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ANN-Based Modelling and Estimation of Wind Pressure Spectra for Hemispherical Dome Roofs

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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 hemispherical dome roofs was established. The emphases of the research were on the study of wind pressure spectra on the meridian with the change of curvature and height as well as the establishment of an ANN-based prediction model. 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 are very accurate comparing to previous regression formulas.

Introduction

Large span roof structures have been widely adopted for their good performance in multiple functionalities and providing innovative ideas for exterior designs. Among these structures, hemispherical dome roof is one of the common types, which is often seen in agricultural storages, stadiums, oil/gas tanks, and so on. However, because of the light-weighted feature, its wind resistant design is usually more critical than earthquake design. Further, the long-span appearance often results in a weak spatial correlation in pressure distributions and hence makes the estimation of wind loads a difficult task.

Spectrum characteristics of wind pressures have been focused as an important investigation subject in estimating wind loads and mentioned in several publications [1~3]. Various aspects of hemispherical dome roofs have also been studied by many researchers. For instance, the effect of surface roughness on the drag and lift forces [4, 5], the Reynolds number effect on basic aerodynamic parameters [6~8], and the aerodynamic database construction for computer-assisted wind load evaluation of domes [9] were carried out for further understanding.

Artificial neural network (ANN) 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. ANNs have been used by several researchers as a computational method to predict wind coefficients and spectra as well as interference effects of adjacent buildings [10~16]. However, not many ANN related applications have been done in dome-like structures except [9].

The development of wind load estimation models for high-rise buildings using artificial neural networks has already been studied by the Wind Engineering Research Center of Tamkang University (WERC-TKU) for a long time [14~16]. 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 paper, power spectra of fluctuating wind pressures on various hemispherical dome roofs were investigated under a suburban terrain flow. By referring to the weighting factor concept proposed by Uematsu et al. [2], the regression approximation of power spectra along the surface was conducted. To provide a more practical tool for engineers, ANN-based modelling was attempted. 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 compare the results of the two approaches.

Wind Tunnel Tests

Systematic wind tunnel tests of pressure measurements were 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 was simulated by properly equipped spires and roughness blocks. The normalized mean wind velocity profile was fitted by the power law with index $\alpha = 0.27$ and the turbulent intensity varies from 18% to 23% at model height ranges.

Testing models were 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 were combined arbitrarily to give a total of 35 testing cases. Figure 1 shows the geometric definition and Table 1 lists the case names of the 35 models.

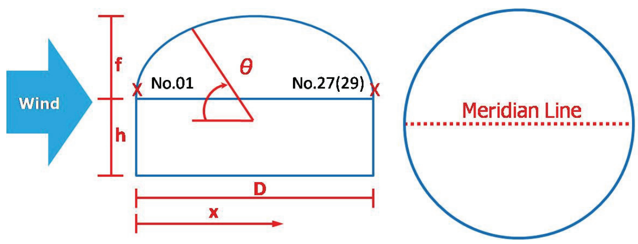


Figure 1. Geometric nomenclature and coordinate system

h/D \ f/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

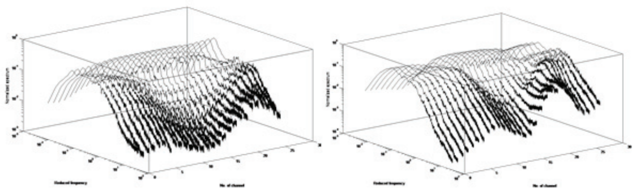
Table 1. Case names of the 35 testing models

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.

Wind Pressure Spectra on Dome Roofs

Instantaneous pressures on the model surfaces 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 analyzed. 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 was estimated and ensemble averaged. For example, Figure 2 shows the reduced power spectra of case C2 and F5 along the central meridian line from tap 1 to 27 (to 29 in the case of F5). 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.



(a) C2 (b) F5

Figure 2. Reduced power spectra along the central meridian line for the C2 and F5 model

Approximation Formula Approach

Approximation formula for circular flat roofs proposed by Uematsu et al. [2] is adopted. In this study, the quadratic form is replaced by a linear form for simplicity and the values of turbulence intensity and length scale are found from experimental results. Based on these assumptions, approximation model for hemispherical dome roofs is proposed by adopting the weighting factor concept as

$$S_p(n) = \kappa_t S_t(n) + \kappa_s S_s(n) + \kappa_w S_w(n) \qquad (1)$$

$$\kappa_t + \kappa_s + \kappa_w = 1 \qquad (2)$$

where

$$S_t(n) = \alpha_t\left\{\rho^2 U_H^2 S_k(n)\right\} \qquad (3)$$

$$\frac{nS_s(n)}{\frac{1}{2}\rho U_H^2} = \alpha_s\left(\frac{nD}{U_H}\right)\left[1+\beta_s\left(\frac{nD}{U_H}\right)^2\right]^{\gamma_s} \qquad (4)$$

$$\frac{nS_w(n)}{\frac{1}{2}\rho U_H^2} = \alpha_w\left(\frac{nD}{U_H}\right)\left[1+\beta_w\left(\frac{nD}{U_H}\right)^2\right]^{\gamma_w} \qquad (5)$$

κ_t, κ_s and κ_w are weighting factors; α_t is a parameter fitted for equation (3) describing the oncoming wind signature; α_s, β_s and γ_s are parameters fitted for equation (4) describing the low-frequency hump near the dome top; α_w, β_w and γ_w are parameters fitted for equation (5) describing the high-frequency hump near the separation. Equation (3) is suggested by an admittance function multiplied by Karman type spectrum. Equation (4) and (5) are in a non-Gaussian form of spectra.

In general, a fairly good agreement can be concluded for the simulations of B0 - F5 cases using the approximation formulas. The variations of turbulence energies from upstream to downstream are described in both qualitative and quantitative way. Details of the fitting model and comparison results can be found in [17].

ANN Formulation

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

Data Selection and Processing

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 original data points for a single 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.

Network Architecture

Radial Basis Function Neural Network (RBFNN) is chosen for its good performance in comparison with all other ANN models. The keys to achieve high accuracy RBFNNs are the size of the hidden layer, the radial basis function and the number of center points. In this research, the Gaussian function is adopted for the radial basis function for our RBFNN, defined by equation (6).

$$\phi\left(\left\|x^* - c\right\|\right) = \exp\left(-\frac{\left\|x^* - c\right\|^2}{2\sigma_c^{\,3}}\right) \qquad (6)$$

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 error (RMSE), which uses fewer center points at first, and gradually increase the number of center points until no obvious improvement in the overall RMSE.

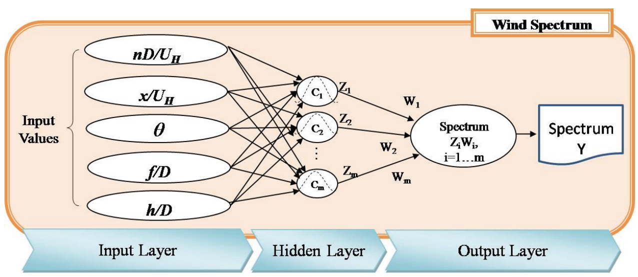


Figure 3. RBFNN Architecture for pressure spectra estimation of hemispherical dome roofs

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.

Input Variables (normalization schema)	θ	$0 \sim \pi$ (× 7)
	x/D	$0 \sim 1$ (× 0.3)
	f/D	$0.2 \sim 0.5$
	h/D	$0.1 \sim 0.5$
	nD/U_H	$0.0112 \sim 8.5$
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	

Table 2. RBFNN schema settings

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.

Data Grouping

At the initial stage of the research, the simulation of spectra at the low frequency section is usually bad. Given more data points using interpolation did not improve the situation as previously encountered. 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 behavior and observation of the experimental results, a 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 accuracy of our ANNs.

Low frequency range ($nD/U_H < 0.3$)	High frequency range ($nD/U_H \geq 0.3$)
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°)	

Table 3. 11 RBFNNs trained for pressure spectra estimation of hemispherical dome roofs

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.

For all the training and validation cases, all the simulation results of power spectra at all tag locations have been checked, and the accuracy are very good. 11 other cases that given in between wind tunnel experimental f/D and h/D have also been examined and the outcomes are satisfactory as well. Please refer to Wang et al. [17] for detailed descriptions.

Results Comparison

Predictions based on ANN approach are compared with the approximation formula model and experimental results in Figure 4. From the four examples plotted in Figure 4, it shows that the approximation formula by equation (1) provides generally good agreements of the turbulent signatures at low and high reduced frequency ranges although not always matched precisely.

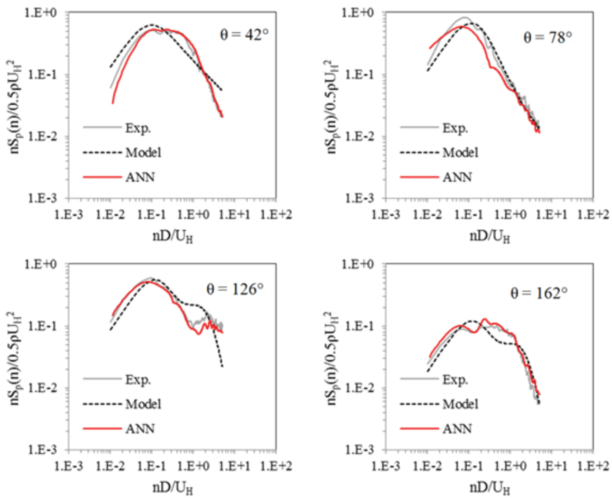


Figure 4. ANN prediction, approximation formula and experiential spectra of the F4 validation case at 4 different tap locations

Low frequency range		High frequency range	
ANN region	rmse	ANN region	rmse
Windward region	0.2364	Windward region	0.2064
Separation region 1	0.1889	Separation region 1	0.2028
		Separation region 2	0.1876
Separation region 2	0.1804	Separation region 3	0.1959
		Separation region 4	0.1961
Wake region 1	0.2198	Wake region	0.1841
Wake region 2	0.2115		

Table 4. The root mean squared errors (averaged over all tap locations in an ANN) of the 11 RBFNNs for the validation case F4

On the other hand, the ANN approach provides even better agreements with wind tunnel results with very high accuracy. ANN prediction results of other model cases, which are not shown here, also give almost equally good agreement as Figure 4. Table 4 lists the average errors of F4. However, ANN approach relies on large amount of experimental data to select enough training and validation data sets. It also requires complicated selection and organization of input parameters as well as fine tuning of the parameters and network architecture; therefore, for the initial estimation of fluctuating turbulence, approximation formula models based on reasonable assumptions are very desirable.

Conclusions

In this study, power spectra of fluctuating wind pressures on various hemispherical dome 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 hemispherical dome roofs. 20 experimental models were selected from 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 prior researches [14, 15], 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 hemispherical dome roofs with accurate results. Preliminary tests indicated that the ANN prediction model is consistent and provides better agreements with the experimental results than the previous regression formulas. However, complete quantitative comparison over all the tap locations needs to be done to draw final conclusions.

The regression formulas are theoretical understandable but complicated. On the contrary, the ANN simulation model is accurate and straightforward. 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. Therefore, the ANN model is being 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.

What is different from previous efforts in terms of ANN application can be listed as follows: (1) Smoothed data were always used in the pass for ANN simulation of wind spectra. (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. (3) Input variable normalization schema is surprisingly influential to the accuracy of the result, which needs more investigation.

In the future, the preliminary assumptions and the selection of basis function may be adjusted to reduce the parameters for each network layer. Nevertheless, it is worth mentioning that, one turbulent flow simulated in this research may limit the practical application of the proposed ANN model. Different flow conditions and more testing models will be included next.

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