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Data assimilation for PIV based on adaptive neuro fuzzy inference system (ANFIS)

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Abstract

For the AI based data assimilation, the multi-dimensional machine learning method is used to learn the flow behavior and predict the flow based on the learning process and intelligence of method. An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is used with experimental data to predict the flow inside the domain. To built-up the method, different number of input membership function, epoch and percentage of training data was used. The results show that there is a great agreement between experimental observation and intelligent algorithms. This new method is also capable to find all missing points of data that experimental observation cannot detect and the ANFIS method predict the flow in the neural mesh.

1 Introduction

Post-processing of PIV data is a critical step for reducing errors and finding or refining missing information in measured velocity data. However, PIV measurements are often challenged by sources of various experimental errors, such as equipment alignment, insufficient tracer particles, and background noise. Turbulence flows generally represent multidimensional physics including space and time, which have high in dimensions with rotating and transforming intermittent structures. This feature provides an opportunity for Artificial Intelligence (AI), machine learning to predict the modeling and analysis of turbulent flow. The use of neural networks is popular in various areas, including self-driving cars and weather forecasts. The use of neural networks began to leave footprints in fluid dynamics, especially turbulence modeling by Kutz. J. N (2017). Gamahara, M. et al. (2017) introduced an artificial neural network (ANN) as a tool for finding new sub-grid models of sub-grid scale (SGS) stress in Large-eddy simulations. In general, soft computing such as Adaptive Neuro-Fuzzy Inference System (ANFIS) by developed Jang (1993) is a smart way in the building systems which are smart in calculating. ANFIS method with the ability to learn many physical models can be very useful in the processes of chemical engineering, pharmaceutics and industry. This method of computing changes linguistic concepts into mathematical or computational ones. It is possible for the fuzzy logic systems to be employed to transfer linguistic concepts to mathematical and computational architecture; however, there is a problem with it that is they detect and learn physical processes not in an accurate manner meaning that the boundary condition change. Also, it can change its behavior in altering environments and learn to calculate the behavior of lots of processes which may not be certain. But using a combination of ANN and fuzzy logic approaches help to develop both the learning process and the detection ability. So, the combination is called ANFIS combining that is the natural language description of fuzzy systems and learning properties of neural-networks. In this study, the fuzzy inference system applied to predict 3D flow field. The system has three inputs which are x, y, z and three velocity component outputs which u, v, w. In order to begin, the fuzzy learning model was selected for the ANFIS network.

2 Method

Figure 1 shows the simple structure of the employed ANFIS model for predicting 3D flow characteristic for the side mirror models with 2 input membership function. Various inputs which are x, y, z coordinates are applied to obtain 3 velocity component, 3D velocity components are applied as output. The current study used the first-order Sugeno fuzzy model, with fuzzy if-then rules as it follows:

Rule 1: if x is A and y is C then $u_1 = p_1 x + q_1 y + r_1 z + s_1$ (1)
Rule 2: if x is B and y is D then $u_2 = p_2 x + q_2 y + r_2 z + s_2$ (2)

The output of the i^{th} node in layer l is represented as $\mathrm{O}_{\mathrm{l,i}}$.

Layer 1: Each node i in this first layer is an adaptive node with a node function.

$\mathrm{O}_{\mathrm{l,i}} = \mu_{\mathrm{Ai}}(\mathrm{x}), \text{for } \mathrm{i} = 1, 2,$
or $\mathrm{O}_{\mathrm{l,i}} = \mu_{\mathrm{Bi-2}}(\mathrm{y}), \text{for } \mathrm{i} = 3, 4$
or $\mathrm{O}_{\mathrm{l,i}} = \mu_{\mathrm{Ci-4}}(z), \text{ for } \mathrm{i} = 5, 6$ (3)

where x or y or z is the input to node i and $\mathrm{A_i}$ or $\mathrm{B_{i-2}}$ or $\mathrm{C_{i-4}}$ is an associated linguistic label. To put it in another way $\mathrm{O}_{\mathrm{l,i}}$ is the membership grade of a fuzzy setA and B and C($= \mathrm{A_1, A_2, B_1, B_2, C_1, C_2}$). In the same example, the membership function can be any appropriate parameterized membership function. A fuzzy set is entirely described by the help of its membership function. Several types of membership function are existed; For instance, triangular, trapezoidal, gaussian, generalized bell and sigmoidal. Triangular and trapezoidal functions are composed of straight-line segment but the problem which stays with is that they are not smooth at the corner points which specified by the parameters. However, other functions meet these criteria, worth to mention that Smoothness and concise notations are 2 reasons that gaussian and generalized bell functions are the well-liked ones in order to specify fuzzy sets. The former functions are well known in probability and statistics. The latter function has one more parameter than the gaussian function, and therefore it has one more degree of freedom to adjust the steepness at the crossover points. The generalized bell function was applied in this study because of its great abilities for the generalization of nonlinear parameters:

$$\mu_A(x) = \frac{1}{1+\left(\frac{x-c_i}{a_i}\right)^{2b_i}} \quad (4)$$

where $\{\mathrm{a_i, b_i, c_i}\}$ is the variable set. The bell-shaped function differs accordingly as the values of the variables change, so it shows various kinds of membership functions for fuzzy set A. Variables in the first layer are known as premise variables.

Layer 2: Each node in the 2nd layer is a fixed one and its output is the consequent of the whole incoming signals:

$$O_{2,i} = w_i = \mu_{\mathrm{Ai}}(x)\mu_{\mathrm{Bi}}(y)\mu_{\mathrm{Ci}}(z), \ \mathrm{i} = 1, 2, 3 \quad (5)$$

Every node output indicates the firing strength of a rule.

Layer 3: Each node in the 3rd layer is a fixed one. The ith node computes the proportion of the firing strength of the ith rule to the sum of the firing strength of all rules':

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2} \text{ , i = 1, 2, 3} \tag{6}$$

For the sake of convenience, outputs of this layer are called normalized firing strengths.

Layer 4: Each node I in this 4th layer is an adaptive node with a node function

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i} u_i = \overline{w_i}(p_i x + q_i y + r_i z + s_i) \tag{7}$$

where $\overline{w_i}$ is a normalized firing strength from the 3rd layer; in addition, $\{p_i, q_i, r_i\}$ is this node's variable set. In the mentioned layer, variables are referred to as consequent parameters.

Layer 5: In this 5th layer, the single node is a fixed node, and therefore the fixed node computes the total output as the summation of all incoming signals:

$$O_{5,i} = \sum_i \overline{w_i} u_i = \sum_i w_i u_i \,/\, \sum_i w_i \tag{8}$$

Different variables in the ANFIS structures are identified by using the hybrid learning method. In its forward pass, functional signals move forward until they reach Layer 4. Also, Consequent variables are identified by the least squares estimate. In the backward pass, the error rates move backwards. The gradient descent updating the premise parameters.

Figure 2 shows the simple example of the ANFIS prediction process. The ANFIS setup was used with 2 input membership function using generalized bell function and 8 rules. Input 1, 2, 3 mean x/H, y/H, z/H value, respectively and output is the U/U_∞. Each horizontal axis of the input represents the value of the coordinate and the vertical axis represents the value of the generalized bell function. On the first layer of ANFIS, this layer calculates generalized bell function value for each input, and then multiply each value on 2nd layer. Then, 3rd and 4th layer calculate the proportion of the weighting factor for predicting the target velocity component. For optimizing the generalized bell function and node variable set, the gradient descent updating the premise parameters in backward pass.

The effect of various ANFIS setting parameters which include membership function and percentage of training data and epoch on the prediction accuracy. The performance and accuracy of the ANFIS method is calculated based on the statistic parameters.

Root Mean Square Error (RMSE) is used to calculate the difference between the ANFIS prediction values and measurement data

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \tag{9}$$

where O is the measurement data, P is predicted data and n is the number of data.

Coefficient of determination (R^2) is a criterion that illustrates how well the ANFIS data fits a statistical model.

$$R2=[\sum_{i=1}^{n}(O_i-\overline{O}_i)(P_i-\overline{P}_i)]^2 \,/\, \sum_{i=1}^{n}(O_i-\overline{O}_i)\sum_{i=1}^{n}(P_i-\overline{P}_i) \quad (10)$$

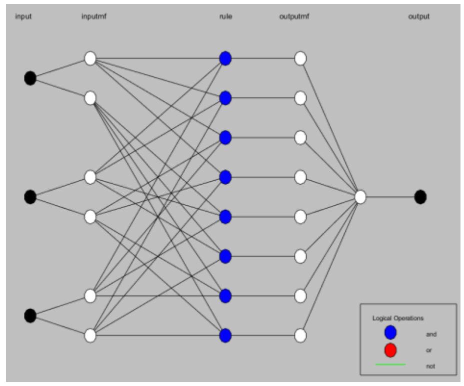


Figure 1: The ANFIS structure with 3-input first order Sugeno fuzzy model

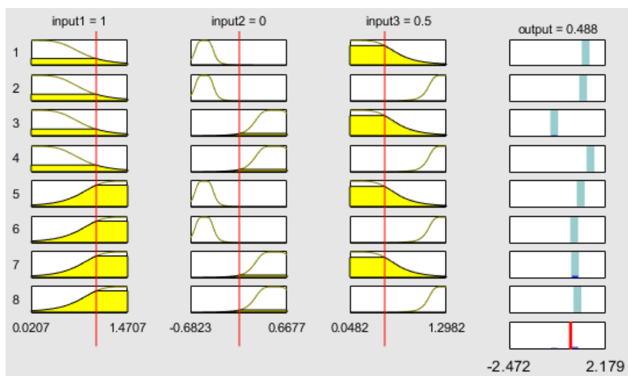
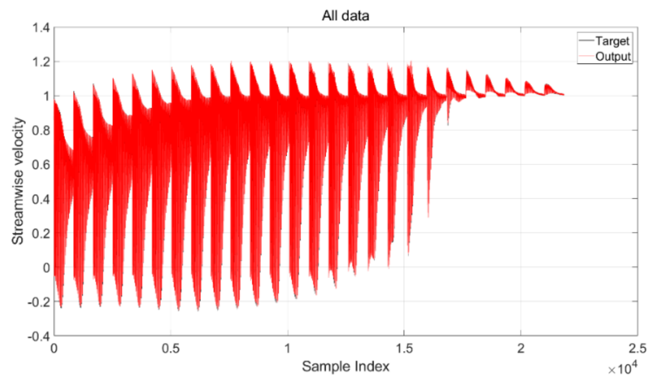


Figure 2: The ANFIS prediction with 2 input membership function and 8 rules

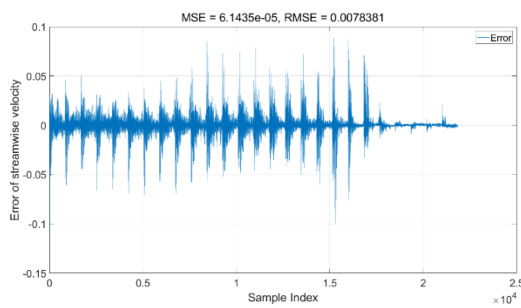
3 Sensitivity and accuracy of ANFIS setting prameters

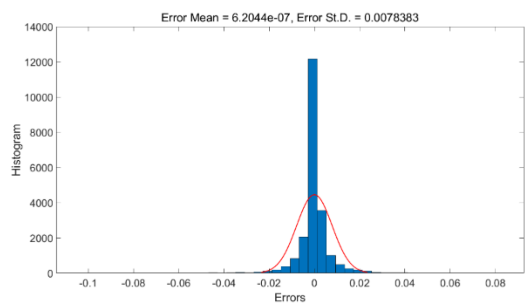
The MATALB R2017b has been used to develop the ANFIS model. Figure 5.3 shows the flow chart of the ANFIS prediction process. The first step is to load the measured 3D PIV data and set the domain of the desired area. After that, ANFIS parameters are applied for training AI. The ANFIS generation parameters include percentage of the training and testing data, number of membership function, input membership function type, output membership function type. For training ANFIS structure, parameters include number of epochs, error goal, initial step size, step size decrease and increase rate. After setting up the ANFIS parameters, it can start the ANFIS training using the measured data and check the convergence. In this study, the values of convergence criteria are based on $R2 > 0.99$, $RMSE < 0.01$. If the values of convergence criteria are satisfied, the obtained ANFIS result was applied to testing data. After checking convergence of the test data, the ANFIS model for data assimilation of 3D PIV data was adopted. A good ANFIS model can be used for a completely new prediction in which none of data has used in the training process. A new ANFIS mesh domain was generated and then the developed ANFIS model is used to predict the required results.

Figure 3 shows the ANFIS model's error of average streamwise velocity compared with measurement data for reference model. Figure 5.3 (a) shows the comparison with measurement data (target) and ANFIS result (output). For training, the RMSE value of streamwise velocity is 0.0078. This result shows that the error between the predicted data and measurement value is less than 0.78 % for streamwise velocity component. Consequently, this shows the high degree of linear dependence R2 between the ANFIS and measurement result in the training process. Consequently, the ANFIS model can accurately predict the 3D PIV velocity and aerodynamics with an error of less than 0.78 %. This error can be reduced with more input membership function.



(a) Streamwise velocity compared with raw data and ANFIS





(b) Error value of ANFIS (c) Histogram of predicted error

Figure 3: Accuracy of ANFIS model for average streamwise velocity for reference model

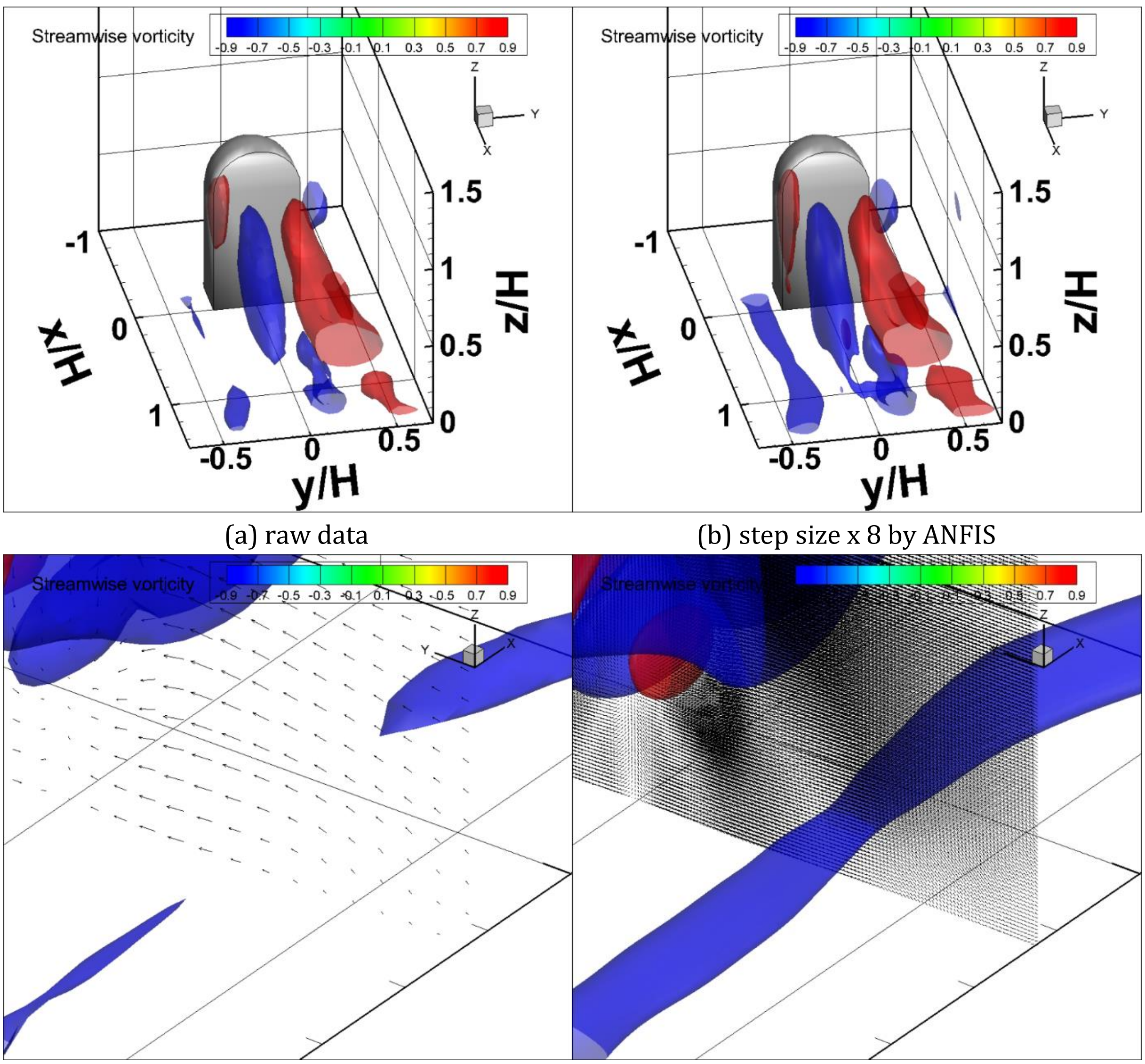
4 Results and discussion

The ANFIS method can predict the aerodynamics of side mirror models in less computational time and provide continuous results. The number of raw data in x/H, y/H, and z/H mesh coordinate is 28 x 30 x 26 nodes which have total of 21,840 data. This coordinate has a step size of 0.05 mm between the node. For ANFIS based data assimilation of 3D PIV, x/H, y/H, and z/H from 0 to 1.5, -0.7 to 0.7, and 0 to 1.3 with step size of 0.00625 are predicted using the ANFIS model. This means the spatial resolution of raw data will increase 8 times. The total number of nodes for each case is 241 x 225 x 209 nodes (11,333,025 data).

The increase in spatial resolution is that the vorticity, which a function of the gradient of velocity and space, can be well distinguished. Figure 4 shows the comparison of average streamwise vortex between raw data and ANFIS data assimilation on side view mirror model. In the case of reference model, the connection of horseshoe vortex from the bottom of model was very well discovered. Raw data as shown in Figure 4 (b) shows that horseshoe vortex is broken due to a lack of spatial resolution, while it is recovered by ANFIS data assimilation.

Figure 4 (c), (d) shows a sub-volume of the space in which horseshoe vortex occurs to ensure a detailed view of these results. As the vector field became dense, the missing data could be found.

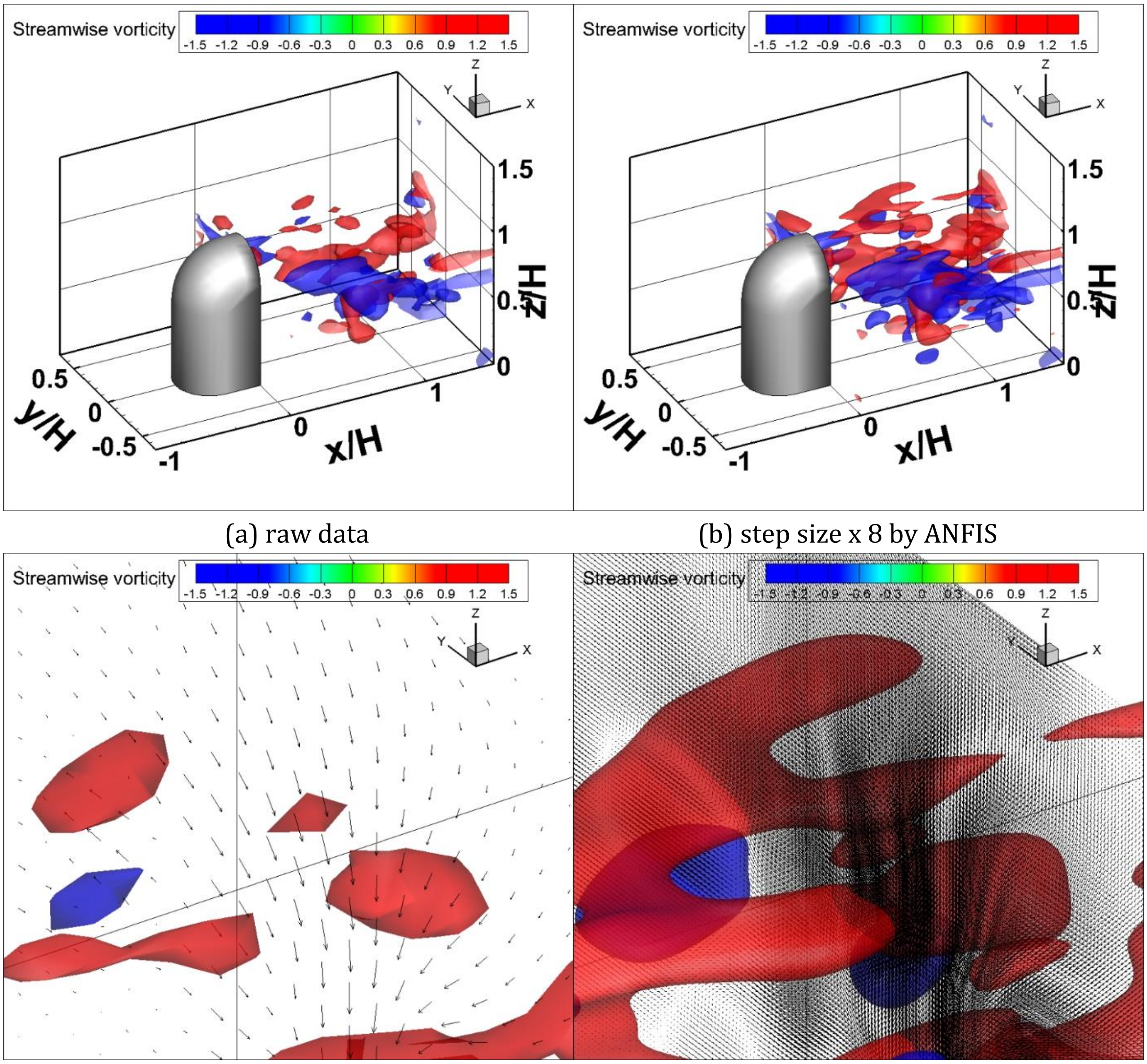
To identify the advantages of AI data assimilation, instantaneous velocity field on reference model was used for data assimilation. Instantaneous velocity field have more vortex structure, so high spatial resolution is essential to discover vortex structure. Figure 5 shows the instantaneous streamwise vortex for the side view mirror model. Comparing with the results of the averaged results, the effect of data assimilation is certainly greater. Compared with raw data, the data assimilation results show small vortex structure was found by increasing spatial resolution. These data assimilation results provide a better understanding of the small turbulence structure and allow for more in-depth analysis through missed data.



(a) raw data (b) step size x 8 by ANFIS

(c) raw data in sub-volume (d) step size x 8 by ANFIS in sub-volume

Figure 4: Comparison of average streamwise vortex between raw data and ANFIS.



(a) raw data (b) step size x 8 by ANFIS

(c) raw data in sub-volume (d) step size x 8 by ANFIS in sub-volume

Figure 5: Comparison of instantaneous streamwise vortex between raw data and ANFIS.

5 Conclusion

In this study, to increase spatial resolutions of velocity field, Artificial Intelligence (AI) based data assimilation method has applied. For the AI based data assimilation, this work shows that there is a possibility to train ANFIS model in multiple dimensions which is very interesting to deal with fluid flow geometry analysis. This type of analysis enables us to learn from each node (image pixels), showing local learning model and present the results in neural network nodes which is fully independent of PIV technique and complex mesh analysis of it. Optimization of fluid parameters is very time consuming and computationally expensive. The ANFIS model can be a great assistant tool for numerical and experimental method to optimize few case studies without doing those conditions with exp methods. This method can also enable us for mesh refinement with small computational time. This research shows us how we can use train ANFIS model in different dimensions to make independent methods for learning and prediction. There is a great agreement between experimental and ANFIS method showing that intelligent algorithm can be replaced with numerical method and avoid expensive computational time. Using the developed technique, accurate real-time turbulence quantities will be obtained, which are almost impossible to measure experimentally through the combination between experiment and AI. The measurement of the 4D instantaneous field data will enable to analyze sound pressure spectra and noise sources to be determined at any location within the space, enabling the design of features to eliminate the main noise source. As a result, understanding of the flow noise mechanism and developing a new turbulence model will be possible.

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