Application of an Artificial Neural Network Model for Boundary Layer Wind Tunnel Profile Development

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ABSTRACT

For wind load studies on buildings and other structures in boundary layer wind tunnels (BLWT), the effect of upwind terrain roughness on the mean wind velocity and turbulence intensity profiles can be simulated through the use of spires and the application of proper wind tunnel floor roughness over the long working section of the tunnel upwind of the test section. Usually, the size and shape of the floor roughness elements and spires required to simulate a target flow (e.g. urban, suburban, and open) are determined by a trial-and-error process that can be long and cumbersome. The present study focuses on the application of an artificial neural network (ANN) model to assist in the selection of a particular spire/floor roughness setup to achieve a particular target profile. Experimental data were collected in RWDI USA LLC's BLWT in order to train and test the ANN model. ANN results compared well with an independent set of experimental data used for testing, demonstrating the feasibility of the NN model approach to assist in the selection of floor roughness and spire characteristics for efficiently generating appropriate target wind velocity and turbulence intensity profiles for boundary layer wind tunnel testing.

Key Words: Artificial neural network, velocity profile, turbulence intensity, roughness length, boundary layer wind tunnel

INTRODUCTION

Wind loading studies on buildings and other structures can be carried out in Boundary Layer Wind Tunnels (BLWT), which are specifically suited to model the appropriate flow characteristics (wind profile) of the atmospheric boundary layer. A significant challenge in the commissioning of a BLWT is in defining the proper physical setup of the devices in the wind tunnel that will provide for the desired flow characteristics (i.e. wind flow over typical suburban terrain) to be simulated. Traditionally this has been accomplished through trial and error and engineering intuition, which can be a long and cumbersome process. The present study will illustrate on the application of artificial neural networks (NN) to assist the selection of floor roughness height and spire widths (top and bottom) required to generate a particular target wind profile.

Many uses of neural networks in wind engineering have been reported in literature. Khanduri et al. (1997) suggested a NN approach for the assessment of wind-induced interference effects on design loads for buildings. English and Fricke (1999) described a NN application for analysis of interference index. Bitsuamlak et al. (1999, 2007) applied NN to predict wind pressure coefficients and speed-up ratios due to topographic effects. Chen et al. (2003) applied NN to predict pressure coefficients on roofs of low rise buildings. Fu et al. (2005, 2007) used neural network to predict wind loads on large roofs. More recently, Yasushi and Tsuruishi (2008) used a computer-assisted wind load evaluation system for the design of roof cladding of spherical domes using ANN, aerodynamic database and time-series simulation technique.

The present application of artificial neural networks (NN) focuses to model the effect of boundary layer wind tunnel upwind surface roughness and spire dimensions on the longitudinal mean velocity and turbulence intensity profiles (i.e. variation with height above ground). To illustrate the suitability of ANN for the present study, ANN modeling has been applied (i) to predict mean longitudinal velocity and turbulence intensity profiles and (ii) to estimate the tunnel surface roughness and spire dimensions required to generate a target mean longitudinal velocity and turbulence profiles. Note that (ii) is the inverse problem of (i). In both cases BLWT measurements has been used for training as well as validating the ANN models. The following sections will discuss each in detail.

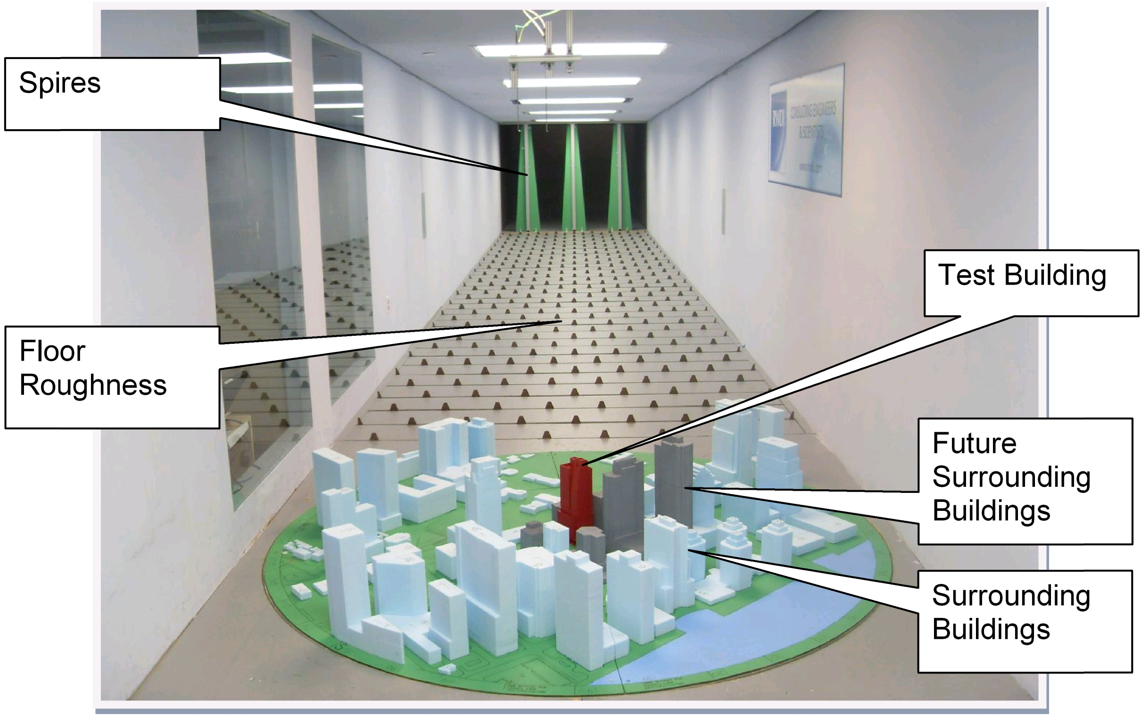
BOUNDARY LAYER WIND TUNNEL

Wind profile data was collected in the recently commissioned BLWT at RWDI USA LLC in Miramar, Florida. The unique characteristic of BLWTs is an extended working section downwind of the contraction over which an appropriate wind profile is developed. This particular wind tunnel is a closed-circuit tunnel with a 40 ft long and 8 ft wide working section upwind of the wind tunnel model, which is mounted on a turntable at the end of the working section. The ceiling height varies from 6 ft to 7 ft above the turntable. This wind tunnel employs the spire-roughness technique to develop the wind profile, as described by Irwin [1].

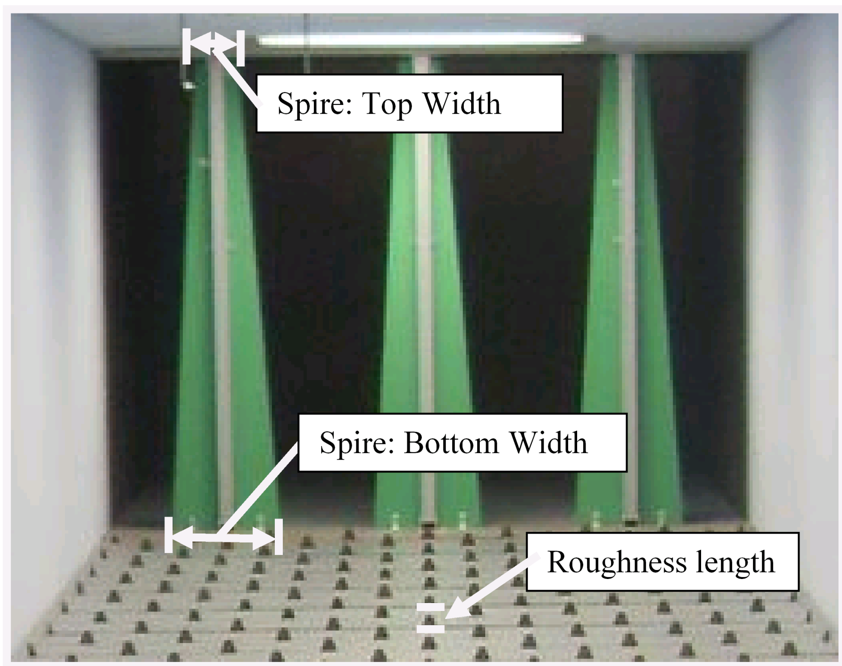
Figure 1 shows the working section of the BLWT. Three trapezoidal spires extending from the wind tunnel floor to ceiling are situated at the entrance to the working section. The floor is covered with triangular roughness elements in 40 staggered rows 1 ft apart. Spires of various dimensions can be interchanged manually as necessary, while the roughness elements are raised lowered by means of mechanical actuators controlled from the wind tunnel control room in order to save testing time. Massing models of the test building, present and future surrounding buildings are mounted on the turntable at the end of the working section, which can rotate 360 degrees to simulate wind from any direction.

PROBLEM SCOPE AND COLLECTION OF TRAINING DATA

In the use of the spire-roughness technique for boundary layer wind flow simulation, the fundamental question to be answered is the following: "What size, shape, location and number of spires, and what floor roughness height is needed to recreate a particular target atmospheric boundary layer wind profile in the wind tunnel?" While there are a multitude of combinations of spire sizes, shapes, locations and floor roughness heights, the problem was reduced to a manageable size through previous experience. Three trapezoidal spires spaced on the centerline and 18" from the tunnel wall, and uniform floor roughness were kept constant. Thus, the remaining design variables were the top and bottom spire widths, and the uniform floor roughness height. These design variables are summarized in Table 1, along with the variable ranges that were used. It was desired to collect data for various combinations of these variables in order to train and test the artificial neural network model.



(a)



(b)

Figure 1: RWDI USA LLC (a) Boundary Layer Wind Tunnel Working Section, (b) spire and roughness parameters.

Table 1: Spire-Roughness Design Variables

Variables	Range
Spires:	
Top Width	5" to 8"
Bottom Width	10" to 19.5"
Floor Roughness:	
Height	0" to 3" in increments of ½"

Pressure data were collected with a "pitot rake" positioned at the centerline of the working section, at the upwind edge of the turntable. The rake consisted of 53 pitot tubes. The pitot tubes were spaced at ½" intervals up to 5" above the tunnel floor, at 1" intervals up to 30", and at 2" intervals from 30" to 66" above the tunnel floor. At a typical model scale of 1:400, the uppermost measurement location equates to a full-scale height of 2200 ft. The pressure data were sampled at 512 Hz for 36 seconds. From these time series of pressure, longitudinal velocities and longitudinal turbulence intensities were determined. The velocity ratio was defined as the ratio of the mean velocity at a particular pitot to the mean velocity of the pitot at a reference height of 60" above the tunnel floor (see Equation 1). The turbulence intensity was defined as the ratio of the rms to the mean velocity at a particular pitot (see Equation 2). Thus, for each combination of design variable values, profiles of velocity ratio and turbulence intensity from 1" to 66" above the wind tunnel floor were determined.

$$\overline{U}_i = \frac{\overline{u}_i}{\overline{u}_{60}} \tag{1}$$

$$Iu_i = \frac{\sigma_i}{\overline{u}_i} \tag{2}$$

ARTIFICIAL NEURAL NETWORK MODEL DEVELOPMENT

The most practical design considerations to build and train a neural network include the selection of an appropriate internal error criterion, efficiency of learning algorithm as well as choice of network topology and optimum stopping criterion for maximum performance. In the present work the neural network tool for prediction of wind profiles or estimation of roughness height and spire dimensions required to generate a specific target profiles is developed based on the cascade correlation algorithm using object-oriented methodology following the methodology described in Bitsuamlak et al. 2007. The architecture of a CCNN is shown in Figure 2. In this algorithm new hidden neurons are installed one at time during run-time as required from a pool of candidate hidden neurons, which are initialized to different weights and trained separately in the background. Note that the candidate neurons are not connected to the rest of CCNN during training. Thus, for each new hidden neuron, the present algorithm tries to maximize the magnitude of the correlation between the new neurons output and the residual error signal of the CCNN (details are given below). Installation of new hidden neurons is automatically stopped when the network meets the error criteria or exceeds the maximum number of hidden neurons set by the user.

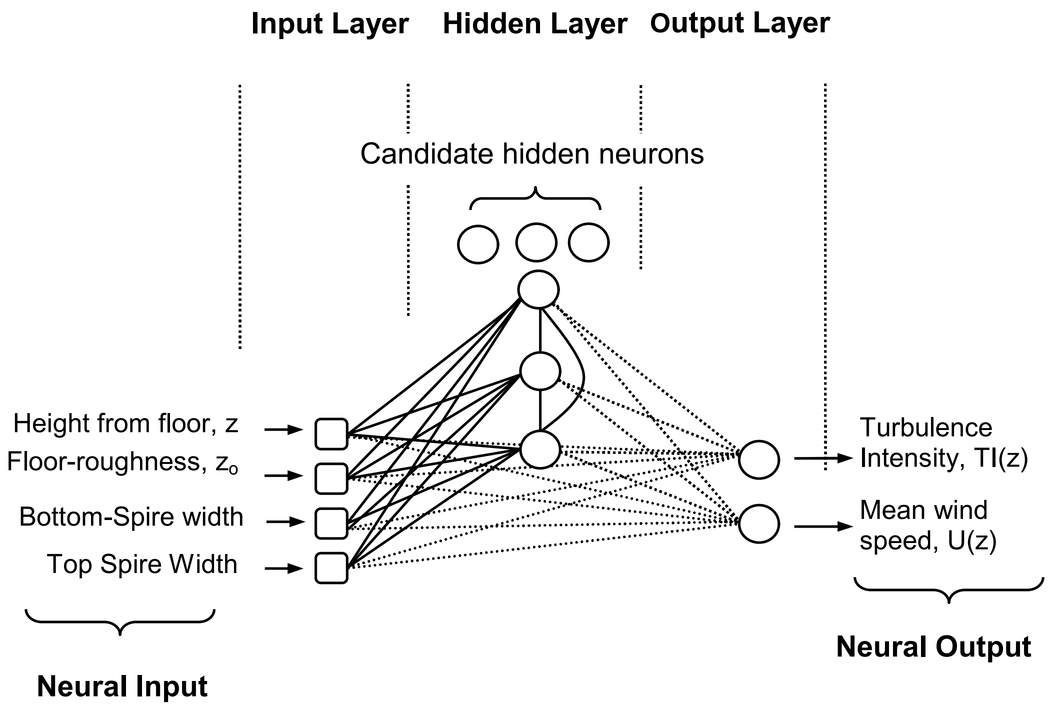


Figure 2: ANN model for wind profile prediction with cascade-correlation architecture after three hidden neurons have been added. Squares represent non-processing and circles represent processing neurons.

RESULT AND DISCUSSION: WIND PROFILE PREDICTION

In this part of the study, the neural network is trained to predict mean longitudinal velocity and turbulence intensity profiles from four input parameters, namely, height above which velocity measurements are taken, roughness length, top and bottom spire widths as shown in Fig. 2. Samples are taken randomly from the available data to train the network and then predictions are made on the remaining data. Some of the inputs are normalized with respect to the maximum values for better efficiency. Comparison of the predicted velocity profile and turbulence intensity with observed values showed a very good match, as is shown in the Figs 3 and 4 for mean longitudinal velocity and turbulence intensity respectively.

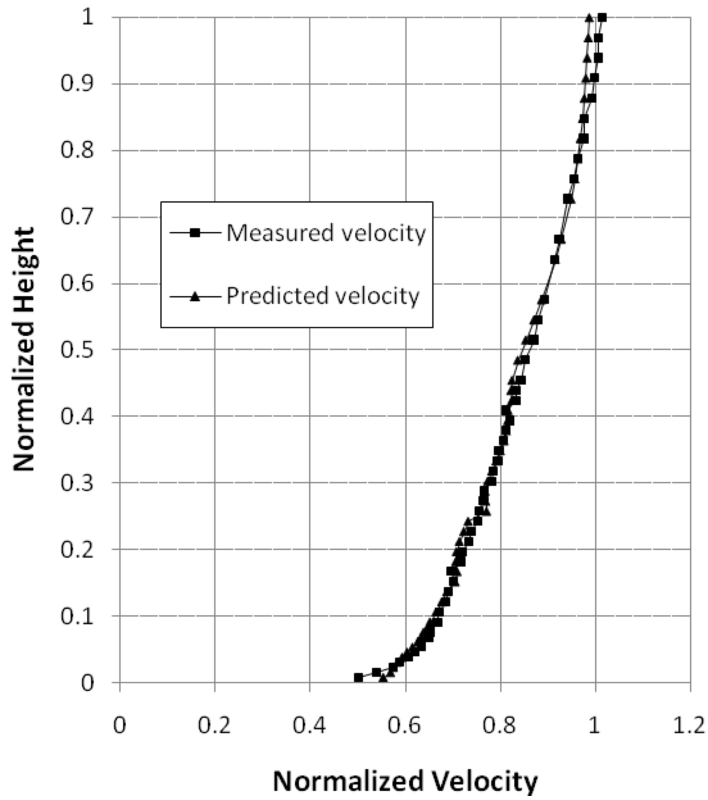


Figure 3 Measured versus predicted velocity profiles

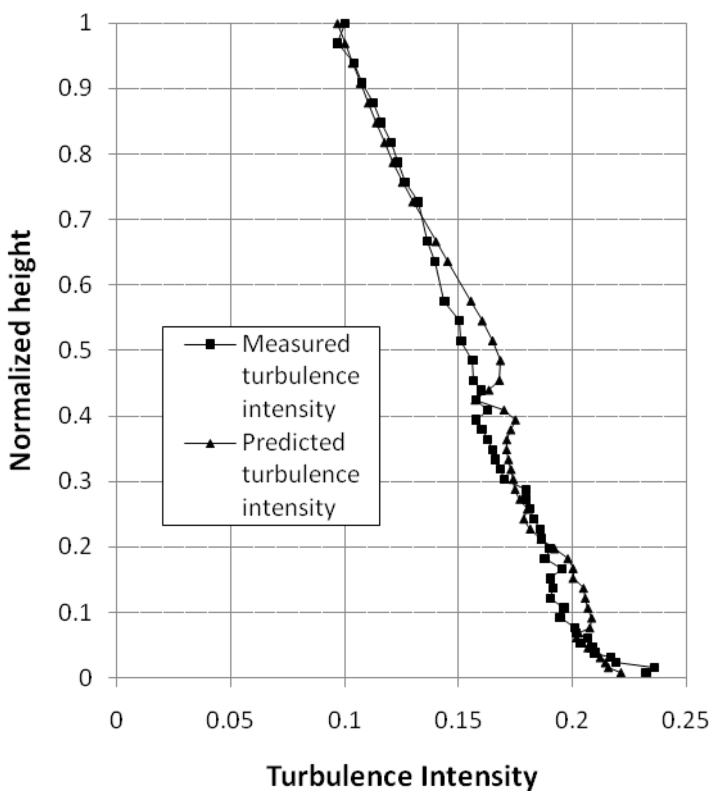


Figure 4 Measured versus predicted turbulence intensity profiles

Estimation of Tunnel Surface Roughness and Spire Dimensions

The inverse problem of determining roughness length and width of spire is done in the same way as the forward problem but by switching the inputs and outputs. Thus for the inverse ANN modeling the following three inputs are used: Target mean longitudinal velocity profile, target turbulence intensity, and height above which velocity measurements are taken. The outputs include the roughness length (of the wind tunnel floor), and the ratio of width of spire at height z divided by the bottom spire width. The inverse modeling is noticed to require more iteration to converge to the solution for a given tolerance (mean square error). For one test setup, the spire widths and roughness length are kept the same while measurements of velocity are conducted at different height. Hence, it is expected that the inverse ANN model to predict a single value of roughness length and Top and Bottom width of a Spire. Table 2 shows the comparison of the measured and ANN predicted values. These values can be used as starting values for further wind tunnel verification thus reducing cycle in the trial and error process.

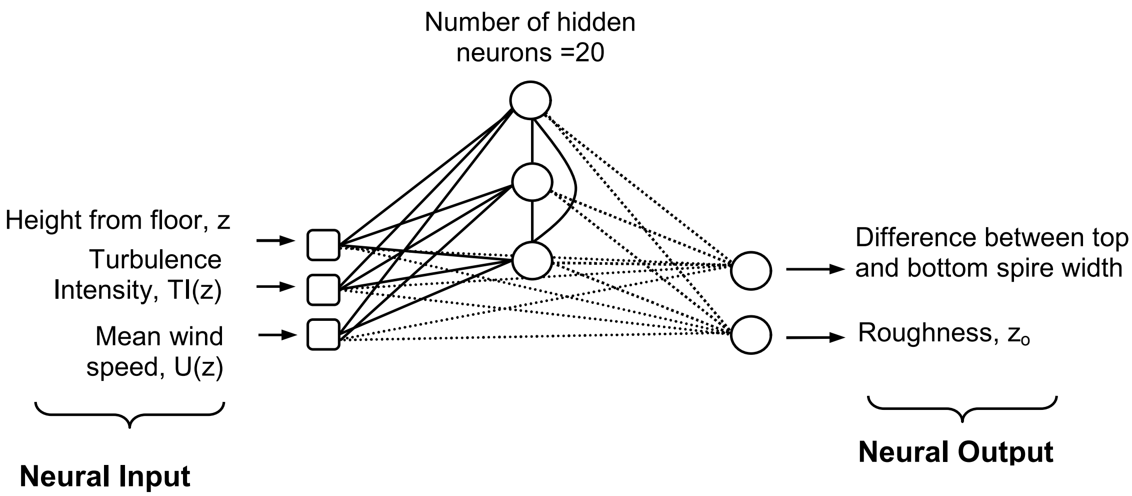


Figure 5: ANN architecture for inverse modeling.

Table 2: Measured and ANN predicted roughness length and Bottom-Top Spire width difference

Test set 1	**Actual value**	**Predicted value**
Spire width difference	12 in	10.2 in
Floor roughness	2 in	2.2 in
Test set 2		
Spire width difference	5 in	6.2 in
Floor roughness	1 in	1.1in

CONCLUSIONS

Artificial neural networks are used to predict wind velocity and turbulence intensity profiles in a wind tunnel for a given floor roughness and spire dimensions with the objective of assisting the flow management process. The neural network model is trained with part of the wind tunnel data collected for various roughness length and spire dimensions. The results predicted by the neural network model have shown excellent agreement with the observed data for both mean longitudinal velocity and turbulence intensity profiles considered in this study. The inverse problem of determining roughness length and spire dimensions has also shown good agreement despite the relatively difficult nature of the problem due to discrete-valued parameters. In future other family error optimization techniques appropriate step functions can be used to improve learning efficiency and performance the inverse ANN models for discrete outputs.

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