System Identification and Control of a Wind Turbine System Using Model Predictive Control

J.D. Molina, M. Santos, and J.E. Sierra-García

Abstract— **This paper addresses the problem of rotor speed regulation in wind turbines operating above rated wind speed through pitch control. A Model Predictive Control (MPC) scheme based on local Autoregressive Exogenous (ARX) models is proposed. The key contribution lies in the explicit incorporation of wind speed as a modeled disturbance within the prediction model, enabling the controller to anticipate and mitigate exogenous variations proactively. The performance of the proposed controller is evaluated against a conventional Proportional-Integral-Derivative (PID) controller tuned via the Internal Model Control (IMC) method with a 4T filter ($K_p = 0.179$ and $K_i = 0.31$). Simulation results across the wind turbine's distinct operating regions demonstrate that the MPC consistently outperforms the PID benchmark, achieving lower Integral Absolute Error (IAE) under variable wind conditions, with reductions of 80% on average. Furthermore, the MPC delivers notably smoother control actions and a reduced tendency to saturate the pitch actuator, indicating significant potential for mitigating mechanical loads. These results demonstrate the value of advanced, model-based predictive strategies for enhancing the autonomy and reliability of wind energy conversion systems and establish a practical foundation for the extended application of MPCs across full operating envelopes.**

I. INTRODUCTION

The global expansion of wind energy, particularly into offshore installations, has intensified the demand for highly autonomous and reliable control systems [1]. Wind turbines operating in remote locations require controllers capable of maintaining performance under significant exogenous disturbances while minimizing mechanical stress [2]. Within this context, generator speed regulation represents a fundamental control challenge due to the inherently nonlinear aerodynamics of the rotor and the stochastic nature of wind disturbances [3].

Conventional approaches to wind turbine control have predominantly relied on Proportional-Integral-Derivative (PID) controllers, valued for their simplicity, previous application to the system [4] and established tuning methodologies such as Internal Model Control (IMC) [5]. However, the limitations of linear feedback controllers in handling strong nonlinearities and variable disturbances have motivated the exploration of advanced strategies, such as sliding mode control [6], adaptative control for both pitch [7] and torque [8], and, specially, Model Predictive Control (MPC), which has emerged as a promising alternative due to its ability to handle multivariable interactions, incorporate constraints, and exploit preview information of disturbances [9].

Previous research has demonstrated the potential of MPC for wind turbine applications [10]. Kumar and Stol [11] proposed a scheduled MPC approach using linearized models derived from FAST simulations. More recently, Klein [12] presents a validation on a full-scale WT of a control strategy that combines an extended Kalman filter for nonlinear state estimation with robust linear time-varying MPC under real conditions. The paper by Li et al. [13] proposes a data-driven Model Predictive Control (MPC) for wind turbine control for fore-aft tower bending mitigation using a rectified linear unit (ReLU) neural network to suppress fore-aft tower bending. Soliman et al. [14] present a data-driven model predictive control to improve active power regulation for a variable-speed, variable-pitch wind turbine that is compared with the conventional Multiple Model Predictive Control strategy. While effective, such methodologies rely on specialized linearization routines that are not easily transferable to systems identified purely from empirical data. This limitation motivates the need for data-driven modeling approaches that can be implemented using standard system identification techniques.

This paper addresses this gap by presenting a MISO MPC controller for rotor speed regulation using pitch actuation only. The key innovation lies in the explicit incorporation of wind speed as a modeled disturbance within local ARX models identified from input-output data. This structure enables the controller to anticipate wind variations rather than react to them, contrasting with traditional feedback-only approaches.

The main contributions of this work are threefold: (i) a systematic methodology for identifying ARX models that incorporate wind as an exogenous input across distinct operating regions; (ii) a comparative evaluation demonstrating that the proposed MPC consistently outperforms a well-tuned IMC-based PID controller; and (iii) an analysis showing that performance improvements arise from disturbance modeling

[1]*Research supported by the Spanish Ministry of Science and Innovation under the projects MCI/AEI/FEDER number PID2021-123543OB-C21 and PID2024-155653OB-C21.

Juan D. Molina González is with Complutense University of Madrid, Spain. juandm04@ucm.es.

Matilde Santos is with Institute of Knowledge Technology, Complutense University of Madrid, Spain, msantos@ucm.es.

Jesús Enrique Sierra-García Department of Digitalization, University of Burgos, Burgos, Spain, jesierra@ubu.es.

rather than aggressive tuning, with benefits including smoother actuation and reduced saturation.

The remainder of this paper is organized as follows: Section II presents the wind turbine mathematical model and details the operating region analysis. Section III explains the MPC formulation and implementation, and the ARX model identification procedure. Section IV presents comparative results against the PID benchmark. Finally, Section V concludes and discusses future research directions.

II. Mathematical Model of the Wind Turbine

The mathematical model used as the base for the development of the control is based on the work of Sierra-Garcia and Santos [15], which presents a theoretical approach to the modelling of a 7 KW wind turbine. This model serves as the base for proving the concept of the applicability of the proposed control, which, upon success, shall be applied to more complex models.

The model defines the mechanical torque, which sets the rotor torque as a function of the power coefficient (C_p), air density, turbine-blade swept area, wind speed, and angular rotor speed. Additionally, the pitch actuator is modelled as a second-order system, which is a common assumption to model pitch systems in wind turbines and other mechanical actuators.

Finally, the model introduces the combination of the mechanical and electrical domains as part of the dynamics of the generator, which is done by the presentation of the relationship between the rotor speed and the mechanical torque in a continuous current generator.

The previous, put in mathematical terms, means that the turbine is modeled as a rotor with inertia J, subjected to the aerodynamic torque T_m, the generator electromagnetic torque T_{em}, and friction:

$$J\frac{d\omega}{dt} = T_m - T_{em} - K_f\omega \tag{1}$$

The electromagnetic torque T_{em} is calculated using a DC generator model, defined by the parameters: R_a (armature resistance), L_a (armature inductance), K_g (dimensionless generator constant), and K_{phi} (electromagnetic flux constant):

$$T_{em} = K_g K_{phi} I_a \tag{2}$$

$$L_a\frac{I_a}{dt} = E_a - V - R_a I_a \tag{3}$$

$$E_a = K_g K_{phi}\omega \tag{4}$$

$$\dot{I}_a = \frac{1}{L_a}(K_g K_{phi}\omega - (R_a + R_L)I_a) \tag{5}$$

On the other hand, the aerodynamic torque T_m (eq. 6) is calculated from the maximum wind power in the section A swept by the rotor, reduced by an efficiency factor C_p. This coefficient can be modeled using empirical expressions (eqs. 8, 9) as a function of the blade pitch angle θ and the tip-speed ratio λ (eq. 7).

$$T_m = \frac{C_p(\lambda,\theta)\rho A v^3}{2\omega} \tag{6}$$

$$\lambda = \frac{\omega R}{v} \tag{7}$$

$$\lambda_i(\lambda,\theta) = [\frac{1}{\lambda + c_8} - \frac{c_9}{\theta^3+1}] \tag{8}$$

$$C_p(\lambda_i,\theta) = c_1[\frac{c_2}{\lambda_i} - c_3\theta - c_4\theta^{c_5} - c_6]e^{c_7/\lambda_i} \tag{9}$$

Finally, the only modification to the implemented model relative to the reference article is the blade dynamics model, implemented as a first-order system with saturation of the derivative, to account for nonlinear limitations.

$$\theta' = max(-\theta'_{max}, min(\theta'_{max}, \frac{1}{\tau_\theta}(\theta_{ref} - \theta))) \tag{10}$$

A. Operating Regions

The studied turbine model presents nonlinear dynamics in which the influence of pitch on the generator is strongly dependent on the wind speed.

From the Electric Power vs Wind Speed plot, three operating regions are identified:

- Region R1 (3–7 m/s): low wind, low pitch authority.
- Region R2 (7–10 m/s): medium wind, transition.
- Region R3 (10–14.5 m/s): high wind, active pitch control.

Fig. 1 shows the Electric Power vs Wind Speed plot obtained at steady-state conditions, which justifies the separation into these three regions.

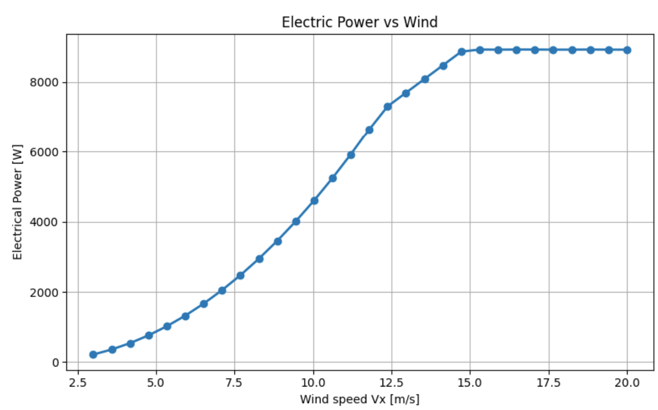

Figure 1. Electric Power vs Wind

This separation supports the application of linear models for each region as the base for the proposed MPC.

Additionally, the system's nonlinearity can be observed in how the pitch gain changes as wind disturbs the system. This behavior is summarized in Fig. 2.

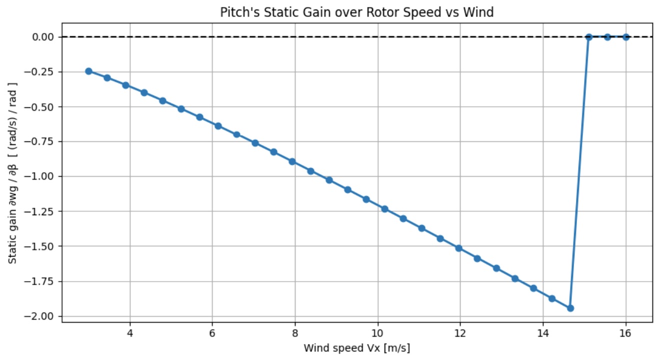

Figure 2. Static gain of pitch over rotor speed as a function of the wind speed.

III. MPC CONTROLLER

This article proposes a Multiple Input Single Output (MISO) Model Predictive Control (MPC), which aims to allow for a softer and more accurate control of the wind turbine when the system is exposed to variable wind. The structure of the implementation of the proposed control is summarized in Fig. 3.

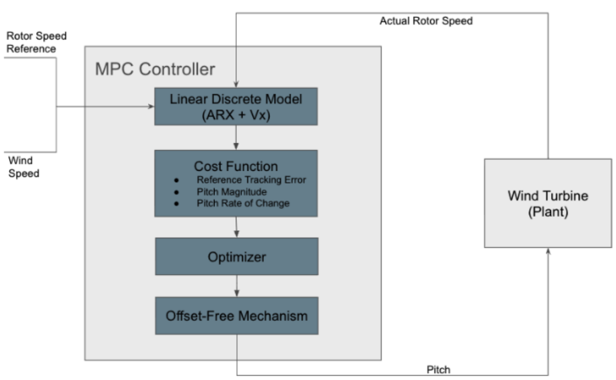

Figure 3. Referential Diagram for the Controller Design

The proposed control scheme is based on a linear model that is used for the prediction of the system dynamics. Such a model considers two inputs: the pitch, which is the manipulated variable in the controller design, and the wind speed, which is the main disturbance variable for the system. The only output for the proposed controller is the rotor speed.

The controller also has an optimizer, which is the piece responsible for defining the most appropriate control output at a given point in time based on a series of criteria. For the purpose of this research, an objective function that penalizes both the error from a reference and the control effort was carved and included variable coefficients that allow for the tuning of the scheme when implemented over slightly different systems.

The objective function of the optimizer is shown below as a function of the prediction horizon (N_p), the control horizon (N_c), the predicted and reference rotor speed ($\widehat{\omega}_k$ and ω_k^{ref}), and the controller action (u_k); along with weights that penalize the reference tracking error (Q_e), the controller effort (R_u), and its rate of change ($R_{\Delta u}$).

$$J = \sum_{k=0}^{N_p-1} Q_e(\widehat{\omega}_k - \omega_k^{ref})^2 + \sum_{k=0}^{N_c-1}(R_u u_k^2 + R_{\Delta u}(u_k - u_{k-1})^2) \quad (11)$$

Additionally, the proposed MPC includes an offset-free mechanism, which seeks to eliminate stationary errors due to small plant model mismatch. This type of mechanism is a key feature in most commercial industrial process control tools, as it allows the use of slightly inaccurate models, which are often the most reliable ones obtainable from real system step testing. This addition aims to make the proposal robust enough for real-world applications.

The offset-free mechanism uses the residual between the prediction and the actual value, to which a compensation term is added to account for the plant-model mismatch. Such a compensation term is adjusted in each iteration and has a tunable parameter that sets the speed of such adjustment.

$$\hat{y}_{corrr}(k) = \hat{y}(k) + \hat{d}(k) \quad (12)$$

$$\hat{d}(k+1) = \hat{d}(k) + L_d[y(k) - \hat{y}_{corrr}(k)] \quad (13)$$

The controller also incorporates physical restrictions imposed by the system's mechanics, ensuring that the control actions are executable. Such restrictions are the following:

- The pitch needs to be between 0 and 90°.
- The pitch rate cannot be higher than 5°/s.

It is worth noting that the proposed scheme is identical for the three identified regions; then, the specific model to be used is an input to the simulation.

For reproducibility the configuration of the MPCs is presented on the table below.

TABLE I. MPC CONFIGURATION

Parameter	Symbol	Value	Description
Sampling time	Ts	0.2	Controller sampling period
Prediction horizon	Np	30	Number of prediction steps
Control horizon	Nc	10	Number of optimized control moves
Tracking weight	Qe	250	Output tracking penalty
Integral weight	Qi	10	Integral error penalty
Absolute input weight	Ru	0	Control effort penalty
Incremental input weight	Rdu	0.01	Penalty on control variation
Feedforward weight	Rff	0.3	Wind feedforward contribution
Offset-free gain	Ld	0.25	Gain of the offset-free observer

Finally, in terms of stability, although a formal Lyapunov proof is not developed in this study, the proposed MPC is expected to be locally stabilizing around each operating point.

Traditional MPC theory shows that the objective function or optimal cost can be interpreted as a Lyapunov-function candidate, with formal guarantees typically obtained through terminal stabilizing terms [16]. Similar stability-oriented MPC formulations have also been applied to wind-turbine control [17]. In this work, stable local models, a positive-definite tracking objective, penalties on pitch effort and rate, and hard actuator constraints promote convergence toward the equilibrium while avoiding excessively aggressive control actions. Hence, the closed-loop behavior is considered consistent with a local Lyapunov-stability interpretation, although a rigorous proof would require explicit terminal conditions.

A. Lineal Model Identification

In a first iteration, model identification was carried out for a SISO system, using local ARX structures around different operating points, considering only the pitch angle as the single input and the rotor speed as the output. Although these models exhibited an excellent fit rate during identification (fit values above 97%), it was later observed that their predictive capability in closed loop was limited under significant wind variations, being unable to reject the associated disturbances.

The main cause of the observed limitations was primarily due to treating wind as an unmodeled disturbance, leaving its management solely to the offset-free mechanism. This approach resulted in a reactive behavior of the designed controller, which led to compensation of dynamics not represented in the models. The main consequence of this approach was worse performance than that of a well-tuned PID, which does not justify the use of a more complex control strategy such as MPC.

The second and current iteration of the identification methodology introduced several fundamental changes compared to the initial version, leading to improved control compared to what was previously observed. These modifications are presented below.

- Explicit inclusion of wind as an exogenous input.
- Incremental identification around real equilibria.
- Robust delay selection.

For model identification, the system was excited with Pseudorandom Binary Sequences (PRBSs) that respected the physical limitations of the pitch. The plant was also subjected to input signals that modified the wind speed.

Using the obtained data, discrete ARX models were identified for each region. The orders and delays were selected through cross-validation, prioritizing low-order models with a good fit.

The models followed the general equation below:

$$\Delta\omega[k] = \sum_{i=1}^{n_a} a_i \Delta\omega[k-i] + \sum_{j=1}^{n_b} b_j \Delta\beta[k-(n_k+j-1)] + \sum_{m=1}^{n_g} g_m \Delta V_x[k-(n_v+m-1)] \quad (14)$$

For all the models, the final orders were: $n_a = 2$, $n_b = 2$, $n_k = 1$, $n_g = 2$ and $n_v = 0$.

The following figures (Fig. 4-6) show the validation results of the models against real data, where a satisfactory fit (high fit value) is observed for all regions in which identification was performed. The real signal is presented in blue and the obtained one in red. This color code is kept along all these figures. In these figures, a fit percentage greater than 99.5% and an RMSE/peak lower than 0.4% can be observed, results that, in the absence of overfitting, make satisfactory closed-loop control expected.

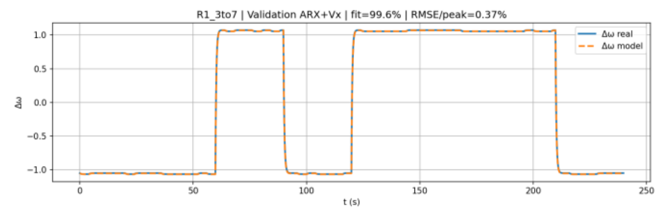

Figure 4. Validation of the identified model for Region 1.

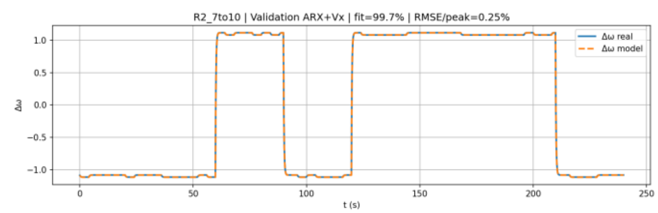

Figure 5. Validation of the identified model for Region 2.

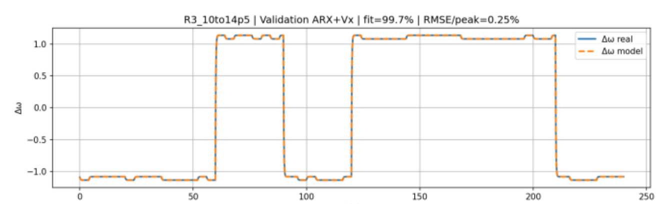

Figure 6. Validation of the identified model for Region 3.

IV. Results Discussion

The proposed controlled scheme based on the previously identified linear models was compared to a well-tuned PID controller, whose tuning parameters were determined through the Internal Model Control (IMC) tuning method [4] with a 4T filter, which led to the following tuning: $K_p = 0.179$ and $K_i = 0.31$.

One test scenario was run for each region with a sinusoidal wind acting as the main disturbance to the system. To guarantee a meaningful comparison, reachable references were defined for each scenario so that the controllers would not cause the actuator to saturate.

The results for each scenario are summarized in Fig. 7-9 for regions 1, 2 and 3, respectively.

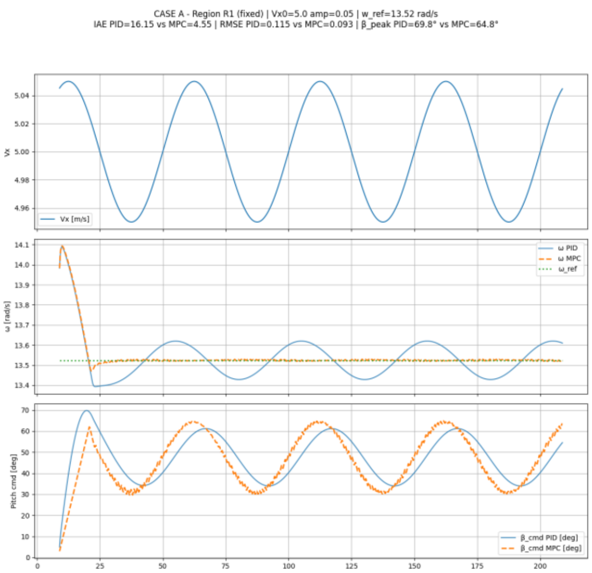

Figure 7. Results of the comparison MPC vs PID for Region 1.

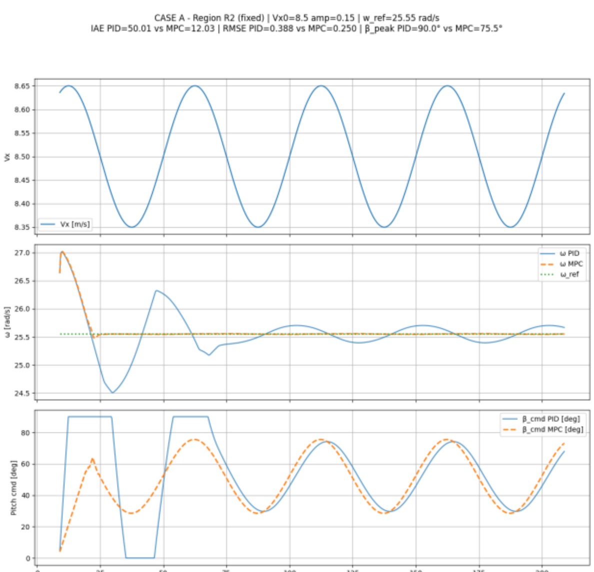

Figure 8. Results of the comparison MPC vs PID for Region 2.

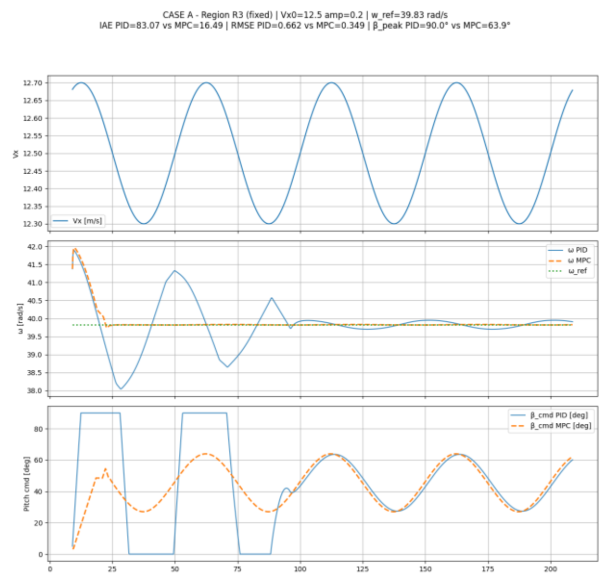

Figure 9. Results of the comparison MPC vs PID for Region 3.

It is consistently observed that the MPC achieves lower integral error (IAE) than the PID in all individual scenarios. Additionally, it does so with the following benefits:

- It keeps pitch within more reasonable ranges than the PID; that is, it has a lower tendency to saturate the actuator.
- It applies less aggressive actions on pitch, which is beneficial when mechanical loads are considered.

This behavior is clearly seen in the pitch peaks shown in the figures, where the PID reaches 90° while the MPC remains well below.

In response to the tendency of the pitch to saturate under the established PID tuning, a small experiment was run with a detuned controller, a common industry practice to prevent overshooting and saturation due to the aggressiveness of the integral action. As expected, this resulted in a slightly worse reference tracking but with less saturation, and ultimately a still inferior performance when compared to the proposed MPC.

V. Conclusions and Future Work

This paper has presented the design, implementation, and evaluation of a Model Predictive Control scheme for wind turbine rotor speed regulation based on local ARX models that explicitly incorporate wind speed as a modeled disturbance. The key findings and contributions are summarized below.

The simulation results demonstrate that the proposed MPC consistently outperforms a well-tuned IMC-based PID controller across all three defined operating regions. The performance superiority is evidenced by lower Integral Absolute Error (IAE) values under variable wind conditions, with reductions of 80% on average, achieved while maintaining smoother control actions and reduced actuator saturation. Notably, the PID controller exhibited a tendency to drive the pitch to its saturation limit of 90°, whereas the MPC maintained operation within more moderate ranges.

A critical insight from this research is that the superior performance of the MPC does not stem from more aggressive tuning parameters. Rather, it originates from the explicit representation of wind speed as a modeled disturbance within the ARX structure. This formulation allows the controller to anticipate the steady-state effects of wind variations, enabling proactive compensation consistent with system physics. In contrast, the PID controller, treating wind as an unmodeled disturbance, must react to errors after they occur, inevitably leading to larger deviations and more aggressive corrective actions.

The main contributions of this work are: (i) a practical methodology for identifying ARX models from input-output data that incorporate wind as an exogenous input, validated across three distinct operating regions; (ii) experimental evidence that data-driven MPC can surpass traditional PID performance even with relatively simple linear models, provided disturbance dynamics are properly structured; and (iii) demonstration that performance improvements translate into operational benefits including reduced actuator saturation and smoother pitch actuation, which are directly relevant to mechanical load mitigation.

This study has been conducted using a simplified 7 kW turbine model. While useful for control algorithm validation, this model does not capture the full complexity of utility-scale turbine dynamics, particularly regarding structural flexibility and aerodynamic interactions.

Based on the findings presented, several directions for future research are identified: 1) Gain Scheduling Integration: Extend the current approach to incorporate a gain scheduling mechanism that enables seamless transition [18] between local models, allowing a single MPC controller to operate across the entire wind speed range; in such sense, different options should be considered for the transition between regions, being examples of those: (i) a direct transition with a hysteresis logic, and (ii) a linear combination of the individual MPC outputs near the boundaries [11]. 2) High-Fidelity Validation: Validate the proposed control strategy using more rigorous turbine models, such as OpenFAST, to assess performance under more realistic aerodynamic and structural conditions; this will also allow for a better assessment of the mechanical loads the system would be subject to under the proposed control scheme. 3) MIMO Extension: Develop a full MIMO formulation that incorporates additional control objectives, such as generator torque control, to achieve more comprehensive regulation across the entire turbine operating envelope. 4) Nonlinear Modeling Comparison: Investigate alternative methods for capturing nonlinear dynamics—including neural networks, LPV systems, or Wiener-Hammerstein structures and compare their performance against the linear ARX approach presented here. 5) Experimental Validation: Pursue hardware-in-the-loop or small-scale experimental validation to assess real-time implementation feasibility and practical challenges.

REFERENCES

[1] E. E. Ambarita, A. Karlsen, O. Osen, and A. Hasan, "Towards fully autonomous floating offshore wind farm operation & maintenance", *Energy Reports*, vol. 9, pp. 103-108, 2023.

[2] C. Serrano, J. E. Sierra-García, and M. Santos, M, "Hybrid optimized fuzzy pitch controller of a floating wind turbine with fatigue analysis", *Journal of Marine Science and Engineering*, vol. 10, no. 11, pp. 1769, 2022.

[3] P. Prajzendanc, and C. Kreischer, "A review of new technologies in the design and application of wind turbine generators", *Energies,* vol. 18, no. 15, pp. 4082, 2025.

[4] N. Rosmin, *Internal Model Control (IMC) design for a stall-regulated variable-speed wind turbine system*, Doctoral dissertation, Loughborough University, 2015.

[5] U. M. Nath, C. Dey, and R. K. Mudi, "Review on IMC-based PID controller design approach with experimental validations", *IETE Journal of Research*, vol. 69, no. 3, pp. 1640-1660, 2023.

[6] N. B. Son, T. U. Le Anh, M. T. Hai, and N. T. T. Vu, "Pitch angle control for variable speed wind turbine using fractional-order sliding mode control, *Journal of Engineering Science and Technology*, vol. 21, no. 1, pp. 66-83, 2026.

[7] H. Ren, Z. Zhe Tian, L. Han, S. Meng, and Y. Yang "Adaptive pitch control for power stabilization of floating offshore wind turbines" *Renewable Energy* 125392, 2026.

[8] M. Ganesh, and J. H. Jeong "A lightweight adaptive torque control of PMSG-based offshore wind turbines using a finite-step incremental search strategy for region-III operation under variable air density conditions", *Ocean Engineering* vol. 352, 124377, 2026.

[9] S. I. Khather, M. A. Ibrahim, and A. I. Abdullah, A. I., "Review and Performance Analysis of Nonlinear Model Predictive Control--Current Prospects, Challenges and Future Directions", *Journal Européen des Systèmes Automatisés*, vol. 56, no. 4, 2023.

[10] W. H. Lio, J. A. Rossiter, and B. L. Jones, "A review on applications of model predictive control to wind turbines". In *2014 IEEE Ukacc International Conference on Control,* 2024, pp. 673-678.

[11] A. Kumar, K. and Stol, "Scheduled Model Predictive Control of a Wind Turbine" in *47th AIAA Aerospace Sciences Meeting Including The New Horizons Forum and Aerospace Exposition* 5 - 8 January 2009, Orlando, Florida, 2009.

[12] A. Klein, T. Wintermeyer-Kallen, J. Zierath, K. Kluge, D. Abel, H. Vallery, and N. Basler, "Design and practical evaluation of robust model predictive wind turbine control", *Wind Energy*, vol. 28, no. 5, e70011, 2025.

[13] Z. Li, X. Wang, Q. Liu, and Y. Zhang, "Data-Driven MPC for Advanced wind turbine control considering load mitigation", in *International Conference on Computing, Intelligence and Data Analytics*, July 2024, pp. 203-219. Cham: Springer Nature Switzerland.

[14] Soliman, M., Tayyab, M., Metry, M., & Alqaisi, W. (2025, June). Improving Active Power Regulation for Wind Turbines: A Data-Driven MPC Approach. In 2025 IEEE 34th International Symposium on Industrial Electronics (ISIE) (pp. 1-6). IEEE.

[15] J. E. Sierra-García, and M. Santos, "Performance analysis of a wind turbine pitch neurocontroller with unsupervised learning" *Complexity* 4681767, 2020.

[16] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. M. Scokaert, "Constrained model predictive control: Stability and optimality", *Automatica*, vol. 36, no. 6, pp. 789–814, 2000.

[17] L. C. Henriksen, M. H. Hansen, and N. K. Poulsen, "Wind turbine control with constraint handling: A model predictive control approach", *IET Control Theory & Applications*, vol. 6, no. 11, pp. 1722–1734, 2012.

[18] Q. Hawari, T. Kim, C. Ward, and J. Fleming, "A robust gain scheduling method for a PI collective pitch controller of multi-MW onshore wind turbines", *Renewable Energy*, vol. 192, pp. 443-455, 2022.