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Expert Control Systems Implemented in a Pitch Control of Wind Turbine: A Review

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ABSTRACT Wind energy is the strongest renewable energy source developed in recent decades. Being systems that are directly connected to the grid of the electrical system, it is essential to use the maximum available power of the wind and obtain the maximum electrical power converted from the turbine. In this paper, the fundamental problem of the wind turbine is how to obtain at all times the maximum output power of the turbine in a wide range of wind speed. The randomness of the wind adds an intrinsic difficulty to be able to plan the available wind energy in advance. To solve this problem, it is not necessary to know the dynamic operation of the system; we must anticipate the control response to each one of the different probable scenarios. An expert control system can be used based on human knowledge and experience, which, through proper management of its variables and adequate control of criteria to manipulate stored data, provides a way to determine solutions. In other words, it is a model of the experience of professionals in this field. The more variables in the system are considered, the more complete the model will be, and the more information will be available for decision-making, with a more efficient system and higher results in power generation as a response. For this reason, the objective of this paper is to present expert systems developed in recent years and, thus, offer a control solution that approximates the conditions of different wind turbines.

INDEX TERMS Artificial neural network, fuzzy logic, genetic algorithms, wind power generation, control systems.

I. INTRODUCTION

Energy is a necessary condition for the elaboration and use of almost all consumer goods and services of the modern world. Energy is indispensable for the growth of the economy, development of work, centers, contributes directly, and indirectly to the generation of employment and growth in each country, therefore, it is imperative that the sector is able to meet energy needs [1].

In this context, it is necessary to increase the generation of energy to meet demand that the world will requires in the coming years, opting for alternatives renewable with lower environmental impact. Wind energy, in particular, reflects great technological advances in reliability and efficiency [2].

The Global Wind Energy Council (GWEC) in February 2018 reported that in 2017 more than 54 GW of wind power was installed, comprised in more than 90 countries, nine of them with more than 10,000 MW installed, and 29 that have now exceeded 1,000 MW. Accumulated capacity grew by 12.6% to reach 486.8 GW [3].

Wind energy is harnessed to rotate a turbine, which transforms the kinetic energy of the wind, by mechanical energy. The amount of energy that can be obtained is a function of the size of the rotor. The greater the length of the blades, the more power and, therefore, the more energy is produced. The capacity and size of wind turbines have increased exponentially in recent decades. In 2016 the typical wind turbine had a nominal power of 7.5 MW and a rotor diameter greater than 125 m [4]. The wind turbine with one of the largest installed capacities is Vestas V164 with power rated of 9.5MW. These units were first installed in 2016 [5]. The V164-10.0 MW is available for sale now and can be delivered for commercial installation beginning in 2021 [6].

The main disadvantage of wind energy is our inability to predict and control the wind. The latest meteorological advances for wind forecasting have greatly improved the situation, but it is still a problem. When there are wide fluctuations in the wind speed, it is necessary to find the optimal speed, that it will generate maximum energy. To achieve this objective a controller is needed for tracking the maximum peak power irrespective of the wind speed [7].

The blade pitch control is an effective method to improve the aerodynamic response of a wind turbine. The inclination angle controller is based on rotating the blades simultaneously, with independent or shared actuator. The angle used with the wind speed below the nominal value is zero, and then the angle increases when the wind speed is higher than the nominal speed [8], [9].

For the control system of a wind turbine, the pitch control subsystems have a critical role, the move of the pitch angle is important to limit the capture of power in situations of strong winds. If the wind exceeds the specifications of the wind turbine, it is mandatory to disconnect that circuit from the network or change the inclination of the blades so that they stop turning, as high velocity wind may damage the structure [10].

Simultaneous movement is used to restrict the generation of energy in strong winds, while individual pitching has the additional advantage of mitigating fatigue damage caused by cyclical loads that are detrimental to the turbines [11].

Various methods of control have been used for pitch angle control, as proportional-integral (PI) [12], [13] and intelligent systems based on fuzzy logic (FL) [14], [15] or combined methods [16]. Research has been developed on adaptive control that adjusts to the dynamic behavior of the system in various situations of electrical generation and safety [17].

The literature review presents a trend in the implementation of pitch control by expert systems, various authors support it to be a variable problem over time and its solution is based on deducting situation from probabilistic data or prediction as conditions of weather. In addition to the difficulty involved in complex mathematical models.

The objective of this work is to present a review on expert systems developed in recent years, and thus offer a control solution that approximates the conditions of different wind turbines. To develop an expert control system is not only necessary to know the dynamic operation of the system, we must anticipate the control response to each of the different probable scenarios. The more variables of the system are considered, the more information will be available for decision-making, having as a response a more efficient system and greater results in power generation. That is why an expert control system is based on human knowledge and experience and that, through good management of its variables and an adequate control of criteria to manipulate stored data, provides a way to determine solutions. In other words, it is a control model of the experience of professionals in this area.

II. WIND TURBINE GENERATOR SYSTEMS

Wind turbines are machines that convert the kinetic energy of the wind into electrical energy. The configuration of wind turbine in this work is shown in Fig. 1. The three main components are the blade rotor, gearbox and electric generator. The rotor captures the kinetic energy of the wind to rotate the slow shaft; the gearbox multiplies this speed and transmits it to the fast shaft. With a higher speed, the fast shaft is connected to the generator and thus produces alternating current [18]. Some systems convert AC to DC using a rectifier and convert DC back to AC to match the frequency and phase of the network [19].

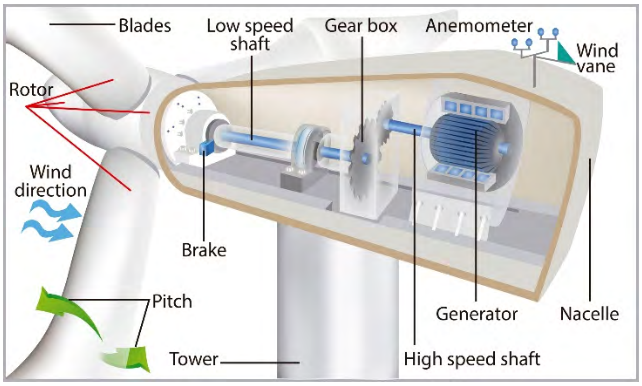

FIGURE 1. Parts of a wind turbine.

Of these types of wind turbines, the maximum energy can be extracted only of variable speed wind turbines. The rotor speed can also be controlled to minimize the stress on the tower structure, gears and shaft, since the blades absorb peaks of torque during the variation of the speed of rotation, leading to a longer installation life [13].

A. AERODYNAMIC MODEL

The analysis to extract the maximum power of wind that passes through a turbine starts with the wind that crosses sweeping area of the rotor. The boundary that separates the affected flow area from the unaffected flow area is the limit surface, which forms a tube of current with constant flow in a circular sweeping area. The approaching undisturbed wind is V, and it becomes slow when the turbine extracts a part of its kinetic energy. The wind that crosses the turbine is Va, has a lower speed and its pressure is reduced. The wind speed through the plane of the rotor blades is Vb. This phenomenon is shown in Fig. 2 [20].

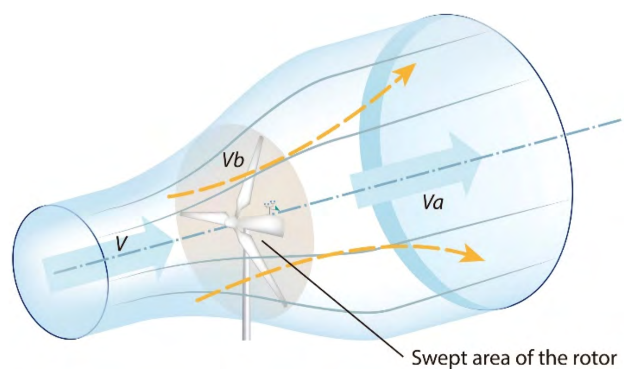

FIGURE 2. Airflow through an actuator disc.

The rotor power extracted by the blades is equal to the difference of kinetic energy between the ascending and descending airflow rates:

$$P_{rotor} = \frac{1}{2}m(V^2 - V_a^2) \quad (1)$$

The air mass flow m within the flow tube is the same everywhere. The point to determine the mass flow is in the plane of the rotor where the area of the cross section is only the area of rotor A and the wind density ρ.

$$m = \rho AVb \quad (2)$$

If the wind speed through the rotor plane V_b is the average of V and V_a then:

$$P_{rotor} = \frac{1}{2}\rho A\left(\frac{V+V_a}{2}\right)(V^2 - V_a^2) \quad (3)$$

If the power coefficient C_p is given by:

$$Cp = \frac{1}{2}\left(1+\frac{V_a}{V}\right)\left(1-(\frac{V_a}{V})^2\right) \quad (4)$$

Therefore the expression for the rotor power is:

$$P_{rotor} = \frac{1}{2}\rho AV^3 Cp \quad (5)$$

It is usual to select a wind turbine according to the performance of the rotor as a function of the specific speed, λ, defined as the coefficient of the tangential speed at the blade tip and wind speed.

$$\lambda = \frac{\Omega R}{V} = \frac{2\pi nR}{60V} \quad (6)$$

where Ω is the rotation frequency in rad / sec, n is the speed of rotation in rpm, R is the radius of the rotor and V is the wind speed.

It is possible to use a method of approximate values dependent on λ and on the pitch angle of the blade β, based on the characteristics of the turbine. The Cp is defined by:

$$Cp\,(\lambda,\beta) = C_1\left(\frac{C_2}{\lambda_i} - C_3\beta - C_4\beta^{C_5} - C_6\right)e^{-\frac{C_7}{\lambda_i}} \quad (7)$$

where:

$$\lambda_i = \left[\left(\frac{1}{\lambda + C_8\beta}\right) - \left(\frac{C_9}{\beta^3+1}\right)\right]^{-1} \quad (8)$$

The values of the constants for variable speed are c1=0.73, $c2 = 151, c3 = 0.58, c4 = 0.002, c5 = 2.14, c6 = 13.2, c7 = 18.4, c8 = -0.02\ yc9 = -0.003$. To minimize the error between the curve in the manufacturer's documentation and the curve obtained by means of equations (7) and (8), multidimensional optimization was applied [21], [22].

Fig. 3 shows the power coefficient curves of the wind turbine as a function of the tip-speed ratio and pitch angle.

Once the C_p has been calculated, it is possible to determine the torque of the rotor [23], [24].

$$T_{rotor} = \frac{1}{2}\rho\pi R^3 v^2 C_t \quad (9)$$

where torque coefficient C_t is:

$$C_t = \frac{C_p}{\lambda} \quad (10)$$

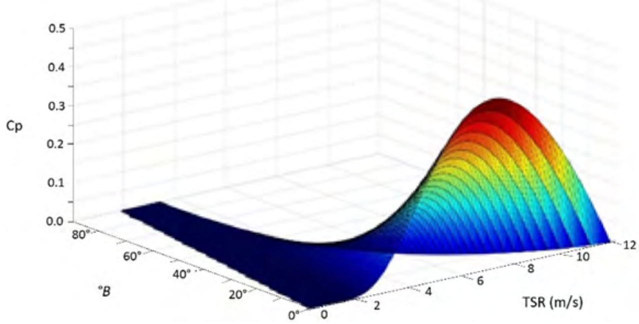

FIGURE 3. Power coefficient curves.

B. MECHANIC MODEL

The mechanical transmission system or power train is composed of all the elements that transmit mechanical torque to the axis of rotation. In the bibliography, you can find a diversity of mechanical models, from those that simplify the whole system in a single mass to the more complex ones that use up to six masses. The aerodynamic and electric pair will be the inputs to the model, while the speeds of rotation will be the output. Fig. 4 shows some of these models proposed in [25].

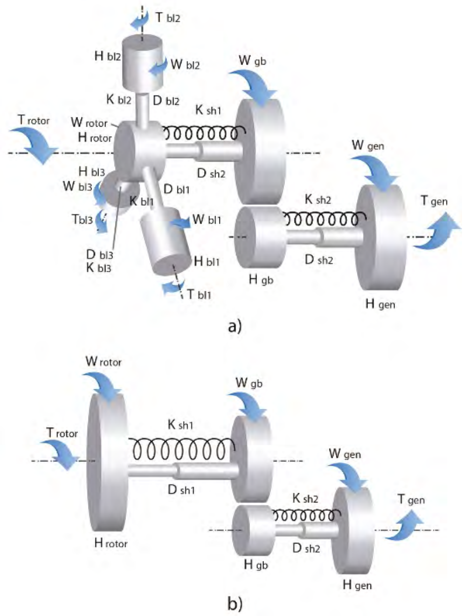

FIGURE 4. Drive train models of wind turbine. a) Six-mass model, b) Transformed three-mass system.

However, the model is two masses is the most common model for wind turbine transmissions and can be used without losing accuracy. This model of two masses is shown in Fig. 5. The transmission system comprising two masses joined by a shaft, all referred to the same side of the gearbox [9], [26].

The mechanical model of two masses corresponds to (11) and (12). The aerodynamic torque of the wind turbine rotor and the electromechanical torque of the direct

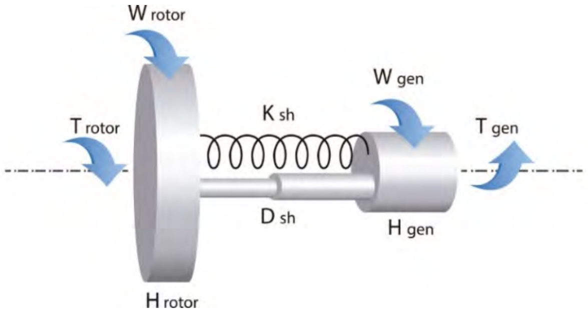

FIGURE 5. Two masses model.

connection induction generator act in opposition to each other [27].

$$2H_{rotor}\frac{dw_{rotor}}{dt} = T_{rotor} - d_{sh}\left(w_{rotor} - w_{gen}\right) - k_{sh}\left(\theta_{rotor} - \theta_{gen}\right) \quad (11)$$

$$2H_{gen}\frac{dw_{gen}}{dt} = d_{sh}\left(w_{rotor} - w_{gen}\right) + k_{sh}\left(\theta_{rotor} - \theta_{gen}\right) - T_{gen} \quad (12)$$

The inertial constant is obtained from moments of inertia that depend exclusively on the geometry and distribution of the mass of the element and are calculated according to (13) and (14).

$$H_{rotor} = \frac{J_{rotor}w_{rotor}^2}{2P_n} \quad (13)$$

$$H_{gen} = \frac{J_{gen}w_{gen}^2}{2P_n} \quad (14)$$

Its value describes the time during which the generator could generate its nominal power having as the only source of available energy the kinetics stored in its rotation masses [26].

In the case of the wind rotor, the inertia can be approximated according to (15).

$$J_{rotor} = \frac{1}{8}m_r R^2 \quad (15)$$

where m_r represents the mass of the rotor (includes the three blades) and R is the radius of the rotor.

C. GENERATOR

The generator is an electromechanical component that converts mechanical power into electrical power, typically having a stator and a rotor. The stator is a housing with mounted coils. The rotor is the rotating part and its function is to produce a magnetic field. The rotor can be a permanent magnet or an electromagnet. By rotating its magnetic field, it is induced to the windings of the stator causing a voltage at the stator terminals. Two main types of generators used in the industry are synchronous generator (SG), when the magnetic field of the stator is following the magnetic field of the rotor. Moreover, asynchronous generator (AG), when there is no tracking between magnetic fields [18].

Two types of SGs are used in wind turbines. Wound Rotor Synchronous Generator (WRSG) where the stator windings are connected directly to the grid and, therefore, the rotation speed is set by the frequency of the supply grid. In the rotor of winding, direct current flows and generates the exciter magnetic field, which rotates at a synchronous speed. Moreover, the Permanent Magnet Synchronous Generator (PMSG) with a wound stator and a permanent magnet rotor. It has a high efficiency since its excitation is provided without any power supply. It requires the use of an AC/DC/AC power converter to adjust the voltage and frequency supply grid [28].

The AGs needs a reactive magnetization current in the stator that is supply directly by the grid to obtain its excitation, this causes transmission losses and, in some situations, it can make the grid unstable. To avoid this, capacitor banks or electronic power converters are used [23]. The interaction of the associated magnetic field of the rotor with the stator field results in a torque acting on the wind turbine rotor [18]. The rotor of AGs can be designed as a Short Circuit rotor (SCIG) or as a Wound Rotor (WRIG). The rotor of a SCIG cannot be controlled from the outside; its speed should change only in a small percentage, since its slip varies with changes in wind speed so that fluctuations in wind energy are transmit directly to the grid. These transients are especially critical during the connection to grid, so it is required to equip with a soft start mechanism. In a WRIG the rotor windings are connected through slip rings to electronic power equipment. Two types of WRIG configurations are used. OptiSlip or FlexiSlip induction generators (OSIG or FSIG), these connect the rotor windings with a variable external resistance. The range of the dynamic speed control depends on the size of the resistance, normally, the slip for OSIG is 10%, while for FSIG it is approximately 16%. The double feed induction generators (DFIG), where the stator windings are directly connected to the constant frequency grid, while the rotor is connected to the grid through a backup power converter. The size of this converter is related to the selected speed range, generally, only a fraction of up to 70% of the speed range is used [21].

According to the needs of the market and different generators, four different topologies have been identified: Type I fixed speed, SCIG or WRSG directly connected to grid, speed operation fixed whit 1-2% slip. Type II limited speed, OSIG or FISIG directly connected to grid, speed operation fixed with 10% slip. Type III variable speed partial size, DFIG connected to frequency convert, speed operation variable whit −30% to +40% slip. Finally, Type IV variable speed, PMSG connected to full size frequency converter, speed operation fully variable [29].

III. PITCH CONTROL

The objectives of the control system of a wind turbine are based on three tasks, operate at the maximum power point (MPP), protect the rotor, the generator and the electronic equipment from overload during high-burst winds and finally when the generator is disconnected of the network, under this condition the rotor speed must be zero. Active or passive pitch control is used to capture as much energy as possible and protect the mechanical and electronic system. With the control of pitch, speed, acceleration and deceleration are controlled to reduce the mechanical tensions in the blades, the bucket and the tower, as well as the electrical current peaks. Passive pitch control (Stall control). The blades are attached to the hub and the wind attack angle of the wings is fixed. The design of rotor aerodynamic causes losing efficiency when the wind speed exceeds a rated value. Active Pitch control. The blades can rotate to change the angle of attack with the wind, when the power output is too high or too low and must be able to adjust by a fraction of a degree at a time, corresponding to a change in wind speed, to maintain a constant power output [30].

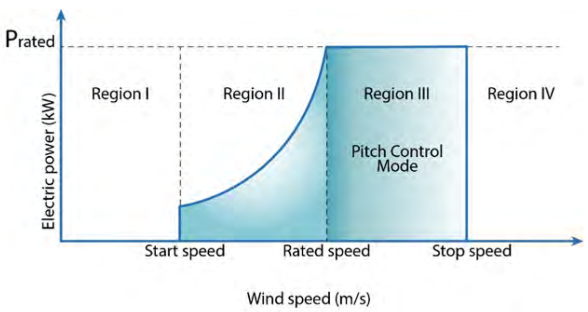

FIGURE 6. **Operating regions of a wind turbine.**

The active pitch control system operate in a specific range of wind speeds. There are four regions of operation as shown in Fig. 6. Region I represents wind speed below the lower limit required to start rotation and where the power generated is zero. When this speed is exceeded, the rotor starts to rotate and enters a region II that is bounded by the starting speed and the cutting speed where the generator rotates at its nominal speed. The third region, covers from the nominal speed to the stoppage speed, which is the limit speed to which design and safety requires rotation to stop. Finally the IV region, where for safety the wind turbine the assembly must have a mechanical brake [31], [32].

The purpose of a feedback control system is to reduce the error e(k), between any variable and its value set to zero as quickly as possible. The error is expressed in (16) [12].

$$e(t) = \omega_{ref} - \omega_{rotor}(t) \tag{16}$$

The pitch actuator is modeled as an integrator or a first-order delay system with a time constant (τ_c) and it is expressed in (17) [14].

$$\frac{d\beta}{dt} = -\frac{1}{\tau_c}\beta + 1\frac{1}{\tau_c}\beta_{ref} \tag{17}$$

Which is subject to $\beta_{min} \leq \beta \leq \beta_{max}$, $\left(\frac{d\beta}{dt}\right)_{min} \leq \frac{d\beta}{dt} \leq \left(\frac{d\beta}{dt}\right)_{max}$ Where β_{min} and β_{max} are the minimum and maximum pitch angles, respectively.

IV. EXPERT CONTROL SYSTEMS

Professor Edward Feigenbaum at the World Congress of Artificial Intelligence of 1980 defines for the first time an Expert System (ES) as an intelligent computer program that uses the knowledge and inference procedure to solve a problem that is quite difficult and requires special skills of the humans. According to the above definition, it can be explained as experience, which is the vast body of task-specific knowledge, transferred from a human to a computer. The computer can make inferences and reach a specific conclusion through any formality [33].

ES's may possess quality information, probability theory, fuzzy set theory, and a series of arithmetic and logical rules, based on heuristic expectations. By using the knowledge acquired, an ES can analyze input information and make exit decisions, which are usually optimal [34].

ES provide powerful and flexible means to obtain solutions to a variety of problems that often can not be addressed by other more traditional methods. Therefore, its use is proliferating in many technological sectors [35].

Contrary to conventional computer programs that use algorithms, ES select a solution from a vast search space in the most efficient way possible. To achieve this, they use knowledge to abort non-promising branches and focus on useful data. They provide a perfectly valid solution in most cases within the specific application for which they were designed [36].

An important advantage of expert systems is the ease with which the knowledge bases can be modified as new rules and facts are known. This is for its architecture that separates the knowledge base from the inference engine [37].

Several techniques can be used as a basis for the development of expert control, fuzzy logic, neural network, and intelligent search algorithms [38]. According to the analyzed bibliography, a variety of expert systems used in the pitch control for wind turbines were found that could be classified in a probabilistic model, where neural networks are used for the recognition of patterns, learning, classification and abstraction of various situations. Rule-based model, where according to the knowledge base obtained from previous events, provide a wide range of possibilities for making inferences, and finally, Optimization model, where from a series of data the algorithm selects the optimal solution. Several hybrid models were also found, which not only combine different models, but also combine solutions with conventional controller models for example PID.

A. FUZZY LOGIC CONTROL

Fuzzy logic (FL) is a means for transforming linguistic knowledge into a mathematical model; uses control rules based on set theory for decision-making [39].

A properly designed Fuzzy Logic Controller (FLC) has higher performance in the presence of variations in input parameters and external disturbances than traditional controllers do, because works without a mathematical model.

FLC can compensate the negative effects by nonlinearity, uncertainties and unknown parameters [40].

In general, according to [41]–[45] there are three stages in FLC.

1) FUZZIFICATION

It consists of taking the inputs and convert them to a fuzzy set using linguistic terms and membership functions (MFs). The following is a short list of methods described in the literature to assign membership values or functions to fuzzy variables.

- Intuition: Capacity of humans to develop membership functions through their own understanding.
- Inference: It uses knowledge to deduce a conclusion, given a body of facts and knowledge.
- Rank ordering: It assign membership values to a fuzzy variable through assessing by an expert, a committee, a poll, and other opinion methods.
- Inductive reasoning: Membership functions than can derives from a consensus to a particular (derives the generic from the specific).

2) FUZZY RULES

This step consists of a database along the development action rules that governing a fuzzy controller; it can be described using words or simple sentences in natural language as opposed to formal predicate calculus statements. Typically, the rule base is made up of a list of rules described in two methods:

Mamdani Inference Model:

$$IFx_1 = A_1 andx_2 = A_2 THENy = B$$

Takagi-Sugeno-Kang:

$$IFx_1 = A_1 andx_2 = A_2 THENy = f(x_1, x_2)$$

3) DEFUZZIFICATION

It consists of the conversion of the aggregated fuzzy set to a precise action with real value. There are several methods for doing this, consist in to satisfying mathematical expressions, the most commons are: Centroid, Centroid of Area, Bisector, Mean of Maximum, Height, Center of Sums.

Expert systems based on FLC with application in wind turbines have been developed to reduce the effects of rapid and sudden variation in wind speed. In applications for pitch control, different types of controllers were found, this is normal considering that the rules to describe the application are not programmed by the same expert engineer. The works found with this type of controllers were grouped into two blocks. First, those with a simple FLC to obtain a pitch angle command with two input variables. Second, works that combine FLC whit traditional controllers Proportional-Integral-Derivative for to have a better performance.

In the first group of FLC's, works were found where PSMG, DFIG and SCIG are used. For turbines with PMSG, a type of FLC was found for common pitch control for operate at the MPP or nominal power, which is described in Fig. 7. The developed of this FLC consists of two input signals and one output signal. However, different amounts of rules were used, with contributions from 25 rules predominating. The difference between the active power and the rated value (eP) and the variation of the power error Δ(eP) are used in [8] and [46]–[49] as the controller inputs. (eP) and Δ(eP) are defined in (18) and (19).

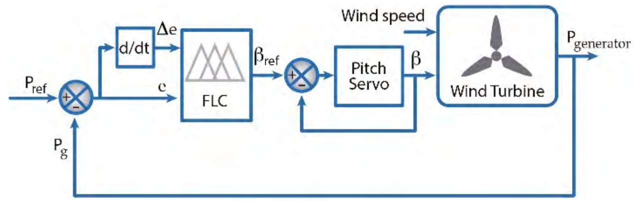

FIGURE 7. Basic scheme of FLC for pitch angle.

$$eP = P_g(t) - P_{g,rated}(t) \tag{18}$$

$$\Delta\,(eP) = eP(t) - eP(t-1) \tag{19}$$

In [26], [50], and [51] is used the same control logic to get pitch angle control but use as inputs the error of the generator shaft speed (eω) and the error difference Δ(eω). However,

Habibi et al. [26] combined pitch FLC with a torque FLC to maintain the power generated at a nominal value. Balasubramanian et al. [7] used as input the error of the torque (eτ) and the error difference Δ(eτ). Tiwari et al. [42] investigated the performance of the control strategies in PMSG in terms of aerodynamic torque, generator speed and the generator power. Use as inputs the error of the Power (eP) and generated shaft speed (eω). Finally, for PMSG, Van et al. [14] added a third variable to an FLC, used the error power (eP), variation of the power error Δ(eP) and generated speed error (eω), unlike the previous authors used TSK as an inference model and did experimentation whit a PMSG of 2.68kW.

Hassan et al. [16], Elfergani et al. [43], and Naik and Gupta [52] repeat the same control strategy used in PMSG for a SCIG. However, [40] and [53] also combine torque control at the same time as a pitch control for a DFIG. Renuka and Reji [54] proposed changing the input variables to wind speed (υ) and the error in the speed of rotation of the generator (eω) also for a DFIG motor. Finally

Zeddini et al. [55] used as input the voltage (V) and the error in voltage (eV) for an OSIG.

All the authors that presented this scheme of FLC, used as simulation software MatLab-Simulink. Table 1, presents a summary of these works, presents the conditions for their simulations, as well as the results obtained.

The second group of FLC for pitch presents more elaborate control strategies, is complemented with a closed loop control action defined by a mathematical model with respect to the input signal. The standard PID controller is well known and are considered one of the most traditional control loops that are used on industrial.

A PID controller is continuously calculates an error value e(t) as the difference between a desired set-point (SP) and

TABLE 1. Summary of pitch angle FLC, traditional scheme based of two inputs.

Reference	Generator parameter	Wind speed ranges	FLC - rules	Analysis of results
Kesraoui et al., 2015	PMSG 18kW	16 - 34 m/s	Mamdani 25 rules	Simulation was carried out with three different wind conditions. In all cases, FLC had better performance than a PI controller.
Smida and Sakly, 2016	PMSG 3.5kW	4-13 m/s	Mamdani 25 rules	It was compared with a PI control obtaining a better average error of 0.018% to 0.0088%, in absolute values it was reduced from 65.8% to 29.02%
Slah et al., 2016	PMSG	8- 14 m/s	Mamdani 25 rules	FLC has better performance by reducing overshoot than a PI controller
Slimen et al., 2017	PMSG 4kW	3 - 25 m/s	Mamdani 25 rules	Graphic results demonstrated better performance for FLC schemes than a PI control
Al-Toma et al., 2017	PMSG 2MW	7 - 20 m/s	Mamdani 9 rules	FLC reduces the overshoot by about 10% compared whit a PI controller
Xue et al., 2015	PMSG 39.3kW	13 - 17 m/s	Mamdani 25 rules	Graphic results show than fluctuation of output power under proposed FLC is much smaller and the fluctuation of rotor speed is slightly larger than on traditional pitch control.
Habibi et al., 2016	PMSG 4.8 MW	12 - 25 m/s	Mamdani 49 rules	It was compared with a proposed PI with better response time of 130s versus 400s. Overshoot reduction 1%.
Kumar et al., 2016	PMSG	10 - 17 m/s	Mamdani 49 rules	It compared whit a PI controller. The settling time are Pitch angle 0.9s for PI and 0.3 for FLC. Torque 1.0s for PI and 0.25s for FLC. Rotor speed 0.95s for PI and 0.43s for FLC. And EM torque 0.9s for PI and 0.3s for FLC.
Narasimalu and Chellaiah, 2017	PMSG 18 kW	11 - 12 m/s	Mamdani 15 rules	Power generation with FLC is comparatively higher than the power generated from the PID control and gain scheduling.
Tiwari et al., 2018	PMSG 20kW	10 - 15 m/s	Mamdani 25 rules	With a PI controller the average power is 16.9 kW and generator speed is varying. With FLC the average power is 17.2 kW and the generator speed was established14.2 rad/s.
Van et al., 2015	PMSG 2MW	10 - 15 m/S	TSK-75 rules	The average output power simulate in 2MW PMSG with the proposed methods is 2.36%, 1.07% y 1.5% respectively higher.
Renuka and Reji, 2015	DFIG	12 - 20 m/s	Mamdani 25 rules	It was tested at different wind speeds, showing better behavior at high wind speeds.
Zeddini et al., 2015	OSIG	8 - 20 m/s	TSK model 25 rules	The terminal voltage and frequency was maintained at normalized values for different perturbations of wind.
Sahoo et al., 2016	DFIG	18 - 22 m/s	Mamdani 9 rules	The power output reaches target value after some time but fluctuation is reduced completely and for torque, it reaches the target quickly but slightly fluctuates around the target value.
Hassan et al., 2017	SCIG 500kW	0-30 m/s	Mamdani 49 rules	Comparing proposed controller and PI controller, the overshoot of FLC (5.4%) is better than PI (52%).
Naik and Gupta, 2017	SCIG 1.5MW	11 - 17 m/s	Mamdani 35 rules	The proposed controller gives approximately 2.98% higher output power than a PI controller.
Elfergani et al., 2018	SCIG 1.5MW	9 - 11 m/s	Mamdani 9 rules	Graphic results demonstrated FLC reduce overshoot almost 10% than a PI control
Shahmaleki, 2018	DFIG	6 - 18 m/s	TSK model 16 rules	It could observed that the settling time is reduced by around 50% and the speed error domain has decreased by about 8.4 %.

a measured process-variable (PV) and applies a correction based on proportional, integral, and derivative gains. The Proportional value depends on the current error. The Integral depends on past errors and the Derivative is a prediction of future errors. The sum of these three actions is used to adjust the process by means of a control element, in this case the actuator to vary the pitch angle. The controller requires tuning the values of PID gain parameters in order to get the best performance of the controller. Changing these Parameters will cause changes in the system response compared to the required response [56], [57].

Yang *et al.* [58] work with two controllers. A PD torque control and PD pitch control; however, there is the problem when the nominal speed is exceeded. To resolve this, three FLC modules are integrated to work in parallel. FLC1 for angle position Pitch, FLC2 for torque and FLC3 for to control the speeding.

Civelek *et al.* [59] proposed a pitch controller combining FLC-PID principles. Fuzzy is the medium for to change the gains of PID according to the error of process variable, if the error is negative or positive or the measured value exceeds in a great extent. Xiao *et al.* [60] added a feed forward FLC. The effect of feed forward FLC is providing a reasonable value of pitch angle for to improve the response rapidness according to the increment of wind speed, then plus it with the output value of FLC-PID controller. However, Vega *et al.* [61] change the concept of using an adaptive controller of variable-gain and uses two independent controllers. A PI when the system is stable and FLC when the variation of energy is very big. The control actions are combines using a correlation factor defined by the error and error derivative. When the error and error derivative are small, this puts more weight on the control action PI. Otherwise, if error and error derivative it are large, it is give greater weight on the FLC. Huang *et al.* [62] used a similar technique but also adds to feedforward FLC to compensate the pitch angle for to inhibit disturbance of wind speed.

A FLC has been propose that develops gains for a PI control as output variable. These gains are added to the previously calculated earnings of a PI controller. This effective gain establishes the control action [52], [56]. Shrinath *et al.* [63] add control action of two fuzzy controllers namely: PI-type FLC (PIT-FLC) and Pitch Angle Tuning FLC (PAT-FLC). This controller eventually improves the performance of the entire system. Baburajan [64] proposed a Fuzzy adaptive PID. By means of an FLC the gains of a PID controller are obtained, the sum of these three actions are added with actions of PID control developed with fixed gain values.

Motivated by the dynamic loads in ever-larger wind turbines. Different researchers have developed mitigation measures from the control systems managing to reduce these unbalanced structural loads and regulate the power. This includes the pitch control individually for each blade. Han *et al.* [65] proposed three different FLC. The first FLC has been used for controlling the collective pitch angle and wind rotor torque, the second and third FLC are related to d-q axis blade moment. To adjust the blade pitch angles β_1, β_2 and β_3, the individual blade pitch make activity within a certain range to achieve the purpose of fatigue load reduction. Similarly, Lasheen and Elshafei [66] propose the control action derived from three controllers. The first is component is a PI individual pitch controller, the main objective is to reduce the flap-wise moment on the turbine blades. The steady state pitch angle operating point is the second component. It depends on the average wind speed and is based on a gap-metric criterion. The gap metric is a measure of the maximum difference between the two transfer functions. This transfer function is a linearized model of a speed wind range. This value can be pre-stores through a table of values. The collective pitch component is the third component. A model predictive is used, and it depends of model of system for predicting the future output over a selected environment. At every sampling instant, an optimization problem is solved on-line to get the control action. The control model in [67] works with three controllers too. A first FLC define a proportional gain for tuning a second individual pitch controller. The control action of this controller is added to the control action of a collective pitch control.

Elyaalaoui *et al.* [68] propose a hierarchal PI-Fuzzy-PI (PIFPI) controller for to generate the active power reference for the load frequency control and the pitch angle for the pitch control. The power error is multiplied by gains of a first PI (or PD) and the result is the input to FLC. The FLC output is the integration constant of a second PI controller. In [41] an artificial organic controllers (AOC) is presented. This controller is developed using a hierarchal model. Proportional and derivative (PD) strategy are the input for a FLC with molecular inference system as control law. The integration of the output FLC for computing a PI-output response added to the PD-output response. This design considers a PID-based artificial organic controller (PID-AOC).

In [69] a fuzzy hybrid is proposed. Divide into 5 sections of pitch angle, where stability is observed. Each section works with a different PID. A FLC is used to select the controller, according to the required reference angle.

Table 2, presents a summary of these works, presents the conditions for their simulations, as well as the results obtained.

B. ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANN) are computational models inspired by the human brain as a non-linear dynamic system using set of processing units (artificial neurons) and an interconnected structure (artificial synapses). In its structure, the neurons are interconnected in three layers. The data enters through the ''input layer'', passes through the ''hidden layer'' (one or several) and leaves through the ''output layer''. Each layer has a certain number of neurons that operate in parallel and are connected to the neurons of other layers and each connection has an associated weight that modulate the effect of the associated input signals, and the nonlinear characteristic of neurons is represented by mathematical model. A model of ANN is showed in Fig. 8 [70].

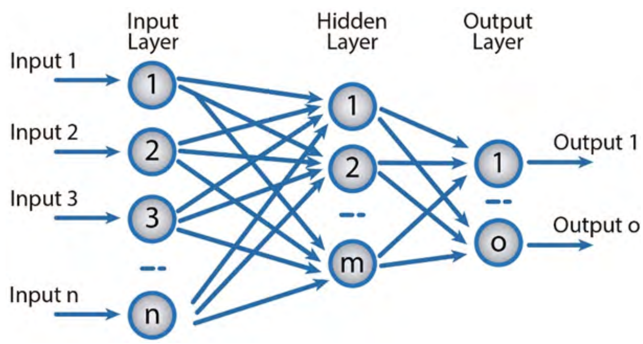

FIGURE 8. Architecture of a multi-layer neural network.

The inputs xi ($x_1, \ldots, x_n$) of n external neurons to a neuron j, are considered unidirectional. Each j-th neuron is characterized by a numerical value called activation state θ_j; associated to each one there is an output function, fj, which transforms the current state of activation into an output signal y_j. Said signal is sent through the unidirectional communication channels to other neuron of the network; in these channels the signal is modified according to the synapse (the weight, w_{ij}) associated to each of them. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance a learning algorithm. It can be depicted as in Fig. 9 [38].

Training is the process of modifying the connection weights using a learning method, in which an input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce

TABLE 2. Summary of pitch angle FLC, scheme combined with PID feedback control models.

Reference	Simulation Parameters	FLC - Rules	Analysis of results
Barburajan, 2018	No information	Mamdani 49 rules	Was compared the responses of the Fuzzy-PID and PID controllers. F-PID reduces rise time of 4.21s to 0.63s. PID has oscillations with a peak overshoot of 11.8% and F-PID of 0.02%.
Elyaalaoui et al., 2018	3 MW SCIG 8 - 10 m/s	Mamndani 25 rules	Comparing PI, PDFPI and PIFPI controllers, the maximum settling time is 4s, 4.7s and 2s respectively. The deviation (HZ) are -0.06 for IC, -0.04 for PI, -0.045 for PDFPI, and -0.01 for PIFPI.
Ponce et al., 2018	DFIG 12 - 15 m/s	Mamdani 9 rules	Pitch angle is smaller with PID-AOC (5.2◦) than with PID controller (8.2◦). Stator and rotor power increase significantly, 10.8 and 30.5%, respectively. PID generates 2.5% of overshooting, while PID-AOC reaches 0.8%, increasing the performance in 68.0%.
Alarcaon et al., 2017	20kW PMSG	Mamdani 25 rules	According to error criteria compared between PID, diffuse and Hybrid (F-PID-5) controllers. The F-PID-5 obtained a minor error in the reference change. 66.16% better than FLC basic controller and 2.4% with respect to a PID.
Civelek et al., 2017	1.5 MW Mean 16 m/s	TSK Model 9 rules	A reduction of 71% was achieved at the time of rocking the base of the tower, a reduction of 84% at the time of rotation of the base of the tower and a reduction of 83% at the time of rotation of the local tower.
Huang et al., 2017	1.3 MW PMSG 12 - 17 m/s	Mamdani 35+49 rules	Results show that generator speed response improves from 3.68s to 3.28s on proposed method. Performance is improved in the attenuate oscillations of the actuator and the overshoot of the generator speed has been reduced.
Shrinath et al., 2017	5 Kw DFIG	Mamdani 49 rules	The comparison with the PI, FLC and STPAFLC is in terms of poor, good and better. PI is better at steady-state error, poor at transient performance and good at robustness at wind speed. FLC is good and STPAFLC has the best performance in all three parameters.
Han et al., 2016	2 MW 11.96 - 16.38 m/s	Mamdani 49 rules	The blade root flap-wise moment was reduced by 20–25%, tower top pitching moment was reduced 28–31% and tower base pitching moment decrease 15–18%.
Ibrahim, 2016	No information	Mamdani 7 rules	The results of FLC-PI was compared with PID and FLC. The time response was PI-10.9s, FLC-3.15s and FLC-PI-2.58s. The steady-State error was PI-0.17618°, FLC-0.0834222° and FLC-PI-0.0038°.
Lasheen, 2016	5 MW Mean 20 m/s	TSK Model 3 rules	Reduces generator speed error 659% and 37.4%. Reduces the power generation error 307% and 22.7%. And it reduces the error of the flap-wise moment 132.5% and 15.8%. Values compared to a PI and a robust controller, respectively.
Naik and Gupta, 2016	1.5 MW SCIG 8 - 13 m/s	Mamdani 7 rules	Graphic results show that the active and reactive power have almost identical variations which are being smoothening by the proposed controller. Fluctuations in the rotor speed are smoothened out due to continuous fine-tuning of the pitch-angle.
Civelek et al., 2015	500kW SCIG 0 - 30 m/s	Mamdani 25 rules	A PI reached best response time, an error in 1% in 1.5, FLC 3.5s and FLC-PID in 0.35s. Maximum Overshoot of the output power was reached to 790kW-PI, 740kW-FLC and 530kW-FLC-PID.
Cortés et al., 2015	750kW SCIG 11 - 16 m/s	Mamndani 25 rules	The proposed combined controller FLC-PI has a better response than the PI controller and the FLC, this has been proved with a lower error of 0.4% compared to 0.66% from the PI and 1.33% from the FLC.
Xiao et al., 2015	1.5 MW PMSG 14-16, 22-24 m/s	Mamdani 49 +49 rules	According to simulations, the proposed controller provides better performance compared to a PID. Its behavior is better near the nominal wind speed reducing the power overshoot to 3% than the cut-speed with only 0.4%.
Yang et al., 2015	3MW PMSG 13 - 32 m/s	Mamdani 57 rules	The average power for a conventional controller and the proposed is 2.98MW and 3.01MW, respectively. The speed rotor reached by gross controller is 19.7rpm, higher than speed cut. Proposed controller reaches 19.15rpm, lower than speed cut.

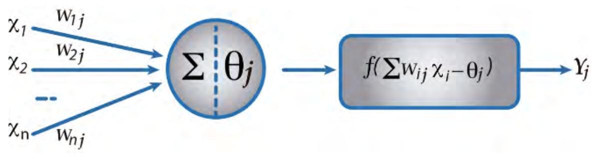

FIGURE 9. Artificial neuron mode.

the desired output. The weights after training contain meaningful information whereas before training they are random and have no meaning [71].

Four basic variables characterize an ANN, topology, training method, type of association input-output data, and the presentation of the information. More than 50 types of ANN can be distinguished, for example: multilayer perceptron (MLP); radial basis function neural network (RBFNN); backpropagation networks (BPNN); Wavelet neural network (Wavelet NN); self-organized-map NN (SOMNN); Recurrent NN; time delay NN; Hopfield network; auto-associative NN; convolutional NN; learning vector quantization networks; adaptive resonance theory (ART) NN; neuro-fuzzy networks; dynamic NN [72].

ANN has two disadvantages. First, the processing is not a time function. The relationship between the inputs and the outputs is a momentary corresponding relationship. In addition, the accumulation effect of the inputs are not taken into consideration on the outputs. A momentary output just depends on the current inputs without reference to earlier inputs. The main advantages are they can learn to perform tasks through a training process, create their own structure, still operate when its structure is damaged and they can be implemented in parallel and work fast. Consequently, they are programmed to carry out online processes [73].

The ANN are useful for solving a wide range of problems. They can detect patterns in a dataset, the data similarities or dissimilarities are identified and classified via unsupervised learning. ANNs can be applied to problems where a theoretical model cannot be applied. They can approximate the input data to a function with a certain degree of detail. With ANN, solutions that maximizes, or minimizes, a function subject to different constraints can be found and can be trained to obtain a prediction of the future behavior. Finally, it is possible to do control, determine the inputs that will cause a desired system behavior [72].

ANNs have been widely used in a wide range of industry applications such as medicine, chemistry, robotics, geospatial analysis, etc. In wind energy field, the control systems operate in different scenarios, as they can adapt the operation mode to specific conditions of wind.

In [74], an adaptive neural pitch angle control strategy is proposed for the wind turbines operating in region III. A filtered regulation error technique is utilized to transform complex system into a simple one, and thus the feedback linearization can be utilized. Then, an online learning approximation (OLA) two-layer NN is employed to estimate the unknown nonlinear aerodynamics and thus the proposed NN controller is parameters-free and can be readily extended to various types of wind turbines with different system parameters. In addition, a high-gain observer is implemented to obtain an estimation of rotor acceleration, which rejects the need of additional sensors. Rigid theoretical analysis guarantees the tracking of rotor speed/generator power and the boundedness of all other signals of the closed-loop system.

Tiwari *et al.* [42] proposed two methodologies to generate pitch angle, Radial Basis Function Network (RBFN) and Feed-forward based Back propagation network (BPN). The control techniques implemented is able to compensate the nonlinear characteristic of wind speed. The rotor is smoothly controlled to maintain the generator power and the mechanical torque to the rated value without any fluctuation during rapid variation in wind speed. BPN uses wind speed and generator speed as the input variable and generates pitch angle in order to obtain desired performance of turbine. The BPN is trained with two hidden layers thus, they have four layers: Input layer, hidden layer I, hidden layer II and output layer. The nodal operation of BPN is processed as "2-3-1" neurons in these layers. For the proposed RBFN controller consists of three layers: an input layer, a hidden layer with nonlinear RBF activation function and a linear output layer. Wind speed and generator speed feed the input neurons that are used to compute the pitch angle as the output neuron. The neurons in the hidden layer perform Gaussian function, which is used as the membership function in RBFN.

Mjabber *et al.* [75] investigated an RBFNN that was used in order to estimate the nonlinear part of a wind turbine system. The RBFNN consisted of one input layer for the electrical power error, one hidden layer with 25 neurons, and one output layer with the approximated nonlinear part so, the nodal operation is processed as "2-3-1" The training algorithm is a descendant gradient. The result is more stability in extraction from wind power.

Han *et al.* [76] developed an individual pitch controller based on a RBFNN model based on feedforward or preview-measuring the wind speed with light detection and ranging (LIDAR). The proposed controller presents as input the error in the shaft speed and the measurement of the wind speed with LIDAR, nevertheless the neuronal network was not report in detail. Better behavior than a PI controller was obtained, but once the wind speed has greater disturbances, the RBFNN controller has a poor performance. The reason is that the wind speed measurements delay RBFNN controller, and the RBFNN + LIDAR controller can not anticipates the wind speed, which should be avoided in large disturbances to alleviate the structural loads of the wind turbine and extend the life of the wind turbine.

Liu *et al.* [77] developed another individual pitch controller. They presented a RBFNN with online training. A sensor obtains the network input signals used for training. Then, network can regulate the parameters of a PID controller. For obtaining both constant power control and load mitigation, the pitch command are mixed whit a collective pitch controller.

Bagheri and Sun [78] for to maximize power capture, propose a Nussbaum-type function that is utilized to address the non-affine nature of the dynamic equations and an adaptive RBFNN to approximate on-parametric uncertainties of controllers for variable-speed and variable-pitch. The control strategy is, first, to increase the rotor speed up to the cutting speed, the torque of the generator is used as input in this phase. However, as the rotor speed increases and approaches its nominal value, the generator torque also reaches its nominal value. Therefore, it can no longer be used as an entry. Therefore, the angle of inclination is adopted as an input to maintain the speed of the rotor at its nominal value.

Dahbi *et al.* [79] present other studies that aim to maximize the power generation by controlling the pitch angle. Pitch angle control is developed using only one low cost circuit based on ANN, which allows the PMSG to operate at an optimal speed. ANN is composed of an input layer with two neurons for receive power coefficient and tip speed ratio. Two hidden layers, with 20 and 10 neurons respectively, and an output layer with one neuron where the SP of the pitch angle is generated. Pitch angle controller is based on that $Cp_{ref} = Cp_{opt}$. When the wind speed is higher than the rated speed, Cp_{opt} must take small value, so ANN generates higher corresponding value of β_{ref}; however, when the wind speed is less than the rated one, Cpopt takes higher value till its maximum, so ANN generates less corresponding value of β_{ref} till the minimum. The training process was under taken by using Levenberge Marquardt algorithm to search the optimal synaptic weights. It is an algorithm for the optimization of the quadratic error due to its fast convergence properties and robustness.

Kang *et al.* [80] presented a control method based on adaptive PID neural network where, the parameters of the PID neural network are self-regulating. The improved method of gradient descent is used to optimize the weights of the networks and to avoid that the weights of the neural networks fall in local optima; the PSO algorithm is adopted to select initial weights. In the controller, the three-layer PID neural network is constructed by combining PID and a forward neural network. The input layer has 2n neurons, half are used to enter values of objects, and the others are used to enter values that returned from the output of the control system. The hidden layer has 3n neurons, including n proportions, n integration neurons and n differentiation neurons. The output layer has n neurons, n is the number of control loops.

Perng *et al.* [81] suggested a RBFNN to determine control system functions. Depending on the control system, the optimal kp −ki parameters in different d k can be determined for various conditions. The RBF parameters used are, hidden neurons = 7, learning rate = 0.01, training times = 5000, and number of training data = 21. The early stopping rule is used in the upper bounds to allow the RBFNN algorithms to converge. When the mean squared error generated by the error output began to increase, the RBFNN algorithm is stopped.

Jafarnejadsani *et al.* [82] developed a RBFNN for adaptive control of pitch angle of the blades. The number of inputs is less than four. The input domain is divided by uniformly-spaced grid and the system nonlinearity is evaluated in each node. To train the RBF NN is used the Lyapunov stability analysis to derive the updating rules for RBF network weights. A robust controller was obtained for the uncertainty.

Raza and Rahim [83] presented a pitch controller; the gains of the PI controller are obtained from a trained ANN. The input-output training data was generated by differential evolution optimization method (DEIT), this technique is a method which finds the optimum value of an objective function subject to satisfying the system constraints. In the pitch control algorithm, the input to the network is the set of wind speeds collected for a sample time and the output-trained variables are the controller gains. The proposed ANN model is trained using adaptive back-propagation algorithm; the weights are updated to minimize the sum of the squares of errors.

Poultangari *et al.* [84] propose an optimal PI collective pitch controller, the RBF neural network must be trained with optimal training dataset. This RBF neural network then gives the optimal PI gains. In order to obtain an optimal training data set, particle swarm optimization (PSO) evolutionary algorithm is used. Using PSO and for some constant wind speed above the rated, a pair of optimal PI gains are obtained for the corresponding constant wind speed. The proposed controller adapted itself to any wind speed profile.

Lin and Hong [85] designed an Elman neural network (IENN)-based algorithm designed to allow the pitch angle adjustment for power regulation for optimal wind-energy. The architecture of the IENN including the input layer, hidden layer, context layer and output layer. With two inputs, error of shaft speed and error of pitch angle. An online training IENN controller use back-propagation (BP) learning algorithm with modified particle swarm optimization (MPSO). The connecting weights of the IENN are trained online by BP methodology. MPSO is adopted to adjust the learning rates in the BP process to improve the learning capability.

Wang and Hyun [86] used an ANN pitch angle controller for the output power control of wind turbine. This approach was based on Auto-Regression Moving Average (ARMA) wind speed prediction model, where is combined with Autoregressive model (AR) and MA model (Moving average model). The wind speed is predicted using its past data and estimation error in a time series model form. This predicted was used in calculation of the pitch angle control value. The last pitch angles, last rotor speed and real power output data are used as the input of the ANN controller and predicted wind speed is used to calculate the future value of rotor speed. The ANN is trained offline using a training data set that covers the entire operating range of the system. In this scheme, sensors are used to sample the rotation speed of the shaft and the power of the generator. The results showed that the proposed control method was effective.

According to the aforementioned research works, Table 3 presents a summary with the results with each experiment.

C. INTELLIGENT SEARCH ALGORITHMS

Intelligent search algorithms (ISA) is a solving method based on phenomena in nature, an example is the simulation of the law of biological evolution. Two primary characteristics of this algorithms are population search strategy and information exchange among individuals in a population. Because of the universality of the search algorithms, it has broad applications and is especially suitable for handling complex and non-linear problems. These algorithms has intelligent characteristics such as self-organization, adopts simples coding technology to express complex structures, self-adaptability, guides the system to learn or determine the search direction, self-learning, the way a population organizes a search; and the parallel processing because it can search many regions in the solution space at the same time [73]. Classic ISA include Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), and they can be used to solve such problems as optimization and machine learning [38].

TABLE 3. Summary of pitch angle controllers with ANN models.

Reference	ANN proposed	Generator	Analysis of results
Jiao et al., 2019	OLA	1.5 MW	With turbulent wind the standard deviation of generator shaft speed is 0.0206 rad/s for NN controller, and 0.0351 rad/s for the PI counterpart. The NN controller can produce smaller oscillation and provide electrical energy with higher quality for grid integration.
Tiwary et al., 2017	RBFNN and BPNN	2 MW PMSG	The proposed controller gives 2.021%, 4.623% and 9.893% more power during below rated wind speed and during above rated wind speed it produces 0.187%, 1.67%, 3.67% and 5.38% of rated generator power than the BPN, FLC and PI controller respectively.
Mjabber et al., 2017	RBFNN	600 kW	Compared with a PI controller. Rotor speed is very stable and its fluctuation are considerably reduced. The pitch angle variations are much lower. The generator torque is very stable, the mean value is only 133.5-kNm than the 139.4kNm given by PI.
Han et al., 2017	RBFNN	2 MW	The baseline controller is compared whit PI controller. The effectiveness of controller is evaluated based on the damage equivalent loads. The tower base fore–aft moment was reduced by 15.3%, the tower base side-to-side moment was reduced by 9.8%, and the tower base torsional moment was reduced by 10.4%.
Liu et al., 2016	RBFNN	2 MW	The flap moments of the blade 1 are 549.329 kNm and 273.312kNm, for blade 2 are 582.253 kNm and 274.922 kNm and blade 3 are 569.547 kNm and 276.470 kNm, for proposed controller and collective pitch controller.
Bagheri and Sun, 2016	RBFNN	5 MW	The simulation results are analyzed along side a PI controller and the controller designed for Jafarnejadsani et al. (2013). The proposed controller can precisely track the desired rotor speed in second region, but not the other controllers. The tracking error of the proposed controller is lower resulting in a lower generator torque.
Dahbi et al., 2016	Levenberge Marquardt	6.6 kW	Graphic results show good behavior on the optimal rotor speed. Increased efficiency and performance of the turbine. The grid voltages and injected currents are in phase, therefore, unit power factor is reached.
Jena and Rajendran, 2015	Gradiente descent	No reported	It was compared between traditional PID, PID-NN though standard PSO and adaptive PID-NN. Was documented the errors varied with time, with a time interval of 0.001s. The adaptive PID-NN controller has fast convergence speed, high accuracy and stability.
Perng et al., 2014	RBFNN	275 kW	Graphic result show that proposed algorithm was used to determined the system stability boundaries and optimal operating points of the PID controller. The method was effective in systems with and without time delay.
Jafarnejadsani et al., 2012	RBFNN	5 MW	Compares with PI controller, the NN controller has improved the power generation by 33 kW while reducing the amplitude of power fluctuations. However, the NN control has more pitch activity, these oscillations induce wear and fatigue loads in mechanical components and cause fluctuations in power and generator torque.
Raza and Rahim, 2012	BPNN	DFIG pu	The pitch controller designed through the ANN was tested for various wind speed conditions. Pitch controller transfers the wind power to the generator with minimum transients. The steady state response is also very good.
Poultangari et al., 2012	RBFNN	5 MW	A comparison with PI controller, pitch angle variations in proposed controller is smoother with smaller amplitude. Also, the fluctuations of generator power around the rated value is considerably smaller so that the quality of output power is more favorable.
Lin and Hong, 2011	BPNN	750 W	The power averages are 225W, 218W and 207W for the ANN, FLC and PI controllers respectively. The increase in power is 8.7% for ANN (IENN-MPSO) and 5.3% for FLC with respect to PI. The efficiency of each controller is 85%, 77% and 68%.
Wang and Hyun, 2011	ARMA	1.5 MW	For the comparison of the performances, a conventional PI controller is adopted. ARMA-ANN control is proved to be efficient to show smoother output power and voltage.

GA's can be viewed as a general-purpose search method, an optimization method or a learning mechanism. These represent an optimization approach where a search is made to ''evolve'' a solution algorithm that will retain the ''most fit'' components, in a procedure that is analogous to the Darwinian principles of biological evolution: reproduction and ''survival of the fittest'' [38]. According to [88], the evolutionary process begins with randomized or manually initialized solutions. Normally, a population of solutions is used and the candidate solutions are called individuals or chromosomes. The selection algorithms are responsible for choosing which solution will have the opportunity to reproduce and which will not. For all solutions of the population, crossing and mutation operators can be designed in the basic structure of an AG it is also necessary to know the transition from one generation to another, which consists of four basic elements which are shown in Fig. 10.

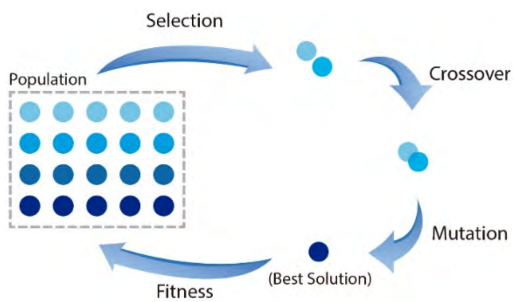

FIGURE 10. Cycle of the genetic algorithm.

In the AG, the crossing is the main fusion method on the genetic information of two individuals; if the coding is chosen properly; two good solutions will produce a successful solution. The mutation has the effect of safely disturbing the solutions in order to introduce new features that were not present in any solution of the population. The best solutions that have been generated in this way are selected for the next generation. The replacement or insertion is the procedure to create a new generation of solutions to the previous one with its descendants. A space is created for offspring in the solution population eliminating the original solutions from it. Finally, the evolutionary cycle examines, if the termination condition has been met, and genetic optimization of execution continues, if this is not yet the case [87].

The basic idea of PSO is to find the optimal solution through collaboration and information sharing among individuals in a population. The main motivation stems directly from of the group of animal on nature, such as bird flocks, fish schools, ant colonies and swarm of bees, which exhibit an amazing self-organization and collective and social adaptation capabilities. A swarm is a population that is grouped even though each individual seems to move in a random direction. Therefore, the behavior of an individual is often insignificant, but their collective and social behavior is important, since the intelligence of the swarm comes from their collective adaptation to different circumstances in nature [38].

Initially, in PSO algorithm a swarm of particles is randomly generated. A great number of individual or particles move around in a solution space to a problem, each individual has a position and a velocity zero which is dynamically adjusted according to the experiences of its own and those of its companions; and represents a potential solution to the optimization problem. Therefore, each individual is led to a stochastically weighted average of the best previous point of his own and of the population. In each step of the procedure, the global best solution obtained in the entire population is updated. Using all of this information, particles realize the locations of the search space where success was obtained, and are guided by these successes until finding an optimal solution [88].

The parameters that must be adjusted to not exceed processing resources are the population size since each particle is a potential solution of the problem and the detention criteria according to a predefined number of iterations without obtaining better results. The advantages of PSO are simplicity, ease of implementation, and no adjustment of many parameters [89].

DE is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. DE also uses the global searching strategy based on population, and can do mutation, crossover and the selection operations are based on the difference of best solutions. DE is used for multidimensional real-valued functions therefore also be used on problems that are not even continuous, are noisy, change over time, etc. [89].

Initially, a random population is generated, and then any two individuals are weighted and a third individual is added according to certain rules to produce new individual. A predetermined individual is compared to the new individual and if the fitness of the new individual is better than the aptitude of the predetermined individual, then in the next generation the new individual will replace the predetermined individual, otherwise we must keep the predetermined individual. Through iterations, we can maintain good individuals, eliminate inferior individuals and guide the search process towards the optimal solution [38].

The main advantages of the DE algorithm can be summarized as the following three points: few parameters when using simple differential mutation, robustness since not easy to fall into local optimum, and faster convergence rate [39].

DE is an ISA, showing particular similarities to GA and hence can be called as a genetic-type method. DE has certain differences, particularly; the mutation is different, except it serves the same purpose of avoiding minimum or maximum local. DE has a notion of population similar to PSO rather than GA as its population members are called agents rather than chromosomes [38].

ISA are a combinatorial optimization method that has been applied in diverse automatic control areas, power systems, and power electronics [39]. In the control of pitch of wind turbines, there are several documented articles. In [90], gain scheduling control (GSC) approach is employed to control the blades pitch angle of a wind turbine in the above rated wind speeds and minimizing the destructive mechanical fatigue loads, while acquiring a fast and accurate response in the operational range of the mechanical components. Here, the GSC approach uses a set of linear quadratic Gaussian controllers to achieve the mentioned objectives. A number of operating points are selected, each representing the system state in a specific wind speed in the above rated wind speed span (region III). Subsequently, a time-invariant linear control model is designed, derived from the non-linear state space system for each of them. Finally, a gain scheduling procedure is planned using DE optimization algorithm, in order to apply on the suitable controller as the operating point changes, such that the controller suppresses transient excursions and achieves a good and fast regulation in steady-state operation.

In [91] an intelligent GA algorithm approach has been suggested for the PID parameter setting optimization of the blade pitch controller. The algorithm rearranging the mutation rate and the crossover point number together according to the algorithm progress. The algorithm defines an iteration number for convergence to an optimal value of population. The iteration number may show some varieties according to system function. After the iteration number given for convergence is passed, the algorithm agrees that there are the local minima or maxima. In order to recover the local minima or maxima, the algorithm implements two operations. One of them is that the mutation rate is increased a predetermined range when the algorithm passes the iteration number. The increase continues until the maximum mutation limit. The mutation value returns the starting mutation value after the maximum mutation limit. If the algorithm gets rid of the maxima and minima local, the mutation rate is returned the starting value. Other is that the crossover point value is increased for to enrich the population when the iteration limit value is passed; and if the fitness function repetitive

TABLE 4. Summary of pitch angle controllers with ISA models.

Reference	ISA proposed	Generator	Analysis of results
Ebrahim et al., 2018	MFO	100 kW	According to simulations, the suggested design can guarantee system stability under increased mechanical torque perturbations and excessive wind speed with controller parameters uncertainties. Thus, the proposed approach succeeded in proving its capability to select the most robust PID controller.
Hodzic and Tai, 2016	PSO	600 kW	The performance of the PI-PSO controller produces less oscillations in every analyzed case, especially when wind speed is higher. However, the overshoots are bigger and settling times are longer.
Behera et al., 2016	PSO	1.5 MW	The standard deviation in angular speed of rotor is seen to be low with the proposed PI-PSO controller (0.0338pu) as compared to the standard P control (0.0384pu) and without control (0.0482pu). Similarly, the pitch angle has increased less (5.0911°) as compared to P control (7.0107°).
Civelek et al., 2016	GA	500 kW	According to the results, an appreciable improvement of 17% was calculated on power overshoot whit intelligent GA respect to classic GA. Furthermore, stability time was 0.79 better, with controller proposed.
Abbas et al., 2013	DE	225 kW	Compared with a conventional controller, graphic results show that the proposed controller has effectively and smoothly regulated the shaft speed and the output power on their nominal values, while keeping he twist of the shaft almost constant which guarantees minimum mechanical loads.

value being same exceeds the iteration limit, the crossover point is raised. Two criteria were taken into consideration when determining the fitness function. First that the total error of the system being as small as possible and second the acceptable maximum overshoot value.

Behera *et al.* [12] and Hodzic and Tai [92] use a Proportional-Integral controller with gain Kp and Ki in pitch angle control loop. However, the proportional gain Kp and integral gain Ki are tuned through PSO algorithm.

Ebrahim *et al.* [93] proposed a pitch controller based on The Moth-Flame Optimization (MFO) algorithm. MFO technique is a novel nature-inspired optimization paradigm. MFO algorithm mimics the navigation method of the moths in nature. Moths fly in the night by maintaining a fixed angle on the moon for traveling in a straight line for long distances. In the proposed MFO technique, it is assumed that the candidate's solutions are moths and the PID parameters are the position of moths in the search space. Therefore, the moths can fly in 3-D space representing the three controller parameters Kp, Ki and Kd with changing their position vectors.

Table 4 presents a summary of the results of each technological development carried out with ISA for pitch control in a wind turbine.

ISA are algorithms that adopt a natural evolutionary mechanism to perform a complex optimization process and can solve several difficult problems quickly and effectively. However for pitch control applications, they are regularly only used as a search complement for optimal control parameters of control, for example, in the previous section the works of [84] and [85] where ISA algorithms were used to optimally initiate an ANN. In section 4.4, ISA algorithm works are mentioned combined with different techniques of an expert system.

D. HYBRID SYSTEMS

FLC, ANN and ISA have similar objectives but their methods are different. Therefore, the combination of these methods forms new processing patterns and we can improve the performance of the control algorithms. Combining fuzzy logic with a neural network, we can construct various fuzzy neural network models that not only mimic a human being's logical thinking, but also can have a learning trait. In addition, the learning process of a neural network requires a search in a large space in which many local optimal points exist, so sometimes it is easier to solve training problem for a neural network with a search algorithm [38].

In the pitch control of wind turbine, there are two different techniques. In one of this techniques, authors that obtain a pitch control signal directly, they apply FLC methods combined with optimal search engines for their membership function or use ISA algorithms for optimal training of a neural network. Hybrid proposed developments are able to select rules that are more productive for an FLC from an ANN, these types of systems are known as Neuro-Fuzzy. In [94] the author proposes a GA based methods planed for in breeding fuzzy if-then states. GA generates a set of fuzzy if-then rules and it estimates each fuzzy if-then solution in the progression sets. Next, genetic algorithm results in new fuzzy if-then laws by genetic operation like: crossover, mutation, selection. The algorithm restores a part of the progression with newly generated fuzzy if-then rules. If a pre-identified stopping share isn't content, comeback to second step. Finally, the algorithm replaces the worst fuzzy if-then rules with the smallest fitness values with the newly generated fuzzy if-then rules with the utmost fitness values. The number of removed fuzzy if-then rules is usually the same as that of added rules in classic genetic algorithm. Controller has two inputs and one output. This controller provides a suitable pitch angle upon catch wind speed. Kasiri *et al.* [94] add a neural network to your proposal. In this new approach, NN has been trained by speculative data. That being so this method uses the NN results in definitional of Fitness Function. Fitness function includes two sections; the first compares generated rules with optimal values, thus a rule that covers most of the best values could be a desired rule. In the second, numeral equivalent of

TABLE 5. Summary of pitch angle controllers with hybrid expert controller.

Reference	Expert System	Analysis of results
Kasiri et al., 2016	AG - FLC	Graphic results shown that in below rated wind speed, optimal power is attained by regulating; thus, the pitch angle is kept at a mechanical minimum and rotor speed is controlled in such a way that is always acquired, akin to MPP tracking.
Kasiri et al., 2016	AG - ANN - FLC	The proposed model allow an accurate approximation of the dynamic response of the wind turbine operating with different winds, although the wind turbines generate the maximum reactive power.
Kasiri et al., 2016	FGS - ANN - FLC	The main result is that the pitch actuator does not suffer from excessive activity despite the strong turbulence. This aprouch outperformed others in controlling the production through wind fluctuation.
Muneer and Bilal, 2013	ANN - FLC	As time increases the controller parameters are tuned and the performance improves. The oscillations in the pitch angle and speed of shaft generator reduces. The most important result was the ability of the controller to learn and to converge towards the true weight values. All the weights are converging and consequently the controller performance is improving with increased learning.
Poultangari et al., 2013	ANN - ISA	According to the simulation results, the proposed controller in comparison with conventional PI controller has more effective performance in pitch angle control. The proposed controller keeps generator speed around rated generator speed (122.9rad/s) with fewer variations.

rules are being calculated on wind turbine power formula, thus these rules calculated on NN either, a rule that gives the least value of trained slip could be a good rule. These rules set pitch angle in the best setting to optimally control wind turbine.

In [94], other investigation presents that the algorithm objective is tuning the membership tasks of the linguistic terms of the property for approximation null values in relational database organization is ready as follows above algorithm. This kind of objective function recommends the optimality of a chromosome or string in a genetic algorithm is Fitness Function. Accordingly that definite string way be rated aggressive all the strings. Ideal string, or not less than strings which are more optimal, are sanction to fabricate and combination.

Table 5 presents a summary of the results of hybrid expert controller where control signal is directly obtain.

Other techniques use a series of input data (rotor speed, blade angle of inclination and power coefficient) and are defined as input for the learning technique. The functions for each combination build an ANFIS model and then train respectively. Subsequently, the performance achieved is reported. From the beginning, the most impressive input in the prediction of the output was identified and determined. It means that the dissipation of errors of the estimation of the output parameter will be the smallest and the influence of the input will be greater for the determined output.

Asghar and Liu [95] proposed an expert system of hybrid learning control in lines based on neuro-fuzzy inference systems where instantaneous wind values, TSR, rotor speed and mechanical power are estimated through fuzzy membership functions. The values obtained for the instantaneous wind speed are used to determine the optimal speed of the rotor and obtain the maximum power. The ANN trains the input membership functions by using latest square method and back propagation gradient decent method to accurately estimate the effective wind speed without using any mechanical wind speed sensor. Then, the estimated effective wind speed and optimal TSR are used to design an optimal rotor speed estimator.

Morshedizadeh *et al.* [96] examine common Supervisory Control and Data Acquisition (SCADA) data over a period of 20 months for 2.3 MW turbines. In this study, an algorithm is proposed to impute values of data that are missing, out-of-range, or outliers. It is shown that an appropriate combination of a decision tree and mean value for imputation can improve the data analysis and prediction performance by the creation of a smoother dataset. In addition, principal component analysis is employed to extract parameters with power production influence based on all available signals in the SCADA data. Then, a new data fusion technique is applied, combining dynamic multilayer perceptron (MLP) and adaptive neuro-fuzzy inference system (ANFIS) networks to predict future performance of wind turbines. This prediction is made on a scale of one-hour intervals. This novel combination of feature extraction, imputation, and MLP/ANFIS fusion performs well with favorably low prediction error levels.

In [97] a novel algorithm for wind speed estimation in wind-power generation systems is proposed, which is based on adaptive neuro-fuzzy inference system (ANFIS). The inputs of the ANFIS wind speed estimator are chosen as the wind turbine power coefficient, rotational speed and blade pitch angle. During the offline training, a specified model, which relates the inputs to the output, is obtained. Then, the wind speed is determined online from the instantaneous inputs. Neural network in ANFIS adjusts parameters of membership function in the fuzzy logic of the fuzzy inference system (FIS).

V. CONCLUSION

The theories and methods presented in this paper mimic the patterns of biological behavior to develop information processing capacity and intelligent decision making. A diffuse system is based on brain functions such as language and inference, processes information and adopts rules of solution according to the experience defined by human beings. This technique began its application in pitch control for wind turbines as an adaptive and robust control medium for conditions of sudden changes in wind speed since its response does not depend on a mathematical model but on the experience of the programmer. Because a PID controller (or any of its variants) can achieve a faster stability and obtain a high precision in steady state, fuzzy logic was used for the tuning of this type of controllers, which is functional in different speed ranges of wind; however, in this way the severe disturbances in the wind speed are not resolved. For this, a PID feedback control and an FLC are used separately, PID working in steady state and FLC in higher wind oscillations. Another option is for a PID controller and an FLC to work in parallel, where the control actions are added to obtain a single one. Eventually a hierarchical system is used where from an FLC the gains are obtained from a PID control, which in turn is the gain of the integral part of a PI controller. These techniques are also used for an individual pitch control with the intention of reducing the torsional moments caused in the blades or the tower.

A neural network deals with information that is difficult to analyze in a systemic way, forms own patterns based on self-learning, its connection weights can predict changes in its input variables and its parallel operation makes the convergence to a solution faster. The use of neural networks in wind energy systems is aimed at predicting the behavior of the air to give an optimal and anticipated solution in the control signal for the pitch angle. The most elaborated contributions directly obtain the value of the pitch angle using real values taken directly from sensors.

ISAs are used to modify the gains of a PID controller on line with different wind speeds. It follows that ISAs are applicable in expert control, particularly when optimization is an objective.

The combination of these techniques has advantages in response time and effectiveness, for example, the learning process of a neural network requires a search in a large space in which there are many local optimal points, so it is sometimes difficult to solve a training problem. A genetic algorithm is very suitable for large-scale searches and can find an optimal global solution with high probability. The combination of a neural network and an intelligent search algorithm can build a neural network whose connection weights evolve continuously with the change in the environment, and can simulate biological neural networks much more reality. This type of combination reduces the processing time, approximates the behavior of the wind and obtains a better and anticipated response of the control signal for the pitch angle.

Most important success factor of neuro fuzzy systems structure is the accessibility of valuable learning algorithms. Planned approaches optimally control Wind Energy Conversion Systems with changing Pitch angle and estimates parameters. In addition, access to accurate power production prediction of a wind turbine in future hours enables operators to detect possible underperformance and anomalies in advance. This may enable more proactive and strategic operations optimization. The most important contribution of the hybrid expert controller is the ability to realize the non-linear relationships between input/output data.

After making a study of the recent works in the field of expert systems applied in pitch control in wind turbines, FLC, ANN and ISA are considered as the most developed and cutting-edge techniques. They develop adaptation to control problems where it is not possible to have a developed mathematical model of the system. They facilitate the handling of information of multiple variables, organizing behavior patterns for the prediction and anticipation of the control signal, as well as the search for the optimal solution among the possible solutions. The main contribution of expert systems in the wind turbines is to solve the non-linearity of the systems, since the behavior of the air in frequency and speed is unpredictable.

The combination of these techniques leads us to new methods of control. For example, we can combine fuzzy systems, neural networks and search algorithms, so that establish a diffuse neural network with evolutionary capacity to implement and express human thought effectively.

Modern wind turbines require complex tasks with high precision, in unforeseen conditions. They face climatic adversities that cause various oscillations in the system, which increases mechanical stress, and the risks to the system and the environment grow exponentially. Conventional control techniques may not be very effective under these conditions, while expert control has great potential.

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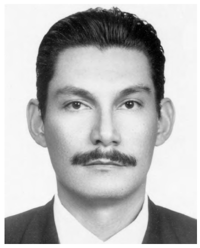

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