CFD-based surrogate modelling of urban wind farms using artificial neural networks: double rotor arrangements

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Abstract. Extensive characterization studies are required to identify optimal wind farm layouts and achieve high power density, i.e., power per land area. Performing such studies using experimental or high-fidelity numerical methods can be timely and computationally expensive. To alleviate this obstacle, surrogate models can be developed to mimic the behavior of the simulation/experiment. In this paper, a shallow feed-forward artificial neural network (ANN) surrogate model is developed. The Levenberg-Marquardt algorithm is used to train a model with 3 layers and 10 hidden nodes. The model correlates the arrangement of a double-rotor vertical axis wind turbine array, as the fundamental generating cell of the wind farm, with its overall power performance. The inputs are the relative distance (R) and angle (Φ) between the rotors, and the output is the overall power coefficient of the array. In total, 96 CFD-simulated arrangements are used as data points to train, validate and test the model. The trained model has a mean square error of $2.10 \times 10^{-5}$ and R-squared of 0.99, indicating its accuracy and generalizability. The average and maximum errors are 3% and 10%, respectively. The employed method can be expanded to accommodate more rotors towards optimal urban wind farm layout design.

1. Introduction

Urban wind farms can provide a clean and sustainable alternative to the green-house-gas-emitting fossil fuels in the built environment. These wind farms can also reduce infrastructure costs as well as the losses due to the long-distance energy transmission [1]. However, the variation in the wind direction, a main characteristic of the urban wind field, is expected to have a significant impact on the performance of these farms. Vertical axis wind turbines (VAWTs) are promising candidates for wind energy harvesting in urban areas due to their insensitivity to wind direction and higher space efficiency, i.e., more energy generation per land area, compared to horizontal axis wind turbines (HAWTs). This is especially appreciated in dense urban areas where the available area for wind energy harvesting is limited [2]. However, research on optimal VAWT farm arrangements is rather limited, and extensive characterization studies are required to identify the optimal layouts. Performing such studies using experimental or high-fidelity numerical simulations can be timely and computationally expensive [3].

Nomenclature

$c = $ Airfoil chord length [m]  
$n = $ number of airfoils [-]  
$U_\infty = $ Freestream velocity [m/s]  
$d = $ Turbine diameter [m]  
$q = $ Dynamic pressure [Pa]  
$\lambda = $ Tip speed ratio [-]  
$M = $ Moment [Nm]  
$q_{\infty} = $ [-]  
$R = $ Relative distance [-]  
$\sigma = $ Solidity [-]  
$\Phi = $ Relative angle [°]  
$\Omega = $ Rotational speed [rad/s]  

Rec = Chord-based Reynolds number [-]  
TI = Turbulence intensity [%]
To alleviate this obstacle, data-driven surrogate models can be developed and utilized. These models mimic the behavior of the simulation/experiment as closely as possible while being comparatively cheaper and circumvent the need for a large number of simulations/experiments.

In this paper, the arrangement of two VAWTs in close proximity, as the fundamental generating cell of urban wind farms, is investigated. In total, 96 high-fidelity transient CFD simulations, validated with experimental data, are carried out on different arrangements to create a high-quality training dataset, which is used to train an artificial neural network (ANN) surrogate model. The developed ANN surrogate model can be used to accurately predict and optimize the power performance of double VAWT arrays and identify the optimal arrangements. To the best of our knowledge, such a model has not yet been developed for urban VAWT farms.

The remainder of the paper is organized as follows: the numerical model used for generating the training dataset is introduced in Section 2. The development of the ANN model is described in Section 3. The training dataset for the model, its inputs and output are detailed in Section 3.1. The results are presented in Section 4. A discussion and the main conclusions are given in Sections 5 and 6, respectively.

2. Numerical model: computational fluid dynamics (CFD)

A large number of high-fidelity unsteady Reynolds-averaged Navier-Stokes (URANS) simulations, validated with experimental measurements, are performed for a double-rotor VAWT array in the following arrangements (Figure 1a):

- Relative distance (R), defined as the length of the rotor’s center to center line: 1.25d, 1.5d, 1.75d, 2.25d, 3d, 5d and 10d.
- Relative angle (Φ), defined as the angle between the rotor’s center to center line and the X-axis: 0°, ±5°, ±10°, ±15°, ±30°, ±45°, ±60°, ±75° and ±90°.

A detailed sensitivity analysis shows that for R ≥ 10d, the effects of the turbines on one another is negligible. Therefore, R > 10d distances are not included in the studied arrangements. The number of studied levels for each input factor is selected based on the available computational budget.

The simulations are performed on single-straight-bladed Darrieus H-type VAWTs. The geometrical and operational characteristics of the rotors (Table 1) are selected with respect to the wind-tunnel measurements by Tescione et al. [4], which is also employed for CFD validation.

The geometry is simplified by excluding the shaft, connection rods, and subsequent blades to reduce the computational cost. According to Rezaeih et al. [5,6] these simplifications do not significantly affect the results and the aerodynamic performance and the wake of low-solidity VAWTs operating within the optimal regime are marginally affected by the number of blades. Figure 1a depicts the computational domain in which two rotating cores for the two rotors and a fixed surrounding domain are considered. Based on the best practice guidelines for CFD simulations of VAWTs [7,8], a 35d × 40d domain is developed.

| Parameter                  | Value | Parameter                  | Value |
|----------------------------|-------|----------------------------|-------|
| Airfoil type               | NACA0018 | Tip speed ratio, λ [-]     | 4     |
| Number of blades, n [-]    | 1     | Rotational speed, Ω [rad/s]| 74.4  |
| Airfoil chord length, c [m]| 0.06  | Freestream velocity, U∞ [m/s]| 9.3 |
| Diameter, d [m]           | 1     | Turbulent intensity, TI [%]| 5     |
| Solidity, σ [-]           | 0.06  | Chord-based Reynolds number, Re_c [-]| 1.57 × 10^5 |

Figure 1b-e shows the computational grid for a sample arrangement consisting of ≈ 850,000 quadrilateral cells. The number of cells ranges from 0.7 to 1.2 million cells for different arrangements. The maximum and average y+ on the blade are 4.2 and 1.8 for all arrangements, respectively.

Table 2 details the rest of the settings for the CFD simulations, which are based on the best practice guidelines for simulation of VAWTs [5–8]. Unsteady Reynolds-averaged Navier-Stokes (URANS) equations are solved using the ANSYS Fluent v19.1 solver. Further details on the numerical model, including the solution verification and validation, are provided in Ref. [2]. The CFD results are used to create a training dataset for a surrogate model, as described in Section 3.
3. Surrogate model: artificial neural network (ANN)

To develop a surrogate model, a dataset is required. This is a collection of data points, i.e., inputs and their corresponding outputs. In this study, high-fidelity CFD simulations are performed on 96 double rotor VAWT arrangements to create the dataset. The arrangement is given by $R$ and $\Phi$ as the inputs (Section 2 and Figure 1a). The output is the overall power coefficient of the array, $C_{P_{\text{Overall}}}$, defined as the arithmetic mean of the individual power coefficients of the two rotors. Based on the best practice guidelines for the development of ANNs [9], the developed dataset is randomly divided into three sets: (i) 70% for training (68 arrangements), (ii) 15% for validation (14 arrangements), and (iii) 15% for testing (14 arrangements).

3.1. Developing ANN

In this study, an artificial neural network (ANN) is used to develop a surrogate model. ANN has been successfully used for many different engineering applications mainly due to its ability to implicitly detect and model non-linear correlations between dependent and independent variables [9].

A shallow feed-forward artificial neural network (ANN) [10] is used to model the correlation between the inputs and the output. The developed ANN consists of three layers:

1. An input layer with two neurons, one for each input factor, i.e., $R$ and $\Phi$;
2. A hidden layer in which the neurons take in the inputs, apply weights and biases and pass the results through a non-linear activation function to produce the output. The number of neurons in this layer is decided based on model evaluation (see Section 3.3). $\tanh n = \frac{2}{1+\exp(-2n)} - 1$ is used as the activation function in which $n$ is the net input of the function.
3. An output layer with one neuron for the output, i.e., $C_{P_{\text{Overall}}}$, conveying the model prediction.
3.2. Training phase
Minimization of the mean squared error (MSE) between the trained model predictions and data points is the aim of the training phase. The model is initially fitted on the training dataset. Subsequently, the predictions of the trained model are compared against the simulation results in the validation set to assess the performance of the model and avoid overfitting. The training, i.e., coefficient (weight) optimization in hidden nodes, stops when the MSE of the validation set stops to decrease for 6 consecutive training cycles. The test dataset is an independent set, which is not used during the training phase. In the end, to reach an unbiased evaluation of the developed ANN, the predictions of the trained model are evaluated against the test dataset [10,11].

A number of different algorithms have been developed to train the ANN models, all with the goal of reducing the model error, i.e., the difference between the modelled and simulated output response. The two most common methods are the backpropagation and Gauss-newton methods. In this study, the Levenberg-Marquardt (LM) algorithm is used, which combines both of the aforementioned methods and is reported to result in lower errors than both [12].

Figure 2 depicts the learning rate of the developed ANN through its training cycles. Adaptive learning rate is used starting from \( \approx 4 \times 10^{-3} \) and updating the learning rate in response to estimated error in each training cycle. The training stops after 12 cycles with a learning rate of \( \approx 10^{-5} \) in the final cycle.

3.3. Model evaluation
The developed model is evaluated using MSE and R-squared (R\(^2\)); Eq. 1 and 2 respectively:

\[
\text{MSE} = \frac{1}{n} \sum_{j=1}^{n} (t_j - o_j)^2 \\
R^2 = 1 - \frac{\text{RSS}}{\text{TSS}}
\]

where \( n \), \( o \) and \( t \) are the number of data points, ANN predicted and CFD simulated values, respectively. RSS is the sum of squares of residuals and TSS is the total sum of squares.

The iterative process of model training and evaluation is started from a network with three hidden neurons. The variations of MSE with the increase of the number of hidden neurons is monitored for ANNs with 3 to 15 hidden neurons. It is found that an ANN with 10 hidden neurons results in the minimum value of \( \text{MSE} = 2.1 \times 10^{-5}, 4.7 \times 10^{-5} \) and \( 7.5 \times 10^{-5} \) for the training, validation and data sets, corresponding to \( R^2 \) values of 0.99, 0.99 and 0.98 for the training, validation and data sets, respectively. Performance evaluation of the ANN model is presented by error histogram and regression plots (Figure 3). The bell-shape error histogram indicates the normal distribution of error in the model.

![Figure 2. Learning rate during the training phase.](image)

![Figure 3. (a) ANN error histogram and predicted vs CFD output for (b) training set, (c) validation set and (d) test set.](image)
4. Results

The developed ANN model is presented in Eq. A.1 in Appendix. Figure 4 illustrates the ANN model prediction of normalized $C_{P_{\text{Overall}}}$ against the CFD simulation results in different relative distances and angles. For easier comparison, all values are normalized by the power coefficient of an isolated solo VAWT ($C_{P_{\text{Solo}}} = 0.2871$) with the same operational and geometrical characteristics (Table 1). The figure clearly shows the accuracy of the developed ANN model and its ability to model the response.

The average error of the ANN model from the CFD simulations in all the 96 simulated arrangements is about 3% with a maximum error of about 10% occurring for an array with $R/d = 5$ and $\Phi = 0^\circ$. The average error of the model for arrangements with $0.95 < C_{P_{\text{Overall}}} / C_{P_{\text{Solo}}} < 1.02$, i.e., arrangements in which the two rotors are operating as efficiently as or better than an isolated solo rotor is less than 1.5%. The Olden and Jackson method [13] is used to quantify the sensitivity of the model output to inputs. Accordingly, the sensitivity of the $C_{P_{\text{Overall}}}$ to $\Phi$ is 1.65 times that of $R$.

![Figure 4](image)

**Figure 4.** ANN modeled vs CFD-simulated normalized overall power coefficients ($C_{P_{\text{Overall}}} / C_{P_{\text{Solo}}}$) for different relative angles ($\Phi$) at a relative distance of (a) $R = 1.5d$, (b) $R = 1.75d$, (c) $R = 2.25d$, (d) $R = 3d$ and different relative distances ($R$) at a relative angle of (e) $\Phi = -5^\circ$ and (f) $\Phi = -60^\circ$.

5. Discussion

The developed ANN model in this study is trained for two adjacent co-rotating VAWTs with specific geometrical and operational conditions (Table 1) in a specific range of relative distances and angles (see Section 2). This model should be used with caution for arrangements with different specifications such as the number of blades or tip speed ratio. The accuracy of the model outside the $R$-$\Phi$ range that it is trained for, is not assessed.

6. Conclusions

In this study, an ANN surrogate model is developed to estimate the overall power performance of two adjacent VAWTs, as the fundamental generating cell of an urban wind farm, using $R$ and $\Phi$ as the model inputs and the $C_{P_{\text{Overall}}}$ as the output. The employed dataset to train the model is based on 96 high-fidelity URANS CFD simulations, validated with experimental data.

The following conclusions are made:

- The developed model has an average and maximum deviation of about 3% and 10% from CFD.
- For the $R$-$\Phi$ range in which the array has its best overall performance, $0.95 < C_{P_{\text{Overall}}} / C_{P_{\text{Solo}}} < 1.02$, the model has about 1.5% deviation from CFD.
• $C_{p,\text{Overall}}$ is found to be 1.65 times more sensitive to $\Phi$ than $R$.

The developed surrogate model has the potential to accurately predict the power performance of the studied arrangement, circumventing the need for time-consuming and computationally expensive simulations.measurements. The model is especially suited for optimization purposes aiming to find the optimal rotor arrangements. It can be used as a tool by city planners, consultants, and urban authorities for designing optimal wind farm layouts with high power densities. This is especially valuable in urban areas with limited allocable land for wind energy harvesting.

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Appendix
Eq. A.1 represents the developed ANN model:

\[
C_{p,\text{Overall}} = 0.24381594 + 0.549427339 \tanh (0.5 \times ((-0.334822218) + 0.10310329\Phi - 0.022899025R)) \\
- 0.510131364 \tanh (0.5 \times ((-0.513457287) + 0.088526373\Phi - 0.054712435R) - 0.167618536\tanh (0.5 \times (0.49165101 - 0.05589276\Phi + 0.218607685R))) + 0.09838189\tanh (0.5 \times (0.135217219 - 0.024500059 + 0.04206426R)) \\
- 0.009080448 \tanh (0.5 \times ((-4.124436399) - 0.010472683\Phi + 0.721164672R)) + 0.16327651\tanh (0.5 \times ((-0.451861495) + 0.090794916\Phi + 0.081888207R))) \\
- 0.244919206\tanh (0.5 \times (0.451260757 + 0.14208519\Phi + 0.080861904R)) + 0.027619408 \tanh (0.5 \times ((-1.906727436) + 0.029731357\Phi + 0.803630401R)) + 0.096984858 \tanh (0.5 \times ((-0.594204424) - 0.45957852\Phi + 0.403897281R))) + 0.112499974\tanh (0.5 \times (0.992189592 + 0.006045916\Phi - 0.107091122R)) \\
(A.1)
\]

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