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Improvement of Dynamic Performance in SEIG by Using Adaptive Sliding Mode Controller

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Abstract:
Although RES play a crucial role in sustainable development, they pose difficulties for effective regulation because to their nonlinear, time-varying, and unpredictable character. In the face of such unknowns, Sliding Mode Control (SMC) provides resilience, while AI methods boost performance and adaptability. An extensive investigation of the use of artificial intelligence in conjunction with adaptive sliding mode control (ASMC) to improve the performance of renewable energy systems is detailed in this work. In most of the existing systems, Fuzzy Controller, Neural Network based Controller and Artificial Neuro-Fuzzy Inference System (ANFIS) have been used for SMC. However, still adaptivity is the major issue due to the dynamic energy environment. In this paper, we proposed an AI-inspired ASMC (AI-ASMC) for RES. Each of SMC and Self-Excited Induction Motor (SEIG) big efforts was its own concentration. On the other hand, wind systems perform better under dynamic situations when SEIG and SMC are integrated. We present a hybrid AI method for AMC and SEIG integrated control in this paper.We delve into the theory, design process, simulation findings, and performance evaluation of AI-based ASMC in several renewable energy source (RES) applications, including solar and wind power plants. The simulations made in MATLAB show that the proposed work shows better results in stability, reliability as well as power outputs.
Keywords: SMC, Wind Energy System, AI,
Fuzzy Logic, PSO.

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I. Introduction

The implementation of renewable energy systems (RES) has been expedited due to the increasing need for environmentally friendly power. Wind turbines and solar photovoltaic (PV) systems are examples of such nonlinear systems that are susceptible to environmental fluctuations and uncertainty. Optimal performance under these situations is typically lost when using traditional control tactics. For its ability to withstand disruptions and model errors, SMC has gained renown. Chattering and lack of flexibility can occur with fixed-parameter SMCs. Integrating AI into control techniques enables systems to acquire new knowledge and adjust accordingly in real-time. In this research, we present a framework for Adaptive Sliding Mode Control (ASMC) that makes use of artificial intelligence (AI) tools such neural networks, reinforcement learning, and fuzzy logic. Our goal is to show how ASMC with AI enhancements make RES more efficient, stable, and reliable.

Depending on the generator's rotor, wind turbines used to generate wind power are either inductive or synchronous [1]. In the beginning, doubly-fed induction generators were the norm for wind power generation. These generators allowed operators to adjust the operating speed with a slip. Offshore wind power generation complexes are only one example of a scenario where permanent magnet synchronous generators are finding growing use due to their high generation capacity, low maintenance management requirements, and cost effectiveness. Benefits of permanent magnet synchronous generators (PMSG) include lighter generators, less maintenance required, lower operating noise from permanent magnets in the rotors, and lower production costs as a result of processing technological advancements. Because of their high efficiency and magnetic flux density, they are able to produce more torque than doubly-fed induction generators, which is a major benefit [2, 3].

Both fixed- and variable-speed designs are possible for wind turbines [4]. Induction generators directly linked to a three-phase power grid convert wind energy into electrical energy in fixed-speed operating systems. A fixed-ratio gearbox keeps the wind turbine's rotor speed constant while it's connected to the generator shaft. In contrast, synchronous generators often make use of variable speed operating systems, which allow the generator's rotors to spin at different speeds. Aerodynamic control allows the operator to alter the generator's torque, speed, and power, and variable operating wind power generators link to the grid via a converter rather than a direct connection. As a result, the wind power turbine may be fine-tuned to run at its maximum output coefficient throughout a broader range of wind speeds, with less mechanical stress and aerodynamic noise [5].

Max power point tracking (MPPT) is the control approach used here to ensure energy production is done at its most efficient [6]. For different wind speeds, an MPPT controller determines the best rotor rotation speed. Consequently, it is reasonable to assume that the placement and precision of the wind speed sensors are critical variables. Conventional vector control using proportional-integral loops is one example of a linear controller that uses an estimated linear model to maximize power extraction [7], [8]. Because the PMSG is a nonlinear system with wide-range operation points, various control solutions might not work as expected. A feedback linearizing control based MPPT is suggested to enhance performance. This technique involves designing the mechanical rotation speed controller and current controllers using linear control methods. Nevertheless, this leads to a control rule that is complicated and not very resilient to changes in parameters or outside influences. Because wind speeds differ depending on where on the turbine they are measured—and because wind power turbine rotors often have quite large diameters—wind speed readings might not always be an appropriate number for maximizing energy output. Since both the measurement site and the sensors themselves contribute to environmental uncertainty, wind speed measurement is better suited to systems with high levels of noise. Due to the high degree of mechanical uncertainty in wind power turbine systems, control strategies are necessary to address this issue.

Among the several robust control approaches, sliding mode control (SMC) has seen extensive usage as a robust control for disturbance and uncertainty. The use of SMC in wind energy conversion systems has been the subject of a few published articles in the last several decades [9]. Using SMC for MPPT in a wind energy conversion system with uncertainties was done in the early investigations of [10]. An ideal torque SMC technique is suggested for the implementation of MPPT tasks in a system of variable speed wind turbines. So, to manage the electromagnetic torque in MPPT for PMSG, the SMC technique was used. An unstructured uncertainty wind energy conversion system is subjected to SMC and an input-output linearization approach. A PMSG wind turbine system that is linked to the grid was used to test and develop an SMC that is based on the Enhanced Exponential Reaching Law. By utilizing SMC, we were able to decrease inaccuracies between the actual current on the d- and q-axis and the required command values, and we increased resilience under changing operating situations such parameter changes and load fluctuation. A sliding mode controller and a suggested artificial neural network controller were used in the construction of an induction generator (IG) speed drive. The ideal sliding surface was established by studying the relationship between rotor speed and torque in [11]. In [12], researchers looked into adaptive SMCs by first creating one to fix PMSG's rotor speed inaccuracy, then another to fix controller gain and mechanical torque estimate.

When it comes to renewable energy, SMC has been the subject of a great deal of research. While adaptive systems were developed subsequently, fixed-gain SMC was the primary focus of early research. The improved handling of nonlinearities and uncertainties made possible by AI integration has attracted a lot of interest. Important contributions encompass:

- Fuzzy-based SMC to mitigate chattering.
- Neural Network-based adaptive controllers for maximum power point tracking (MPPT).
- Reinforcement learning for dynamic tuning of control parameters.

II. Related Works

For floating wind turbine systems, this research suggests an adaptive switched sliding mode controller that can improve performance even when actuators fail or when the environment is unclear. Floating wind turbines that take the average stay duration into account are modeled using a control-oriented switching linear model. The suggested controller is based on an adaptive law and a full-order state observer, which make up for the impaired control outputs caused by identifying mistakes, disturbances, and defects. A combination of the linear matrix inequality method, the average dwell time approach, and the Lyapunov stability theory provide stability theorems, from which the control parameters are determined. On the NREL 5MW wind turbine and spar-buoy platform, the suggested model and controller are tested with the help of the high-fidelity fatigue, aerodynamics, structures, and turbulence (FAST) code. Under varying wind-wave combination circumstances, the suggested controller's performance is contrasted with that of an optimum gain-scheduling proportional-integral controller. Whether the floating wind turbine is operating normally or not, the findings demonstrate that the suggested controller reduces mechanical stresses and enhances power quality. Clinicians, Please Take Note—There has been a lot of buzz about floating wind turbines as a sustainable energy source. It is critical for offshore floating wind turbines to be able to withstand component failures and continue producing steady power quality when operating in rough seas. Finding a solution that lessens the impact of a defect on the wind turbine system is no easy feat. For floating wind turbines, this study suggests an adaptive fault-tolerant control approach for when actuator faults occur [13].

The renewable energy sector is greatly affected by hybrid energy storage systems because of their significance in improving grid stability and regulating its fluctuation. But sophisticated control tactics are needed to put these systems into action so they work as intended. In this study, we offer an algorithm for the control and power phases of a hybrid energy storage system that combines a bidirectional Zeta converter, a battery, and a supercapacitor. A power circuit parameter-co-designed adaptive sliding-mode controller is used in the control stage. Compatibility with inexpensive microcontrollers and protection of the battery against life-reducing high-frequency transients are features of the design methodology. The Zeta converter's constant output current also keeps the load, microgrid, and battery free of current harmonics. The suggested method outperforms a traditional cascade PI architecture, as shown in an application example run using the PSIM electrical simulation program (version 2024.0) [14].

This article proposes an adaptive fractional sliding-mode control (AFSMC) method based on improved convergence rate performance of the FOPMSG to track accuracy, response speed, and robustness, as a solution to the Mittag-Leffler synchronization (MLS) problem of a wind turbine system based on a fractional-order permanent magnet synchronous generator (FOPMSG) that is subject to unknown disturbances like variations in the external load torque and uncertainties in the system parameters. Simplifying the system's time to the sliding-mode surface and improving the chattering in the control signal are the main goals of the AFSMC technique, which is based on a fractional-order term integrated into the new rule for reaching the sliding mode. The robust controller that was built ensures the robust sliding-mode dynamics by deriving sufficient requirements. For the first time, this study proposes an adaptive sliding-mode control (ASMC) with a terminal function that, at a predetermined time, correctly manages the FOPMSG model. In addition, the ASMC that was created can eliminate the reaching phase according to Lyapunov stability theory, which effectively reduces the presence of disturbances and uncertainties [15].

Using an adaptive reference model called Model Reference Adaptive Control (MRAC), this work provides a direct power control (DPC) solution for the Doubly Fed Induction Generator (DFIG). In order to circumvent the problems that arise from using PID controllers alone, this method is based on the conventional DPC. To overcome these constraints, solutions frequently include balancing speed and efficiency or, in the case of fast changes in wind speed, deviating from peak power. These are the DFIG (Double Fed Induction Generator) equations in the d-q reference frame. Then, to regulate the DFIG, we create a direct power control (DPC) method that uses PID controllers and space vector modulation (SVM) to keep the switching frequency constant. One level of stator side power factor is maintained via the Maximum Power Point Tracking (MPPT) method. In the DPC architecture, Model Reference Adaptive Control (MRAC) takes the role of traditional PID controllers. In addition, we compare and contrast the performance of the PID controller with that of DPC-based MRAC [16].

This paper introduces an adaptive supertwisting sliding mode controller (AST-SMC) that enhances the original benefits of sliding mode control (SMC) by eliminating chattering and prioritizing reliability through dynamic control setting adjustments that do not require prior knowledge of uncertainty limits. We begin by simulating and constructing the wind turbine system using three distinct controllers: the AST-SMC, the ST-SMC, and eventually the FOSMC. A different comparison is required. Due to concealed state information, which utilizes the whole system state, the control law only has access to the rotor speed. An asymptotic observer triangle is employed to estimate the unknown rotor acceleration with the goal of minimizing observing errors over time. The optimal controller is discovered using particle swarm optimization by enhancing the control law of AST-SMC. Applying the Lyapunov stability theorem, we prove that AST-SMC is stable for limited time. When compared to conventional SMC, the results of the simulation show that it performs better in controlling the system of wind turbines. In terms of energy consumption, settling time, tracking precision, and the smoothness of control inputs, it shines [17].

Due of its low impact on the environment, wind energy conversion systems (WECSs) are currently the subject of intense research and development efforts. An appealing advancement is the maximum power extraction (MPE) that is affected by changes in wind speed. The MPE with parametric variation and wind speed is the focus of this work. Creating a GGSMC, or generalized global sliding mode control, to monitor wind turbine speeds accomplishes this goal. Feed forward neural networks (FFNNs) are used to predict the nonlinear drift terms and input channels, which often change in the presence of uncertainty. Starting from the beginning with suppressed chattering, the planned GGSMC algorithm imposed sliding mode. Because of this, the maximum power point tracking (MPPT) management is extremely robust right from the start, which is something that is always required in real-world situations. Thoroughly presenting the results of the suggested design's closed loop stability study and conducting simulations to validate the robust MPE [18].

To successfully address the problems generated by measurement noise in the system, our controller implements an Arbitrary Order Sliding Mode Control (AOSMC), which is its fundamental uniqueness. An input-output form that is control-convenient is created from the model that is being studied. In order to further improve the system performance, we also incorporate a high-gain differentiator (HGO) and feedforward neural networks (FFNN) into the control mechanism all at once. In contrast to the FFNN, which calculates essential nonlinear functions like the input channel and drift term, the HGO calculates higher derivatives of the system's outputs and feeds them back into the control algorithms. The control rule becomes more realistic with HGO since it lessens the sensitivity of the sensors to noise. Our extensive MATLAB-based simulation studies verify the remarkable efficacy of the suggested innovative control method in optimizing power extraction in standalone wind energy applications, and we compare the findings to those in the existing literature to back up our claims [19].

The use of renewable energy sources to create electricity is a developing trend globally in recent years. The fundamental parameters impacting the power production of wind turbines—the wind's speed and direction—are dynamic and ever-changing. Changing the blade angle is one way to regulate the power output of a wind turbine. The wind turbine pitch angle is controlled using an adaptive control approach in this article. The sliding mode control coefficients were computed using the particle swarm optimization-support vector machine approach, and they form the basis of the proposed method. A comparison with the Model Reference Adaptive Controller (MRAC) in operating under disturbance was conducted to assess the efficacy of the suggested technique. The findings demonstrate that when disturbances are present, the suggested controller outperforms the MRAC. Power production at various wind velocities has, according to simulations, accelerated to its maximum potential [20].

III. Proposed AI-ASMC Model

3.1. Mathematical Model of Wind System

The system model is depicted The wind, the primary force behind wind turbines (WTs), is both swift and directional. It starts with air masses moving through the atmosphere as a result of pressure or temperature variations. Delays in wind speed and direction caused by frictional forces and obstructions in the lower atmosphere are known as wind deceleration. The turbulent flows begin here. Because turbulence grows with increasing ground roughness and diminishes with increasing distance from the ground, wind speed varies over a large frequency and amplitude range. The essential feature of lower-layer winds, as described by the Van der Hoven spectra, is the distribution of kinetic energy in the frequency domain. Eq.(1) expresses the model's prediction that the wind speed (v) may be divided into two parts: a deterministic component with a slow variable (vm) and a stochastic component with a fast variable (vt):

$$v = v_m + v_t \tag{1}$$

In the turbulence domain, the turbulence spectra seen by a blade element in motion deviate from those at a fixed point, where a portion of the kinetic energy is concentrated at higher frequencies; in the stationary domain, changes in wind speed over the rotor disc are caused by tower shadow effects and wind shear, which is the change in mean wind speed with height due to earth's skin friction.

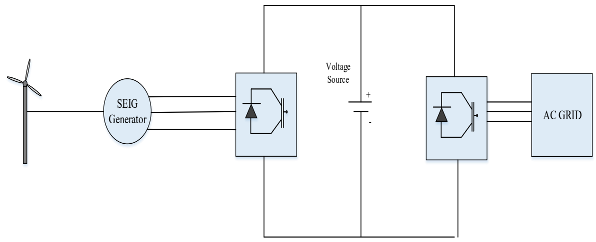


Fig.1. Wind Energy System Model

In major works, SMC and SEIG focused individually. However, integration of SEIG and SMC improves the overall efficacy of the wind systems under dynamic conditions. In this work we have proposed a hybrid AI algorithm for integrated control of AMC and SEIG. It works as follows,

1. A wind turbine is used to power the SEIG by transforming the energy of the wind into mechanical energy.

2. Self-Excitation: The SEIG can generate electricity without an external excitation source, such as a DC voltage supply, because it functions in self-excited mode. Capacitors or a power converter attached to the stator terminals of the generator instead supply the reactive power.

3. SMC (sliding mode controller): When the wind speed and direction fluctuate in a wind energy system, an SEIG's performance is controlled using an SMC. SMC offers reliable control and is capable of enduring interruptions from outside sources.

4. Converting Power: The SEIG can produce alternating current (AC), which can be rectified into direct current (DC) and then inverted back into AC at grid frequency. During this conversion process, the SMC assists in stabilizing the DC connection voltage and frequency.

3.2. ASMC Model

One method for designing nonlinear systems for control is SMC, which involves using a discontinuous control signal to alter the dynamics of a nonlinear system such that it follows a segment of its ideal behavior.
As a recursive approach, the BSMC technique ensures that the closed-loop system is globally asymptotically stable by connecting the selected Lyapunov function to the specified feedback controller.

In order for the PV voltage, XUX, to follow the reference voltage, $Xfef$, the controller design in this work aims to modify the DC-DC converter's duty cycle. Thus, the PV system may be optimized to harvest the highest amount of electricity possible.

The PV system's MPPT was efficiently controlled by a BSMC. The PV system has the capability to operate near MPP by adjusting the duty cycle. How is the tracking error defined as,

$e_1 = V_{ref} - V_W$and $e_2 = e_1 + K_1 e_1$.

$$S = c_2 - K_2 e_1 = (K_1 - K_2) e_1 + e_1$$

The following eqn shows the control input variable, $u_{BSMC}(t)$,

$$u_{BSMC}(t) = u_{aq}(t) + u_{\infty}(t)$$

where$u_{eq}(t)$ and $u_{co}(t)$ are defined in (9):

$$u_{eq}(t) = \frac{-\frac{V_{PV}}{L} + i_{pv} - C_1 \bar{V}_{rf} + C_1(K_2 - K_1) i}{\delta L}$$

$$u_{c0}(t) = \frac{-C_1 a(S + \mathrm{ssgn}\,(S))}{\delta L}$$

Because of sgn (S), the control signal is discontinuous and we have hard switching. In [26], the dynamic of the sliding surface is defined as (10).

$$\dot{S} = -a(S + b\mathrm{sgn}\,(S))$$

Asymptotic stability of the sliding surface and the convergence to reference voltage were ensured using the following Lyapunov function (11) as in [26]:

$$\begin{cases} V_1 = \dfrac{e_1^2}{2} \\ V_{lyp} = V_1 + \dfrac{S^2}{2} = \dfrac{e_1^2 + S^2}{2} \end{cases}$$

3.3. AI-ASMC Model

The sliding mode speed controller that was suggested is seen in Figure 2. Here we define the state variables,

$$x_1(t) = w_{opt} - w_r(t)$$

$$x_1\acute{}(t) = -w_r(t) = -x_2(t)$$

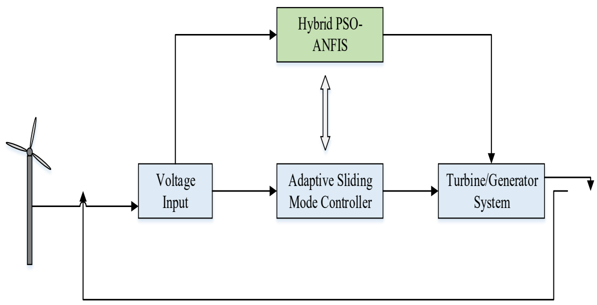


Fig.2 Closed Loop Block Diagram of Hybrid ASMC

Next, the following state-space representation can be used to describe the IG drive system:

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 0 & -B/J \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ K_t/J \end{bmatrix} i_{qs}^*(t) + \begin{bmatrix} o \\ -1/J \end{bmatrix} \dot{T}_m$$

We can rewrite the above eqn as follows,

$$\dot{X}(t) = AX(t) + BU(t) + D\dot{T}_m$$

where

$$A = \begin{bmatrix} 0 & -1 \\ 0 & -B/J \end{bmatrix}, B = \begin{bmatrix} 0 \\ K_t/J \end{bmatrix}, D = \begin{bmatrix} 0 \\ -1/J \end{bmatrix}, U(t) = i_{qs}^*(t)$$

and$U(t)$ is output of the proposed sliding mode controller.

As seen in Figure 4, the suggested ANN controller is implemented using a three-layer neural network. The first layer of the artificial neural network (ANN) is fed by the variables x_1^1=ὺ_opt-ὺ_r and x_2^1=ὺ_"opt " in this research. Multiple processing units, each linked to a sigmoidal function, are located in the hidden and output layers. In the hidden layer, node j's net input (net _j) and output (O_j) are

$$net_j = \Sigma(W_{ji} \cdot O_i) + \theta_j \quad , \quad O_j = f(\text{ net }_j)$$

where f is the sigmoidal activation function that is used.

$$f(\text{ net }_j) = \frac{1}{1 + e^{-net_j}}$$

in addition to the net input (net_k) and matching output (O_k) for node k in the output layer,

$$net_k = \sum (W_{kj} \cdot O_j) + \theta_k \quad , \quad O_k = f(net_k) = du_p$$

SEIG Design

In order to design the dynamic model of SEIG, we have utilized the following equations.

$$x = f(x, y, z)$$
$$z = g(x, u)$$

Here $x$is state variables, z is output variables, u is the input variables. It can be summarized as follows:

$$z = [v_{dr}, v_{qr}, v_{dg}, v_{qg}]^T u = [v_{ds}, v_{qs}, v_{dg}, v_{qg}]^T$$
$$x = [\omega, \beta, \theta_{tw}, s, i_{ds}, i_{qs}, x_1, x_2, x_3, x_4, E'_d, E'_q, V_{DC}]^T$$

Hybrid AI Algorithm Design

The FIS is built using if-then rules, which allow the regulations to establish the link between input and output variables. Because standard prediction approaches do not take data uncertainties into account when operating in scenarios with extremely uncertain input and output data, this model can be used as a prediction tool in such cases. The two main inference systems used in fuzzy logic are Mamdani and Takagi-Sugeno. The inference system of Takagi-Sugeno is typically used to apply ANFIS.

Figure 3 shows that the ANFIS structure has five layers. Nodes in each layer can be either fixed or flexible. Layers 2, 3, and 5's (circular) nodes stand for fixed nodes in this system, whereas layers 1 and 4's (square) nodes, or adaptive nodes, are nodes that may learn new parameters.

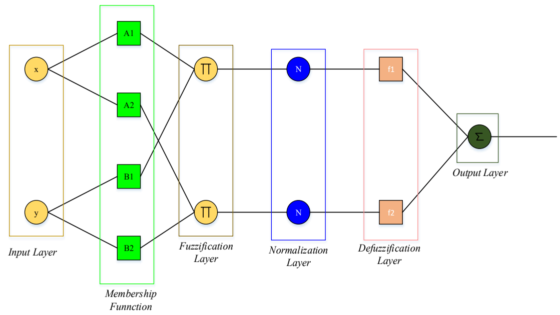


Fig.3 ANFIS Model

In order to explain the rules of each layer, we take two fuzzy if-then rules into consideration as follows:

$$Rule\ 1: If\ x\ is\ A_1 and\ y\ is\ B_1, Then\ f = p_1x + q_1y + r_1$$

$$Rule\ 2: If\ x\ is\ A_2\ and\ y\ is\ B_2, Then\ f = p_2x + q_2y + r_2$$

The output (linguistic variables) is denoted by f, whereas the input variables are x and y, the fuzzy sets are Ai and Bi. You should measure the subsequent parameters {pi, qi, ri} while you are training ANFIS. Here is how to measure the function of each layer:

Layer 1: In this layer, a membership function defines each node, i. In fuzzy logic, membership functions make the variables more nebulous. Membership functions are curves that convert points in the input space to membership values between 0 and 1. Triangular, trapezoidum, and Gaussian membership functions are the most prevalent types among many more.

$$O_{1,f} = \sigma A_1(x)$$

$$O_{1,f} = \sigma B_1(x)$$

That is, x is the data that node i and O1 receive as input.Ai's membership function, denoted by i, is often described by the following Gaussian function:

$$\sigma A_t(x) = \exp\left(\frac{-(x-c)^2}{\sigma^2}\right)$$

Standard deviation (σ) and the center of the Gaussian membership function (C), which are referred to as antecedent parameters, are included in this calculation. The optimization algorithm measures the value of these parameters, which are crucial to membership functions.

Layer 2: We may define the firing strength of a rule using the following relation:

$$w_1 = \sigma A_x \times \sigma B_1(x)$$

Layer 3: By dividing the firing strength of the ith rule by the total firing power of all rules, the firing strength of each rule is normalized.

$$\sigma_{3,t} = \overline{w_t} = \frac{w_t}{w_1 + w_2}$$

Layer 4: The following is the measurement for the fuzzy rule's outcome section:

$$\sigma_{4,t} = \overline{w_t}(p_1 x + q_1 y + r_t)$$

The set of subsequent parameters, which are calculated by the optimization process, are represented here by {pi, qi, ri}.

Layer 5: This layer simply adds up all of Layer 4's outputs.

$$\sigma_{5,1} = \sum_{t=1}^{R} \overline{w_t} f_t$$

Antecedent and consequent parameters are the two main structural parameters in the ANFIS model. When fine-tuning the ANFIS model's antecedent and consequent parameters, gradient-based approaches are typically employed. One drawback of gradient-based approaches is their sluggish convergence rate and the fact that they place the solution in the context of local optimality. If you're having trouble with the gradient-based approaches, try using a metaheuristic optimization algorithm like GA or particle swarm optimization (PSO). Figure 4 shows the ANFIS model training process using PSO and GA, two metaheuristic optimization methods.

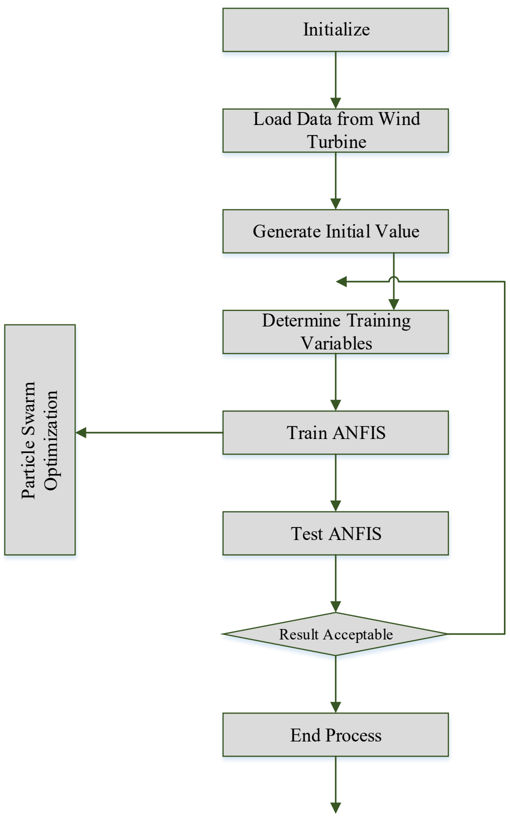


Fig.4 Flow of Hybrid ANFIS Model

In a manner similar to the genetic algorithm, the method generates a population of solutions at random and then searches the problem area for the answer, much like the PSO algorithm. However, PSO algorithms differ from genetic algorithms in that they randomly assign velocities to each particle—or possible solution to the optimization problem—so that any given particle's velocity can be changed in each iteration. In particle swarm optimization, the speed of individual particles determines their relative positions. Particle i's location in the search space at time step t is denoted by x_i (t). Unless otherwise specified, t stands for discrete time steps. Adding a velocity, v_i (t), to the particle's present position changes its position:

$$x_i(t) = x_i(t) + v_i(t)$$

$$v_i(t) = c_1 r_1\big(pbest(t) - x_i(t)\big) + c_2 r_2\big(gbest(t) - x_i(t)\big)$$

The variables r_1 and r_2 are random vectors, the acceleration coefficients c_1 and c_2 are given, and the variables pbest and gbest are the local best and global best, respectively. One possible method for fixing the ANFIS issues is PSO. With respect to PSO, ANFIS is like a particle, and the factors that affect the ANFIS process are like its dimensions. In contrast, the PSO has particles, which represent competing ANFIS processes that aim to solve the objective function problem.

IV. Experimental Analysis

4.1. Simulation Setup

Figure 3 depicts the total system block diagram. Here are the parameters of the wind turbine generating system that was utilized in the simulation:

(1) This wind turbine has the following parameters: Pmec=3.5KW, ρ=1.25Ns 2 /m4, R=2.51M, J=0.0466Nmsec2, B=0.0077Nmsec/rad, C1(β)=-0.11, C2(β)=0.067, and C3(β)= 0.07.

(2) The induction generator's parameters are as follows: stator resistance (2.12 Ω), rotor resistance (0.04 Ω), stator inductance (0.0059 Ω), rotor inductance (0.0069 Ω), magnetizaton inductance (0.0061 Ω), gear ratio (N1/N2)=1.

Table 1. Characteristics of the DC generator.

Quantity	**Unit**	**Value**
Resistance (*R*)	Ω	3
Inductance (*L*)	µH	700
Back-emf constant (K_b)	mV/rpm	8.01
Torque constant (K_i)	mNm/A	68.2
Viscous-friction (*B*)	-	0.001876
Rotor inertia (*J*)	g/cm^2	100

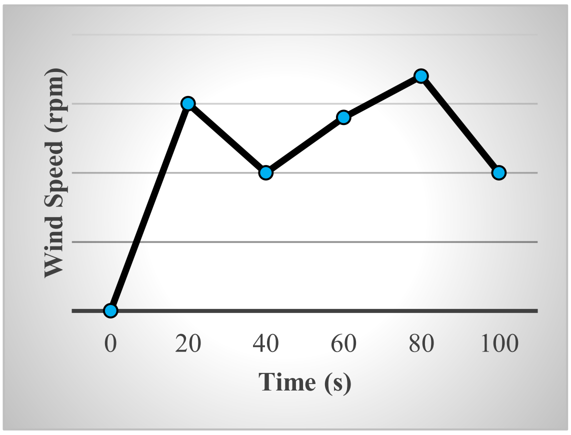


Fig.5 Wind Speed Profile

4.2. Comparative Analysis

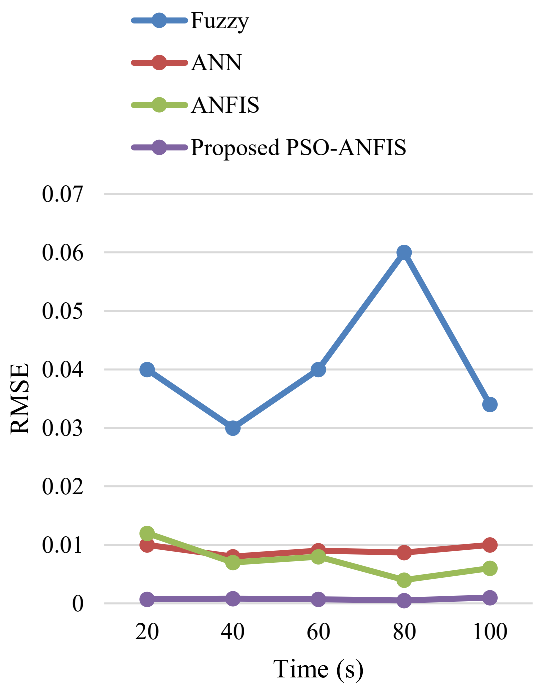
The constructed ANN is validated by checking the values of the correlation coefficient (Rcor), root-mean-square error (RMSE), and relative error (RE) given in equations (25) to (27). Table 1 lists the characteristics of the created ANN, which showed acceptable correlation values.

$$RMSE = \sqrt{\frac{1}{n_T}\sum_{n=1}^{n_T}\left(y_p - y_T\right)^2}$$

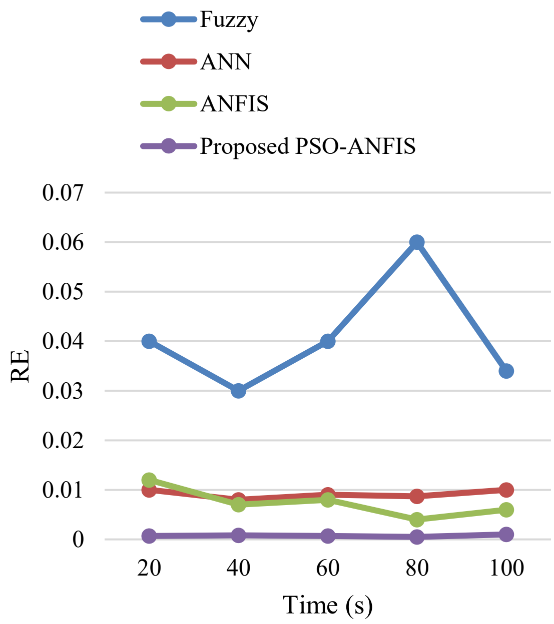
$$RE = \frac{RMSE}{y_p}$$

$$R_{Cor} = \frac{\sum_{ieT}\left(y_p - \overline{y_p}\right)\sum_{ieT}\left(y_T - \overline{y_T}\right)}{\sqrt{\sum_{ieT}\left(y_p - \overline{y_p}\right)}\sqrt{\sum_{ieT}\left(y_T - \overline{y_T}\right)}}$$

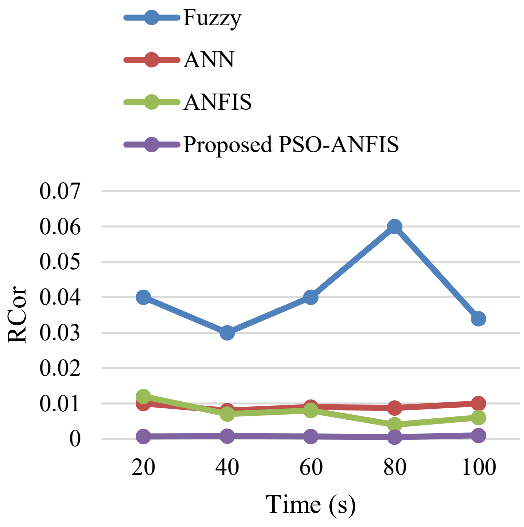
According to Figure 6, the speed controller has bad performance and that improving it requires adjusting the parameters of the three PI controllers. Most tuning is done by trial and error, which is a tedious process because finding the best values is not easy. Also, the wind turbine's linked electrical and mechanical equations make it different from a single-input-output linear system, which is the basis for the PI controller's development. The identical PI regulators utilized for the current and voltage controllers in the previous experiment are employed in Figure 7, which applies a sliding mode speed controller with a constant sliding gain γ. While speed tracking is enhanced, the voltage regulation is impacted by the modifications made to the speed steps. As shown in Figure 8, the adaptive SMC speed controller improves speed tracking and voltage regulation by adjusting the sliding gain online and compensating for its influence on the torque turbine through estimate.



(a)



(b)



(c)

Fig.6 Comparative Analysis on (a) RMSE (b) RE (c) RCor

It can be seen that the proposed hybrid ANFIS model reduces the error in all forms when compared to the original ANFIS model. This is due to the improvement in training phase using PSO.

V. Conclusion

The nonlinear, time-varying, and unpredictable nature of RES makes effective control of them challenging, despite their critical significance in sustainable development. When confronted with such uncertainties, Sliding Mode Control (SMC) offers durability, while artificial intelligence technologies enhance performance and flexibility. This article details an exhaustive examination of the application of AI with adaptive sliding mode control (ASMC) to enhance the performance of renewable energy systems. Artificial Neuro-Fuzzy Inference System (ANFIS), Fuzzy Controller, and Neural Network based Controller are the most often utilized methods for SMC in current systems. Nevertheless, in light of the ever-changing energy landscape, adaptability remains the key concern. Our proposal for RES is an AI-inspired ASMC, which we call AI-ASMC. Our investigation of artificial intelligence (AI)-based ASMC for use in solar and wind power plants, among other RES applications, covers its theory, design process, simulation results, and performance assessment. Results in stability, dependability, and power outputs are all improved by the suggested work, according to the MATLAB simulations.

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