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NON-PARAMETER SYSTEM IDENTIFICATION OF ISOLATED BRIDGE BY NEURAL NETWORKS ALGORITHM

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ABSTRACT

The objective of this theme is to non-parameter identify and to compare the dynamic properties of the Lion-head river bridge located at Chia-I. The east bound of the bridge is designed and constructed as conventional, and the west bound as bridge isolated by lead-rubber bearings. Signals collected from the accelerometers installed on the bridge by the Central Weather Bureau will be processed. Back-propagation algorithm of Neural networks will be adopted and the nonlinear behavior of lead-rubber bearings will be simulated.

INTRODUCTION

Earthquakes occurred frequently due to Taiwan located between Eurasia plate and Philippine plate. The Central Weather Bureau equips the strong ground motion sensor for many bridges, and obtains much ground motion data. These data were measured by the bridges which equipped with accelerometers could analyses the responses of bridges. The responses of earthquakes could be predicted more accuracy result from these data which could be also utilized to identify the structural parameters.

The Lion-head river bridge which equipped with accelerometers connects to Chia-I, Taiwan, and the data were measured by accelerometers could be transferred to the useful data by high pass and low pass filter procedure. At first, using the earthquake data and the finite element analyses to create and train the Neural networks model might compare the simulation and practical results. Proving the non-parameter system identification method can represent the bridge structural response, and can detect the bridge structural characteristics changes.

The east bound of the bridge is designed and constructed as conventional, and the west bound of the bridge as bridge isolated by lead-rubber bearings. The instrument deployed diagram with the bridge is shown as Fig.1, and the five earthquake records information of the bridge is shown as Table 1.

BACK-PROPAGATION NEURAL NETWORKS

The feedforward, multilayered, supervised neural networks with the error backpropagation algorithm, the alleged backpropagation neural networks (BPNN), is by far the most commonly applied neural networks learning model owing to its simplicity. A general multiplayer feedforward network consists of an input layer, one or more hidden layers, an output layer and weight values. A neural networks with a hidden layer is shown in Fig. 2. [1] The basic structure is narrated as follows:

i Input layer:

In order to express the input variable of the network, the processing several elements would be depend upon the problems, the signal of the network would input from here, and among each artificial neuron would use linear activation functions.

ii Hidden layer:

In order to express the influence of each input element, the number of elements would be without any standard method, but usually would be decided the best numbers by try and error method, and among each artificial neuron would use nonlinear activation functions.

iii Output layer:

In order to express the output variable of the network, the processing several units would be depend upon the problems, the signal of the network would output from here, and among each artificial neuron would use nonlinear activation functions.

iv Weight value:

Generally speaking, the training final purpose of the neural networks is to get the best weight value. It is to make the particular relation between input layer and output layer.

The hidden layer of the neural networks model is represented in terms of a threshold type of nonlinear layer. In this paper, we considered Tan-Sigmoid Transfer function to represent the activity in this layer.

$$Y_j = \frac{e^{net_j} - e^{-net_j}}{e^{net_j} + e^{-net_j}} \quad (1)$$

APPRAISAL OF BACKPROPAGATION NEURAL NETWORKS

NN have many different types, all kinds of network is suitable for dealing with different problems. Back-propagation neural networks's advantage and shortcoming as follow:

i advantage of NNBP:

a. High precision learning;
b. Fast recall speed.

ii shortcoming of NNBP:

a. Low learning speed;
b. Virtual minimum convergence value.
c. The decisions of network structure and dynamic parameter lack the systematized method.

Levenberg - Marquardt learning algorithm (LM)

Gradient-based training algorithms are the basic theme commonly used by researchers and backpropagation is one of it, but they are not efficient. However, Newton algorithms, improved from Gradient-based algorithms, could converges quickly as the solution is approached. But it has to calculate complex Hessian Matrix. So, LM algorithm applies second order training procedure, it doesn't need to calculate complex Hessian Matrix, and use $\boldsymbol{G}=\boldsymbol{H}+\boldsymbol{\mu I}$ to solve the problems of Newton numerical analysis. If LM approaches Hessian Matrix $\boldsymbol{H}$, characteristic value $\{\lambda_1, \lambda_2, \ldots, \lambda_n\}$and characteristic vector $\{v_1, v_2, \ldots, v_n\}$, then:

$$Gv_i = [H + \mu I]v_i = Hv_i + \mu v_i = \lambda_i \mu_i + \mu v_i = (\lambda_i + \mu_i)v_i \quad (2)$$

Thus, $\boldsymbol{G}$ and $\boldsymbol{H}$ have the same characteristic vector, and $\boldsymbol{G}$ characteristic value is $(\lambda_i + \mu)$. When the value of μ increases, it will make all the value of $(\lambda_i + \mu)$ bigger than zero, $\boldsymbol{G}$ is positive definite and it will obtain $\boldsymbol{G}^{-1}$. From the above, we know that LM algorithm is also using the procedure of approaching Hessian Matrix, then the basic process of Newton algorithm can be written as:

$$\Delta x = \left[J^T J + \mu \quad I \right]^{-1} J^T E \quad (3)$$

where $\boldsymbol{E}$ is a vector of size n calculated as

$$E = [t_1 - y_1 \quad t_2 - y_2 \quad \ldots \quad t_n - y_n] \quad (4)$$

Here $\boldsymbol{J}^T \boldsymbol{J}$ is referred as the Hessian matrix. $\boldsymbol{I}$ is the identity matrix, μ is the learning parameter. For $\mu = 0$ the algorithm becomes Gauss-Newton method. For very large μ the LM algorithm becomes steepest decent or the error Backpropagation algorithm. The parameter is automatically adjusted at each iteration in order to secure convergence. The LM algorithm requires computation of the Jacobian Matrix $\boldsymbol{J}$ at each iteration step and the inversion of $\boldsymbol{J}^T \boldsymbol{J}$ Square Matrix.

APPLICATION AND ESTABLISHMENT OF NEURAL NETWORKS MODEL

Establishment

Using the neural networks toolbox in Matlab math software could easily build up the model. Unlike putting many commends in order to make the network function.

The LM-BPNN toolbox Establishing:

The structure of LM-BPNN is showing as the Fig. 3.In this paper we select several function to represent the diverse layer, snowing as follows:

Input layer applied *Linear Activation function*.
Hidden layer applied *Nonliner Activation function*.
Output layer applied *Linear Activation function*.
Performance function applied *Mean Square Error Method*.
Training function applied *TRAINLM Method.*
Adoption learning function applied *LEARNGDM Method.*

Training procedures:

Pre-procedure of the training data

To make neural networks training more sufficient, we need to do pro-procedure. The original data through normalization, its maximum value at +1 and minimum value at -1, so that the input value and objective value could be always within the range of +1, -1, and the related factor of normalized data could be remained. The factor will also be used to transform normalized data back to previous scale. Hence, the peak values of different data will be the same after normalized. The adoption of the model will be more flexible. There won't be missing peak value of simulation data. See Fig. 4.

Training details:

The numerical NN model used 3 points input data value (X, Y and Z axis) of the in input layer, used 10 neurons of the hidden layer, 2 points output data value (X and Y axis), and call it 3-10-2 model. The structure of Isolation bridge NN model would be depend upon the channel of the sensor at the bridge. The NN model structure of Sensor No.6 to Sensor No.9 of the east bound bridge is 2-10-1. The NN model structure of Sensor No.7 to Sensor No.10 of the west bound bridge is 2-10-2.

Training Analyzing

We will compare the output data with the target data by the regression analysis after NN model training. The Prostreg Function can be used to run linear regression analysis at Matlab software, and the result will come out the related factor R. R can represent the degree of similarity of the two datum.
If R = 1, it indicates that the output and target is perfect related. The result of NN model training R will be shown as Table 2, and Table 3.

If each R of each isolated bridge of NN model is greater than 0.82, then the NN models would be displayed as reliable training, which every R of every numerical bridge is greater than 0.9.

Simulation of Neural networks Model

After NN model training, we will utilize other four earthquakes records by putting them into simulation, and the output of NN model will be compared with the actual data after simulation. Using the same method of the Training Analysis, R is representing the degree of similarity of simulation data and exact record. The result of NN model training R would be shown as Table 4, and Table 5, and each time series fig shown as Fig. 5 to Fig. 8.

If each R of each isolated bridge of NN model is greater than 0.94, then the NN models would be displayed as reliable simulation, which every R of every numerical bridge is greater than 0.95.

Proving the non-parameter system identify method can represent the bridge structural response, and can predict the earthquake response in the future.

THE HILBERT-HUNG TRANSFORM ANALYZING OF THE SIMULATION DATA

In order to gain important information of earthquake records, we use Fourier Transform traditionally. With the development of information technology, all kinds of signal management technologies come into being and flourish in recent 20 years, such as Hilbert-Huang Transform.

A new Hilbert-Huang Transform (HHT)-based method for nondestructive instrument structure health monitoring is developed. The essence of the method is the newly developed HHT for nonstationary and nonlinear time series analysis, which consists of the empirical mode decomposition and Hilbert spectral analysis [2].

In this paper, we will use Fourier Transform and Hilbert-Huang Transform (HHT)-based method to analyzing the NN model simulation data and exact recode at frequency domain, and sown spectral as Fig. 9 to Fig. 15.

CONCLUSION

In this paper, we used the collecting code of the earthquake from the bridge at Lion-head River to proceed system identification and to approve the effect ion of neural networks when it is applied to the local data. The result shows:

1. The natural frequency of system identification is match with the exact value.
2. The phase and peak value of system identification of time-domain are approaching the exact signal.
3. The finite element model output data which creates neural networks model will have the same results of 1 and 2..
4. Using the pro-procedure could solve the problem of inaccurate peak value.

ACKNOWLEDGMENTS

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REFERENCES

[1] Deepak Mishra, Abhishek Yadav, Sudipta Ray, and Prem K. Kalra, 2005, "Levenberg-Marquardt Learning Algorithm for Integrate-and-Fire Neuron Model", Neural Information Processing - Letters and Reviews, Vol.9, No.2.

[2] Norden E. Huang and Samuel S. P. Shen, Pub: 9, 2005," Hilbert-Huang Transform and Its Applications", World Scientific Publishing Co., pp. 305-334.

Table 1. The five earthquake records information

data	***11/04/ 2001***	***11/24/ 2001***	***03/31/ 2002***	***05/15/ 2002***	***09/30/ 2002***
Intensity	***2***	***3***	***4***	***2***	***4***
Remark	***Sensor S3 Channel 07 is error record at the 11/04/2001 data.***				

Table 2. The training related factor R of Isolation bridge NN model

date	11/04/01	11/24/01	03/31/02	05/15/02	09/30/02
related factor R(E-W)	0.9620	0.8634	0.9259	0.9897	0.9399
related factor R(N-S)	0.8783	0.8257	0.9731	0.9934	0.9674

Table 3. The training related factor R of Numerical bridge NN model(train data: chichi Chy035 PGA 0.5g)

Bound of bridge	East Bound (Pot Bearing)	West Bound (Lead Rubber Bearing)
related factor R(E-W)	0.935	0.954
related factor R(N-S)	0.963	0.923

Table 4. The simulation related factor R of Isolation bridge NN model(NN model create by 11/04/01 data)

date	11/04/01	11/24/01	03/31/02	05/15/02	09/30/02
related factor R(E-W)	-	0.9782	0.9502	0.9791	0.9733
related factor R(N-S)	-	0.9632	0.9472	0.9699	0.9890

Table 5. The simulation related factor R of Numerical bridge NN model(train data: chichi Chy035 PGA 0.5g)

Bound of bridge	East Bound (Pot Bearing)		West Bound (Lead Rubber Bearing)	
Simu. data	03/31/02 PGA0.33g	09/30/02 PGA0.33g	03/31/02 PGA0.33g	09/30/02 PGA0.33g
related factor R(E-W)	0.9959	0.9682	0.9891	0.9790
related factor R(N-S)	0.9995	0.9965	0.9985	0.9890

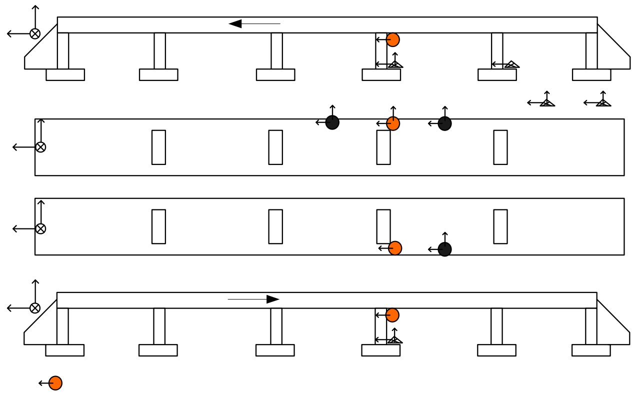

Fig. 1 The instrument deployed diagram

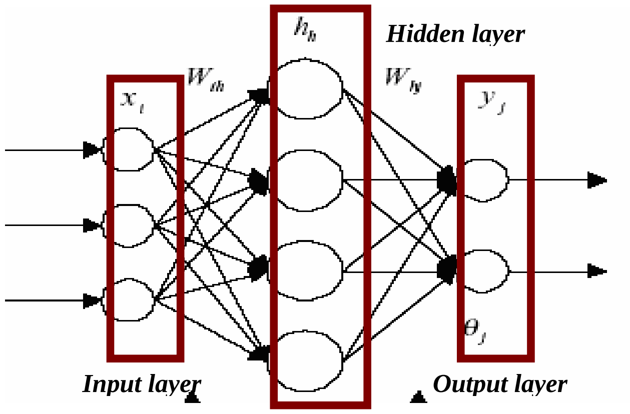

Fig. 2 Backpropagation neural networks sketch map

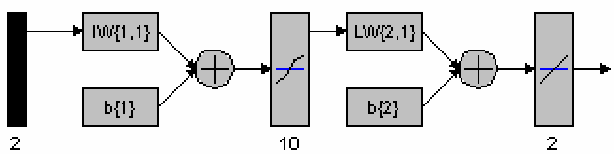

Fig. 3 The structure of LM-BPNN

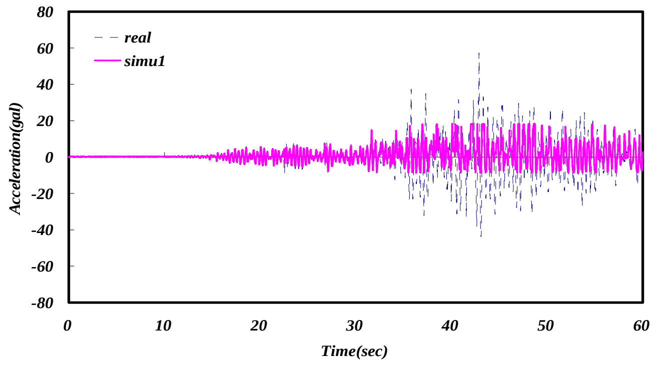

Fig. 4 The missing peak value of simulation data

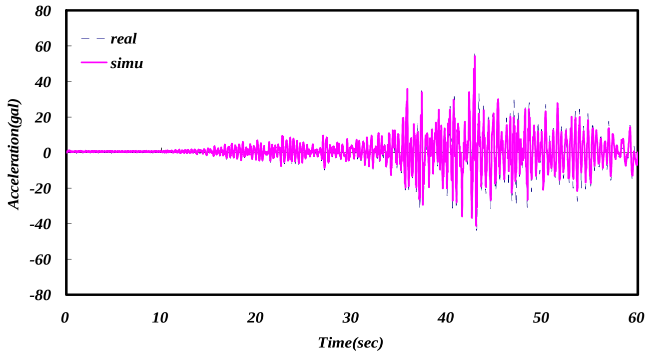

Fig.5 Time-History Comparison of Network Output (Solid Pink-Line) and Reference West Bound Bridge (Channel No.22) Response Accelerations (Dashed Blue-Line) (Train Model: 11/04/2001; Simulation Data: 03/31/2002)

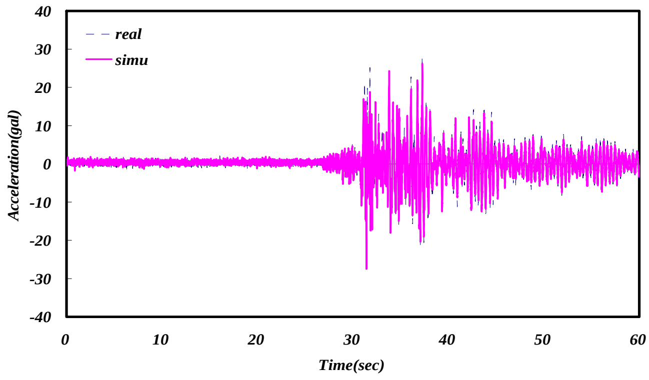

Fig.6 Time-History Comparison of Network Output (Solid Pink-Line) and Reference West Bound Bridge (Channel No.22) Response Accelerations (Dashed Blue-Line) (Train Model: 11/04/2001; Simulation Data: 09/30/2002)

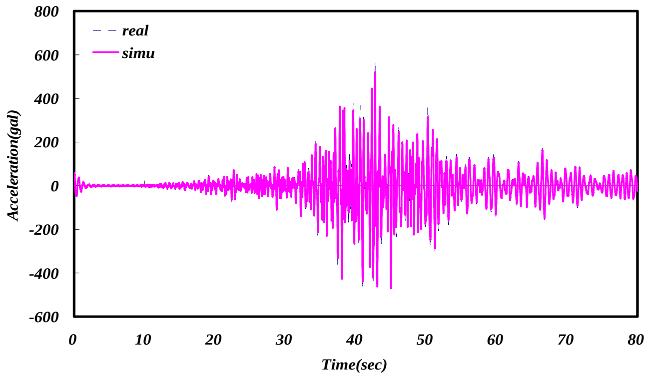

Fig.7 Time-History Comparison of Network Output (Solid Pink-Line) and Reference Numerical Output (E-W X Axial) Response Accelerations (Dashed Blue-Line) (Train Model: Chi-Chi Chy035 Data PGA 0.5g; Simulation Data: 03/31/2002 Data PGA 0.33g)

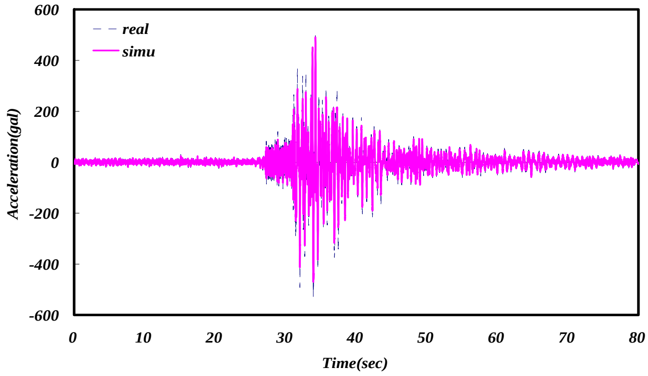

Fig.8 Time-History Comparison of Network Output (Solid Pink-Line) and Reference Numerical Output (E-W X Axial) Response Accelerations (Dashed Blue-Line) (Train Model: Chi-Chi Chy035 Data PGA 0.5g; Simulation Data: 09/30/2002 Data PGA 0.33g)

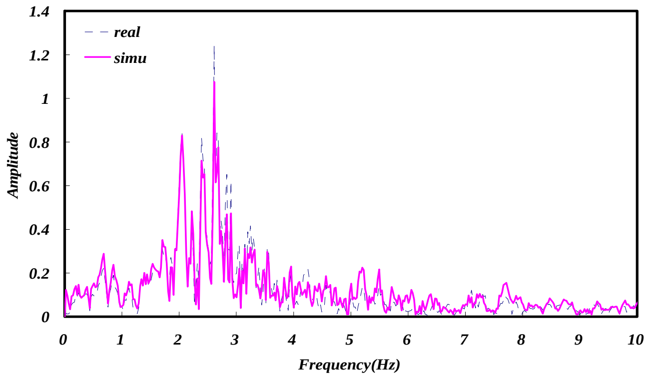

Fig.9 FFT Spectrum Comparison of Network Output (Solid Pink-Line) and Reference West Bound Bridge (Channel No.22) Response Accelerations (Dashed Blue-Line) (Train Model: 11/04/2001; Simulation Data: 03/31/2002)

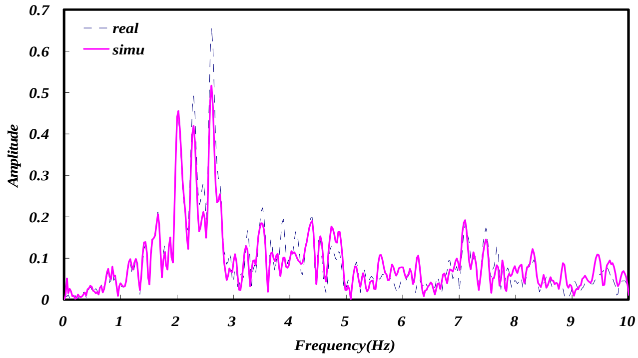

Fig.10 FFT Spectrum Comparison of Network Output (Solid Pink-Line) and Reference West Bound Bridge (Channel No.22) Response Accelerations (Dashed Blue-Line) (Train Model: 11/04/2001; Simulation Data: 09/30/2002)

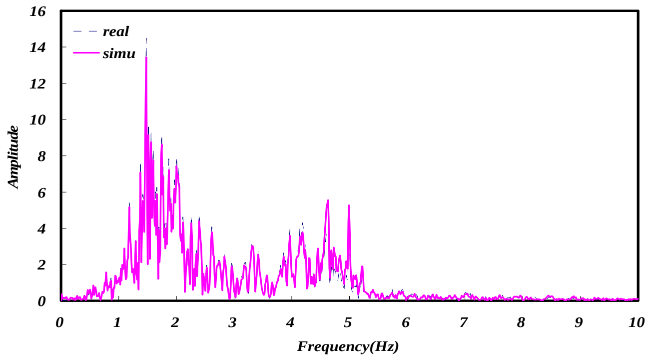

Fig.11 FFT Spectrum Comparison of Network Output (Solid Pink-Line) and Reference Numerical Output (E-W X Axial) Response Accelerations (Dashed Blue-Line) (Train model: Chi-Chi Chy035 Data PGA 0.5g; Simulation Data: 03/31/2002 Data PGA 0.33g)

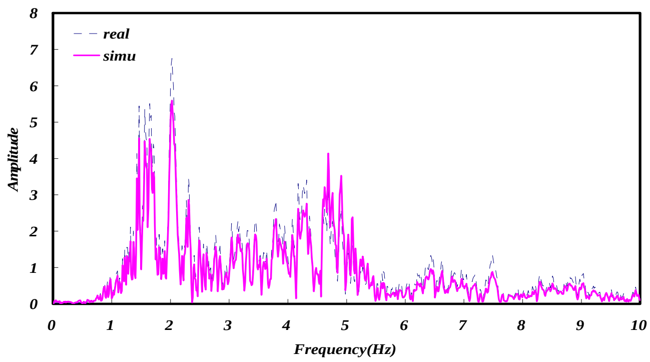

Fig.12 FFT Spectrum Comparison of Network Output (Solid Pink-Line) and Reference Numerical Output (E-W X Axial) Response Accelerations (Dashed Blue-Line) (Train Model: Chi-Chi Chy035 Data PGA 0.5g; Simulation Data: 09/30/2002 Data PGA 0.33g)

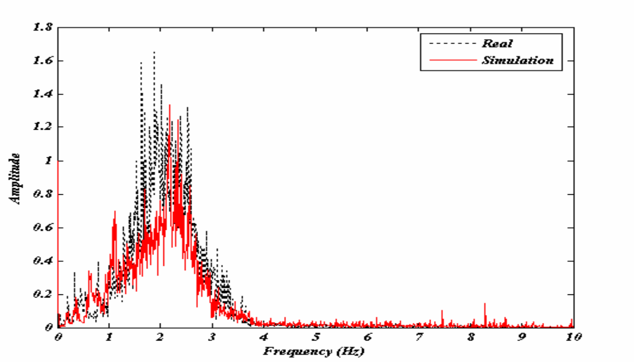

Fig.13 Marginal Hilbert Spectrum Comparison of Network Output (Solid Pink-Line) and Reference West Bound Bridge (Channel No.22) Response Accelerations (Dashed Blue-Line) (Train Model: 11/04/2001; Simulation Data: 03/31/2002)

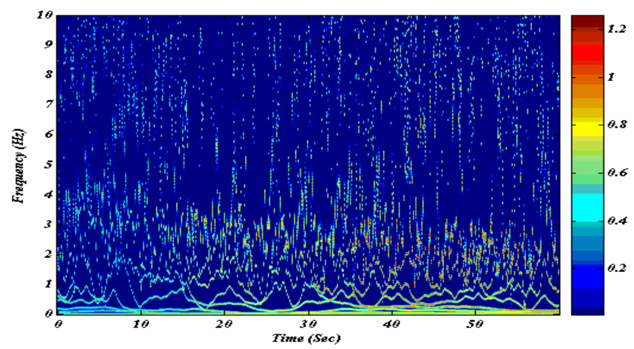

Fig.14 The Hilbert Spectrum of The West Bound Bridge Data (03/31/2002 Channel No.22) with 1024 frequency cells.

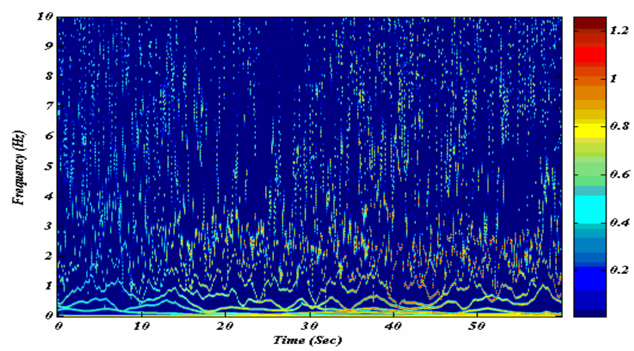

Fig.15 The Hilbert Spectrum of Network Output Data (Channel No.22) with 1024 frequency cells (Train Model: 11/04/2001; Simulation Input Data: 03/31/2002)