THE ESTABLISHMENT OF WIND SPECTRUM ESTIMATION MODELS FOR DOME-LIKE STRUCTURES USING ARTIFICIAL NEURAL NETWORKS

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Abstract: Wind tunnel test results of 35 dome models with rise/span ratio (*f/D*) from 0 to 0.5 and height/span ratio (*h/D*) from 0 to 0.5 in boundary layer flow with power law index 0.27 were collected. A wind pressure database for the dome-like roofs was established. The focus of the research reported in this paper was on the differences of wind pressure spectra on the meridian with the change of curvature and height. Random center selection method was used to write Radial Basis Function Neural Network (RBFNN) programs to train, validate and test the ANNs. Several network architectures, data processing and data grouping methods were investigated. The final estimation models found not only accurate but also theoretically consistent. Models were also compared with previous regression formula, and the results were much better. In the future, the ANN models will be implemented using a network platform and a simple web browser user interface. Wind pressure spectra calculated by the server can be easily obtained with simple parameter inputs, which can be used as preliminary estimations before wind tunnel tests.

Keywords: ANN, RBFNN, wind engineering, wind pressure spectrum, hemispherical dome, large span structure

1 INTRODUCTION

Wind resistant design of buildings often needs to acquire wind spectra from wind tunnel tests. Using regression formulas to process and analyze experimental data of wind spectra usually is not very accurate. Therefore, one of the most important issues is how to use experimental wind load aerodynamic database more effectively.

The development of wind load estimation models for high-rise buildings using artificial neural networks (ANNs) has already been studied by the Wind Engineering Research Center of Tamkang University (WERC-TKU) for a long time. However, no comprehensive research about dome structures using ANNS has been conducted. Only a large-span research project in 2011 conducted by research assistant Hsin-Chieh Chung trained ANNs for the predictions of wind spectra of fixed shape dome, which examined the axis and circle relation to coherence wind spectra. Never the less, there are a lot of rooms for further development of the estimation models for different shapes of domes.

In this study, the wind pressure database of dome models that established by Dr. Yuan-Lung, Lo was used. Wind tunnel tests of 35 models with rise/span ratio (*f/D*) from 0 to 0.5 and height/span ratio (*h/D*) from 0 to 0.5 were conducted in boundary layer flow with power law index 0.27. Comparing with the data that used by Hsin-Chieh Chung, the focus was more on the differences of wind pressure spectra on the meridian with the change of curvature and height.

Random center selection method was used to write Radial Basis Function Neural Network (RBFNN) programs to train, validate and test the ANNs. Several network architectures, data processing and data grouping methods were investigated. The final estimation models found not only accurate but also theoretically consistent. Models were also compared with previous regression formula, and the results were much better.

In the future, the ANN models will be implemented using a network platform and a simple web browser user interface. Wind pressure spectra calculated by the server can be easily obtained with simple parameter inputs, which can be used as preliminary estimations before wind tunnel tests.

In the following sections, we explain the wind pressure data characteristics and classification, present the ANN learning algorithm and parameter settings of the RBFNNs used, and discuss the results and future researches.

2 RESEARCH BACKGROUNDS

2.1 Previous Researches

Larg span building strucutures have been widely adapted these days, and dome-like roof is a design commonly used. Spectrum characteristics of wind pressures have been focused as an important investigation subject in estimating wind loads and mentioned in several publications (Ogawa et al., 1991; Uematsu et al., 1997 and 2008; Li et al., 2006). Many other researches regarding the dome-like roofs have also been done in various aspects (e.g., Maher, 1965; Letchford and Sarkar, 2000; Taylor, 1991; Cheng and Fu, 2010; Qiu et al., 2010 and 2014).
However, there is no systematic discussion in terms of basic parameters, such as the ratio of roof rise to roof span, the ratio of base wall height to roof span, or the location over the surface.

Artificial neural network is an approach to simulate or predict the results of complex domain by using similar (but highly simplified) models of the biological structures found in human brain. Training ANNs with existing cases with reasonable answers can deduct multivariable nonlinear models to simulate or predict the results of similar problems. Artificial neural networks have been used by several researchers as a computational method to predict wind coefficients and spectra as well as interference effects of adjacent buildings (e.g., Chen et al., 2003; English and Fricke, 1999; Huang and Gu, 2005; Khanduri et al., 1997; Zhang and Zhang, 2004; Cheng et al., 2007; Wang and Cheng, 2010, 2011 and 2015). However, not many ANN related applications have been done in dome-like structures.

2.2 Wind Tunnel Tests

Systematic wind tunnel tests of pressure measurements are conducted in a wind tunnel with the cross section of 12.5 m in length, 1.8 m in height and 1.8 m in width. A turbulent boundary layer flow is simulated by properly equipped spires and roughness blocks. The normalized mean wind velocity profile is fitted by the power law with index α = 0.27 and the turbulent intensity varies from 18% to 23% at model height ranges.

Testing models are manufactured by two parts, the acrylic roof model and the acrylic circular base model. The geometric size of the former is adjusted by the rise/span ratio (*f/D*) and the latter is by the height/span ratio (*h/D*). Both models are combined arbitrarily to give in total 35 cases of testing models. Figure 1 shows the geometric definition and Table 1 lists the case names of 35 models.

The total pressure tap numbers on the meridian line for different models are slightly different due to the curvature change. For the B and C series, the total tap numbers are 27. Otherwise, 29 taps were used for all the other models.

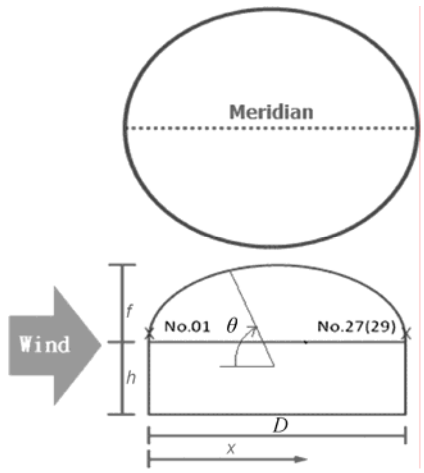

Figure 1. Geometric nomenclature and coordinate system

Table 1. Case names of the 35 testing models

f/D \ h/D	0.0	0.1	0.2	0.3	0.4	0.5
0.0	--	B0	C0	D0	E0	F0
0.1	A1	B1	C1	D1	E1	F1
0.2	A2	B2	C2	D2	E2	F2
0.3	A3	B3	C3	D3	E3	F3
0.4	A4	B4	C4	D4	E4	F4
0.5	A5	B5	C5	D5	E5	F5

2.3 Wind Pressure Characteristics on Dome Roof

Instantaneous pressures on the model surface were scanned and normalized. The mean and RMS values were then estimated to examine the basic aerodynamic characteristics. The ensemble averages of mean and RMS pressure coefficients along the central meridian line of all cases were plotted and analized. Some consistent characteristics can be pointed out in terms of *f/D* and *h/D*, which may help the ANN estimations of power spectra in the following section.

Power spectrum of fluctuating pressures at each tap is estimated and ensemble averaged. For example, Figure 2 shows the F5 case of reduced power spectra along the central meridian line in elevation angle (θ) order. From the figure, it is clearly indicated that the spectrum characteristics gradually changes from upstream to downstream. Several signatures may be identified for describing their spectrum characteristics.

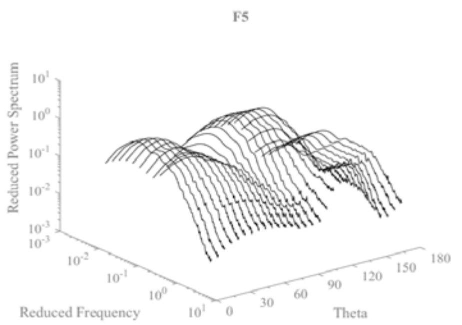

Figure 2. Reduced power spectra along the central meridian line for the F5 model

3 ANN FORMULATION

This section explains several important issues regarding ANN simulation of the reduced power spectra along the central meridian line.

3.1 Data Selection and Proccessing

The data used to train, simulate and validate the spectra were selected from 20 dome models with *f/D* = 0.2, 0.3, 0.4, 0.5 and *h/D* = 0.1, 0.2, 0.3, 0.4, 0.5. They are the cases indicated with shaded background in Table 1. The cases of *f/D* = 0.0 and 0.1 are not included to avoid the bias due to the separation in the frontal sharp edge.

The total number of data points for each of the original spectrum is 4095; the reduced frequencies are from 0.01 to 23. To reduce the burden of computing resource and speed up the ANN training process, only 1523 data points were selected (frequency from 0.0112 to 8.5).

Different from previous ANN spectrum trainings conducted at WERC-TKU, unsmoothed spectrum data were deliberately used this time to investigate their influence on ANN prediction outcomes.

3.2 Network Architecture

Radial Basis Function Neural Network (RBFNN) is chosen for its good performance in comparison with all other ANN models. The keys to keep the accuracy of a RBFNN are the size of the hidden layer, the radial basis function and the number of center points. In this research, the Gaussian function is assumed for the radial basis function for our RBFNN, defined by Eq. 1.

$$\phi\left(\left\|x^{*}-c\right\|\right)=\exp\left(-\frac{\left\|x^{*}-c\right\|^{2}}{2\sigma_{c}^{3}}\right) \qquad (1)$$

where σ_c is the standard deviation of the distance between centers; $\|x^{*}-c\|$ is the Euclidean distance between x^{*} and c. The neuron centers of the RBFNN are selected randomly and the number of center points is determined using a gradually increasing algorithm based on the calculation of root-mean-square estimate (RMSE), which uses fewer center points at first, and gradually increase the number of center points until no obvious improvement in the overall RMSE.

The RBFNN program, used for training, simulation and plotting, was implemented in MATLAB. Figure 3 shows the architecture diagram of the RBFNN. The input layer includes five variables as shown in Table 2, and the output layer has one output variable, which is the spectrum value at the corresponding reduced frequency. Table 2 lists the training and validation cases, and the properties of the variables.

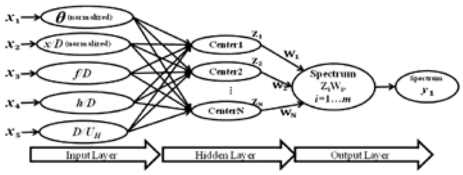

Figure 3. RBFNN Architecture for pressure spectra estimation of dome-like roofs

Note that, the location of a pressure tap on the meridian line of the dome roof can be defined either by *x/D* or *θ*. The two variables are not fully independent. However, the trained networks of using only one of them at the beginning of the research yielded unstable results. After testing different combinations of input variables, the five input variables selected in Figure 3 and Table 2 gave best answers. Another important issue is the normalization of the input variables. This particular experience tells us that ANN training results are very sensitive to the magnitude of elevation angle *θ*, which is currently set as its radian value times 7.

Table 2. RBFNN schema settings

Input Variables (normalization schema)	θ	0 ~ π (× 7)
	x/D	0 ~ 1 (× 0.3)
	f/D	0.2 ~ 0.5
	h/D	0.1 ~ 0.5
	nD/U_H	0.0112 ~ 8.5
Output Variable	Spectrum Value	
Training Cases	C1, C3, C5, D1, D3, D5, E1, E3, E5, F1, F3, F5	
Validation Cases	C2, C4, D2, D4, E2, E4, F2, F4	

3.3 Data Grouping

At the initial stage of the research, the simulation of spectra at the low frequency section is usually bad. Given more data point using interpretation did not improve the situation as before. Further, to correctly predict the two humps shown in low-frequency and high-frequency energies, the input variable, reduced frequency, is divided by a selected threshold value, 0.3, into two sections for ANN training and prediction. That is, the data were divided into two groups for every spectrum, and two RBFNNs were trained separately for the two sections. There are 9 overlapping points in the two sections. When the ANNs are used for simulation, the spectra are connected together using data smoothing technique over the 9 points to ensure the appearance of a smooth spectrum curve.

Based on the aerodynamic behaviour and observation of the experimental results, the roof surface can be categorized into three regions, windward, separation and wake region. Pressure spectra located at the same region present similar characteristics. With this concept in mind, spectrum data can be further grouped for training to improve the accuracy of our ANNs.

After numerous trials and network parameter adjustments, we formulated 11 neural networks, 5 for the low-frequency range and 6 for the high frequency range of spectra, for the full coverage of the problem scope. Table 3 lists the application region of each of the ANN. The grouping method is different between low and high frequency range. It is because the numbers of data points in the two frequency range are different and the numbers of pressure taps in different region are also different. The total number of data points has to be adequate when training a neural network. Too few, the network cannot converge. Too many, it becomes slow and sometimes lost accuracy. On the practical side, we want to keep the number of ANNs down for better usability. Complicated grouping is a compromise between accuracy and various reasons mentioned above.

Table 3. RBFNNs trained for pressure spectra estimation of dome-like roofs

Low frequency range ($nD/UH < 0.3$)	High frequency range ($nD/UH \geqslant 0.3$)
Windward region (0° ~ 80°)	Windward region (0° ~ 80°)
Separation region 1 (80° ~ 90°)	Separation region 1 (80° ~ 85°)
	Separation region 2 (85° ~ 90°)
Separation region 2 (90° ~ 130°)	Separation region 3 (90° ~ 110°)
	Separation region 4 (110° ~ 130°)
Wake region 1 (130° ~ 150°)	Wake region (130° ~ 180°)
Wake region 2 (150° ~ 180°)	

4 NETWORK TESTING AND DISCUSSION

In this section, a case (*f/D* = 0.25 & *h/D* = 0.45) is given below to test the spectrum estimation capability of the ANNs developed. Figure 4 shows the power spectrum predicted by ANN at roof location No. 1 compared with 4 adjacent cases, C4, C5, D4 and D5. For the same case, the power spectrum at tag location No. 25 is shown in Figure 5.

The red dotted lines in the two figures are the ANN estimated spectra, which are conservatively located within the boundary of the results of the neighbouring cases that have wind tunnel test data. All the 29 tag locations of this case have been checked with similar results. 11 other cases that given in between wind tunnel experimental *f/D* and *h/D* have also been examined and the outcomes are satisfactory.

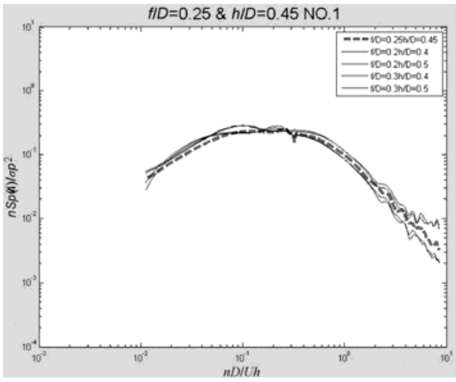

Figure 4. ANN tested for f/D=0.25 & h/D=0.45 at tag location No. 1 with 4 similar cases

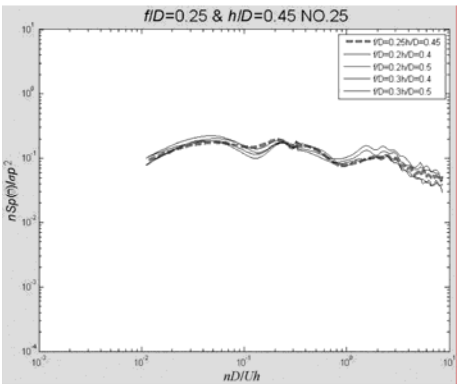

Figure 5. ANN tested for f/D=0.25 & h/D=0.45 at tag location No. 25 with 4 similar cases

5 CONCLUSIONS

In this study, power spectra of fluctuating wind pressures on various dome-like roofs were investigated under a suburban terrain flow. By examining the mean and RMS pressure coefficients, basic flow patterns were demonstrated in terms of the rise/span and height/span ratios.

The technology of artificial neural network was then proposed to simulate the variations of power spectra of fluctuating pressures over the dome-like roofs. Taking 20 experimental models out off the 35 in the database, 12 cases were used to train our ANNs and 8 were taken as validation cases. Based on our previous experiences, Radial Basis Function Neural Network (RBFNN), which delivered very good performance simulating wind force coefficients and spectra in our previous researches, was chosen. After the initial struggle, RBFNN performed equally well this time. 11 RBFNNs were trained to simulate pressure spectra along the meridian line of dome-like roofs with accurate results. Preliminary tests indicated that the ANN prediction model is consistent and provides better agreements with the empirical results than the previous regression formulas.

What is different from previous efforts can be listed as follows:

(1) Smoothed data were always used in the pass for ANN simulation of wind spectra. This is the first time unsmoothed data was used and the prediction results are unaffected. The tendency, continuity and accuracy agree with the original experimental spectra well.

(2) Not only data was divided into different training groups according to the aerodynamic characteristics of different flow fields along the meridian line but also every spectrum was divided into two sections for training. The sophisticated data classification strategy is unique to this study and improved the accuracy of our ANN model dramatically, which can be adopted in similar future researches.

(3) Input variable normalization schema is surprisingly influential to the accuracy of the result, which needs more investigation.

The preliminary assumptions and the selection of basis function may be adjusted in the future to reduce the parameters for each network layer. From the viewpoint of average structural engineers, the aerodynamic database based ANN models are a convenient and practical tool if an easy-to-use GUI can be provided.

Nevertheless, it is worth mentioning that, one turbulent flow simulated in this research may limit the practical application of the proposed ANN model. It is expected in the near future to include different flow conditions and more testing models.

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