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Robust Design of ANFIS-Based Blade Pitch Controller for Wind Energy Conversion Systems Against Wind Speed Fluctuations

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ABSTRACT Wind speed fluctuations and load demand variations represent the big challenges against wind energy conversion systems (WECS). Besides, the inefficient measuring devices and the environmental impacts (e.g. temperature, humidity, and noise signals) affect the system equipment, leading to increased system uncertainty issues. In addition, the time delay due to the communication channels can make a gap between the transmitted control signal and the WECS that causes instability for the WECS operation. To tackle these issues, this paper proposes an adaptive neuro-fuzzy inference system (ANFIS) as an effective control technique for blade pitch control of the WECS instead of the conventional controllers. However, the ANFIS requires a suitable dataset for training and testing to adjust its membership functions in order to provide effective performance. In this regard, this paper also suggests an effective strategy to prepare a sufficient dataset for training and testing of the ANFIS controller. Specifically, a new optimization algorithm named the mayfly optimization algorithm (MOA) is developed to find the optimal parameters of the proportional integral derivative (PID) controller to find the optimal dataset for training and testing of the ANFIS controller. To demonstrate the advantages of the proposed technique, it is compared with different three algorithms in the literature. Another contribution is that a new time-domain named figure of demerit is established to confirm the minimization of settling time and the maximum overshoot in a simultaneous manner. A lot of test scenarios are performed to confirm the effectiveness and robustness of the proposed ANFIS based technique. The robustness of the proposed method is verified based on the frequency domain conditions that are driven from Hermite–Biehler theorem. The results emphases that the proposed controller provides superior performance against the wind speed fluctuations, load demand variations, system parameters uncertainties, and the time delay of the communication channels.

INDEX TERMS Wind energy, artificial intelligence, optimization algorithm, ANFIS controller, fluctuations.

I. INTRODUCTION

In recent years, great interest has been attracted to generate electricity from various renewable energy sources (RESs). Specifically, wind power is one of the most promising types in the energy market worldwide and is expected to preserve quick development in the next years [1], [2]. Driven by these benefits, the European Parliament is on the way to adopting a strategy to make the European Union (EU) world leader in the sector of renewable energy. The package sets targets for further reduction of greenhouse gas (GHG) emissions, for energy efficiency, and increasing RESs by the year 2030 [3]. For example, Finland has the second-highest part of renewable energy in the EU, while contributing to the wind power of 9% concerning all generation in 2018 [4]. Wind energy conversion systems (WECS) are a pollution-free and

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effective source to be integrated into both distribution and transmission systems [5], [6]. An essential requirement with the increasing trend of WECS in the unified power systems is to abstract the maximum accessible power from the wind power considering the fluctuations of the wind speed and direction [7], [8]. Because of such intermittent nature of unexpected wind speed, determining the optimum speed of WECS so as to attain the maximum wind power is obligatory at any wind speed. The common procedure is to control the pitch angle of WECS blades and the rotational speed so that the output generated power can be managed. For this target, appropriate approaches must be developed which can also increase the WECS efficiency while improving its dynamic performance.

In the literature, many research papers have been directed to blade pitch control of WECS interconnected to power systems. It is a fact that modeling of the suitable blade pitch control scheme is the major requirement for WECS to preserve the power generated from the wind turbine at its highest value while improving aerodynamic characteristics [9], [10]. However, it is a challenging task to build a comprehensive WECS dynamical model due to the highly fluctuated profiles and nonlinearity [11]. For this purpose, this dynamical system can be decomposed into a wind turbine and generator system during the design stage of the controller. the authors of [12] have proposed the blade pitch control algorithm based on an approximated blade pitch model that neglects the dynamics of blade torsional. In [13], a novel approximated blade pitch reasonable model has been introduced based on taking into consideration the actuator, the pitch servo motor, and blade torsional dynamics. The authors of [14] have addressed the problem of controlling power generation in wind energy conversion systems. In [15], a control-winding direct power control strategy has been investigated to upgrade the dynamic performance of generating systems. The integration of a battery energy storage system has been proposed in [16] for a doubly-fed induction generator-based wind energy conversion unit. In [17], sliding mode control based on a linear matrix inequality has been introduced to estimate the rotor position of the WECS generator that enhances system reliability.

More recently, artificial intelligence methods have been applied for blade pitch control of WECS to cover the limitations of traditional approaches [18]. Advanced adaptive neuro/fuzzy control techniques have been proposed in [19]–[22] that are promising tools in diverse applications. Common examples for artificial intelligence-based methods are particle swarm optimization (PSO), artificial neural networks (ANNs), genetic algorithms (GAs), ant colony optimization (ACO), fuzzy logic control (FLC), and artificial bee colony (ABC). Further, the use of proportional–integral–derivative (PID) control schemes has widely been employed for controlling the WECS blade pitch due to its simplicity and its superior dynamic response.

However, the PID performance can be degraded considerably on the occurrence of alerting controller parameters. The authors of [23] have computed the optimal parameters of the blade pitch control system using GA. Moreover, the use of PSO is investigated in [13] to optimize an integral controller (PI) for WECS. In [24], [25], the learning ability of artificial intelligence is combined with the control abilities of an FLC resulting in the adaptive neuro-fuzzy inference system (ANFIS). Accordingly, the ANFIS controller requires a proper training stage for the optimal tuning of membership functions and rules to give a good performance. Focusing on the main issue of wind energy that causes an intermittent in electrical power due to the wind speed fluctuations, besides that, it can cause various issues; like generator speed regulation in the operation of the electrical scheme. Therefore, ANFIS can show promising results for various controlling issues in power systems. However, its proper application to blade pitch control of WECS against wind speed fluctuations is not yet sufficiently investigated. In addition, the wind turbine speed and its output power must be regulated. Thence, the WECS requires an effective adaptive controller (e.g. the proposed ANFIS based mayfly optimizer) instead of the conventional controllers for blade pitch control (BPC) to overcome the fluctuations of wind speed, which is considered the main motivation of this work that covered here.

To cover the gap in the literature, this paper proposes an ANFIS based technique for blade pitch control of the WECS, which overcomes the traditional controllers. To generate a suitable dataset for training and testing to adjust its membership functions, this paper also suggests a new strategy to make a training and testing dataset for the ANFIS controller. For this purpose, a new optimization algorithm named the mayfly optimization algorithm (MOA) is utilized to accurately find the optimal parameters of the PID controller. The proposed technique is compared with different algorithms in the literature to prove its merits. To approve the effectiveness and robustness of the proposed ANFIS based technique, several test scenarios are performed. The advantage features of the proposed controller provide superior performance against the fluctuations of wind speed, variations of load demand, parameter uncertainties, and the time delay of the communication channels.

The novelty and contributions of this paper can be summarized in the following points,

- Introducing an effective strategy to prepare a sufficient dataset for training and testing of the ANFIS controller to cope with wind speed fluctuations and load demand variations.
- The optimal dataset for training and testing of the ANFIS controller is driven based on a new intelligent technique named MOA.
- A new time-domain named figure of demerit is developed to confirm the minimization of settling time and the maximum overshoot simultaneously.
- The proposed technique is compared with different algorithms in the literature to ensure the effectiveness of the proposed ANFIS controller based on MOA.

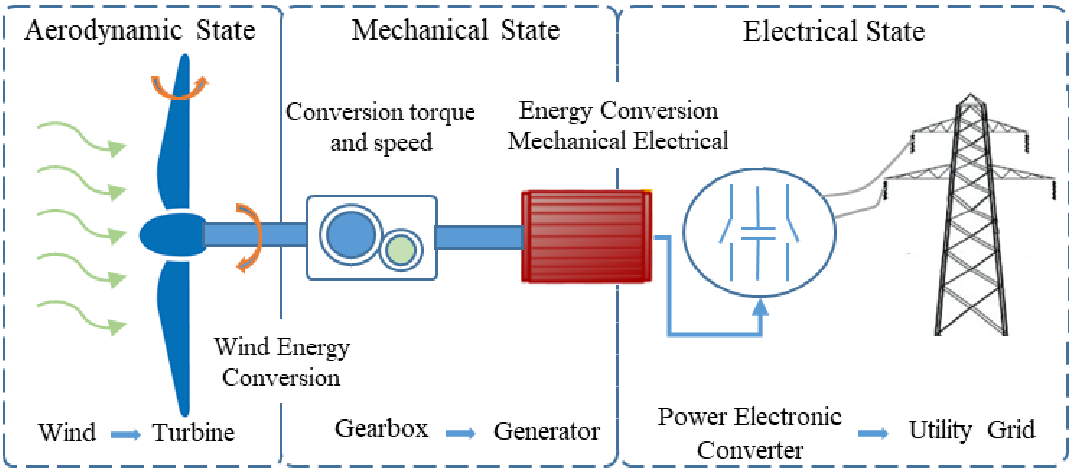

FIGURE 1. Schematic diagram for the WECS.

- The robustness of the proposed method is confirmed based on the frequency domain conditions driven from Hermite–Biehler theorem.
- Different test scenarios are performed to confirm the performance of the proposed ANFIS based technique.
- The results emphases that the proposed controller provides superior performance against the wind speed fluctuations, load demand variations, system parameters uncertainties, and the time delay of the communication channels.

II. WIND ENERGY CONVERSION SYSTEM

Figure 1 describes a suggested WECS which consists of three states including the aerodynamic model, mechanical model, and electrical model. The first model represents the wind energy conversion, in which the wind energy is first captured by the turbine with a specially designed blade to create the rotational movement of the turbine. In the second state, the mechanical energy of the rotational movement is transferred to the rotor of the generator. Then, the electrical energy is generated from the mechanical energy by the generator. In the electrical state, the electrical energy is transmitted to the electrical grid through the overhead transmission lines. A power electronics conversion system is utilized to supply the load demands by the required power.

The operations of the BPC of the WECS can be described by a developed block diagram as seen in Fig. 2. In this study, a model control based on ANFIS is adopted for the controller. The proposed WECS factors and parameters are listed in the Appendix of this paper [8], [9].

The state dynamic formulation of the WECS are at normal load point is described as follows,

The rotor and synchronous generator model can be described using Eqs. (1)-(6).

$$\omega^{\bullet} = \frac{\omega_o}{2h}(P_m - P_g) \tag{1}$$

$$\delta^{\bullet} = \omega \tag{2}$$

$$e_q^{\bullet} = -\frac{K_4}{t'_{do}}\delta - \frac{1}{t'_{do}K_2}e_q + \frac{1}{t'_{do}}V_f \tag{3}$$

$$V_f^{\bullet} = -\frac{K_eK_5}{t_e}\delta - \frac{K_eK_6}{t_e}e_q - \frac{1}{t'_e}V_f \tag{4}$$

$$P_g = K_1\delta + K_2e_q \tag{5}$$

$$P_m = K_{th}X_4 + V_w \tag{6}$$

where ω and δ represent the synchronous generator angular speed rotor angle respectively. ω_0 describes the base angular speed of the generator, while h represents the WECS inertia. P_g and P_m represent the electrical and mechanical powers respectively. e_q describes the equivalent terminal voltage of the generator. K_1 to K_6 represent the model power-dependent constant parameters that are evaluated at a certain operating point. V_f is the field voltage. t_e and t'_{do} are the exciters and sub-transient time constants respectively, while K_e is the exciter constants. X_4 is the arbitrary signal which is defined by the rotational power. The wind speed V_w and the torque factor K_{th} are used to define the mechanical power.

The Wind turbine dynamics of the WECS can be modeled using Eqs. (7)-(9).

$$X_4^{\bullet} = X_5 \tag{7}$$

$$X_5^{\bullet} = -\omega_n^2X_4 - 2\xi\omega_nX_5 + \omega_n^2X_6 \tag{8}$$

$$X_6^{\bullet} = -\frac{1}{t_p}X_6 + \frac{1}{t_p}u \tag{9}$$

where the X_5 is the mechanical rotational power, X_6 represents the blade actuating signal of the wind turbine, ξ is the damping coefficients, and ω_n is the natural frequency. t_p is the wind turbine filter time constant and u is the control signal.

III. DESCRIPTION OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Adaptive neuro-fuzzy inference system (ANFIS) is known as a kind of artificial neural network that integrates with the Takagi–Sugeno fuzzy inference system [25]. The ANFIS technique has been widely applied successfully for control

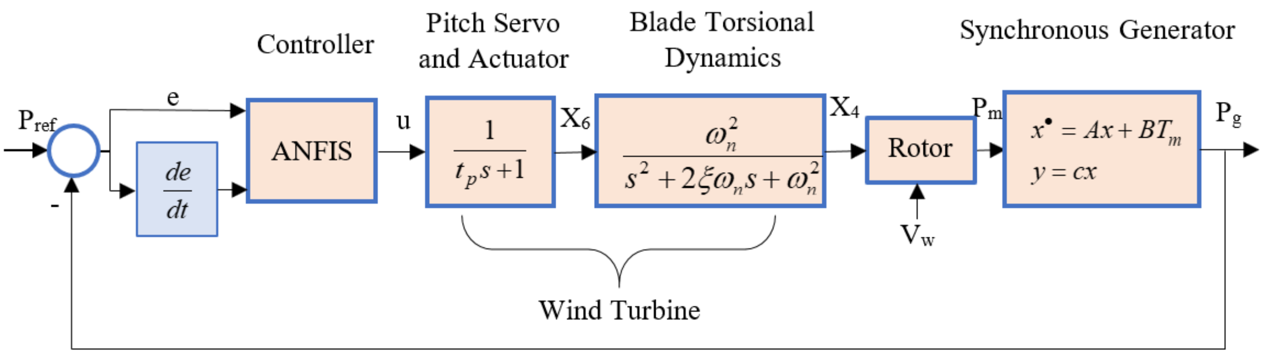

FIGURE 2. Block diagram representation for the wind turbine with BPC.

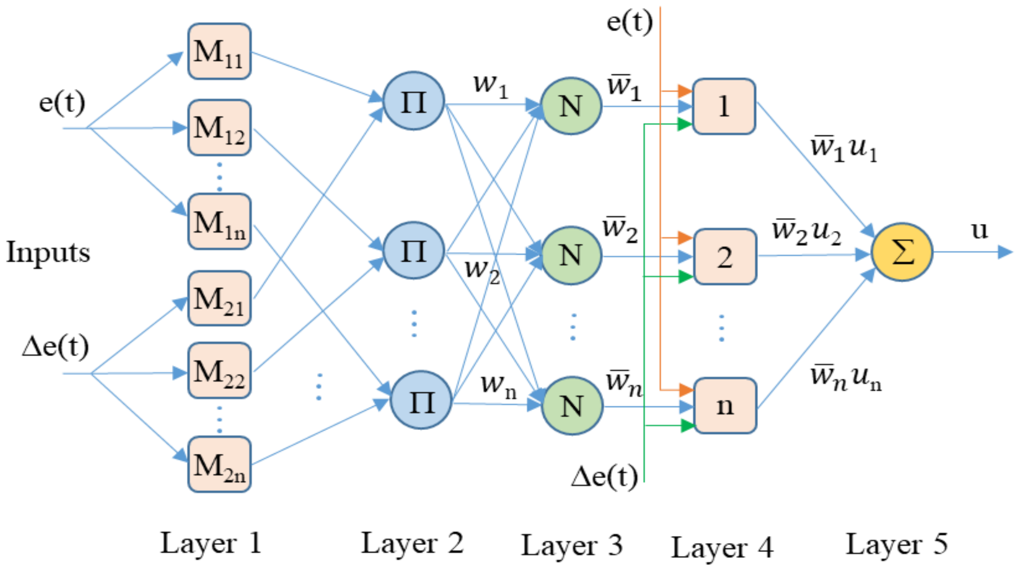

FIGURE 3. Schematic diagram for ANFIS architecture.

models because it presents a proper combination of the neural network and fuzzy logic. The method uses a given observation dataset with the input and output to construct the fuzzy inference system. The parameters of the membership function are adjusted through the learning process using the back-propagation algorithm. A proposed ANFIS architecture is shown in Fig. 3. The structure has two inputs of errors e and Δe, five layers of artificial neural network (ANN) structure, and one output represent the control signal u of blade pitch control.

ANFIS algorithm uses the Sugeno fuzzy model [26], in which the fuzzy if-then rules can be described in Eq. (10),

$$R_n = if\ M_{1i}(e)\ and\ M_{2i}(\Delta e),\ then\ f = p_n e(t) + q_n \Delta e(t) + r_n \tag{10}$$

where n is the number of rules, M_{1i} and M_{2i} are fuzzy membership functions p_n, q_n, r_n are the linear parameters of the consequent part of the n^{th} rule.

The first layer of ANFIS represents the basic Fuzzification, the degrees of membership functions are determined based on the input variable. Each node in this layer stands for an adaptive node function formulated in Eq. (11),

$$M_{1i} = \frac{1}{1 + \left[\frac{x - c_i}{a_i}\right]^{b_i}} \tag{11}$$

where (a_i, b_i, c_i) is the parameter set.

Layer 2 is the inference layer where each node labeled with Π is in accordance with the firing strength of a fuzzy rule. The outputs w_i of this layer can be described as:

$$w_i = M_{1i}(e) \times M_{2i}(\Delta e) \tag{12}$$

The third layer is a normalization layer where the computed firing strengths from the previous layer are normalized,

$$\overline{w}_i = \frac{w_i}{\sum_i (w_i)} \tag{13}$$

Layer 4 takes the normalized values from the third layer as the input values. Every node in this layer is an adaptive mode with a node function formulated in Eq. (14),

$$\overline{w}_i u = \overline{w}_i (p_i e + q_i \Delta e + r_i) \tag{14}$$

where (p, q, r) represents the consequence parameter set and u is the control signal.

In the last layer is the output layer that calculates the summation of all incoming signals to defuzzification the consequent part of rules [26].

$$\sum_i (\overline{w}_i u) = \frac{\sum_i w_i u}{\sum_i w_i} \tag{15}$$

IV. MAYFLY OPTIMIZATION ALGORITHM DESCRIPTIONS

Mayfly optimization algorithm (MOA) was introduced by Zervoudakis and Tsafarakis [27]. The MOA is a powerful tool for the feature selection problem with high dimensionality. Since the MOA presents an appropriate combination of classical optimization methods such as particle swarm optimization (PSO) [28], genetic algorithm (GA) [29], and firefly algorithm [30]. It is able to provide better performance in cases of small and large-scale feature sets [31]. In MOA, the position of individuals can be updated based on their current positions $a_i(t)$ and velocity $v_i(t)$ in Eq. (16),

$$a_i (t + 1) = a_i (t) + v_i(t + 1) \tag{16}$$

The new velocity $v_i (t + 1)$ is updated in different ways depending on the movements of the male and female mayflies.

A. MALE MAYFLY MOVEMENT

Male mayflies tend to gather in swarms, their positions are depending on both their own experience and neighbors. Assuming that the male mayflies can fly constantly. The velocity of a male mayfly i in dimension k is updated in Eq. (17).

$$v_{ik} (t + 1) = \begin{cases} v_{ik} (t) + \sigma_1^{-\beta r_h^2} (x_{hi} - x_i (t)) + \sigma_2^{-\beta r_g^2} \left(x_g - x_{ik} (t)\right), \\ \quad iff\ (x_{ik}) > f\ (x_{hi}) \\ v_{ik} (t) + d * r, \\ \quad iff\ (x_{ik}) \leq f\ (x_{hi}) \end{cases} \tag{17}$$

where σ_1 and σ_2 represent positive attraction constants. x_{hi} represents the historical best position of the male mayfly i. x_g is the best position in the next time step. x_{ik} is the current position of the mayfly i in dimension k. r_g and r_h describe the Cartesian displacement between the agents and their best positions. d represents a random dance factor and r represents the random factor in the range $[-1, 1]$. The distance is formulated as in Eq. (18).

$$\|x_i - x_j\| = \sqrt{\sum_{z=1}^{n} \left(x_{ik} - x_{jk}\right)^2} \tag{18}$$

B. MOVEMENTS OF FEMALE MAYFLIES

It is different from a male mayfly, the female mayfly flies ahead of the male for breeding. The new female mayfly position is generated using Eq. (16). The attraction process between the male and female is according to their fitness function, where the best male will come with the best female. Therefore, female velocities are formulated in Eq. (19).

$$v_{ik} (t + 1) = \begin{cases} v_{ik} (t) + \sigma_3^{-\beta r_{ms}^2} (x_{ik} (t) - b_{ik} (t)), \\ \quad iff\ (b_i) > f\ (x_i) \\ v_{ik} (t) + f_r * r, \\ \quad iff\ (b_i) \leq f\ (x_i) \end{cases} \tag{19}$$

where σ_3 is a constant used to balance the velocities and β is a fixed coefficient. $b_{ik} (t)$ is the current position of the female mayfly i in dimension k at the time step t. The Cartesian displacement within male mayfly and female mayfly is named r_{ms}. f_r represents a random walk factor if a male does not come to a female, and r is a random factor inside the range [1, 1].

C. MATING OF MAYFLIES

The mating process between two mayflies is conducted by choosing a male mayfly and then a female. The selection operation is performed according to the fitness value. Their offspring would be randomly related to their parents as shown in (20) and (21).

$$off\,spring1 = r_o * male + (1 - r_o) * female \tag{20}$$

$$off\,spring2 = r_o * female + (1 - r_o) * male \tag{21}$$

where r_o represents a random factor within a certain range and the initial velocities of the offspring are equal to zero.

This paper utilizes the MOA to find the best dataset for the training and testing of the ANFIS controller. The MOA searches about the optimal parameters of the PID controller based on the minimization of the time-domain objective function as shown in Fig. 4. Then, the PID controller is combined with the WECS in order to collect the dataset that represented by the error 'e' and the derivative of the error ($\Delta e = de/dt$) as inputs for the ANFIS and the output dataset that represented by the control signal 'u' as output for the ANFIS. Then, the ANFIS is trained and tested based on the collected datasets. Finally, the developed model of the ANFIS is combined with the WECS to provide an online control signal for BPC in order to stabilize the system against

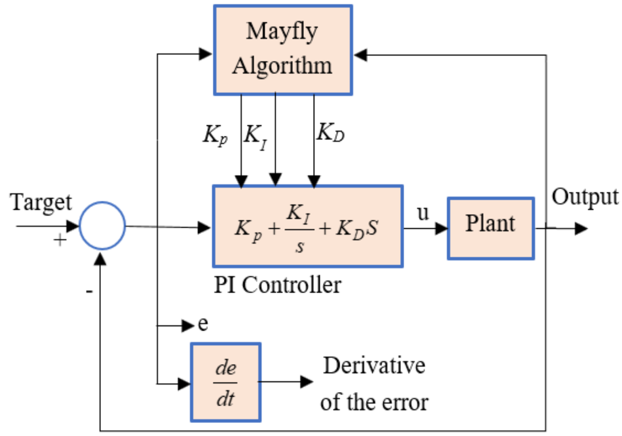

FIGURE 4. Schematic diagram for the MOA- based PID control loop.

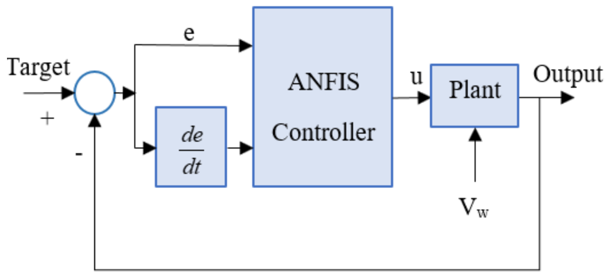

FIGURE 5. Schematic diagram for the ANFIS control loop.

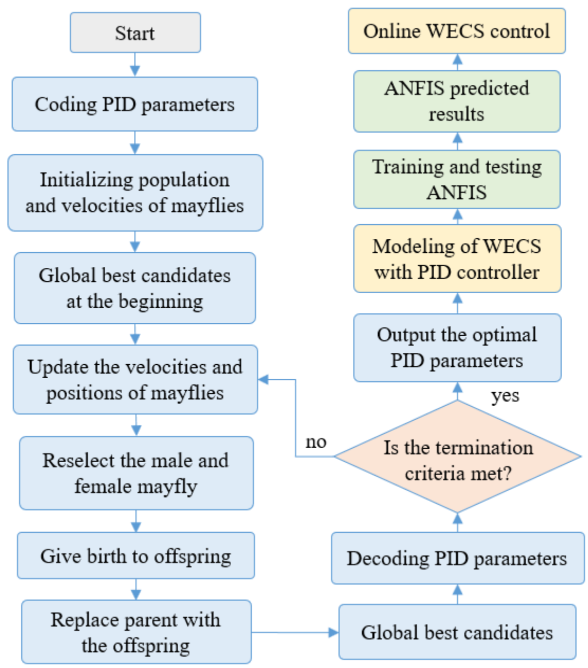

FIGURE 6. Solution steps of the proposed ANFIS based on MOA for the BPC of the WECS.

any disturbance as clear in Fig. 5. The solution steps of the proposed ANFIS based on MOA for the BPC of the wind energy conversion system are described in Fig. 6.

V. RESULTS AND DISCUSSION

A. NUMERICAL EXPERIMENT

In this part, the proposed MOA is applied to select the optimal gains of PID controllers. Then, this PID controller with its optimized gains can be combined with the WECS to prepare the optimal dataset for the proposed ANFIS. The MOA searches about the best parameters of the PID controller that can achieve good damping characteristics for the performance of the WECS based on the minimization of the system overshoot and settling time simultaneously. To accomplish the minimization of system response overshoot and settling time simultaneously, the proposed MOA can do this purpose based on the minimization of a developed performance index that is formulated as follows,

$$I = (1 - e^{-\omega})(M_o + E_{ss}) + e^{-\omega}(S_t - R_t) \tag{22}$$

Algorithm 1 The Pseudo-Code of Data Acquisition, Validation of the ANFIS Model for the WECS

Start the initial population of MOA to optimize the PID controller
Evaluate the performance index in (22) for all agents of MOA
Select the best position
While iter<itermax
  Update the position of each individual by (16)
  Update the velocity of a male mayfly by (17)
  Determine the female velocities by (19)
  Perform the mating process by (20) and (21)
  Evaluate the performance index in (22) for all agents of MOA
  Select the best position
End while
Out the optimal parameters of PID controller
Simulate the WECS by the PID controller
Out the dataset e, Δe, and U
Train and Test the ANFIS
Combine the ANFIS model the WECS for online control

where M_o is the maximum overshoot, E_{ss} is the steady-state error, S_t and R_t are the settling time and rise time respectively. This performance index 'I' can adjust the minimization of system response overshoot and settling time-based on the value of the weighting factor 'ω'. When $\omega > 0.7$ the optimization operation focuses to minimize the settling time. Otherwise, the optimization operation focuses to minimize the system overshoot when $\omega < 0.7$. In this research, the weighting factor is selected as $\omega = 0.7$ to balance the minimization of system response overshoot and settling time simultaneously. The operations of the data acquisition and validation of the ANFIS model are summarized by following pseudo-code in Algorithm 1.

The proposed MOA is compared with GWO, ABC, MFO [23], [32] algorithms in literature applied in the same WECS for a fair comparison. Table 1 records the parameters of the PID controller based on every optimization technique with the corresponding performance index value. Figure 7 shows the performance index of every algorithm in a vertical bar display as a clarified presentation for comparison. It is clear from Table 1 and Fig. 7 that the proposed MOA can perform the minimum value of the performance index compared with other algorithms.

A certain range of load demand is created, $P\epsilon$ [0.5 1] and $Q\epsilon$ [− 0.2 0.5] to carry out the sensitivity analysis in order to demonstrate the robustness of the obtained controller gains against the variations of system parameters according to [33]. The characteristic equation of the WECS in Fig. 2 is represented as $P(j\mu) = G(\mu) + jwH(\mu)$ where $\mu = w^2$. Then, frequency bands of polynomials G and H are obtained at the minimum load demand and the maximum load demand. Figure 8 shows the frequency bands of polynomials G and H.

TABLE 1. The performance index of each technique and the corresponding parameters of PID controller parameters.

	GWO	ABC	MFO	Proposed MOA
PID parameters	K_P= 0.339, K_I= 0.409, K_D= 0.085	K_P= 0.342, K_I= 1.178, K_D= 0.053	K_P= 0.179, K_I= 0.458, K_D= 0.033	K_P= 0.4329, K_I= 0.5056, K_D= 0.0624
J	0.5614	0.4997	0.3507	**0.0791**

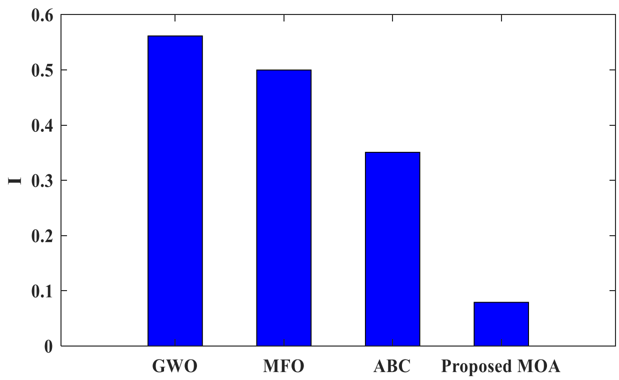

FIGURE 7. The performance index of different optimization techniques.

As clear in this figure, the frequency bands of G and H are alternate and do not overlap that achieves the stability frequency domain conditions of the perturbed polynomial P that driven from Hermite–Biehler theorem, for more details see [33]. Hence, the controller gains based on the proposed MOA are robust against the variations of the WECS parameters.

After obtaining the optimal parameters of the PID controller based on the proposed MOA, the results of the MOA-based PID controller are utilized to produce a suitable dataset to train and test the ANFIS controller. Then, the ANFIS can be utilized as an adaptive controller instead of the PID controller. Further test cases are done to confirm the ability of the proposed ANFIS based on MFO to stabilize the WECS with high damping performance against the changes of load demand, wind speed penetrations, the time delay due to communication channels, and the uncertainties of the system factors.

B. SCENARIO 1: NOMINAL SYSTEM PARAMETERS WITH 10% STEP DEVIATION IN POWER GENERATION

This scenario is performed at nominal load demand 'P = 0.9 p.u, Q = 0.2 p.u' with a 10 % step deviation in the power generation reference. The output power response based on different techniques is presented in Fig. 9. Furthermore, the response characteristics according to the system overshoot and settling time are recorded in Table 2. The proposed ANFIS based-MOA can sufficiently minimize the output response of maximum overshoot compared with PID based-GWO, PID based-MFO, and PID based-ABC by 0.7989 %, 2.8818 %, 3.6732 %, and 15.3842 %, respectively. While the settling time decreases by 0.4497 s compared with 1.5402 s, 0.9102 s, and 0.9898 s, respectively. Showing a superior parameter response of the proposed ANFIS based-MOA controller compared with the other three techniques. It is clear from Fig. 9 and Table 2 that the proposed MOA-based ANFIS improves the system damping performance without any oscillations. Furthermore, the proposed MOA-based ANFIS has the least overshoot and settling time compared with other methods as clear in Table 2.

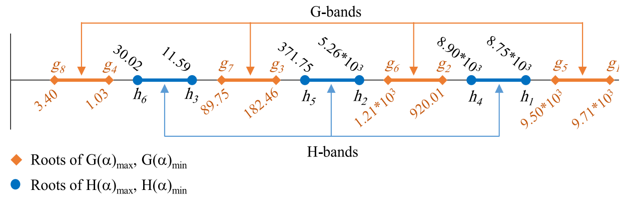

FIGURE 8. The frequency bands of polynomials G and H.

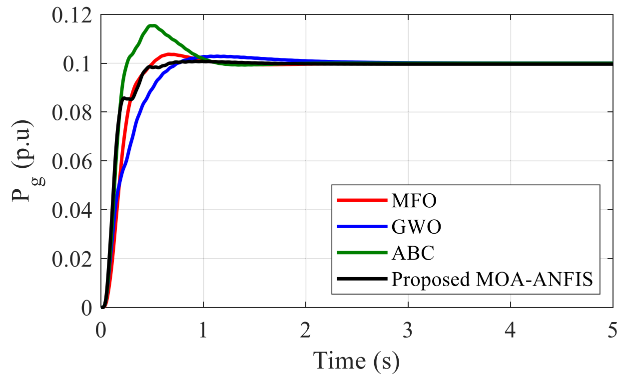

FIGURE 9. The output power generation based on different techniques in case of scenario 1.

TABLE 2. The response of power generation characteristics in case of different techniques.

	MFO-PID	GWO-PID	ABC-PID	Proposed MOA-ANFIS
M_o (%)	3.6732	2.8818	15.3842	**0.7989**
S_t (s)	0.9102	1.5402	0.9898	**0.4497**

C. SCENARIO 2: VARIATIONS OF LOAD DEMAND POWERS

This test is created to test the performance of the proposed MOA-based ANFIS against the variations of load demand. A load of 'P = 1 p.u, Q = 0.5 p.u' is applied to represent heavy loading, and a load of 'P = 0.5 p.u, Q = −0.2 p.u' is applied to represent light loading during the testing operation. Figure 10 presents the output power generation of the WECS in the case of load demand variations. It is clear from Fig. 10 that the system performance based on the proposed control method has negligible change against the variations of load demand.

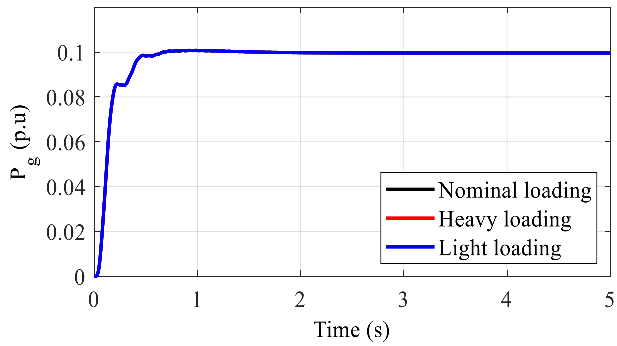

FIGURE 10. The output power generation based on the proposed technique in case of load demand variations.

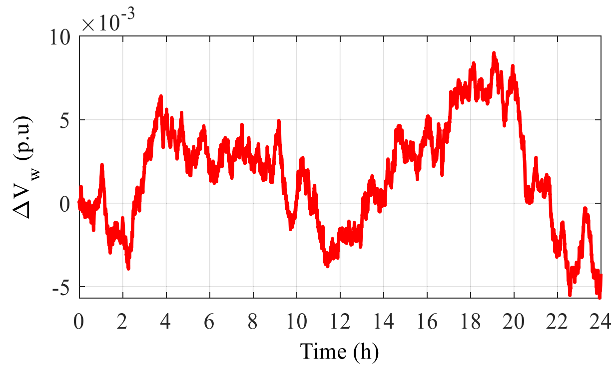

FIGURE 11. The variations of wind speed during 24 hours.

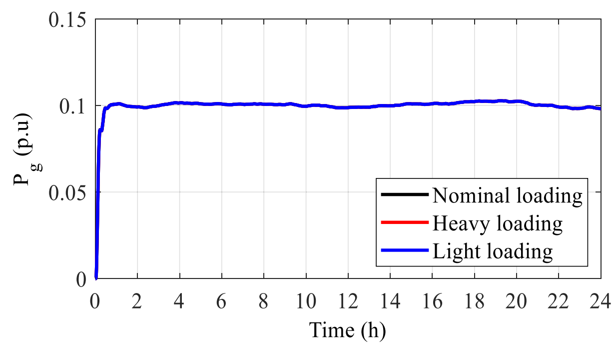

FIGURE 12. The output power generation in case of wind speed and load demand variations.

D. SCENARIO 3: VARIATIONS OF LOAD POWERS AND WIND SPEED FLUCTUATIONS

The penetrations of the wind speed represent the big challenge against the WECS. So, this test is carried out by applying variations in the wind speed as shown in Fig. 11 besides variations in load demand to ensure the capability of the proposed MOA-based ANFIS. Figure 12 shows the output response of the WECS based on the proposed technique in the case of load demand and wind speed fluctuations. It is clear from Fig. 12 that the proposed MOA-based ANFIS has a superior damping performance against the variations of load demand and wind speed fluctuations.

E. SCENARIO 4: ROBUSTNESS TEST AGAINST INERTIA CONSTANT UNCERTAINTY

The uncertainties in the system parameters due to the inefficient measuring devices and environmental effects in the system components represent big trouble between the practice and test implementation. So, this test is created by making $\pm 20\%$ uncertainty in the system inertia constant to confirm the performance of the proposed MOA-based ANFIS against the system parameters variations. The output response of the WECS based on the proposed method due to this test is presented in Fig. 13. The proposed MOA-based ANFIS stills provide a good response with negligible change against the system parameters uncertainty as clear in Fig. 13.

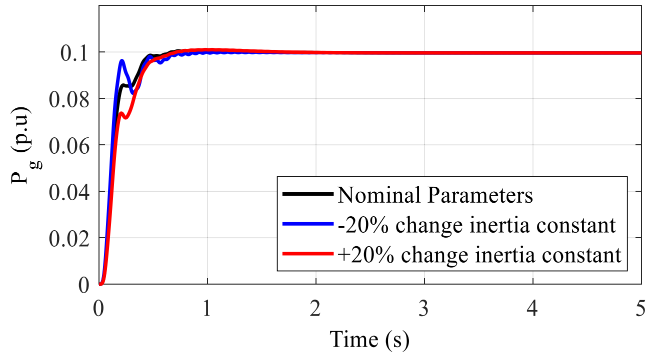

FIGURE 13. The output power generation of the WECS against system parameters uncertainty.

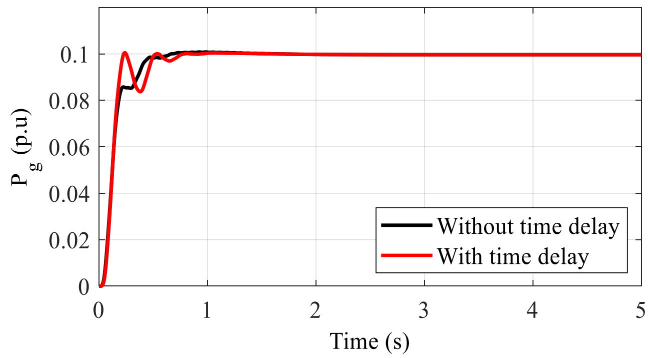

FIGURE 14. The output power generation of the WECS in case of time delay scenario.

F. SCENARIO 5: TIME DELAY TEST

This test is performed to ensure the performance of the proposed MOA-based ANFIS against the time delay issue of the communication channels. A time delay equal to 50 ms is applied between the control signal of the proposed technique and the WECS to carry out this test scenario. Figure 14 presents the response of the WECS based on the proposed control technique against the time delay of the communication channels. It is clear from this figure that the proposed method is robust and overcomes the time delay issue.

G. SCENARIO 6: VARIATIONS OF RANDOM WIND SPEED FLUCTUATIONS

This scenario demonstrates the capability of the proposed ANFIS against the high fluctuations of random wind speed. A random wind speed is created to carry out this test as shown in Fig. 15. The output response of the WECS based on the

TABLE 3. The values of the WECS factors.

Factor	P_o	Q_o	v_{to}	N	K_{th}	R_{tl}	x_e
Value	0.9 p.u	0.2 p.u	1 p.u	37.5	11.86	0	0.02 p.u
Factor	N_r	r_b	V_w	PP	h	ξ	R_a
Value	40 r.p.m	62.5	10 m/s	4	9.5	0.02	0.018 p.u
Factor	x_d	x_q	$x_{d'}$	$x_{d''}$	$x_{q''}$	$t_{do'}$	$t_{do''}$
Value	2.21 p.u	1.064 p.u	0.165 p.u	0.128 p.u	0.193 p.u	1.94212 s	0.01096 s
Factor	$t_{qo''}$	ω_o	ω_n	t_p	t_e	k_e	
Value	0.0623 s	100 π	100	0.0589 s	0.05 s	30	

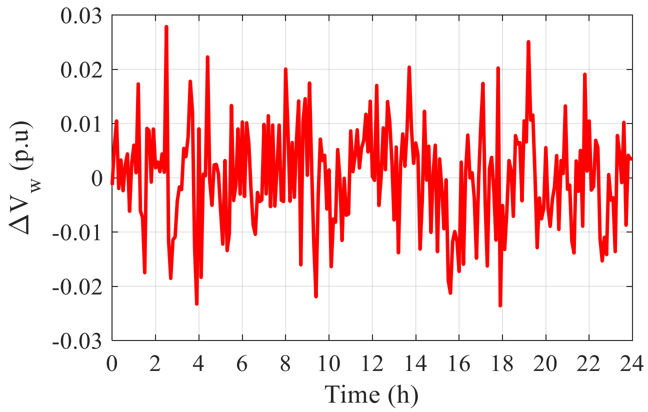

FIGURE 15. High random fluctuations of wind speed.

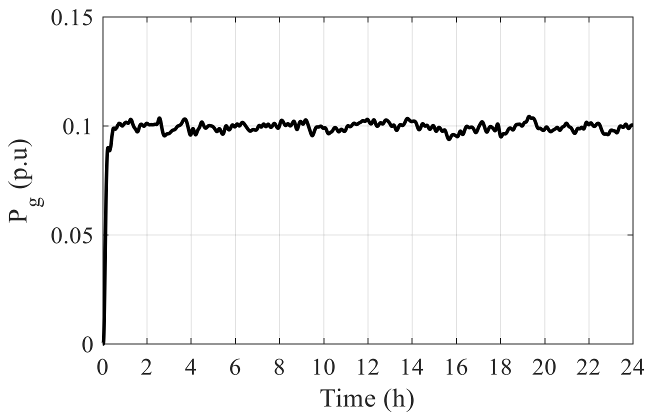

FIGURE 16. The output power generation in case of random wind speed fluctuations.

proposed technique is shown in Fig. 16. This figure describes that the proposed ANFIS can stabilize the WECS and cope with the random fluctuations of wind speed.

H. DISCUSSIONS

The following points conclude the advantages of the proposed technique:

- In the case of nominal load, the proposed MOA-based ANFIS can improve the system damping performance without any oscillations. Besides, the proposed technique improves the system response with the least overshoot and settling compared with other techniques.
- The proposed method is robust and achieves the frequency domain conditions that are driven from Hermite–Biehler theorem.
- Scenario 2 shows that the damping performance of the proposed method is effective against the variations of the load demand.
- The proposed MOA-based ANFIS has a superior damping performance against the variations of load demand and wind speed fluctuations together as presented in scenario 3.
- The proposed technique can cope with the high fluctuations of the random wind speed as cleared in scenario 6.
- The proposed MOA-based ANFIS can cope with the system parameters uncertainty and perform a good response with negligible change.
- The proposed method diminished the time delay issue and performed a stable response.

The proposed technique requires a proper selection for training data, the type of membership function, and the number of epochs to provide a good solution, this issue represents the main challenge that faces the ANFIS. This issue is solved in this paper by utilizing the proposed MOA technique, which is considered the main motivation of this work.

VI. CONCLUSION

In this research paper, a new control strategy is applied to WECS based on the ANFIS and MOA intelligent techniques. The MOA is introduced as a new effective optimization algorithm to optimize a suitable dataset for training and testing the ANFIS controller. Besides, a developed time-domain performance index is created to accomplish the minimization of the system overshoot and the settling time simultaneously. The proposed technique is compared with different algorithms that have been applied to the same WECS model for a fair comparison. Specifically, the proposed technique confirms the superior minimization of settling time and the maximum overshoot with 0.4497 s and 0.7989 %, respectively, compared with the other three techniques. The proposed MOA-based ANFIS can stabilize the WECS and cope with the fluctuations of wind speed, load demand variations, time delay issues, and system parameters uncertainty. This uncertainty test has been created by making ±20 % uncertainty in the system inertia constant that confirms the high performance of the proposed MOA-based ANFIS against the system parameters variations. Furthermore, the new design strategy of ANFIS can be applied to solve other power system issues like voltage and frequency regulation in future work.

APPENDIX

The proposed WECS parameters are recorded in Table 3 [23], [32].

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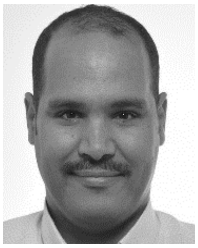

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