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ENHANCING WIND TURBINE POWER OUTPUT ESTIMATION USING CAUSAL INFERENCE AND ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

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ABSTRACT

Wind turbines have attracted much attention from scientists who are aiming to achieve a prominent level of performance due to the environmental changes during the year. To meet the demand for renewable energy at the lowest cost, wind energy became the target of machine learning algorithms and was employed to predict the output power of wind turbines. The aim of this study is to utilise a causal inference approach to estimate the power output of wind turbines. Initially, the outcomes derived from numerical prediction are examined using a structural causal model. After causal discovery, we identify potential confounders for the filter factors that have the most significant impact on the outcome and decide whether to include or exclude these prospective confounders in our model. This method guarantees precise predictions using the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is a hybrid learning approach that combines neural network and fuzzy logic system for estimating the output model for nonlinear relationships. ANFIS employed the pressure surface, wind speed and air pressure as input data while the power of the wind turbine served as the output of the predicted model. Various practical experiments were conducted using different membership functions in neuro-fuzzy training to achieve the lowest possible mean square error. The data were gathered over two months on a farm in Egypt on the Suez Gulf. Approximately 85% of the data was utilised to train the three inputs, while the rest was used to evaluate the predicted model and assess the efficiency using Akaike Information Criterion (AIC) to choose the best fit model. A further study showed that changing the ANFIS parameters could deviate from the path of efficient outcomes, compared with the neural network approach.

KEYWORDS

ANFIS System; Wind Turbine Power; Confounders; Modelling and Estimation; Causal Inference.

1. INTRODUCTION

As the world increasingly prioritises clean renewable energy over fossil fuels, a main goal for researchers has become exploring various technologies to meet the demand for clean energy. Policymakers, researchers and stakeholders have set the stage for detailed analysis based on renewable energy datasets. Wind turbines are considered the fastest growing energy sector, largely due to their ease of installation. Their contribution to total global power capacity reached 8% in 2018 (Tchakoua et al., 2013). Recent statistics on the amount of renewable energy as a percentage of total electricity generation across different countries showed that wind turbines contributed 2.098 Giga Watt per hour (GWh) globally in 2022. This was distributed as follows: 522 GWh produced in Europe, 12.996 GWh in Africa, 869 GWh in Asia, 5.828 GWh in America, and 40.66 GWh in Eurasia (Renewable and Agency, 2021). The demand for wind energy has increased. An Economics Times article showed that China is the largest wind energy user in the world with 221 GW followed by the United States and Germany. However, harsh atmospheric conditions such as humidity, air temperature and pressure can directly affect the output power of turbines and their performance. For example, a study by (Pérez et al., 2023) showed that the coastal region of Mexico experienced unstable atmospheric conditions, occurring 80% of the time during the measurement period, followed by neutral conditions 12% of the time, and stable conditions 6%.

Many researchers have employed Artificial Neural Networks (ANNs) to evaluate and model the effects of the weather on wind turbine generation (Routray, Reddy and Hur, 2023), and to estimate the maximum storage ability of network wind turbines during their operation. A wind turbine is a complex system, and it can be exposed to diverse types of faults and failures during its operation. Different studies have discussed fault detection and classification methods in order to improve the shutdown and operational efficiency of turbines on wind farms (Tchakoua et al., 2014;Karaman, 2023). Artificial Intelligence (AI) technologies have contributed to optimising reliability and minimising power loss (Issa and Majeed, 2012) they can be utilised to analyse the turbine positions and rotor radius in a multicriteria decision making issue.

The area of causal discovery has attracted increasing interest and advancement in recent years, owing to its broad applicability to numerous domains, especially machine learning (Hoyer et al., 2008). Machine learning algorithms are notorious for encountering numerous challenges when applied to real-world scenarios. These challenges include the interpretability of the outcomes, prediction bias, fairness, and adaptability, especially when using observational data or data from uncontrolled environments. Advanced techniques, like deep learning, are often less prone to under fitting but are more susceptible to issues of robustness and interpretability (Simon and Sisi Ma, 2024).

Causal models can uncover the true causal impact between meteorological variables and power outputs. The concept of causality can be employed to elucidate the reasons behind the outcomes produced by our prediction models. Once the causation has been identified, additional research can be conducted to determine the variables that truly influence wind power output, and these can be used for accurate power forecasting. The wind power production of different plants may vary because of variations in geographical conditions and climate, which in turn can influence the variables that affect the plants. Causal models enable more accurate scientific predictions in various geographical areas.

In this study, we employ a causal inference approach to improve the interpretability of wind power forecasting models. We utilise a causal model to perform causal identification on numerical predictor data, then design a model using an Adaptive Neuro Fuzzy Inference System (ANFIS) to estimate the power output from wind turbines and lower the mean square error as far as possible. The design, training, and the effectiveness of the proposed ANFIS are investigated and presented.

The rest of the paper is discussed as follows: Section 2 shows the literature review and most related works. Section 3 presents the main problem and the main contribution of this paper. In section 4, the methodology is discussed in detail including the causal inference and adaptive neuro-fuzzy inference system (ANFIS). Section 5 presents the main results of the proposed methods and section 6 makes small discussion and summarizes the crucial points from this study.

2. RELATED STUDY

Different techniques and approaches have been utilised to find the output power of wind turbines. Various algorithms, such as machine learning, fuzzy logic, genetic algorithm, and neural network, have been used to improve wind power system performance in complex environments (Chen and Kim, 2022). Another study concern focuses on two aspects: The Maximum Power Point Tracking (MPPT) and the Fatigue Load Balance. AI advancements play a crucial role in minimising the wear and tear on the turbine components and maximising the power output (Song et al., 2024;Kadhem and Hasan, 2021), but another main issue affecting the power of wind turbines is the blade pitch, blade size and speed ratio. The blade pitch is controlled by actuators that take orders from the proportional-integral derivative (PID), but the wind speed can change faster than the PID is able to handle. Therefore, AI algorithms have been adopted to predict mechanical faults or imminent failure (Farrar, Ali and Dasgupta, 2023). AI wind power system schemes are summarised in Table 1.

Despite all the technological achievements contributing to finding the optimal output power of wind turbines, there is lack of control over each turbine individually (on a wind turbine farm), which may lead to extensive weak interactions and a loss of energy. Thus, it is necessary to design an efficient wind control strategy to utilise the overall operation energy and match the grid requirements (Alyousuf and Korkmaz, 2023).

In addition, most of the afore-mentioned control schemes were based on analytical models. The AI algorithms are needed to manage the dynamic modelling changing; these algorithms provide a level of understanding of changes on wind farms, enabling improved control strategies that optimise the output power and lower the use of control commands (Ebrahimi, Khayatiyan and Farjah, 2016).

By decentralising the control of wind turbines to optimise their operation within a farm, an algorithm such as population-games assistance can improve coordination and decision-making processes. The challenge lies that all turbines don't work at a fixed induction factor. Therefore, turbines don't give optimal results due to wind speed deficit and collect benefit from the entire wind farm (Barreiro-Gomez et al., 2019).

Table 1. The algorithms utilised and the parameter measures.

	Authors	Algorithms	Findings
1	(Wang et al., 2019)	- Artificial neural networks (ANNs). - Support vector machines (SVMs). - Swarm optimisation algorithms (SOAs).	Can be used to predict wind speed, wind density and power output.
2	(Civelek et al., 2016)	Genetic algorithm with PID controller.	Increases the efficiency of blade pitch control.
3	(Chatterjee, Naithani and Mukherjee, 2016)	Teaching learning-based optimisation and machine learning approach (TLBO).	Minimises damping phenomena, oscillation in rotor currents, and fluctuations in electromagnetic torque related with PID.
4	(Hafiz and Abdennour, 2016).	Adaptive neuro-fuzzy inertia controller (ANFIS)	Measure the performance of various wind speed turbine.
5	(Yin, Jiang and Pan, 2020).	Recurrent neural network (RNN)	Maintains the optimum rotation speed of the wind turbine
6	(Yin and Zhao, 2021)	Deep neural learning (DNL) with long short-term memory (LSTM)	Maximises the wind farm power generation output.
7	(Alencar et al., 2018).	An autoregressive integrated moving average optimisation function (ARMINA) with ANN.	Predicts wind speed.
8	(Ulkat and Günay, 2018)	Geographical and atmospheric monthly variables with ANN	Finds the wind power generation output.
9	(Wang et al., 2023a)	Using potential-outcomes models from causal models.	A wind power forecasting method using causal inference

For the wind farms, the estimation of wind turbine output power is relative to its parameter of measures. Due to uncertainties associated with wind power, it is crucial to develop a forecasting model to improve the operation efficiency in wind farm. LSTM is an effective forecasting task, used to predict the wind energy output based on wind speed as an input. The LSTM model performed efficiently in forecasting the output in time series. The analysis of uncertainty using LSTM method is crucial for operational decision making. However, the study underscores the need of environmental factors and operational characteristics when assessing forecasting performance (Zhang et al., 2019).

In Poland (Bochenek et al., 2021), data were collected for two years (2018–2019) to train a model to predict day-ahead wind power generation, based on the forecast weather conditions. Different machine learning approaches were used the find the fitted model, such as Extreme Gradient Boosting (XGB), Random Forest (RF), and ANN. Certain parameters were optimised to avoid overfitting, such as an early stopping threshold which was used to stop the training process if there was no improvement in the outcome after a certain number of rounds. Manipulation of these parameters can achieve accurate predictions.

Despite the machine learning algorithms used, there are limitations to the forecasting models, especially when dealing with renewable energy generators such as wind turbines. The study by (Bochenek et al., 2021) depended on a numerical weather prediction. If the weather changed for the better, the model required up-to-date information to accurately predict the wind power output. Despite common methods for acquiring energy, countries are in a race to utilise their resources such as solar panels, whose efficiency reduces to 20% because of dust, winter months and dirt. In the study by Gökkuş (2023), ANFIS was used to predict real-time output power in Turkey. The wind speed, which is considered a primary factor for predicting output power, and the air density, which influences the kinetic energy in the wind, were the two input variables used to train the model and predict the output power. In contrast with the previous studies, this paper emphasised the flexibility of ANFIS in changing the parameters to estimate the power output for different wind turbine models. It also uses less atmospheric data, which is considered efficient for wind energy resources. ANFIS is also used to predict the efficiency of wind turbine gearbox oil temperature using meteorological variables (wind speed, ambient temperature, humidity and air pressure) in order to reduce the cost of maintenance and operation (Adedeji et al., 2023). ANFIS can also be utilised to estimate the aerodynamic power of wind turbines in relation to variations in wind speed, by using iterative neuro-fuzzy Hammerstein model. The objective was to improve the accuracy of the wind turbine model and ensure that the non-linear characteristics of wind turbines are gathered and precisely calculated (Xu et al., 2023; Jović, 2020).

Wang et al. (2023) utilised a causal inference methodology to improve wind power forecasting approaches. Rather than employing traditional neural networks, the researchers in this study examined numerical weather prediction results using potential-outcome models from causal inference. The meteorological data acquired from the numerical weather prediction (NWP) were filtered based on elements that causally influence wind power output. The importance of these causal impacts was measured and served as the foundation for a novel approach to enhance the optimisation of wind power production prediction. This methodology was proved with a case study using one year's NWP data from a single wind power station. The study showcased the ability of this strategy to enhance the accuracy of forecasts by focusing on factors that have a causal relationship with the outcome. However, while this study employed causal inference methodology to enhance wind power forecasting approaches, it did not utilise neural network prediction methods for further optimisation. By integrating the neural network prediction approach with the causal model, it would be possible to enhance the forecasting method's interpretability for wind power output estimates while maintaining accuracy.

As well as the mathematical models Support Vector Machine (SVM), Multilayer Perception (MLP), Random Forest (RF), and decision Tree (DT), which are considered robust and achievable techniques, the wind speed and ambient surface temperature are used in several studies as input parameters for the irregular and non-linear power output to achieve optimal output energy (Rahmani et al., 2013;Jamii et al., 2022).

3. THE PROBLEM AND CONTRIBUTION OF THIS STUDY

Weather variations, represented by the temperature, wind speed and air pressure, are considered the main parameters that affect the output power from wind turbines. The aim of this study is to obtain scientifically valid findings regarding the effect of weather variation on wind power output. Our methodology involves determining cause-and-effect linkages between the variables being examined, rather than just identifying relationships based on correlation, to improve the interpretability of wind power forecasting models. While statistical knowledge is sufficient for prediction and diagnosis, causal knowledge is essential for action and intervention. Our objective is to comprehend the fundamental causal structures to determine whether the variables have a causal impact on wind power output and to estimate the causal effect. The findings can be utilized to improve the estimation of wind turbine power production by employing ANFIS. The approach was to design a model with a low mean square error that could effectively estimate the power of wind turbines. We evaluated the model with the input dataset and estimated the output from the Gabal El-Zeit wind turbine located in the Northeastern Desert, on the Suez Gulf, Egypt. These data were taken from ref. (Sharkawy et al. ,2024). To generate learning data for the ANFIS, the surface temperature (Kelvin), wind pressure (kilo Pascal) and wind speed (metre/second) were measured along with the output power (kilowatt) for two months (Oct. 2023 to Dec. 2023). At the end of this period, the learning data contained 1488 pairs of input-output data. 85% of the learning data was utilised for training purposes, and the rest were used for evaluating the model.

4. METHODOLOGY

In this section, the proposed structure of the framework is as shown in Fig. 1. Multiple Linear Regression was employed to understand the directions of the three input variables and obtain the coefficients, which we used to assess the causal inference of the predictor variables on the output (Nassar and Khaleel, 2019). Based on these observations, we explored the ANFIS model implementation. A detail explanation of the causality is given below.

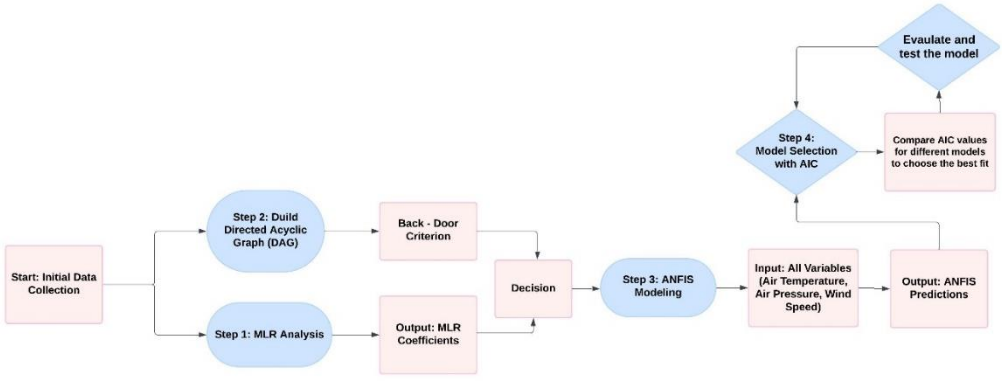

Fig. 1. The structure of the framework to obtain the best fit model.

4.1. Causal Models

A. Causality:

The primary goal of causal models is the establishment of causation. Causality can be defined as the relationship between cause and effect.

Definition 4.1 (Pearl, 2011) Causal Effect: Given two disjointed sets of variables, X and Y, denoted as P(y|do(x)), is a function from X to the space of probability distribution on Y. The distribution of Y after intervening on X and setting it to x is distinct from the distribution of Y before setting X to x.

Judea Pearl, the recipient of the prestigious Turing prize in 2011, has made substantial advancements in the field of causal analysis by developing a framework grounded on mathematics and probability theory (Bareinboim et al., 2022). In short, it states that a causal relationship between X and Y is established when manipulating X directly leads to a corresponding change in Y, but altering the value of Y does not affect the value of X. A false correlation occurs when there is a third variable Z that is a common cause for both X and Y. Using a spurious correlation and feeding it into a machine learning model during training can result in the generated results being difficult to interpret.

Traditional approaches that are specifically developed to address correlation problems are not suitable for solving causal problems since causality and correlation are distinct concepts. Thus, it is necessary to develop new frameworks to establish causal models.

B. Causal Models:

In this study we will talk about two causal model frameworks: Causal Graphical Models (CGMs) and Structural Causal Models (SCMs). CGMs are utilised to describe the structure and causality of variables and are graphically depicted using a Directed Acyclic Graph (DAG).

Definition 4.2 (Montero-Hernandez, 2019) Directed Acyclic Graph (DAG): G is a pair (V,E) where V is the set of nodes $\{V_1, \ldots, V_n\}$ and E is the set of edges consisting of ordered pairs (V_i, V_j) which implies $V_i \rightarrow V_j$ where $i \neq j$ and also has no cycles.

A DAG is particularly significant in the analysis of causal relationships because it possesses two key characteristics: directed edges and the absence of cycles. Directed edges enable the encoding of information flow between variables, whereas the absence of cycles prevents the occurrence of recursive causal relationships. The SCM consists of a CGM together with a collection of structural equations (Rubenstein et al., 2017). Within the SCM, we can carry out intervention operations to observe the causal effects that result from various factors. In a DAG, we can carry out interventions and adjust confounding factors a using backdoor criterion. This allows us to examine causal effects and discover new interventional distributions for the variables.

In the theorem of causal effect identifiability by (Pearl, 2011), in a causal diagram G representing a Markov model, the causal effect P(y|do(x)) can be identified if the subset of measured variables V includes $\{X \cup Y \cup PA_x\}$, meaning that X, Y, and all parents of variables in X are measured. The expression is obtained by adjusting for PA_x.as in the Eq. 1:

$$P(y|x_i') = \sum_{pa_i} P(y|x_i', pa_i)P(pa_i) \qquad (1)$$

Where $P(y|x_i', pa_i)$ and $P(pa_i)$ are pre-intervention probabilities.

C. The Backdoor Criterion:

Given a causal diagram G and non-experimental data on a subset V of observable variables in G, our goal is to estimate the effects of interventions do (X = x) on a set of response parameters Y, in which X and Y are subsets of V. In a clear approach, our intention is to calculate the probability P(y | do(X=x)) based on the estimate of P(v). Then, the backdoor criterion can be applied directly to the causal diagram (DAG) in order to test if the set of a variable (covariates) $Z \subseteq V$ is sufficient for causal inferences.

Definition 4.3 (Pearl, 2011) Backdoor: A set of variables Z fulfils the backdoor requirement with respect to a pair of variables (X_i, X_j) arranged in a certain order in DAG G if:

i. No node in Z is a descendant of Xi and

ii. Z blocks all paths between Xi and Xj that have an arrow pointing towards Xi.

Similarly, if X and Y are two distinct subsets of nodes in G that have no elements in common, then Z is said to satisfy the backdoor criteria with respect to (X, Y) if it satisfies the criterion with respect to any pair (Xi, Xj) such that $Xi \in X$ and $Xj \in Y$.

In the backdoor criterion, the paths where arrows point towards X_i must be blocked; these paths can be thought of as entering X_i through the back door. In Fig. 2, our DAG, the set Z{A, T}, meets the backdoor criterion. When we condition on any element of the set Z we will block the backdoor path.

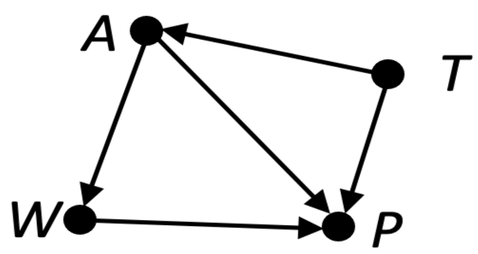

Fig. 2. The DAG for Wind Turbine Power Output Estimation (A is Air pressure, T is Temperature, W is wind speed, and P is the power output).

Backdoor Adjustment: if a set of variables for example W is sufficient with the backdoor criterion relevant to (X, Y) then we can identify the causal effect of X on Y by the following formula:

$$P(Y \mid do(X = x)) = \sum_z P(Y \mid X = x, Z = z) P(Z = z) \qquad (2)$$

Where $P(Y \mid do(X = x))$ is the causal effect of X on Y representing the distribution of Y under the intervention $do(X = x)$, Z is the set of variables that satisfy the backdoor criterion, $P(Y \mid X = x, Z = z)$ is the conditional probability of Y given X and Z, which we estimate for observe data, and $P(Z = z)$ is the marginal probability of Z.

4.2. ANFIS Model

ANFIS is an AI method usually used to estimate complex and nonlinear systems such as risk estimation in the context of smart home (Atlam and Wills, 2023). ANFIS, proposed by (Hafiz and Abdennour, 2016), has similar capabilities to ANN and is integrated with the neural network with a structure (hybrid learning algorithm). To learn the neuro fuzzy, the ANFIS regulates the membership function along with the input-output dataset with the propagation neural network (Hadi et al., 2024). A detailed explanation of ANFIS is given in Calp (2019) and Shah and Shah (2024). We first determined the input-output for the model, with the inputs being surface temperature, air pressure, and wind speed, and the output being power energy from the wind turbine in kilowatts. 85% of the dataset was employed for training purposes and the remaining was used for testing. The study was designed in MATLAB 2020b with the neuro-fuzzy toolbox. To determine the wind turbine power, the physical kinetic energy is given as:

$$KE = 0.5\, ma * Ve^2 \qquad (3)$$

Where ma is the mass of the air weather, and Ve is wind speed in m/s. However, the wind turbine is affected with some Betz limitations, which refer to the maximum possible energy conversion efficiency of a wind turbine. The final kinetic power energy is given as:

$$P = 0.5 * \rho * C_p * S_A * V^3 \tag{4}$$

These factors consist of air density (ρ), the power coefficient C_p, equal to 0.48 in this study. In addition, the turbine swept air influences the swept area of the blade pitch, S_A which is given in Eq. 5:

$$S_A = \pi r^2 \tag{5}$$

where r is the rotor radius (40 m). The parameters chosen in the ANFIS model are given in Table 2. Note: a further experiment was conducted to find the predicted output power from the wind turbine.

Table 2. Setting up the parameters for the ANFIS model

Parameters	Types
Number of membership functions	5 for each input.
Membership function type	Trimf (triangular)
Number of fuzzy rules	125
Number of inputs	3
Number of outputs	1
And method	Prod
OR method	Probar

Takagi-Sugeno Fuzzy type with hybrid is used in this model. The goal is to enable FIS to learn the input and update itself with the weather condition information with the help of the output model. The ANFIS structure consists of five layers. The first layer generates the membership grade of the fuzzy set with the node function defined in Eq. 6:

$$O_i^1 = \mu_{Ai}(x) \tag{6}$$

where x the input to node 1, and A_i is the linguistic value associated with the specific node function in layer 1. Layer 2, the second layer, is the fuzzification layer where we have set five rules for each input. The Eq. 7 was given for three inputs:

$$O_i^2 = \mu_{Ai}(x) \times \mu_{Bi}(y) \times \mu_{ci}(z) \; for\; i = 1.2.3 \tag{7}$$

The third layer is the number of rules (ratio of the ith rule's firing weight to the sum of all the rules' firing weights) created by the FIS and multiplied by the grades of layer 2, where we have 125 rules in total. The generalised equation can be written as:

$$O_i^3 = \overline{w} = \frac{w_i}{w_1 + w_{2+} + w_3} \; for\; i = 1.2.3 \tag{8}$$

The fourth layer is the normalisation layer, which provides the output rule overall. For simplicity, the equation for three inputs can be written as:

$$\mathrm{O_i^4} = \overline{\mathrm{w}}\mathrm{f_i} = \overline{\mathrm{w_i}}(\mathrm{a_i x + b_i y + c_i z + d_i}) \text{ for i} = 1.2.3 \tag{9}$$

where $\overline{w}$ is the output of layer 3 and $a_i x + b_i y + c_i z + d_i$ are the set of parameters. Finally, the fifth layer is the de-fuzzification layer, which finds the overall results. The ANFIS architecture is shown in Fig. 3.

$$O_i^5 = \sum_i \overline{w}_i f_i \tag{10}$$

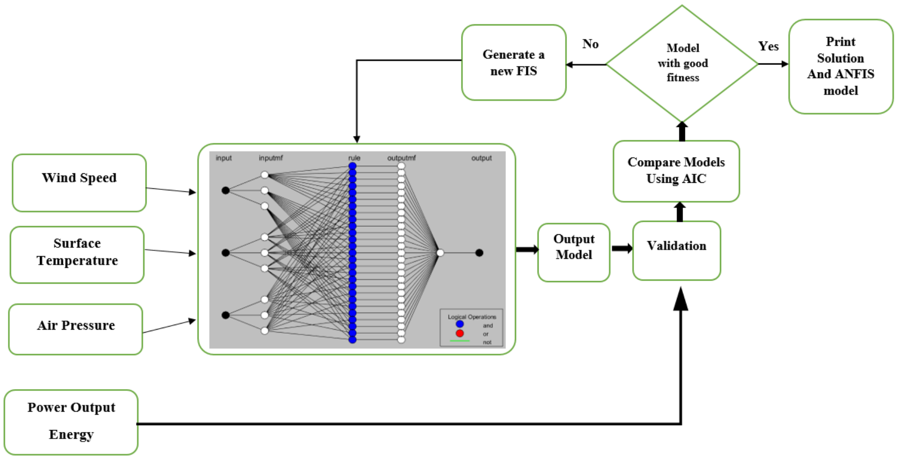

Fig. 3. The proposed architecture of the ANFIS model for the wind turbine.

5. RESULTS

The results of the experiment and the analysis of the model are presented in this section. Before we applied the ANFIS, we first applied Multiple Linear Regression (MLR) to clarify the linear relationship between the variables and assess the relative importance of the coefficients (Mignon, 2024). R-square was equal to 80.2% for the 1488 observations. MLR helped to determine which variables had the most significant impact on the outcome (as shown in Table 3), i.e. it identified how changes in wind speed, air pressure, and air temperature influenced the output power energy, based on causality observations. Eq. 11 identifies the significance effect in linear context, where it is clear that wind speed has the largest effect on the outcome.

$$Y = 1039 - 1.85\ \beta_0 - 103.1\ \beta_1 + 151.9\ \beta_2 \tag{11}$$

Where:

β_0 Represents the effect of air temperature on wind power energy

β_1 Represents the effect of air pressure on wind power energy

β_2 Represents the effect of wind speed on wind power energy.

Table 3 shows that air pressure and wind speed are significant predictors of wind energy, while air temperature is not significant. The F-statistic and low p-value for the overall model suggest that the model is statistically significant and can explain a good portion of the wind energy. However, the MLR assumes that all the relationships between the three variables are not affected by any potential confounders. We speculate that confounders may constitute a major concern. It is crucial to evaluate confounder issues and take into consideration all the potential confounders when data are available, because they might affect the model outcome (Chilton and Rozema, 2024). Theoretically, we consider air pressure and temperature as confounders, because they affect both the predictor and outcome variables (Pearl, 2011). Therefore, we applied MLR to establish which predictor had the largest effect on the output, address the problem of confounders and find unbiased causal estimation.

Table 3: ANOVA summary for assessing Model Fit in Multiple Linear Regression.

ANOVA

	df	**SS**	**MS**	**F**	**Significance F**
Regression	3	225457319.2	75152439.73	2007.3465	0
Residual	1484	55559028.08	37438.69816		
Total	1487	281016347.3			

	Coefficients	**Standard Error**	**t Stat**	**P-value**	**Lower 95%**	**Upper 95%**	**Lower 95.0%**	**Upper 95.0%**
Intercept	10397.18302	2641.740529	3.935732109	8.67806E-05	5215.240348	15579.1257	5215.240348	15579.1257
Temperature (Kelvin)	-1.859297554	1.731115064	-1.074046199	0.282976581	-5.254990254	1.536395145	-5.254990254	1.536395145
Pressure KPascal	-103.1134002	23.64006397	-4.361807156	1.37892E-05	-149.4848947	-56.74190571	-149.4848947	-56.74190571
Wind speed	151.9859066	2.180756371	69.69412476	0	147.7082137	156.2635994	147.7082137	156.2635994

As can be seen from Table 3, for this case, wind speed has the most significant causal impact on power output, while air pressure (A) and temperature (T) also influence the plant's power output. Therefore, it can be inferred that these confounding factors have a direct causal effect on wind power output. However, it is uncertain whether there are other hidden confounders that have not been observed or considered. The case study indicates that variables like air pressure and temperature act as confounders, but they are causally related variables. These variables cannot simply be omitted when making predictions, as doing so would compromise the interpretability of the results.

Therefore, the ANFIS model should capture all the relevant complexity between the three variables (air temperature, air pressure, and wind speed) to predict the wind energy. Incorporating all of the relevant variables in ANFIS will enhance the model's capability to predict the outcome accurately and reliably.

The ANFIS produces a well fitted model for the actual power energy generated from the wind turbine with a 1245 x 4 trained dataset. The Root Mean Square Error (RMSE) is calculated in Eq. 12:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x})^2} \tag{12}$$

The RMSE is 0.636 for eight-rule membership functions for each of the three inputs. The coefficient of determination R^2 is equal to 1 with an accuracy of 98.71 when the error is converged at 125 iterations. Fig. 4 shows the regression of how well the trained data fitted, compared with the real output. Different experimental trials were conducted and evaluated to check for the lowest RMSE. Table 4 shows the types of features chosen for the ANFIS training program.

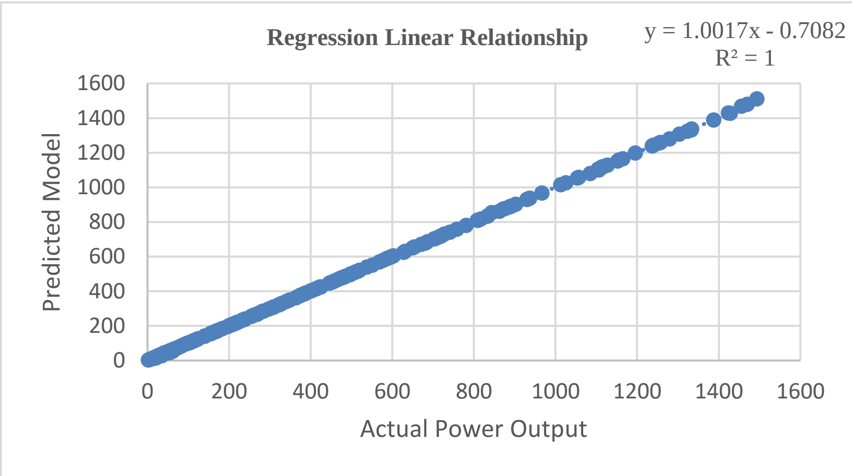

Fig. 4. The regression curve with high correlation between the predicted model and the actual power output from wind turbines, using the ANFIS method.

Table 4: Shows the trials for different features and membership functions. Where 1245 samples of the dataset selected as trained data, while 243 samples designated for testing.

Trial 1

Type of membership	Input membership function	Number of rules	RMSE	MSE	Convergence Epochs
Trimf	[9 9 9]	729	0.38804	0.1506	187
Trimf	[10 10 10]	1000	0.356518	0.1271	120
Trimf	[8 8 8]	512	0.636	0.404	125
Trimf	[12 12 12]	1728	0.27338	0.0747	45
Gauss2mf	[5 5 5]	125	1.394	1.943	100
gbellmf	[5 5 5]	125	0.7639	0.583	280

Trial 2

Type of membership	Input membership function	Number of rules	RMSE In neuro-fuzzy toolbox	RMSE MATLAB coding	MSE For ANFIS toolbox	Convergence Epochs	AIC
Trimf	[5 5 5]	125	0.644	0.5044	0.414	25	1003.1
Trimf	[5 5 5]	125	0.644	0.2747		100	
Trimf	[6 6 6]	216	0.3364	0.3033	0.1128	12	1197.5
Trimf	[6 6 6]	216	0.3364	0.159		100	
Trimf	[4 4 4]	64	1.666	1.35	2.776	20	1645.9
Trimf	[4 4 4]	64	1.666	0.574		100	
Guass2mf	[4 4 4]	64	0.563	0.444	0.316	165	1003.3
Guass2mf	[4 4 4]	64	0.563	0.312		185	
gbellmf	[4 4 4]	64	0.112	0.056	0.0125	250	44.22
gbellmf	[4 4 4]	64	0.1125	0.0517		400	
Trimf	[8 8 8]	512	0.636	0.0619	0.404	150	1076.1
Trimf	[8 8 8]	512	0.958	0.0699		53	

We validated our results with the Gaussian Process Regression (GPR), using the same dataset in the Regression Leaner app toolbox in MATLAB 2020b. The RMSE is given in Table 5.

Table 5. Training the data using different types of kernel functions.

	RMSE	R-square	Training time
Exponential GPR	11.88	1	139 sec.
Rational Quadratic GPR	0.185	1	189 sec.
GPR Matern 5/2	0.628	1	83 sec.

The GPR in the MATLAB toolbox provided the prediction in three types of different kernel functions, which influence the model behaviour and the nature of the predictions. The kernel function provides information about the similarity of the input points and the shape and smoothness of the predicted model.

Fig. 5 shows the residual of the true response model with accuracy equal to 99.81 for the GPR Matern 5/2. The Matern kernel is utilised in models to obtain smoothness, and it is considered a middle ground between exponential kernels and the relational quadratic kernels. The choice of the type of kernel function in GPR can impact how the model interprets the data prediction and its smoothness.

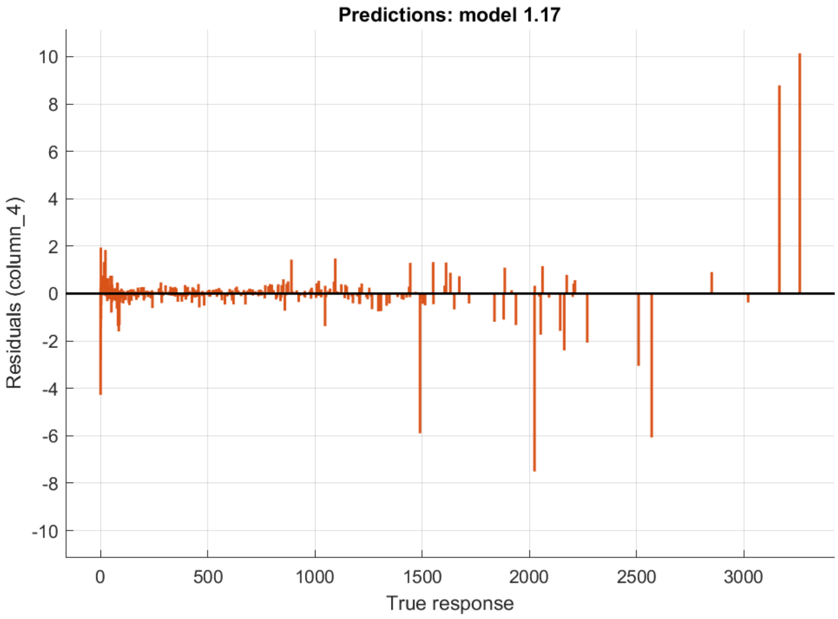

Fig. 5. The residual of the observed data in Matern GPR.

A further investigation was carried out for the 1245 combination input-output dataset. This time a coded ANFIS was implemented and compared with the set of features in the neuro-fuzzy designer toolbox in MATLAB 2020b. We set the output membership function type to linear instead of constant. The different trials are shown in Table 4. We observed different outputs between the ANFIS model trained via code and the one trained using MATLAB's Neuro-Fuzzy Designer app. Depending on the membership function type, some trials were converged in the app before reaching the desired RMSE outcome in the ANFIS code. There could be several reasons for the discrepancy; for example, the training parameters and options in the app might have limits of optionality, unlike the coded one. Furthermore, the normalisation and scaling might not be consistent and might lead to variation in the results. Hence, there was uncertainty over which was the right model to employ. The Akaike Information Criterion (AIC) was chosen to compare the models and choose the best among them, including those obtained from neuro-fuzzy systems (Galdi, Piccolo and Siano, 2008). The AIC equation is given as:

$$\mathrm{AIC} = -2\log \mathrm{L} + 2\,\mathrm{K} \qquad (13)$$

Where log L is the log-likelihood of the model, and k is the number of parameters in the model. The log-likelihood is the natural logarithm of the likelihood function, which measures the probability of the observed data given the model parameters. A higher log-likelihood means a better fit of the model, while a lower log-likelihood means a poor fit and that the model deviates from the actual power output. Since our output model had close relations with the real power output obtained from the wind turbine, we considered the residuals to be normally distributed, therefore the log-likelihood function could be derived based on the sum of square error (SSE) from Eq. 14:

$$\log \mathrm{L} = -2\,\mathrm{n}\log\left(2\pi * \frac{\mathrm{SSE}}{\mathrm{n}}\right) - 2\,\mathrm{n} \qquad (14)$$

With the assistance of AIC, we were able to choose the best model among several candidates. AIC compared different models on the same results. A model with a low AIC value indicates a well-balanced goodness of fit and model complexity. Fig. 6 shows the accuracy between the output model with the tested output power. At 150 epochs, the training data converged with RMSE 0.112 for four-membership functions and with RMSE 0.0636 for eight-membership functions for each input.

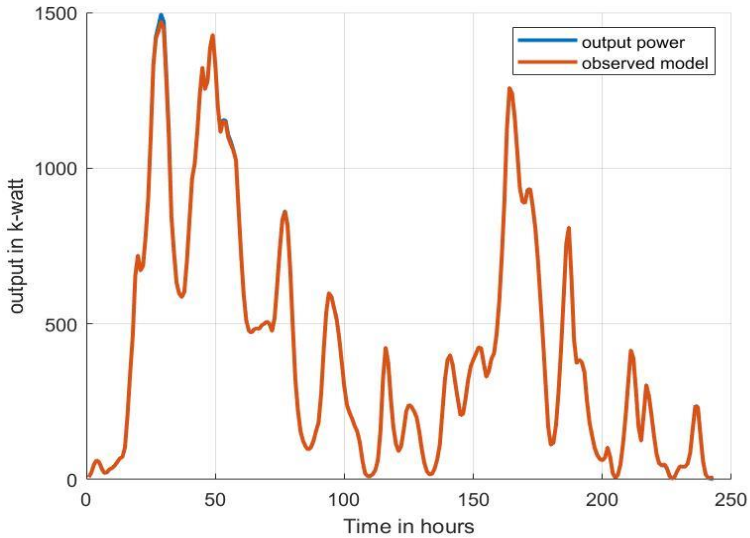

Fig. 6.a. The accuracy between the predicted model power from ANFIS and the real total power from the wind turbine.

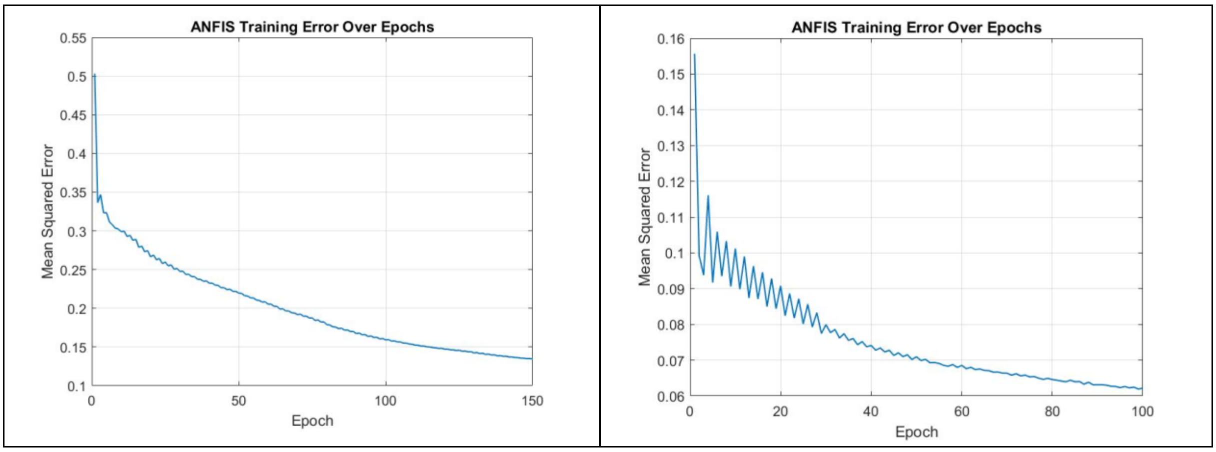

Fig. 6.b. The error convergence at four-membership function and at eight-membership function. The graphs illustrate the error convergence for two different membership functions: the left graph represents the convergence with four membership function, while the right graph shows the eight-membership function, which summarize the key difference of the speed of convergence and final errors.

6. DISCUSSION AND CONCLUSION

To reduce the power loss, and grid disturbance of wind turbines, it is important to achieve the best performance and predict the output power from the turbines. ANFIS was suggested for training three conditions that affect the power of wind turbines: the surface temperature, air pressure and wind speed. The dataset was gathered from the Gabal El-Zeit wind turbine located in the Northeastern Desert in Egypt for two months. We first applied causal inference by constructing the DAG and finding causal relationships between the variables included in the study. We then determined the potential confounders by applying MLR to check the relationship direction of the coefficients and provide an accurate estimate of the causal effect using causal inference approach. Based on the observations, we concluded that all three inputs should contribute to predicting the outcome in the ANFIS model. ANFIS employed 85% of the dataset for training, and the remaining was used to evaluate the training process. Using (AIC), we were able to identify the optimal model from several candidates. A lower AIC value suggest a favourable balance between goodness of fit and model complexity. At 150 epochs, the trained data converged with 0.112 for four membership function and 0.0636 for the model with eight membership function.

For the discussion section, we state that this experimental study contrasted with the other relevant methods in compare with Yang et al. (2016). The aim was to clarify the importance of the ANFIS structure and its parameters in changing the results of the RMSE. We found that it affected the estimation of output power in various weather conditions. The structural design, parameters chosen, and examination of RMSE were taken into consideration. Following the previous study by Sharkawy et al. (2024), the same dataset was measured by using three neural network approaches: Multilayer Feed-Forward Neural Network (MLFFNN), Cascaded Forward Neural Network (CFNN) and Recurrent Neural Network (RNN). However, we could not achieve the same level of performance with all three and found that the ANFIS model was the best method in terms of accuracy. In neural networks there are many parameters to adjust, including weights and biases in each layer, and each layer contains multiple neurons with their weights and bias, which can grow exponentially with the size and depth of the network. Regarding parameter complexity in neuro fuzzy networks, these typically have five layers, containing several rules (if-then rules) and the membership functions are mapped to a fuzzy set and there are multiple types, such as triangular, and Gaussian membership. These require a more careful design of the rule-base in choosing the membership function. We conclude that the suggested approach has the advantages of simplicity along with achieving high accuracy and dependability for a smaller number of inputs, in comparison with neural network algorithms.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The dataset is available under request from the last author (Abdel-Nasser Sharkawy). The used data was taken from previous paper Sharkawy et al. (2024) which was originally available at: https://power.larc.nasa.gov/data-access-viewer/

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