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Elman Neural Network with Customized Particle Swarm Optimization for Hydraulic Pitch Control Strategy of Offshore Wind Turbine

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Abstract: Offshore wind turbines have garnered significant attention recently due to their substantial wind energy harvesting capabilities. Pitch control plays a crucial role in maintaining the rated generator speed, particularly in offshore environments characterized by highly turbulent winds, which pose a huge challenge. Moreover, hydraulic pitch systems are favored in large-scale offshore wind turbines due to their superior power-to-weight ratio compared to electrical systems. In this study, a proportional valve-controlled hydraulic pitch system is developed along with an intelligent pitch control strategy aimed at developing rated power in offshore wind turbines. The proposed strategy utilizes a cascade configuration of an improved recurrent Elman neural network, with its parameters optimized using a customized particle swarm optimization algorithm. To assess its effectiveness, the proposed strategy is compared with two other intelligent pitch control strategies, the cascade improved Elman neural network and cascade Elman neural network, and tested in a benchmark wind turbine simulator. Results demonstrate effective power generation, with the proposed strategy yielding a 78.14% and 87.10% enhancement in the mean standard deviation of generator power error compared to the cascade improved Elman neural network and cascade Elman neural network, respectively. These findings underscore the efficacy of the proposed approach in generating rated power.

Keywords: intelligent hydraulic pitch control strategy; customized particle swarm optimization; improved recurrent Elman neural network; rated power generation; offshore wind turbine



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1. Introduction

The global demand for energy is increasing at a fast pace, and there is a growing awareness of the need to reduce one's carbon footprint in response to this concern. Promoting the utilization of renewable sources is recommended to fulfill the global energy requirements. Out of all, wind power stands out as a highly promising, eco-friendly, and readily available form of renewable energy [1]. At a worldwide level, the year 2022 saw the incorporation of 77.6 GW of wind power capacity into power grids, leading to a total

installed wind turbine (WT) capacity of 906 GW. This denotes a 9% expansion compared to the preceding year, 2021, and it is also expected to increase by 500 GW by 2030 [2].

Nowadays, more interest is shown to the offshore WTs than onshore WTs. Since offshore WTs can harvest more wind energy than onshore WTs, such phenomena are observed. However, in the case of offshore WTs, the control systems are crucial for maintaining safety, producing consistent power, and reducing dynamic loads [3]. The two most important control parameters in WTs are the generator torque and the blade pitch angle. Generally, pitch angle control is employed in medium- to large-scale WTs. In the context of WTs operating beyond rated wind speeds, it is common practice to maintain constant generator torque, with pitch control configured to uphold rotor speed [4]. Typically, the mechanism for pitch actuation involves the use of both electrical pitch systems (EPSs) and hydraulic pitch systems (HPSs) [5]. The EPS has been extensively studied in the various literature, covering the analysis of double closed-loop control [6], direct torque pitch control [7], system design [8], dynamic characteristics [9], adaptive pitch control [10], and fuzzy logic pitch control [11]. Though EPS is relatively accurate, the power–mass ratio and robustness are relatively low. Moreover, high-pressure HPSs are generally stiffer than EPSs when subject to high load [12]. The HPS is significantly reliable, has less backlash, is economical, simple, versatile, safe, and produces constant force irrespective of the disturbances (externally).

A linear model is sufficient for instances when the system is running normally; nevertheless, a nonlinear model is required for the study of the fault diagnosis of a system. In a study by [13], a nonlinear mathematical model was incorporated into a National Renewable Energy Laboratory (NREL) WT simulator under operational conditions and during hydraulic actuator failure. To alleviate fluctuations in drivetrain torque and output power for WTs, authors in [14] introduced a distinctive HPS. This system incorporates an inherent hydro-mechanical position control loop, enabling sensorless pitch control, along with an external open control loop that enhances pitching motion. This pitch control system's dynamic features, stability analysis, and modeling are also discussed. The efficiency and effectiveness of this system in power and torque regulation have been proven by comparative experiments. In the work by [15], a proportional valve-driving asymmetric double-acting actuator has been studied to change the pitch angle under external loads. The pitch actuation mechanism can ensure the safety of the WT blade exposed to extreme loads during high wind speed and generate rated power, resulting in improved overall efficiency. To facilitate pitch adjustments in horizontal axis WTs, an HPS employing a proportional valve-controlled semi-rotary actuator was created [16]. Unlike a linear hydraulic actuator system, a semi-rotary actuator can be directly affixed to the WT blade, minimizing mechanical intricacies. The system incorporates a feedforward Fractional-Order Proportional–Integral–Derivative (FOPID) controller with adaptive learning-based optimization. The performance of the suggested controller has been evaluated using step, sinusoidal, and real wind data. The feedforward FOPID controller's performance has been compared to other traditional controllers and the proposed controller performed better.

In recent times, neural network (NN) techniques have been the focus of research because of their adaptive learning, robustness, simplicity of integration into the system, and fault tolerance [17]. Moreover, authors have explored the significance of NN methods in forecasting the wind speed and power. In [18], authors investigated the Wavelet Neural Network (WNN) in forecasting the wind speed. Results demonstrated more accurate wind speed forecasting by the WNN model when compared with counterparts. In [19], the Recurrent Neural Network (RNN) optimized by the Levy CryStal structure algorithm for forecasting the wind speed was proposed. Upon comparison with other NN techniques that used different optimization methods, the proposed method showcased relatively better forecasting accuracy. Further, authors in [20,21] explored RNN models in forecasting the

wind power. Various datasets were collected and the models were trained. Through several case studies, it was concluded that the accuracy of the RNN in forecasting wind power is more accurate than other models. All these studies revealed that NN models are more accurate in forecasting wind speed and power. Furthermore, authors started to explore NN models in the pitch control of WTs, since it plays a vital role in power generation.

Multiple NN-based pitch controllers have been investigated by [22], including the Feedforward Neural Network (FFNN), radial basis function NN, and backpropagation NN. The authors suggest that the NN-based pitch controller was superior to the conventional pitch controller. In the work by [23], an extreme learning machine has undergone online training to accurately model the nonlinear characteristics of WTs, leading to the development of a closed control loop pitch system. Additionally, leveraging the capabilities of the extreme learning machine, a predictive pitch controller was implemented to enhance the overall performance of the pitch control. Comparative experimental results indicate that both the predictive pitch controller and the hydraulic pitch system (HPS) configurations significantly enhance the regulation of drivetrain torque and output power. Moreover, [24] introduced a pitch controller based on the Feedforward Backpropagation Neural Network (FFBPNN), validated using real-time wind speed data, showcasing notable performance improvements compared to fuzzy and proportional integral (PI)-based pitch controllers. The improved elman neural network (IENN) has been established for pitch control for WTs in [25]. In this context, the parameters of the elman neural network (ENN) were tuned using a custom optimization approach known as customized particle swarm optimization (CPSO). Simulation results reveal that the performance of the IENN was superior to other methods. Subsequently, authors [26–28] explored the customized heuristic algorithms and improved NNs. The improved NN and customized heuristic algorithm showed effective performance over the conventional algorithms.

The prevailing literature has extensively employed intelligent pitch control strategies in EPS while comparatively neglecting their exploration in HPS. Subsequently, researchers have started to focus on the RNN models, which showcase superior performance over other NN models [29,30]. Among them, the ENN has been widely preferred as a pitch controller due to its advantage of having an extra context layer. However, the highly variable wind speeds in the offshore environment diminish the performance of the ENN, which affects the power generation in the Wind Generator System (WGS). Thus, there is a need to improve the ENN model. Subsequently, the performance of the NN is significantly improved by optimizing it via heuristic-based methods. Considering all this, the primary contributions of this study are outlined as follows:

- An improved recurrent Elman neural network (IRENN)-based intelligent hydraulic pitch control strategy (IHPCS) is established for generating rated power for the offshore WGS. Moreover, the conventional Elman neural network (ENN) is extended by incorporating an additional recurrent layer (in IRENN), leading to improved operational efficiency. A key advantage of the proposed IHPCS is its reduced dependency on wind speed measurements for algorithmic execution, thereby minimizing the need for wind speed sensors.
- Using the CPSO technique, the parameters of the established NN are methodically fine-tuned which improves the NN's performance.
- Several case studies are conducted in a benchmark Fatigue Aero-Elastic Structure Turbulence (FAST) simulator to validate the performance of the proposed IHPCS. In each case study, varying wind speed scenarios were utilized.
- Additionally, to further demonstrate the effectiveness of the proposed IHPCS, it is compared against two other intelligent strategies. Moreover, one of these strategies is designed based on insights derived from existing research.

The remaining sections of this paper are organized as follows: The suggested pitch system and operating concept are discussed in Section 2. In Section 3, the dynamic models of the WGS and HPS are presented. The structure of the pitch control strategy is described in Section 4. Details on the simulation study and related discussions are provided in Section 5. Finally, Section 6 concludes with an overview of the key discoveries and outcomes.

2. System Description

The schematic of the proposed system comprising the HPS, WGS, and IHPCS is shown in Figure 1.

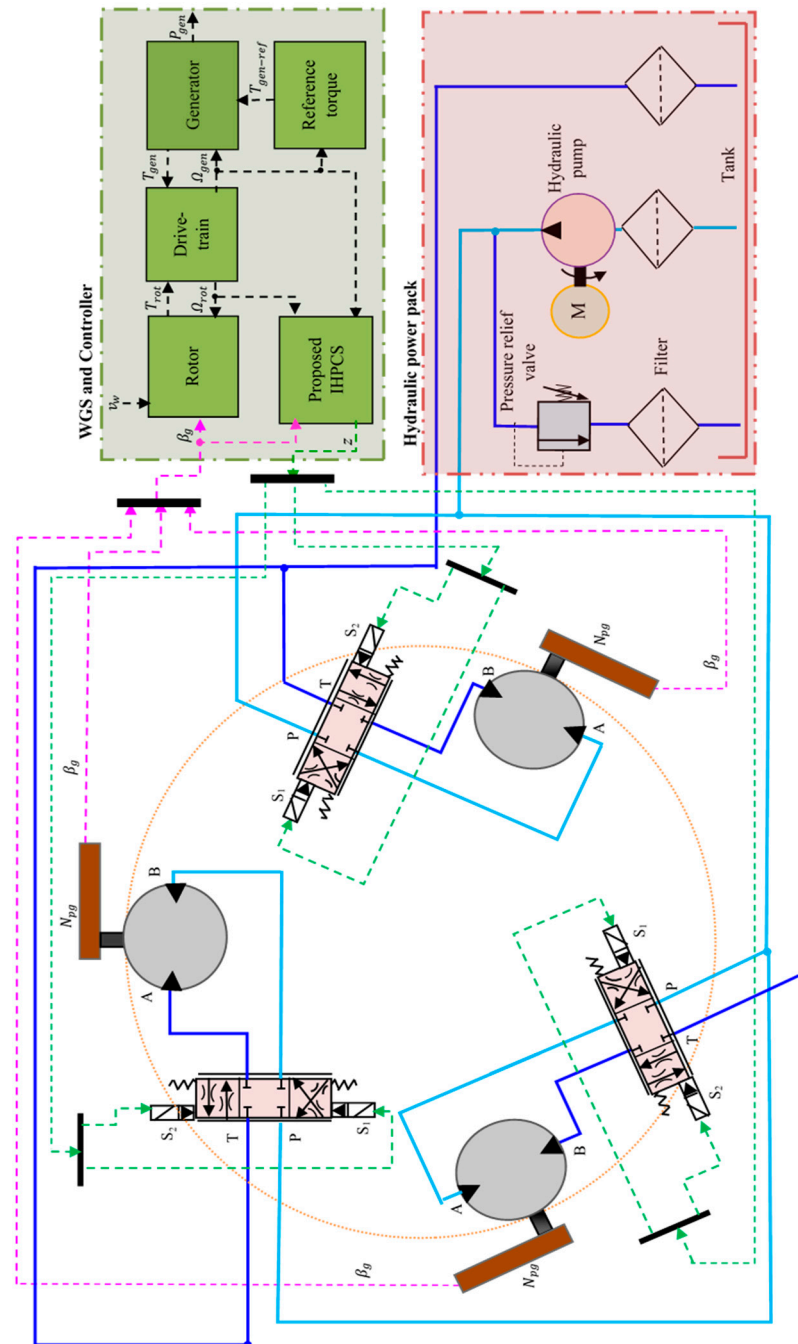


Figure 1. Proposed pitch system.

The major components of the HPS are three proportional direction control valves (PDCVs), a hydraulic pump, a pressure relief valve, an electric motor (servo motor) that

drives the hydraulic pump, and three hydraulic motors (connected to N_{pg}), whereas the pitch angle is measured at the pitch gear using a rotary encoder which is connected to the blades. The hydraulic power unit (as seen in Figure 1) is considered to be the same for all the actuators (hydraulic motors). The pressure relief valve is used to maintain system pressure within the safer limits in the hydraulic circuit. Consequently, the PDCV is utilized in the developed HPS. The PDCV is a proportional valve having four ports (P, T, A, and B), and an infinite spool position can be achieved, which maintains the direction of the actuator's motion and velocity. The motion of the spool is generated by solenoids (S_1 and S_2) under the command of the proposed IHPCS. The pitch demand (collective pitch control) is developed by the proposed IHPCS based on the WGS parameters (when subject to wind speeds), and the motion of the spool is shifted right or left based on the pitch error (difference between pitch demand and pitch angle), whereas the pitch angle is measured by an angular displacement sensor connected at the WT blades. In case of a positive error, the pressurized fluid from the pump reaches port P, and it is transferred to port A (actuator). Subsequently, the low-pressure fluid from the actuator is delivered to the tank (port T) through port B. Through this action, the hydraulic motor rotates clockwise which increases the pitch angle. For the anticlockwise rotation (in case of a negative pitch error) of the hydraulic motor, the pressurized fluid from port P reaches port B (the spool in the PDCV is shifted), and from the actuator, the hydraulic fluid reaches port A and then port T, which results in a decreasing pitch angle. Furthermore, when the pitch error is zero, none of the solenoids in the PDCV are activated, preventing any hydraulic fluid flow between the ports. As a consequence, there is no alteration in the pitch angle. Based on the WGS parameters and pitch angle error, necessary control action is taken by the proposed IHPCS.

3. System Modeling

The system model is essential for designing the pitch control strategy. Therefore, in this section, the modeling of the WGS and HPS is carried out.

3.1. WGS Model

The WGS model includes the rotor, drivetrain, and generator (as seen in Figure 1). The WGS parameter values used during the modeling are provided in Table A1 (Appendix A).

3.1.1. Rotor

The P_{rot} is represented as

$$P_{rot} = \frac{\rho_{air} \cdot \pi \cdot R_{rot}^2 \cdot v_w^3 \cdot C_p(\lambda, \beta_g)}{2} \quad (1)$$

where C_p is a function of λ and β_g [31], which is described as

$$C_p(\lambda, \beta_g) = C_1 \left[\frac{C_2}{\lambda_i} - C_3 \cdot \beta_g - C_4 \right] e^{-\left(\frac{C_5}{\lambda_i}\right)} + C_6 \cdot \lambda \quad (2)$$

wherein

$$\lambda_i = \left[\left(\frac{1}{\lambda + 0.08\beta_g} \right) - \left(\frac{0.035}{\beta_g^3 + 1} \right) \right]^{-1} \quad (3)$$

where the constant values [31] are $C_1 = 0.5176$, $C_2 = 116$, $C_3 = 0.4$, $C_4 = 5$, $C_5 = 21$, and $C_6 = 0.0068$.

The torque at the rotor T_{rot} is expressed as

$$T_{rot} = \frac{\rho_{air} \cdot \pi \cdot R_{rot}^3 \cdot v_w^2 \cdot C_T(\lambda, \beta_g)}{2} \quad (4)$$

where C_T is given by

$$C_T = \frac{C_p}{\lambda} \quad (5)$$

3.1.2. Drivetrain

To model the drivetrain, a two-mass model is considered as shown in Figure 2, and the dynamics [32] are given by

$$J_{rot} \cdot \dot{\Omega}_{rot} = T_{rot} - T_{ls} - (K_{rot} \cdot \Omega_{rot}) \quad (6a)$$

$$T_{ls} = F_{ls}(\Omega_{rot} - \Omega_{ls}) + K_{ls}(\Psi_{rot} - \Psi_{ls}) \quad (6b)$$

$$J_{gen} \cdot \dot{\Omega}_{gen} = T_{hs} - T_{gen} - (K_{gen} \cdot \Omega_{gen}) \quad (6c)$$

wherein

$$i_g = \frac{\Omega_{gen}}{\Omega_{ls}} \quad (6d)$$

Considering previous equations, the overall dynamics is denoted as

$$\begin{bmatrix} \dot{\Omega}_{rot} \\ \dot{\Omega}_{gen} \\ \dot{T}_{ls} \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix} \cdot \begin{bmatrix} \Omega_{rot} \\ \Omega_{gen} \\ T_{ls} \end{bmatrix} + \begin{bmatrix} y_{11} \\ y_{21} \\ y_{31} \end{bmatrix} \cdot T_{rot} + \begin{bmatrix} z_{11} \\ z_{21} \\ z_{31} \end{bmatrix} \cdot T_{gen} \quad (7)$$

where

$$\begin{aligned} x_{11} &= -\frac{K_{rot}}{J_{rot}}, x_{12} = 0, x_{13} = -\frac{1}{J_{rot}}, x_{21} = 0, x_{22} = -\frac{K_{gen}}{J_{gen}}, x_{23} = \frac{1}{i_g J_{gen}}, \\ x_{31} &= K_{ls} - \frac{F_{ls} K_{rot}}{J_{rot}}, x_{32} = \frac{1}{i_g} \left(\frac{F_{ls} K_{gen}}{J_{gen}} - K_{ls} \right), x_{33} = -F_{ls} \left(\frac{J_{rot} + i_g^2 J_{gen}}{i_g^2 J_{gen} J_{rot}} \right), \\ y_{31} &= \frac{F_{ls}}{J_{rot}}, y_{21} = 0, y_{11} = \frac{1}{J_{rot}}, z_{31} = \frac{F_{ls}}{i_g J_{gen}}, z_{21} = -\frac{1}{J_{gen}}, z_{11} = 0. \end{aligned}$$

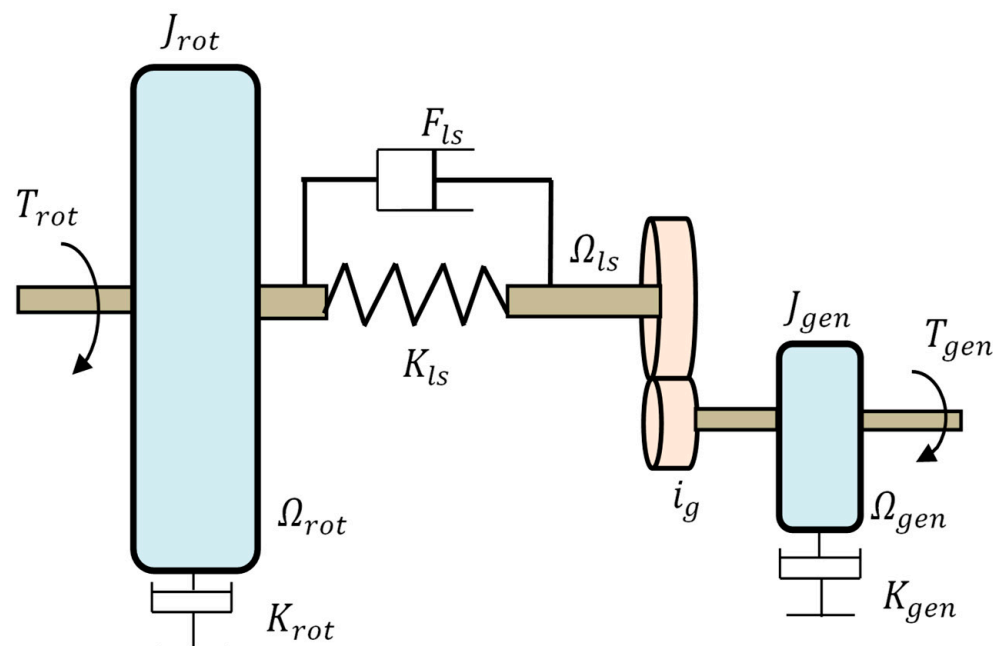


Figure 2. Drivetrain dynamics.

3.1.3. Generator

The first-order model of the generator torque [33] is described as

$$\dot{T}_{gen} = \frac{T_{gen-ref}}{t_{gen}} - \frac{T_{gen}}{t_{gen}} \quad (8)$$

The reference torque can be formulated as

$$T_{gen-ref} = \begin{cases} 0 & \text{Region 1} \\ k_g \cdot \Omega_{gen}^2 & \text{Region 2} \\ T_{gen-rtd} & \text{Region 3} \end{cases} \quad (9)$$

The power generated is given by

$$P_{gen} = T_{gen} \cdot \Omega_{gen} \cdot \eta_{gen} \quad (10)$$

In this study, the primary emphasis is on examining pitch control, with the turbine being regarded as off-grid. Therefore, employing a first-order generator appears to be a reasonable approach.

3.2. Hydraulic Pitch System Model

The HPS consists of several components, and the modeling of each component is as follows:

For modeling a servo motor, an ideal equation is considered as given below:

$$\Omega_{em} = V_{em} \cdot K_{em} \quad (11)$$

The servo motor is connected to a hydraulic pump to generate pressurized fluid. The flow rate of the hydraulic pump [34] is given by

$$Q_{hyp} = (V_{hyp} \cdot \Omega_{em}) - (C_{hyp} \cdot P_{ld}) \quad (12)$$

The hydraulic fluid from the pump reaches the PDCV. The dynamics of proportional valve flow [35] are represented as

$$Q_1 = \left\{ (C_{lek} + \bar{C}_{v_1} \cdot z) \cdot [P_P - P_T]^{\frac{1}{2}} \right\} - \left\{ [P_A - P_T]^{\frac{1}{2}} \cdot C_{lek} \right\} \text{ for } z > z_0 \quad (13a)$$

$$Q_2 = \left\{ (C_{lek} + \bar{C}_{v_4} \cdot z) \cdot [P_B - P_T]^{\frac{1}{2}} \right\} - \left\{ [P_P - P_B]^{\frac{1}{2}} \cdot C_{lek} \right\} \text{ for } z > z_0 \quad (13b)$$

$$Q_1 = \left\{ (C_{lek} + \bar{C}_{v_2} \cdot z) \cdot [P_A - P_T]^{\frac{1}{2}} \right\} - \left\{ [P_A - P_T]^{\frac{1}{2}} \cdot C_{lek} \right\} \text{ for } z < z_0 \quad (13c)$$

$$Q_2 = \left\{ (C_{lek} + \bar{C}_{v_3} \cdot z) \cdot [P_P - P_B]^{\frac{1}{2}} \right\} - \left\{ [P_P - P_B]^{\frac{1}{2}} \cdot C_{lek} \right\} \text{ for } z < z_0 \quad (13d)$$

where, z_0 is caused by the valve spool overlap [35].

Moreover, the flow from the PDCV reaches the hydraulic motor. The flow rate of the hydraulic motor [36] is given as follows:

$$Q_{hym} = C_{hym} \cdot P_{hym} + \frac{V_t \cdot \dot{P}_{hym}}{4\beta_{eb}} + V_{hym} \cdot \dot{\beta}_{hym} \quad (14)$$

Consequently, the hydraulic motor torque balance equation [37] is given by

$$V_{hym} = \frac{J_{hym} \cdot \ddot{\beta}_{hym} + G_b \cdot \beta_{hym} + L_p(t)}{\Delta P_{hym}} \quad (15)$$

Finally, the pitch angle is generated at the pitch gear, and it is formulated as

$$\beta_g = \frac{\beta_{hym}}{N_{pg}} \quad (16)$$

where N_{pg} is obtained from

$$N_{pg} = \frac{P_L}{L_{phm}} \quad (17)$$

where P_L [14] is estimated by

$$P_L = \frac{1}{2 \cdot \eta_{pb}} \cdot \Omega_{rot}^2 \cdot \rho_b \cdot \sum_{r=0}^{R_{rot}} [\sin 2\beta_g \cdot \Delta r \cdot (J_{y1} - J_{x1})] \quad (18)$$

4. Pitch Control Strategy Design

In this section, three pitch control strategies are designed, namely the following: proposed IHPCS, cascade IENN, and cascade ENN. The other two pitch control strategies (cascade IENN and cascade ENN) are developed as performance comparisons to the proposed IHPCS. A detailed explanation of each pitch control strategy design is given below.

4.1. Proposed IHPCS

Figure 3 shows the framework of the proposed IHPCS. The proposed IHPCS is structured as a cascade arrangement of an improved recurrent elman neural network (IRENN). Within the IRENN, a RENN is carefully constructed [38,39], and its parameters undergo optimization through the CPSO algorithm. As seen in Figure 3, the IRENN-based WGS controller estimates the β_{dem} based on the WGS parameters, and then the IRENN-based HPS controller commands (collective pitch control) the HPS to track the β_{dem} .

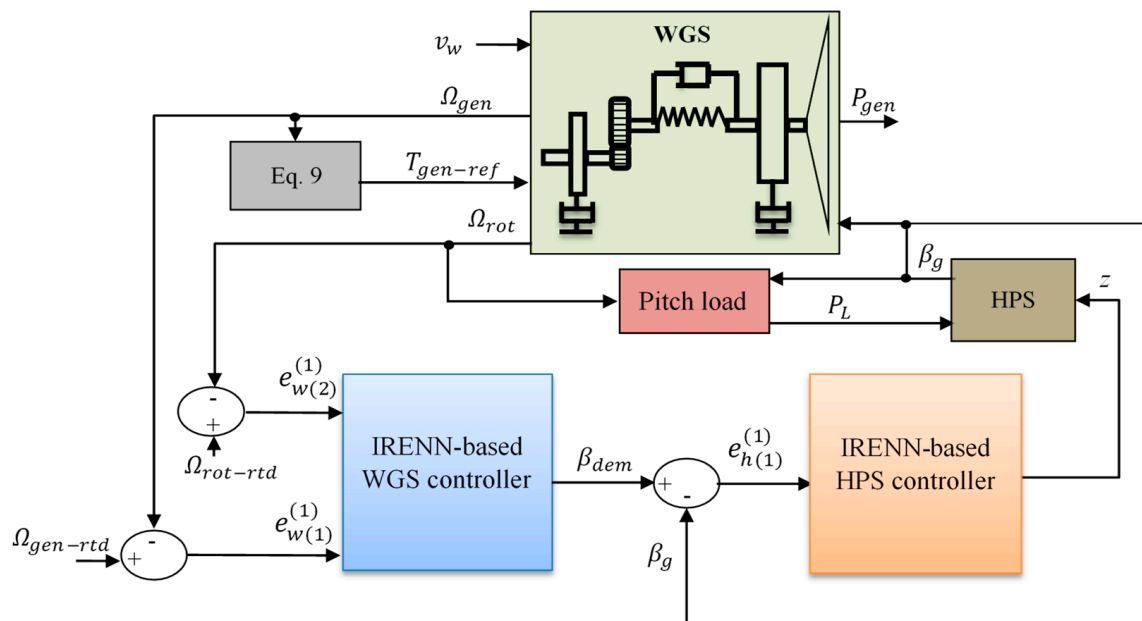


Figure 3. Proposed IHPCS framework.

4.1.1. Neural Network Design

The neural network architecture under consideration comprises five layers: layer u (input layer), layer v (hidden layer), layer c (context layer), layer r (recurrent layer), and layer w (output layer), as illustrated in Figure 4. Additionally, Z^{-1} serves as a feedback unit. The Z^{-1} facilitates the recurrence of the hidden layer's output to the context layer. Similarly, Z^{-1} is employed in the recurrent connection of the output layer's output to the hidden layer, as depicted in Figure 4.

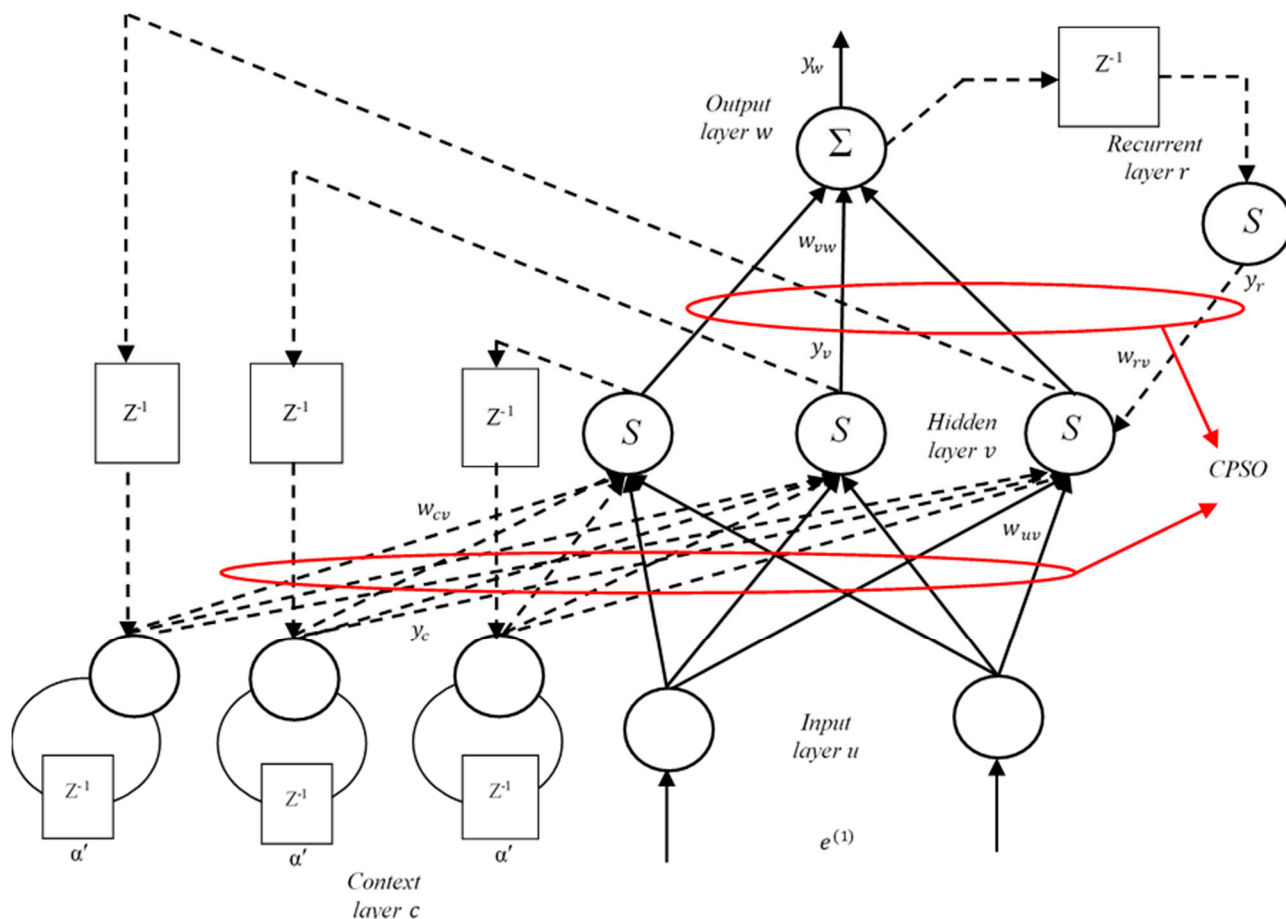


Figure 4. Structure of IRENN.

The WGS controller has two inputs, and they are $e_{w(1)}^{(1)}$ and $e_{w(2)}^{(1)}$, where $e_{w(1)}^{(1)} = \Omega_{gen-rtd} - \Omega_{gen}$ and $e_{w(2)}^{(1)} = \Omega_{rot-rtd} - \Omega_{rot}$, and the output is β_{dem} . Consequently, the HPS controller has one input $e_{h(1)}^{(1)} = \beta_{dem} - \beta_g$ and gives z as an output to control the PDCV in the HPS.

Further, the nodes in each layer of the proposed NN are described as given below:

Layer u —Input Layer

The node in this layer is represented as

$$y_u^{(1)}(n) = f_u^{(1)}(net_u^{(1)}(n)) \quad (19a)$$

$$et_u^{(1)}(n) = e^{(1)}(n) \quad (19b)$$

where $e^{(1)} = e_{w(1)}^{(1)}$ and $e_{w(2)}^{(1)}$ for the WGS controller and $e^{(1)} = e_{h(1)}^{(1)}$ for the HPS controller.

Layer v —Hidden Layer

This layer node is defined as

$$y_v^{(2)}(n) = S\left(net_v^{(2)}(n)\right) \quad (20a)$$

$$net_v^{(2)}(n) = \sum_{u=1}^2 w_{uv} \cdot y_u^{(1)}(n) + \sum_{c=1}^m w_{cv} \cdot y_c^{(3)}(n) + \sum_r w_{rv} \cdot y_r^{(4)}(n), \quad v = 1, 2, \dots, m \quad (20b)$$

Layer c —Context Layer

The node in this layer is described as

$$y_c^{(3)}(q) = \alpha' \cdot y_c^{(3)}(n-1) + y_v^{(2)}(n-1), \quad c = 1, 2, \dots, m \quad (21)$$

where the value of α' is assigned as $0 \leq \alpha' \leq 1$.

Layer r —Recurrent Layer

To facilitate the learning process, an activation function $\exp(-x^2)$ is utilized that facilitates this layer. Here, the node is expressed as

$$x_r^{(4)}(n) = y_w^{(5)}(n-1) \quad (22a)$$

$$y_r^{(4)} = \exp\left[-\left(x_r^{(4)}(n)^2\right)\right] \quad (22b)$$

Layer w —Output Layer

The node in this layer is expressed as

$$y_w^{(5)}(n) = f_w^{(5)}\left(net_w^{(5)}(n)\right) \quad (23)$$

where $net_w^{(5)}$ is represented as

$$net_w^{(5)}(n) = \sum_v w_{vw} \cdot y_v^{(2)}(n) \quad (24)$$

The process detailed in the next section describes how the connecting weights of neurons in each layer are adjusted.

4.1.2. Learning and Training Process

Firstly, the designed NN is trained via gradient descent approach. The learning method utilizes chain rules to refine the network's parameters. Moreover, the chain rule is used to determine each layer's error terms. The goal of this learning and training process is to minimize the error terms by regulating suitable connection weights between neurons. Further, the error function of the two controllers, WGS (ξ_w) and HPS (ξ_h), are denoted as

$$\xi_w = \frac{1}{2} \left(\Omega_{gen-rtd} - \Omega_{gen} \right)^2 \quad (25)$$

$$\xi_h = \frac{1}{2} \left(\beta_{dem} - \beta_g \right)^2 \quad (26)$$

The chain rule process is outlined below. Since this process remains identical for both the controllers (WGS and HPS), a unified error function (ξ) is used.

Rule 1: Update Weight w_{vw} in the Output Layer

The error term is formulated as

$$\delta_w^{(5)} = -\frac{\partial \xi}{\partial net_w^{(5)}} = \left[-\frac{\partial \xi}{\partial y_w^{(5)}} \frac{\partial y_w^{(5)}}{\partial net_w^{(5)}} \right] \quad (27)$$

Then, the weight w_{vw} is adjusted by

$$\Delta w_{vw} = -\frac{\partial \xi}{\partial w_{vw}} = \left[-\frac{\partial \xi}{\partial y_w^{(5)}} \cdot \frac{\partial y_w^{(5)}}{\partial net_w^{(5)}} \right] \left[\frac{\partial net_w^{(5)}}{\partial w_{vw}} \right] = \delta_w^{(5)} \cdot y_v^{(5)} \quad (28)$$

The output layer weights are adjusted by

$$w_{vw}(n+1) = w_{vw}(n) + \phi_1 \cdot \Delta w_{vw} \quad (29)$$

Rule 2: Update Weight w_{rv} in the Recurrent Layer

The update law of w_{rv} is given using the chain rule by

$$\Delta w_{rv} = -\frac{\partial \xi}{\partial w_{rv}} = \left[-\frac{\partial \xi}{\partial y_w^{(5)}} \cdot \frac{\partial y_w^{(5)}}{\partial net_w^{(5)}} \right] \left[\frac{\partial net_w^{(5)}}{\partial y_r^{(4)}} \cdot \frac{\partial y_r^{(4)}}{\partial w_{rv}} \right] \quad (30)$$

$$= \delta_w^{(5)} \cdot w_{rv} \cdot y_v^{(2)} \cdot [1 - y_v^{(2)}] \cdot y_r^{(4)} \quad (31)$$

The weight in the recurrent layer is updated by

$$w_{rv}(n+1) = w_{rv}(n) + \phi_2 \cdot \Delta w_{rv} \quad (32)$$

Rule 3: Update Weight w_{cv} in the Context Layer

Using the chain rule, the update law of w_{cv} is expressed as

$$\Delta w_{cv} = -\frac{\partial \xi}{\partial w_{cv}} = \left[-\frac{\partial \xi}{\partial y_w^{(5)}} \cdot \frac{\partial y_w^{(5)}}{\partial net_w^{(5)}} \right] \left[\frac{\partial net_w^{(5)}}{\partial y_v^{(2)}} \cdot \frac{\partial y_v^{(2)}}{\partial w_{cv}} \right] \quad (33)$$

$$= \delta_w^{(5)} \cdot w_{cv} \cdot y_v^{(2)} \cdot [1 - y_v^{(2)}] \cdot y_c^{(3)} \quad (34)$$

The context layer weight w_{cv} is adjusted by

$$w_{cv}(n+1) = w_{cv}(n) + \phi_3 \cdot \Delta w_{cv} \quad (35)$$

Rule 4: Update Weight w_{uv} in the Input Layer

Using the chain rule, the update law of w_{uv} is denoted by

$$\Delta w_{uv} = -\frac{\partial \xi}{\partial w_{uv}} = \left[-\frac{\partial \xi}{\partial y_w^{(5)}} \cdot \frac{\partial y_w^{(5)}}{\partial net_w^{(5)}} \right] \left[\frac{\partial net_w^{(5)}}{\partial y_v^{(2)}} \cdot \frac{\partial y_v^{(2)}}{\partial w_{uv}} \right] \quad (36)$$

$$= \delta_c^{(5)} \cdot w_{uv} \cdot y_b^{(2)} \cdot [1 - y_b^{(2)}] \cdot y_u^{(1)} \quad (37)$$

The connecting weight w_{uv} of the input layer is given by

$$w_{uv}(n+1) = w_{uv}(n) + \phi_4 \cdot \Delta w_{uv} \quad (38)$$

4.1.3. CPSO-Based Learning Rate Adjustment

The CPSO algorithm has been employed to adjust the learning rate, and the training process occurs offline. The CPSO determines its optimal solution by leveraging the current population of particles. Additionally, each persisting population represents a potential solution to the problem. In this research, the CPSO is applied to adjust the learning rates ϕ_1 , ϕ_2 , ϕ_3 , and ϕ_4 of the designed NN.

Step 1: Preliminary Parameter Initialization

The training set first defines the initial parameter, which is then tuned later. The particles are defined by $Z_i^D = [Z_i^1, Z_i^2, Z_i^3, Z_i^4]$, where Z_i^1 , Z_i^2 , Z_i^3 , and Z_i^4 are the particles of ϕ_1 , ϕ_2 , ϕ_3 , and ϕ_4 , respectively. For both controllers (WGS and HPS), the population size and particle dimension are fixed as $p = 250$ and $D = 4$, respectively.

Step 2: Tuning of Location and Velocity

The preliminary location $Z_i^D(N)$ and the velocities $V_i^D(N)$ of all particles are randomly generated. A particle's initial p_{best} is fixed on the basis of the current position, and a group's g_{best} is chosen among the p_{best} . The vector $Z_i^D(N)$ elements are randomly allocated by

$$Z_i^D \sim U[\sigma_{min}^D, \sigma_{max}^D] \quad (39)$$

where $U[\sigma_{min}^D, \sigma_{max}^D]$ represents the outcome of a random variable uniformly distributed between the learning rate's lower bound σ_{min}^D and the upper bound σ_{max}^D .

Step 3: Velocity and Position Adjustment

The position Z and the speed V [25] of the particles are updated by

$$V_i^D(N+1) = V_i^D(N) \cdot W + \left[(P_{best_i^D} - Z_i^D(N)) \cdot R/1 \cdot C/1 \right] + \left[(g_{best_i^D} - Z_i^D(N)) \cdot R/2 \cdot C/2 \right] \quad (40)$$

$$Z_i^D(N+1) = V_i^D(N+1) + Z_i^D(N), i = 1, 2, \dots, p \quad (41)$$

where $R/1$ and $R/2$ vary in the interval $[0, 1]$.

Step 4: Adjust p_{best}

Until the particle's current position interrupts g_{best} , the objective function is computed. Following this, if the present state of fitness surpasses the previous p_{best} , then p_{best} is substituted with the current position. The fitness of the particle for the WGS controller (F_w) and HPS controller (F_h) is estimated by

$$F_w = \frac{1}{0.1 + abs(\Omega_{rot-rtd} - \Omega_{rot}) * abs(\Omega_{gen-rtd} - \Omega_{gen})} \quad (42)$$

$$F_h = \frac{1}{0.1 + abs(\beta_{dem} - \beta_g)} \quad (43)$$

Considering these equations, progressive increases are demonstrated in the following steps.

Step 5: Update g_{best}

The optimal p_{best} is substituted for g_{best} . Each particle's fitness value Z_i^D is recorded, and the highest value is opted from the population's best performing vector in $p_{best_i^D} = [p_{best_1^D}, p_{best_2^D}, \dots, p_{best_p^D}]$. At the first iteration, Z_i^D is assigned as $p_{best_i^D}$, and the global best g_{best} is identified as the most optimal p_{best} .

Step 6: Check Convergence

Until g_{best} attains the best fitness value or maximum iteration, steps 3–6 are continued. The optimal learning rates (ϕ_1 , ϕ_2 , ϕ_3 , and ϕ_4) are obtained from the peak fitness value of g_{best}^D . The distance moved by the particle is governed by the acceleration coefficients C_1 and C_2 . Here, the C_1 and C_2 values (for both controllers) are set to 2.0. Further, the inertia weight W plays a crucial role in determining the convergence behavior of the PSO algorithm [38]. A lower value of W facilitates faster convergence, whereas a higher value may result in divergence. Typically, the inertia weight W is defined by

$$W = W_{\max} - \left[\left(\frac{W_{\max} - W_{\min}}{i_{x-\max}} \right) \cdot i_x \right] \quad (44)$$

where the minimum value of the inertia weight $W_{\min} = 0.2$ and the maximum value of the inertia weight $W_{\max} = 0.6$ (for both WGS and HPS controllers).

4.2. Cascade IENN

Considering the IRENN developed in [25], here, the cascade IRENN (as illustrated in Figure 5) is established where the IRENN is deployed as the WGS and HPS controller. The IENN features the ENN (four layered NN: input, hidden, context, and output), and the parameters of this NN are similarly optimized by the CPSO algorithm as executed in [25].

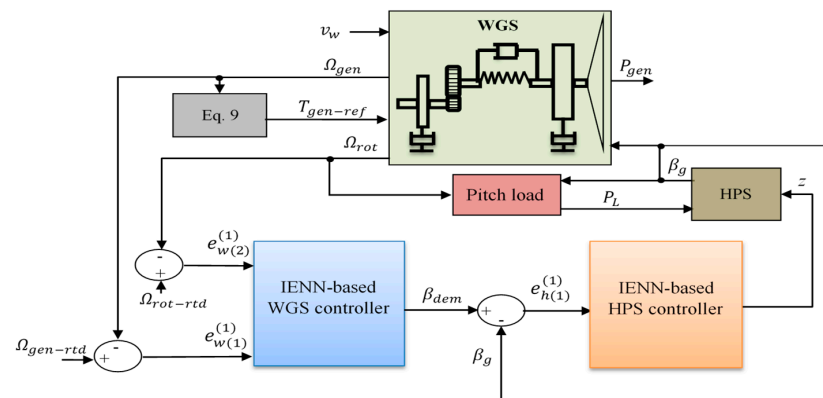


Figure 5. Cascade IENN framework.

4.3. Cascade ENN

Figure 6 displays the framework of the cascade ENN. Here, the ENN (four layered: input, hidden, context, and output) is deployed as the WGS and HPS controller. Moreover, the parameters of this NN are optimized by the conventional Levenberg–Marquardt algorithm.

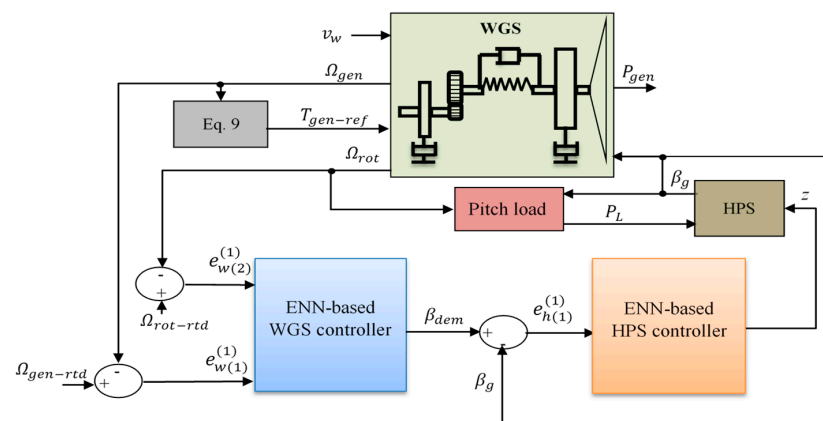


Figure 6. Cascade ENN framework.

Remark 1. For data collection (supervised), multiple wind speeds (region III) ranging from 11.5 m/s to 25 m/s (rated wind speed: 11.4 m/s and cut-out wind speed: 25 m/s [31]) with a step size of 0.25 m/s were generated using the Kaimal wind model (IEC 61400-3) [39]. These wind speeds are characterized by minimal fluctuations (up to 10 Hz). Consequently, these wind speeds can serve as an appropriate alternative to a constant wind speed that is preferred in the literature [33]. For a more realistic optimization, it is advisable to perform the optimization process with varying wind speed data. Approximately 40,000 datasets were gathered for each NN. Out of these datasets, 28,000 (70%) were utilized for training the NNs, and the remaining 12,000 (30%) were employed for testing purposes. Additionally, to assess the effective convergence performance of the proposed IHPCS, a comparison was conducted with other pitch control strategies, namely the cascade IENN and the cascade ENN (designed in Sections 4.2 and 4.3). As mentioned previously, offline training is conducted (using the collected datasets), and the convergence performance of the pitch control strategies is tabulated in Table 1. On considering the WGS controller training performance, relative to the IENN and ENN, the proposed IRENN improved the Mean Square Error (MSE) by 71.21%, and 91.85%, respectively. Similarly, in the case of HPS controllers, compared to the IENN and ENN, the proposed IRENN enhanced the MSE by 55.15% and 93.17%, respectively. Results reveal that the proposed pitch control strategy reaches the least MSE faster (in fewer iterations) than its counterparts.

Table 1. Convergence performance.

Pitch Control Strategies		MSE	Iterations
Proposed IHPCS	IRENN-based WGS controller	0.0078	197
	IRENN-based HPS controller	0.0061	178
Cascade IENN	IENN-based WGS controller	0.0271	247
	IENN-based HPS controller	0.0136	224
Cascade ENN	ENN-based WGS controller	0.0957	398
	ENN-based HPS controller	0.0894	376

5. Results and Discussion

The performance of the proposed IHPCS is tested through various simulation studies using a benchmark FAST simulator (FAST V8.0). More realistic performance of the WT can be executed using the FAST simulator. The FAST operates in conjunction with the AeroDyn aerodynamic subroutine, which offers a comprehensive analysis of aerodynamics using dynamic stall and blade element momentum theory [40]. The proposed IHPCS deployed in FAST is depicted in Figure 7.

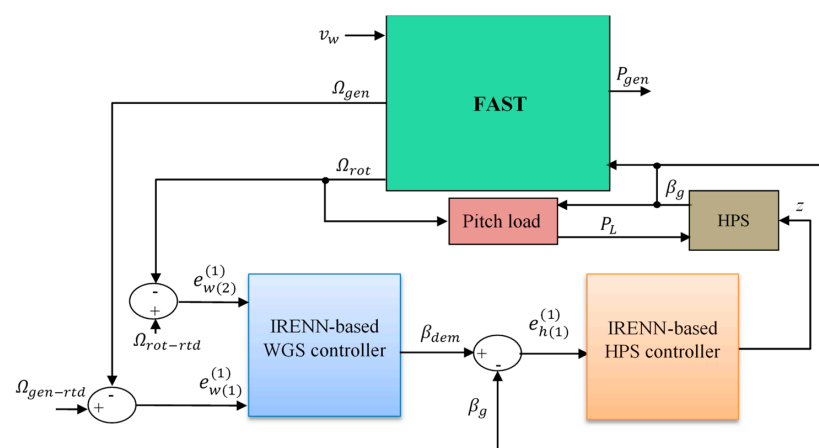


Figure 7. Proposed pitch control strategy implemented in FAST.

In the simulation studies, eighteen wind speed profiles were utilized, which were developed using the Kaimal wind model (IEC 61400-3) [39]. The developed eighteen wind speed profiles have different standard deviations (STDs) (0.5 m/s, 1.0 m/s, 1.5 m/s, and 2.0 m/s), and mean wind speeds (15 m/s, 17 m/s, 19 m/s, 21 m/s, and 23 m/s). Especially for the wind speed with a mean of 23 m/s, only the wind speeds with STDs of 0.5 m/s and 1 m/s were considered, and the rest (STD of 1.5 m/s and 2.0 m/s) were not included, since they mostly covered region IV (above cut-out wind speed). These wind speeds were utilized to evaluate the performance of the proposed IHPCS, and these multiple wind speeds with different STDs and means can be more appropriate to depict the offshore wind scenario. Moreover, in all the studies, the same pitch control strategies (the cascade IENN and cascade ENN that are described in Sections 4.2 and 4.3, respectively) were used as a comparison to the proposed IHPCS. In all the simulation studies, STD was used as the performance evaluation metric, which is one of the most preferred evaluation metrics in the literature [3]. However, multiple studies have reported that the traditional pitch controllers (PI, proportional integral derivative) developed for NREL 5MW WT are underperforming compared to intelligent pitch controllers [33,41], and also the first-order pitch actuator (which is mostly preferred in NREL 5MW) may not be an equivalent comparison for the developed HPS, thus, traditional pitch controllers and pitch actuators are not considered in these simulation studies. Each simulation was conducted for 350 s, and the performance of the pitch control strategies is shown in Figure 8, Figure 9 and Table 2.

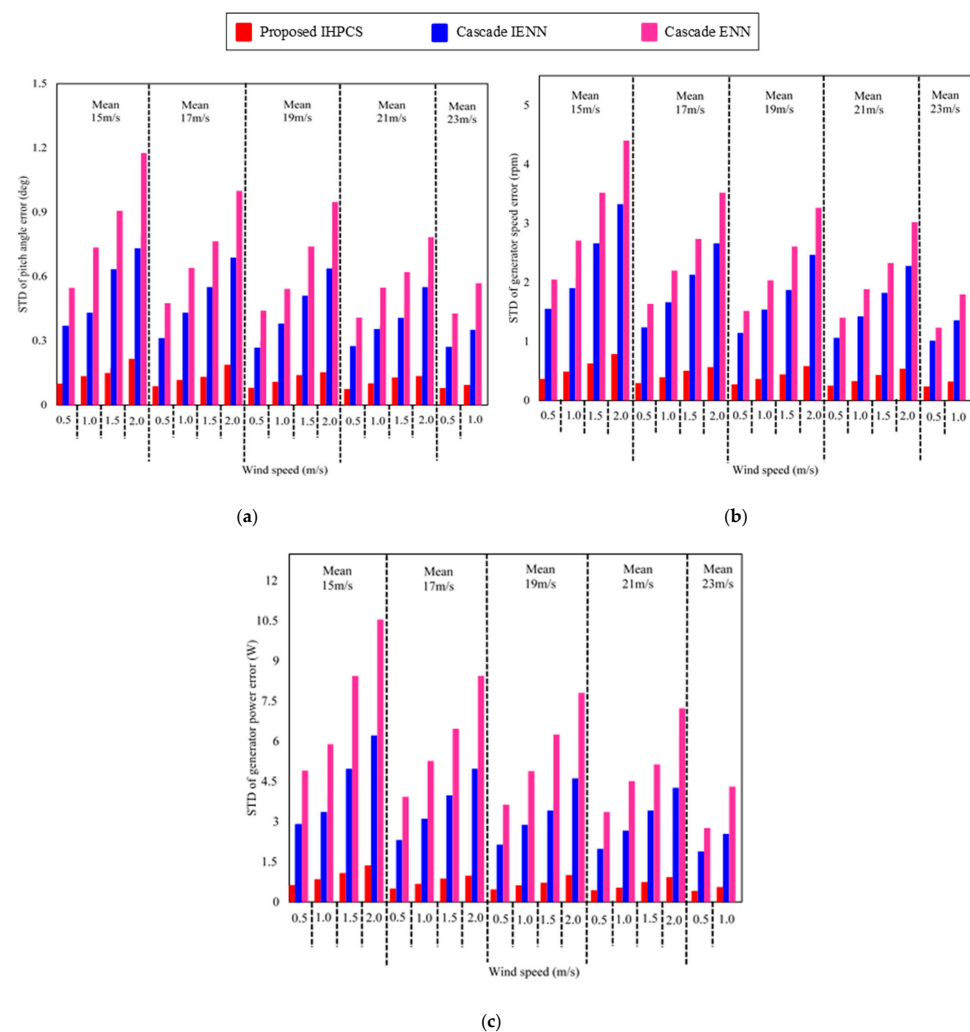


Figure 8. Validation via FAST: (a) STD of pitch angle error; (b) STD of generator speed error; (c) STD of generator power error.

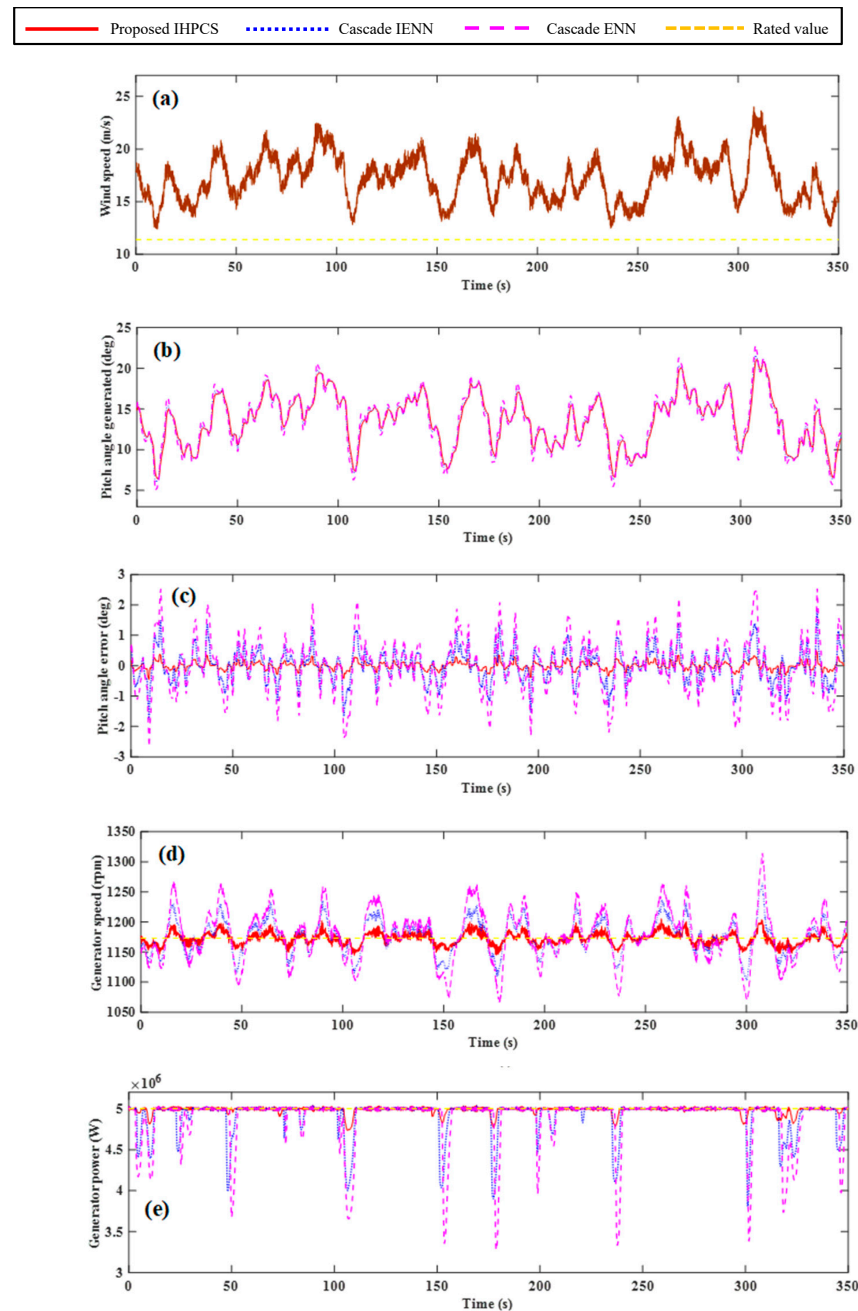


Figure 9. Validation via FAST: (a) wind speed; (b) pitch angle generated; (c) pitch angle error; (d) generator speed; (e) generator power.

Table 2. Statistical analysis of Figure 8.

Pitch Control Strategies	Mean STD of Pitch Angle Error (deg)	Mean STD of Generator Speed Error (rpm)	Mean STD of Generator Power Error (W)
Proposed IHPCS	0.128	0.438	0.759
Cascade IENN	0.471	1.854	3.472
Cascade ENN	0.702	2.455	5.885

The pitching performances (STD of pitch angle error) of the strategies under several wind speed conditions are illustrated in Figure 8a. The pitch control strategies resulted in pitch angle error STD ranging from 0.074 deg (achieved by the proposed IHPCS) to 1.176 deg (produced by the cascade ENN), wherein the cascade ENN demonstrates the highest STD, signifying inadequate pitch regulation. As shown in Table 2, the proposed

IHPCS achieves a 72.82% enhancement in reducing the mean standard deviation of pitch angle error when compared to the cascade IENN. Considering the cascade ENN, the IHPCS demonstrates an 81.76% improvement in minimizing the mean STD of pitch angle error. These findings highlight that the IHPCS surpasses other pitch control approaches by delivering superior pitch accuracy while maintaining the lowest mean STD.

Figure 8b illustrates the STD of the generator speed error. The values range from 0.238 rpm (achieved by the proposed IHPCS) to 4.401 rpm (produced by the cascade ENN). The proposed IHPCS demonstrates effective performance in generator speed. When compared to the cascade IENN, the proposed IHPCS achieves a 76.38% reduction in the mean STD of generator speed error. Similarly, when evaluated against the cascade ENN, it exhibits an 82.16% improvement in the mean STD. From these results it is understood that the proposed IHPCS effectively maintains generator speed closer to the rated value compared to other pitch control approaches. Among all strategies, the cascade ENN delivers the least efficient generator speed regulation, exhibiting the highest STD. A lower STD in generator speed error generated by the IHPCS suggests reduced torque fluctuations in the rotor, which is crucial in WGS performance.

The STD of the generator power error is illustrated in Figure 8c. The error fluctuates between 0.413 W, achieved by the proposed IHPCS, and 10.553 W, observed in the cascade ENN. When compared to the cascade IENN, the IHPCS reduces the mean STD of the generator power error by 78.14%. Furthermore, in contrast to the cascade ENN, the IHPCS achieves an 87.10% improvement. Considering the outcomes, it is clear that the cascade ENN exhibits the highest generator power error and minimal mean STD in generator power error, while the IHPCS suggests that the power output remains more stable and closer to the rated capacity.

In order to visualize at least one (among eighteen simulated results) of these results, Figure 9a displays the wind speed inputted into the FAST simulator. The wind speed has an STD of 2 m/s and a mean of 17 m/s. Based on the inputted wind speed, the outputs obtained are shown in Figure 9b–e, whereas the pitching performance is displayed in Figure 9b,c showcasing the pitch angle generated and pitch angle error, respectively. These pitch results indicate that the proposed IHPCS excels in pitch angle tracking with a minimal pitch angle error. Moreover, the highest pitch angle error is recorded in the cascade ENN. Further, to analyze the generator performance for the pitch angle generated, the developed pitch angle is supplied to the FAST simulator. As a consequence of the pitch angle generated, the corresponding generator performance (generator speed and power) is illustrated in Figure 9d,e. In both the results (generator speed and power), the proposed IHPCS was able to develop rated generator speed and power. Moreover, the least fluctuation or variation in the generator speed and power was noted in the proposed IHPCS. However, the performances of the cascade IENN and cascade ENN were relatively lesser than the proposed IHPCS. The rated power generation by the proposed IHPCS is possible due to the effective pitch angle generation.

Meanwhile, offshore WGSs frequently encounter extreme wind speed conditions, including high turbulence, sudden gusts, and rapid wind direction changes. These factors can cause significant fluctuations in rotor speed and generator power, affecting overall system stability and energy output. To assess the robustness of the proposed IHPCS, extensive simulations were conducted using the FAST simulator. The system was tested under highly fluctuating wind profiles. The simulation results demonstrate that the IHPCS effectively stabilizes generator power output, reducing deviations from the rated power. In addition to external environmental challenges, internal system faults in the HPS can significantly impact pitch control effectiveness. Common failures include internal leakage, valve malfunctions, and actuator faults, which may lead to deviations in pitch angle and

reduced system responsiveness. The proposed IRENN-based controller leverages its adaptive learning capability to dynamically adjust control commands in response to unexpected system variations. This adaptability ensures continued effective performance even in the presence of system faults. In addition, the CPSO-optimized tuning mechanism refines control precision by continuously optimizing network parameters, effectively compensating for measurement noise, sensor inaccuracies, and external disturbances.

Moreover, the proposed methodology is highly adaptable to different WGS models and scalable across various large-scale WGSs. Generally, the NN model relies on datasets, thus training it with versatile datasets makes it adaptable and scalable to various turbine models [17,42,43]. As previously discussed, HPSs are preferred in large-scale WGSs due to their superior power-to-weight ratio, making them a standard choice in both offshore and onshore WGSs [12]. The HPS utilized in our study is designed based on industry-standard PDCVs, which are widely implemented across different large-scale WGS models, ensuring broad applicability. Further, the proposed IRENN is trained on a dataset covering a diverse range of wind conditions, allowing it to generalize beyond the specific WGS model used in our study. In terms of scalability, the proposed technique is applicable to both onshore and offshore WGSs, making it suitable for deployment across a range of turbine capacities. The methodology can be extended to larger or different WGS models by collecting appropriate training datasets and tuning the control parameters to accommodate specific operational requirements. This ensures effective performance across different turbine sizes and environmental conditions, further reinforcing its adaptability and scalability.

To further enhance system resilience, future research will focus on integrating fault detection mechanisms and predictive maintenance strategies. These additions will help detect and mitigate potential failures at an early stage, ensuring prolonged operational reliability and efficiency of the HPS and WGS. While grid disturbances and communication delays were not explicitly considered in this study, this void gives us a huge scope for future investigations. Further, we aim to extend the study to grid-connected WGSs, incorporating grid-side dynamics, power electronics modeling, communication delays, and managing the power fluctuations. Subsequently, this work will be extended by incorporating more complex generator models, including the squirrel-cage induction generator, doubly fed induction generators, and permanent magnet synchronous generators, to further enhance the applicability of our methodology across different WGSs. Furthermore, appropriate measures will be taken to integrate load mitigation while ensuring that the generator's performance remains unaffected.

6. Conclusions

In this work, a hydraulic pitch system with proportional direction control valves controlled by an intelligent hydraulic pitch control strategy designed for generating rated power at above-rated wind speeds in the offshore WGS has been successfully investigated. The suggested pitch control strategy involves a cascaded configuration of an improved recurrent Elman neural network. Here, the parameters of the developed neural network were optimized using a customized heuristic algorithm. Moreover, to validate the performance of the proposed pitch control strategy, several simulation studies (with the benchmark FAST simulator) are conducted using eighteen wind speeds, and the proposed pitch control strategy has been compared to the cascade IENN and cascade ENN. Using the eighteen wind speeds and considering the cascade IENN and cascade ENN, the proposed IHPCS leads to an improvement of 72.82% and 81.76% in the mean STD of the pitch angle error, respectively. Relative to the cascade IENN and cascade ENN, the proposed pitch control strategy improved the mean STD of generator power error by 78.14% and 87.10%, respectively. From these results, it is noted that the proposed pitch strategy delivered

power generation with minimal fluctuation and also near rated power against other control strategies. Being tested in a benchmark FAST simulator reveals that the proposed pitch control strategy can be applicable in real-world WT applications. The effective training of the proposed NN is the main reason for such accomplishments.

In future research, the pressure dynamics, internal leakage, and fault tolerance of the pitch system will be thoroughly investigated. Consequently, necessary steps will be taken to incorporate load mitigation without creating conflict with the generator's performance, and also complex generator models with grid integration will be studied. As a whole, the findings will be more useful for the researchers and also WT industries for the successful deployment of the intelligent hydraulic pitch system.

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Abbreviations

The following abbreviations are used in this manuscript:

CPSO	Customized Particle Swarm Optimization
ENN	Elman Neural Network
EPS	Electrical Pitch System
FAST	Fatigue Aero-Elastic Structure Turbulence
FFBPNN	Feedforward Back Propagation Neural Network
FFNN	Feedforward Neural Network
FOPID	Fractional-Order Proportional–Integral–Derivative
GW	Gigawatt
HPS	Hydraulic Pitch System
IENN	Improved Elman Neural Network
IHPCS	Intelligent Hydraulic Pitch Control Strategy
IRENN	Improved Recurrent Elman Neural Network
MSE	Mean Square Error
MW	Megawatt
NN	Neural Network
NREL	National Renewable Energy Laboratory
PDCV	Proportional Direction Control Valves
PI	Proportional Integral
PSO	Particle Swarm Optimization
RENN	Recurrent Elman Neural Network
RNN	Recurrent Neural Network
STD	Standard Deviation
WNN	Wavelet Neural Network
WGS	Wind Generator System
WT	Wind Turbine
Notations	
Ψ_{rot} and Ψ_{ls}	Angular deviations at rotor-side and gearbox-side

β_{hym}	Angular displacement of hydraulic motor
Δr	Blade incremental radius
C_p	Co-efficient of power
C_T	Co-efficient of torque
$C/1$ and $C/2$	Confidence coefficients of CPSO
$w_{uv}, w_{vw}, w_{rv}, w_{cv}$	Connecting weights between layers of neural network
$C_1, C_2, \dots, C_6$	Constants of co-efficient of power
z and z_0	Control signal and dead band signal
i_x	Current iteration of CPSO
ρ_{air}	Density of air
ρ_b	Density of the blade material
D	Dimension
F_{ls}	Drivetrain damping constant
K_{ls}	Drivetrain spring constant
ξ_h	Error function of HPS controller
ξ_w	Error function of WGS controller
F_h	Fitness function of CPSO for HPS controller
F_w	Fitness function of CPSO for WGS controller
$\bar{C}_{v1}, \bar{C}_{v2}, \bar{C}_{v3}, \bar{C}_{v4}$	Flow coefficients of respective proportional valve port
Q_{hym}	Flow rate of hydraulic motor
Q_{hyp}	Flow rate of hydraulic pump
Q_1 and Q_2	Flow rate of the proportional valve
i_g	Gearbox ratio
Ω_{gen}	Generator angular speed
η_{gen}	Generator efficiency
P_{gen}	Generator power
T_{gen}	Generator torque
g_{best}	Global best position
T_{hs}	High-speed shaft torque
β_{eb}	Hydraulic fluid effective bulk modulus
C_{hym}	Hydraulic motor leakage coefficient
J_{hym}	Inertia of hydraulic motor
W	Inertia weight of CPSO
$x_r^{(4)}$	Input of the recurrent layer of NN
V_{em}	Input voltage
C_{lek}	Leakage flow coefficient
$\phi_1, \phi_2, \phi_3, \phi_4$	Learning rate
L_{phm}	Load at hydraulic motor
P_{ld}	Load pressure across the hydraulic pump
P_{best}	Local best position
σ_{min}^D	Lower bounded value of learning rate
T_{ls}	Low-speed shaft torque
W_{max}	Maximum inertia weight of CPSO
W_{min}	Minimum inertia weight of CPSO
J_{x1}	Moment of inertia of the aerofoil about x_1 axis
J_{y1}	Moment of inertia of the aerofoil about y_1 axis
n	n th iteration
m	Number of neurons
$y_c^{(3)}$	Output of the context layer of NN
$y_o^{(2)}$	Output of the hidden layer of NN
$y_u^{(1)}$	Output of the input layer of NN
$y_w^{(5)}$	Output of the output layer of NN
$y_r^{(4)}$	Output of the recurrent layer of NN

β_g	Pitch angle generated
η_{pb}	Pitch bearing efficiency
β_{dem}	Pitch demand
N_{pg}	Pitch gear ratio
P_L	Pitch load
$L_p(t)$	Pitch load nonlinearities at time t
G_b	Pitch load spring gradient
Z	Position of CPSO particles
P_A and P_B	Pressure at port A and B of the hydraulic pump
ΔP_{hym}	Pressure difference across the hydraulic motor
P_{hym}	Pressure load across the hydraulic motor
P_P and P_T	Pump and tank side pressure
C_{hyp}	Pump leakage coefficient
R_{t1} and R_{t2}	Random numbers of CPSO
$\Omega_{rot-rtd}$	Rated generator speed
$T_{gen-rtd}$	Rated generator torque
$T_{gen-ref}$	Reference generator torque
k_g	Reference torque gain of generator
Ω_{rot}	Rotor angular speed
J_{rot}	Rotor moment of inertia
P_{rot}	Rotor power
R_{rot}	Rotor radius
T_{rot}	Rotor torque
α_f	Self-connection feedback gain
K_{em}	Servo gain
Ω_{em}	Servo motor speed
$S(x)$	Sigmoidal function
S_1 and S_2	Solenoids of proportional valve
Z^{-1}	Time delay
λ	Tip speed ratio
e_h	Tracking error of HPS controller
e_w	Tracking error of WGS controller
σ_{max}^D	Upper bounded value of learning rate
V	Velocity of CPSO particles
V_t	Volume of the hydraulic motor
V_{hym}	Volumetric displacement of hydraulic motor
V_{hyp}	Volumetric displacement of the hydraulic pump
v_w	Wind speed

Appendix A

Table A1. WGS parameters [31].

Parameter	Symbol	Value
Blade radius	R_{rot}	63 m
Cut-in, rated, and cut-out	v_{cin} , v_{rtd} , and v_{cout}	3 m/s, 11.4 m/s, and 25 m/s
Drivetrain damping constant	F_{ls}	6,215,000 N.m/(rad/s)
Drivetrain ratio	i_g	97
Drivetrain spring constant	K_{ls}	867,636,000 N.m/rad
Generator efficiency	η_{gen}	94.4%
Generator inertia	J_{gen}	534.116 kg.m ²
Generator time constant	t_{gen}	0.1
Rated generator speed	$\Omega_{gen-rtd}$	1173.61 rpm
Rated generator torque	$T_{gen-rtd}$	43.094 KNm
Rated power	$P_{gen-rtd}$	5 MW
Rated rotor speed	$\Omega_{rot-rtd}$	12.1 rpm
Rotor inertia	J_{rot}	38,768,000 kg.m ²

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