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## CALIBRATION OF TRIPLE-WIRE PROBES USING AN ARTIFICIAL NEURAL NETWORK

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### ABSTRACT

*Hot-wire anemometry is an established technique for velocity measurements in turbulent flows. Calibration of hot-wire probes is challenging due to the nonlinear relationship between the probe output voltage and the velocity, and the sensitivity to the temperature difference between the heated wire and the ambient flow. A triple-wire probe contains three mutually orthogonal wires that permit the three components of the local instantaneous velocity vector to be measured simultaneously. Calibration data reduction methods for multi-wire probes, based on variable-angle calibration techniques, may include curve-fits and direct-interpolation schemes. In the present study, a novel calibration data reduction method for a triple-wire probe is reported which uses an artificial neural network. Such a method has been successfully applied by other researchers for the calibration of seven-hole pressure probes. For the triple-wire probe, the neural network is used to produce a calibration relation between the three probe output voltages and the three components of the local velocity vector. Variable-angle calibration data were obtained for a triple-wire probe for velocity magnitudes from 5 to 40 m/s, yaw angles from* $-35^\circ$ *to* $+35^\circ$*, and roll angles from* $0^\circ$ *to* $345^\circ$*. A three-layer perceptron feed-forward network, using a Levenberg-Marquardt training algorithm, was applied to the calibration data, to map the mean voltages to the mean velocity components. The network was tested using an independent data set. The present results yielded standard errors of approximately* $\pm 0.38$ *m/s,* $\pm 0.25$ *m/s and* $\pm 0.26$ *m/s in the magnitudes of the streamwise, vertical, and cross-flow velocity components, respectively. The results showed that the present neural network model is not significantly sensitive to the size of the calibration data set, suggesting it may be a more convenient calibration data reduction method compared to other methods.*

### INTRODUCTION

Turbulent flows occur in many engineering and industrial applications. Since turbulent flows are inherently three-dimensional, measurements of all three components of veloc-

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ity are needed for improved physical understanding of turbulent flow fields. There are different types of measurement instruments that can be used for three-component velocity measurements in turbulent flows, including five- and seven-hole pressure probes, multi-sensor hot-wire anemometry (HWA) probes (including a triple-wire probe), three-component laser Doppler anemometry (LDA), and stereoscopic particle image velocimetry (SPIV). Among these measurement techniques, the triple-wire probe is perhaps the most suitable for measurement of turbulent flows with high-frequency fluctuations in velocity [1].

HWA is an indirect velocimetry technique, in which the turbulent flow velocity magnitude is nonlinearly related to the convective heat transfer from a heated sensor. In the most common mode of operation, constant-temperature anemometry, the heated wire is maintained at a constant temperature (well above the ambient temperature of the air) by the anemometer unit while it is being convectively cooled by the turbulent air flow. A calibration is then performed to determine the relationship between the air velocity magnitude, $U$, and the anemometer output voltage, $E$. Calibration of a single-sensor (single-wire) hot-wire probe requires subjecting the probe to flows of known velocity magnitude. For multi-sensor (multi-wire) probes used for measuring two and three components of the velocity vector, such as an X-wire probe or triple-wire probe, calibration requires subjecting the probe to flows of known velocity magnitude and direction. A calibration data-reduction method is then employed. The nonlinear nature of the velocity-voltage relationship makes calibration of hot-wire sensors challenging, particularly in thermally varying flows and for multi-sensor probes. Many different calibration data-reduction methods have been adopted [1].

Calibration of a single normal wire is based on the response equation for the output voltage from an anemometer connected to a given hot-wire sensor expressed in the form of a simple power law known as the generalized King's Law relationship

$$E^2 = A + BU^n, \tag{1}$$

where $A$, $B$ and $n$ are the constants determined from calibration.

Directional sensitivity of a single normal wire can be explained by considering the components of the velocity vector acting on the sensor. Figure 1 shows the velocity components in a wire-fixed coordinate system for a single normal wire probe. In this figure, $U_N$, $U_T$ and $U_B$ are respectively the normal, tangential and binormal components of the velocity vector, and $\theta$ and $\alpha$ are the probe yaw and pitch angles, respectively. Assuming that the tangential component of velocity has negligible effect on the wire, the probe responds mainly to the normal and binormal (transverse) components. It is also assumed that the pitch angle of the probe, $\alpha$, with respect to the velocity vector does not influence the measured velocity magnitude so that the output voltage of the anemometer is a function of only probe yaw angle, $\theta$, and the velocity magnitude, $U$. This leads to the definition of an effective velocity to which the probe responds,

$$V_e = f_\theta \times |U|, \tag{2}$$

where $f_\theta$ is the yaw function which is determined during the calibration procedure. Several functions have been proposed for the yaw function. One of the proposed functions is "the Cosine Cooling Law" where $f_\theta = cos\theta$. Using the Cosine Cooling Law, it is assumed that the probe responds only to the velocity component normal to the wire. When the effective velocity, $V_e$, is obtained from Cosine Cooling Law, it replaces the velocity $(U)$ in Equation (1).

Calibration of an X-wire can be done with the cosine cooling law and effective velocity approach which yields directly two response equations for velocity (U) and yaw angle ($\theta$). In this method, the wire angles must be known exactly and the flow angle (the angle between the velocity vector, $U$, and the probe axis) should not exceed the angle of acceptance for the given probe and must be kept small in order to avoid directional ambiguity. The Cosine Cooling Law is limited to small yaw angles and low turbulence intensities [1]. Furthermore, to use the Cosine Cooling Law, it is assumed that all wires see the same flow and have same resistance. All the aforementioned assumptions limit the application of the Cosine Cooling Law to probes with two or more wires.

The main shortcoming of the above method relates to the use of the Cosine Cooling Law, and this has motivated the use of variable-angle calibration techniques, where the probe is subjected to a full range of flow velocities and flow directions, encompassing the entire expected angular range. For X-wire probes, one of the calibration data-reduction methods is the polynomial curve fitting method in which curves are fit to the voltage data collected from the calibration, so that the response equations can be obtained. For example, Oster and Wygnanski [2] proposed third-order polynomials in voltages $E_1$ and $E_2$ to evaluate the velocity magnitude ($U$) and yaw angle ($\theta$). Another calibration data-reduction method for X-wire probes is the look-up-table method or direct interpolation method, in which the calibration data are directly interpolated and there is no need to use curve fits [1].

The calibration data-reduction methods commonly used for X-wire probes have been extended for use with triple-wire probes, while other researchers have proposed their own, unique methods. For triple-wire probes, calibration data reduction methods have been presented by Huffman [3], Skinner and Rae [4], Lakshminarayana and Davino [5] and Gieseke and Guezennec [6], using the expression proposed by J$\phi$rgensen [7] for the effective velocity as

$$V_e{}^2 = U_N{}^2 + k^2 U_T{}^2 + h^2 U_B{}^2, \tag{3}$$

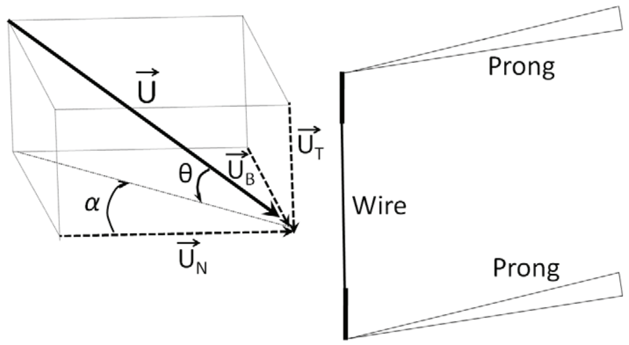


**FIGURE 1**. A WIRE-FIXED COORDINATE SYSTEM AND THE CORRESPONDING VELOCITY COMPONENTS.

where $k$ is the parallel cooling coefficient and $h$ is the binormal cooling coefficient. In these calibration data reduction methods, the values of $k$ and $h$ are often determined using the equations related to the calibration of a single wire. These calibration techniques may require accurate measurement of the wire angles, since the values of $k$ and $h$ are sensitive to errors in the known values of these angles [7]. Researchers have obtained values for $k$ and $h$ in the ranges of 0.17-0.28 and 1.01-1.12 for different models of triple-wire probes. Again, since the factors $k$ and $h$, and the angles of the wires with respect to the probe axis, are difficult to determine accurately, the effective cooling velocity approach and the Cosine Cooling Law cannot be followed with reasonable accuracy for triple-wire probes. Furthermore, as the constants in King's Law relation are functions of the difference between the wire temperature, $T_w$, and the ambient temperature, $T_a$, the calibration data reduction process may be further complicated for thermally varying flows.

With modern high-power computers, models with more degrees of freedom can be used to obtain a more accurate calibration. Indirect and direct functional fit techniques are among those models that can be used for multi-sensor HWA probes. Applying Equation (2) to King's law relation yields

$$E_i = f_i(u, v, w), \tag{4}$$

where $i$ is the wire number (which varies from 1 to 3 for a triple-wire probe) and $u$, $v$ and $w$ are respectively the streamwise, vertical, and cross-flow velocity components in a space-fixed coordinate system. In this indirect functional fit technique, the objective is to adopt a suitable model for the functions $f_i$ in order to obtain an acceptable accuracy. Van Dijk and Nieuwstadt [8] proposed a collection of product polynomials for $f_i$ with coefficients estimated from a least squares optimization on a calibration dataset using the method of Lemonis and Dracos [9]. In this technique, in order to estimate the velocity vector from a collection of measured responses, one must solve the velocity components ($u$, $v$, and $w$) from the response relations since the coefficients in those relations express the response of the probe as a function of the velocity vector and not voltages.

In practice, one is interested in velocity as a function of voltage. So, to interpret any sample of measured response equation in terms of velocity, one needs to invert the indirect response relations. This will be numerically expensive when large datasets are to be processed [8]. According to Tsinober et al. [10], the inversion procedure can be avoided by adopting direct calibration relations, which express the velocity components as a function of voltages:

$$U_i = g_i(E_1, E_2, E_3). \tag{5}$$

As with the indirect functional model, van Dijk and Nieuwstadt [8] proposed a collection of product polynomials for $g_i(E_1, E_2, E_3)$ with coefficients estimated from a least squares fit on a calibration dataset. It is noted that large systematic errors were found in both the indirect and direct polynomial models used by van Dijk and Nieuwstadt [8].

A direct interpolation lookup-table method is another technique to calibrate multi-sensor HWA probes. This technique has been used by many researchers such as Lueptow et al. [11], Browne et al. [12] and Wubben [13]. To apply the lookup-table method, one should collect a set of calibration voltage samples for a number of velocity values and probe orientations each with regular intervals. To interpret a collection of response voltages, one scans the calibration samples for the calibration voltage sample that has the smallest value of the mean square response difference with the measured voltage sample. Then, this procedure is checked for other coordinate directions. A detailed explanation of this technique was presented in the study by Van Dijk and Nieuwstadt [8].

A potential problem with the lookup-table method is that poor calibration samples can introduce systematic errors in their neighborhoods when local interpolations are used. However, by using fast data-logging devices and by applying automated calibration methods the accuracy of the sample should not be a limiting factor to applying the lookup-table method [8]. Also, in order to achieve acceptable accuracy in this method, a large number of samples is needed since the lookup-table method works based on the interpolation between one data set and the data in neighborhood.

In the present study, a calibration data-reduction method involving an artificial neural network (ANN) model is proposed for the calibration of a triple-wire probe. Neural-network approaches to calibration of velocity probes have been undertaken by other researchers but are not widely used. For example, Rediniotis and Chrisanthakopoulos [14] calibrated a seven-hole pressure probe using a neural network and fuzzy logic systems, and Rediniotis and Vijayagopal [15] developed a neural model to calibrate miniature multi-hole pressure probes; their proposed model yielded accuracies of $\pm 0.28°$ in flow angle and $\pm 0.35\%$ in velocity magnitude. Baskaran et al. [16] also studied the calibration of multi-hole pressure probes using neural networks. In hot-wire anemometry applications, Erdil and Arcaklioglu [17] calibrated a single-wire probe using an artificial neural network, varying the air temperature and humidity during the calibration procedure. Also, Ashhab and Salaymeh [18] used an artificial neural network model to identify the transfer function response curve of a novel thermal flow sensor.

In the present study using the triple-wire probe, the ANN calibration data-reduction method is used to establish the relationship between the three measured wire voltages, $E_1$, $E_2$, $E_3$, and their corresponding velocity vector components, $u$, $v$, $w$. The main advantages of the ANN calibration data reduction method are that it avoids the limitations of the Cosine Cooling Law, no knowledge of the wire angles is required, no response equations are required, and the method can be readily extended to operate in thermally varying flows if a variable-angle, variable-temperature calibration is performed.

## PROBE CALIBRATION PROCEDURE AND EXPERIMENTAL SET-UP

A six-channel Dantec Dynamics StreamLine hot-wire anemometry system was used in the present study. The anemometer unit was connected to an NI SCXI-1140 simultaneous-sampling differential amplifier module and a 16-bit PCIe-6259 data acquisition card and controlled through a personal computer running the Dantec Dynamics Streamware software.

The triple-wire probe used in the present study was a Dantec Dynamics 55P91 tri-axial probe. This probe has three mutually perpendicular sensors that form an orthogonal system with an acceptance cone of 70.4°. The sensors are platinum-plated tungsten with a 5 $\mu$m diameter and a 1.25 mm length, while the overall wire length is 3 mm. The sensor resistance is approximately 3.75 $\Omega$ at a reference temperature of 20°C. The temperature coefficient of resistance is $\alpha_{20} = 0.0036°\mathrm{C}^{-1}$. To avoid oxidization, the maximum sensor temperature must be kept below 300°C. The sensors were operated on a constant temperature circuit at an overheat ratio of 1.8.

A variable-angle calibration of the triple-wire probe was performed using a Dantec Dynamics 90H02 Flow Unit calibrator fitted with a yaw-roll manipulator. Pressurized air was supplied to the unit from an external source, and was filtered and regulated before entering the calibrator unit. An MKS model 1559A mass flow controller was added upstream of the calibrator to improve the accuracy and steadiness of the flow rate during the calibration. The calibrator creates a free jet with a uniform, low-turbulence velocity profile, in which the probe is immersed. The velocity magnitude set-points are controlled from the StreamWare software and the yaw and roll angle set points of the probe were set manually.

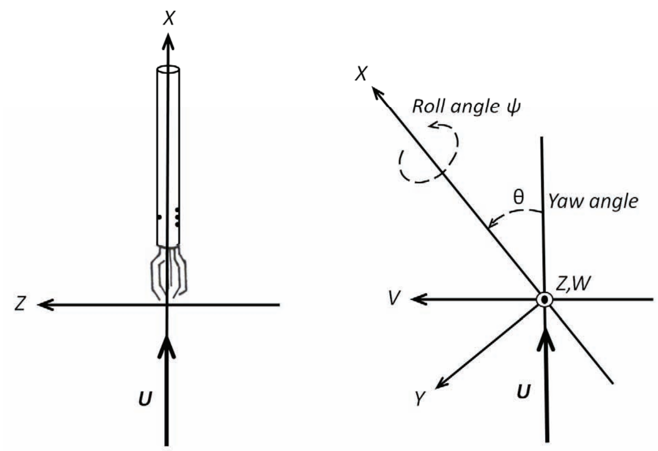


**FIGURE 2**. SCHEMATIC OF A TRIPLE-WIRE PROBE DURING CALIBRATION AND THE REPRESENTATION OF ITS ROLL AND YAW-ANGLES.

Fig. 2 shows the coordinate system for the calibration procedure as well as the probe yaw angle, $\theta$, and roll angle, $\psi$. In this figure, the $x$-axis corresponds to the probe axis. To ensure proper alignment of the probe in the calibrator unit, sensor 3 was placed in the $x$-$z$ plane while the probe yaw angle was set at $\theta = 0°$; this ensured the probe was set at $\psi = 0°$ [19].

During the calibration, the reference ambient temperature was kept constant at 22.15°C. The signal from each sensor was offset and filtered, and then sampled at a sampling frequency of 2.5 kHz. The calibration was performed at eight velocity magnitudes (ranging from 5 m/s $\leq U \leq$ 40 m/s in increments of 5 m/s), nine values of yaw angle, (ranging from -35° $\leq \theta \leq$ +35° in increments of 10°), and 24 values of roll angle (ranging from $0° \leq \psi \leq 345°$ in increments of 15°), for a total of 1728 calibration set points. For each individual calibration set point, comprising $U$, $\theta$, and $\psi$, three mean voltages were acquired, $E_1$, $E_2$, and $E_3$, each corresponding to one of the three wires. These voltages were the input data for the neural network, which is explained in the next section. After collecting the calibration data, about 100 random data set points at different arbitrary velocities, yaw angles and roll angles were collected in order to test the proposed neural network with an independent set of data. The uncertainties in the velocity magnitude, yaw angle and roll angle, of the calibration data set, were estimated as $\pm 0.2$ m/s, $\pm 1°$, and $\pm 1°$, respectively.

## NETWORK ARCHITECTURE AND TRAINING PROCESS DESCRIPTION

A multi-layer perceptron (MLP) feed-forward network using the well-known Levenberg-Marquardt training algorithm was used to map the inputs of the network (the mean wire voltages, $E_1$, $E_2$, and $E_3$) to the corresponding target values (the mean velocity components $u$, $v$, and $w$). The velocity components can be found using the following equations:

$$u = U cos\theta cos\psi \tag{6}$$

$$v = U cos\theta sin\psi \tag{7}$$

$$w = U sin\theta \tag{8}$$

where $U$ is the velocity magnitude and $\theta$ and $\psi$ are yaw and roll angle, respectively.

The 1728 data points of the calibration data set were randomly divided into three subsets: training, 70%, validating, 15%, and testing, 15%. The latter testing set is distinct from the independent set of data, comprised of 100 random data points, mentioned in the previous section, and was used to prevent the network to over fit. The developed MLP has two hidden layers each of 10 neurons and an output layer of 3 neurons. Tangent sigmoid transfer functions were used for the hidden layers while the output layer had linear transfer functions. A schematic view of the network model is shown in Fig. 3. The calibration data set was pre-processed by scaling the minimum and maximum values of inputs and targets so that all the data elements fall between -1 and +1. Before scaling, the input values ($E_1$, $E_2$, and $E_3$) ranges from approximately 2.3 to 9.6 volts. The mean square error (MSE) was minimized as the network performance function and its value was monitored during the training process. This minimum value for the present network is equal to 0.0453. The early stopping method was implemented as the stopping criterion. A detailed explaination of the neural network and training algorithm used can be found in references [20]- [22].

The weights and biases of the neural network model are reported to make the results of the present study reproducible. Note that in these matrices $W_{\{1,i\}}$ are the weights to layer 1 from the input layer, $W_{\{2,1\}}$ are the weights to layer 2 from layer 1, $W_{\{3,2\}}$ are the weights to layer 3 from layer 2, and $b_{\{i\}}$ is the bias to layer $i$.

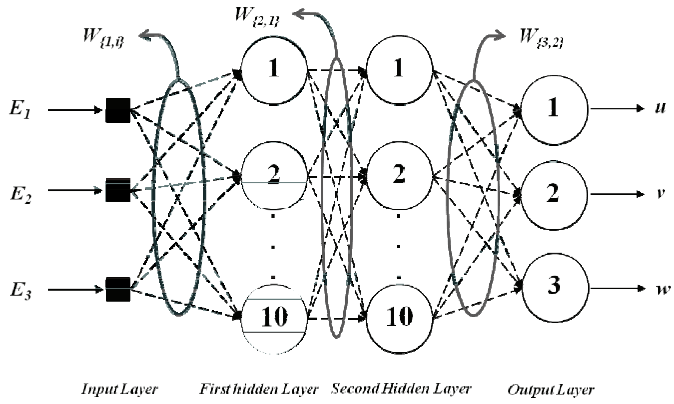


**FIGURE 3**. SCHEMATIC VIEW OF THE PROPOSED NEURAL NETWORK MODEL AND ITS INPUTS, OUTPUTS, AND WEIGHTS.

$$W_{\{1,i\}} = \begin{bmatrix} -0.75 & +2.01 & -1.18 \\ +1.02 & -2.46 & +1.45 \\ -1.06 & -0.16 & -0.45 \\ -2.27 & +1.22 & +1.36 \\ -0.64 & -0.11 & -0.28 \\ +1.00 & +1.32 & -2.14 \\ -1.41 & +0.47 & +1.61 \\ -0.36 & +0.16 & +0.21 \\ -2.15 & +1.69 & +1.96 \\ -2.43 & +1.18 & +1.08 \end{bmatrix}$$

$$W_{\{2,1\}} = \begin{bmatrix} +0.89 & +0.11 & +0.17 & -0.16 & +0.61 & +0.23 & -0.06 & -4.28 & -0.16 & -0.09 \\ -1.49 & +2.69 & +0.57 & -0.60 & -0.19 & -3.02 & -1.12 & -1.32 & +1.07 & -1.56 \\ -0.55 & -1.44 & -1.10 & +4.46 & -2.77 & -0.30 & -0.81 & -1.31 & -2.60 & -3.02 \\ +2.12 & +1.06 & -1.99 & -1.34 & +0.93 & +0.53 & -0.61 & +0.17 & +3.14 & +0.51 \\ +0.98 & +0.40 & -0.23 & +0.34 & -0.69 & +0.73 & +0.11 & +3.73 & +3.42 & -0.25 \\ +7.00 & -6.38 & -5.45 & +4.12 & -9.21 & -14.19 & +0.30 & -7.16 & +5.17 & +19.90 \\ -3.96 & -1.99 & -3.06 & +0.93 & +1.65 & -0.12 & -0.68 & -0.22 & +1.87 & -0.72 \\ +3.44 & +5.26 & -1.66 & +3.06 & +1.27 & -6.03 & +1.67 & +1.96 & -0.80 & +1.54 \\ -0.52 & -1.42 & +2.10 & -4.35 & -0.86 & -1.92 & +4.86 & +1.80 & -1.50 & +0.12 \\ -0.20 & -0.21 & +0.25 & +0.20 & +0.62 & -0.23 & -0.11 & +3.07 & +1.05 & +0.01 \end{bmatrix}$$

$$W_{\{3,2\}} = \begin{bmatrix} -5.80 & +3.92 & +0.10 & +1.32 & +2.81 & +3.12 & -0.23 & -2.55 & -0.22 & -0.92 \\ +4.50 & -1.39 & -0.01 & -0.20 & +0.15 & -1.20 & +0.00 & -2.26 & +0.02 & -3.42 \\ +1.52 & +1.83 & -0.05 & -0.54 & -3.01 & -2.74 & +0.09 & +0.38 & +0.07 & -6.40 \end{bmatrix}$$

$$b_{\{1\}} = \begin{bmatrix} -0.97 \\ +0.88 \\ +1.93 \\ +1.10 \\ -0.15 \\ +1.00 \\ +1.23 \\ -1.38 \\ +6.08 \\ +0.88 \end{bmatrix}, b_{\{2\}} = \begin{bmatrix} -1.53 \\ +3.32 \\ +1.94 \\ +2.17 \\ -1.71 \\ +7.22 \\ -0.78 \\ -2.72 \\ -1.10 \\ +3.16 \end{bmatrix}, b_{\{3\}} = \begin{bmatrix} -2.70 \\ -0.37 \\ +3.63 \end{bmatrix}$$

## RESULTS AND DISCUSSION

After calibrating the triple-wire probe and reducing the calibration data to the neural network, the probe can be used to measure the turbulent velocity field of an unknown flow. The instantaneous measured output voltages ($E_1$, $E_2$ and $E_3$) from the anemometer are converted to instantaneous velocity components ($u$, $v$ and $w$) using the ANN model. Standard temperature corrections [1, 23], to account for ambient temperature variations, can be applied to the output voltages before they are input to the ANN model. In the present study, the calibration data and the independent set of data were all acquired at the same, constant value of ambient temperature.

A comparison of the streamwise components of velocity ($u$) from the calibration to those predicted by the artificial neural network is shown in Fig. 4. In this figure, the solid line represents the identity of the ANN and the random experimental test dataset. According to this figure, both the ANN data and the experimental test data collapse well onto the target line. A standard error of approximately $\pm 0.38$ m/s was determined for the magnitude of the streamwise component of the velocity.

The performance of the proposed artificial neural network for the transverse component of velocity ($v$) can be seen in Fig. 5. According to Fig. 5, there is a good agreement between the experimentally collected test data and those predicted by the ANN model. A standard error of approximately $\pm 0.25$ m/s was determined for this component of velocity.

Fig. 6 shows the comparison of the predicted and the experimental test data for the cross-flow component of velocity ($w$). A standard error of approximately $\pm 0.26$ m/s was determined for this component of velocity. In this figure, the solid line is the target line representing the identity of the experimental data and the predicted ANN data.

The above standard errors in the velocity components translate into errors of $\pm 0.39$ m/s in velocity magnitude, $\pm 0.76^\circ$ in yaw angle, and $\pm 0.82^\circ$ in roll angle.

Variable-angle calibrations of multi-component velocity probes can be sensitive to the size of the calibration data set and the increments used in the velocity magnitude and flow angles [24]. As a further evaluation of the performance of the ANN calibration data-reduction method, it was tested with a smaller sample number, namely 300 sample data sets (about 20% of the total collected sample data set). Applying the neural network to this number of samples, comparable standard errors of $\pm 0.41$, $\pm 0.27$ and $\pm 0.29$ m/s were estimated in the magnitudes of the streamwise, vertical, and cross-flow velocity components, respectively, indicating good performance of the ANN model even for smaller calibration data sets. This result suggests that the ANN calibration data reduction method may be relatively insensitive to the size of the calibration data set, meaning that larger velocity and angular increments can be used when collecting the calibration data. This would significantly reduce the time required for calibrating a triple-wire probe, and is another potential advantage of the neural network calibration data reduction technique over a direct-interpolation (lookup-table) method, in which smaller increments in velocity, yaw angle and roll angle are required to achieve an acceptable accuracy for the velocity components [8].

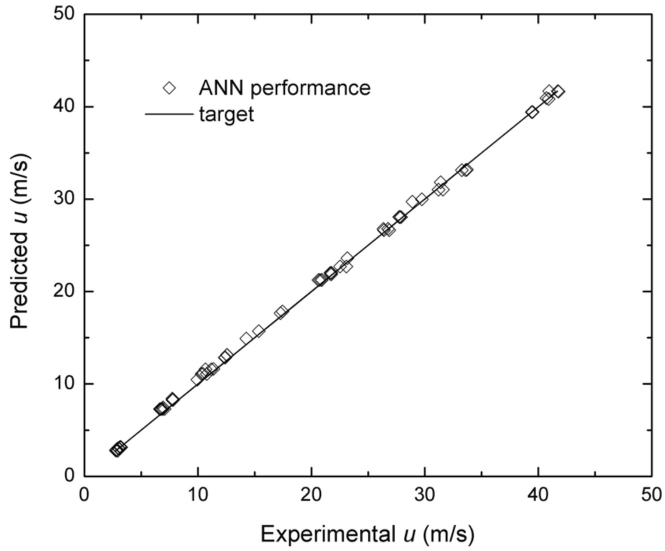


**FIGURE 4**. COMPARISON OF EXPERIMENTAL AND PREDICTED STREAMWISE VELOCITY COMPONENTS, *u*.

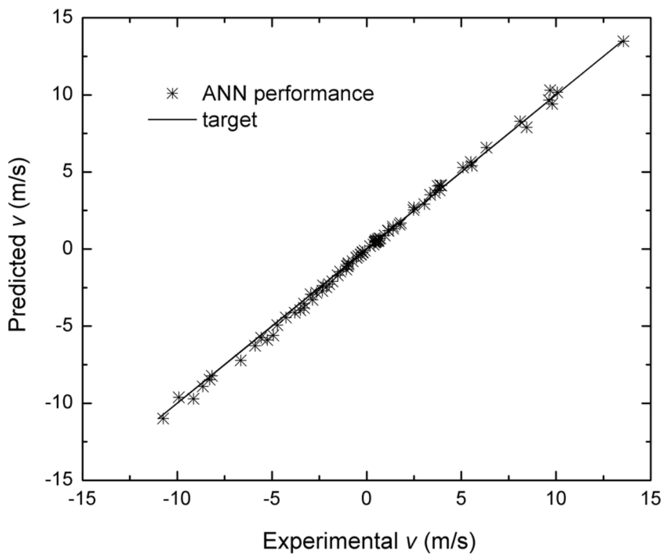


**FIGURE 5**. COMPARISON OF EXPERIMENTAL AND PREDICTED TRANSVERSE VELOCITY COMPONENTS, *v*.

## CONCLUSIONS

In the present study, a multi-layer perceptron feed-forward artificial neural network (ANN), developed using the Levenberg-Marquardt training algorithm, was used as a calibration data-reduction method for a Dantec 55P91 triple-wire probe. The

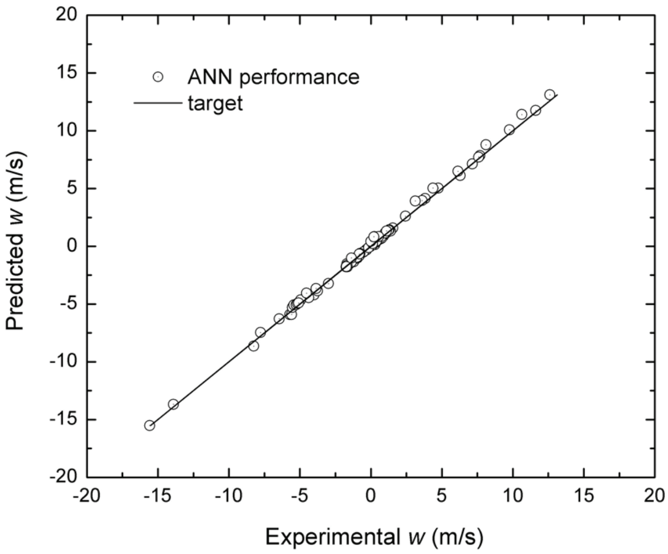


**FIGURE 6**. COMPARISON OF EXPERIMENTAL AND PREDICTED BINORMAL VELOCITY COMPONENTS, *w*.

ANN was used to relate the measured anemometer output voltages to the corresponding values of the velocity components. Of the 1728 calibration data points, 70%, 15% and 15% of the points were randomly selected for training, validating and testing of the neural network, respectively. The results from the present study yielded standard errors of approximately $\pm0.38$ m/s, $\pm0.25$ m/s, and $\pm0.26$ m/s in the magnitudes of the streamwise ($u$), vertical ($v$), and cross-flow ($w$) velocity components, respectively.

The proposed ANN calibration data-reduction method was also tested using a subset of the full calibration data set, amounting to about 20% of the collected data set, to check the sensitivity of the network to the sample number. In this case, the neural network had comparable standard errors of approximately $\pm0.41$ m/s, $\pm0.27$ m/s, and $\pm0.29$ m/s in the magnitudes of the streamwise, vertical, and cross-flow velocity components, respectively. This suggests that the use of a neural-network calibration data-reduction method can significantly reduce the time required to calibrate a triple-wire probe, since larger increments in velocity magnitude, yaw angle, and roll angle can be used in the variable-angle calibration process, without significantly impacting the measurement uncertainty.

A further potential advantage of the ANN calibration data-reduction method would be to extend the network to account for the effects of ambient temperature variation. This could be done by collecting several calibration data sets, each at a different ambient temperature, and incorporating this temperature information into the construction of the neural network.

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