

Artificial Neural Network-Based Modeling and Stability Assessment of Solar PV-Integrated Microgrids

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ABSTRACT

The characteristics of photovoltaic (PV) distributed generation and its modeling using Artificial Neural Networks (ANN) have been presented. The proposed NARX-ANN control-based feedback design incorporates a recurrent feedback loop, allowing the weights matrix to adapt within the range of error variations. This controller design is also applied to the dynamic behavior of the Phase-Locked Loop (PLL) between the converter station and the Point of Coupling (PC). The proposed controller model is derived from a set of differential equations. The performance of this control system is validated through a small-signal model, and dynamic oscillation damping is verified in terms of load variations and stability, assessed using a root locus plot with the aid of MATLAB/Simulink software.

Keywords: Artificial Neural Network (ANN), Distributed Energy Resources (DER), Point of Common Coupling (PCC), Proportional Integral Derivative (PID), Phase Locked Loop (PLL), Nonlinear Auto-Regressive Exogenous

INTRODUCTION

Currently, conventional energy generation has been significantly replaced by renewable-based distributed energy resources (DER), which have become deeply integrated into distribution networks. Various factors, such as environmental concerns, government policies, regulations, and cost-effectiveness, drive the extensive use of renewable energy sources like photovoltaic (PV) systems, wind turbine generators (WTGs), small hydropower plants, fuel cells, and diesel generators. Traditional radial distribution networks in many countries suffer from issues like poor efficiency, low quality, and inadequate reliability and stability. To address these weaknesses, the concept of microgrids (MG) has emerged as a promising solution. The fundamental idea behind microgrids is that they are small-scale power systems that include various local generation sources, known as distributed generators (DGs), along with energy storage systems and a connection to the utility grid. DGs are categorized into two types based on their grid connection. The first category includes gas turbines (GT), internal combustion (IC) engines, and micro alternators, while the second category encompasses renewable energy sources like PV systems, WTGs, and fuel cells, which require power electronics devices for integration. Microgrids offer several benefits, such as lower financial costs, environmentally friendly operation, enhanced reliability, and reduced sensitivity to transmission line interruptions. Additionally, they contribute to improved reliability, lower costs, and lower carbon emissions, promoting green energy production. However, microgrids still face technical and regulatory challenges. These include issues like complex energy markets, government regulations, site requirements, and technical concerns related to power quality, protection, relay coordination, and system stability.

In recent years, the microgrid concept has gained popularity due to these advantages and the successful implementation of real-time projects worldwide, particularly in countries like China, Venezuela, Brazil, and the United States. These projects have increased the confidence of utilities in the integration of microgrids into power systems.

In this paper, a model with an additional PV cell as a distributed generator (DG) is simulated using a Nonlinear Auto-Regressive Exogenous Input (NARX) recurrent neural network, and the results are compared with fuzzy logic and PID controllers.

MODEL ANALYSIS

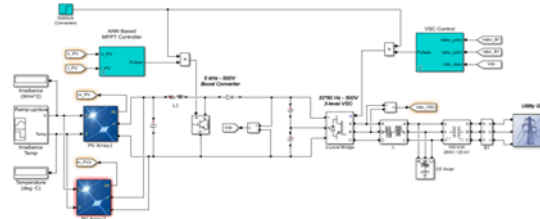


Figure 1. sMatlab Simulink model

In Figure-1, the analysis of the coordinated use of two photovoltaic (PV) cells, combined with the power electronics applications of DC to DC converters (such as Boost converters) and a three-phase voltage source inverter, is implemented in a grid-connected system using MATLAB/Simulink software. The characteristics of the PV system, including voltage, current, and frequency, have been studied [3]. To further evaluate the coordinated performance of both PV systems with the proposed technique, the microgrid system under consideration was subjected to load changes and partial shading conditions. The results obtained clearly demonstrate the novelty, functionality, and robustness of the coordinated microgrid system with the proposed ANN-based controller technique when compared to the Fuzzy and PID control techniques.

Modeling of PV

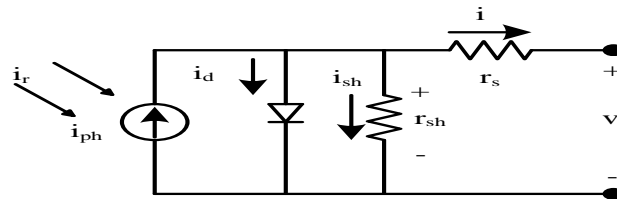


Figure 2. Circuit diagram of PV cell

By applying KCL in the above equivalent circuit we can find the governing equation for the current,

$$i = i_{ph} - i_d - i_{sh} \quad (1)$$

Here,

i_{ph} : Current due to emission.

i_d : The voltage dependent current loss in process of recombination

i_{sh} : The shunt resistance current.

In this circuit model, i_d is modelled using the equation for an ideal diode:

$$i_d = i_0 \left[e^{\frac{q(v+i r_s)}{k t n}} - 1 \right] \quad (2)$$

Where n is the ideal factor between 1 and 2. i_0 is the dissemination current, k is Boltzmann's factor, $1.381 \times 10^{-23} \text{ J/K}$ r_s is the series resistance (Ω), v is the cell voltage t is the cell temperature, q is the elementary charge $1.602 \times 10^{-19} \text{ C}$

$$i = \frac{v + i \times r_s}{r_{sh}} \quad (3)$$

Modeling of Boost Converter

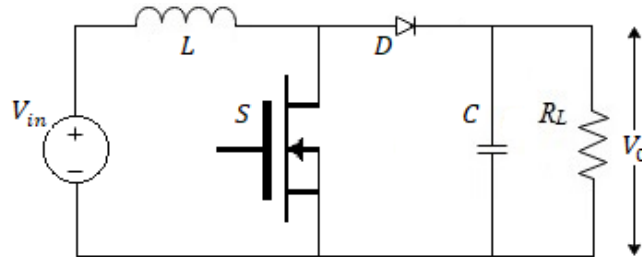


Figure 3. Boost converter

In a boost converter, the output voltage 'V_o' is greater than the input voltage 'V_{in}'. In this converter, an inductor 'L' is connected in series with input voltage as shown in Fig.4 that contributes to energy storage during 'T_{on}'. When the switch is off, as the inductor does not allow sudden change in current, this current is forced to flow through the diodes and load for a time 'T_{off}'. However as the current decreases, the polarity of emf in the inductor will change [4]. The relation between output voltage and input voltage is shown in equation (4):

$$V_o = \left(\frac{1}{1-T} \right) * V_{in} \quad (4)$$

Design of Controllers

Here three controllers such as PID, ANN and NARX are applied to a PV based micro grid and simulated to eliminate the instability in the system.

PID Controller

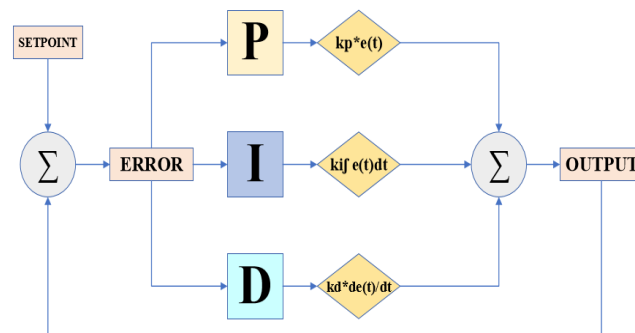


Figure 4. Conventional PID controller

PID is one type of linear controller and it is the combination of proportional (P), integration (I) and derivative (D). The PID controller represents three parameters as, K_P, K_I, and K_D. K_P represents the proportional gain which decreases the rise time but cannot control the steady-state error. K_I represents the integral gain which is reducing the steady-state error but it creates a poor transient response [5][6]. K_D represents the derivative gain which is reducing the peak overshoot, increase the transient response and also it creates a more stable system. That's why all the parameters depend upon each other.

$$c(t) = k_p e(t) + k_i \int_0^t e(T) + k_d \frac{de(t)}{dt} \quad (5)$$

$$C(s) = k_p + \frac{k_i}{s} + k_d s = \frac{k_d s^2 + k_p s + k_i}{s} \quad (6)$$

Artificial Neural Network (ANN)

The artificial neural network (NN) takes some information to be processed in a systematic way that imitators the function of a biological nerve system with integrating a time delay [7]. The ANN structure has input layers, hidden layers, and output layers those are consistent and operated in parallel mode transmitting the signals for achieving the task processing. The self-learning algorithm characteristics provide easy design for various operating conditions and grid disturbances [8][9].

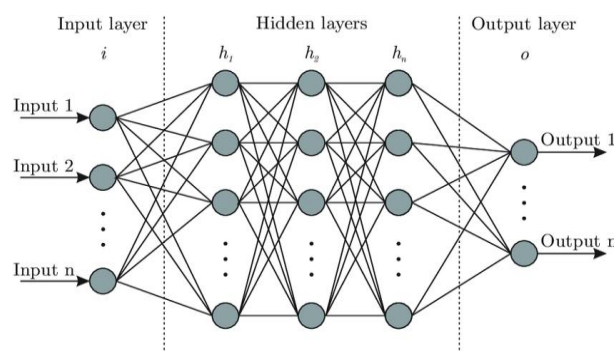


Figure 5. Neural Network structure

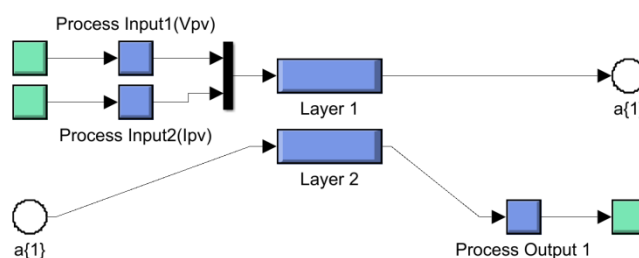


Fig. 6. NARX ANN

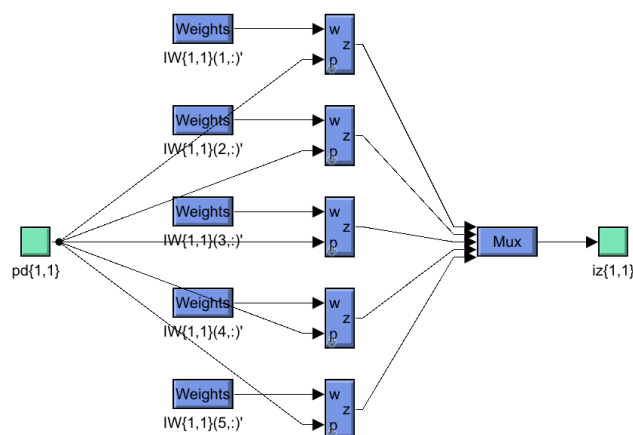


Figure 7. Expanded Figure of Hidden Layers

DESCRIPTION AND IMPLEMENTATION OF PROPOSED NARX BASED ANN TECHNIQUE

Nonlinear Auto Regressive Exogenous input recurrent neural network is a kind of neural network [10][11] which recognizes time series data as input for a nonlinear system. NARX based controller is more accurate and robust than other traditional neural network systems, because of its recurrent nature where the NARX takes input from the output value or takes the desired output values along with the input variables as shown in figure.6 and

figure.7. Further it possesses another greater advantage among all the classical neural network systems of allowing more number of input variables due to which the accuracy of the system in predicting the fault is much higher. It becomes relatively easy to identify, understand and predict the power system disturbances. Exogenous input recurrent neural network also requires a training technique such as Levenberg-Marquardt training method, Scaled Conjugate method and Bayesian Regularization method [12][13]. The Levenberg-Marquardt algorithm[14] is best suited training algorithm as compared to other two because of its fastest back propagation nature through which it can train large number of data sets and quickly update the system weights.[15][16].

Mathematical Design of NARX model in Microgrid

The NARX recurrent neural network is defined by a class of discrete time nonlinear systems. The ultimate nature of a dynamic system is to maintain the instantaneous values of the input signal with respect to its past values to obtain a better output. The proposed controller satisfies the above criterion in a robust manner. The mathematical design of NARX is given as:

$$y(t) = f(u(t-n_k), u(t-n_k-1), \dots, u(t-n_k-n_u), u(t-n_y)) \quad (7)$$

In the above equation ' $y(t)$ ' and ' $u(t)$ ' denote the output and input data corresponding to the system at a discrete time step where $n_y \geq 1$, $n_u \geq 1$, $n_u \leq n_y$ represent the input and output memory orders or delay, $n_k \geq 0$ is the input sample count later which the output is influenced by the input and ' f ' is considered as a nonlinear mapping function. When the mapping function is approximated by a Multi-Layer Perceptron (MLP) [17], the subsequent output is identified as NARX neural network. Hence, a NARX network consists of a MLP that takes as input a window of past independent (exogenous) input (2 inputs) have been considered such as V_o , V_{sc} , and past output as recurrent input such as (Sw_6) and then computes the instantaneous output. It is probable to familiarize ' x ' as the vector of the state variables, so that ' $x_i(t)$ ' is the ' i 'th state variable in the proposed NARX system. Then the states of NARX given by a set of two tapper delay lines as ' n_u ' taps as the input values and ' n_y ' taps as the output values are instantaneously updated according to the law described as:

$$x_i(t+1) = \begin{cases} u(t-n_k) \dots \dots \dots i = n \\ y(t) \dots \dots \dots i = n_u + n_y \\ x_{i+1}(t) \dots \dots \dots 1 \leq n_u \text{ or } n_u < i < n_u + n_y \end{cases} \quad (8)$$

Consequently at the time ' t ' the tap corresponds to the values specified in equation (9)

$$x(t) = [u(t-n_k-1) \dots \dots u(t-n_k-n_u), y(t-1) \dots \dots y(t-n_y)] \quad (9)$$

The organization of MLP structure consists of two layers a hidden layer and an output layer. The nodes of the hidden layer execute the function y .

$$Z_i(t) = x_i(t+1) = \sigma \left[\sum_{j=1}^N a_{ij} j x_j(t) b_i u(t) + c_i \right]$$

$$i = 1, \dots, N_k \quad (10)$$

Where ' a_i ', ' j ', ' b_i ' and ' c_i ' denote constant real weights, ' σ ' represents the sigmoidal function and ' N ' denotes the quantity of state variables.

At last the output layer of Proposed NARX model can be written as:

$$y(t) = \sum_{j=1}^{N_k} \omega_j jZ(t) + \omega \quad (11)$$

The sigmoidal function ‘ σ ’ denotes the activation function of the hidden neuron layer, which estimates the heavy side step function to access if the input is beyond or underneath a specified value. The activation function associated with the output neuron should be linear for a continuous desired output.

B. Steps taken to calculate the optimum weight:

Step-1: Calculate $Z_i(t)$ at iteration $i = 1, \dots, N_k$; ‘ i ’ represent the number of iterations.

Step-2: Select a suitable value of $x_i(t+1)$ say $x_i(t+1) = u(t - n_k)$

Step-3: Solve equation (7) for optimum values of taps on the input values and taps of the output value.

Step-4: If $1 \leq i \leq n_u$ or $n_u < i < n_u + n_y$ then point $x_{i+1}(t)$ else go back to step 3.

Step-5: Compute equation (8) if the solution contains suitable values of a_i, j, b_i, c_i real weights then execute the activation function else go back to step-3.

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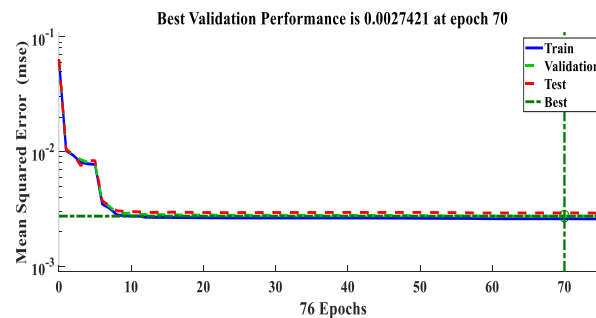


Figure 8. Mean square Error of ANN

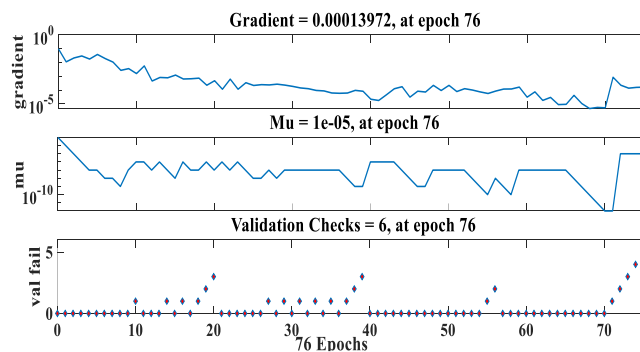


Figure 9. Validation Gradient plot

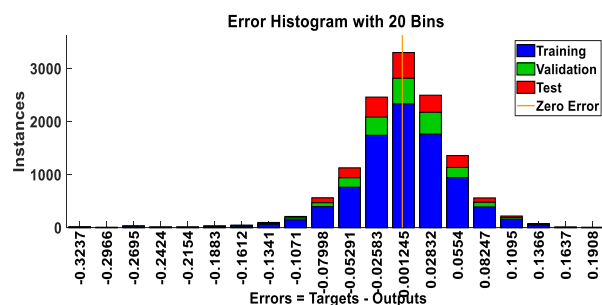


Figure 10. Error Histogram

RESULTS AND ANALYSIS

Figure-11, Figure-12 shows the different performance of conventional control, fuzzy and proposed control. The model is simulated during load change at point of common coupling. The performances of the controllers are compared under load change and voltage, current is plotted. As shown in the result, the proposed control is more stable than conventional control.

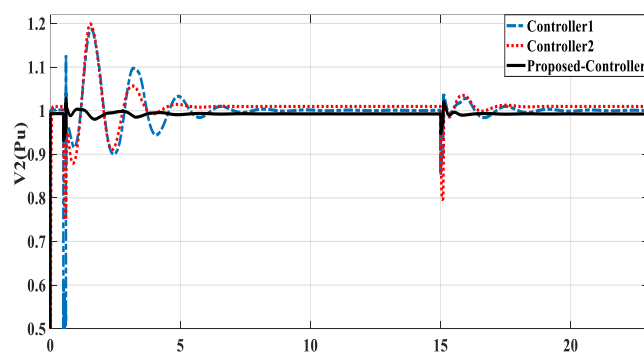


Figure.11. Voltage performance under load change

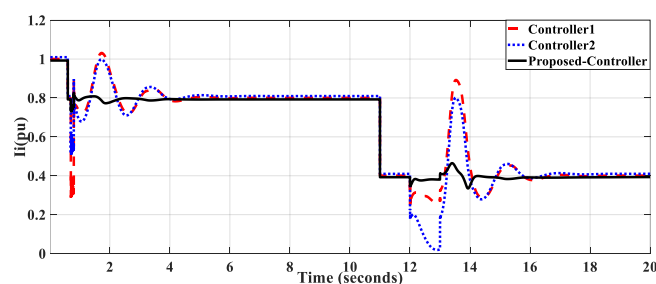


Figure.12 Current performance under load change

Figure-13 to Figure-15 confirms the remarkable result of performance under partial shading. This scenario is made throughout 1-3 sec to see that the difference between these two performances. The proposed control proves its robustness as compared to traditional PID and Fuzzy control techniques.

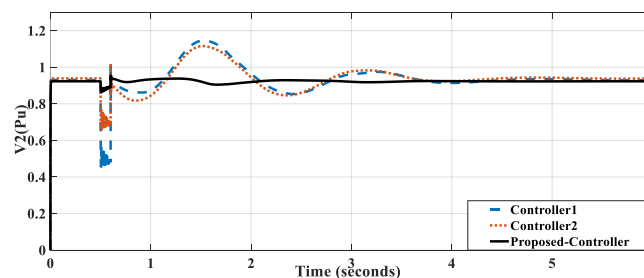


Figure 13. Voltage performance under partial shading

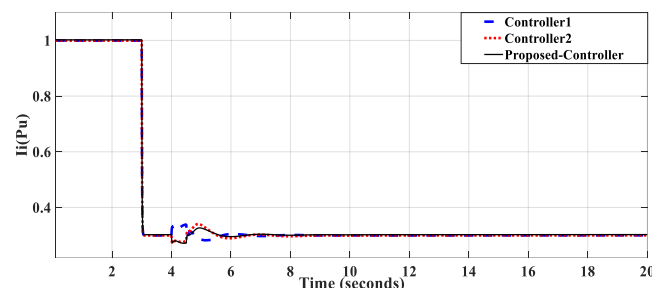


Figure 14. Current performance under partial shading

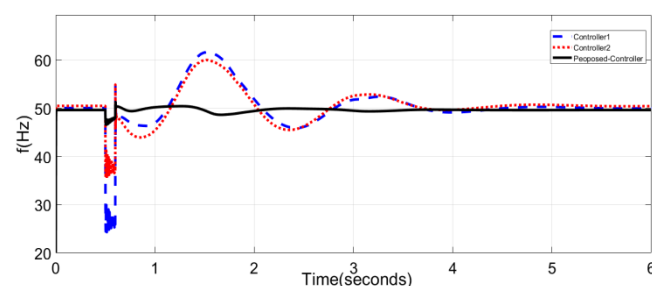


Figure 15. Frequency performance under partial shading

Stability Analysis with Roost Locus

The poles and zeros play an essential role in determining the system stability. The root locus is an effective technique used in many classical control system problems for stability analysis. It is used to determine the location of poles and roots in the s-plane to determine the overall system's stability performance and analysis of error. In a

$$1 + G(s)H(s) = 0 \quad (12)$$

Where $G(s)$ is the forward path gain and $H(s)$ is the feedback gain. Figure-15 to Figure-17, demonstrate the root-locus of conventional PID, Fuzzy and NARX Based ANN. In all these plots, it is found that the poles lie as complex conjugate pair on the LHS of the s-plane and are therefore stable. However, the conventional PID illustrated in Fig.16 is confined to a tiny stable region. The Fuzzy shown in Fig.17 covers a much broader stable region than traditional PID. The NARX Based ANN [18][19] depicted in Fig.18 covers the widest region of optimal stability as compared to Fuzzy and conventional PID

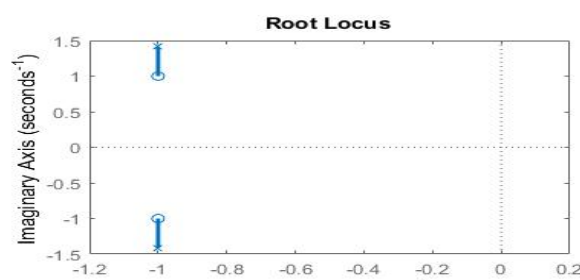


Figure 16. Root Locus of PID controller

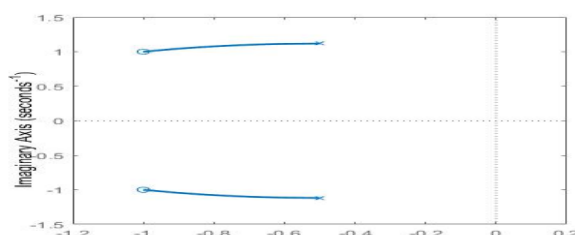


Figure 17. Root locus of ANN Controller

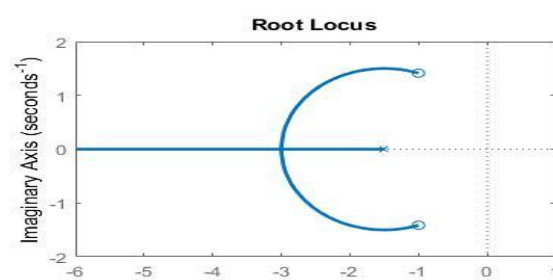


Figure 18. Root locus of NARX ANN

CONCLUSION

In the proposed NARX-ANN control-based feedback design, an adaptive nature is introduced through its recurrent feedback loop, allowing the weights of the weight matrix to adjust dynamically within the same range of error variations. The controller design incorporates the dynamic behavior of the Phase-Locked Loop (PLL) between the converter station and the Point of Coupling (PC), as shown in Fig. 11. The proposed controller model is derived using sets of differential equations in these two sections. The performance of the control system is validated through a small-signal model and dynamic oscillation damping analysis. The proposed NARX-ANN controller proves to be highly effective in ensuring stability for PV-based Distributed Generation (DG) integration in Microgrid applications.

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