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Optimum Fuzzy Logic Control System Design using Cuckoo Search Algorithm for Pitch Control of a Wind Turbine

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Abstract

Renewable Energy Systems (RES) are being widely accepted as an alternative to standard conventional energy sources due to depletion of natural resources and their consequential environmental impact. With improving techniques, reducing costs and low environmental impact, wind energy has the potential to become the major part in the world's energy future. The efficiency and control of wind generator is of outmost importance as wind is an intermittent resource. Pitch angle control is the most common means for adjusting the aerodynamic torque of the wind turbine when the wind speed is above rated speed.

This paper presents a methodology for designing an optimised Fuzzy Logic Controller (FLC) system using Cuckoo Search Algorithm (CSA) for enhancing the performance of wind turbine by maximizing the captured energy. The simulation results clearly show that the controller demonstrated high performance than conventional PID controller.

Key words

Wind turbine, pitch control, fuzzy logic, optimization, cuckoo search algorithm, renewable energy.

1. Introduction

Due to increasing environmental concern during the 20th Century the research focus has moved from conventional electricity sources to renewable and alternative energy solutions [1]

[2]. Countries are modifying their energy production plans for the near future by encouraging green energy technologies via government funding and tax reductions. In renewable power generation, wind energy has been noted as the fastest-growing energy technology in the world as the world has enormous resources of wind energy. It has been estimated that tapping barely 10% of the wind energy available could supply all the electricity needs of the world [1].

In present days, most the wind turbines being installed, are having pitch control systems with traditional Proportional –Integral (PI) algorithms [2]. These control systems are designed to perform near the nominal wind speeds and power extraction values. These mechanisms are popular due to their good response for linear model systems as well as their implementation simplicity. However, the large wind turbines make them highly non – linear systems, therefore, in case of large wind turbines to obtain maximum power extraction, non – linear control algorithms would be required.

Fuzzy logic has emerged as one of the active areas of research, particularly in control applications. It is a very powerful method of reasoning when mathematical models are not available and input data are imprecise [3][4][5] [6-11].

This paper represents the design of an optimum fuzzy logic control system for the pitch control of a 1.5 MW horizontal axis wind turbine, using Cuckoo search algorithm. There are different methods for solving an optimization problem [12]. Many of them are inspired from natural processes. For example, Genetic Algorithm (GA) which is inspired by natural genetic variation and natural selection [13] [14], Particle Swarm Optimization (PSO) developed by Eberhard and Kennedy in 1995, which is inspired by social behaviour of bird flocking or fish schooling [15-17] and many more. The investigations on nature inspired optimization algorithms are still being done and new methods are being developed to continually solve some sort of nonlinear problems.

Cuckoo Search is a new evolutionary optimization algorithm which is inspired by lifestyle of a bird family called cuckoo developed by Xin-she Yang and Suash Deb in 2009 [19]. Specific egg laying and breeding of cuckoos is the basis of this novel optimization algorithm [12] [18] [19]. CSA is being explored by researchers for finding solutions of different optimisation problems. In [29] authors have applied CSA for the validation against structural engineering optimization problems. In this work, CSA has been subsequently applied to 13 design problems reported in the specialized literature. In their works [30] the authors presented a CSA based parameter estimation method to extract the parameters of single-diode models for commercial PV generators. Some researchers have demonstrated a methodology to optimally size three different system schemes viz. Photovoltaic-Battery, Wind-Battery and Photovoltaic-Wind-Battery system for a remote area using CSA [31].

In this present work, CSA has been used to optimise the pre-processor parameters of the fuzzy logic control system for the pitch control of a wind turbine. Performance curves were analysed and the results are discussed.

2. Wind turbine model

A wind turbine model is basically constructed with a mechanical turbine (*low speed rotor and blades*), gearbox (*multiplicative*) and the electric generator (*high speed rotor*) and can be represented as in Fig. 2.1 [2].

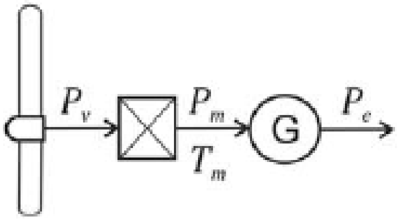

Fig. 2.1 Wind turbine model diagram. Mechanical wind turbine (*left*), gearbox (*middle*), squirrel cage induction generator (*right*) [2].

The power in the wind is proportional to the cube of the wind speed and may be expressed as [24]

$$P_v = 0.5\ \rho\ A\ v_w^3 \qquad (2.1)$$

where ρ is air density, *A* is the area swept by blades and υ_w is wind speed. A wind turbine can only extract part of the power from the wind, limited by the Betz limit which can achieve a maximum value of 59%. This fraction is described by the power coefficient of the turbine, C_p, which is a function of the blade pitch angle and the tip speed ratio.

The gearbox is the mechanical element that multiplies rotational speed of the mechanical turbine into the speed needed for the electric generator. The mechanical power P_m delivered at the output of an ideal gearbox as the one considered in this work is the same as the one extracted from wind and multiplied by the power coefficient C_p [2] . For wind at standard conditions (*101.3 kPa y 273 K*) density value is ρ = 0.647 (*kg/m²*), Pm can be represented by the following equation:

$$P_m = Cp\ (\beta,\lambda)\ P_v \qquad 2.2$$

Therefore, the mechanical power of the wind turbine extracted from the wind is [2]

$$P_m = 0.647\ C_p\ (\beta,\lambda)\ ½\ Av_w^3 \qquad (2.3)$$

where C_p is the power coefficient of the wind turbine, β is the blade pitch angle and λ is the tip speed ratio. The tip speed ratio is defined as the ratio between the blade tip speed and the wind speed υ_w

$$\lambda = \frac{\Omega R}{\upsilon_w} \qquad (2.4)$$

where **Ω** is the turbine rotor speed and *R* is the radius of the wind turbine blade.

The performance curves commonly used to design a wind turbine for a chosen average site wind speed are the $C_p - \lambda$ curves. These curves show information regarding wind speed and angle of attack at which maximum power coefficient C_{pmax} is obtained. The C_p relates with λ with the following expressions [25] [2]:

$$C_p = c_1 \left(\frac{c2}{\lambda i} - c_3\beta - c_4 \right) e^{-c5/\lambda i} \qquad (2.5)$$

$$\frac{1}{\lambda i} = \frac{1}{\lambda + c6\beta} - \frac{c7}{\beta^3 + 1} \qquad (2.6)$$

Where c_1 , c_2,….. c_7 are specific constants for each wind turbine aerodynamic design. *β (deg)* is the wind angle of attack at the blade.

Fig. 2.2 shows C_p - λ curves for different β of the studied for a 1.5 MW wind turbine [2] from which it can be observed that the mechanical power converted from the turbine blade is a function of the rotational speed, and the converted power is maximized at the particular rotational speed for various wind speed.

For this project, a squirrel cage induction generator was selected as these type of generator is the most commonly used for wind energy generation.

The complete wind turbine model was implemented and analysed using *Simulink/ MATLAB* programming. The mechanical turbine was constructed with equations 2.2 – 2.5. Parameters for the 1.5 MW wind turbine and wind turbine aerodynamic parameters can be found in Table 2.1 and 2.2[2].

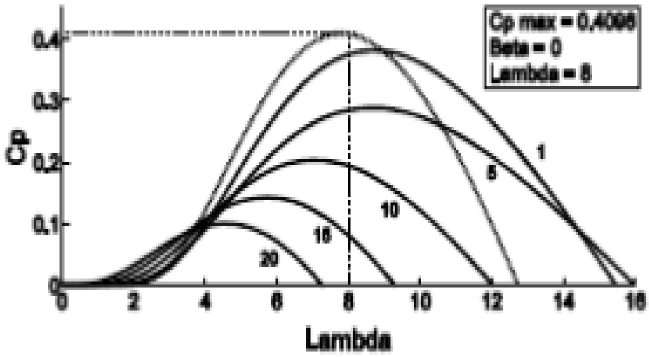

Fig. 2.2 C_p - λ curves for different values of β [2]

Table 2.1 Wind turbine model parameters

Mechanical turbine		
r	=	$34\ m$
A	=	πr^2
Gearbox		
n	=	152.49
Generator		
P_{nom}	=	$1.5\ MW$
V_{nom}	=	$575\ V$
F_{nom}	=	$60\ Hz$
R_s	=	$0.004843\ pu$
L_{ls}	=	$0.1248\ pu$
R_r	=	$0.004377\ pu$
L_{lr}	=	$0.1791\ pu$
L_m	=	$6.77\ pu$
H	=	$H_{tur} + H_g = 4.125\ s$
F	=	$0.01\ pu$
poles	=	3

Table 2.2 Wind turbine aerodynamic parameters [2]

β	=	*0, 1, 5, 10, 15 y 20*
c_1	=	0.4654
c_2	=	116
c_3	=	0.4
c_4	=	5
c_5	=	20.24
c_6	=	0.08
c_7	=	0.035
λ	=	*0 to 16*

3. Fuzzy logic controller (FLC)

Recently fuzzy control techniques have been applied to many industrial processes. FLCs are rule-based systems which are useful in the context of complex ill-defined processes, especially those which can be controlled by a skilled human operator without knowledge of their underlying dynamics [20][22][23][28][32]. Fuzzy control system is a control mechanism based on fuzzy set theory. As per the fuzzy theory and logic, a decision is made by mainly three operations: fuzzification process, an inference engine for rule base and defuzzification process [21]. It is a mathematical system that analyses analogue input values in terms of logical variables that takes a continuous value between 0 and 1, unlike classical logic and operates on discrete values of either 1 or 0. It utilises the knowledge of an experienced user to design the knowledge base of the controller. Fig. 3.1 represents the configuration of proposed fuzzy logic control.

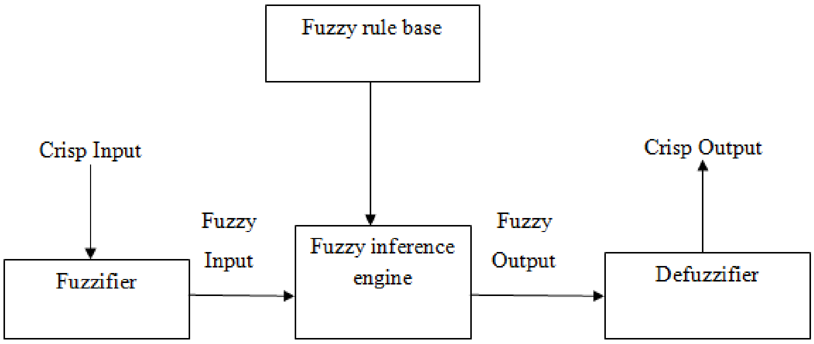

Fig. 3.1 Configuration of fuzzy logic

4. Cuckoo search algorithm (CSA)

Cuckoo Search Algorithm (CSA) is a very powerful optimization technique which is based on the interesting breeding behaviour such as brood parasitism of certain species of cuckoos [19]. Cuckoo has aggressive reproduction strategy. These kinds of birds lay their eggs in the nests of other host birds with amazing abilities such as selecting the recently spawned nests and removing existing eggs that increase hatching probability of their eggs [26]. The host bird presumes those eggs as their own and takes care of them. However, if the host birds can discover the eggs as not as their own, they will either throw out the alien eggs or abundant the nest and build their new nests in new locations. This cuckoo breeding analogy is the inspiration behind the CSA. The details of CSA could be found in [19] [12]. The basic steps of the Cuckoo Search (CS) can be summarized as below [27].

Step 1, →

Specify current place of residence of cuckoos randomly

Step 2, →

Assign a number of eggs to each cuckoo.

Step 3, →

Specify the laying radius of each cuckoo.

Step 4, →

Cuckoos are laying on the host nests in their lay radius.

Step 5, →

Eggs that are identified by the host birds are destroyed

Step 6, →

Cuckoo eggs that have not been identified are grown.

Step 7, →

Evaluate the place of residence of new cuckoos.

Step 8, →

Specify the maximum number of cuckoos that are in a place to live
and eliminate those that are in unsuitable places.

Step 9, →

cluster the cuckoos using k-means clustering method and specify the best group of cuckoos as the objective place of residence.

Step 10, →

New cuckoo's population are moving to the objective location.

Step 11, →

stop if the stop condition has been established, otherwise, go to step 2.

In this work, CSA has been used to optimize the pre-processor parts of the FLC to extract maximum power form a 1.5 MW wind turbine under variable wind speed.

5. Fuzzy logic controller design

In this paper, a self-tuned fuzzy controller is used for pitch angle control for variable speed wind turbine. The main objective of replacing linear by fuzzy control is to harvest maximum power from the wind by pitch control. For the proposed FLC, inputs to the controller are wind speed *v(t)* and an error signal *e(t)* as the one in [2]. The closed loop diagram for the proposed system can be shown in Fig. 5.1

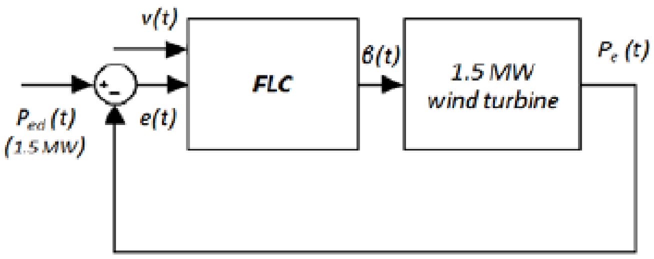

Fig 5.1 Feedback control closed loop for the proposed FLC [2]

According to Figure 5.1, the input signals to the fuzzy controller are the wind speed V and the error (difference between reference power and generated power). The output of the FLC system is β.

The detailed structure of the FLC used in this paper can be represented in Fig 5.2 [27].

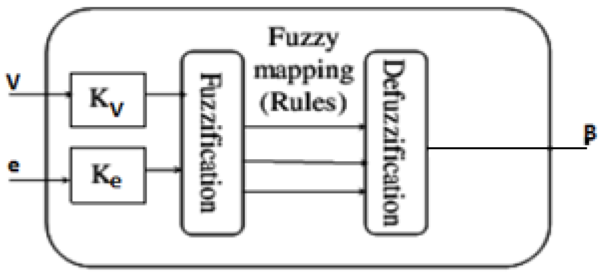

Fig 5.2 The structure of the FLC

The pitching to feather methodology to obtain electric power from the wind turbine can be analysed using performance curves. P_e -v curve is the most useful powerful performance curves for this purpose. These curves show generated electric power versus wind velocity at constant chosen β angles. Fig. 5.3 shows some of these curves [2]. The P_e – v curves were drawn for chosen β =0, 2, 12, 18 and 23. From the curves it is can be clearly understood that β angle should be changed to maintain a 1.5 MW power generation under different wind speed conditions.

Observing the performance curves, the membership functions and the rules of the FLC is designed. The input and output membership functions are shown in Fig's 5.4 – 5.6 and the system rules are described in table 5.1.

Coefficients Ke and Kv shown in table 5.2 have a key role in the system performance. Selection of the appropriate values for the coefficients is very important. In this paper to strengthen the performance of the fuzzy controller, the pre-processors parts of fuzzy controller are optimally selected by CSA in a specified range. The objective function is selected to maximise the generated power for a given period. The parameters used to develop the Cuckoo

Search is presented in table 5.3. Range of the optimization variables (bound of the search domain) presented in Table 5.4. The optimization is done using MATLAB programming.

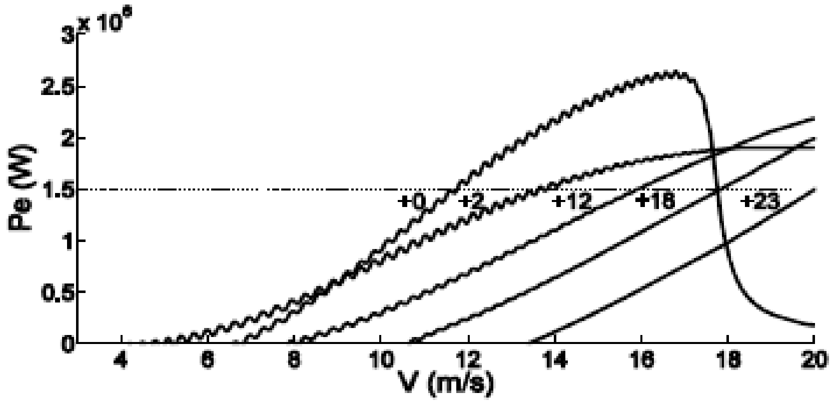

Fig. 5.3 $P_e - v$ curves for β =*0, 2, 12, 18* and *23*. Optimum β angle for current wind speed can be obtained at the intersection with the 1.5 MW dotted line [2].

Table 5.1 FLC rules

	Power e(t)				
v (m/s)	NegVB	NegB	Accept	PosB	PosVB
5	0	1	2	2	2
7	0	1	2	2	2
9	2	2	1	1	0
11	1	0	0	0	0
11.7	1	0	0	0	0
12.6	6	2	1	0	0
13.8	10	6	2	1	0
14.8	14	10	6	2	1
15.5	18	14	10	6	2
16.5	20	18	14	10	6
17.8	20	20	18	14	10
18.6	22	22	20	18	14
19.5	24	24	22	20	18
20.5	24	24	24	22	20

Table 5.2 Optimized values of the pre-processing parameters

K_v	Ke
1.685074075795595	1.208470477655286

Table 5.3 Cuckoo Search parameters

Number of iterations	1000
Number of nests	25
Discovery rate of alien egg/solutions	0.25

Table 5.4 The limits of the optimization variables

	K_v	K_e
Upper limit	.05	.05
Lower limit	2	2

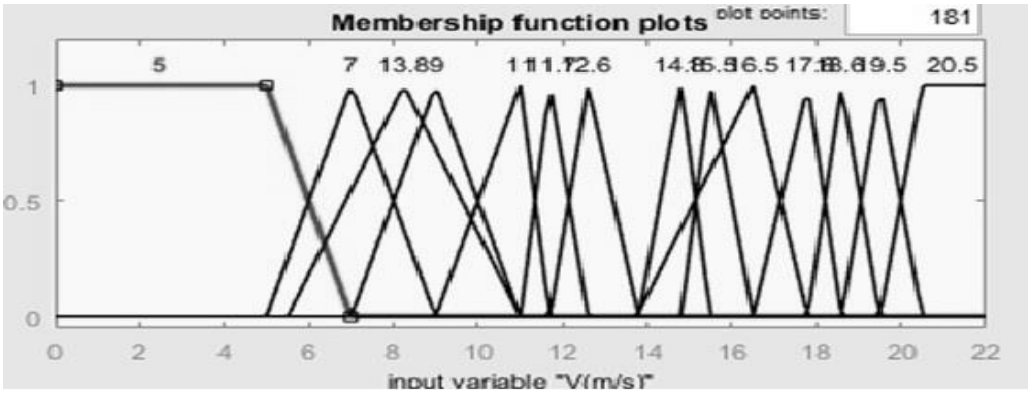

Fig 5.4 Membership functions of the input variable V(m/s) (Wind speed) [2]

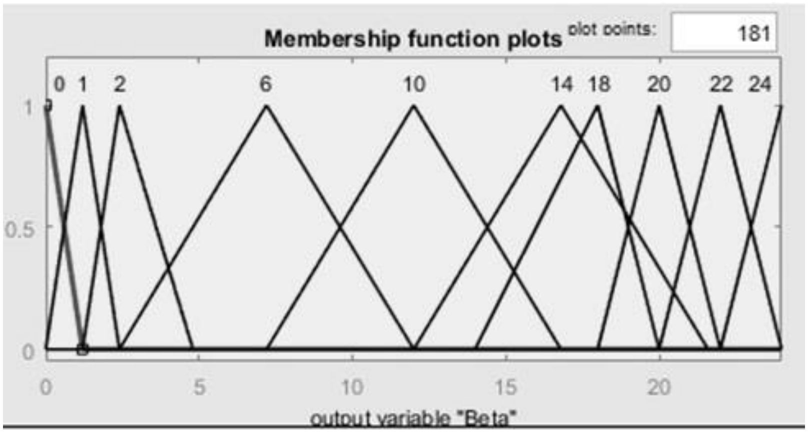

Fig 5.5 Membership functions of the output variable Beta (pitch angle) [2]

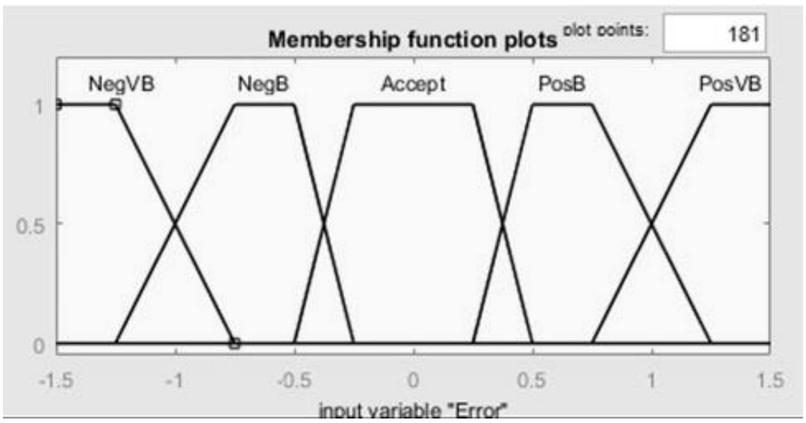

Fig 5.6 Membership functions of the input variable Error (Power error) [2]

6. Simulation results and Discussions

In order to verify control principle given in this paper, detailed model of the system has been developed using MATLAB programming. For simulation purposes, wind signal was constructed. Randomly varying wind speed variation is illustrated in Fig. 6.1, where the wind speeds are varying from 8m/s to 17m/s (rated speed 13m/s). The wind speeds have been used to evaluate the performance of the proposed wind turbine system using optimised fuzzy logic control system over a PI controller. For continuously varying wind speeds, the power output of the wind turbine generator will change accordingly.

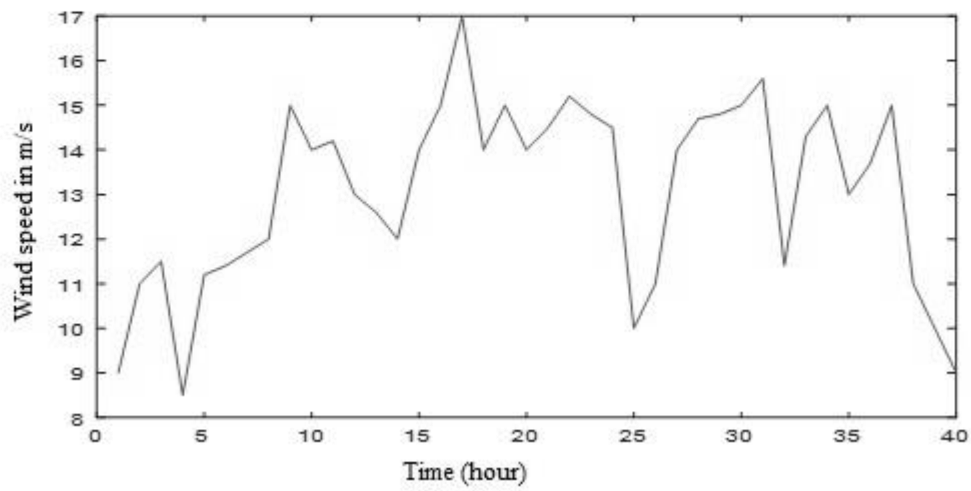

Fig 6.1 Wind speed variation (m/s)

Fig 6.2 shows the comparison between the output power of the wind power system with FLC without the pre-processor parts and output power of the wind power system with PI controller. Fig 6.3 shows the comparison between the output power of the wind power system with FLC with optimised pre-processing parameters and output power of the wind power system with PI controller.

From Fig 6.2 it can be clearly seen that for the given wind speed, the power generated by the FLC is more compared with the standard PI controller. In other words, the FLC provides better results compared with the standard PI controller, especially at the lower wind speeds.

Furthermore, from Fig 6.3, it can also be observed that the FLC system with optimized pre-processor parameters performs better that the FLC without optimised pre-processor parameter at lower wind speed by extracting more power from the wind turbine. Hence, it can be stated that the CSA could successfully optimise the pre-processor parameters of the FLC system enabling the system to perform better than standard PI controller as well as an unoptimized FLC.

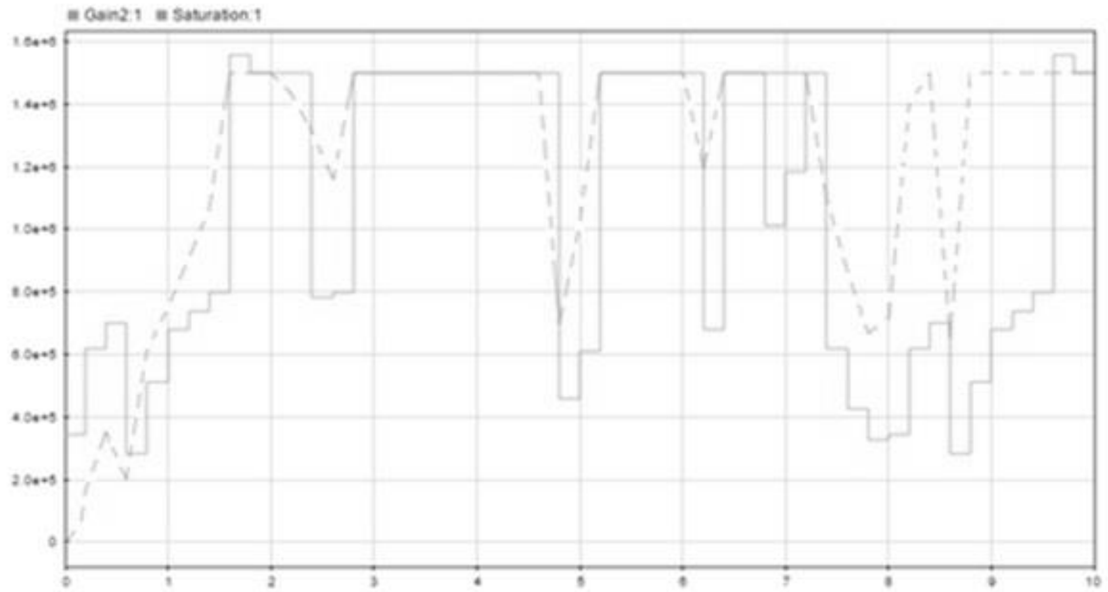

Fig 6.2 The X axis represents the time and the Y axis represnts the genarated power.
The solid line represents the generated power of the wind power system with PI controller and dotted line represents the generated power of the wind power system with FLC -without pre-processors.

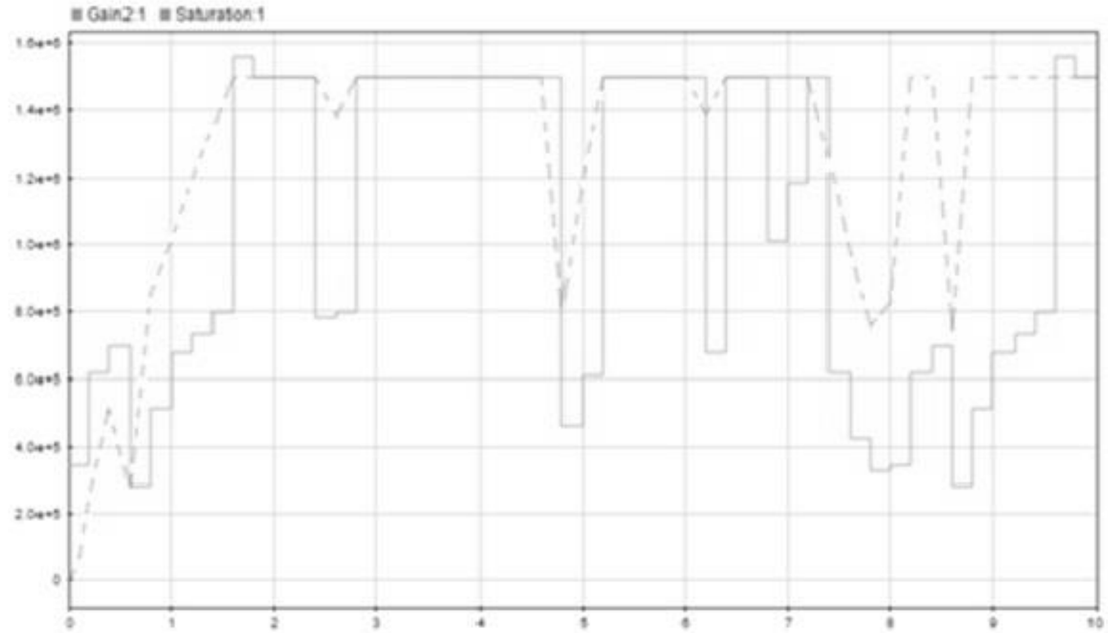

Fig 6.3 The X axis represents the time and the Y axis represnts the genarated power.
The solid line represents the generated power of the wind power system with PI controller and dotted line represents the generated power of the wind power system with FLC with optimized pre-processing parameters.

7. Conclusion

From the perspective of efficiency and generation, control mechanism of wind generator is of outmost importance. In this paper, an efficient and effective tuning approach based on Cuckoo Search Algorithm is presented to optimally tune the pre-processor parameters of a Fuzzy Logic Controller to extract maximum power from a 1.5 MW wind turbine using pitch control mechanism. It was evident from the results that, the incorporating FLC significantly improved the results compared with standard PI controller, especially at the lower wind speeds. Simulation results also show clearly that the optimized FLC system demonstrated better performance compared with un-optimised FLC system or PI controller in lower wind speed conditions due to its inherent characteristics to deal with non-linear models. It also performs quite satisfactorily at higher and rated speed compared to the un-optimised FLC system and standard PI controller. Results show the robustness of the optimally tuned FLC system using CSA. Soft, nonlinear control action of this controller improve the wind turbine performance at low, and rated wind speeds.

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