.39566
12	1	0	0	1	1	0	0	0	0	1	1	0	0	1	1	0	0	1	1	0	0	0.0224	-32.995	0.0526	-25.5803
13	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	0.75	-2.49877	0.6955	-3.15406
14	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	0	0	1	1	1	1	0.7541	-2.45142	0.7026	-3.06584
15	1	0	0	0	0	1	1	0	0	1	1	1	1	0	0	1	1	0	0	0	0	0.8856	-1.05525	0.8626	-1.28381
16	1	0	0	0	0	1	1	0	0	1	1	1	1	0	0	0	0	1	1	1	1	0.0995	-20.0435	0.1013	-19.8878
17	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	0.1836	-14.7225	0.1167	-18.6586
18	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0.1534	-16.2835	0.1076	-19.3638
19	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	1	0	1	0	1	0	0.4361	-7.20828	0.2987	-10.4953
20	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0.6423	-3.84524	0.5758	-4.79457
21	0	1	0	0	1	0	1	1	0	1	0	0	1	0	1	1	0	1	0	0	1	0.9131	-0.78963	0.884	-1.07095
22	0	1	0	0	1	0	1	1	0	1	0	0	1	0	1	0	1	0	1	1	0	0.6974	-3.13036	0.675	-3.41392
23	0	1	0	0	1	0	1	0	1	0	1	1	0	1	0	1	0	1	0	0	1	0.8284	-1.6352	0.7936	-2.00797
24	0	1	0	0	1	0	1	0	1	0	1	1	0	1	0	0	1	0	1	1	0	0.879	-1.12022	0.8438	-1.47521
25	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	0	0.0436	-27.2103	0.2664	-11.4893
26	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	0	1	1	0	0	1	0.7639	-2.33927	0.7201	-2.85214
27	0	0	1	1	0	0	1	0	1	1	0	0	1	1	0	1	0	0	1	1	0	0.8949	-0.96451	0.878	-1.13011
28	0	0	1	1	0	0	1	0	1	1	0	0	1	1	0	0	1	1	0	0	1	0.8101	-1.82923	0.7905	-2.04196
29	0	0	1	0	1	1	0	1	0	0	1	0	1	1	0	1	0	0	1	0	1	0.1818	-14.8081	0.0817	-21.7556
30	0	0	1	0	1	1	0	1	0	0	1	0	1	1	0	0	1	1	0	1	0	0.364	-8.77797	0.3255	-9.74898
31	0	0	1	0	1	1	0	0	1	1	0	1	0	0	1	1	0	0	1	0	1	0.3979	-8.00452	0.3093	-10.1924
32	0	0	1	0	1	1	0	0	1	1	0	1	0	0	1	0	1	1	0	1	0	0.5422	-5.31681	0.4436	-7.06017

Table 4. Assistance Chart of RW56VZ

	X0(MACH)	X1(ALT)	X2(WT)	X3(XCG)	X4(NX)	X5(NY)	X6(NZ)
1	-145.799	-108.457	-123.655	-139.021	-102.884	-104.289	-69.6573
0	-113.414	-150.757	-135.558	-120.193	-156.329	-154.925	-189.556
	X7(P)	X8(Q)	X9(R)	X10(α)	X11(δLEF)	X12(δTEF)	X13(δHT)
1	-131.672	-68.2178	-120.597	-141.817	-158.254	-128.292	-146.044
0	-127.541	-190.995	-138.617	-117.397	-100.959	-130.921	-113.169
	X14(δAIL)	X15(δHA)	X16(β)	X17(δR)	X18(PDOT)	X19(QDOT)	X20(RDOT)
1	-138.431	-150.331	-112.314	-143.17	-181.234	-122.819	-109.22
0	-120.783	-108.882	-146.899	-116.044	-77.979	-136.394	-149.994

Table 5. Assistance Chart of LW56VZ

	X0(MACH)	X1(ALT)	X2(WT)	X3(XCG)	X4(NX)	X5(NY)	X6(NZ)
1	-136.523	-120.309	-118.239	-126.441	-105.28	-127.913	-58.3855
0	-121.724	-137.938	-140.008	-131.807	-152.967	-130.335	-199.862
	X7(P)	X8(Q)	X9(R)	X10(α)	X11(δLEF)	X12(δTEF)	X13(δHT)
1	-133.92	-77.7046	-128.24	-136.987	-145.231	-133.643	-152.271
0	-124.327	-180.543	-130.008	-121.261	-113.017	-124.605	-105.977
	X14(δAIL)	X15(δHA)	X16(β)	X17(δR)	X18(PDOT)	X19(QDOT)	X20(RDOT)
1	-120.397	-146.877	-113.768	-143.321	-170.06	-116.32	-123.988
0	-137.85	-111.37	-144.48	-114.927	-88.1877	-141.928	-134.26

Table 6. Input Parameters Priority List

Taguchi	RW56VZ	Taguchi	LW56VZ	Type I S.I.	RW56VZ	Type I S.I.	LW56VZ
X8(Q)	-68.2178	X6(NZ)	-58.3855	X6(NZ)	333.6184	X6(NZ)	378.7388
X6(NZ)	-69.6573	X8(Q)	-77.7046	X8(Q)	92.5428	X8(Q)	94.5356
X4(NX)	-102.884	X4(NX)	-105.28	X13(δHT)	82.9022	X13(δHT)	89.3251
X5(NY)	-104.289	X16(β)	-113.768	X10(α)	73.7274	X4(NX)	63.4875
X1(ALT)	-108.457	X19(QDOT)	-116.32	X4(NX)	61.574	X10(α)	50.8612
X20(RDOT)	-109.22	X2(WT)	-118.239	X3(XCG)	23.867	X20(RDOT)	31.5273
X16(β)	-112.314	X1(ALT)	-120.309	X20(RDOT)	23.6685	X3(XCG)	31.1493
X9(R)	-120.597	X14(δAIL)	-120.397	X2(WT)	10.7755	X2(WT)	12.8283
X19(QDOT)	-122.819	X20(RDOT)	-123.988	X12(δTEF)	4.9398	X17(δR)	7.3728
X2(WT)	-123.655	X3(XCG)	-126.441	X18(PDOT)	3.9782	X15(δHA)	6.6764
X12(δTEF)	-128.292	X5(NY)	-127.913	X9(R)	3.1963	X0(MACH)	5.8623
X7(P)	-131.672	X9(R)	-128.24	X16(β)	3.1225	X9(R)	4.7065
X14(δAIL)	-138.431	X12(δTEF)	-133.643	X11(δLEF)	3.0184	X12(δTEF)	3.4127
X3(XCG)	-139.021	X7(P)	-133.92	X15(δHA)	3.0043	X7(P)	3.2671
X10(α)	-141.817	X0(MACH)	-136.523	X14(δAIL)	2.8275	X18(PDOT)	3.2635
X17(δR)	-143.17	X10(α)	-136.987	X19(QDOT)	2.2445	X5(NY)	2.4367
X0(MACH)	-145.799	X17(δR)	-143.321	X17(R)	1.8335	X1(ALT)	2.3127
X13(δHT)	-146.044	X11(δLEF)	-145.231	X1(ALT)	1.7166	X19(QDOT)	2.2179
X15(δHA)	-150.331	X15(δHA)	-146.877	X5(NY)	1.2621	X16(β)	2.0188
X11(δLEF)	-158.254	X13(δHT)	-152.271	X7(P)	1.1252	X11(δLEF)	1.4269
X18(PDOT)	-181.234	X18(PDOT)	-170.06	X0(MACH)	1.1034	X14(δAIL)	1.1917

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Table 7. Identification Rate List

	TQEM		TSI	
	RW56VZ	LW56VZ	RW56VZ	LW56VZ
First 10	0.9556	0.9399	0.9464	0.9333
First 8	0.9078	0.8847	0.8949	0.8715
First 5	0.9512	0.9390	0.9145	0.8969
First 3	0.9385	0.9285	0.8990	0.8888

Appendix 1. The Larger-is-Better S/N Formula

Figure 1 shows a simplified relationship between quality loss and the amount of deviation from the target value. As shown in this figure, quality loss caused by deviation equals zero when y = m. The quality loss will increase when the value of the functional characteristic moves in either upward or downward direction from point m. When the value of the functional characteristic exceeds either one of the limits, $m+\Delta$ or $m-\Delta$ (where Δ is defined as the tolerance and 2Δ is the tolerance limit), the quality loss is said to be the cost of the product's disposal or manufacturing.

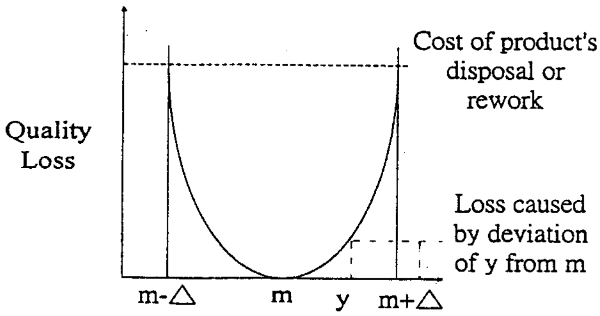

Figure 1. Relationship between quality loss and deviation from the target value (m).

Then denote the loss function by L(y) and expand it in a Taylor series about the target value m:

$$L(y) = L(m+y-m)$$
$$= L(m)+\frac{L'(m)}{1!}(y-m)+\frac{L''(m)}{2!}(y-m)^2+\Lambda \quad (1)$$

Because L(y)=0 when y=m (by definition, quality loss is zero when y=m), and the minimum value of the function is attained at this point (Fig. 1), its first derivation with respect to m, $L'(m)$, is zero. The first two terms of Eq. (1), then, are equal to zero. When we neglect terms with powers higher then 2, Eq. (1) reduces to

$$L(y) = \frac{L''(m)}{2!}(y-m)^2 = k(y-m)^2 \quad (2)$$

Where k is a proportionality constant.

A The-Larger-is-Better type tolerance involves a nonnegative characteristic, whose ideal value is ∞. According to the Larger-is-Better characteristic relationship from figure 2, we got:

$$L(\infty) = 0 \quad (3)$$

$$L'(\infty) = 0 \quad (4)$$

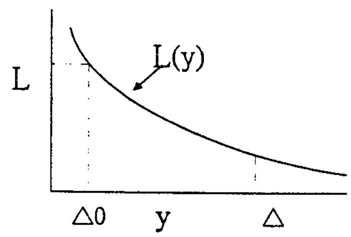

Figure 2. Characteristic of Loss Function L(y)

When $y=\infty$, we denote the loss function L(y) and expend it in Taylor series as 1/y :

$$L(y) = L(\infty)+\frac{L'(\infty)}{1!}\times\frac{1}{y}+\frac{L''(\infty)}{2!}\times\frac{1}{y^2}+\Lambda \quad (5)$$

Take Eq. (3), (4) instead of (5), neglect terms with powers higher then 2, Eq. (5) reduce to

$$L(y) = k\times\frac{1}{y^2} \quad (6)$$

Signal-to Noise ratio (S/N) is the inverse proportion of loss function, so we got the formula of the S/N:

$$S/N = \frac{1}{\sigma^2} \tag{7}$$

to avoid the data scatter, we got the dB scale :

$$S/N = -10\log\sigma^2 \tag{8}$$

Where σ^2 is variation, and log is the logarithm base on 10.

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n} y_i^2 \tag{9}$$

Where y is system output (network converge time).

Appendix 2. Correlation Coefficient Function

According the defection:

$$\begin{aligned} C_{xy} &= Corr(x,y) \\ &= \frac{Cov(x,y)}{\sqrt{V(x)\times V(y)}} \end{aligned} \tag{1}$$

Where Corr(x,y) is the correlation coefficient function of x and y, Cov(x,y) is the common variance of x and y, V(x) is the variance of x, V(y) is the variance of y.

(i)

$$\begin{aligned} Cov(x,y) &= E[[x-E(x)]\times[y-E(y)]] \\ &= E[(x-\bar{x})\times(y-\bar{y})] \\ &= E(x\cdot y - x\cdot\bar{y} - \bar{x}\cdot y + \bar{x}\cdot\bar{y}) \\ &= E(x\cdot y) - \bar{y}E(x) - \bar{x}E(y) + \bar{x}\cdot\bar{y} \\ &= E(x\cdot y) - \bar{x}\cdot\bar{y} - \bar{x}\cdot\bar{y} + \bar{x}\cdot\bar{y} \\ &= E(x\cdot y) - E(x)\times E(y) \\ &= \frac{\sum x\cdot y}{N} - \frac{(\sum x)\times(\sum y)}{N^2} \end{aligned} \tag{2}$$

Where E[] is expectation value, N is the number of x, y.

(ii)

$$\begin{aligned} V(x) &= E[[x-E(x)]^2] \\ &= \frac{\sum(x-\bar{x})^2}{N} \\ &= \frac{\sum(x^2 - 2\cdot x\cdot\bar{x} + \bar{x}^2)}{N} \\ &= \frac{1}{N}\sum\left[x^2 - 2\cdot x\cdot\frac{\sum x}{N} + (\frac{\sum x}{N})^2\right] \\ &= \frac{\sum(x)^2}{N} - 2\times\frac{\sum x}{N}\times\frac{\sum x}{N} + (\frac{\sum x}{N})^2 \\ &= \frac{\sum(x)^2}{N} - (\frac{\sum x}{N})^2 \end{aligned} \tag{3}$$

From the same:

$$V(y) = \frac{\sum(y)^2}{N} - (\frac{\sum y}{N})^2 \tag{4}$$

(III) Take Eq. (2), (3), (4) instead of (1), the correlation coefficient was shown as follow :

$$C_{xy} = \frac{N\times\sum(X\cdot Y) - (\sum X)\times(\sum Y)}{\{[N\times\sum(X^2) - (\sum X)^2]\times[N\times\sum(Y^2) - (\sum Y)^2]\}^{\frac{1}{2}}} \tag{5}$$