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*Original Article*

# Kalman Filter Prediction Method for Tracking the Fuzzy-Based Maximum Power Point in Wind Turbine Generators

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## ABSTRACT

The wind energy sector has grown significantly over the past few decades and is expected to continue this trend as power electronic converters advance. This paper presents a novel control approach for wind turbine systems that combines Kalman Filter prediction with fuzzy logic-based maximum power point tracking (MPPT). The method addresses the challenge of optimizing power generation amid variable wind conditions by proactively adjusting turbine rotational speed and pitch angle. The system uses a Kalman Filter to predict wind speed changes and a fuzzy logic controller to optimize MPPT performance. The model comprises a wind power generation model, power electronic converters, and an MPPT controller. Simulation results in MATLAB demonstrate that compared to traditional vector control and proportional integral methods, the proposed approach achieves superior performance reduced delay time (4.93 seconds vs 5.6 seconds), faster rise time (0.06 seconds vs 3.5 seconds), quicker settling time (0.1 seconds vs 26 seconds), zero overshoot (2% vs 12.46%), and elimination of permanent error. These improvements enable more efficient and stable wind energy generation under variable conditions.



*Keywords: Maximum Power point Tracking, Kalman Filter, Wind Turbine Generator, Fuzzy Logic Controller.*

## 1 Introduction

The most important task of a power system is to supply electrical energy to subscribers while considering the desired quality. It ensures the continuity of energy supply without interruption and considers the optimal operational mode to minimize production costs. Due to the decrease in fossil fuel reserves, it is necessary to use distributed generation sources such as wind and solar power. The use of renewable and clean energy has grown significantly in recent decades, especially after the 1970s, the share of renewable resources in humanity's energy supply increased steadily [1]. A recent report from the International Energy Agency (IEA) highlights the rapid growth of wind energy as a key contributor to the present global energy transition, predicting that wind energy could account for almost 20% of global electricity generation by 2050 [2].

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Wind energy is an integral part of renewable energy systems due to its numerous benefits, including its role in creating a diverse and reliable energy supply. As a clean and renewable resource, it generates electricity without emitting greenhouse gases, helping to reduce dependence on fossil fuels and combat climate change [3]. Wind energy improves air quality and encourages sustainable energy practices by reducing carbon dioxide emissions and other air pollutants, which is achieved by augmenting electricity generation from fossil fuels. The environmental advantages, economic impacts, and ongoing technological developments position wind energy as a key contributor to the world’s renewable power transition [4].

Wind turbines are the essential technology for converting wind energy into electricity. The essential technology for converting wind energy into electricity is represented by wind turbines, which serve as the fundamental elements within a wind energy system, featuring rotor blades designed to harness kinetic energy and get the rotational mechanical energy. The output power of a wind turbine is closely related to wind speed, with the power curve of the turbine indicating peak power at a given speed.

Technological advancements have also led to improvements in turbine design, allowing them to operate at lower wind speeds and increasing their overall energy output [5]. At varying wind speeds, wind turbines face different challenges. The energy yield is low and the turbine efficiency decreases at low speeds. In contrast, excessive speed can damage the turbine structure and even cause it to be stopped for maintenance. Also, sudden changes in wind speed can negatively affect the stability and efficiency of energy generation systems. Increased wind speeds also lead to increased turbine noise, which can cause problems for the surrounding environment. For these reasons, controlling the turbine's response to wind conditions through pitch angle and rotational speed adjustments is essential to adapt to different wind speed conditions and optimize efficiency [6]. However, maximizing the efficiency of wind turbines remains a challenge due to the variability and unpredictability of wind conditions. One of the key techniques to enhance performance is Maximum Power Point Tracking (MPPT), which ensures that wind turbines operate at their peak efficiency by adjusting to changing wind speeds. Traditional MPPT methods can struggle with real-time adaptation to these fluctuations. Predictive control of modern turbines poses many challenges for design engineers [7].

Many researchers have devised techniques to restrict the generator's output power when wind speeds exceed the rated threshold. Classic controllers such as PID are used in blade angle control to limit the output power of wind turbines at wind speeds above the rated wind speed. Fingerish and Carlin have used classical controllers to control wind turbines to increase the energy taken from them for wind speeds below the rated wind speed, to control the torque of the turbine [8]. Enslin and Van Wyk conducted a study[9] that tested a simple and direct speed control method on wind turbines, in which they increased and decreased the turbine speed according to changes in wind speed. Unfortunately, not all turbines react well to changes in wind speed. In particular, turbines with high rotational inertia require a relatively long time to change speed and reach the point of maximum aerodynamic efficiency. At the same time, changes in wind speed occur in brief moments. In other words, the control systems capable of accelerating or decelerating the turbine with high reliability for small turbines are not effective for large turbines.

De Freitas, N., M. Silva and M.S. Sakamoto conducted a study [10] showing that when wind turbines are exposed to changes in wind conditions, the load torque applied to the turbine can be reduced to zero before an increase in load, provided that wind changes are anticipated through wind forecasts. This means the wind turbine accelerates quickly and reaches its optimal operating point more quickly. So when the wind speed increases and the turbine has the potential to extract more energy, it has already reached its optimal point, resulting in higher energy production. So far, various methods have been proposed to control the extraction of maximum power. In this paper, an attempt is made to design a control system based on predicting of actual wind speed. When the wind speed increases or decreases, the turbine's acceleration can be optimally increased or decreased. However, the turbine can be placed at the optimal point faster to extract energy finally. The method presented in this article is compared with traditional PI and vector control methods.

This study addresses the challenges of optimizing the efficiency and stability of wind turbines under variable wind conditions, despite advancements in turbine technology and Maximum Power Point Tracking (MPPT) systems. Traditional MPPT methods, such as PID and vector control, often struggle with real-time adaptability and fail to achieve optimal efficiency due to the unpredictability of wind speed variations. To overcome these limitations, this paper proposes an innovative approach integrating fuzzy logic-based MPPT with advanced filtering techniques like the Kalman filter. Fuzzy logic provides a flexible and adaptive control strategy for nonlinear systems, such as wind turbines. At the same time, the Kalman filter offers a robust prediction method to estimate system states and improve tracking performance accurately.

Integrating fuzzy logic with the Kalman filter enhances the wind turbine system's ability to sustain optimal power generation despite fluctuating wind conditions. The proposed approach aims to proactively adjust the turbine's rotational speed and pitch angle to optimize energy extraction and then improve the system's accuracy, stability, and responsiveness. The research compares the proposed method to traditional control approaches, demonstrating superior response time, stability, and error reduction performance. By leveraging the strengths of fuzzy logic and the Kalman filter, this method seeks to improve the reliability and efficiency of wind energy systems, ultimately contributing to sustainable energy generation and reducing reliance on fossil fuels.

## 2 Wind Turbine Modeling

The electricity generated by wind turbines is known as wind turbine power. It is derived by converting wind energy into mechanical energy and subsequently transforming it into electrical energy using synchronous generators. This process relies on key factors such as air density, wind speed, and the rotor blades swept area, collectively influencing the turbine's power output. Understanding these parameters is essential for optimizing energy production and enhancing turbine performance. The mathematical foundation of wind turbines relies on kinetic and energy principles, allowing for the prediction and modelling of their behavior under various conditions.

This mathematical model is essential for accurately simulating and predicting the performance of wind turbines, providing valuable insights into their operation and efficiency. These calculations help engineers predict how turbines respond to changes in environmental factors, such as variations in wind speed. This allows for developing efficient control systems that ensure maximum energy extraction while maintaining system stability. Ultimately, this knowledge contributes to advancing wind turbine technology, enabling cleaner, more reliable energy generation to meet growing demands. The energy produced by the motion of air possessing a mass m and velocity v may be shown in equation 1 [11]:

$$Ek = \frac{1}{2}mv2 \quad (1)$$

In time t, the mass of air going throughout cross-section A at velocity ν is equal to:

$$m{=}\rho Avt \quad (2)$$

In this regard, $\rho$ is equal to air density. Based on the above two equations, the relationship related to the wind power of the propeller rotation can be written as in equation 3:

$$p = \frac{1}{2}\rho Av3 \quad (3)$$

Specific power, or wind power density, is represented by the following relationship:

$$Pden{=}\ p\ /\mathrm{A}{=}\ PA = \frac{1}{2}\rho\ v3 \quad (4)$$

It is emphasized that wind power density directly correlates with wind speed. The real energy derived by the rotor blades from the wind energy is equal to the deviation between the wind power of the upper flow of the turbine and the power of the wind flow of the lower turbine [12] :

$$P{=}\frac{1}{2}km\ (v2{-}v02) \quad (5)$$

Accordingly, the wind speed of the upper flow of the turbine at the inlet of the turbine blades is $v0$ is the wind speed of the lower flow at the outlet of the turbine blades. Where $K_m$ is the mass ratio of the wind movement, which is obtained by the following relationship:

$$K_m = \rho A\frac{(v+v_0)}{2} \quad (6)$$

Where A is the cross-sectional area carried by the turbine blades. The rotational energy derived by the rotor $(p)$ and rotor power factor coefficient $(C_p)$are given by equations 7 and 8, respectively:

$$p = \frac{1}{2}(\rho A\frac{(v+v_0)}{2}(v^2 - v_0^2)) \quad (7)$$

$$C_p = \frac{1}{2}(1 + \frac{v_0}{v})\left(1 - \frac{v_0^2}{v^2}\right) \quad (8)$$

Figure 1 shows the rotor power coefficient $Cp$ a s a function of speed ratio, which denotes a portion of the power the rotor blades can capture from the wind, which should theoretically not exceed 59%. The Betz limit is the common name for this restriction. Based on the design, a turbine's practical efficiency can range from 40% to 50% for large turbines and from 30% to 40% for small turbines. The graph displays a typical bell-shaped curve, where $Cp$ rises with the tip speed ratio until it reaches a maximum efficiency point, at which time; it starts to decrease. This means the turbine operates most efficiently at a specific tip speed ratio. Beyond this point, drag and aerodynamic losses reduce its efficiency.

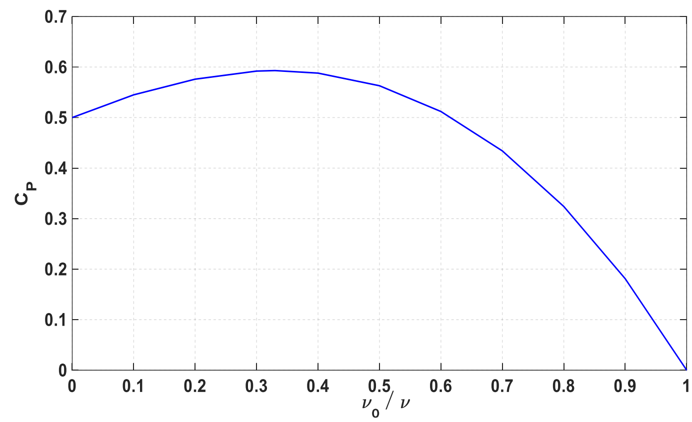


**Figure 1:** Theoretical Rotor Efficiency Curve as a Function of Tip Speed Ratio ( v_0/v ) [12].

The relationship between blade tip velocity and wind velocity is represented by $\lambda$. The value of $\lambda$ can be found from the turbine blade's peak speed to the speed of the wind, which is stated as equation 9 [3]:

$$\lambda{=}\omega R/v \quad (9)$$

Where $R$ represents the radius of the rotor blade, and $\omega$ represents the angular velocity of the rotor part. The velocity of the blade tip is directly related to the operational point of the wind turbine, which allows for optimal power extraction. The most outstanding efficiency of the rotor $Cp$ is obtained in a specific ratio of blade tip velocity to wind velocity, which is given by the aerodynamic design specifications of the wind turbine. For turbines with variable blade tip speed ratio, the rotor speed changes with the change of wind speed so that the speed ratio remains constant at the optimal level. Variable-speed ratio turbines can produce more power than fixed-speed turbines. The above calculations demonstrate the operation of wind turbines under ideal conditions. Various parameters affect the output of wind turbines. Weather conditions, wind profiles (both vertical and horizontal), turbine installation location, and height all affect the turbine's efficiency. The power developed by a turbine is determined by several factors, including the effective cross-sectional area of the turbine blades, the velocity of the wind, and the conditions of the wind flow within the rotor, $C_p$. Therefore, the energy generated by a turbine can be changed by altering the virtual cross-section or the wind conditions in the rotor system. Controlling these parameters is fundamental to the operation of wind power systems.

## 3 Methodology

### 3.1 Kalman filter prediction

The Kalman filter is an algorithm used for estimation, prediction, and updating the states of a dynamic system amidst noise and other uncertainties. To predict future states of the system, the current state estimate and system dynamics are required. This step also requires the missing components for accurate forecasting [13]. Also, some the related methods work by directly measuring the rotation speed and using it as an input to the speed adjustment section. These sets need sensors to measure the speed, which will increase the cost of the control operation. However, there are also methods to measure speed without a sensor [14, 15]. In this article, we used the Kalman Filter to make predictions. R. E. Kalman proposed the regression method for discrete data analysis. With the simultaneous development of digital computers, the Kalman filter method was introduced for real-time applications. For using the Kalman filter, it is assumed that a random process is modelled as follows [16] :

$$X_{k+1} = \phi_k X_k + w_k \tag{10}$$

Observations from the system are described according to the following relationship:

$$Z_k = H_k X_k + v_k \tag{11}$$

$X_k(n\times1)$ = State vector in time $t_k$ (12)

$\varphi_k(n\times n)$ = State transition matrix related to the states $X_k$ and $X_{k+1}$ (13)

$w_k(n\times1)$ = Uncorrelated white noise vector with known covariance (14)

$Z_k(m\times1)$ = A vector measured in time $t_k$ (15)

$H_k(m\times n)$ = The matrix expressing the relationship between the state vector and the measured values in time $t_k$ (16)

$v_k(m\times1)$ = Measured error of white noise with known covariance and uncorrelated vector $w_k$ (17)

As a result, the covariance matrices are as Eq. (18). Where k is the prediction correction instant state, which comprises estimates of the state vector. It is assumed that at the moment $t_k$, an initial estimate of the available system states, which is based on the information obtained from the previous system state. If this estimate is represented by $\hat{x}_k^-$, where the hat symbol denotes the forecast and the negative sign indicates the best estimate, and assuming that the estimation error at step $t_k$ is known, we obtain Eq. (19).

$$\begin{aligned} &E\left[w_k w_i^T\right] = \begin{cases} Q_k & i = k \\ 0 & i \neq k \end{cases} \\ &E\left[v_k v_i^T\right] = \begin{cases} R_k & i = k \\ 0 & i \neq k \end{cases} \\ &E\left[w_k v_i^T\right] = 0 \qquad for\ \ all\ \ i\ \ and\ \ k \end{aligned} \tag{18}$$

$$e_k^- = x_k - \hat{x}_k^- \tag{19}$$

As a result, the covariance matrix related to this error is equal to:

$$P_k = E\left[e_k e_k^T\right] = E\left[\left(x - \hat{x}_k^-\right)\left(x - \hat{x}_k^-\right)^T\right] \tag{20}$$

The Kalman filter model assumes known noise levels (known covariance) and well-defined initial conditions for the state vector estimates. These assumptions are critical to the filter's ability to minimize mean squared error and provide accurate condition predictions.

Assuming the previously estimated state is known, the measurements are used to improve the estimate. Here, the following linear combination is used to improve the estimation error.

$$\hat{x}_k = \hat{x}_k^- + K_k\left(Z_k - H_k \hat{x}_k^-\right) \tag{21}$$

$\hat{x}_k$ = Updated estimated value and $K_k$ = Combination factor

The challenge is to determine the most effective combination of coefficients that keeps the estimated values consistent with their best corresponding values. To achieve the most accurate estimates, the mean square error minimization criterion is applied.

$$K_k = P_k^- H_k^T \left(H_k P_k^- H_k^T + R_k\right)^{-1} \tag{22}$$

Then, the error covariance matrix is calculated using the following equation.

$$P_k = \left(I - K_k H_k\right) P_k^- \tag{23}$$

The Kalman filter provides estimates of a system's states by utilizing control feedback mechanisms. It first calculates the states of the system at a given time and subsequently incorporates the measurements obtained from the system to refine these estimates. In this way, the Kalman filter equations are divided into two groups, updating the time equations and updating the measurements.

Figure 2 illustrates the Kalman filter process, which operates in two primary phases: prediction and correction. In the prediction phase, the state variables and error covariances are projected forward to estimate the system's state at the next time step, incorporating system dynamics. In the correction phase, the predicted estimates are updated using real-time measurements by calculating the Kalman gain, which determines the weight assigned to new measurements versus prior forecast. This iterative process involves updating the state estimate and error covariance to minimize the mean squared error, ensuring accurate and robust predictions even in the presence of noise and uncertainties.

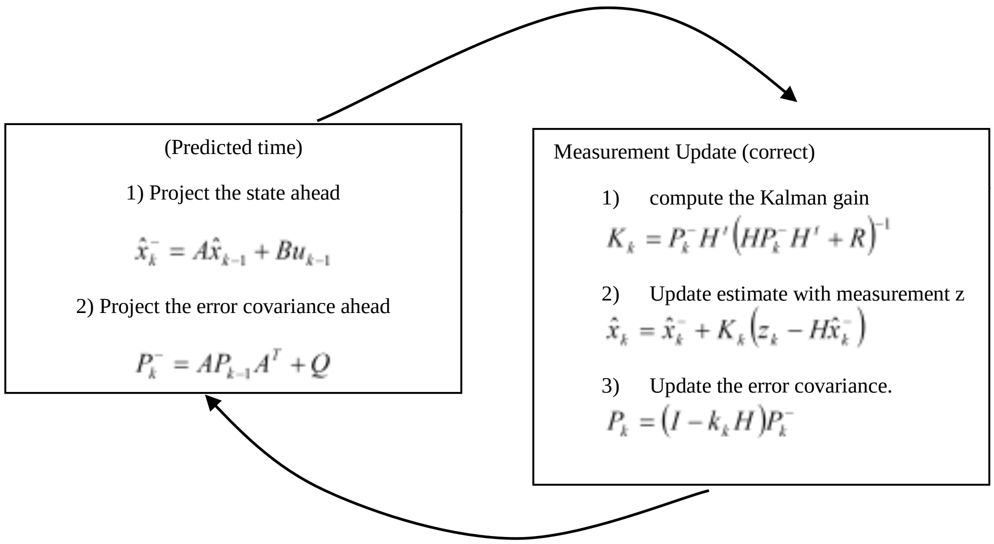


**Figure 2:** Full image of the Kalman filter process.

As shown in Figure 2, in the correcting process, the state variables in time $t_k$ are first estimated. Then in the prediction part, the state variable in time $t_k+1$ is predicted from the state variable in time $t_k$. The wind forecast is modelled by Kalman filter as follows:

$$X_{k+1} = \phi_k X_k + w_k$$
$$y_k = \begin{bmatrix} y_{k-1} & y_{k-2} & \cdots & y_{k-m} \end{bmatrix} \tag{24}$$

## 3.2 Fuzzy-Based Maximum Power Tracking

Fuzzy MPPT is a control strategy used to optimize the power output of a system such as a wind turbine. The main goal of MPPT is to ensure that the system operates at its maximum power point (MPP) under ambient conditions, such as fluctuating wind speeds or varying sunlight intensity [17]. A method that uses fuzzy logic for optimizing the Maximum Power Point (MPP) adjusts system settings, such as the converter's duty cycle and the turbine's speed, based on predefined fuzzy control rules. This approach is better at dealing with unpredictable and complex parts of the system compared to traditional methods [18].

In this paper, wind turbine speed control is analyzed using fuzzy logic to achieve maximum power generation. According to the wind speed-turbine rotation speed-turbine production power curve shown in Figure 3, it can be seen that for a specific rotation speed, the power output of a wind turbine reaches its maximum at a corresponding wind speed. The relationship between wind speed and turbine rotation speed highlights the importance of precise control over the turbine's rotational speed to align with optimal wind conditions, ensuring that the turbine operates at its peak efficiency and generates the highest possible power output.

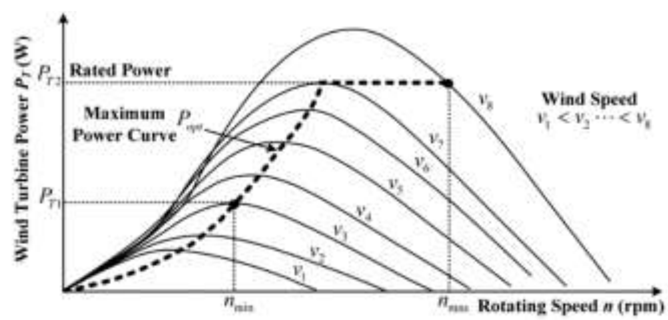


**Figure 3:** Power change curve according to wind speed and turbine rotation [19].

Strategies this figure to enhance efficiency include optimizing pitch control and variable-speed operation to follow the maximum power curve at all sub-rated wind speeds and curtailing power appropriately at higher wind speeds to protect the turbine while maintaining consistent energy production.

Figure 4 shows the schematic block diagram of the simulated power system with the wind turbine energy system, which is used in this paper. The system harnesses wind energy through a variable-speed wind turbine connected to a synchronous generator (SG), which converts mechanical energy into electrical power. The generated AC power is rectified via three-phase rectifiers and further processed through an AC-DC converter and a DC-DC chopper circuit to transmit power to the DC link. An inverter connects the DC link to the load, completing the energy conversion process. To optimize system performance, a fuzzy-based Kalman filter is employed, with a controller ensuring efficient energy regulation and management throughout the system.

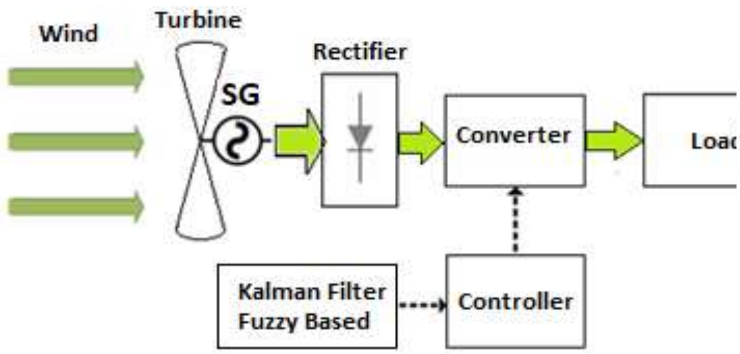


**Figure 4:** Schematic of the simulated power system.

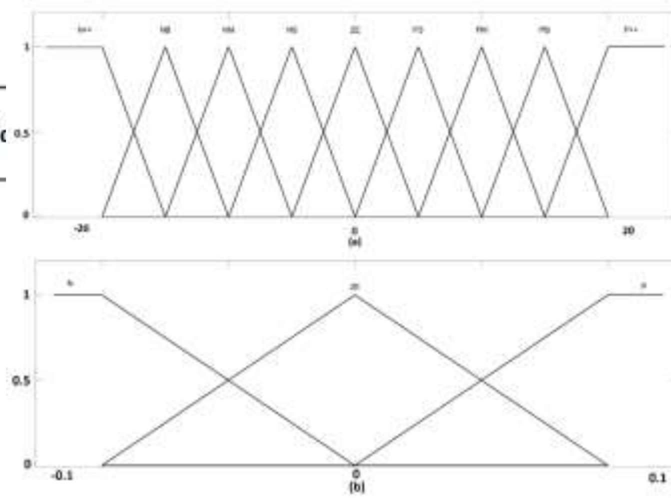


**Figure 5:** Input Membership functions (a) power variable and (b) the speed deviations.

Figure 5 shows the fuzzy logic membership functions for a wind turbine control system. The first input, which is the change in power of the wind turbine, has nine membership functions: "Negative Very Large" (N++), "Negative Big" (NB), "Negative Medium" (NM), "Negative Small" (NS), "Zero" (ZE), "Positive Small" (PS), "Positive Medium" (PM), "Positive Big" (PB), and "Positive Very Large" (P++). The second input, which is the speed deviation, has three membership functions: "Negative" (N), "Zero" (ZE), and "Positive" (P). These membership functions help the fuzzy logic controller decide how much a specific value fits into each category, even when the information is unclear precise. Output membership functions are similar to input 1, but it varies between -0.15 and 0.15. At a stable condition, swinging and quick tracking speeds are decreased using the FLC rules base given in Table 1.

**Table 1:** Fuzzy Logic Controller Rules Table.

| $\Delta\omega$ | $\Delta Pm$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | N++ | NB | NM | NS | ZE | PS | PM | PB | P++ |
| **N** | P++ | PB | PM | PS | ZE | NS | NM | NB | N++ |
| **ZE** | NB | NM | NS | NS | ZE | PS | PM | PM | PB |
| **P** | N++ | NB | NM | NS | ZE | PM | PM | PB | PB |

Table 1 provides a detailed set of fuzzy logic controller (FLC) rules designed to optimize wind turbine performance by adjusting control parameters in response to varying wind conditions. The table specifies the relationships between two key inputs—power variation and speed deviation—and the resulting control actions. The inputs are categorized into linguistic variables, such as "Negative Very Large" (N++), "Negative Big" (NB), and "Positive Very Large" (P++), for power variation, and "Negative" (N), "Zero" (ZE), and "Positive" (P) for speed deviation. These variables are mapped through predefined fuzzy rules to generate corresponding outputs, which dictate the extent of corrective action required. The rules are meticulously designed to ensure smooth system operation, minimize fluctuations, and accurately track the Maximum Power Point (MPP).

## 4 The Results and Discussion

A wind turbine with a permanent magnet synchronous generator is connected to an electrical load by a power electronic converter. The simulation parameters are presented in Table 2. To indirectly measure the generator's rotational speed based on the active power-frequency relationship, the generator's output active power is measured, and a control system utilizing the Kalman Filter is employed. Figure 6 illustrates a block diagram of a pitch control system for a wind turbine. The system receives two input signals: the wind speed ($v_\alpha$) and the blade pitch angle ($v_\beta$). These signals are multiplied by the cosine and sine functions, respectively, to obtain the components of the wind speed vector in the blade coordinate system. The resulting components are then summed and passed through a proportional-integral (PI) controller, which generates a control signal ($\hat{\theta}v$) to adjust the blade pitch angle. This control signal is designed to optimize the turbine's power output by regulating the amount of wind energy captured by the blades.

**Table 2:** The simulation parameters wind turbine synchronous generator.

| Parameters | The value |
|---|---|
| Air density | 1.2 kg/m$^3$ |
| The inertia constant of the set | 0.011 kg/m$^2$ |
| Nominal power of the generator (base power) | 2000 VA |
| Synchronous generator speed | 3000 rpm |
| Generator inductance | 0.000795 H |
| Generator resistance | 0.05 Ω |
| The radius of the turbine | 3.8 m |
| DC link voltage | 560 V |
| generator type | Flat pole |

| | |
|---|---|
| Number of phases | 3 |
| Leakage flux | 0.192 Wb |
| The resistance of the converter | 0.001 Ω |
| The snubber resistance of the converter | 100 kΩ |
| Proportional coefficient of speed control | 0.5 |
| Integral coefficient of speed control | 100 |

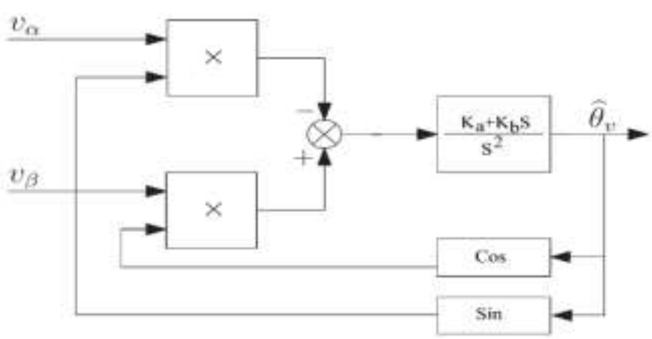


**Figure 6:** Block diagram of indirect generator speed measurement.

Figure 7 shows the simulated wind speed changes for this system. To evaluate the system's performance under varying wind speed conditions, the speed function has been treated as a variable amplitude. It illustrates how the wind speed changes over time. It starts at a low value, then increases abruptly, reaching a peak, and then decreases gradually before stabilizing at a new level. This profile could represent a sudden gust of wind followed by a gradual decrease in wind velocity, a typical scenario in wind turbine operations.

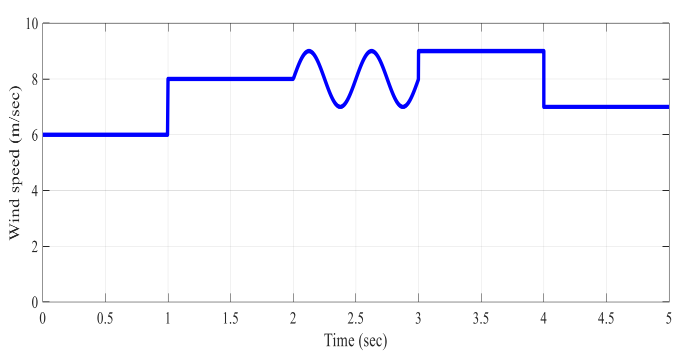


**Figure 7:** Wind speed changes.

Figure 8 illustrates the rotational speed of the generator in rpm, with the generator operating under a torque control system. As the wind speed fluctuates, the rotational speed and working frequency of the generator dynamically adjust to optimize power output. This demonstrates how the generator's rotational speed adapts in response to the wind speed variations depicted in Figure 7, ensuring maximum power extraction under changing conditions.

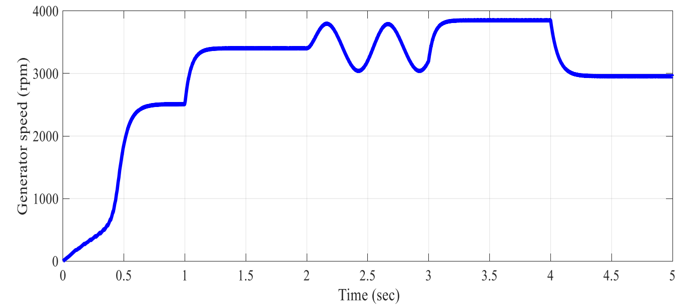


**Figure 8:** Generator rotation speed.

Figure 9 shows the changes in the active power output of the generator, which is used as one of the inputs of the phase control section. It illustrates a time-domain signal representing the change in active power for 5 seconds. The signal undergoes several fluctuations, indicating varying power disturbances. These fluctuations diminish and stabilize toward the end of the time window, suggesting a system response to disturbances that eventually subsides and stabilizes.

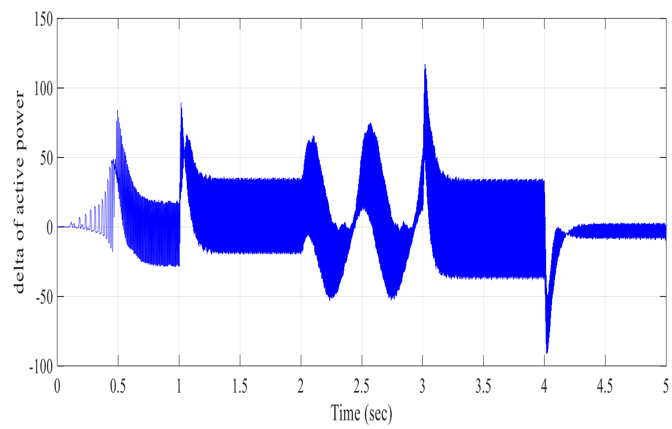


**Figure 9:** Changes in active generator output power

Figure 10 shows the changes in the output speed of the generator, which is used as another input of the phase control section. Specifically, it shows how the generator's rotational speed deviates from a reference or nominal speed, which could be due to control actions. The large fluctuations in the plot indicate how the generator reacts to control actions in the system. The oscillations in the graph indicate periods where the generator's speed varies significantly before stabilizing, and the sharp drop at around 4 seconds suggests a rapid change in load, after which the system starts to recover.

Figure 11 shows the output of a fuzzy logic controller used in a wind turbine control system. It demonstrates how the fuzzy logic controller output varies in with wind velocity. The dynamic nature of the output indicates that the controller actively adjusts the control command to maintain optimal turbine performance. Additionally, the output reflects the extent to which the controller activates or deactivates specific control actions.

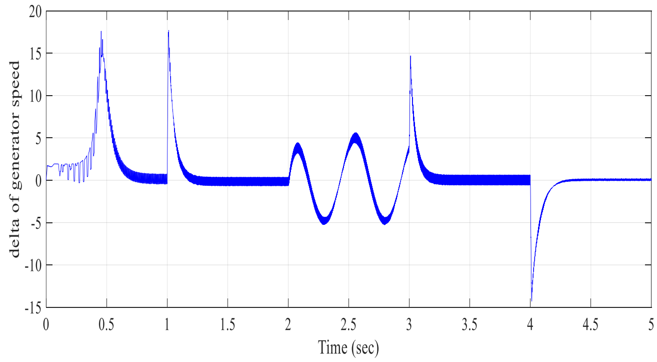


**Figure 10:** Generator output speed changes.

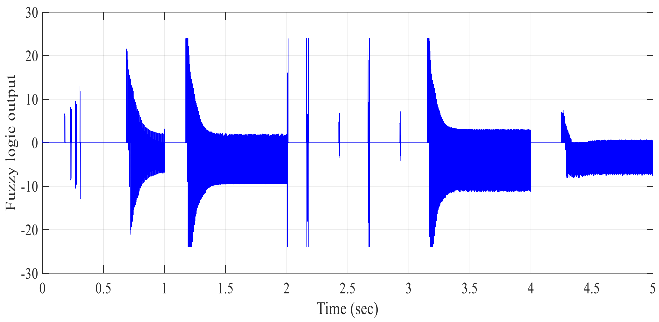


**Figure 11:** Fuzzy Logic Controller Output.

Figure 12 illustrates the power transferred from the synchronous generator to the load. It can be observed that the maximum power transferred to the load varies with wind velocity, which consequently affects the generator's rotational speed. The blue line illustrates how the load power changes over time. It begins at a low value, increases rapidly to reach its peak, and then gradually decreases before stabilizing at a new steady level. This profile could represent a sudden increase in demand for electricity from the grid, followed by a gradual decrease as the demand stabilizes.

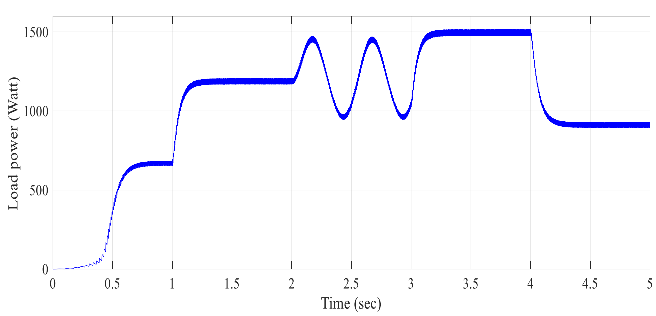


**Figure 12:** Transferring power to the load.

Figure13 shows the profile of load voltage of a wind turbine system developed by synchronous generator. It illustrates how the load voltage changes during operation. Initially, the load voltage starts low and increases rapidly, reaching a peak and then fluctuating slightly due to variations in wind speed and the control signals of the turbine's pitch control system. The load voltage then stabilizes at a new level, reflecting the steady-state operating conditions. The fluctuations in load voltage are likely due to changes in grid demand, variations in wind speed, and the controller's efforts to maintain the turbine's power output within the desired range.

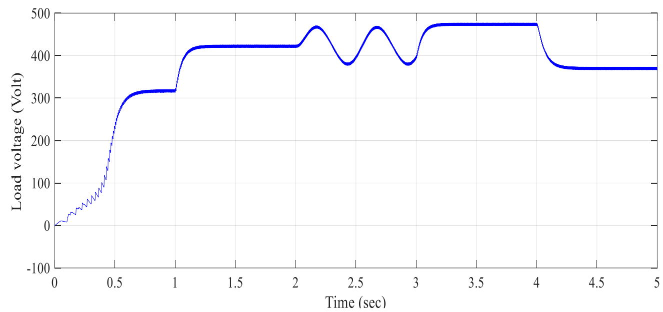


**Figure 13:** The DC voltage profile.

Table 3 compares the performance of three control methods for a wind turbine system: The Kalman filter prediction Tracking Fuzzy Based MPP method, traditional vector control, and proportional-integral control. The comparison evaluates key performance metrics, including delay time, rise time, settling time, overshoot, and permanent error. The numbers related to the traditional vector control method and the proportional integral controller in the table below are extracted from the references and presented along with the results of the proposed method.

The proposed Kalman filter-based fuzzy logic controller demonstrates superior performance across all evaluated metrics, making it a highly effective approach for wind turbine control. This method achieves the fastest response, with a delay time of 4.93 seconds, a rise time of 0.06 seconds, and a settling time of 0.1 seconds, significantly outperforming alternative techniques. Moreover, it eliminates overshoot and permanent errors, ensuring precise and stable control under varying wind conditions. In contrast, traditional vector and PI control methods show slower response times, higher overshoot (up to 12.46%), and longer settling times, underscoring their limitations in dynamic and nonlinear wind environments. These results highlight the effectiveness of the proposed method in optimizing wind turbine performance and ensuring operational stability.

## 5 Conclusion

Wind is the main component of a wind turbine system's operation. The wind speed varies and disturbs the property of wind turbine generators. In this paper, the wind turbine energy system is modelled using MATLAB Simulink. The model will be composed of different components: wind turbine, synchronous generator, rectifier, converter, and MPPT control unit using Kalman filter prediction-based fuzzy logic controller for tracking maximum power point. A feedback system proposed that adjusts the turbine's speed based on real-time changes in wind.

**Table 1:** Comparison of the proposed method with traditional vector control method and proportional integral controller.

| | Kalman Filter Prediction Tracking Fuzzy- Based MPP | Traditional vector control method [20] | Traditional proportional integral method [21] |
|---|---|---|---|
| **Delay Time (seconds)** | 4.93 | 5.6 | 4 |
| **Rise Time (seconds)** | 0.06 | 3.5 | 3 |
| **Settling Time (seconds)** | 0.1 | 26 | 21 |
| **Overshoot%** | 0 | 2 | 12.46 |
| **Permanent error** | 0 | 0 | 0 |

This helps the turbine run at its best efficiency, producing maximum power even when the wind speed keeps changing.

The integration of a Kalman Filter and a Fuzzy Logic Controller for wind turbine synchronous generator control has been examined in this paper. The fuzzy logic controller's real-time data input accuracy is raised by the Kalman Filter, which provides an optimal estimation of the system conditions. In contrast, fuzzy logic offers a robust, flexible control technique that can manage the uncertainty and nonlinearity present in wind turbine systems. The system runs better regarding stability, efficiency, and adaptability as the outcome of this arrangement.

This paper presents a transient analysis of a variable-speed wind turbine generator operating at full load to maximize power output under wind speed disturbances. The simulation results demonstrate that the proposed model offers superior performance and effectively controls the wind turbine, ensuring maximum power extraction. The results indicate that the Kalman filter-based fuzzy logic MPPT controller performs better than traditional vector control and proportional-integral (PI) control by achieving zero overshoot and no permanent error, ensuring high stability and precise control. It also reduces the delay time to 4.93 seconds compared to 5.6 seconds with vector control while maintaining more excellent stability than PI control, which suffers from higher overshoot (12.46%) and slower response times. Furthermore, the controller offers a faster response, with a rise time of 0.06 seconds (versus 3.5 and 3 seconds in traditional methods) and a settling time of 0.1 seconds (compared to 26 and 21 seconds), confirming its effectiveness in optimizing wind turbine operation. This approach provides a viable solution for real-world wind energy systems, enhancing reliability and minimizing downtime caused by speed fluctuations. Future work could explore integrating real-time wind forecasting data to optimize system performance further.

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