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Wind Speed Forecasting for Pitch Control in Wind Turbines: A Comprehensive Review

Sanae Arkhouch [a,1,*], Ikrame Arrassi [a,2], Ilyass El Myasse [b,3], Faiza Dib [a,4], Nabil Benaya [a,5], Khaddouj Ben Meziane [c,6]

[a] LDRSI Laboratory, FST Al-Hoceima, Abdelmalek Essaadi University, Tetouan, Morocco
[b] LSIB Laboratory, FST Mohammedia, Hassan II University of Casablanca, Mohammedia, Morocco
[c] LDRSI Laboratory, ISGA Campus, Sidi Mohamed Ben Abdellah University, Fez, Morocco
[1] sanae.arkhouch@etu.uae.ac.ma; [2] ikrame.arrassi@etu.uae.ac.ma; [3] ilyass.elmyasse-etu@etu.univh2c.ma;
[4] fdib@uae.ac.ma; [5] nbenaya@uae.ac.ma; [6] khaddouj.benmeziane@yahoo.com
[*] Corresponding Author

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ABSTRACT

Wind energy is a pillar of the clean-energy transition, yet wind-speed variability remains a major challenge for wind turbine control. Blade pitch control is essential for safe operation and power regulation, but conventional strategies are mostly reactive and may struggle with gusts, nonlinear aerodynamics, and actuator limits. In above-rated conditions (wind speeds above the rated value, where pitching limits aerodynamic power), insufficient anticipation can increase structural loads, accelerate fatigue, and reduce power quality. Short-term wind speed forecasting offers a solution by providing feedforward information that complements feedback control and enables earlier disturbance rejection. However, existing reviews often examine wind forecasting and pitch control separately, limiting guidance for aligning forecasting design choices with pitch-control requirements. This review analyses how forecasting horizons, input data, latency constraints, and uncertainty characteristics can be aligned with pitch control objectives and real-time implementation requirements in turbines. Forecasting approaches are grouped into physical, statistical, AI-based, and hybrid methods, and pitch control strategies are discussed with emphasis on controllers integrating predictive signals. Across the reviewed studies, forecasting-informed pitch control is reported to deliver measurable gains, including up to 24% MSE reduction for enhanced PID schemes and around 40–45% reduction in power oscillations with forecast-driven MPC. Overall, integrating wind forecasts into pitch control can improve load mitigation and power regulation, provided that practical constraints and forecast uncertainty are explicitly addressed.

1. Introduction

Wind energy is crucial for its renewable, non-polluting nature and substantial energy potential, offering a sustainable response to the growing environmental challenges associated with conventional energy sources [1], [2]. It is also recognized for its reliability and its capacity to generate electricity on a large scale [3]–[5]. Furthermore, with significant advances in wind technology, this energy source is now more competitive than traditional energy sources in terms of cost. These advantages have

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encouraged many engineers to favor renewable energy resources [2].

Indeed, the wind energy sector has experienced notable growth in recent years, increasing from 17.4 GW in 2000 to 743 GW in 2020, with an average rate of about 12.6% per year. It was projected that this sector would provide 12% of the required electricity in 2020 [6]. According to the International Renewable Energy Agency (IRENA), this trend has continued and reached 898.856 GW by the end of 2022 [3].

In 2023, an additional growth of 108 GW was recorded, bringing the global installed capacity to 1008 GW [7]. Furthermore, according to the Global Wind Energy Council (GWEC), about 550 GW of new wind capacity is expected to be installed between 2023 and 2027, averaging 110 GW per year [3]. The rapid development of the sector has led to a total of over 250 000 wind turbines in operation worldwide [2].

Future estimates confirm this trend, with an expected installed capacity of 1787 GW in 2030 and 5044 GW in 2050 [8], and a share of wind in global electricity production estimated at 29.1% and then 34.2% [6]. Fig. 1 provides a schematic overview of the wind-to-electricity conversion chain and highlights where the blade pitch control system acts.

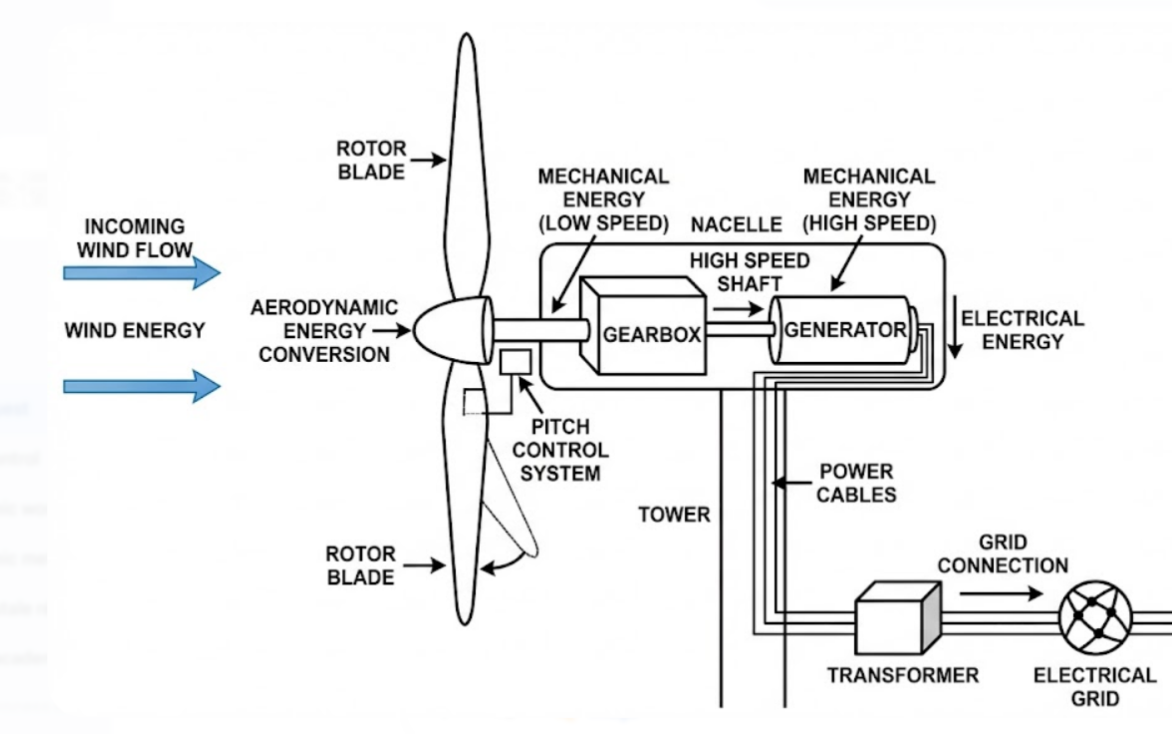

Fig. 1. Wind-to-electricity conversion process in a horizontal-axis wind turbine

In this context of accelerated development, floating offshore wind turbines (FOWTs)—i.e., wind turbines installed on floating platforms to enable deployment in deep-water sites— offer new prospects, as they enable installation in deep waters where winds are more consistent and powerful [7].

However, this rapid development comes with major technical challenges, particularly in terms of turbine control and regulation in the face of changing weather conditions. Wind turbines must cope with high wind variability, which can affect their performance and safety. Pitch control allows the adjustment of blade angles to optimize energy production and limit loads on the blades. However, traditional pitch control methods remain primarily reactive: they adjust the blade angle after conditions have changed, revealing their limitations in dealing with sudden wind fluctuations. This can reduce energy efficiency and accelerate equipment wear.

Therefore, the integration of accurate wind forecasts emerges as a promising solution. With these forecasts, pitch control systems can anticipate changes in wind conditions and adjust blade angles accordingly, thereby improving energy efficiency and reducing equipment wear. This approach, supported by recent advances in artificial intelligence and hybrid methods, makes it possible to overcome the limitations of traditional strategies and enhance both the performance and reliability of wind energy systems [9]–[11] Consequently, advanced forecasting and proactive control strategies are increasingly important to support large-scale deployment and address emerging operational challenges.

Numerous review articles have surveyed wind speed, covering physical, statistical, AI-based, and hybrid approaches, including recent deep-learning developments for wind speed prediction [12]–[15]. In parallel, several review studies have examined wind turbine pitch control and advanced control strategies, particularly for operation above rated wind speed and under complex turbine dynamics [7], [9], [16]. However, these two research streams are commonly reviewed separately, and practical guidance that explicitly connects forecasting outputs to implementable pitch-control integration under real-time constraints, actuator limitations, and forecast uncertainty remains limited.

This gap motivates the present review, which bridges wind forecasting and pitch regulation from an integration and implementation perspective. This review is not restricted to a single emerging trend; however, Digital Twin–based frameworks and deep reinforcement learning approaches are discussed when they provide relevant mechanisms for forecast-informed pitch control. Therefore, the problem addressed in this review is the lack of practical, integration-oriented guidance for using wind forecasts to improve pitch regulation in utility-scale turbines under real-time constraints. The objective of this paper is to consolidate and critically analyze forecasting and pitch-control literature in a unified framework that supports implementable forecast-informed control design. To this end, we focus on how forecasting horizon, latency, and uncertainty interact with controller robustness, actuator duty, and load/power performance.

The contribution of this review is threefold: (i) to provide a structured taxonomy of wind speed forecasting methods with emphasis on their practical requirements; (ii) to survey pitch control techniques from classical to intelligent and hybrid schemes; and (iii) to synthesize how forecasting can be embedded into pitch control architectures to enable proactive regulation, while highlighting key implementation constraints and future research directions.

The paper is organized as follows. Section 2 presents the review methodology, including the literature sources, search strategy, inclusion and exclusion criteria, and the classification and synthesis process. Section 3 presents the various wind forecasting techniques, detailing in turn traditional methods, AI-based approaches, and hybrid methods. Section 4 is dedicated to pitch control techniques, encompassing classical methods, advanced nonlinear approaches, intelligent control strategies, and hybrid control schemes that combine elements from multiple paradigms. Section 5 addresses the integration of wind forecasting into pitch control. Finally, Section 6 provides a general synthesis and discusses future research directions.

2. Methodology

The overall review methodology is summarized in Fig. 2 and consists of four main stages: (i) literature identification, (ii) screening and selection, (iii) classification, and (iv) synthesis. Relevant studies were retrieved from major scientific databases, including Web of Science, Scopus, IEEE Xplore, and ScienceDirect, using combinations of keywords related to wind speed forecasting, pitch control, and wind turbine control. During screening, duplicate records were removed and non-relevant papers were excluded based on title/abstract inspection followed by full-text assessment.

The final set of selected papers was then classified according to the forecasting approach, pitch-control strategy, prediction horizon, and evaluation setting. Finally, a comparative synthesis was performed to consolidate reported quantitative benefits, identify practical limitations (e.g., real-time computational constraints and sensitivity to forecast uncertainty/latency), and highlight open research gaps.

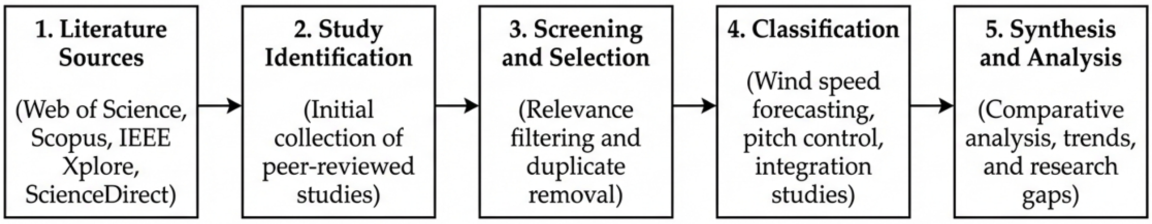

Fig. 2. Workflow of the literature review

3. Wind Forecasting Approach

Wind speed forecasting is crucial for the development of wind energy, due to the high variability, instability, and nonlinear nature of wind [17]–[19]. Accurate forecasting not only enhances the stability and quality of power generation but also reduces losses, improves safety, and increases the competitiveness of the wind energy sector in the energy market [17], [18].

In wind speed forecasting, the choice of the forecasting horizon is critical, as it directly influences the selection of suitable techniques and models. According to the literature, four types of forecasting horizons are generally distinguished [20]–[22], as illustrated in the following diagram [21] shown in Fig. 3:

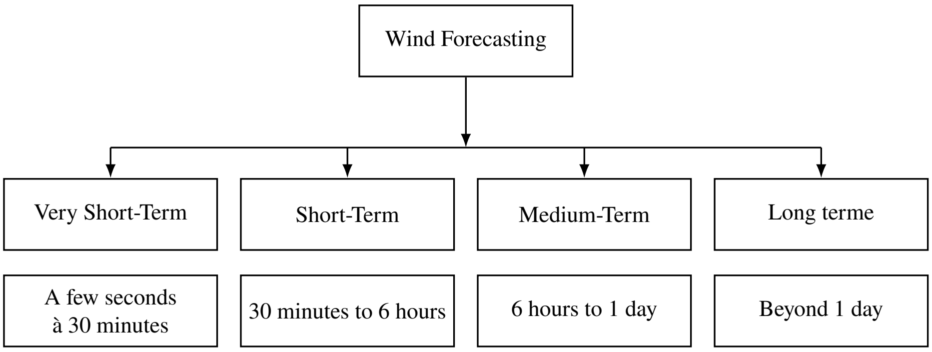

Fig. 3. Diagram of wind forecasting classification [23]

3.1. Conventional Approach

According to the literature, two main categories of conventional approach for wind forecasting are generally distinguished: physical methods and statistical methods [24]. Physical wind forecasting methods are based on numerical modeling of the atmosphere, particularly through Numerical Weather Prediction (NWP) models [24], [25]. These models represent atmospheric behavior by solving hydrodynamic and thermodynamic equations [25], using real-time atmospheric data such as wind speed and direction, barometric pressure, and humidity to make forecasts [24]. This method offers an accurate representation of the physical phenomena governing wind dynamics, enabling reliable forecasts for wind power management and optimization [24], [25].

Numerous studies have demonstrated the effectiveness of physical approaches for predicting wind speed. For example, Cheng et al. [24] examined the sensitivity of wind forecasts generated by the WRF model depending on the physical schemes chosen, testing different parameters under various weather conditions over a wind farm in Colorado. Their work shows that the choice of surface, boundary layer, and microphysics schemes has a significant impact on the accuracy of wind speed predictions, especially during convective summer events.

Funami et al. [25] investigated the variability of WRF model forecasts using various combinations of physical schemes to anticipate major forecasting errors in irradiance and wind in Japan. They showed that fluctuations in results depending on the selected schemes can serve as an indicator of forecast uncertainty, particularly during local weather events.

Finally, Sile et al. [26] evaluated the performance of the WRF model for wind speed forecasting in Latvia. Forecasts were compared to observations from 24 meteorological stations. The results revealed a systematic positive bias, with accuracy varying by hour and location, particularly in coastal areas.

Recently, Doppler lidar sensors have enabled fine-scale wind observations at altitude, providing continuous vertical profiles of wind speed and direction. Unlike conventional instruments limited to point measurements, lidar offers a comprehensive view of wind structure in the atmospheric boundary layer, improving forecast model evaluation. The study by Pentikäinen et al. [27] illustrates this complementarity by comparing profiles simulated by the ECMWF IFS physical model with lidar observations at six sites with varying characteristics. The results show that the model reproduces wind patterns well in marine environments but presents significant discrepancies in complex terrains such as mountainous regions. This study highlights the value of using lidar measurements to validate and enhance the vertical representation of wind in numerical forecasting models.

In addition to physical approaches, statistical methods have also been widely used for wind speed forecasting. According to recent literature, they largely rely on the analysis of historical measurements. The objective is to identify recurring patterns or cycles in wind speed data to build models capable of anticipating future values [28].

To this end, several mathematical tools are employed, such as autoregressive models (AR, ARMA, ARIMA) [21], or Kalman filter-based approaches, which translate the temporal structure of the data into predictive equations [21], [29].

For instance, the autoregressive (AR) model was applied in Corsica to simulate and forecast wind speed. According to results from Poggi et al. [30], the proposed method offers satisfactory accuracy, as it can reproduce key statistical characteristics of observed wind series, such as the mean and variance. Similarly, the ARMA model is commonly used for very short-term wind forecasting. For example, Erdem and Shi [31] applied different ARMA variants, alone or combined with multivariate models like VAR, to jointly forecast wind speed and direction. The results show that these approaches effectively model hourly wind fluctuations, accounting for both the individual evolution of each variable and their temporal interactions. This confirms the ARMA model's capacity to provide reliable forecasts.

Following this line, Radziukynas and Klementavicius [32] used a univariate ARIMA model based solely on historical wind speed data to make medium-term forecasts, demonstrating good prediction accuracy. When seasonality is present, the SARIMA model an extension of ARIMA proves particularly effective. The study by Tyass et al. [33] shows that SARIMA improves wind forecasting under such conditions.

Finally, the Kalman filter can also be applied to wind speed forecasting. Zhang and Wang [34] used an ARMA model combined with an Ensemble Kalman Filter (EnKF) to predict short-term wind speed based on offshore measurement data. The method produced satisfactory results for a 10-minute forecast horizon, demonstrating the Kalman filter's effectiveness in this context.

Despite their solid performance, these approaches have certain limitations, particularly in handling the nonlinearity and complexity inherent to wind time series. These shortcomings have thus motivated the emergence of new methods based on artificial intelligence [28], [29].

3.2. Artificial Intelligence-Based Approaches

In recent years, artificial intelligence (AI) has profoundly transformed wind speed forecasting, thanks to the emergence of methods capable of modeling complex, nonlinear, and non-stationary phenomena—characteristics of meteorological time series data [35]. Two main families of AI techniques are distinguished in the literature:

- Machine learning, which includes methods such as artificial neural networks (ANN), support vector machines (SVM), and random forests (RF) [36].
- Deep learning, based on deep neural architectures (CNN, RNN, LSTM, GRU, etc.), as well as hybrid models combining multiple networks [35], [36].

Machine-learning models such as ANN, SVM and RF are generally well suited for short- and very-short-term forecasting. They can capture nonlinear relationships between wind speed and explanatory variables with moderate computational cost, and they are relatively easy to implement using standard SCADA data. However, their ability to represent long-term temporal dependencies remains limited, as it strongly depends on the chosen input window and feature engineering strategy.

Among machine learning techniques, the Random Forest model stands out for its ability to model nonlinearity, avoid overfitting, and provide robustness to noise in the data. For instance, the work of Sathyaraj and Sankardoss [37] shows that Random Forest Regression outperforms neural networks and SVMs in forecasting complex time series built from SCADA data.

Other recent studies also confirm the effectiveness of machine learning models in wind forecasting. For example, Cai and al. [38] demonstrated, through a direct comparison between XGBoost, neural networks, and linear regression, that XGBoost consistently yields the best performance based on various error metrics (MAE, RMSE, R^2) in short-term wind forecasting using real-world data.

In addition, Reja et al. [39] developed a multivariate model based on an artificial neural network (ANN) for short-term wind speed forecasting, using SCADA data from a wind farm in Turkey, recorded every ten minutes. The model incorporates several explanatory variables, including wind speed and direction, active power, and the theoretical power curve. The results demonstrate high model performance.

The study by Al-Hasani et al. [40] assessed the effectiveness of two machine learning algorithms: Random Forest (RF) and Support Vector Machine (SVM), for predicting monthly wind speed. The results indicate a slight superiority of SVM over RF in terms of RMSE, MAE, and R^2, particularly with a 12-month lag, highlighting the value of these traditional methods for short-term predictions in real-world wind production contexts.

In recent years, deep neural networks have emerged as particularly effective tools for wind speed forecasting due to their ability to model the nonlinearity and temporal dependence inherent to meteorological time series. Among these architectures, Long Short-Term Memory (LSTM) networks are widely used for multi-horizon forecasting, as demonstrated by Elsaraiti and Merabet [41], who showed that LSTM significantly improves performance compared to traditional statistical methods when applied to real hourly data.

Other studies have further explored comparisons between different deep learning architectures. For instance, Ibrahim et al. [42] evaluated the performance of ANN, CNN, LSTM, and ConvLSTM on short-term wind speed series, concluding that LSTM and ConvLSTM are better at capturing complex temporal dynamics, while CNN provides modest gains in detecting local patterns. Similarly, Khan and al. [43] presented a comparative analysis of five advanced models, including LSTM, GRU, and CNN-LSTM, against classical methods like Random Forest and SVR. Their results highlight the superiority of LSTM and GRU architectures in capturing long-term temporal dependencies, with a high coefficient of determination R^2 for wind speed prediction.

Likewise, Janakiraman and Chitra [44] showed using NREL data that CNN, LSTM, GRU, RNN, and particularly CNN-LSTM networks yield high performance for hourly wind forecasting, with CNN-LSTM offering notable improvements in MAE and RMSE compared to individual architectures. The recent literature thus converges on recognizing LSTM, GRU, CNN, and their variants as reference models for wind forecasting, each offering advantages depending on the forecasting horizon and data structure. In this vein, Zhang et al. [45] proposed a model based on Gated Recurrent Unit (GRU), tested on wind farm data in China. Their results show that GRU achieves higher accuracy than LSTM and ARMA while benefiting from a lighter structure and reduced training time. This study reinforces the potential of GRU as an effective alternative in practical contexts, particularly for short-term forecasting.

Finally, Gangwar et al. [46] compared the performance of LSTM and SVM on open meteorological datasets and confirmed the superiority of LSTM in capturing temporal relationships in the data, further emphasizing the relevance of deep learning approaches over classical methods.

Overall, these studies indicate that AI-based models, and in particular deep neural networks, now play a central role in wind speed forecasting. However, their deployment in operational wind farms must account for data quality issues in SCADA measurements, the risk of overfitting to specific sites, and the computational cost of training and inference. These aspects are especially important when forecasts are intended to be integrated into real-time control loops such as pitch regulation.

As noted by Liu and Yang [36], despite their effectiveness, AI methods alone are not always sufficient to fully capture the complexity of wind behavior. This has led to the recent rise of hybrid approaches, which combine multiple techniques to improve forecasting accuracy and robustness.

3.3. Hybrid Approaches

In recent years, hybrid approaches have gained popularity in the field of wind speed forecasting. By combining multiple techniques such as signal decomposition, neural networks, and optimization algorithms, these methods aim to better capture the complexity of wind data. In most cases, they offer more accurate and robust performance than individual models [47]–[49]. Hybrid architectures can be broadly grouped into decomposition–forecasting schemes, models enhanced by optimisation algorithms, and deep hybrid structures that integrate several learning paradigms within a unified framework.

Yan et al. [47] proposed a hybrid model combining SARIMA, EEMD, and LSTM to separate the linear and nonlinear components of the wind signal. The method is based on time series decomposition followed by sequential modeling. Results show improved accuracy and stability compared to standalone SARIMA or LSTM models. Pei et al. [48] applied wavelet transform (WT) decomposition followed by CNN for feature extraction and LSTM for temporal prediction, yielding robust forecasting results. Suo et al. [17] implemented an adaptive TVF-EMD decomposition, followed by component selection using PACF and a hybrid ChOA-BiGRU model: the Chimp Optimization Algorithm is used to optimize BiGRU weights initialized chaotically, resulting in a reduction in RMSE over four months of data and a significant increase in correlation (R).

Numerous studies have integrated optimization algorithms to enhance the performance and robustness of wind forecasting models. Shi et al. [50] used PSO to automatically tune the hyperparameters of an LSSVM, then applied XGBoost to correct residual errors, yielding a highly stable and accurate wind speed forecasting model. Following a similar approach, Shao et al. [51] optimized an LSTM using the Firework Algorithm (FWA) to automatically select its hyperparameters, followed by residual error correction, leading to significantly improved forecasting stability. Barhmi et al. [52] optimized both SVM and neural networks at the Tangier station using a GA-PSO combination, significantly improving the coefficient of determination and reducing prediction errors compared to a non-optimized SVM. Liu et al. [53] proposed a GA-PSO-CNN model that simultaneously optimizes the hyperparameters and weights of a CNN, resulting in notable improvements in all error metrics compared to a conventional CNN. Finally, Wang and Zhang [54] combined Tuna Swarm Optimization with VMD decomposition and BiLSTM to extract frequency modes and fine-tune network parameters, achieving the best overall accuracy among the compared architectures.

Other researchers have developed new hybrid architectures to enhance wind forecasting. Yao et al. [55] introduced an EEMD-GS-GRU model combining EEMD decomposition and GRU, with hyperparameters optimized via grid search. The model reduced RMSE from 1.411 m/s to 0.685 m/s, outperforming LSTM-based models. Nana et al. [56] introduced a CNN-GRU hybrid model, where CNNs extract features (wind speed, direction, and NWP forecasts) from a temporally continuous matrix, and a GRU performs the prediction, significantly improving error metrics over standalone CNN or GRU models.

Lawal et al. [57] proposed a 1D CNN-BLSTM hybrid architecture: a CNN extracts local spatiotemporal features, and a BLSTM captures bidirectional temporal dependencies from time series measured at multiple heights, achieving better performance than other benchmark models. Chen et al. [58] developed an EEMD-GA-LSTM method, where EEMD decomposes a long historical series, and a genetic algorithm selects an optimal subset of components as input to the LSTM, reducing RMSE by nearly 28% compared to a pure LSTM on high temporal resolution data.

In other work, Hur [10] proposed an ultra-short-term forecasting method coupling an Extended Kalman Filter (EKF) with a supervised learning model. This approach enables real-time forecast updating, enhancing the system's responsiveness. Finally, Band et al. [49] developed a system based on Deep Reinforcement Learning (DRL), capable of dynamically adjusting its forecasts based on the observed environment, thus opening a new path for intelligent, unsupervised solutions.

Overall, these contributions confirm that hybrid models are able to exploit the complementary strengths of decomposition techniques, learning architectures and optimisation algorithms, leading to more accurate and stable forecasts than single models. However, they also introduce additional complexity in terms of model design, parameter tuning and computational cost. For applications where forecasts are intended to support real-time control decisions, such as predictive pitch regulation, a careful balance is required between accuracy, robustness and implementation feasibility.

3.4. Comparative Analysis of Forecasting Approaches

In the literature, several methods have been developed to forecast wind speed. These are generally classified into three main categories: traditional methods (physical and statistical), artificial intelligence (AI), and hybrid methods that combine different approaches.

Performance Evaluation Metrics. To compare the forecasting performance of the different models, several standard metrics are used. These include:

- **MAE (Mean Absolute Error)**: Measures the average of the absolute differences between predicted and actual values:

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|K_t - L_t| \tag{1}$$

- **MAPE (Mean Absolute Percentage Error)**: Represents the average percentage error between forecasts and actual values:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{K_t - L_t}{F_t}\right| \tag{2}$$

- **R² (Coefficient of Determination)**: Indicates how well the predicted values approximate the actual data:

$$R^2 = 1 - \frac{S_e^2}{S_y^2} \tag{3}$$

Where S_e^2 is the sum of squared errors and S_y^2 is the total variance.

- **RMSE (Root Mean Squared Error)**: The square root of MSE, widely used to quantify the magnitude of prediction errors:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(K_t - L_t)^2} \tag{4}$$

Each method has its own advantages, limitations, and specific application domains. Table 1 summarizes these key characteristics in a simple way to allow a clear comparison between the different approaches.

Table 1. General comparison of wind speed forecasting methods

Methods	Advantages	Limitations	Applications
Physical	Realistic representation of atmospheric dynamics; based on known physical laws [24].	Strong dependence on initial data, poor performance at small scale when spatial resolution is limited; high computational cost [24], [59], [60].	Medium- and long-term forecasts; used for regional wind power planning [60].
Statistical	Low computational cost, easy to use, efficient in the short term on stationary time series [33], [60].	Low performance on highly nonlinear data, sensitive to sudden variations and noise, decreasing accuracy over the long term [29], [33], [60].	Short-term local forecasting (hours to days); production management and grid adjustment [28], [33], [60].
Machine learning	Able to model complex nonlinear relationships, performs well in short and medium term, well suited to multidimensional and noisy data [29], [37], [60].	Requires large training datasets; sensitive to overfitting, complex hyperparameter optimization, low interpretability for deep models [29], [61].	Used for short- and medium-term wind forecasting, dynamic production control, smart grid integration, and wind variability management [29], [37], [61].
Deep learning	Capable of modeling complex nonlinear relationships and temporal dependencies, enables automatic feature extraction without manual engineering, offers high accuracy for short- and medium-term forecasts [29], [41], [44].	Requires large datasets, high computational cost, low interoperability, sensitive to hyperparameter tuning [29], [43], [61].	Used for fine-grained short-term wind speed or power forecasting, dynamic production management, adaptive turbine control, smart grids, and predictive maintenance [41], [44], [61].
Hybrid	Combine the complementary strengths of different models (e.g., robustness of statistical models, accuracy of ML/DL models), better performance on non-stationary and noisy data, high flexibility for various forecast horizons [29], [47], [60].	More complex design and training, risk of error accumulation between sub-models, increased data and computation requirements [60], [61].	Short- and medium-term wind speed or power forecasting; integrated management in hybrid energy systems; dynamic control, operational planning, and uncertainty reduction in smart grids [46], [60].

Table 2 presents the performance of different traditional wind speed forecasting methods. It includes both physical models, which simulate atmospheric processes, and statistical methods based on time series analysis and Table 3 summarizes the performance of artificial intelligence methods for wind speed forecasting, highlighting their error metrics (MAE, RMSE, etc.) and the datasets used.

Table 4 compares hybrid approaches, which combine statistical models with machine/deep learning techniques, detailing their accuracy measures, forecasting horizons, and the characteristics of the datasets employed. The comparative analysis of the four categories of wind speed forecasting methods highlights the strengths and limitations of each approach. Traditional methods, such as physical and statistical models, remain relevant for medium to long-term forecasting and provide interpretable results, but they often suffer from lower accuracy, especially under nonlinear and rapidly changing conditions. Artificial intelligence techniques including machine learning and deep learning demonstrate superior accuracy, particularly for short-term forecasts, thanks to their ability to model complex patterns and temporal dependencies.

However, they require large volumes of high-quality data and often involve complex training processes. Hybrid methods, which combine the advantages of traditional and AI-based models, consistently deliver the best performance in terms of error metrics (MAE, RMSE, R^2), but at the cost of increased model complexity and computational requirements. Overall, the choice of forecasting technique should be guided by the forecast horizon, the availability and quality of data, and the operational context of the wind energy system.

Table 2. Performance comparison of traditional wind speed forecasting methods

Ref	**Method used**	**MAE**	**RMSE**	**R^2**	**Forecast horizon**	**Data used**
[24]	WRF: Noah LSM + YSU PBL + Lin	2.8 (winter) 2.4 (summer)	—	—	Medium	GFS + SCADA
[25]	WRF (7 phys.) microphysics, surface, PBL, radiation	—	Threshold > 0.25 kW/m^2	—	Medium	GFS + irradiance, wind, humidity, cloud cover
[26]	WRF: Noah LSM, YSU PBL, WSM5, RRTM, Dudhia	—	Up to 2 m/s	—	Medium to long	GFS + wind, pressure, temperature, radiation, wind direction
[27]	NWP ensemble (SCALE–RM) + Doppler lidar (simulated DA)	MAE_s: 0.5–2.5 MAE_dir: 10–40° MAE_v: 1–4	—	—	Short to medium	Lidar (6 sites) + radiosonde (T, p, RH, wind speed/dir.)
[30]	AR (autoregr.) on time series	—	9.38%	0.957	Short	Météo-France + wind speed (3 h)
[32]	ARIMA	1.02 (6 h) 1.82 (12 h) $>$ 2.5 (12 h) $>$ 4 (48 h)	≈ 1.0 (6 h) ≈ 1.8 (12 h) $>$ 2.5 (24 h) $>$ 4 (48 h)	—	Short	Laukžeme WF (Lithuania) + wind
[33]	SARIMA	0.75 (Mar) 0.88 (Jul) 1.01 (Oct)	1.04 (Mar) 1.11 (Jul) 1.68 (Oct)	—	Short	Koudia Al Baida weather station + wind
[34]	ARMA + EnKF	0.3380 m/s	1.0062 m/s	—	Very short	NDBC Buoy 41002 (USA) + 10-min avg wind

4. Pitch Control Techniques

The pitch-control system is the onboard mechanism of large multi-megawatt wind turbines that rotates the blades about their longitudinal (pitch) axis to change their angle of attack and adjust the aerodynamic torque on the rotor, so that the electrical power remains approximately constant over a wide range of wind speeds above the rated speed [16].

Designed as a core strategy for pitch-regulated turbines, it dynamically adjusts this torque to keep the electrical power at its rated value in high winds while limiting structural loads and gust-induced vibrations [62]. Its objectives are threefold: first, to operate continuously at the turbine's maximum power point; second, to protect the rotor, generator, and power electronics from mechanical or electrical overload; and third, to execute a controlled, feathered shutdown of the blades once the cut-out wind speed is exceeded [9], [62].

To satisfy these diverse and stringent requirements, the literature commonly classifies pitch-control strategies into four main categories:

Table 3. Performance comparison of artificial intelligence methods for wind speed forecasting

Ref	Method	MAE	RMSE	R^2	MAPE (%)	Horizon	Data used	Time
[37]	Random Forest Regression (RFR)	0.250(winter) 0.179(spring) 0.049(summer) 0.111(autumn)	0.782(winter) 0.558(spring) 0.182(summer) 0.390(autumn)	0.968 (winter) 0.984(spring) 0.996(summer) 0.988(autumn)	2.465(winter) 2.252(spring) 1.180(summer) 1.359(autumn)	Very short term	SCADA Wind speed Wind direction Active & theoretical power	–
[38]	Extreme Gradient Boosting (XGBoost)	1.5292 (Sep) 1.8492 (Oct) 2.0872 (Nov) 1.9330 (Dec)	1.9796 (Sep) 2.3915 (Oct) 2.6753 (Nov) 2.4855 (Dec)	0.4183 (Sep) 0.2011 (Oct) 0.2192 (Nov) 0.6045 (Dec)	–	Very short term	Wind farm, Solar radiation, Temperature, Pressure, Humidity Wind direction Sunrise/Sunset time	–
[39]	Multivariate ANN	–	0.833	0.96	–	Short term	SCADA Wind speed Wind direction Active & theoretical power	–
[40]	RF, SVM	RF: 0.180 SVM: 0.171	RF: 0.237 SVM: 0.223	RF: 0.836 SVM: 0.856	–	Long term	ERA5 reanalysis Historical wind speeds	–
[41]	LSTM	–	8.51 (Mar) 4.77 (Jul)	–	–	Medium term	SCADA (Halifax Dockyard) Wind speed	–
[42]	ConvLSTM	0.1177 (5 min) 0.4741 (30 min) 0.6369 (60 min)	0.2419 (5 min) 0.6463 (30 min) 0.8717 (60 min)	0.9876 (5 min) 0.9098 (30 min) 0.8316 (60 min)	–	Very short to short term	West Texas Mesonet Historical wind speeds	5 min: 1.73 min 30 min: 0.38 min 60 min: 0.15 min
[44]	RNN CNN GRU LSTM CNN–LSTM	RNN: 0.971 CNN: 1.179 GRU: 0.606 LSTM: 0.579 CNN–LSTM: 0.282	RNN: 1.206 CNN: 1.354 GRU: 0.728 LSTM: 0.747 CNN–LSTM: 0.351	–	RNN: 25.6 CNN: 33.2 GRU: 17 LSTM: 8.6 CNN–LSTM: 11	Short term	NREL Wind speed, temperature, humidity pressure, wind direction date/time	–
[46]	LSTM SVM	–	LSTM: 0.427 SVM: 0.768	–	–	Short term	Jena weather dataset (Kaggle)Wind, pressure, RH,temperature solar radiation	–

Table 4. Performance comparison of hybrid methods for wind speed forecasting

Ref	Method used	MAE	RMSE	R^2	MAPE (%)	Horizon	Data used	Time
[17]	TVFEMD PACF ICHOA BiGRU	Jan: 0.1909 Apr: 0.0784 Jul: 0.1445 Oct: 0.2307	Jan: 0.2452 Apr: 0.1031 Jul: 0.1817 Oct: 0.2307	Jan: 0.9902 Apr: 0.9968 Jul: 0.9957 Oct: 0.9928	–	Short term	NDBC Station 46060 Wind speed (10 min)	–
[47]	SARIMA EEMD LSTM	15min:0.3027 30min:0.3983 60min:0.5318	15min:0.4102 30min:0.5273 60min:0.6874	15min:0.9924 30min:0.9872 60min:0.9782	15min:8.6502 30min:10.6061 60min:12.9362	Very short Short term	SCADA (wind speed)	15min:358s 30min:134s 60min:66s
[48]	WT–CNN–LSTM	0.46	0.64	0.988	2.67	Short term	Measurement tower Wind speed	–
[50]	PSO LSSVM XGBoost	–	Apr: 0.1578 Sep: 0.0753	–	Apr: 2.94 Sep: 1.25	Short term	Lianyungang wind farm Wind speed	–
[51]	FWA–LSTM	0.46	0.64	–	30.05	Short term	Measured data from a wind farm Wind speed	–
[52]	SVM–GA SVM–PSO NN–PSO NN–GA	SVM GA: 0.1238 PSO: 0.1281 NN PSO: 0.0124 GA: 0.00091	SVM 2.42×10^{-2} 2.60×10^{-2} NN 5.27×10^{-4} 4.71×10^{-4}	SVM 0.19, 0.13 NN 0.9881, 0.9834	–	Short term	IRESEN Wind direction Humidity Temperature Past wind speed	–
[53]	GA–PSO–CNN	0.0895	0.1364	0.9882	3.33	Very short term	SCADA Wind power Temperature Humidity Wind speed Wind direction	–
[54]	TSO VMD BiLSTM	Jan: 0.54 May: 0.38	Jan: 0.81 May: 0.48	–	Jan: 6.89 May: 3.17	Short term	Open-source wind farm data Wind speed Wind direction Pressure Temperature	–
[55]	EEMD–GS–GRU	0.571	0.685	0.971	–	Short term	Wind farm Wind speed	117 min
[56]	CNN–GRU	2.573	3.398	–	5.32	Ultra-short term	Real wind farm data Wind speed Wind direction	–
[57]	CNN–BLSTM	98 m: 0.2981 18 m: 0.3051	98 m: 0.4280 18 m: 0.4295	–	98 m: 115 18 m: 118	Short term	Wind data measured in Saudi Arabia	–
[58]	EEMD–GA–LSTM	0.0570	0.1337	–	1.0622	Ultra-short term	WIND Toolkit Wind speed	–

- **Classical methods**, which rely predominantly on PI or PID regulators.
- **Nonlinear methods**, including techniques such as sliding-mode control, model predictive control, and H_∞ control.
- **AI-based methods**, for instance fuzzy-logic controllers, neural networks, and other soft-computing

approaches.

- **Hybrid methods**, which combine two or more of the above strategies.

Fig. 4 provides a block diagram of the WECS, highlighting the main components involved in the pitch control process.

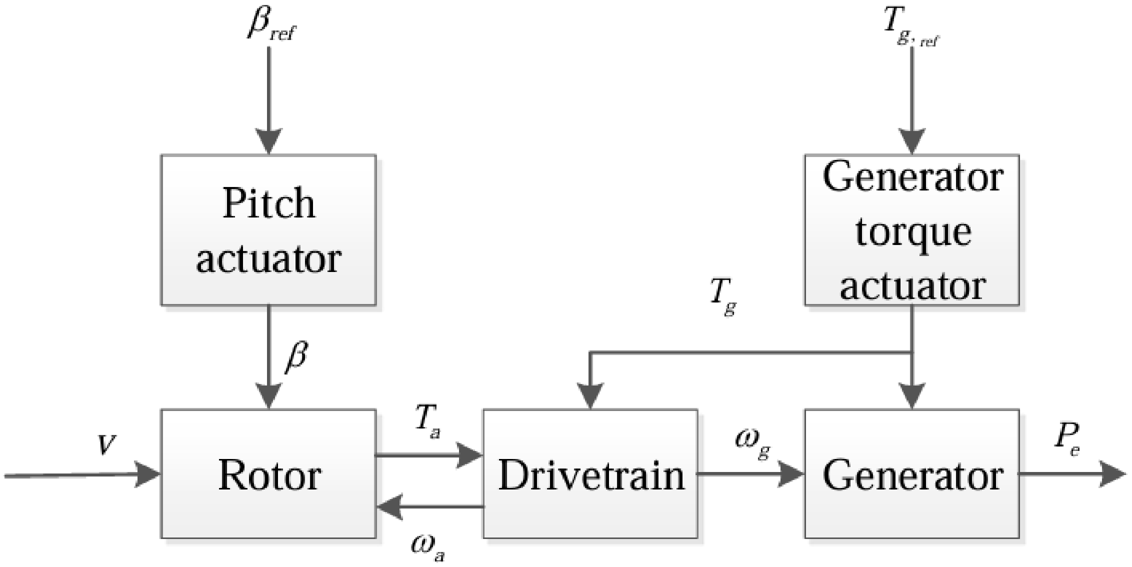

Fig. 4. Block diagram of the WECS [63]

4.1. Classical Method

Pitch angle control in wind turbines still predominantly relies on PI or PID regulators, valued for their ease of implementation and industrial robustness, as highlighted by Hosseini and Shahgholian [64]. Classically, Ziegler–Nichols tuning, as applied by Roussos et al. [65], enables the experimental identification of the critical gains required to achieve rapid convergence to the power setpoint, while maintaining overshoot at approximately 10–15 %. Hwas and Katebi [66] employ a PI controller, initially derived analytically by linearizing the power coefficient law $C_p(\lambda, \beta)$ to formally extract the proportional gain K_p (with $K_i \approx 0$), and subsequently optimized via MATLAB/Simulink simulations incorporating gain scheduling based on wind speed.

This comparison demonstrates that simulation-based PI tuning markedly enhances response speed while containing overshoot across the entire wind-speed range studied. To manage aerodynamic variations and load uncertainties, Baburajan and Ismail [67] design an adaptive PID controller whose continuous gain adjustment reduces overshoot and shortens settling time compared with a fixed-gain PID. Finally, Muljadi and Butterfield [68] emphasize the need for a fast pitch actuator modeled as a first-order system with time constant $\tau \approx 0.5$ s to minimize operating deviations and prevent mechanical overloads during transitions between $C_{p,\max}$ tracking and power limitation. Fig. 5 illustrates the block diagram of the pitch control system employing PI and PID controllers.

Despite their simplicity and widespread use, classical methods such as PI and PID controllers often face limitations under rapidly changing wind conditions and nonlinear aerodynamic effects. To address these challenges, more advanced control strategies particularly nonlinear approaches have been developed, as discussed in the next section.

4.2. Nonlinear Methods

Nonlinear control techniques, such as Sliding Mode Control (SMC), H-infinity (H_∞), and Model Predictive Control (MPC), have emerged to overcome the limitations of classical regulators. Sliding-

Mode Control (SMC) drives the system's trajectory onto a sliding surface $s(x) = 0$, constructed from either the speed error $\omega - \omega^*$ or the power error $P - P^*$ [69]. On an NREL 5 MW model simulated in FAST, Colombo et al. [69] define

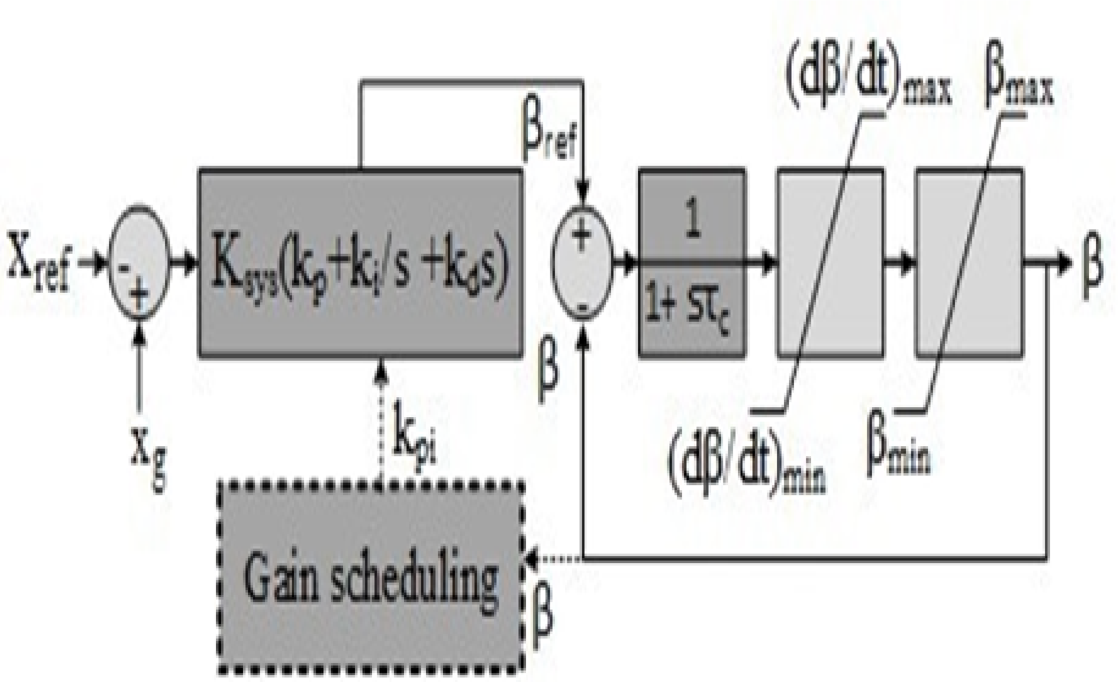

Fig. 5. Block diagram of the pitch control system using PI and PID controllers [64]

$$s(t) = \omega(t) - \omega^* + c_1 \int_0^t [\omega(\tau) - \omega^*]\, d\tau \tag{5}$$

and formally show using the switching control law

$$u_{sw} = -\alpha\, \mathrm{sgn}(s)$$

That once $\alpha > \delta$, the trajectory reaches and remains on $s = 0$ despite aerodynamic disturbances.

To mitigate chattering, Oulad Ben Zarouala and El Mjabber [70] replace the discontinuous sgn(s) with tanh(s) in an integral SMC (ISMC) applied to a 4-DOF flexible model, and prove stability via a Lyapunov function. In a further variant on the same model, they develop a multilevel SMC architecture to enhance structural robustness against tower and blade flexing [71].

El Fadili and Boumhidi [72] extend this idea by introducing a fractional-order SMC that combines sliding-mode action with fractional calculus: the fractional operator smooths the switching even more and reduces set-point overshoot under variable wind profiles.

Finally, a fifth study [73] presents a higher-order SMC with variable gains, capable of reaching the sliding surface in ultra-short time without inducing mechanical chattering.

Control designers have recently embraced H_∞ techniques to overcome the limitations of classical methods in multivariable, cross-coupled systems and to guarantee robust performance and stability despite nonlinear aerodynamic effects and modeling uncertainties in wind turbines [74]. Hassan et al. [75] employ an LMI-based H_∞ synthesis to co-design collective-pitch and generator-torque regulators, demonstrating significant disturbance rejection and load mitigation under parametric uncertainties.

Arya and Dewan [76], apply an H_∞ controller to a 2 MW variable-speed turbine model in MATLAB/Simulink, achieving superior stability margins compared to PID schemes. Yao et al. [77] extend this approach into a gain-scheduled LPV H_∞ framework via convex LMIs, ensuring closed-loop stability across the turbine's full operational envelope. Corcuera et al. [74] develop two-channel MISO H_∞ controllers for collective pitch and torque validated in GH Bladed to substantially reduce fatigue loads under turbulent inflow. Finally, Song et al. [78] design a mixed-sensitivity H_∞ pitch algorithm for the NREL 5 MW turbine, cutting rotor-speed standard deviation by up to 46.61 % in extreme gusts while preserving mean power output. he H_∞ control architecture used to improve robustness and disturbance rejection is depicted in Fig. 6.

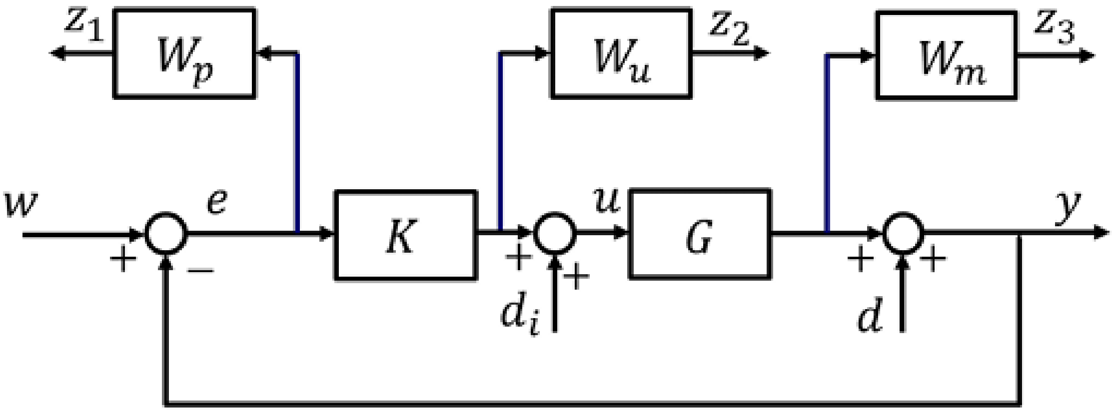

Fig. 6. Block diagram of the H-infinity control [78]

Model-based Predictive Control MPC is a feedback algorithm that uses a model to make prediction about future outputs of the process. Furthermore, MPC adopted the principle of receding horizon, that is, MPC goal is to predict the future behavior of the process over a specified time horizon using the dynamic model. The control action is then obtained such that the cost function is minimized while the provided constrains are satisfied.

Moreover, at each sampling period, only the first control input to the system is applied. At the next sampling time, the procedure is repeated [79]. In wind power applications, MPC has been systematically embedded into multi-level, multi-objective frameworks, ranging from individual turbines to entire farms and wind power clusters. This hierarchical integration enables coordinated control of power output, system stability, and resource efficiency, particularly under fluctuating wind conditions and distributed control architectures [80].

Several studies have demonstrated the effectiveness of MPC and its economic variant (EMPC) for wind energy conversion systems (WECSs). Cui et al. [63] conducted a comparative analysis between tracking MPC and EMPC, showing that EMPC can improve energy efficiency and reduce operational cost by directly optimizing economic objectives over all operating regions. Kong et al. [81] extended this approach with a nonlinear EMPC framework that integrates tower dynamics and drivetrain torsion to enhance structural protection and long-term reliability.

Additionally, Reddy and Hur [82] compared MPC with H_∞ and LQG control strategies for a 5 MW wind turbine and demonstrated that optimal controllersincluding MPC can significantly outperform traditional PID schemes in load mitigation and power regulation. The MPC-based pitch control architecture is illustrated in Fig. 7, demonstrating how future predictions and constraints are integrated into the control process.

Thus, nonlinear control methods overcome many limitations of classical approaches, especially regarding robustness and responsiveness under uncertainty and disturbances. They provide a solid foundation for more advanced strategies, particularly those based on artificial intelligence, which are discussed in the next section.

4.3. AI-Based Methods

Artificial intelligence-based pitch control methods aim to cope with the strong nonlinearities, uncertainties and rapid fluctuations that characterise wind turbine operation. Instead of relying on a fixed linear model, they use data-driven rules or learned representations to adapt the pitch angle in real time. Two major families dominate the literature: fuzzy-logic controllers, which encode expert knowledge in the form of linguistic rules, and neural-network-based controllers, which approximate the nonlinear dynamics directly from data. Artificial intelligence offers flexible and adaptive solutions for pitch control in complex, nonlinear wind environments. Two major approaches are fuzzy logic and neural network-based control. Fuzzy control is a method based on fuzzy mathematics that uses the principles of fuzzy logic to govern a system.

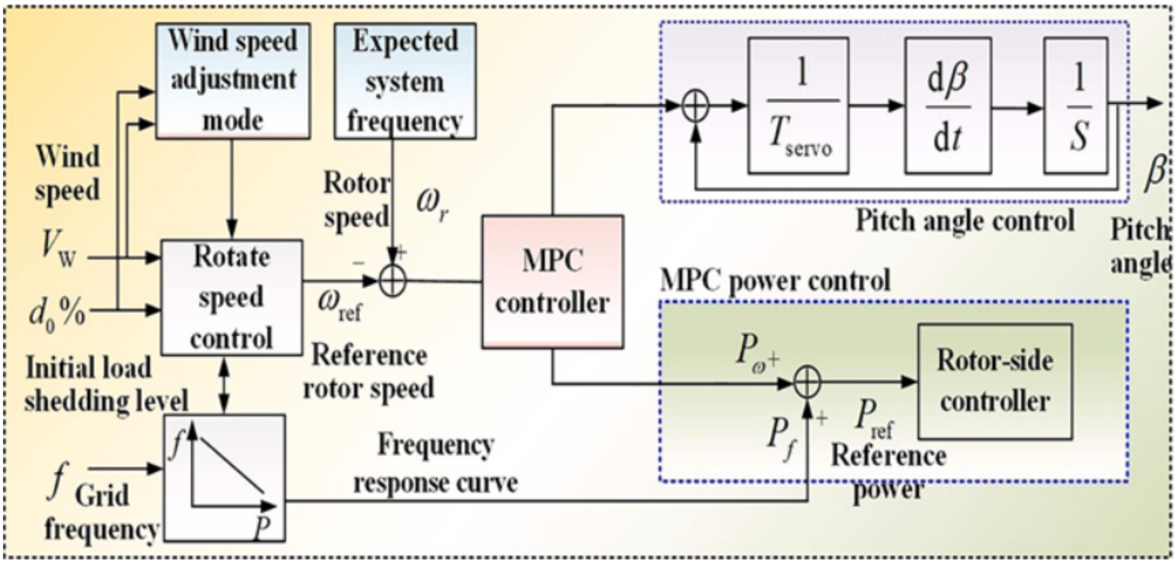

Fig. 7. MPC for wind turbine pitch angle control [83]

It allows the integration of imprecise or linguistic information into a structured mathematical framework. A fuzzy controller generally consists of four key components: fuzzification, the inference engine, the rule base, and defuzzification [16]. This definition is reinforced by Hosseini et al. [84], who state that these four fundamental blocks convert numerical data into fuzzy variables, with rules established from linguistic variables. Pehlivan et al. [85] emphasize that the effectiveness of fuzzy control lies in its ability to reason with imprecise information, and that adjusting the membership functions and decision rules enables the system to respond optimally under variable or uncertain conditions show in Fig. 8.

Numerous studies have applied this technique, presenting fuzzy controllers that show good performance in terms of system stability, power regulation, and response to wind fluctuations. Santoso et al. [86] implemented a basic Mamdani-type fuzzy controller on a 20 kW wind turbine, using power error and wind speed as inputs. The results showed that the output power remained close to its nominal value, with an average error below 0.77%, demonstrating good stability under varying wind conditions. Hosseini et al. [84] proposed a sensorless fuzzy controller for a doubly-fed induction generator (DFIG) wind turbine, relying solely on internal variables such as rotor speed and active power. This approach allows indirect estimation of wind effects based on system behavior. Their results showed improved robustness and greater stability compared to classical PI controllers under variable wind conditions.

Although pitch angle control is still often handled solely by fuzzy logic, several recent studies aim to enhance its performance by combining fuzzy logic controllers (FLCs) with other control techniques, such as PID regulators or optimization algorithms like genetic algorithms (GA) and particle swarm optimization (PSO). These hybrid methods retain fuzzy logic as the core of the control system, aiming to improve system stability and accuracy under wind fluctuations. Among notable examples, Civelek [87] proposed a fuzzy pitch controller based on a Takagi–Sugeno structure, optimized using an advanced genetic algorithm (AIGA). This approach enables automatic tuning of the pitch control parameters.

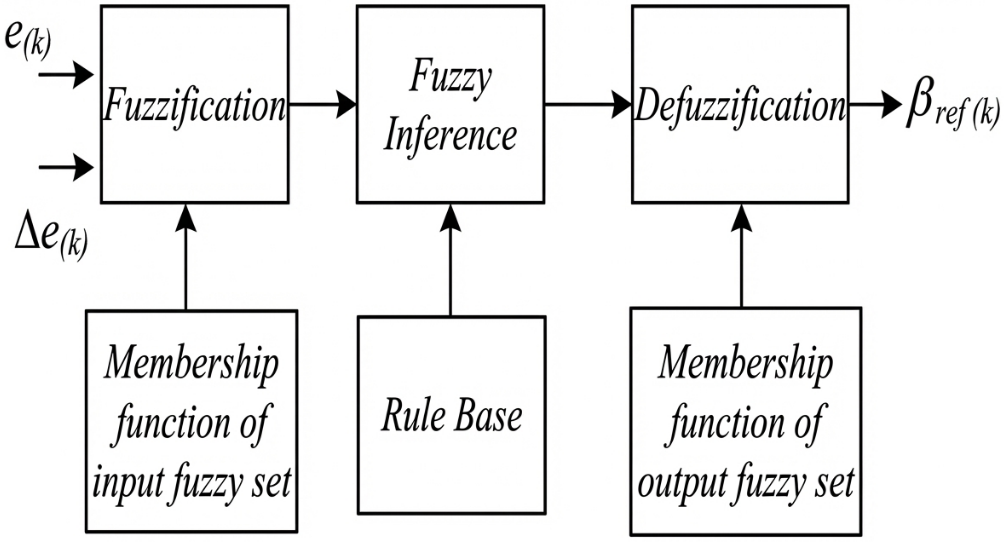

Fig. 8. Structure of FLC

By optimizing the fuzzy controller coefficients, this method improves wind power output management and ensures an effective response to changing wind speeds, which is essential for maintaining stable and secure energy production. Following a similar strategy, Pehlivan et al. [85] developed a multi-criteria fuzzy controller for a 2 MW DFIG wind turbine. Their system, enhanced by genetic algorithms, aims to maximize energy output while maintaining operational safety and stability in the face of wind variability. It uses three input variables: power error, its rate of change, and generator speed.

The genetic algorithm automatically tunes the membership functions, improving adaptability across operational ranges and reducing power oscillations in unstable conditions. Continuing this trend, Adnan and Hussain [88] analyzed various pitch control structures integrating Mamdani and Sugeno fuzzy controllers, as well as a hybrid fuzzy–PID model. These systems were tuned using GA and PSO algorithms. Their study highlighted that standalone fuzzy controllers offer good performance, while combining them with PID regulation and parameter optimization further enhances system stability and active power control in a 500 kW wind turbine shown in Fig. 9.

Despite their advantages, fuzzy controllers may lack adaptability in highly nonlinear and dynamic environments, which has motivated the integration of neural network-based techniques. Neural network-based control is an advanced method grounded in machine learning principles, enabling wind turbine systems to adaptively regulate the pitch angle in response to complex and uncertain environmental conditions. Unlike conventional controllers, neural networks (NNs) can approximate nonlinear system dynamics without requiring an exact model, making them highly suitable for wind energy conversion systems (WECS) [89], [90]. A typical NN-based pitch controller integrates a prediction module, often implemented as a multilayer perceptron or radial basis function (RBF) network, and a control law to maintain output power near its rated value despite varying wind conditions [91], [92].

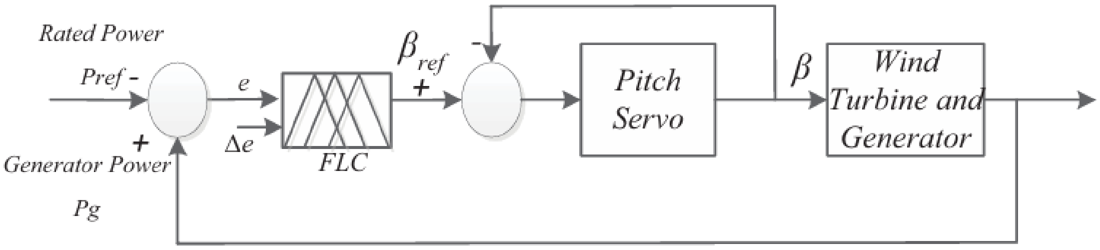

Fig. 9. Basic scheme of FLC for pitch angle [62]

Jiao et al. [89] proposed an adaptive pitch angle controller based on online learning with feedback linearization and a high-gain observer, allowing rotor acceleration to be estimated indirectly. Their system demonstrated improved robustness under model uncertainty and disturbances. In another study, Du and Wang [93] designed a BP neural network–PI pitch controller that dynamically adjusts the PI gains. Simulation results showed better power tracking and reduced oscillations compared to conventional gain-scheduled PI control. Several works focus on optimization of NN-based controllers. Narayanan et al. [94] introduced an improved recurrent RBF neural network (IRRBFNN), whose weights were fine-tuned using Modified Particle Swarm Optimization (MPSO), yielding accurate power regulation and reduced actuator stress. Similarly, Sahoo [95] proposed an adaptive neuro-fuzzy inference system (ANFIS) for pitch control, enhanced by PSO. This controller uses generator speed error and its derivative as inputs to optimize pitch angle. Compared to classical PI and standard ANFIS controllers, the PSO–ANFIS method showed superior performance in reducing speed and power oscillations while improving overall system robustness. El Mjabber et al. [96] analyzed a purely RBF-based pitch controller for variable-speed wind turbines. Their adaptive strategy resulted in effective pitch regulation, improved system stability, and minimized output deviations.

From a system-level optimization perspective, Qin et al. [97] proposed an optimal pitch controller leveraging a BP network for gain scheduling across different operating regions. Similarly, in a comparative framework, various pitch strategies, including neural–PID and neuro-fuzzy approaches, were evaluated to determine trade-offs in robustness, adaptability, and mechanical stress [98].

To improve controller performance under non-stationary wind conditions, Aljundi et al. [79] developed a neural network-based predictive controller (NNPC) for wind turbine pitch regulation. By training a neural model to capture system dynamics, the controller anticipates future responses and generates optimal pitch commands. This approach enhances adaptability and tracking accuracy across varying operating scenarios while ensuring smoother pitch activity and improved power stability. Finally, Li et al. [92] proposed a control strategy in which a neural network regulates the pitch angle during high-wind conditions, while MPPT governs low-wind operation. The multilayer perceptron enables adaptive pitch control, improving generator speed stability and maintaining output power near rated values.

Overall, fuzzy-logic and neural-network-based pitch controllers both contribute to improving stability, tracking accuracy and robustness under variable wind conditions. Fuzzy controllers are particularly attractive when expert knowledge is available and interpretability is important, whereas neural networks are better suited to capturing complex nonlinear dynamics without requiring an accurate mathematical model. In practice, many recent studies combine these techniques with optimisation algorithms or classical controllers to obtain adaptive, high-performance pitch regulation schemes that remain feasible for real-time implementation.

4.4. Hybrid Methods

Hybrid methods in pitch control involve combining different control approaches, such as conventional (PID), intelligent (fuzzy logic, neural networks) or adaptive techniques, to exploit their respective advantages [9]. This combination is particularly well-suited for wind turbine systems, which exhibit highly nonlinear dynamics and significant uncertainties due to environmental conditions [62]. Indeed, the use of hybrid controllers enhances robustness, reduces model dependency, and optimizes the system's dynamic performance, especially under high wind conditions [7].

Among these, hybrid fuzzy-optimization approaches integrate fuzzy logic with metaheuristic algorithms such as Particle Swarm Optimization (PSO) or Genetic Algorithms (GA) to enhance adaptability and control performance by automatically tuning control parameters to respond to wind variations in real time [99].

Adnan and Hussain [100] demonstrated that a hybrid Type-2 Fuzzy-PID controller optimized via PSO significantly improves the stability of power output and reduces both summation and peak tracking errors, even under varying wind speeds. Similarly, Sahoo et al. [101] proposed a PSO-optimized ANFIS controller that effectively regulates generator power and speed. The results show a significant reduction in fluctuations, outperforming conventional PI and standard ANFIS controllers. Sarkar et al. [102] performed a comparative analysis between two hybrid PID controllers, one optimized using Particle Swarm Optimization (PSO) and the other using Ant Colony Optimization (ACO). The ACO-based controller achieved the lowest RMS error (0.00036), demonstrating superior tracking performance and reduced mechanical stress compared to the PSO and conventional PID controllers. Finally, Reddy et al. [103] emphasized that integrating fuzzy logic enables effective handling of system nonlinearities and uncertainties without requiring an accurate mathematical model, making it a reliable and simplified control strategy for pitch regulation.

Neural networks have proven to be effective tools for managing the nonlinear and uncertain behavior of wind turbine systems. When integrated with classical control strategies such as PID, sliding mode control (SMC), or adaptive controllers they offer enhanced adaptability, learning capabilities, and robustness without the need for precise mathematical modeling. Hu et al. [104] introduced an L1 adaptive pitch controller enhanced with a neural network estimator, allowing real-time approximation of unknown nonlinear dynamics and ensuring robust reference tracking despite system uncertainties. Chen et al. [105] proposed a fixed-time neural sliding mode controller to regulate the pitch angle in variable-speed wind turbines. The control scheme ensures convergence within a finite time, significantly improving system stability and disturbance rejection, especially under high wind conditions. Finally, Zhao et al. [106] combined a classical adaptive control structure with a neural network that estimates nonlinear disturbances. Their system reduces oscillations and mechanical stress while maintaining precise rotor speed control, contributing to longer component lifespan and improved reliability. In a related approach, Sierra-García and Santos [107],designed a hybrid pitch control strategy that combines a lookup table with a radial basis function neural network (RBF-NN). The neural network learns online to compensate for errors in the LUT mapping, enhancing power stability under nonlinear operating conditions and reducing control delay.

Neuro-fuzzy systems combine the reasoning structure of fuzzy logic with the learning ability of neural networks. This hybrid modeling is particularly effective in wind turbine pitch control, where both adaptability and interpretability are essential to cope with system nonlinearities and environmental variability [108]. Goyal et al. [109] developed an ANFIS-tuned PID controller in which the fuzzy inference system dynamically adjusts PID gains based on real-time conditions. Their method improved transient response and reduced overshoot compared to conventional PID, particularly under variable wind speeds. Expanding this idea, Fan et al. [110] proposed a hybrid structure combining an ANFIS-based pitch angle predictor with a fuzzy logic controller. The approach achieved faster reaction to wind variations and reduced power fluctuation from 2.93% to 0.18%. Furthermore, an innovative direction was explored by combining fuzzy logic with deep reinforcement learning (DRL). In this approach, a fuzzy-based supervisory architecture coordinates the actions of multiple DRL-trained agents for collective pitch control [111]. This structure enabled the system to adapt decisions dynamically based on reward evaluation, while preserving interpretability through fuzzy rule sets. The method demonstrated improved robustness and stability without requiring wind prediction models.

In addition to the previously mentioned approaches, several recent studies have proposed adaptive and robust control strategies that do not rely on explicit system models. For example, model-free adaptive controllers based on tracking error dynamics offer strong robustness without requiring detailed knowledge of system parameters [112]. To further improve robustness and reduce chattering, hybrid control methods combining fuzzy feedforward structures with sliding mode control have been introduced [113].

These techniques benefit from the disturbance rejection capability of sliding mode control while mitigating high-frequency oscillations through fuzzy-based smoothing. In parallel, optimal adaptive robust controllers that integrate radial basis function neural networks with multi-objective optimization have shown promising results in managing nonlinearities and reducing mechanical loads in variable-speed wind turbines [114]. Continuing along this direction, Zhang et al. [115] proposed an intelligent adaptive sliding mode controller combining PSO-based parameter tuning with SVM-based operating condition classification. This approach enhances robustness to nonlinear disturbances while minimizing chattering, leading to improved overall pitch control performance.

In contrast to these advanced strategies, comparative studies of classical controllers such as PI, PID, and LQR still provide valuable insights into pitch regulation, particularly for permanent magnet synchronous generator (PMSG)-based wind turbines [116]. Although these conventional methods are widely used due to their simplicity and ease of implementation, their performance often degrades under nonlinear and uncertain conditions. To address these limitations, auto-tuned fractional-order proportional-derivative controllers have emerged as a robust, model-free alternative [117]. These controllers dynamically adapt their parameters based on tracking error characteristics and have demonstrated superior disturbance rejection and reduced actuator effort compared to traditional PID control.

4.5. Comparative Analysis of Pitch Control Techniques

Table 5 provides a critical analysis of the main pitch control strategies used in wind turbine systems. The goal of this comparative study is to offer a general overview to researchers interested in the advantages and limitations of various control techniques.

The methods are evaluated according to several qualitative criteria such as algorithm complexity, robustness to disturbances, adaptability, dynamic response at low wind speeds, computational burden, and real-time feasibility. It should be noted that these evaluations do not claim absolute precision, since the methods are often tested under different conditions, platforms, or turbine models. However, common tendencies are well established in the literature and have guided this comparative synthesis.

From this analysis, it appears that PI/PID control remains the simplest to implement and requires little computational power, although its adaptability and robustness are limited. Sliding Mode Control and $H\infty$ control offer higher robustness and faster dynamic response but may suffer from issues like chattering or tuning difficulties.

Model Predictive Control (MPC) stands out by its prediction capability and control precision, at the expense of high computation time. Fuzzy logic and neural network approaches provide strong adaptability and learning capacity, especially under non-linear conditions, but remain more complex to design and tune. Finally, hybrid control methods attempt to combine the strengths of these individual techniques, although their implementation often requires higher computational resources and more complex tuning procedures.

5. Integrating Wind Forecasting Techniques into Pitch Control Strategies

Conventional pitch control approaches, based on local measurements such as rotor speed or nacelle-mounted anemometers, respond with delay to sudden wind variations, which limits their effectiveness, especially under turbulent conditions [9], [62]. To overcome these limitations, several studies suggest integrating short-term wind forecasts, using tools such as Extended Kalman Filters or artificial intelligence models, in order to anticipate gusts and adjust the pitch angle more effectively [11].

Sierra et al. [118] propose a hybrid architecture combining online-trained deep learning for effective wind estimation and a Takagi–Sugeno fuzzy logic controller, enabling proactive pitch adjustments and achieving up to 21% power error reduction compared to conventional PID control.

Similarly, Wei et al. [119] incorporate wind speed forecasting using a Deep Extreme Learning Machine (DELM) to dynamically tune a PI controller via a Radial Basis Function neural network optimized by Particle Swarm Optimization (PSO), improving stability and reducing mechanical loads. Li et al. [120] introduce a model predictive control (MPC) framework driven by LSTM-based short-term forecasting of wind speed and direction. The predicted wind vectors enable real-time optimization of pitch, yaw, and torque, reducing output oscillations by up to 44% and improving rotor speed stability.

Jiao et al. [121] develop a hybrid intelligent pitch control strategy combining feedforward prediction and UDE-based feedback, enhancing system robustness under turbulent wind. Han et al. [122] employ LIDAR-assisted feedforward control using an online-trained RBFNN, which directly adjusts pitch and torque based on upstream wind previews. Simulation results show improved power stability and structural load reduction, including a 15.3% decrease in fore–aft tower base moments.

Table 5. Critical analysis of improvement techniques for pitch control [7], [16], [62], [98], [116]

Criterion	PI & PID	Sliding Mode Control	H-infinity	Model Predictive Control	Fuzzy Logic Control	Neural Network Control	Hybrid Methods
Algorithm complexity	Low	Medium	High	High	Medium	High	Very High
Robustness to disturbances	Medium	High	Very High	High	High	High	Very High
Adaptability	Low	Medium	Moderate	Medium–High	Good	Excellent	Excellent
Dynamic at low speed	Poor	Good	Moderate	High	Good	High	High
Dynamic response	Medium	High	High	High	High	High	Very High
Computation time	Low	Medium	High	High	Low–Medium	High	Very High
Real-time implementation	Easy	Moderate	Moderate	Moderate	Moderate	Moderate	Hardware-intensive
Tuning parameters	Simple	Complex	Complex	Complex	Moderately complex	Complex	Very Complex

Other works further enrich this trend by exploring complementary predictive strategies. For instance, Routray et al. [123] address the challenge of multi-turbine forecasting by training a neural network on data from a single LIDAR-equipped turbine, enabling feedforward MPC across neighboring turbines without additional sensors. In a different context, Sierra and Santos [124] propose a lightweight architecture with dual online-trained neural estimators integrated into a PID controller, particularly suited for offshore floating turbines. Aljundi et al. [79] integrate NN-based wind forecasting with a multi-input MPC framework, coordinating pitch control on a utility-scale turbine. Their approach demonstrates effective power gain and control smoothness, indicating scalability to industrial wind farm systems.

Finally, Li et al. [125] adopt a model-based inverse approach, reconstructing wind speed from aerodynamic torque using Kalman filtering. Their system achieves a 30% faster pitch response and reduces structural loading, offering a robust alternative to neural methods. summarizes representative studies that integrate wind speed forecasting with pitch control strategies and reports their main performance outcomes and practical characteristics. The comparison reveals that forecast-informed controllers consistently outperform purely feedback-based approaches in terms of power regulation and load mitigation, particularly in above-rated operating conditions. Several studies report reductions in rotor speed variance, power fluctuations, or fatigue-related load indicators typically ranging from 20% to 45% when short-term wind predictions are effectively exploited.

The table also highlights important differences among control strategies. Classical PI/PID-based controllers benefit from forecast feedforward but remain more sensitive to prediction errors and communication delays, as their corrective action relies primarily on feedback. In contrast, optimization-based controllers such as MPC and robust H∞ schemes generally demonstrate improved tolerance to forecasting uncertainty due to their explicit consideration of system constraints, disturbance models, and robustness margins.

However, these advanced methods often entail higher computational cost and implementation complexity, which may limit their applicability in real-time industrial environments. Overall, the results reported in Table 6 indicate that the effectiveness of forecast-informed pitch control is not solely determined by controller type, but by the combined suitability of forecasting horizon, prediction reliability, actuator constraints, and real-time computational feasibility.

Table 6. Sensitivity of pitch control strategies to forecasting errors and reported quantitative improvements

Strategy	Sensitivity to forecasting errors	Reported quantitative improvements
PI / PID	High	Up to 24% MSE reduction (PID + neuro-estimators); otherwise not consistently reported.
MPC	Medium	Up to 44% reduction in power oscillations (forecast-driven multi-input MPC).
H∞	Low	Up to 46.61% reduction in rotor-speed standard deviation under gusts.
Hybrid	Low–Medium	15.3% reduction in tower fore–aft base moment; power fluctuation reduced from 2.93% to 0.18%; 30% faster pitch response.

Table 7 provides a structured synthesis of recent studies that embed short-term wind forecasting within pitch control architectures, illustrating a move from purely reactive regulation toward anticipative, forecast-informed designs.

Across the reviewed works, forecasting modules span lightweight regressors and online estimators (e.g., SVR or neural estimators) [126], as well as deep learning predictors (e.g., LSTM- or CNN–LSTM-based models), and are coupled with control strategies including PID/PI tuning, Takagi–Sugeno fuzzy control, and (multi-input) MPC. Overall, the reported evidence indicates that forecast information can improve power and rotor-speed regulation as well as load-mitigation indicators when the prediction horizon matches pitch actuator dynamics and latency and measurement quality are properly managed.

At the same time, practical limitations restrict strict cross-study comparison and field deployment, including heterogeneous turbine models and operating conditions, non-uniform datasets and evaluation metrics, and differing sensing assumptions (SCADA-only versus LiDAR-assisted preview). In this context, learning-assisted MPC schemes are frequently associated with improved multivariable coordination, but may face higher implementation burden due to model complexity, tuning effort, data requirements, and computational cost.

Conversely, lighter predictors are often presented as a more implementable accuracy–complexity compromise for offshore or embedded real-time applications, although their performance may be sensitive to sensor noise, delays, and model mismatch. Therefore, the most consistent cross-study conclusion is that successful forecast-informed pitch control depends not only on prediction accuracy, but also on aligning forecast uncertainty and horizon with actuator constraints and real-time feasibility [127].

Table 7. Comparative analysis of recent wind forecasting-based pitch control strategies

Ref.	**Forecasting Technique**	**Pitch Control Strategy**	**Advantages**	**Limitation**	**Perspectives**
[118]	Online-trained ANN (LSTM)	Takagi–Sugeno Fuzzy Logic (TS–FLC)	Accurate short-term forecasting; smooth pitch control; power error reduced by up to 21%	Needs representative data; fuzzy rule tuning not automatic	Extend DLM to vibration prediction in floating turbines; implement in real systems; scale up to large turbines
[119]	DELM (Deep Extreme Learning Machine)	PI tuned via RBF–NN + PSO	Adaptive gain tuning; reduced loads; wind forecasting without iterative training	Requires high-quality training data; multi-model complexity	—
[120]	CNN–LSTM (hybrid)	MPC (multi-input)	Joint wind speed & direction; strong feature extraction; stable prediction; no iterative training	High model complexity; more parameters to tune; higher inference cost	Investigate real-time deployment; extend to varied wind conditions; enhance MPC robustness
[121]	SVR (Support Vector Regression)	Hybrid feedforward–feedback (SVR + UDE)	Accurate short-term prediction; proactive pitch control; reduced rotor speed & load fluctuations	Needs representative SCADA data; SVR tuning affects accuracy	Extend to low-wind regions; integrate with output-based dead-time modeling
[122]	LIDAR+RBFNN	Feedforward RBFNN pitch; torque control	Reduces structural loads; anticipates turbulence; stabilizes power output	Requires high-fidelity LIDAR; sensitive to turbulence-induced noise	Apply to 5 MW turbine models; enhance fatigue-load mitigation
[123]	Neural network (MLP) trained from single LIDAR	Feedforward MPC (FF–MPC)	Distributed wind estimation without local LIDAR; improved C_p tracking; reduced power fluctuations	Requires turbine alignment; performance sensitive to terrain effects	Extend to full-scale wind farms; integrate with real-time MPC on high-fidelity models (FAST, DNV-Bladed)
[124]	Online-trained NNs (effective wind estimation + forecasting)	PID + lookup table + neuro-estimators	Anticipates wind disturbances; improves power regulation (up to 24% MSE reduction); robust offshore	Requires training period; sensitive to sensor-signal quality & model mismatch	Deploy on real turbine prototypes; scale to large offshore or floating systems
[79]	NN-based forecasting (NNPC)	Multi-input MPC	Accurate short-term prediction; coordinated 3-DOF control; up to 44% reduction in power oscillations	Large training dataset; high computational demand for real-time optimization	Embedded deployment; integrate with fuzzy or reinforcement learning for adaptability

6. Conclusions

This review has provided a comprehensive analysis of wind speed forecasting techniques and their integration into pitch control strategies for wind turbines. Physical and statistical methods remain valuable for medium- to long-term horizons but are limited in accuracy under nonlinear and rapidly changing conditions. Artificial intelligence approaches, particularly deep learning, demonstrate superior performance for short-term forecasting, while hybrid models consistently achieve the most robust results, albeit at the cost of higher computational requirements. For pitch control, classical PI/PID schemes remain widely applied due to their simplicity, yet they struggle in turbulent and nonlinear environments. Advanced strategies such as sliding mode, H∞, MPC, fuzzy logic, and neural networks provide greater robustness and adaptability, while hybrid controllers illustrate the trade-off between performance gains and implementation complexity, highlighting the need for balanced, deployable control design.

Despite these contributions, several limitations remain and motivate future research. Key bottlenecks for practical deployment include the high computational cost of advanced optimization-based controllers such as nonlinear MPC (NMPC) for real-time implementation under fast sampling and constraints. In addition, preview-based approaches relying on LIDAR can be limited by sensor reliability and availability under adverse weather, as well as by added cost, alignment, and maintenance requirements. More generally, data-quality issues in SCADA measurements and forecasting uncertainty, especially for longer horizons, remain key challenges that should be addressed in future work.

The integration of accurate wind forecasting into pitch regulation represents a crucial step toward proactive turbine management. Forecast-informed control enhances energy capture, reduces mechanical stress, and improves system stability. These benefits also support energy efficiency and system longevity by mitigating fatigue loads and reducing actuator duty, thereby reinforcing the environmental value of reliable wind power generation. The research contribution is a unified theoretical perspective that links forecasting horizons, uncertainty characteristics, and real-time constraints with pitch-control objectives, clarifying the trade-offs between performance gains and practical deployability. This review contributes new knowledge by consolidating dispersed results into an integrated framework that highlights dominant trends, key bottlenecks, and actionable research gaps at both turbine and wind-farm levels. Future research should prioritize field validation, uncertainty-aware control integration, and scalable wind-farm deployment (including wake-aware coordination), while also considering system resilience through fault tolerance, data integrity, and secure operation. These directions provide a clear roadmap to motivate further research and accelerate industrial adoption.

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