INDIVIDUAL BLADE PITCH CONTROLLER BASED ON FUZZY LOGIC CONTROL (FLC) AND ARTIFICIAL NEURAL NETWORKS (ANNs) FOR A SMALL H-DARRIEUS VERTICAL AXIS WIND TURBINE

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الملخص

تنقسم توربينات الرياح بشكل أساسي إلى نوعين: توربينات الرياح ذات المحور الأفقي وتوربينات الرياح ذات المحور العمودي. تم دراسة جودة وأداء توربينات الرياح ذات المحور الأفقي على نطاق واسع من قبل الباحثين وتعد وحدة التحكم في زاوية دوران شفرات توربينات الرياح من أكثر التقنيات شيوعاً المستخدمة لتحسين الأداء الديناميكي الهوائي لتوربينات الرياح. على عكس توربينات الرياح ذات المحور الأفقي، تم إجراء القليل من الدراسات مؤخراً لتحسين قدرة البدء الذاتي والأداء الديناميكي الهوائي لتوربينات الرياح ذات المحور الرأسي من النوع H ذات الشفرات المستقيمة (Darrius VAWT). تهدف هذه الدراسة لمعالجة مسألة أداء VAWT باستخدام تقنية التحكم في دوران شفراتها ونظراً للتعقيد الرياضي المرتبط بنمذجة توربينات الرياح ذات المحور الرأسي VAWT، يتم استخدام النتائج التحليلية المستخرجة من نموذج ديناميكيات الموائع الحسابية (CFD) لتصميم نموذج تعريف النظام باستخدام الشبكات العصبية (ANN)، والذي يمكنه تمثيل سلوك نموذج VAWT. بالإضافة إلى ذلك، تم تصميم نظامي تحكم ذكيين يعتمدان على كل من الشبكات العصبية (شبكة MLP) والمنطق الضبابي (FLC) للتحكم في زاوية دوران Darrieus VAWT. علاوة على ذلك، تم المقارنة بين نظامي التحكم الذكيين. تظهر النتائج أن كلا من أنظمة التحكم (ANNs و FLC) يمكن أن تحقق أداء تحكم أفضل من حيث إنتاج الطاقة VAWT.

ABSTRACT

Wind turbines are mainly divided into horizontal and vertical axis wind turbines. The quality and performance of wind turbines have been extensively investigated by researchers. A pitch angle controller is one of the most common techniques used to improve wind turbines' aerodynamic performance. Unlike horizontal axis wind turbines, only a few studies being conducted recently to improve the self-starting capability and aerodynamic performance of H-type Vertical Axis Wind Turbines with straight blades (Darrieus VAWT). This study aims to process the issue of VAWT performance using the pitch angle controller technique. Due to the mathematical complexity associated with addressing the behavior of VAWT, numerical results extracted from a Computational Fluid Dynamics (CFD) model are used to design a system identification model, neural networks (ANNs) based, that can identify the behavior of the VAWT model. In addition, two controllers based on both neural networks (MLP-network) and fuzzy logic (FLC) techniques were designed to control Darrieus VAWT pitch angle. Moreover, comparisons between the two intelligent controllers were provided. Results show that both controllers (ANNs and FLC) can achieve better control performance in terms of VAWT power regulations.

KEYWORDS: Fuzzy Logic Controller (FLC); MLP-Network; Pitch Angle; Computational Fluid Dynamics (CFD); Wind turbine.

INTRODUCTION

Renewable energy technologies play an important role to reduce air pollution and global warming effects. The wind turbine industry is one of the most common alternative solutions; two main types of wind turbines are used to extract power from wind: Horizontal Axis Wind Turbines (HAWTs) and Vertical Axis Wind Turbines (VAWTs). Vertical Axis wind turbines (VAWTs) classify into two principles lift and drag as shown in Figure (1); H-Darrieus is a lift type of VAWTs (H-type VAWTs), in which the blades are straight with fixed or variable pitch angle. In general, VAWTs can receive the wind blowing from any direction, so yawing mechanism is not needed; furthermore, maintenance is relatively quick and easy since the transmission equipment and generator are placed at ground level. Also, the cost is relatively low because of the simplicity of blade design. In contrast, the aerodynamic theories of VAWT are debatable topics and uncertain because of the complex aerodynamic analysis and self-starting capability; therefore, many investigations are being conducted to overcome the drawbacks [1].

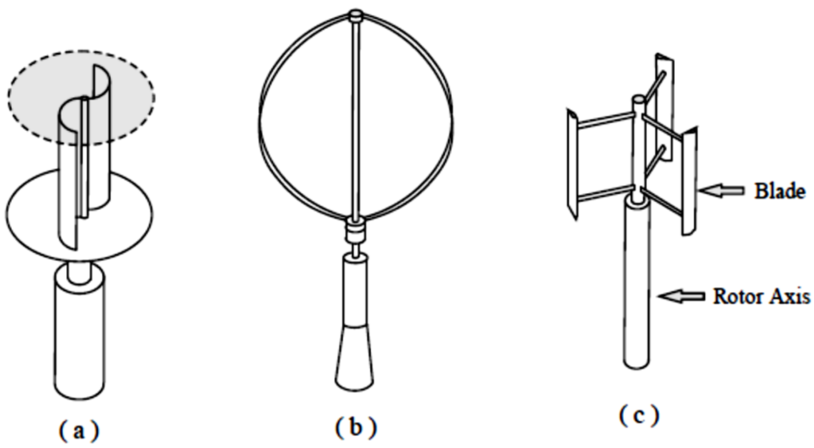

Figure 1: Some types of VAWTs; (a): Savonius- Rotor, (b): Darrieus- Rotor, (c): H-type Darrieus- Rotor.

To improve the performance of VAWTs in terms of power output and self-starting capability, a variable pitch control mechanism is suggested by many researchers. The proportional–integral (PI) or proportional—integral–derivative (PID) based-pitch angle controllers have been often used for power regulation. The performance of this method is, however, low at high non-linearity conditions. Another method is a linear quadratic Gaussian (LQG) control that is used for the pitch angle control [2]. Although it is a robust method, its performance is also limited with a nonlinear system model. Sliding-mode control technique has been applied for the pitch angle control; it has good robustness, but it needs to know the mathematical model for the system [3].

Intelligent control strategies have been proposed as controllers such as fuzzy logic control (FLC) and neural network control (ANNs). The advantage of these methods is that they have an acceptable potential when the system contains strong non-linearity such as strong wind turbulence. Fuzzy logic control is used to investigate the wind turbine performance. Specifically, fuzzy logic control (FLC) is applied to control pitch angle and its performance is robust and reliable [2].

On the other hand, Artificial Neural Network (ANN) can estimate not only several nonlinear functions based on available information for training but also a highly desired degree of accuracy under certain conditions for the system [4].

Problem Statement

A variable pitch mechanism is one of the suggested technologies to maximize the power of the H-Darrieus rotor type and improve its aerodynamic performance. However, most of these technologies need more investigations due to the variation of the flow velocities in the upstream and downstream regions and dynamic cyclic changes in the angle of attack [1]. Because of limiting the capacity of the generator and converter, the generator output power is limited at the rated value. This limitation will be controlled by using pitch angle control strategies to capture the aerodynamic power by the wind turbine at the high-wind speed regions using some mechanical or electrical devices are needed to change the blade pitch angle by rotating the blade around its axis as well as the axis of the rotor. To optimize the wind turbine performance, estimation of the value of pitch angle at each blade position is necessary to generate the highest value of tangential force and torque. The main goal of the present work is to design intelligent controllers based on ANNs and fuzzy logic strategies for blade pitch angles and investigate the effect of blade pitching on the aerodynamic performance of H-type VAWT in terms of power output.

LITERATURE REVIEW

Paraschivoiu [5] claimed that the variable pitch angle technology can improve self-starting, increase power coefficient peaks, and reduce the vibration of the blade caused by the dynamic stall. Miau et al. [6] argued that the starting characteristics for a three-bladed VAWT can be improved by using pitch control strategies. A vertical-axis wind turbine with a variable pitch angle was investigated by Chen, and Zhou [7], and the results showed that the power coefficient is enhanced by pitching. Paraschivoiu and Saeed [8] analyzed an H- Darrieus VAWT to determine the optimal variation of the blades' pitch angle by using two sinusoidal analytical functions; their results presented that 30% in the annual energy production was estimated with a pitch model. In [9], a fixed pitch angle Darrieus vertical axis wind turbine with NACA 0021 was optimized using the CFD model; the CFD results and experimental data were compared; a good agreement was found between them. Sargolzaei [10] applied Artificial Neural Networks (ANNs) to predict the power coefficient and torque for seven different types of Savonius VAWT; the simulated results, which were compared with experimentally collected data, displayed that the power increased by using the ANNs technique. In another study, the ability of the Fuzzy Expert System (FES) to predict the power generation of a small hybrid (Darrieus and Savonius) VAWT was investigated experimentally by Hossain et al. [11]; the results have referred that FES is valid.

COMPUTATIONAL FLUID DYNAMICS (CFD) MODEL

The fluid governing equations can be defined by applying the laws of mechanics to a fluid. The conservation of mass, conservation of momentum, and conservation of energy equations are nonlinear partial differential equations; therefore, it is difficult to solve these equations analytically for many engineering applications. However, CFD can be used to determine approximate computer-based solutions to solve the governing equations [12]. The CFD simulation results of a 2-D Darrieus VAWT were conducted in [13] which were obtained by ANSYS FLUENT 15.0 as one of the computational fluid dynamics (CFD) commercial software package. These CFD results are used in this research.

The aerodynamic performance of a small three-bladed Darrieus VAWT with variable blade pitch angle was predicted at different tip speed ratios (TSRs). The main geometrical dimensions for this wind turbine are listed in Table (1).

Table 1: Main features of the H-type Darrieus wind turbine.

Feature	Value
Rotor radius (R) [mm]	525
Blade height (H) (2D) [mm]	1000
Blades number (Nb) [-]	3
Blade profile [-]	NACA 0012
Chord (c) [mm]	246
Rotor speed (ω_r) [rad/s]	50
Pitch angle (β) [°]	-6, -4, 0, 4, 6
Azimuth angle (θ) [°]	0 to 360
Tip speed ratio (λ or TSR) [-]	1, 1.7, 2, 2.5, 3.3
Rated power $P_{electrical}$ [Watt]	2000
Solidity(σ) [-], $\sigma = \frac{N_b c}{\pi R}$	0.068209

The blade angles for H-type VAWTs, which include the pitch angle (β), angle of attack (α), and relative flow angle (φ), are illustrated in Figure (2).

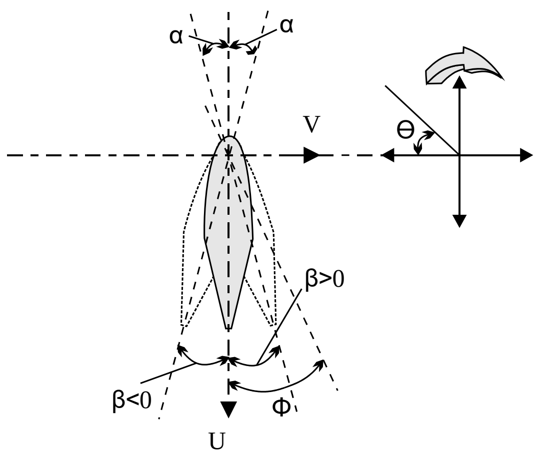

Figure 2: Blade angles: *β* pitch angles, *α* angle of attack, *φ* flow angle.

To study the aerodynamic characteristics around the blade such as dynamic stall, boundary layer etc., some coefficients should be considered such as lift, drag, and moment coefficients. These coefficients (C_L, C_D, and C_m) can be expressed as follows [14]

$$C_l = \frac{2F_l}{\rho A u_\infty^2} \tag{1}$$

$$C_d = \frac{2F_d}{\rho A u_\infty^2} \tag{2}$$

$$C_m = \frac{2\tau_t}{\rho A R u_\infty^2} \tag{3}$$

where ρ is air density in (kg/m^3), A is the swept area by the turbine in (m^2) (e.g., for an H-type VAWT, A=2RH, where H is the blade length), τ_t is the rotor torque in (Nm), and *Fl* and *Fd* are the lift and drag forces. Fluent CFD ANSYS can estimate lift, drag, and moment coefficients for the NACA 0012 airfoil based on the Airfoil Database Tool [15].

Figure (3) shows different experimental data of the NACA0012 [16]. The lift coefficient (C_L) with a varying angle of attack and the relationship between both lift and drag coefficients.

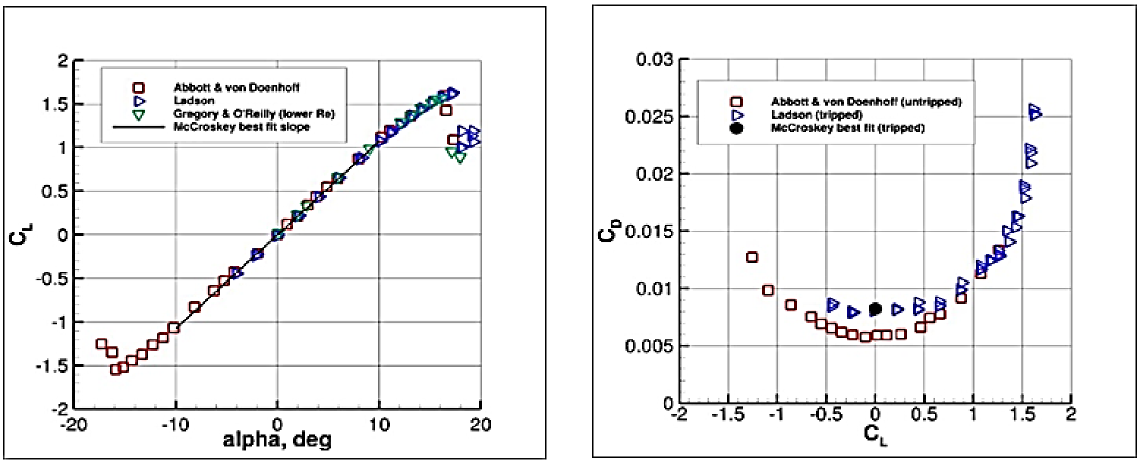

Figure 3: Lift and drag coefficients experimental data for NACA 0012 [16]

The amount of mechanical power, Pm, that can be absorbed by a wind turbine.

$$P_m = \omega_r \tau_t \tag{4}$$

where ωr is the rotational speed of rotor in (rad/sec). The extracted power from the wind is proportional to the cube of the wind speed and can be expressed as:

$$P_{Wind} = \tfrac{1}{2}\rho A u_\infty^3 \tag{5}$$

At different TSRs, the optimum pitch angles β_{opt} as well as the maximum power coefficients are estimated using CFD ANSYS software for each blade along the blade trajectory. In this research, the control strategy based on fuzzy logic and artificial neural networks is proposed to control blade pitch angle (β) for only one blade (the third blade) because the variation in pitch angle compared to the first and second blades is small for all TSRs, making control analysis easier.

In the CFD model, the rotor performance of VAWT is estimated using the power coefficient (Cp). It is the ratio of the mechanical power produced by the wind turbine (Pm) to the power available in the wind (P_{Wind}) [17]:

$$C_p = \frac{P_m}{P_{Wind}} = \frac{2\omega_r \tau_t}{\rho A u_\infty^3} = \frac{2\omega_r \left(C_m \left(0.5\rho A u_\infty^2 R\right)\right)}{\rho A u_\infty^3} = C_m \frac{\omega_r R}{u_\infty} = C_m \lambda \tag{6}$$

H-TYPE VAWT MATLAB MODELING

Aerodynamic Model of an H-Type VAWT

By wind turbines, some parts of power, which is limited by the Betz limit, can be extracted from the wind; the power coefficient of the turbine (C_P) represents this fraction. Therefore, the wind turbine power can be expressed as

$$P_{wt} = \tfrac{1}{2}\rho A u_\infty^3 C_p(\lambda, \beta) \tag{7}$$

where u_∞ is wind speed that is collected at Mulligan's telecommunication site [18]; Variable wind speed, which starts at 2 m/s and reaches around 14 m/s, is set to test the system. Wind speeds varied considerably in short periods as shown in Figure (4).

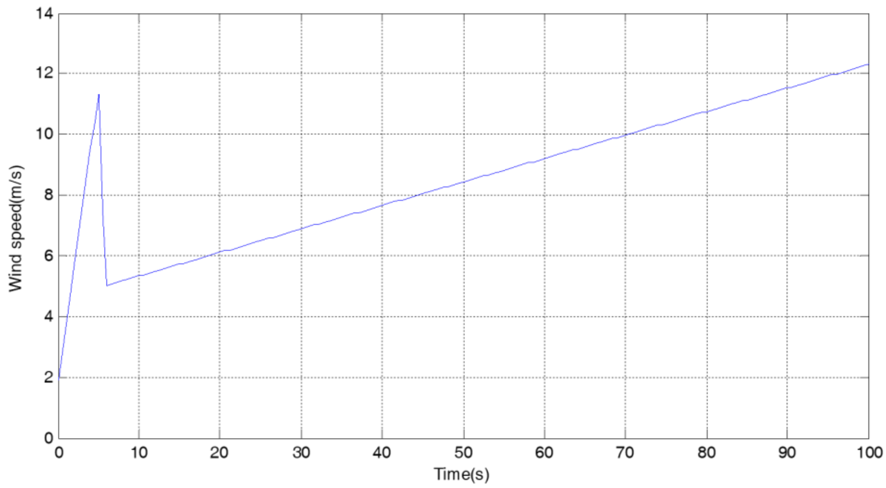

Figure 4: Wind speed for the proposed control system.

The power coefficient C_p is a function of the blade pitch angle β and the tip speed ratio, TSR, (λ) [2]:

$$C_p(\lambda,\beta) = c_1\left(c_2\frac{1}{\lambda_i} - c_3\beta - c_4\beta^x - c_5\right)e^{\left(-c_6\frac{1}{\lambda_i}\right)} \tag{8}$$

where $\frac{1}{\lambda_i} = \frac{1}{\lambda+0.08\beta} - \frac{0.035}{1+\beta^3}$ and c_1=0.5, c_2=116, c_3=0.4, c_4=0, c_5=5, c_6=21, *and* x=0.0

The tip speed ratio λ is defined as the ratio between the blade tip speed and the wind speed u_∞

$$\lambda = \frac{\omega_r R}{u_\infty} \tag{9}$$

Equations 7, 8, and 9 are used for modeling the H-type VAWT plant using MATLAB Simulink.

Pitch Actuator

In this work, the pitch angle for one blade is controlled by an intelligent controller based on fuzzy logic and neural network strategies. The optimum pitch angles β_{opt}, which gives the maximum power coefficient $C_{p,max}$, are defined using Computational Fluid Dynamics (CFD). Moreover, a pitch servo is used to set the blades into the required position by adjusting the rotation of the blades around the longitudinal axes. Because the pitch actuator is a nonlinear servo, it is difficult to describe the dynamic model of the servo. For simplicity, it is assumed that the dynamic model of the servo is a first-order transfer function (i.e., integrator) [19].

$$\dot{\beta} = \frac{1}{\tau_\beta}\beta_c - \frac{1}{\tau_\beta}\beta \tag{10}$$

Where β and $\dot{\beta}$ are the actual pitch angles and their gradients, respectively. β_c is the output pitch angle of the intelligent controllers that should be limited by the time constant τ_β which is typically in the range of 0.2 to 0.25 *s* [2]. In addition, the rate of pitch angle $\dot{\beta}$ is equal to -20 to 20o s^{-1}. Another measure "dead zone" is used to ignore commanded pitch rates less than ± 0.1 o s^{-1}. Figure (5) shows the block diagram of the typical pitch angle control system; the power is controlled by a controller that produces a β_c signal to the pitch actuator.

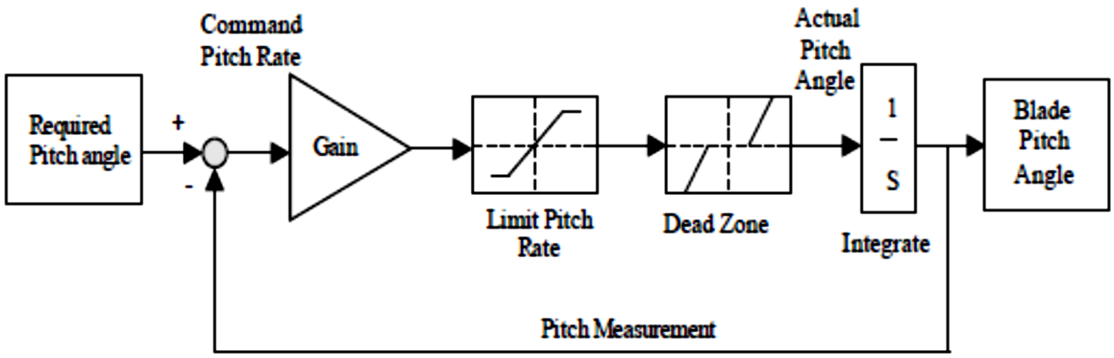

Figure 5: Actuator block diagram [20]**.**

METHODOLOGY

System Identification

System identification is a process to identify the model based on the input and output data. To design the controller, the dynamic model of the system should be presented; moreover, the dynamic parametric models are identified by connecting the input of the system to the output and time [21]. This assumption may lead to unreasonable control results for highly nonlinear systems. As a result, a linear control system does not apply to the process in which conditions change fast relative to the system's time. Because there are no direct methods to parameterize and analyze non-linear dynamic systems, the design of non-linear controllers is more complicated [22]. Therefore, system identification using Artificial Neural Networks (ANNs) is a useful and time-consuming technique that can be used for modelling and mapping nonlinear systems [23]. Model parameters can be determined by training the network using input(s) and output(s) data; thus, developing an exact mathematical model to represent a nonlinear model system is not necessary. The purpose of system identification is to minimize the error between the predicted output and the actual output of the system, this error $e(k+1)$ can be expressed as follows [24];

$$e(k+1) = \left|\hat{y}_p(k+1) - y_p(k+1)\right| \tag{11}$$

where $\hat{y}_p(k+1)$ the predicted output and $y_p(k+1)$ the actual output.

In this work, system identification using MLP-ANNs is presented to model or map the H-type VAWT based on CFD simulation results to behave like the plant (H-type VAWT) which is a nonlinear plant; CFD results are proposed as input and output training data. A fully connected two-layer feedforward MLP-ANN with two inputs and one output unit is considered with the number of hidden nodes and output layers of 20 and 5, respectively, as shown in Figure (6). The sigmoid function is used as the activation function for neurons in the hidden layer. The features (or the set of inputs) of MLP-ANNs are defined as tip speed ratios (1-4) and azimuth angles (0-360 degrees) whereas pitch angle values have been chosen as the output data (targets). Also, the datasets are divided into 75% for training and the remaining 25% for testing with Levenberg-Marquardt (LM) backpropagation algorithm as a training method. This training process consists of executing the LM algorithm for 1000 epochs over the data set. The Mean Squared Error (MSE) is also selected to calculate the performance metric. These procedures are accomplished using MATLAB code and then converted to MATLAB Simulink model.

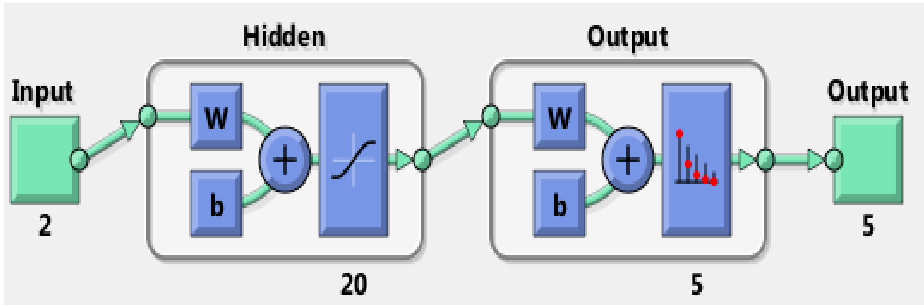

Figure 6: Block diagram of an MLP-ANNs

Figure (7) shows the third blade's optimum pitch angles at different TSRs, and azimuth angles based on CFD results. Five different optimal pitch angles of -4°, -3°, -2°, 0°, and 4° are used to obtain the reference power output of the H-type VAWT (P_{ref}).

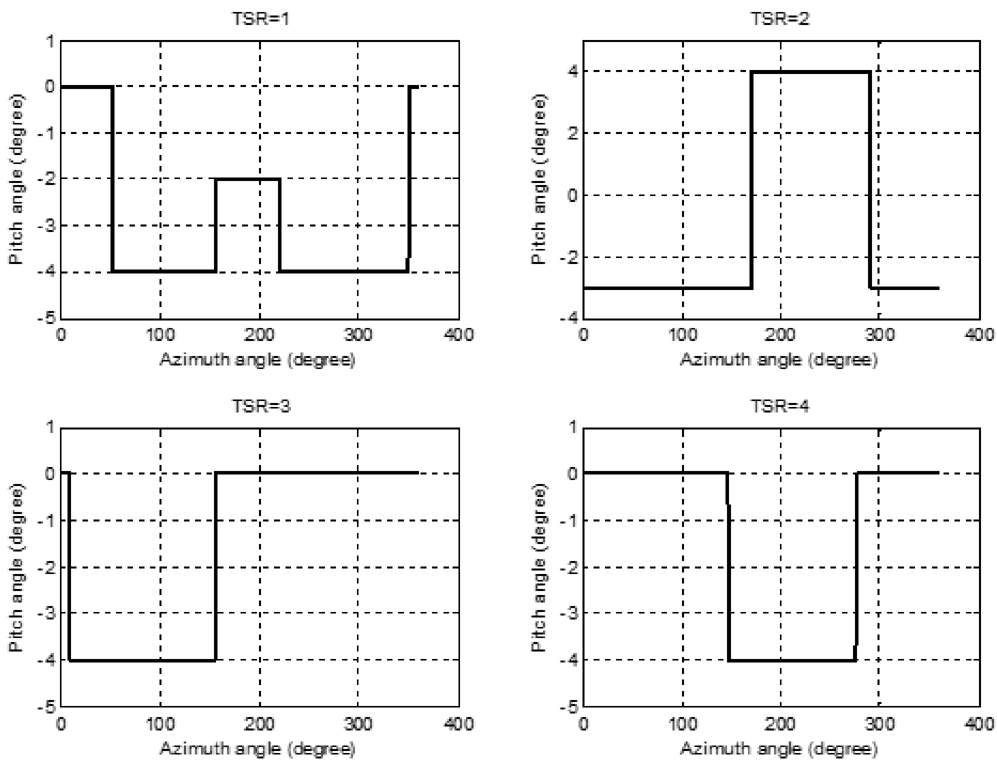

Figure 7: The CFD optimum pitch angles (βopt) for the third blade.

Pitch Angle Control Based on ANNs

As mentioned in the previous section, the dynamics of a vertical axis wind turbine VAWT system has highly nonlinear features; hence, blade pitch control based on MLP-ANNs is proposed in this research. The MLP-ANN structure for system identification and blade pitch control is similar; however, the training data are different in terms of inputs. The set of input consists of three signals: the power deviation from its reference value ΔP (i.e., $error\ (e) = P_{ref} - P_g$), the error variation $\dot{e}$ (δ (ΔP)/δt) and TSRs. The set of inputs is then sent to the MLP-ANNs controller to produce the output signal of the pitch angle β_c and set the blade into the required position using pitch servo as shown in Figure (8). The plant model, which is the actual model of the VAWT, receives the magnitudes of the pitch angle (β_{actual}) to generate the actual VAWT power output (P_g).

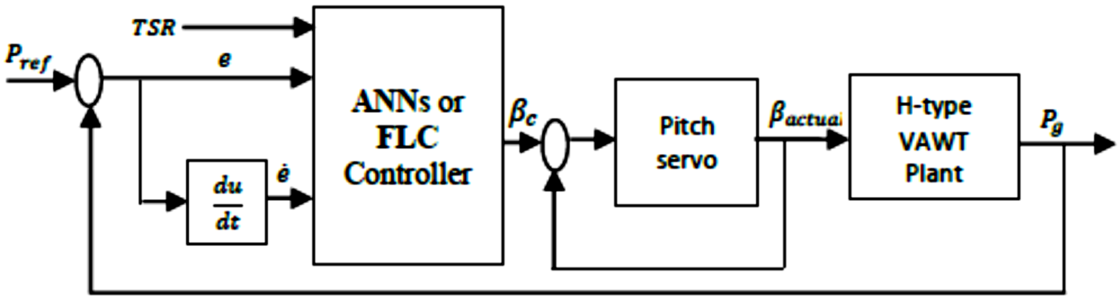

Figure 8: Pitch angle control based on MLP-ANNs and FLC methods.

Fuzzy Logic Control (FLC)

The block diagram in Figure (8) is also used for the proposed FLC system based on Mamdani-type Fuzzy Inference System (FIS). Similarly, the input signals of $e, \dot{e}$, and TSR (crisp inputs) are converted into the fuzzy set (fuzzification) by using the triangular symmetrical membership function as indicated in Figure (9). The design of an FLC includes "if-then" rules that are formulated in linguistic terms based on the developer's knowledge. The rules in this study are created based on CFD results and the previous ANN controller results.

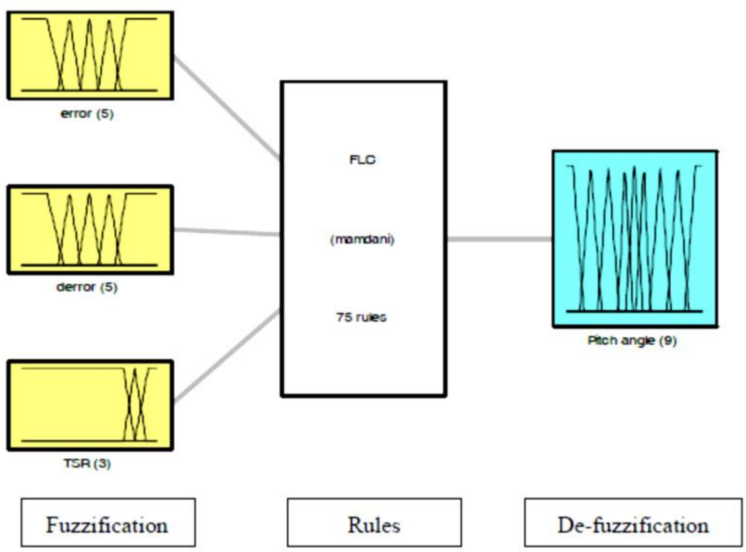

Figure 9: Description of inputs and output for FLC.

The output of the fuzzification process is used to generate the fuzzified output according to the rules set defined. Finally, in the de-fuzzification step, the fuzzified output is transformed into the required output (pitch angle signals) using the centroid method (COA). The pitch angle signals are then used for generating the power output (P_g).

Figure (10) shows the triangular symmetrical membership functions for the fuzzy sets of the input signals ($e, \dot{e}$, and TSR) and output signal (pitch angle). In FIS, the linguistic variables such as TSR e, and $\dot{e}$ can be represented by linguistic values as Negative Large Large (NLL), Negative Medium Large (NML), Negative Medium (NM), Negative Small (NS), Negative (N), Zero (Z), Positive Small Small (PSS), Positive Small (PS), Positive (P), Positive Medium (PM), Positive Medium Large (PML), Positive Large (PL), and Positive Large Large (PLL).

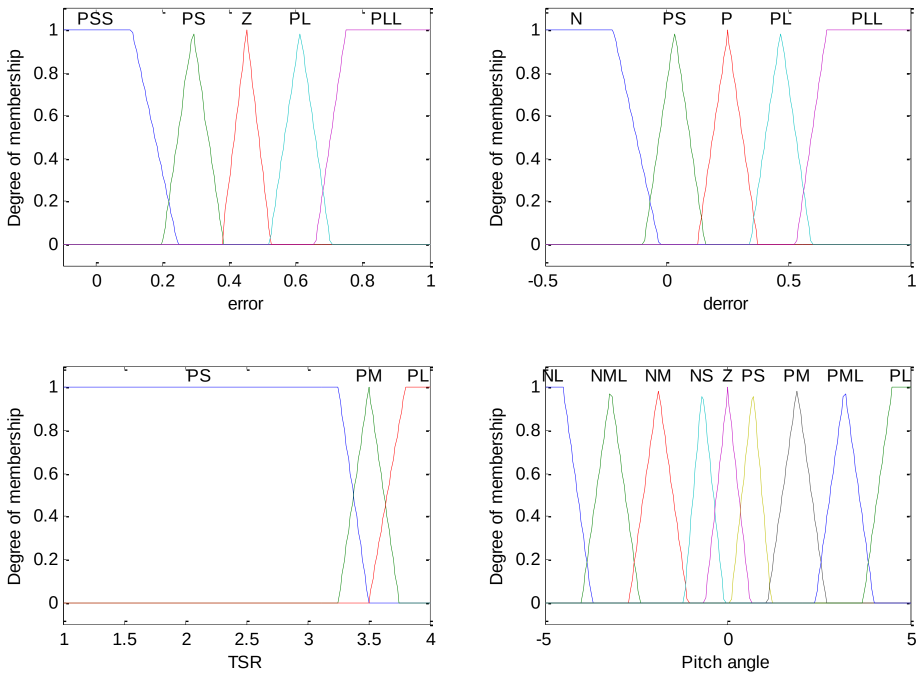

Figure 10: Membership functions of the proposed FLC.

Table (2) shows the FLC rules that are used for mapping the input variables to the output by the following statement: Rule (i): IF TSR (k) is Ai and $e(k)$ is Bi and $\dot{e}(k)$ is Ci THEN β_c is Di. For example: Rule (1) IF TSR is PS and *e* is PSS and $\dot{e}$ is N THEN β_c is NL.

Table 2: Rules of FLC.

TSR		PS					PM					PB				
e		PSS	PS	Z	PL	PLL	PSS	PS	Z	PL	PLL	PSS	PS	Z	PL	PLL
$\dot{e}$	N	NL	NL	NL	NL	NML	NS	NS	NS	PM	PML	PS	PS	PM	PML	PL
	PS	NL	NL	NL	NML	NML	NS	NS	Z	PM	PML	PS	PS	PML	PML	PL
	P	NL	NL	NML	NML	NM	NS	Z	Z	PM	PML	PS	PM	PML	PL	PL
	PL	NL	NML	NML	NM	NM	NS	Z	Z	PML	PML	PM	PM	PL	PL	PL
	PLL	NML	NML	NM	NM	NM	Z	Z	PS	PML	PML	PM	PM	PL	PL	PL

SIMULATION RESULTS

The effectiveness of the proposed blade pitch control system based on MLP-ANNs and FLC for the H-type VAWT is investigated using the MATLAB Simulink tool.

CFD Results

In the CFD simulation, the analysis is carried out for pitch angles of β=-6°, -4°, 0°, 4°, and 6°; TSRs of λ=1,1.7,2,2.5, and 3.3; and mean wind speed of u_∞=10 *m/s*. Figure (11) shows the power coefficients (C_p) curves at the different pitch angles, including the fixed pitch angle case (β=0o). The predicted curves are then compared with other published experimental and CFD results concerning the power coefficient.

For the positive pitch angles, Figure (11) shows that the power coefficient at low TSR of λ=1 was increased by around 12 percent compared to the fixed pitch angle. This means that an enhancement in the self-starting capability of an H-type VAWT can be achieved using the blade pitching technique. Table (3) shows the power coefficients (C_p) values at different TSRs and pitch angles.

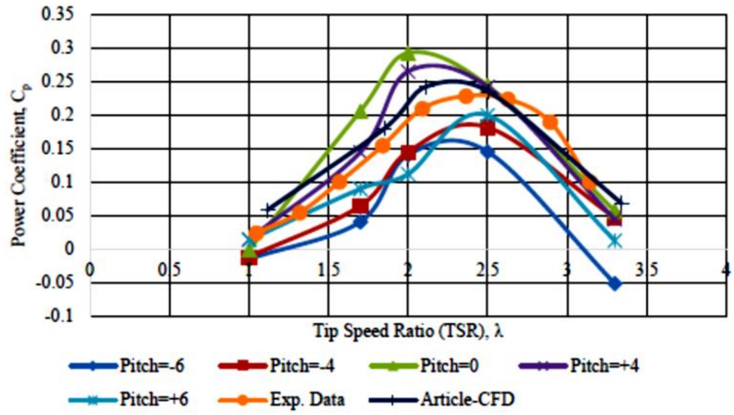

Figure 11. Comparison of the current CFD results with published experimental and CFD results, with respect to the power coefficient versus the TSR at different pitch angles.

Table 3. Power coefficients (C_p) at different TSRs and pitch angles.

TSR	Pitch angles [°]				
	-6	-4	0 (fixed)	4	6
1	-0.01519	-0.01201	-0.00125	0.014456	0.013229
1.7	0.040504	0.0643	0.205944	0.144615	0.089795
2	0.140547	0.145001	0.292979	0.265298	0.111846
2.5	0.145308	0.181745	0.244328	0.242333	0.199989
3.3	-0.05182	0.046705	0.056599	0.044126	0.012437

System Identification Results

The results of the system identification of the H-type VAWT with the third blade are shown in Figure (12). It can be observed that the CFD pitch angle results are accurately mapped by the system identification based on MLP-ANNs. These pitch angles are then used to generate the reference power output P_{ref}. Figure (13) shows that the performance of MLP-ANNs of 0.22529 occurred at several epochs of 66.

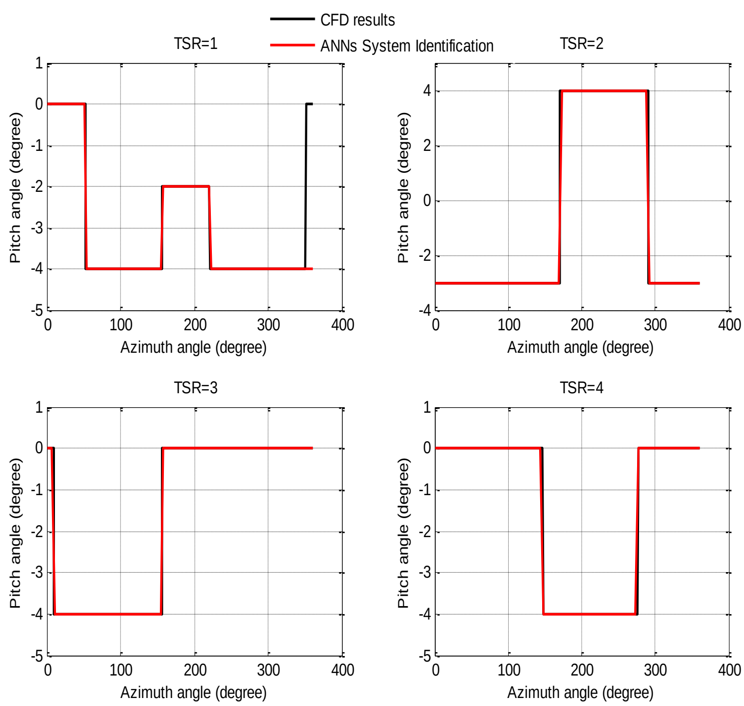

Figure 12: Pitch angle comparisons.

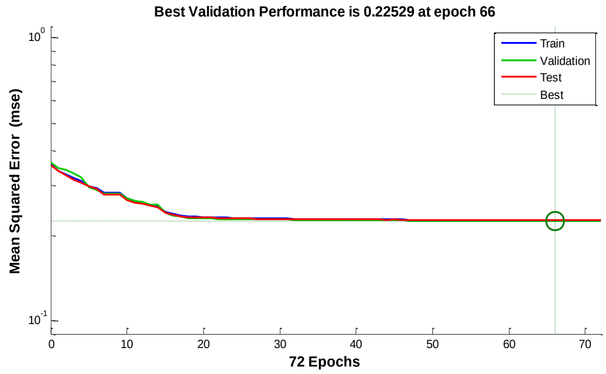

Figure 13: Performance of MLP-ANNs for system identification.

Blade Pitch Control Results

Figure (14) shows the reference and command pitch angle predicted by both the MLP-ANN and the Fuzzy Logic proposed controller for one blade. For one rotor revolution (i.e., θ=0°-360°), pitch angles by the proposed control strategies vary from 0 to -4 degrees. However, the pitch angle is equal to zero in most cases which means the wind turbine works with a fixed pitch angle.

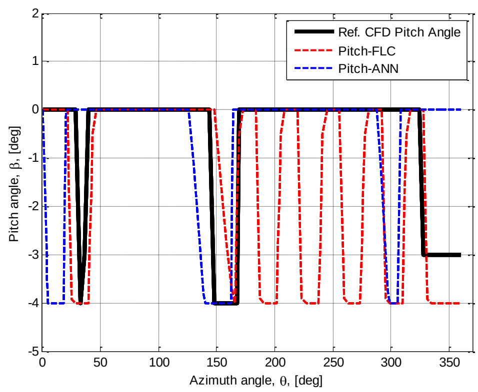

Figure 14: Pitch angle simulation results for both controllers (ANNs and FLC).

The upstream and downstream regions of the H-type VAWT rotor are represented by azimuth angles of (0°-180°) and (180°-360°), respectively. In the upstream region, both controllers can provide a good response for all reference values. However, some delays can be noticed by the MLP-ANNs controller. More fluctuations by FLC occurred in the downstream region, possibly due to the insufficient design parameters of the proposed FLC such as the type of membership functions and rules number.

The differences between the reference pitch signal and measured pitch signals are determined by calculating the root mean square error (RMSE). For both controllers, RMSEs in Table (4) show that a good ability to track the desired pitch angle is produced by the MLP-ANNs controller.

Table 4: Root Mean Square Error (RMSE) results

RMSE	MLP-ANN	FLC
Pitch angle	0.0896	0.149
Power output	0.0158	0.0317

The effect of pitch angle response on the performance of the H-type VAWT in terms of the power output is observed by using both controllers as shown in Figure (15).

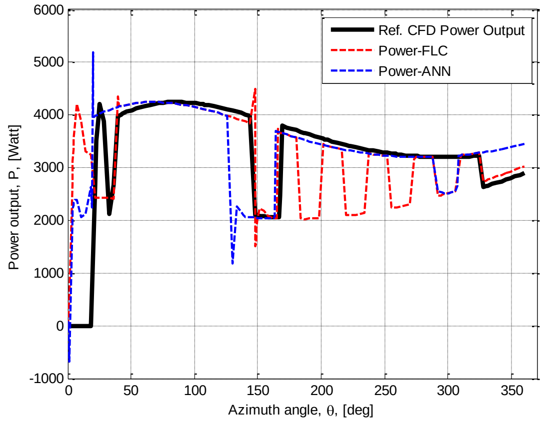

Figure 15: Power generation results for both controllers (ANNs and FLC).

CONCLUSION

Small- and medium-sized VAWTs can be utilized effectively as stand-alone wind energy generation sources if their efficiency can be further enhanced. In this study, two intelligent control algorithms based on neural network and Fuzzy logic approaches are proposed for designing an individual active blade pitch control system for an H-type VAWT. To develop the control scheme, the system identification (ANNs based) of the H-type VAWT model has been designed based on the numerical CFD results. The tip speed ratio (TSR), generator output power, and its rate are selected as the control input variables of both MLP-ANNs and FLC, in which any information on the wind turbine dynamics is not necessary. ANN and Fuzzy logic are two examples of artificially intelligent controls that can be used to enhance the performance of VAWTs. The proposed MLP-ANNs and FLC controllers can respond satisfactorily to all reference values in the upstream region. However, the MLP-ANNs controller can detect some delays. More FLC fluctuations were observed in the downstream region, possibly because of the proposed FLC's inadequate design parameters, such as the type of membership functions and statement of rules. The effect of the responses of both controllers can be seen on the H-type VAWT. However, the proposed pitch angle controllers can regulate the power output of the H-type VAWT.

REFERENCES

[1] C. C. Chen and C. H. Kuo, 2013, Effects of pitch angle and blade camber on flow characteristics and performance of small-size Darrieus VAWT, J. Vis., vol. 16, no. 1, pp. 65–74, doi: 10.1007/s12650-012-0146-x.

[2] T. L. Van, T. H. Nguyen, and D. C. Lee, 2015, Advanced Pitch Angle Control Based on Fuzzy Logic for Variable-Speed Wind Turbine Systems, IEEE Trans. Energy Convers., vol. 30, no. 2, pp. 578–587, doi: 10.1109/TEC.2014.2379293.

[3] S. H. Lee, Y. Joo, J. Back, J. H. Seo, and I. Choy, 2011, Sliding mode controller for torque and pitch control of pmsg wind power systems, J. Power Electron., vol. 11, no. 3, pp. 342–349, doi: 10.6113/JPE.2011.11.3.342.

[4] O. Barambones, 2010, A robust wind turbine control using a neural network based wind speed estimator, Proc. Int. Jt. Conf. Neural Networks, doi: 10.1109/IJCNN.2010.5596859.

[5] I. Paraschivoiu, 2002, Wind Turbine Design: With Emphasis on Darrieus Concept. Presses Inter Polytechnique.

[6] S. J. C. J. J. Miau, S. Y. Liang, R. M. Yu, C. C. Hu, T. S. Leu, J. C. Cheng, 2012, Design

and Test of a Vertical-Axis Wind Turbine with Pitch Control, Appl. Mech. Mater. Trans Tech Publ. Ltd, vol. 225, pp. 338–343,.

[7] W. Chen and C. Modeling, 2009, Application of Numercal Simulation to Obtain the Optimization Pitch Angle for VAWT, in 2009 World Non-Grid-Connected Wind Power and Energy Conference, Nanjing, China, pp. 1–5.

[8] I. Paraschivoiu, O. Trifu, and F. Saeed, 2009, H-Darrieus wind turbine with blade pitch control, Int. J. Rotating Mach., vol. 2009, doi: 10.1155/2009/505343.

[9] M. Islam, D. S. K. Ting, and A. Fartaj, 2008, Aerodynamic models for Darrieus-type straight-bladed vertical axis wind turbines, Renew. Sustain. Energy Rev., vol. 12, no. 4, pp. 1087–1109, doi: 10.1016/j.rser.2006.10.023.

[10] J. Sargolzaei, , 2007, Prediction of the power ratio and torque in wind turbine Savonius rotors using artificial neural networks, Lect. Notes Energy Environ., vol. 1, no. 2, pp. 7–12.

[11] A. Hossain, A. Rahman, M. Rahman, S. Hasan, and J. Hossen, 2009, Prediction of power generation of small scale vertical axis wind turbine using fuzzy logic, J. Urban Environ. Eng., vol. 3, no. 2, pp. 43–51, doi: 10.4090/juee.2009.v3n2.043051.

[12] L. C. Rajesh Bhaskaran, Introduction to CFD Basics. [Online]. Available: http://www.erac.ntut.edu.tw/ezfiles/39/1039/img/832/3-1-00001-intro FiniteDifference.pdf.

[13] G. Abdalrahman, W. Melek, and F.-S. Lien, , 2017, Pitch angle control for a small-scale Darrieus vertical axis wind turbine with straight blades (H-Type VAWT), Renewable Energy. vol. 114, Part B, pp. 1353-1362.

[14] D. Wood, 2011, Small Wind Turbines Analysis, Design, and Application, 2011th edition, 292 pages, Springer.

[15] Airfoil Tools, http://airfoiltools.com/index.

[16] NASA, 1988, 2DN00: 2D NACA 0012 Airfoil Validation Case.

[17] G. Abdalrahman, M. A. Daoud, W. W. Melek, F. S. Lien, and E. Yee, , 2022, Design and Implementation of an Intelligent Blade Pitch Control System and Stability Analysis for a Small Darrieus Vertical-Axis Wind Turbine, Energies, vol. 15, no. 1, doi: 10.3390/en15010235.

[18] and G. K. M. El Badawe, Mohamed, Tariq Iqbal, 2012, Optimization and modeling of a stand-alone wind/PV hybrid energy system, in 25th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE). IEEE, pp. 12–17.

[19] E. B. Muhando, T. Senjyu, A. Uehara, T. Funabashi, and C. H. Kim, , 2009, LQG design for megawatt-class WECS with DFIG based on functional models' fidelity prerequisites, IEEE Trans. Energy Convers., vol. 24, no. 4, pp. 893–904, doi: 10.1109/TEC.2009.2025338.

[20] M. M. Hand, , 1998, Variable-Speed Wind Turbine Controller Systematic Design Methodology: A Comparison of Non-Linear and Linear Model- Based Designs, no. July. p. 117.

[21] S. Mohanty, , 2009, Artificial neural network based system identification and model predictive control of a flotation column, J. Process Control, vol. 19, no. 6, pp. 991–999.

[22] and Y. C. Al Seyab, R. K., , 2008, Nonlinear system identification for predictive control using continuous time recurrent neural networks and automatic differentiation, J. Process Control, vol. 18, no. 6, pp. 568–581.

[23] and Y. N. Funahashi, Ken-ichi, 1993, Approximation of dynamical systems by continuous time recurrent neural networks, Neural networks, vol. 6, no. 6, pp. 801–806.

[24] and C. W. D. S. Karray, Fakhreddine, Fakhreddine O. Karray, 2004, Soft computing and intelligent systems design: theory, tools, and applications. Pearson Education.