Artificial Intelligence-Based Approach for the Control of PMSG Based Wind Energy System

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Abstract

Assessment of wind energy potential is extremely important before installation of wind turbine (WT) in any location. However, the intermittency of wind speed makes it more difficult to estimate the power potential. Thus, in this paper, two intelligent machine learning techniques namely neural network (NN) and adaptive neuro-fuzzy inference system (ANFIS) were employed to estimate the maximum power from the wind turbine and generates a reference torque to drive the rotor of PMSG. A comparative analysis for both NN based WT and ANFIS based WT is presented, while NN based WT estimated more accurate power than the ANFIS based WT. The NN based WT showed an error as low as 0.039% while ANFIS based WT shows 0.453%. Thus, the NN based WT model is selected and coupled with the PMSG system and is tested using wind data recorded at 100 meters height for Yanbu city, KSA. The PMSG was implemented with speed control mode using a PI controller which makes the NN-WT-PMSG effectively tracks the reference rotor speed and torque and generate proportional electromagnetic torque.

Keywords: Wind turbine, Wind Energy Conversion, Neural Network, Adaptive Neuro Fuzzy Inference System, PMSG Control

1. Introduction

Renewable energy (RE) had secured a prominent position in the global energy sector in response to the rise in electricity demand and carbon emission from conventional power generation. The RE market witnessed a total installed power capacity of 2,800 GW from Solar, Wind, Hydro, and other RE resources by 2020 (IRENA, 2021). The total wind capacity as of 2020 was around 733 GW, representing almost 26.2% of the total RE capacity. It is evident from Fig. 1 that the wind energy systems had significantly contributed to the modern RE market as well less assisted the energy market in minimizing the carbon emissions. For almost a decade China has been leading the wind energy market and stands top in 2020 with an installed capacity of 282 GW followed by the USA and Germany with 118 GW and 62 GW respectively (IRENA, 2021). The five leading counties in terms of wind installed capacity is shown in Fig. 2. These five countries also cover almost 72% of global installed wind capacity in 2020.

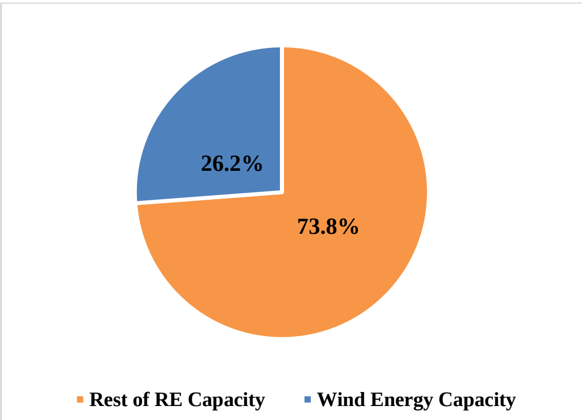

Fig. 1: Installed capacity share from Wind energy and Rest of RE capacity

doi:10.18086/swc.2021.17.01 Available at http://proceedings.ises.org

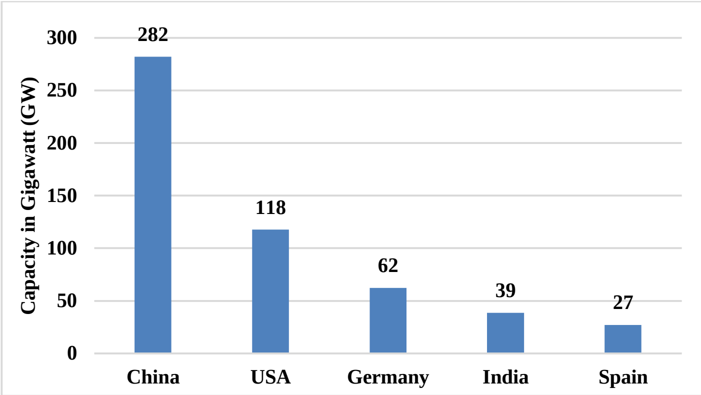

Fig. 2: Wind capacity leader based on the capacity installed in 2020

Assessment of wind potential is a key step that drives the successful installations of wind turbines (WT) in any location. Kingdom of Saudi Arabia is an arid or desert land with a long period of summer than winter but has a high potential for the deployment of a wind turbine. With the ambitious target KSA Vision 2030, to meet 50% of its energy needs from renewables by 2030, which 16 GW is aimed to generate from wind plants (REPDO, 2019). The wind speed has been monitoring by King Abdullah City for Atomic and Renewable Energy (K·A·CARE) over time for selected sites within KSA such as Al-Jouf, Riyadh, Jeddah, Yanbu (K·A·CARE, 2021). The average wind speed in KSA at 100 meters height ranges between 5.3 m/s to 8.4 m/s (Ghamdi, 2020). North of Yanbu city in KSA witness higher wind speed than any other location where the monthly average wind speed ranges between 6.8 m/s to 11.43 m/s at 100-meter height (K·A·CARE, 2021). Dumat al Jandal plant located in Al-jouf has a planned capacity of 400 MW from wind generation emerged as the first utility-scale wind farm (Saudi Gazette, 2020). Other wind farms are also under the predevelopment stage which includes Yanbu (850 MW) and Midyan (400 MW) projects as per the national renewable energy program (Rahman et al., 2021; REPDO, 2019). Thus, there is an extensive need to assess the potential of power generations in KSA utilizing wind resources.

Today, the energy generated from wind turbines is not only used for off-grid and on-grid power generations but also other applications such as desalination (Campione et al., 2020). In the modern world WT are available in two different kinds of namely WT exist in the market based on their axis of rotation ie; the vertical axis and horizontal axis WT. Each type of WT has its pros and cons which are subjected to location, size, application, etc., (M. Saad, 2014). Further, the wind energy conversion system (WECS) is classified based on the type of generators used, permanent magnet synchronous generators (PMSG), and doubly-fed induction generators (DFIG) (Yin et al., 2007). Due to its better efficiency and good power quality of variable speed wind turbine (VSWT) generators fed by PMSG are usually preferred. The wind turbine produces power while subjected to wind speed bounded by cut-in and cut-out wind speed (Baseer, 2017). Over the years the wind turbines had witnessed significant improvements in their size, aerodynamics design, blade structure, overall efficiency (Fatehi et al., 2019; Zhu et al., 2019). However, wind turbine still poses the challenge related to the intermittency of wind speed which makes difficult for power system operators and designers to accurately size the wind turbine (Njiri and Söffker, 2016). The impact on the power system in terms of efficiency, reliability, the transmission was addressed (Albadi and El-Saadany, 2010; Shi et al., 2014).

The power generated from the wind turbines is not only dependent on the wind speed but also several parameters such as tip speed ratio, length of the blades, wind direction, air density rotor speed, type of generator systems. To tackle the challenge of intermittency of wind speed, many researchers have employed several maximum power point tracking (MPPT) algorithms. The most common technique for MPPT algorithms are tip speed ratio (TSR) control, perturb and observe (P&O), power signal feedback (PSF) control, optimal torque (OT) control, and several other algorithms (Abdullah et al., 2012; Kumar and Chatterjee, 2016). Many control methods were used in the literature to name a few are pitch angle controller, grid side inverter controller, MPPT controller (Wang et al., 2014; Yin et al., 2007). Machine learning techniques such as neural networks (NN) and adaptive neuro-fuzzy inference systems (ANFIS) are also used for estimating or predicting wind speed (Chang et al., 2017; Khosravi et al., 2018). Abo-Khalil and Lee proposed MPPT control of wind energy systems by estimating the wind speed based on support vector regression (Abo-khalil and Lee, 2008). This technique was found to be less effective with an error of 3.3%. However, forecasting the wind speed will only help to determine the wind power but since the real system is coupled with the generator, it is extremely important to realize the overall effect on the WECS. On the other side, researchers have also developed control strategies for PMSG based wind turbines by using adapting sliding mode control to track the reference speed (Lee and Chun, 2019) while Kim et al presented tuning methods for PI controller parameters of PMSG wind turbine (Kim et al., 2015).

In this work, two intelligent techniques namely NN and ANFIS were employed to estimate the maximum power from the wind turbine and generates a reference torque to drive the rotor of PMSG. This was done by coupling the PMSG with the NN/ANFIS based WT models. The PMSG system operates in the speed control loop where the PI controller is fed with the error signal arising as a difference between the actual PMSG rotor speed and the reference speed generated from NN/ANFIS based wind turbine model. The performance of the proposed method is tested at first by subjecting experimental wind data from Yanbu city from KSA. The city is selected because it is the city with highest average wind speed and the government in KSA has already selected the city for future projects of a wind farm, which makes more important to assess the wind power potential.

2. Wind Energy Conversion System (WECS) Modeling

The WECS modeled in this work comprises a wind turbine coupled with PMSG and power conditioning units represented by 'm' as shown in Fig. 3. The rotor of the wind turbine is coupled with the PMSG rotor and then to power inverters. The brief model of each component of WECS is described in this section.

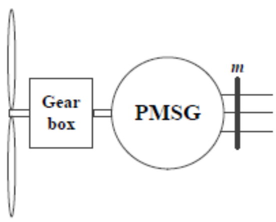

Fig. 3 Simplified representation of WECS model

2.1 Wind Turbine

The kinetic energy from the wind is translated into rotational motion due to the design of the turbine blades. This mechanical form of rotational energy is converted into electrical energy by means of a turbine generator (Sohoni et al., 2016). The expression for the theoretical mechanical power is given by (eq.1)

$$\text{Mechanical aerodynamic power } (P_m) = \frac{1}{2}\rho A V_w^3\, C_p(\lambda,\beta) \quad \text{(eq.1)}$$

Where, ρ is the density of air, A is the swept area of the turbine blade, V_w is the velocity of wind, C_p is the coefficient of power defined by the function of tip speed ratio (λ) and pitch angle (β). (Eq. 2) describes the relation of tip speed ratio with turbine rotor speed ω_r, rad/sec), wind speed and length of blade (R).

$$\lambda = \frac{\omega_r R}{V_w} \quad \text{(eq.2)}$$

The power coefficient is also a function of λ and β, given by (eq.3), while the iterative tip speed ratio (λ_i) is given by (eq.4)

$$C_p(\lambda,\beta) = 0.22\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)e^{\frac{-12.5}{\lambda_i}} + 0.0068\lambda \quad \text{(eq.3)}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \quad \text{(eq.4)}$$

The mechanical torque (T_m) generated from the wind turbine is given by (eq.5)

$$T_m = \frac{P_m}{\omega_r} \quad \text{(eq.5)}$$

2.2 Estimating of MPPT for turbine

Maximum power from the wind turbine is achieved when the coefficient of power is the highest corresponding to the optimal tip speed ratio. Several kinds of literatures proposed that when the blade pitch angle is at zero, the maximum power at a given speed is achieved (Kim et al., 2015; Wang et al., 2014). Optimum tip speed ratio (λ_{opt}) also determines the optimum rotor speed (ω_{opt}) and which the turbine operates corresponding to maximum power (P_{max}). Both the expressions for ($\mathrm{P_{max}}$) and (ω_{opt}) are given by (eq. 6) and (eq.7) respectively. The relation between the turbine power and turbine speed is shown in Fig. 4.

$$P_{max} = \frac{1}{2}\rho A V_w^3\, C_{pmax}(\lambda,\beta) \quad \text{(eq.6)}$$

$$\omega_{opt} = \frac{\lambda_{opt}\, V_w}{R} \quad \text{(eq.7)}$$

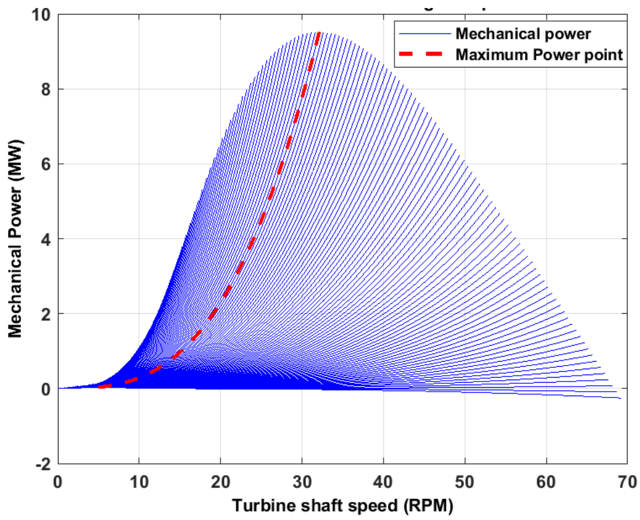

Fig. 4 Relation between the turbine speed and the power generated from turbine

2.3 PMSG

A three-phase permanent magnet synchronous machine is having its stator winding connected in Wye to the point of internal neutral while the rotor can be salient pole or round. When a negative torque is provided the machine operates in generator mode. A three-phase sinusoidal model can be expressed in the d-q frame of reference (MATLAB, 2021a). The equations governing these models are given in (eq.8) to (eq.10).

$$\frac{di_{sd}}{dt} = -\frac{R_{sa}}{L_{sd}} i_{sd} + \omega_s \frac{L_{sq}}{L_{sd}} i_{sq} + \frac{1}{L_{sd}} V_{sd} \quad \text{(eq.8)}$$

$$\frac{di_{sq}}{dt} = -\frac{R_{sa}}{L_{sq}} i_{sq} - \omega_s \left(\frac{L_{sd}}{L_{sq}} i_{sd} + \frac{1}{L_{sq}} \psi_p\right) + \frac{1}{L_{sq}} V_{sq} \quad \text{(eq.9)}$$

$$T_e = \frac{3}{2} * \frac{P}{2}\left[\psi_p i_{sq} + i_{sd} i_{sq}\left(L_{sd} - L_{sq}\right)\right] \quad \text{(eq.10)}$$

Where V_{sd}, V_{sq}, I_{sd} and I_{sq} are the d-q axis stator voltages and currents, respectively. L_{sd} and L_{sq} are the inductances of the generator. P is the number of poles, ψ_p is the permanent flux, stator resistance is represented as R_{sa} and ω_s is the generator's electrical angular frequency. T_e is the electromagnetic torque.

2.4 Machine learning technique

Several machine learning techniques have emerged over the decades but in this section, two technique, will be discussed considering their use in the approach.

(i) Neural Network
(ii) Adaptive neuro fuzzy inference system

Neural network (NN): It is also known as artificial neural network (ANN) is an intelligent technique that resembles a human brain by interconnecting biological neurons or nodes to perform complex computation. They learn from a set of trained data and generates the ability to predict future events (Cao et al., 2018). In several engineering applications, some of the types of NN include feedforward neural network (FFNN), Convolution neural network (CNN), and recurrent neural networks. Typically, FFNN comprises a set of inputs layers, one or more hidden layers, and an output layer (MATLAB, 2021b). During the learning process input and output candidates need to be explicitly defined and in this phase of learning weights are adjusted and the output is estimated by minimizing the error. Upon successful training of the process, testing can be performed to verify the accuracy of the learning process. In general, there are no limitations in selecting the number of input and output candidates.

Adaptive neuro-fuzzy inference system (ANFIS): This method is a hybrid learning process where the input and output data mappings are based on if-then rules (human knowledge) and stipulated input-output pairs (Jang, 1993). It combines the neural network and fuzzy logic principles with the advantage of seeking benefit from both frameworks. The architecture of ANFIS comprises five layers. The first layer accepts the input values by defining some membership functions also called fuzzification. The second layers are the rule layer where a set of rules are generated. The third layer normalizes the layer which is provided to the fourth layer. Finally, the fifth layer is the defuzzification layer to return the final output. The Takagi-Sugeno cannot accept only single-output (MATLAB, 2021c).

3. Methodology

In the proposed methodology of a NN or ANFIS based WT coupled with a PMSG system, the following steps are followed.

1. Generating a data set from a wind turbine.
2. Training NN and ANFIS model
3. Implementing speed control of NN/ANFIS based wind turbine PMSG model

Upon successful completion of the above three steps, the developed strategy is used to explore the wind energy potential for Yanbu city of KSA.

3.1 Data set generation of wind turbine

The data set for a wind turbine is generated by using the model eq.1- eq.4. As the mechanical power obtained from the wind turbine is a cubic function of wind speed as well as an indirect function of tip speed ration (λ), a range of wind speed is selected from 3-19.5 m/s and the range of tip speed ratio is selected from 0.1 - 14. Both the wind speed and tip speed ratio were classified into 280 samples, to generate a matrix to obtain a 280×280 matrix for power. Each row of the power matrix represents the power at one point of wind speed with 280 samples of tip speed ratio. Thus, from each row, a maximum power point is obtained which corresponds to the optimal tip speed point. Similarly, the optimum turbine speed is obtained at the optimal value of tip speed ratio. Finally, as an output of this wind turbine model, 280×1 matrix for maximum power (P_{max}) and optimum rotor speed ω_{opt} is selected.

3.2 Training if NN and ANFIS

The training for both NN and ANFIS starts with defining the inputs and outputs for the model. Clearly, from the data set generation process, sampled wind speed is selected as input while the matrix for maximum power (P_{max}) and optimum rotor speed ω_{opt} is taken as output.

3.2.1 NN training:

In the process, single input and dual output is selected and the model are trained by using a backpropagation algorithm. Ten neurons were selected in the hidden layer between the input and output layer as shown in Fig. 5. Upon successful training process is completed the model becomes a neural network wind turbine model which is capable to estimate maximum power and optimal speed at any wind speed defined within the limits.

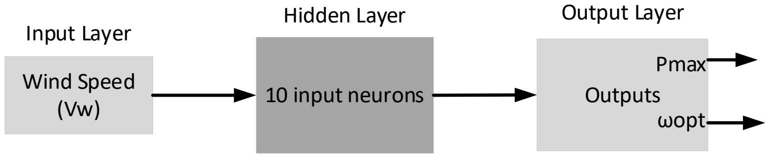

Fig. 5 Simplified representation of Neural network wind turbine model

3.2.2 ANFIS Training

The training process of ANFIS is also similar to NN in terms of defining input and output. However, the ANFIS model is a bit complex than NN as it only accepts a single output, unlike NN. As a result, two ANFIS structures were created one for maximum power output and the second for the speed output. The ANFIS power model is formed by using 10 membership functions in the intermediate layer while the ANFIS speed model is formed by using 5 membership functions. The simplified ANFIS wind turbine model is depicted in Fig. 6

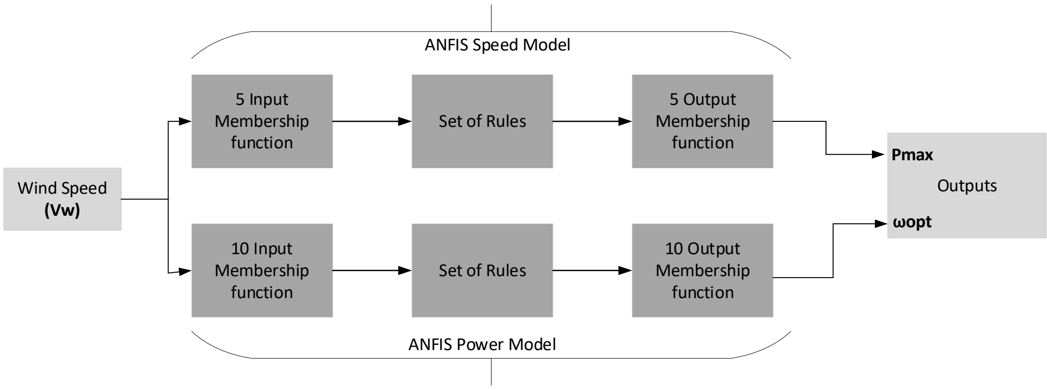

Fig. 6 Simplified representation of ANFIS wind turbine model

3.3 Control Strategy for NN/ANFIS based wind turbine

The strategy to control of PMSG based NN/ANFIS wind turbine in such a way that the torque output generated from the NN or ANFIS based wind turbine model is coupled to a permanent magnet synchronous machine. The negative torque is provided to the machine to operate in generator mode. The PMSG is connected to other power conditioning units such as the PWM inverter and provides the electromagnetic torque (T_e). The strategy implemented to control is presented in Fig. 7. The speed control method adopted is modeled in the d-q frame of reference. Two control loops were designed, the first outer loop is to control the PMSG rotor speed while the inner loop is to control the PMSG stator current. Hence in the outer loop by means of PI controller a reference direct axis current (i_{qref}) is generated by feeding back the error signal from the difference of NN/ANFIS model and PMSG. The reference quadratic axis current (i_{dref}) is selected as zero. The current is transformed back into three phases from the d-q reference and a three-phase reference current (i_{abcr}) is feedback to PWM inverter.

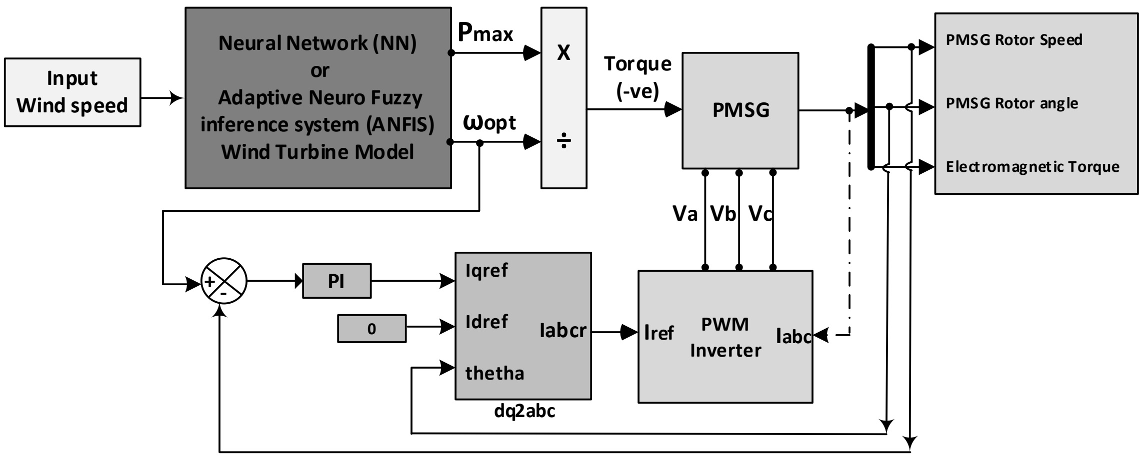

Fig. 7 Proposed control NN/ANFIS based wind turbine PMSG system

4. Results and Discussion

The approach and the methodology presented in the previous section are used to perform simulation in MATLAB/SIMULINK. The input data for the wind speed was collected in the form of monthly average from King Abdullah City for Atomic and Renewable Energy (K·A·CARE) station located in the north of Yanbu (24.34202 ° N, 37.48446° E), KSA. Two separate simulations were performed for NN based wind turbine PMSG model and ANFIS based wind turbine PMSG model. The sampling time selected during the simulation was 2 μs. The profile for monthly average wind speed for Yanbu location is shown in Fig. 8. With respect to the input wind speed, the NN based WT model, as well as ANFIS, based WT estimated the mechanical power and mechanical torque. Fig. 9 shows the power and torque response of the NN based WT model and Fig. 11 shows the power and torque response of the ANFIS based WT model.

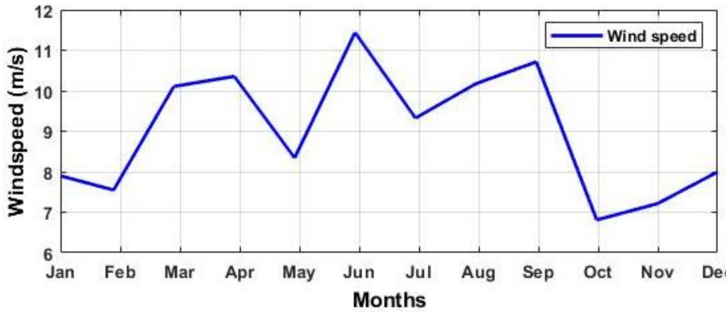

Fig. 8 Monthly average wind profile for Yanbu city in KSA

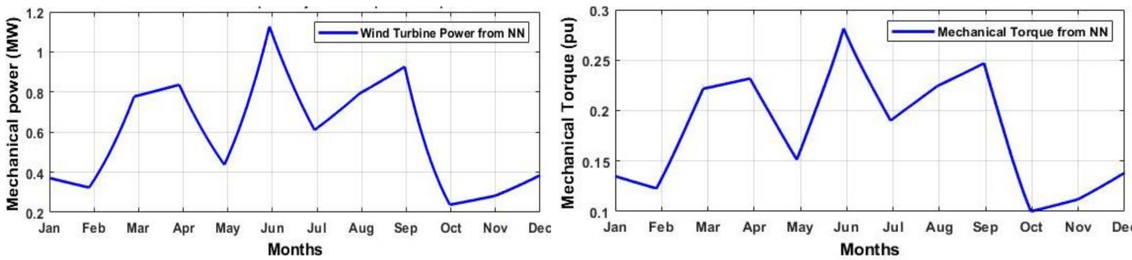

Fig. 9 Mechanical power and mechanical torque generated from NN based WT model

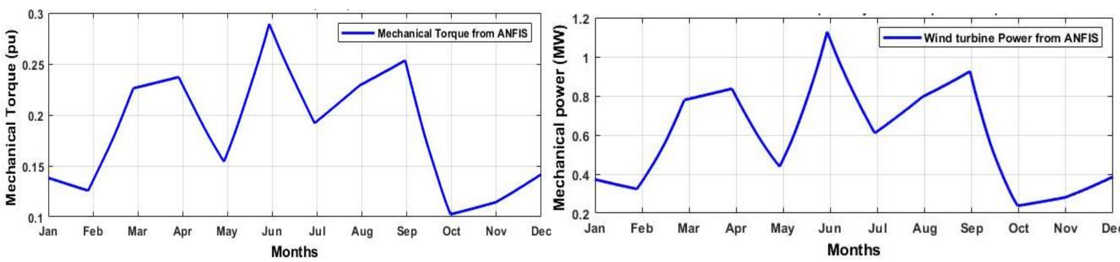

Fig. 10 Mechanical power and mechanical torque generated from ANFIS based WT model

From Table 1, it can be observed that the maximum power was achieved to be 1.12 MW in June in which the highest wind speed was recorded while the lowest power was estimated in October with 0.23 MW. The mechanical power estimated by the NN based wind turbine shows a maximum error of 0.039% while the power estimated by ANFIS based wind turbine shows 0.453 %. Moreover, the ANFIS model is very complex as it involves separate models for speed and power. As a result, several membership functions need to be defined which increases the computation time while performing the simulation. On the other hand, NN based model requires less time for the computation and at the same time, it is more robust than the ANFIS model.

Tab. 1: Comparison of NN-WT and ANFIS-WT model using actual wind speed data

Month	Wind speed (m/s)	Theoretical calculated Maximum power (MW)	Mechanical power generated from designed NN model (MW)	Error (%)	Mechanical power generated from designed ANFIS model (MW)	Error (%)
Jan	7.9	0.37005	0.3700	0.014%	0.37115	0.297%
Feb	7.5	0.32250	0.32250	0.000%	0.32204	0.143%
Mar	10.1	0.7752	0.7749	0.039%	0.77871	0.453%
Apr	10.4	0.83636	0.83633	0.004%	0.83657	0.025%

May	8.3	0.43732	0.43730	0.005%	0.43836	0.238%
Jun	11.4	1.1270	1.12699	0.001%	1.1276	0.053%
Jul	9.3	0.61054	0.610487	0.009%	0.609596	0.155%
Aug	10.2	0.79316	0.793272	0.014%	0.79419	0.130%
Sep	10.7	0.92603	0.92598	0.005%	0.92486	0.126%
Oct	6.8	0.23791	0.237941	0.013%	0.23788	0.013%
Nov	7.2	0.28218	0.28219	0.004%	0.280916	0.448%
Dec	8.0	0.38487	0.38488	0.003%	0.38626	0.361%

Further NN based WT- PMSG model is selected to study the effect of the combined NN model with PMSG. Fig. 11 shows that the speed control of the combined NN based WT- PMSG model is very effective in terms of following the reference rotor speed generated from the NN based WT model. The electromagnetic torque generated from the PMSG model as shown in Fig. 12 also follows the torque profile set by the NN based WT model. The noisy behavior of the electromagnetic torque is due to the presence of noise in the PMSG stator current due to the use of a PWM inverter. However, the angular speed of PMSG does not have noisy behavior as it is prevented by the inertia of the generator. The profile for the voltage of the PWM inverter is shown in Fig. 13.

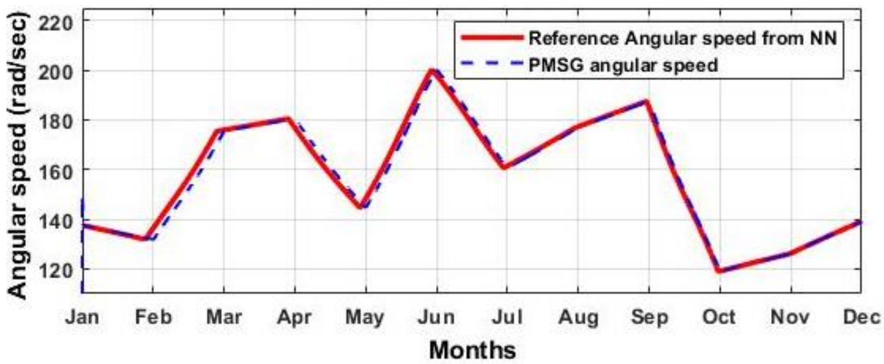

Fig. 11 Tracking of PMSG speed and reference speed from NN based WT- PMSG model

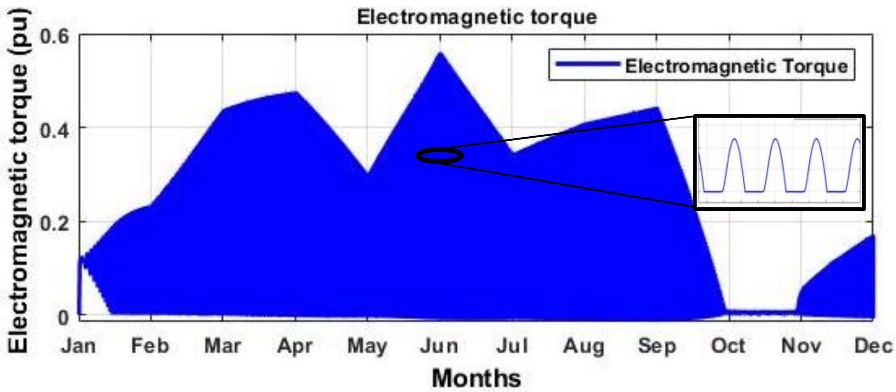

Fig. 12 Electromechanical torque generated from NN based WT- PMSG model

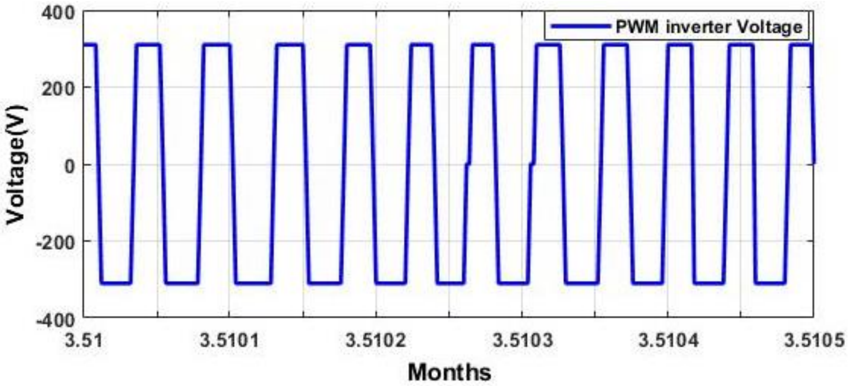

Fig. 13 PWM inverter voltage generated from NN based WT- PMSG model

5. Conclusions

In this paper, a novel control strategy is developed to control a permanent magnet synchronous generator (PMSG) coupled to a neural network and adaptive neuro-fuzzy inference system wind turbine model. The model is tested to assess the wind power potential in Yanbu city of Saudi Arabia. To machine algorithms (NN and ANFIS) are used and NN based WT model was found to be more robust as it is capable to estimate the power more accurately with an error as low as 0.039% when compared to 0.0453% error from ANFIS based WT. Moreover, the computation time needed by the ANFIS approach is 20 times more than the NN approach because of its complex structure. Further, NN based WT is used to provide a reference speed and torque to drive the PMSG rotor which is controlled by means of a PI controller. The Electromechanical torque and speed of the PMSG rotor effectively follow the input wind speed profile. Thus, this study helps to assess the actual power potential of a given wind data which is a primary step towards the deployment of wind turbines.

6. Acknowledgements

Authors like to thank Interdisciplinary Research Center for Renewable Energy and Power Systems (IRC-REPS), Research Institute, King Fahd University of Petroleum & Minerals, (KFUPM), Dhahran 31261, Saudi Arabia. Mohammed Kamal Hossain acknowledges the support received under Interdisciplinary Research Center for Renewable Energy and Power Systems (IRC-REPS) Grant INRE2114. King Abdullah City for Atomic and Renewable Energy (KACARE) is acknowledged for providing the wind speed station data.

7. References

Abdullah, M.A., Yatim, A.H.M., Tan, C.W., Saidur, R., 2012. A review of maximum power point tracking algorithms for wind energy systems. Renew. Sustain. Energy Rev. 16, 3220–3227. https://doi.org/10.1016/j.rser.2012.02.016

Abo-khalil, A.G., Lee, D., 2008. MPPT Control of Wind Generation Systems Based on Estimated Wind Speed Using SVR, in: IEEE Transactions on Industrial Electronics. https://doi.org/10.2460/javma.243.8.1099

Albadi, M.H., El-Saadany, E.F., 2010. Overview of wind power intermittency impacts on power systems. Electr. Power Syst. Res. 80, 627–632. https://doi.org/10.1016/j.epsr.2009.10.035

Baseer, M.A., 2017. Wind resource assessment and gis-based site selection methodology for efficient wind power deployment.

Campione, A., Cipollina, A., Calise, F., Tamburini, A., Galluzzo, M., Micale, G., 2020. Coupling electrodialysis desalination with photovoltaic and wind energy systems for energy storage: Dynamic simulations and control strategy. Energy Convers. Manag. 216, 112940. https://doi.org/10.1016/j.enconman.2020.112940

Cao, W., Wang, X., Ming, Z., Gao, J., 2018. A review on neural networks with random weights. Neurocomputing 275, 278–287. https://doi.org/10.1016/j.neucom.2017.08.040

Chang, G.W., Lu, H.J., Chang, Y.R., Lee, Y.D., 2017. An improved neural network-based approach for short-term wind speed and power forecast. Renew. Energy 105, 301–311. https://doi.org/10.1016/j.renene.2016.12.071

Fatehi, M., Nili-Ahmadabadi, M., Nematollahi, O., Minaiean, A., Kim, K.C., 2019. Aerodynamic performance

improvement of wind turbine blade by cavity shape optimization. Renew. Energy 132, 773–785. https://doi.org/10.1016/j.renene.2018.08.047
Ghamdi, A. Al, 2020. Saudi Arabia Energy Profile. Energy. https://doi.org/10.30573/KS--2020-DP25
IRENA, 2021. Renewable capacity statistics, International Renewable Energy Agency (IRENA),Abu Dhabi.
Jang, J.S.R., 1993. ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Trans. Syst. Man Cybern. 23, 665–685. https://doi.org/10.1109/21.256541
K·A·CARE, 2021. Renewable Resource Atlas, King Abdullah City for Atomic and Renewable Energy (K.A.CARE), Saudi Arabia, [WWW Document]. URL https://rratlas.kacare.gov.sa
Khosravi, A., Koury, R.N.N., Machado, L., Pabon, J.J.G., 2018. Prediction of wind speed and wind direction using artificial neural network, support vector regression and adaptive neuro-fuzzy inference system. Sustain. Energy Technol. Assessments 25, 146–160. https://doi.org/10.1016/j.seta.2018.01.001
Kim, Y.S., Chung, I.Y., Moon, S. Il, 2015. Tuning of the PI controller parameters of a PMSG wind turbine to improve control performance under various wind speeds. Energies 8, 1406–1425. https://doi.org/10.3390/en8021406
Kumar, D., Chatterjee, K., 2016. A review of conventional and advanced MPPT algorithms for wind energy systems. Renew. Sustain. Energy Rev. 55, 957–970. https://doi.org/10.1016/j.rser.2015.11.013
Lee, S.W., Chun, K.H., 2019. Adaptive sliding mode control for PMSG wind turbine systems. Energies 12. https://doi.org/10.3390/en12040595
M. Saad, M.M., 2014. Comparison of Horizontal Axis Wind Turbines and Vertical Axis Wind Turbines. IOSR J. Eng. 4, 27–30. https://doi.org/10.9790/3021-04822730
MATLAB, 2021a. Three-phase PMSG [WWW Document]. URL https://www.mathworks.com/help/physmod/sps/powersys/ref/permanentmagnetsynchronousmachine.html (accessed 10.9.21).
MATLAB, 2021b. What Is a Neural Network? - MATLAB & Simulink [WWW Document]. URL https://www.mathworks.com/discovery/neural-network.html (accessed 10.9.21).
MATLAB, 2021c. Neuro-Adaptive Learning and ANFIS - MATLAB & Simulink [WWW Document]. URL https://www.mathworks.com/help/fuzzy/neuro-adaptive-learning-and-anfis.html (accessed 10.9.21).
Njiri, J.G., Söffker, D., 2016. State-of-the-art in wind turbine control: Trends and challenges. Renew. Sustain. Energy Rev. 60, 377–393. https://doi.org/10.1016/j.rser.2016.01.110
Rahman, S.M., Al-Ismail, F.S., Haque, M.E., Shafiullah, M., Islam, M.R., Chowdhury, M.T., Alam, M.S., Razzak, S.A., Ali, A., Khan, Z.A., 2021. Electricity generation in Saudi Arabia: Tracing opportunities and challenges to reducing greenhouse gas emissions. IEEE Access 9, 116163–116182. https://doi.org/10.1109/ACCESS.2021.3105378
REPDO, 2019. Saudi Arabia National Renewable Energy Program.
Saudi Gazette, 2020. Dumat Al-Jandal wind farm turbine trial run begins [WWW Document]. URL https://saudigazette.com.sa/article/609477 (accessed 10.8.21).
Shi, L., Sun, S., Yao, L., Ni, Y., Bazargan, M., 2014. Effects of wind generation intermittency and volatility on power system transient stability. IET Renew. Power Gener. 8, 509–521. https://doi.org/10.1049/iet-rpg.2013.0028
Sohoni, V., Gupta, S.C., Nema, R.K., 2016. A Critical Review on Wind Turbine Power Curve Modelling Techniques and Their Applications in Wind Based Energy Systems. J. Energy 2016, 1–18. https://doi.org/10.1155/2016/8519785
Wang, C.-N., Lin, W.-C., Le, X.-K., 2014. Modelling of a PMSG Wind Turbine with Autonomous Control. Math. Probl. Eng. 2014, 1–9. https://doi.org/10.1155/2014/856173
Yin, M., Li, G., Zhou, M., Zhao, C., 2007. Modeling of the wind turbine with a permanent magnet synchronous generator for integration. 2007 IEEE Power Eng. Soc. Gen. Meet. PES 1–6. https://doi.org/10.1109/PES.2007.385982
Zhu, Y., Zhu, C., Song, C., Li, Y., Chen, X., Yong, B., 2019. Improvement of reliability and wind power generation based on wind turbine real-time condition assessment. Int. J. Electr. Power Energy Syst. 113, 344–354. https://doi.org/10.1016/j.ijepes.2019.05.027