FORMULATION OF ESTIMATION MODELS FOR WIND FORCE COEFFICIENTS OF RECTANGULAR SHAPED BUILDINGS

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ABSTRACT

In wind-resistant design of structures, the calculation of wind coefficients is usually based on data from wind tunnel tests. The process is very time-consuming and expensive. In order to formulate a model to estimate wind force coefficients of rectangular buildings, various methods including regression analysis and artificial neural networks (ANNs) were investigated. This paper focuses on the presentation of the various approaches with emphasis on the detailed result comparisons and discussions of models developed for alongwind, acrosswind and tortional wind coefficient predictions.

KEYWORDS: WIND FORCE COEFFICIENTS, REGRESSION, ARTIFICIAL NEURAL NETWORKS, AERODYNAMIC DATABASE

Introduction

The wind tunnel measurements and their analysis of various generic building shapes have been performed at Wind Engineering Research Center of Tamkang University (WERC-TKU) to construct an aerodynamic database [Cheng et al. (2008)]. Total of 150-plus building shapes were studied. The wind force coefficients and reduced force spectra in the alongwind, acrosswind and torsional directions of earlier models were measured through HFFB, whereas later were measured through multi-channel electronic pressure scanning system.

Sharing the same goal of similar researches that predict wind coefficients for buildings such as [Bitsuamlak et al. (1999), Chen et al. (2003)] etc., this research selected pressure measurements of several models in the WERC aerodynamic database to investigate the prediction of wind force coefficients. A total of 135 wind tunnel experiment data sets as described in Table 1 were used. The coefficients investigated and their abbreviations are listed in Table 2.

Table 1: Wind tunnel test data selected

Model Cross-section	Square and Rectangular
Terrain Exposure	A, B, C (α =0.32, 0.25, 0.15)
Side Ratio (D/B)	0.2, 0.25, 0.33, 0.5, 1.0, 2.0, 3.0, 4.0, 5.0
Aspect Ratio (H/ $\sqrt{BD}$)	3, 4, 5, 6, 7

Table 2: Wind force coefficient abbreviations

Wind Coefficient Description	Abbreviation
alongwind mean coefficient of base shear	*Cd*
alongwind RMS coefficient of base shear	*Cdd*
acrosswind RMS coefficient of base shear	*Cld*
alongwind mean coefficient of base moment	*Cdm*
alongwind RMS coefficient of base moment	*Cdmd*
acrosswind RMS coefficient of base moment	*Clmd*
RMS coefficient of base torsion	*Ctd*

To formulate a model to estimate wind force coefficients of rectangular buildings, two regression analysis methods, namely polynomial regression and nonlinear regression, were used to compare the results at first. In addition, ANNs were used as well to train, simulate and forecast wind coefficients using terrain, side ratio (D/B) and aspect ratio (H/B) as inputs. The neural networks used include BP (Back Propagation), RBF (Radial Basis Function) and GR (General Regression) neural networks. According to the results of the investigation presented in this paper, RBF neural network is the most effective mean to predict wind coefficients. The final formulation trained three RBF neural networks to estimate alongwind, acrosswind and tortional wind coefficients respectively.

Initial Investigation

At the preliminary stage of this research, alongwind mean coefficient of base shear *Cd* is used as an indicator for selection of the final estimation method. Two regression methods and three neural network methods were used for the forecast of *Cd*. In order to yield better results, data grouping strategies, as described in Table 3, were studied as well.

Table 3: Data grouping methods for *Cd*

Name	Data Grouping	Application
Aspect Ratio Series	3 terrains and 9 side ratios to form 27 sets	polynomial regression
Side Ratio Series	3 terrains and 5 aspect ratios to form 15 sets	polynomial regression
Terrain Series	3 terrains to form 3 sets	nonlinear regression & neural networks
No Grouping	All data in a set	nonlinear regression & neural networks

Regression Analysis

The fitting results, root mean square errors (RMSE) and the maximum errors of the applications in Table 3 are summarized in Table 4 to 6. All the analyses were performed using MATLAB’s build-in regression analysis functions. Note that the aspect ratio, signified as H/B, in the equations is actually $H/\sqrt{\mathrm{BD}}$.

Table 4: Polynomial regression
(needs 27 equations for the H/B series and 15 equations for the D/B series)

Polynomial Regression	RMSE	Max. Error (%)
$C_d = p_1(H/B) + p_2$	0.0209	3.79
$C_d = p_1(D/B) + p_2$	0.3899	118.7

Table **5**: Nonlinear regression (terrain series, one equation for each terrain)

Terrain	Nonlinear Regression	RMSE	Max Error (%)
A	$Cd = 0.9469 \times (D/B)^{-0.9368} - 0.0309 \times (D/B)^{-2.541} \times (H/B)^{0.0799} + 0.1879$	0.091	12.92
B	$Cd = -62.6962 \times (D/B)^{0.0195} - 1.6082 \times (H/B)^{-1.4031} + (D/B)^{0.5744} \times (H/B)^{-0.1149} + 63.204$	0.094	12.46
C	$Cd = -0.0527 \times (D/B)^{-2.1419} + (D/B)^{-0.8133} \times (H/B)^{0.0508} + 0.1238$	0.131	16.54

Table 6: Nonlinear regression
(no grouping, one equation for different terrains, aspect and side ratios)

Nonlinear Regression	RMSE	Max. Error (%)
$Cd = -15.9538 \times (\alpha)^{-0.0339} + 57.3295 \times (D/B)^{-0.0163} - 22.7639 \times (H/B)^{-0.0186} + 0.17 \times (\alpha)^{-0.0834} \times (D/B) - 0.0039 \times (D/B) \times (H/B) - 0.9652 \times (\alpha) \times (H/B)^{0.5736} - 16.8512$	0.098	19.65

ANN Wind Coefficient Predictions

Three different neural network architectures were used, namely BP (Back Propagation), RBF (Radial Basis Function) and GR (General Regression) to forecast *Cd*. All the training and testing were performed using MATLAB's neural network toolbox, and the results are shown in Table 7 and 8. The inputs of the networks in Table 7 are aspect and side ratio and an additional input, terrain, is added for the networks in Table 8. All the ANN output is *Cd*.

Table 7: Errors of neural network estimations
(terrain series, one network for each terrain)

Back Propagation Neural Networks (BPNN) Neuron Center (NC)=2			
Terrain	RMSE	Max. Error (%)	
		Training	Validation
A	0.096	14.535	13.348
B	0.063	12.382	12.660
C	0.097	11.519	10.836
Radial Basis Function Neural Networks (RBFNN) GOAL=0.1 SPREAD=1.105~1.2			
Terrain	RMSE	Max. Error (%)	
		Training	Validation
A	0.038	6.120	5.771
B	0.042	4.878	4.727
C	0.058	6.484	5.476
General Regression Neural Networks (GRNN) SPREAD=0.1			
Terrain	RMSE	Max. Error (%)	
		Training	Validation
A	0.089	8.760	9.625
B	0.053	5.556	6.121
C	0.053	6.445	12.399

Table 8: Errors of neural network estimations
(no grouping, one network for all terrain)

Back Propagation Neural Networks (BPNN) Neuron Center (NC)=3		
RMSE	Max. Error (%)	
	Training	Verification
0.0974	14.0648	12.2302
Radial Basis Function Neural Networks (RBFNN) GOAL=0.2 SPREAD=1.2		
RMSE	Max. Error (%)	
	Training	Verification
0.0464	6.9680	8.3138
General Regression Neural Networks (GRNN) SPREAD=0.1		
RMSE	Max. Error (%)	
	Training	Verification
0.1009	12.5415	12.7313

The Final Formulation

Based on the investigation of prediction of *Cd* in the previous sections, RBFNN was selected as the simulation model for all the 7 wind force coefficients in Table 2. However, the maximum errors of the neural networks trained for alongwind *Cdd*, and acrosswind *Cld* and *Clmd* coefficients were over 15% for either training or validation cases. Instead of using seven RBFNNs, grouping was used again to let neural networks have multiple outputs. This reduced the number of networks, which is good for practical application, and improved accuracy, which may be caused by the increase of training cases. After extensive experiments of different combinations, the final solution was to train three independent RBF neural networks to estimate alongwind, acrosswind and torsional wind coefficients respectively. The root mean square errors and the absolute maximum errors of the three RBFNNs are summarized in Table 9, 10 and 11.

Table 9: Errors of RBFNN for alongwind coefficients

Wind Coefficient	GOAL/SPREAD	RMSE	Max. Error (%)	
			Training	Validation
Cd	0.1/1.136	0.0174	6.583	5.670
Cdd			7.908	8.525
Cdm			6.329	4.907
Cdmd			7.360	8.178

Table 10: Errors of RBFNN for acrosswind coefficients

Wind Coefficient	GOAL/SPREAD	RMSE	Max. Error (%)	
			Training	Validation
Cld	0.001/1.14	0.0022	13.870	18.706
Cldm			14.803	19.091

Table 11: Errors of RBFNN for torsional coefficient

Wind Coefficient	GOAL/SPREAD	RMSE	Max. Error (%)	
			Training	Validation
Ctd	0.001/1.125	0.0035	15.787	24.868

Conclusions

Several methods, including polynomial regression, nonlinear regression and ANN, have been carefully studied for the prediction of wind force coefficients. Our investigation showed that using RBFNN yielded the best results in terms of accuracy and usefulness. Based on this finding, the same RBFNN architecture was applied for the estimation of all the seven wind coefficients in Table 2. Further study demonstrated that instead of using seven RBFNNs for the seven wind coefficients, training three RBF neural networks, one for the alongwind coefficients (*Cd*, *Cdd*, *Cdm* and *Cdmd*), another for the acrosswind coefficients (*Cld* and *Cldm*) and the other for the tortional coefficient *Ctd* is adequate.

References

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