Grid-secluded Induction Generator with ANN and Intreval Type-2 Fuzzy based Controller for Wind Power Generation with Smart Load Control

Arunava Chatterjee, *Member IEEE*, and Bratati Banerjee

Abstract—**Three-phase Induction generators are widely used to extract power from wind both in grid-connected and isolated conditions. This paper proposes an induction generator for standalone operation which is suitable for microgeneration schemes in remote and grid inaccessible areas as a means of extracting electric power from wind. An inverter connected across the generator acts as a source of variable excitation and regulates the load voltage during changing loads or low wind speed conditions. The obtained power is converted to DC and the same is again fed to loads via a three-phase inverter run at fixed frequency. Optimal power generation is ensured using an artificial neural network (ANN) and an interval Type-2 Fuzzy inference system enabled maximum power point tracking (MPPT) based controller. A smart load controller is also proposed based on ANN which can also isolate loads with incipient faults. The novelty of the scheme lies in the ease of implementation, proposal of a new MPPT strategy with smart load control. Appropriate simulation and experimental results validate the proposed strategy along with suitable comparisons.**

Index Terms—**Artificial neural network (ANN), interval Type-2 Fuzzy, maximum power point tracking (MPPT), three-phase induction generator, variable excitation, wind power.**

I. INTRODUCTION

WITH increase in global energy demand and with increase in fossil fuel costs, the use of renewable sources of energy like wind power has become crucial. In a developing country like India, remote and countryside electrification is difficult to establish especially due to economic considerations of high cost of transmission lines and associated losses. Therefore, a suitable standalone renewable source of generation can be used in microgeneration-based applications to cater remote and grid inaccessible loads. Among renewable energy sources, wind is a confined, copious and a clean energy source but with an intermittent nature and hence uncontrollable [1]. Obtaining stable source of power from a wind energy generation system is thus challenging. Induction generators are extensively used in association with wind turbines for generation of electricity in grid connected as well as standalone purposes [2]-[4]. An induction machine has some inherent advantages of low cost, robustness, almost maintenance free and no requirement of dc excitation. Self-excited, induction generators almost always suffer from the problem of voltage regulation as the output voltage is dependent on the terminal connected capacitors [5], [6]. With increase in load, the induction generator's requirement for reactive power increases. Inverter assisted control scheme proposed previously aims to increase the operating range of the generator [7], [8]. However, the issue of load voltage collapse may arise if load current increase, as a single battery may drain out with increase in load. A suitable closed loop scheme with backup power is thus necessary. Load controllers were used previously to keep the output power constant with variable terminal loads [9]. These controllers use a specially designed dump load along with dc link capacitor which increases the overall outlay of the system. The three-phase standalone induction generators can also suffer faults especially inter-turn faults and can be a serious problem when they are operated in standalone mode [10]. Since standalone generations often are used to cater critical loads [11], maintaining generation becomes essential.

In this paper, a three-phase, cage rotor induction machine is used as an induction generator which is driven by a wind-turbine with artificial neural network (ANN) and interval type-2 fuzzy inference based MPPT control. The loads are controlled using a smart ANN based controller and it has the feature to isolate loads with incipient faults. The bulk capacitor is connected across the main winding terminals for providing excitation during initial generation. The inverter assembly connected across the auxiliary terminals consists of a three-phase pulse width modulated PWM inverter for providing the variable excitation. When load increases or alternatively when the wind power becomes low, the inverter assembly provides the necessary additional excitation to maintain the induction generator magnetic field, thereby keeping the real power constant at load terminals. The major takeaways from the proposed generation scheme are:

- An MPPT controller is proposed based on ANN and interval type-2 fuzzy inference-based control. The control is unique with comparatively easier implementation.
- A smart ANN based load control is proposed which is capable to determine loads having incipient faults. The loads can be isolated for further inspection.
- Short-time voltage oscillations can be minimized

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https://doi.org/10.32388/D4GAVP

with proposed control.

The experimental and simulation results justify the suitability of the concept for remote and grid isolated purposes.

II. Proposed Generation Scheme and its Modelling

A three-phase, cage rotor induction machine is used as the induction generator. The induction machine's stator winding terminals are connected to a capacitor of suitable value which will provide the initial VAr required for generation at nominal cut-off speed and no-load conditions. As the machine starts to generate, loads can be connected across the stator winding terminals across the terminal capacitor. However, the maintenance for fixed frequency is assured by using a three-phase fixed frequency inverter connected at the load side. The generator side converter is essentially a three-phase inverter operating in bidirectional mode with its dc bus connected to a capacitor. The load side inverter frequency is maintained at constant 50Hz using a microcontroller which generates the gating pulses for the inverter switches. Provision for storage of this energy is kept by a storage battery connected across the bus. The inverter along with the storage battery constituting the inverter assembly will provide the necessary variable excitation during an increase in terminal electrical load or during low rotor speeds.

The load voltage is kept steady using a closed loop voltage controller to control the inverter output using the artificial neural network (ANN) with interval Type-2 Fuzzy based controller. The load voltage is compared with a reference voltage and is fed to a PI controller. The output is fed to gate driver to generate the PWM pulses. If the wind speed increases or load decreases, the surplus power generated by the generator gets stored in the storage battery. The induction generator can be modeled using the generalized *d-q*-axes machine model in synchronously rotating reference frame having speed ω_e.

$$v_{ds} = R_{ds} i_{ds} + \frac{d}{dt}\psi_{ds} - \omega_e \psi_{qs} \tag{1}$$

$$v_{qs} = R_{qs} i_{qs} + \frac{d}{dt}\psi_{qs} + \omega_e \psi_{ds} \tag{2}$$

$$0 = R_{dr} i_{dr} + \frac{d}{dt}\psi_{dr} - (\omega_e - \omega_r)\psi_{qr} \tag{3}$$

$$0 = R_{qr} i_{qr} + \frac{d}{dt}\psi_{qr} + (\omega_e - \omega_r)\psi_{dr} \tag{4}$$

where, R_{ds}, R_{qs}, are the respectively the d and q axis stator resistances, v_{ds}, v_{qs} are the *d-q*-axis stator voltages, i_{ds}, i_{qs}, i_{dr} and i_{qr} are the stator and rotor *d*-axis and *q*-axis currents respectively. ω_r is the speed of the rotor. Flux relations are,

$$\psi_{ds} = L_{lds} i_{ds} + L_{dm}(i_{ds} + i_{dr}) \tag{5}$$

$$\psi_{qs} = L_{lqs} i_{qs} + L_{qm}(i_{qs} + i_{qr}) \tag{6}$$

$$\psi_{dr} = L_{ldr} i_{dr} + L_{dm}(i_{ds} + i_{dr}) \tag{7}$$

$$\psi_{qr} = L_{lqr} i_{qr} + L_{qm}(i_{qs} + i_{qr}) \tag{8}$$

ψ_{ds}, ψ_{qs}, ψ_{dr} and ψ_{qr} are the stator *d*-axis, *q*-axis and rotor *d*-axis, *q*-axis flux linkages respectively, L_{lds}, L_{lqs}, L_{ldr} and L_{lqr} are the stator *d*-axis, *q*-axis and rotor *d*-axis, *q*-axis leakage inductances. L_{dm} and L_{qm} are the magnetizing inductances of d and q axes respectively.

Now, when an *R-L* load is connected across the generator main winding,

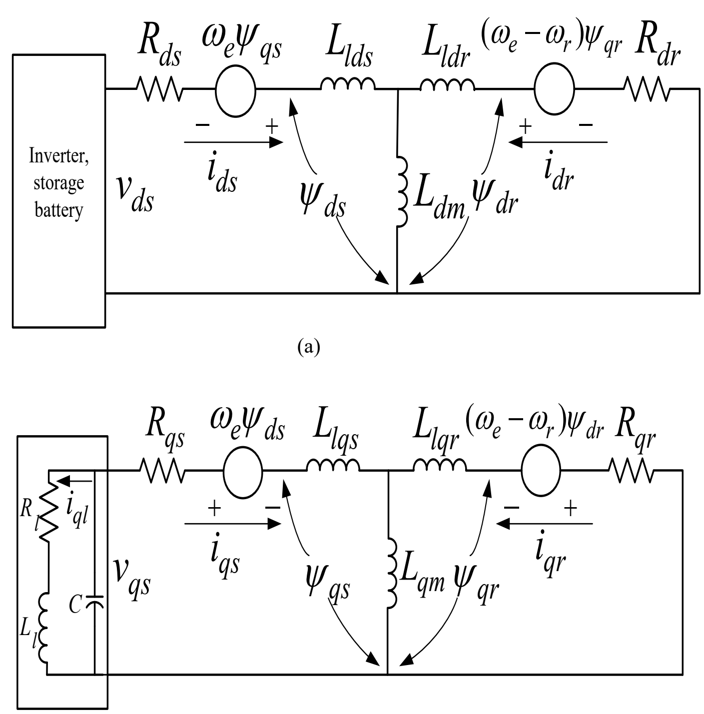
$$C\frac{d}{dt}v_{qs} = -(i_{qs} - i_{ql}) \tag{9}$$

$$v_{qs} = R_l i_{ql} + L_l \frac{d}{dt} i_{ql} + \omega_e L_l i_{dl} \tag{10}$$

where, R_l, L_l, i_{ql}, i_{dl} and C are the load resistance, load inductance, q and d axes load currents and the terminal capacitor respectively. The inverter voltage equation can be given as,

$$v_{ds} = s_{fn}.v_{dc} \tag{11}$$

where, v_{dc} is the dc voltage of the storage battery and S_{fn} is the inverter switching function. Accordingly, the induction generator equivalent circuit can be formed using the abovementioned equations in *d-q* axes synchronously rotating reference frame. Fig.1. shows the equivalent circuit of the induction generator in *d-q* axes synchronously rotating reference frame as obtained from the above equations. Fig.2 (a) is the *d*-axis equivalent circuit whereas Fig.2 (b) is the *q*-axis equivalent circuit.



(a)

(b)

Fig.1. Induction generator (a) *d*-axis and (b) *q*-axis equivalent circuit.

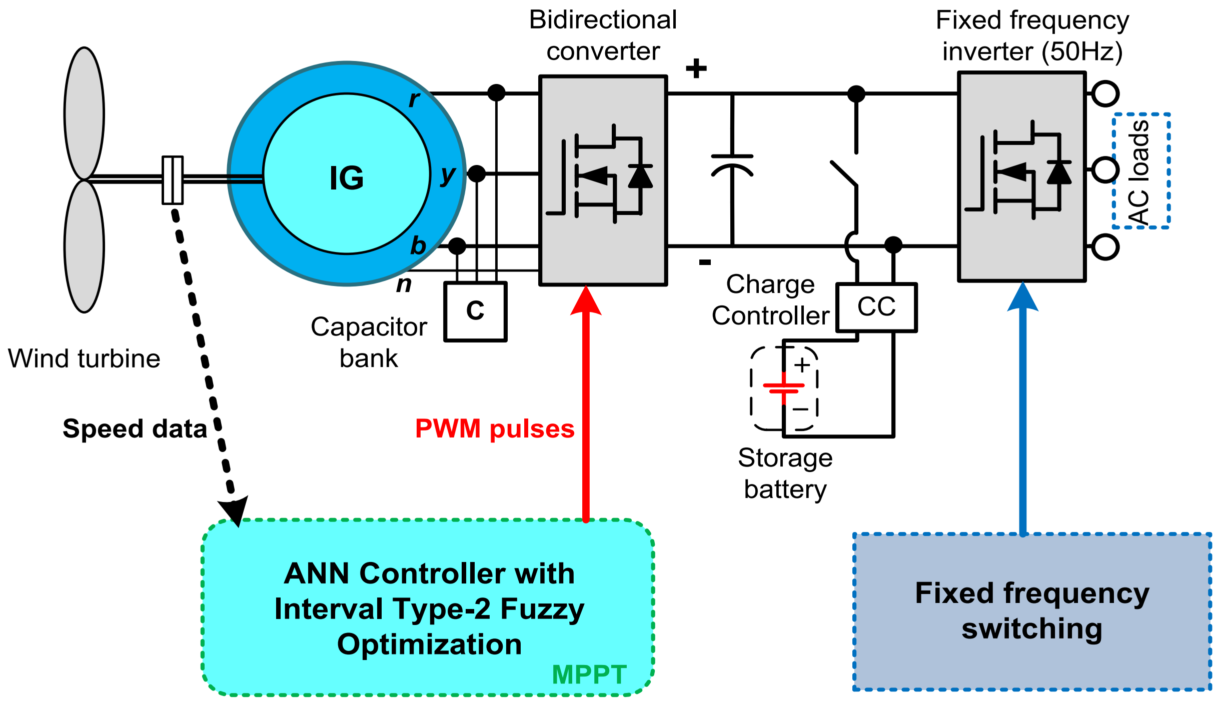


Fig. 2. Setup for the proposed generation scheme.

The proposed setup for the scheme is shown in Fig.2. Now as we know, ANN is a computational model inspired by the structure and working of the human brain [12]. It has also been used for improvement of performance from wind energy conversion systems as in [13]-[14]. It is a type of machine learning algorithm that can be trained to recognize patterns in data and make predictions based on that data. ANNs consist of several layers of interconnected nodes, or "neurons," which process information which can be passed on to the next layer. Each neuron in an ANN receives inputs from other neurons, applies a mathematical function to those inputs, and produces an output that is passed on to other neurons in the network. Through a process of trial and error, the network can learn to adjust the weights of the connections between neurons to improve its performance on a given task. Using ANN based maximum power point tracking MPPT model with interval type-2 fuzzy control, the wind generation can be optimized from the turbine to provide stable voltage to connected loads for the generator.

III. Control Procedure Adopted

A. ANN based controller

ANN is a technology adopted from the functional neural network. An artificial neuron is shown below in Fig.2. In Fig.3, the $x_1 \ldots x_n$ are the inputs to the neural network. The $w_1 \ldots w_n$ are the weights and y_o is the output. In the neural network used, the wind speed is used as the input to the neuron with each individual value of wind speed as the weights. ANN will predict the value of output to each value of wind speed. The output is the voltage value corresponding to the wind speed. The voltage output is predicted as a single layer ANN with wind speed as input.

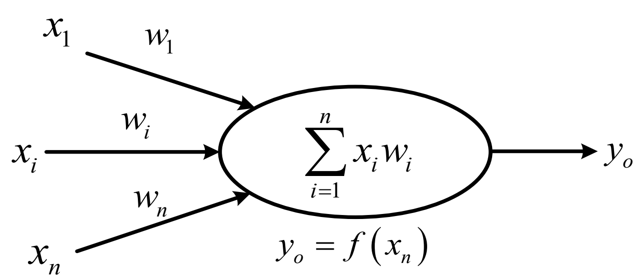


Fig. 3. Artificial Neural Network (ANN) neuron.

For extraction of maximum power, the MPPT used is designed with ANN and interval type-2 fuzzy logic. Here, after the output of ANN, interval type-2 fuzzy inference is used. ANN gives the value of voltage and interval type-2 fuzzy logic is used for generation of optimum duty cycle for pulses of the converter.

B. Interval Type-2 Fuzzy controller

A type-2 fuzzy inference ($\tilde{A}$) is characterized by its membership function $\mu_{\tilde{A}}(z,u)$ [15] as,

$$\tilde{A} = \int_{z \in Z} \int_{u \in J_z \subseteq [0,1]} \mu_{\tilde{A}}(z,u) / (z,u) \tag{12}$$

wherein, z is a primary variable in Z universal set. The variable J_z is primary membership of z, with u as secondary variable. A secondary membership is also given and it is an upright slice of $\mu_{\tilde{A}}(z,u)$. There is a confined area within the primary and secondary functions which is the footprint of uncertainty (*FOU*). The type-2 fuzzy sets involve large computations although they model the uncertainty in a better way than Type-1 fuzzy systems. If it is considered that for all values $\mu_{\tilde{A}}(z,u)=1$, the set converts into an interval type-2 fuzzy set. This reduces computations and complexity of the system as,

$$\tilde{A}=\int_{z\in Z}\left[\int_{u\in J_z\subseteq[0,1]}1/u\right]\Big/z \tag{13}$$

From (13), it is shown than the dimension is reduced which has homogeneous weighted primary membership values. The *FOU* or the bounded region is represented as,

$$FOU\left(\tilde{A}\right)=\bigcup_{z\in Z}J_z \tag{14}$$

The type-2 Fuzzy inference system is shown in Fig.4 below.

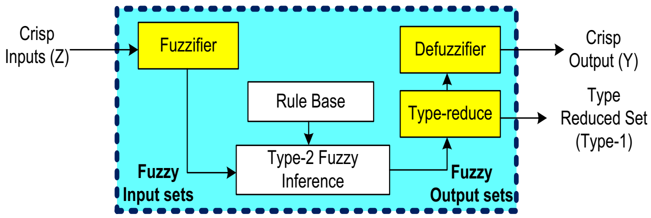


Fig. 4. Type-2 Fuzzy Inference System.

This algorithm is used for designing the controller for providing the output pulses. These two combined controllers are used for designing the final MPPT for the wind turbine control. The combined controller is shown in Fig.5.

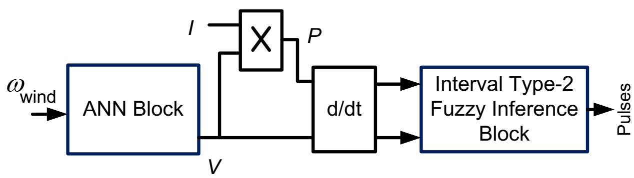


Fig. 5. Combined controller for the bidirectional converter.

The interval type-2 based fuzzy controller generates the pulses for the bidirectional converter. The controller for the fuzzy interface has input membership function of derivative of power dP and voltage dV. The comparative error is taken as the switching function whose membership function is used in the interval type-2 fuzzy inference. The same is shown in Fig.6. Similar to type-1 fuzzy inference, interval type-2 fuzzy inference is represented using membership functions (MFs), with various ways to define shape or class of the set.

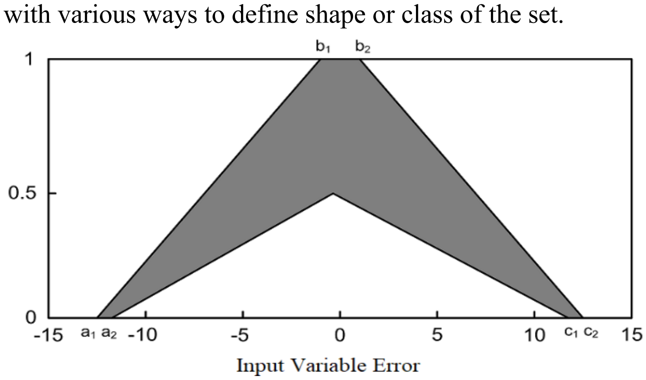


Fig. 6. Membership function for input variable error.

Six parameter sets (a_1, a_2,…,c_2) are demarcated for interval type-2 fuzzy for the present problem like in [16].

C. Load Control

The three-phase fixed frequency inverter is connected at the load side and is driven at 50Hz frequency. The three-phase loads are connected using a smart electronic load controller. The controller is consisting of a relay-controlled switch which is controlled using an *Atmega* based controller. The electronic load controller is different from the conventional load controllers [17]-[18] as it can sense load currents and can also detect incipient faults. Unbalanced loads or excitation [19] can also be detected using the controller. The controller takes the current data and is operated based on requirement and sensed load current. The smart controller is thus also capable to sense faulty loads or loads with incipient fault using the sensed current. If there is a load with incipient fault, the load can be safely isolated using the controller. Similar internet-of-things (IoT) based controllers are often used for load monitoring purposes [20]-[21]. The smart controller is again configured using ANN based logic to obtain the ON/OFF control signals. An algorithm is designed for the same as shown below. The controller hardware is shown in Fig.7.

Algorithm: Control of the connected loads.

1: $\forall j\in L$: read the ON/OFF status of individual loads.

2: $\forall ON_j\in L$: read power consumption using ANN logic.

3: $\forall ON_j\in L$: If, load power >> threshold, consider load turning OFF.
Else if, load power >> generated power, consider load turning OFF/ battery in discharging mode.
Else if, load power << generated power, load may remain ON/ battery in charging mode.

4: $\forall ON_j\in L$: calculate the value of V_j.

5: $V_j>\varepsilon$: load may have incipient fault and is isolated.

6: $\forall ON_j\in ON_\varepsilon$: load is turned OFF.

7: $\forall ON_j\notin ON_\varepsilon$: load can remain ON, go to 3.

8: Collect next time slot data, go to 1.

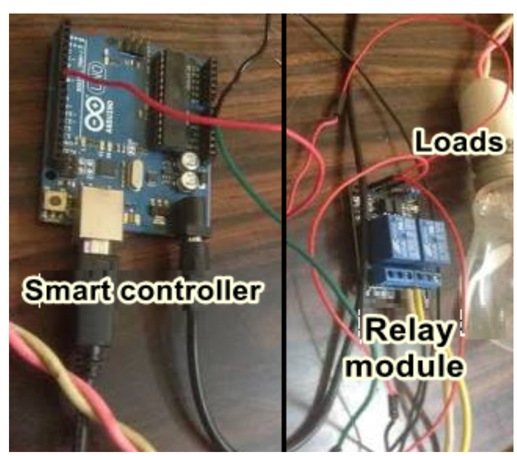


Fig. 7. Smart controller with relay module for load control.

The ANN based load control is proposed which accounts for the control of domestic loads like ceiling fan and lights. It is done as follows:

(i) Data collection: Data is collected for the usage of fan, light and other domestic loads. This data includes variables like time of day, temperature, and humidity (from capacitive humidity sensor).

(ii) Data preparation: Collected data is preprocessed, including normalizing the values and splitting it into training and testing datasets.

(iii) Building the neural network: Feedforward neural network architecture is used with a single hidden layer to train the model. The input layer has neurons for the collected variables, while the output layer has neurons for the control signals.

(iv) Training the neural network: The neural network is trained using the training dataset. Backpropagation is used to adjust the weights and biases of the neurons to minimize the error between the predicted output and the actual output.

(v) Testing the neural network: The testing dataset is used to evaluate the performance of the trained model.

The model is monitored for performance evaluation over time and is retrained it periodically using updated data if necessary. To enhance the model, additional layers or nodes to the neural network may also be added to include more input variables, or use a more advanced neural network architecture. Overall, the neural network architecture for controlling domestic loads like fans and lights using ANN is relatively simple feedforward architecture with a single hidden layer. The architecture for this task includes an input layer, a hidden layer, and an output layer. The input layer has neurons for the input variables, such as time of day, temperature, and humidity represented as s_1, s_2 s_3. The hidden layer has multiple neurons with nonlinear sigmoid activation function. The output layer has neurons for the control signals t_1 and t_2, to turn the fan and light ON/OFF. Each neuron in the hidden layer receives inputs from the input layer, which are weighted and summed, and then passed through a nonlinear activation function. The output of each hidden neuron is then weighted and summed to produce the final output of the network, which represents the control signals as shown in Fig.8.

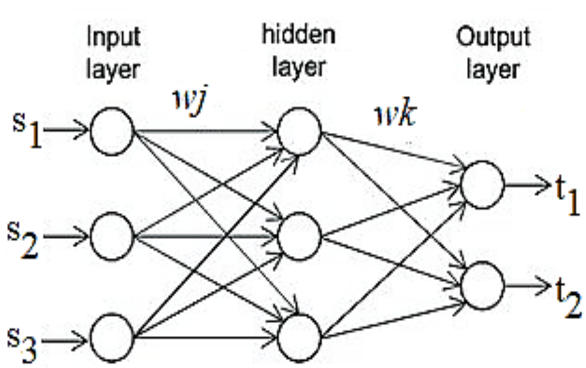


Fig.8. ANN structure for load control.

The individual load powers are calculated and categorized for comparison and calculation of power requirement. All the loads are considered of ON/OFF type. The loads with incipient faults can be determined from the ON/OFF condition K of k^{th} no. of load and corresponding to its fundamental current signal I. The measured product value of the current and the ON/OFF condition and the stored product value is compared from (15). If the difference is significantly higher than a set threshold ε, the load may have incipient fault and needs to be isolated for further check.

$$V_j = \left[\sum_{z \neq j} I_k K_k (meas) - \sum_{z \neq j} I_k K_k \right] \tag{15}$$

IV. Simulation and Experimental Results

The proposed system is simulated and the same system is also built as a laboratory prototype. The induction machine is coupled to a dc motor which is controlled by a dc motor controller for the laboratory prototype. The dc motor along with the motor controller will emulate the characteristics of a wind turbine.

A 1.5kW, 400V, 50Hz, 4-pole, three-phase, cage rotor induction machine is used as induction generator for laboratory experimental purposes. The terminal capacitor bank used is of 30μF connected in delta and is obtained by reactive power balancing [22] of the machine at no-load condition. The bidirectional converter uses MOSFETS, K2611 with 900V, 11A ratings. The MOSFETS are driven by dedicated gate driver circuits using *ATMEGA* microcontroller. The other inverter is operated at a fixed frequency of 50Hz for maintaining fixed frequency voltage at the load terminals. Rechargeable lead-acid battery unit of 77Ah, 48V is used with inherent charge controller.

As the set reaches a cut-off speed, the generator starts to generate. The induction generator with the proposed control is studied for at no-load and rated load conditions. With the proposed control, the induction generator shows stable terminal voltage at no-load and rated load than without the proposed control technique as shown in Fig.9.

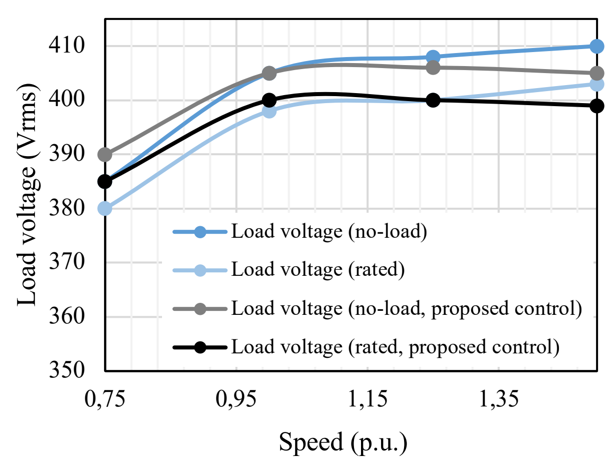


Fig.9. Plot showing generated voltage variation with change in speed.

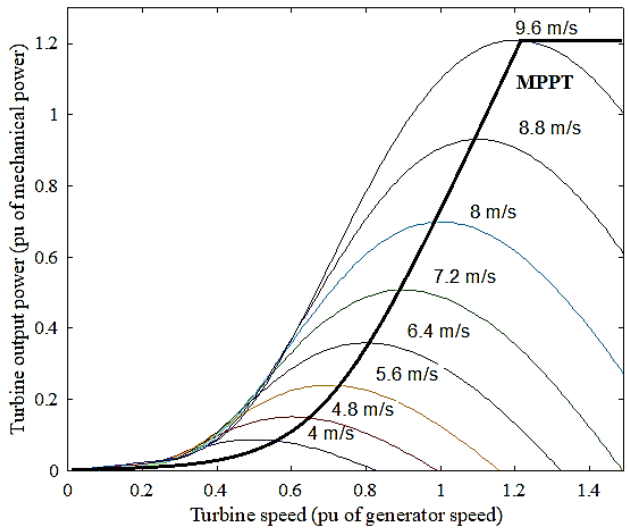


Fig.10. Plot showing the turbine power curves along with MPPT (solid black line).

A simulation study is carried out using *MATLAB/Simulink* platform for simulating the proposed generator with its control. The induction generator model uses the same parameters as that of the experimental machine. The simulated model uses a bidirectional converter and storage battery-PV panel assembly as its dc bus. In simulation however, a wind turbine is used whose power curve characteristics is shown in Fig.10.

The simulated model is then tested for voltage build-up and proposed control with load and speed variations. The simulated results are then compared with the experimental results obtained from the tests. As observed, the experimental results are in good agreement with the simulated model of the generation scheme.

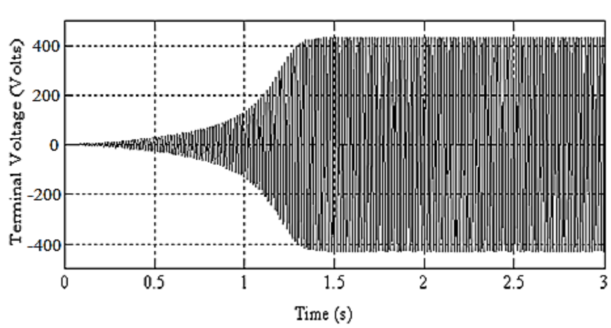


Fig.11. Simulated waveform for terminal voltage build-up of generator.

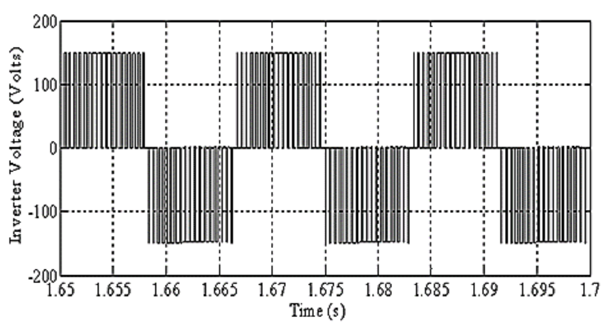


Fig.12. Simulated waveform for bidirectional converter output voltage.

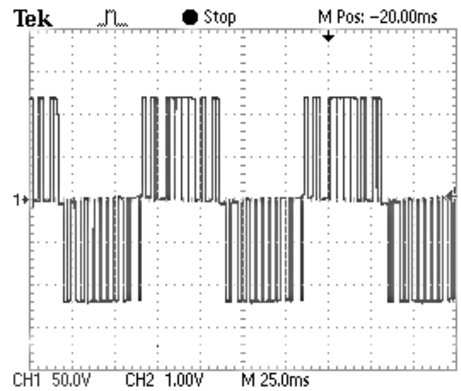
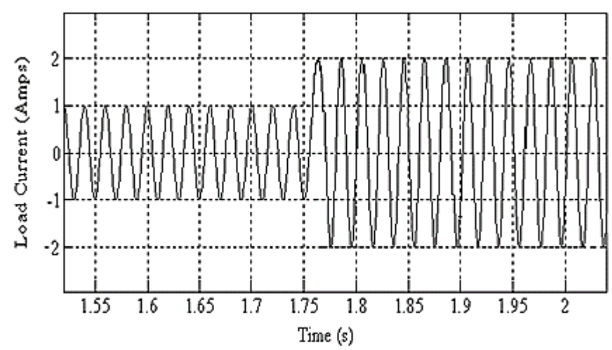
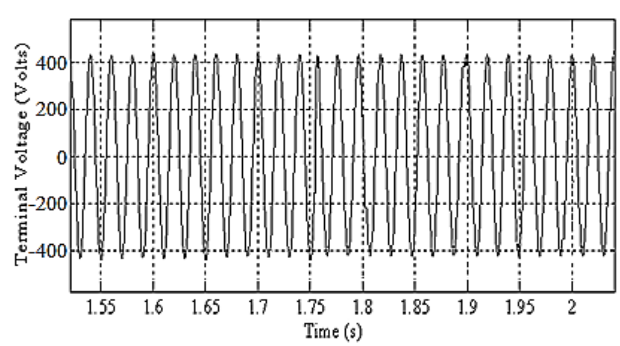


Fig.13. Experimental waveform for inverter output voltage.

The results are in good agreement as shown in the plots. Fig.11 shows the simulated generator terminal voltage build-up waveform and Fig.12 the bidirectional converter working in inverter mode and its output waveform respectively. The experimental bidirectional converter output voltage waveform is shown in Fig.13. Fig.14(a) shows the simulation waveform for the load current when load is varied from 1A to 2A peak current. The corresponding voltage waveform is shown in Fig.14(b). It is also observed that with another 50% increase in load current, the load voltage change is almost insignificant. The same verification is done experimentally.



(a)



(b)

Fig.14. Waveform for variation of (a) load current and its (b) corresponding terminal voltage.

Fig.15 shows the experimental waveform of the load current and terminal voltage when same variation of load is done as in case of simulation performed. The results as shown are in good agreement with the observed simulation results.

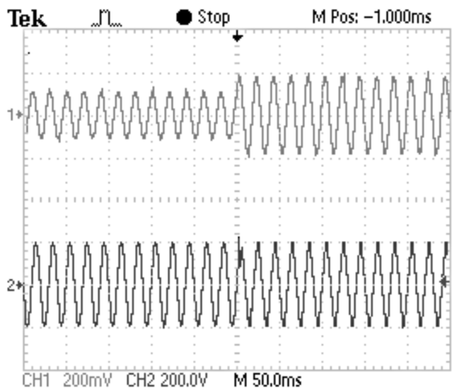


Fig.15. Experimental waveform for load current (CH1, 1.5A/div.) and terminal voltage (CH2, 200V/div.).

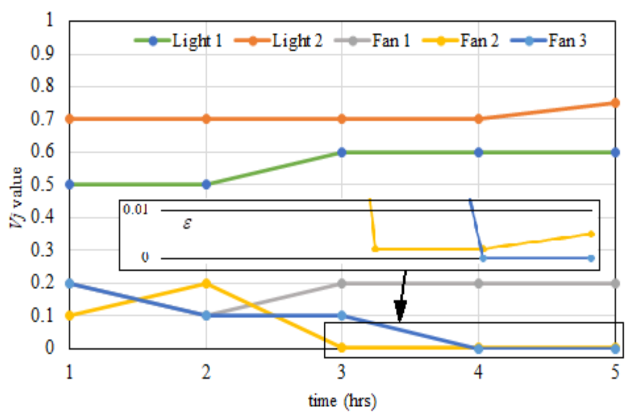


Fig.16. Load fault detection using the proposed scheme.

Fig.16 shows the detection of incipient faults for the loads. For the proposed scheme, different loads like LED lights and ceiling fans are used. The loads are run for 5 hours and their *Vj* signatures are noted using (15). As observed, the Fan 2 load value for the same is lower than the set tolerance value after 3rd hour and it remains same for the rest of the considered time. This indicates that the fan load may have some incipient fault. On contrary, the Fan 3 load has reached zero value indicating the load is turned OFF.

A qualitative comparison analysis is done for the proposed scheme with similar state-of-the-art generating schemes. The comparison is done based on the effectiveness of the different control schemes adopted in recent times for wind power generation and control. The parameters used for the comparison are, the difficulty in implementation due to either complex control or components used, MPPT based power utilization, short time load voltage transients observed and load control availability. For the proposed control, the implementation difficulty is minimal with minimal hardware components used than rest of the compared schemes. Also, the MPPT based wind power utilization using ANN and interval type-2 controller is unique and better. Short time load voltage transients are minimized and hence voltage regulation is better for the proposed scheme. Another chief advantage is the smart load control with incipient fault detection which is a new feature.

TABLE I

COMPARISON WITH SIMILAR WIND GENERATION SCHEMES

Reference, year	Implementation difficulty	MPPT based wind power utilization	Short time voltage transients	Smart load control
[9], 2017	Yes	Yes	No	No
[14], 2020	Yes	Yes	Minimal	No
[10], 2022	Minimal	No	Yes	Yes
Proposed	No	Yes	No	Yes

V. CONCLUSION

An induction generator-based generation scheme is proposed with an ANN and interval type-2 fuzzy inference-based control scheme. The loads can also be operated or controlled based on the proposed scheme. The generation scheme can be easily fabricated in remote and grid isolated areas with a wind turbine for domestic microgeneration applications. The proposed control strategy overcomes the problem of voltage regulation effectively during load or wind speed perturbations. A smart load control is proposed which can also detect incipient load faults effectively using ANN based control. The induction generator along with its control can be a suitable option for utilizing wind energy for standalone, grid secluded applications. In future, the generation scheme can be extended to its connection with a grid and further, better control can be adapted for wider wind speed range utilization.

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