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Advanced Control Strategies for Blade Angle Regulation in Rotational Energy Systems

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استراتيجيات تحكم متقدمة لتنظيم زاوية الشفرة في أنظمة الطاقة الدورانية

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Abstract:
The rapid worldwide shift to sustainable energy has established wind turbines as an essential element of the renewable energy framework. The unpredictable nature of wind speeds and the nonlinear aerodynamic difficulties associated with turbine operation provide considerable hurdles for traditional control systems, especially in attaining optimum power extraction and ensuring structural durability. This research examines the creation of an adaptive, resilient pitch control system aimed at improving wind turbine efficiency under variable climatic situations. A detailed mathematical model of wind turbine dynamics is provided, including aerodynamic, mechanical, and pitch-actuator elements. A comparative performance comparison is undertaken between a traditional Proportional-Integral-Derivative (PID) controller adjusted using the Ziegler-Nichols technique and an intelligent Fuzzy Logic Controller (FLC). Simulation findings indicate that while the PID controller eradicates steady-state error, it is hindered by restricted adaptability to dynamic operating circumstances, displaying an 11.8% peak overshoot and a settling time of 32 seconds. The suggested Fuzzy Logic Controller decreases the delay time to 2.5 seconds, the settling time to 19 seconds, and successfully removes peak overshoot while maintaining zero steady-state error. The findings validate that a heuristic, rule-based fuzzy architecture provides a computationally efficient and pragmatic alternative to model-based and deep-learning control algorithms for wind turbine pitch adjustment.

Keywords: Wind turbine, pitch control, PID controller, Fuzzy Logic Controller, Ziegler-Nichol's tuning, renewable energy, blade angle regulation.

الملخص
أدى التحول العالمي السريع نحو الطاقة المستدامة إلى ترسيخ مكانة توربينات الرياح كعنصر أساسي في منظومة الطاقة المتجددة. وتُشكل طبيعة سرعات الرياح غير المتوقعة والصعوبات الديناميكية الهوائية غير الخطية المرتبطة بتشغيل التوربينات تحديات كبيرة لأنظمة التحكم التقليدية، لا سيما في تحقيق استخلاص الطاقة الأمثل وضمان متانة الهيكل. يبحث هذا البحث في إنشاء نظام تحكم تكيفي ومرن في زاوية ميل الشفرات، بهدف تحسين كفاءة توربينات الرياح في ظل ظروف مناخية متغيرة. ويُقدم نموذج رياضي مفصل لديناميكيات توربينات الرياح، يشمل العناصر الديناميكية الهوائية والميكانيكية وعناصر مشغل زاوية ميل الشفرات. كما تُجرى مقارنة أداء بين وحدة تحكم تقليدية من نوع التناسب والتكامل والتفاضل *(PID)* مُعدلة باستخدام تقنية زيغلر-نيكولز، ووحدة تحكم ذكية من نوع المنطق الضبابي *(FLC)*. تشير نتائج المحاكاة إلى أنه على الرغم من قدرة وحدة التحكم *PID* على إزالة خطأ الحالة المستقرة، إلا أنها تعاني من محدودية التكيف مع ظروف التشغيل الديناميكية، حيث تُظهر تجاوزًا ذرويًا بنسبة 11.8% وزمن استقرار يبلغ 32 ثانية. أما وحدة التحكم المنطقية الضبابية المقترحة، فتُقلل زمن التأخير إلى 2.5 ثانية، وزمن الاستقرار إلى 19 ثانية، وتُزيل التجاوز الذروي بنجاح مع الحفاظ على خطأ صفري في الحالة المستقرة. وتؤكد هذه النتائج أن بنية ضبابية قائمة على القواعد، تعتمد على

الاستدلال، تُوفر بديلاً فعالاً من الناحية الحسابية وعمليًا لخوارزميات التحكم القائمة على النماذج والتعلم العميق لضبط زاوية ميل شفرات توربينات الرياح.

الكلمات المفتاحية: توربينات الرياح، التحكم في زاوية الميل، وحدة تحكم*PID* ، وحدة تحكم منطقية ضبابية، ضبط زيغلر-نيكولز، الطاقة المتجددة، تنظيم زاوية الشفرات.

IntroductionWind energy has gained appeal as a source of clean and sustainable energy in recent years. Wind turbine control systems are essential for the efficient and safe operation of these complex machines. Pitch control is a basic method used for the change of the blade angle, which allows control of power output and safe operation in various wind conditions [1], [2].
The present study is aimed at improving wind turbine pitch control via the use of two major techniques; Proportional-Integral-Derivative (PID) control and Fuzzy Logic control. PID controllers are common in industry because they are simple and effective for systems with well-defined mathematical models. Fuzzy Logic controllers are better suited for systems with uncertainty or nonlinearity, like wind turbines working under stochastic wind conditions [3], [4].
Wind turbine control has various persistent issues including varying and irregular wind conditions, aerodynamic nonlinearity, coupled multi-input multi-output dynamics of the rotor, drivetrain and generator, turbulence and wake effects, mechanical wear and sensor noise. The conventional PID-based pitch control is widely used in industrial applications, but often lacks flexibility in these applications [1], [5].

The objective of this study is to design, model and compare a classical PID pitch controller with an intelligent Fuzzy Logic pitch controller for a horizontal-axis wind turbine. The comparison is based on the standard time-domain metrics: delay time, rise time, settling time, peak overshoot, and steady-state error.

RELATED WORK

Recent research indicates a significant inclination towards intelligent and hybrid pitch control methodologies. Zhou et al. [6] proposed an Input–Output Model-Free Adaptive Control (IO-MFAC) system that reduced generator power variations by 16.2% and speed fluctuations by 33.3% relative to conventional PI control, validated on a FAST 5 MW model. Nabeel et al. [7] introduced a Fuzzy Deep Deterministic Policy Gradient (F-DDPG) controller that amalgamates six reinforcement-learning agents with a fuzzy inference layer, enhancing speed regulation while incurring substantial training and computational demands.

Le Fouest and Mulleners [8] employed a genetic algorithm to optimize the pitch control of individual blades on vertical axis turbines, resulting in a threefold enhancement in power coefficient and a 77% reduction in structural load variations, albeit at the expense of heightened mechanical complexity due to the incorporation of multiple actuators. Stabilization may be achieved exclusively by the incorporation of the mathematical linearization phase, as shown by Karami-Mollaee and Barambones [9], who combined Taylor-series state-feedback linearization with Fractional Particle Swarm Optimization (FPSO). Antonysamy and Joo [10] proposed Generalized Predictive Control for large-scale, fault-prone turbines, while Ameli and Anubi [11] introduced hierarchical fault-tolerant control for the same kind of turbines. Habibi et al. [12] utilized a Barrier Lyapunov Function in conjunction with a Nussbaum-type compensator to constrain sensor-free pitch regulation, whereas Velino et al. [13] implemented genetic-programming-based machine learning control for floating offshore turbines, achieving a fatigue load reduction of approximately 41%. Narayanan et al. [14] and Goyal et al. [15] investigated machine-learning-enhanced and neuro-fuzzy-optimized PID hybrids, respectively, for digital hydraulic and horizontal-axis pitch systems.

A prevalent trend across this body of work is that substantial improvements in tracking and load reduction are often achieved just by the use of deep learning training pipelines, precise mathematical linearization, or specialized multi-actuator hardware. This prompts the present study to use a minimal heuristic Fuzzy Logic approach that removes these dependencies while maintaining competitive transient performance.

WIND TURBINE MODELING

A. Aerodynamic Power and the Betz Limit

The power extracted from an air mass by a turbine rotor of swept area A at wind speed v is

$P = \frac{1}{2}\rho A v^3$……………………………………………………………………………………………..………(1)

where ρ is air density. Betz's Law establishes that no turbine can convert more than 59.3% of the kinetic energy available in the wind, owing to conservation of mass and energy across the rotor disk [2].

The power coefficient Cp depends on the tip-speed ratio λ and pitch angle β as

$Cp(\lambda, \beta) = c1[c2/\beta i - c3\beta - c4\beta^x - c5]e^{(-c6/\beta i)}$ ……………………………………………………………..(2)

$\lambda = \omega R / v$…………………………………………………………………………………………………...(3)

where R is blade radius, ω is rotor angular velocity, and c1–c6 and x are turbine-specific coefficients. Maximum Cp is obtained at zero pitch angle; increasing β reduces the angle of attack, lift force, and consequently rotor speed and output power once rated wind speed is exceeded.

B. Pitch Actuator and Drivetrain Dynamics

The pitch actuator responds to a pitch demand βd with first-order dynamics:

$d\beta/dt = (\beta d - \beta) / T\beta \Rightarrow \beta/\beta d = 1 / (T\beta s + 1)$…………………………………………………………………...(4)

The drivetrain, modeled from Newton's second law with inertia J and damping B, yields the transfer function

$W(s)/T(s) = 1 / (Js + B) = (1/B) / [(J/B)s + 1]$…………………………………………………………………...(5)

Using the turbine parameters (B = 2 N·m/rad/s, $J = 0.75$ kg·m^2), the drivetrain reduces to

$W(s)/T(s) = 0.5 / (0.375s + 1)$………………………………………………………………………………..(6)

The pitch actuator (time constant 0.37 s) and drivetrain (time constant 0.5 s) transfer functions were cascaded in Simulink to form the plant used for controller design and simulation, with a transport delay representing sensor and communication latency.

CONTROLLER DESIGN

A. PID Controller — Ziegler–Nichols Tuning

The PID control law is

$u(t) = Kp\, e(t) + (Kp/Ti)\int e(t)dt + Kp\, Td\, de(t)/dt$ ………………………………………………………………..(7)

Gains were obtained via the Ziegler–Nichols closed-loop method, in which the proportional gain is increased until sustained oscillation occurs at critical gain Kcr and critical period Tcr, giving Kp = 0.6Kcr, Ti = 0.5Tcr, Td =

0.125Tcr [16], [17]. For the plant model above this produced Kp ≈ 1.298, Ti ≈ 0.414 s (integral gain), and Td ≈ −2.183 s, with filter coefficient N ≈ 0.158.

B. Fuzzy Logic Controller

The proposed FLC uses a Mamdani inference structure with two inputs — pitch error e and change in error Δe — and three outputs corresponding to adaptively scheduled PID gains Kp, Ki, and Kd, following the fuzzy-adaptive-PID structure

Kp = Kp(pid) + [Kpf(fuzzy)·Kp(pid)] …………………………………………………………………………..(8)

Ki = Ki(pid) + [Kif(fuzzy)·Ki(pid)]…………………………………………………………………………..(9)

Kd = Kd(pid) + [Kdf(fuzzy)·Kd(pid)]……………………………………………………………………….(10)

Both inputs and all three outputs use seven Gaussian membership functions defined over the linguistic term set {NB, NM, NS, ZO, PS, PM, PB} (Negative Big … Positive Big), spanning the normalized universe of discourse

[−5, 5]. A 7×7 rule base (49 rules per output) maps error and change-in-error combinations to the required gain adjustment, and outputs are defuzzified using the centroid method [18], [19].

SIMULATION RESULTS

All three configurations — uncontrolled plant, PID-controlled plant, and Fuzzy-controlled plant — were simulated in MATLAB/Simulink under a unit-step pitch-angle reference.

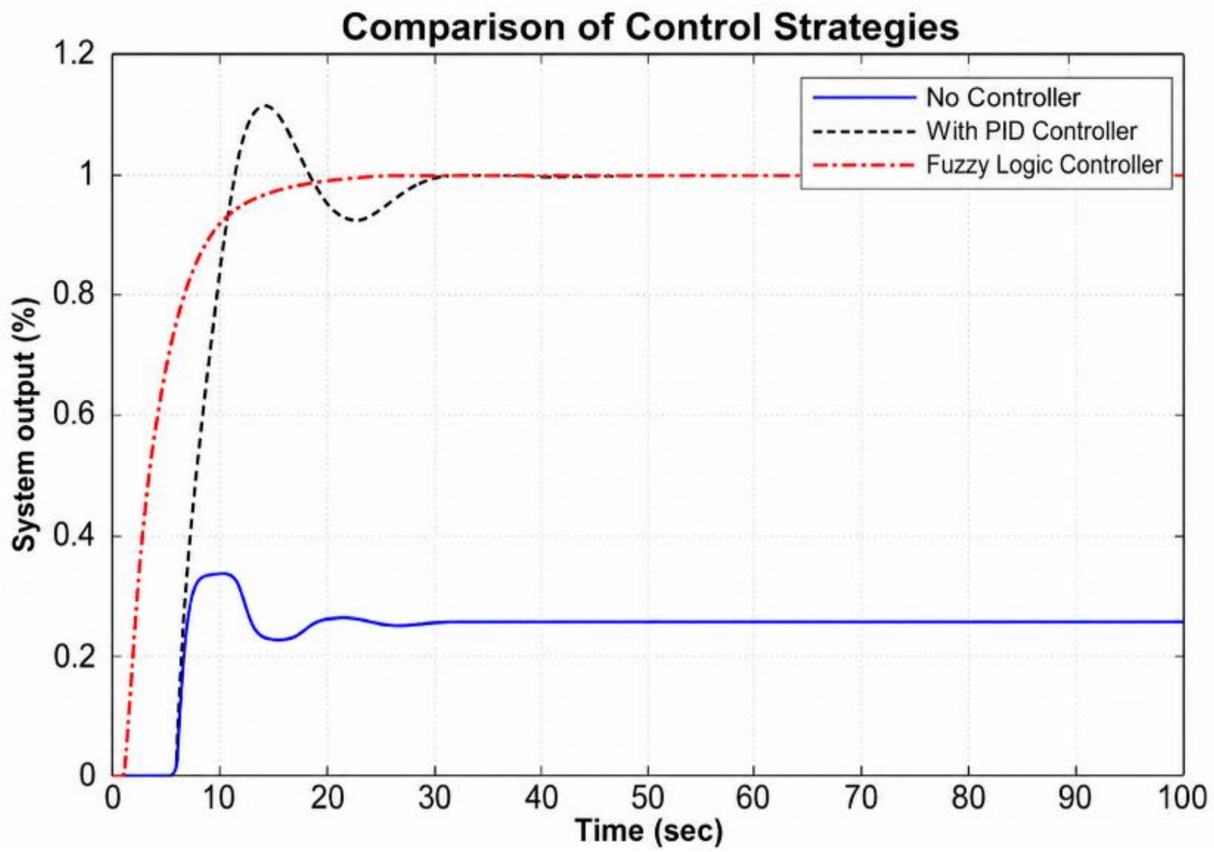

Figure 1. Time-Domain Specifications for all methods.

Table 1 summarizes the extracted time-domain specifications.

Table 1 Comparison of Time-Domain Specifications

Specification	No Controller	PID	Fuzzy
Delay time (s)	6.8	8.5	2.5
Rise time (s)	8.0	10.5	8.0
Settling time (s)	28	32	19
Peak overshoot (%)	32.157	11.8	0
Steady-state error	0.75	0	0

The unmanaged plant has a significant 32.2% overshoot and a notable steady-state inaccuracy of 0.75, underscoring the necessity for active pitch control. The Ziegler–Nichols-tuned PID controller eradicates steady-state error and reduces overshoot to 11.8%, but resulting in an extended settling period of 32 seconds and a somewhat slower reaction to initial disturbances. The Fuzzy Logic Controller attains the shortest delay time (2.5 s) and settling time (19 s) among the three configurations, effectively eliminating overshoot and ensuring zero steady-state error. This demonstrates a more refined, well-damped transient response, resulting in diminished mechanical stress on the pitch actuator and blade root.

The results align with the prevailing literature indicating that fuzzy and adaptive strategies surpass fixed-gain linear controllers in the nonlinear, disturbance-prone conditions characteristic of wind turbine operation, while circumventing the training demands of deep reinforcement learning and the stringent model linearization prerequisites of optimization-based methods.

CONCLUSION

This paper presents a comparison of the performance of PID and Fuzzy Logic pitch controllers for a horizontal-axis wind turbine, based on a detailed aerodynamic, actuator and motor model. The simulation results reveal that the Ziegler–Nichols-tuned PID controller successfully eliminates the steady-state error, but the constant gains constrain its adaptability to the nonlinear, stochastic nature of the plant. This is shown by the 11.8% overshoot and a settling time of 32 seconds. The proposed Mamdani-type 49-rule adaptive gain scheduling Fuzzy Logic Controller improved delay time by 71% compared to the PID design, reduced the settling time by 41%, and eliminated overshoot while requiring only heuristic rule-based computation, instead of deep learning or explicit model linearization. These findings validate the Fuzzy Logic Controller as a promising and feasible implementation for enhancing the pitch control of wind turbines, power quality and structural robustness. This technique will be extended to Interval Type-2 fuzzy sets in future research to boost robustness against measurement noise, provide hardware-in-the-loop validation, and optimize coordinated multivariable pitch-yaw control.

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