Intelligent ANFIS-Based Distributed Generators Energy Control and Power Dispatch of Grid-Connected Microgrids Integrated into Distribution Network

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***Abstract*—Power supply management is a critical problem in the operation of a distribution network, considering the causes of large power losses and interruptions in the main grid caused by the unknown connection of loads and DGs that affect power delivery to customers downstream of a distribution network. The above-mentioned problems can be reduced by the integration of microgrids close to load centers and developing a controller using adaptive control techniques to enhance reliable power supply. For this reason, this paper presents an intelligent method for distributed generators' energy control and power dispatch of microgrids integrated into a distribution network employing an Adaptive Neuro-Fuzzy Inference System (ANFIS). The aim is to control distributed generators energy sources, loads, and power dispatch of grid-connected microgrids among multi-connected power sources to maintain a stable power supply without using any optimization techniques. The proposed intelligent ANFIS system is trained for power-sharing purposes and applied to the microgrid controllers. The mathematical modeling of distributed generators, system design, simulation, and testing of the proposed method were done using MATLAB/Simulink software. The results show that the proposed controller is capable of power dispatch and controls the energy harvest of distributed generators. Additionally, it can assign microgrid power source(s) to additional load(s) connected to the active distribution network without interruptions of power flow. The obtained results outperform similar works that used hybrid ANFIS-PID (Adaptive Neural Fuzzy Inference System-Proportional-Integral-Derivative), PSO-ANFIS (Particle Swarm Optimization-Adaptive Neural Fuzzy Inference System), and GA-ANFIS (Genetic Algorithm-Adaptive Neuro-Fuzzy Inference System) by automatically connecting and controlling distributed generators energy sources with effective power dispatch in mitigating downtime of grid power operations.**

***Index Terms*—Adaptive Neuro-Fuzzy Inference System (ANFIS) controller, distributed energy resources, distribution network, microgrids, power dispatch**

I. Introduction

Power systems consist of the generation, transmission, and distribution of power. The distribution system, being one of the major parts of the power network that supplies power to customers has the greatest losses. Reducing energy losses in power distribution systems has been an important issue, hence the need to integrate microgrids into distribution systems [1]. The key benefit of integrating microgrids into the power system is the improved economic and environmental conditions as well as the greater dependability of the power system and less power losses. The conventional power system is gradually shifting to a more distributed power system as a result of environmental concerns, economic factors, and the rapidly rising integration of renewable energy resources [2]. The primary elements of a microgrid are load, Distributed Generation (DG) units, and energy storage systems [2]. Developing a controller for these elements of microgrid to dispatch individual Distributed Generation (DG) energy sources, and energy storage is challenging. In order to overcome these difficulties, the authors in [3] presented intelligent control of islanded AC microgrids based on an adaptive neuro-fuzzy inference system to control frequency and droop control for power sharing of renewable-based microgrids.

A Hybrid Energy Storage System (HESS), which combines the battery and Super-Capacitor (SC), was created and presented in [4] using an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller for a DC microgrid. The suggested power control method lessens the Battery Energy Storage Systems (BESS's) stress, which lengthens the battery's life. The authors in [5] indicated that randomly positioning of distributed energy resources is the root cause of distribution network problems such as reverse power flow, microgrid system islanding, and relay tripping. It is crucial to reduce the power loss and improve the voltage profile of Distributed Energy Resources (DER) in the Radial Distribution Network (RDN) to eliminate these issues [3, 6]. Therefore, in reference [5] the authors analyzed the placement of dispersed energy resources from both conventional and renewable sources in a radial distribution network using Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Genetic Algorithms (GA), and Improved Particle Swarm Optimization (IPSO) intelligent techniques to reduce power loss hence improving the voltage profile.

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Adaptive Neuro-Fuzzy Interface System (ANFIS) controller-based droop control for a standalone microgrid in the presence of Multiple Sources was introduced in [7] for frequency and voltage regulation of a renewable generation system. Research conducted in [8] introduced a low-voltage microgrid with an ANFIS-based add-on controller for unbalanced voltage compensation. In [9], an ANFIS controller for wind-hydro microgrid and its control for rural energy systems were proposed for standalone microgrid operation. A Reweighted Zero Attractors Least Mean Square (RZALMS) control algorithm was introduced into PWM switching pulses for Voltage Source Inverter (VSI) in order to ensure proper operation of the renewable wind-hydro-based microgrid.

In order to prevent voltage quality problems such as voltage sag, flickering, voltage swell, neutral currents, and reactive power caused by grid-connected nonlinear loads, the creation of a reference voltage signal with a lower active filter rating, the authors in [10] proposed an adaptive neuro-fuzzy inference system controller for a Grid-Connected Solar Photovoltaic, wind turbine hybrid energy system. According to the authors of the paper [11], redesigning the distribution network is an efficient way to reduce active power losses in power distribution networks while maintaining load balance in each feeder, necessitating the use of the ANFIS approach for distribution network reconfiguration. Voltage stability enhancement, frequency, active, and reactive power (power quality) improvement using ANFIS controller were proposed in [7, 9, 10, 12] to enhance energy management of distributed generators for reliable power delivery to customers of a connected grid. Optimizing the voltage profile and minimizing the active and reactive power losses with proper size and location of Distributed Generators (DGs) using fuzzy logic controller were proposed in [13]. It was emphasized that the load flow analysis was optimized using a forward or backward sweep methodology to calculate real and reactive power losses as well as the voltage profile with and without the utilization of distributed generators. Research conducted on frequency and voltage regulation for power quality of renewable energy systems of a standalone microgrid having multiple sources using an Adaptive Neuro-Fuzzy Logic Interface System (ANFIS) controller was proposed in reference [14]. It was indicated that Adaptive Neuro Fuzzy Interface technology was used to reduce the issues caused by decreasing voltage and frequency fluctuations in a microgrid. Genetic Algorithm-Adaptive Neuro-Fuzzy Inference System (GA-ANFIS) controller was introduced in [15] to control microgrid voltage despite changes in power generation in a PV-Wind hybrid microgrid with a Battery Energy Storage System (BESS). An investigation into employing an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller to adjust load voltage and frequency with a focus on improving the efficiency and power management of an independent hybrid fuel cell and wind power generation is presented in [16]. It was further stated that there was a 21% settling time for the ANFIS controller as compared with other conventional controllers. Research conducted on a droop control strategy of power management in hybrid AC–DC microgrids based on an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller and proportional integral derivative (PID) controller in [17] revealed that the ANFIS controller outperformed that of the PID controller in management of power. However, in the same work [17], an optimizer based on the elephant herding optimization algorithm (EHOA) was formulated to reduce the running cost prices for PV, wind, and battery power.

Other research was conducted on Artificial Intelligence-based control using ANFIS for optimal and stable operation of converter-dominated microgrids considering optimizing the virtual inertia, damping, current state feedback factor, and reactive power sharing [18], and minimizing the irregular frequency and power deviations within microgrid was done in Reference [19] considering a distributed generator. In Reference [20], frequency regulation using ANFIS controller in microgrid for coordinating the performance of charging and discharging storage system to enhance real power balance was investigated with the aim of increasing storage equipment lifespan. A synthesis procedure for an energy management system (EMS) based on ANFIS controller and hyperplane clustering was investigated in [21] to maximize the profit of energy exchange between a microgrid and the main grid.

Thermoelectric Energy Harvesting using ANFIS-Based Maximum Power Point Tracking (MPPT) Controller for DC microgrid is proposed in reference [22] for optimizing the output power of a PV plant and monitoring the uniform and non-uniform wind velocity of a wind turbine. Power Prediction in microgrids using PSO-ANFIS Controller for Short-Term PV Power Prediction is proposed in [23], whilst using PSO-ANFIS controller for energy storage devices to regulate active and reactive power (P-Q), voltage, and frequency stability is proposed in [24] in a grid-connected microgrid. In [25], the authors introduced an ANFIS controller for fuel cell, PV, and battery storage energy management in a microgrid for efficient supply-demand balance. Voltage regulation for boost converter is essential in optimal power generation and management for off-grid microgrids, hence the use of a hybrid ANFIS-PID controller in reference [26]. However, the authors in [27] proposed an energy management system in a microgrid using a Heuristic Algorithm with ANFIS Controller. From the above pieces of literature, it is clear that much work on voltage, frequency, active, and reactive power control using ANFIS controller has been done, while little attention on using ANFIS controller for distributed generators energy control and power dispatching of grid-connected microgrids in a distribution network is yet to be accomplished.

From the above works, there has not been any work found that employs an intelligent controller system to assign power source(s) to additional load connected to the distribution network during active engagement of power supply networks during the day. This condition could cause interruption in power supply, hence immediate attention is required on developing adaptive control for microgrids to minimize this occurrence without interruption of system power flow.

The modern power distribution network integrates microgrids with various Distributed Energy Resources (DERs) to reduce losses through long distribution lines, however unknown connection of loads presents a significant challenge to the control and management of energy. These energy sources without prior notification to power supply distributors make the control and energy management of distribution network systems present a significant challenge [1, 11]. The integration of renewable energy-based DGs in power systems has become an important research field considering the many benefits such as less power losses, and small infrastructure, however, DG integration has several drawbacks such as difficulty integrating DGs into an existing distribution network due to its intermittent nature. In addition, integrating microgrids with DG imparts power quality and voltage instability, among others. As a result, grid-connected microgrids in a distribution network with large integration of DGs urgently require a new intelligent energy management system capable of scheduling distributed energy resources and enabling maximum harvesting of renewable energy among multi-connected sources and capable of assigning power source(s) to an additional load connected to an active distribution network by maintaining system stability of power flow.

Therefore, in this paper, an intelligent energy management utilizing ANFIS controller for effective energy dispatch of a grid-connected microgrid in a distribution network is proposed to alleviate the above-mentioned power supply challenges.

The main contributions of this paper are

1) Employing an adaptive controller to assign power source(s) to an additional load connected to the active distribution network without interruption of system power flow.
2) Utilizing an intelligent ANFIS-based technique to design a controller for microgrid distributed energy sources to aid in maximum power harvesting.
3) Develop adaptive power dispatching mechanism for multiple grid-connected microgrids.
4) Employing ANFIS to control the Pitch angle and two mass drive train of the wind turbine, charging and discharging of battery storage.

As a result, the remaining part of this paper is structured as follows: Materials and methods used are presented in Section II. Results and discussion are done in Section III. Section IV presents the conclusions of the proposed research.

II. Materials and Methods

Under this section, the proposed ANFIS controller design and training are carried out. The step-by-step approach of mathematical modeling of the various distributed generators (DGs) used in achieving the construction of a microgrid was done using MATLAB/SIMULINK Software.

A. Mathematical Modeling of PV

Photovoltaic modules have been developed utilizing mathematical modeling of PV electrical characteristics in the MATLAB platform. Fig. 1 represents the solar cell model, with the various parameters that were considered during the modeling. Where I_{Ph} is the photo-generated current, R_s series cell resistance, R_{sh} shunt cell resistance, I_{D} diode current, I_{PV} is the PV output current, and Vpv represents the terminal voltage of the PV.

In Fig. 1, Kirchhoff's Current law (KCL) was used to formulate the photo-generated current and the PV output current as indicated in Eqs. (1) and (2):

$$I_{\mathrm{Ph}} = [I_{\mathrm{sc}} K_i (T_{\mathrm{act}} - T_{\mathrm{ref}})] \left(\frac{\beta}{1000}\right) \quad (1)$$

$$I_{\mathrm{PV}} = I_{\mathrm{Ph}} - (I_D + I_{\mathrm{Sh}}) \quad (2)$$

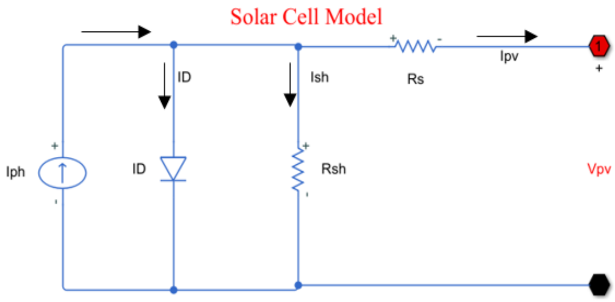

Fig. 1. Solar cell model.

The diode current, reverse saturated current, short circuit current, and PV cell open circuit voltage are mathematically calculated using Eqs. (3), (4), (5), and (6) respectively. The I_{pv} is then calculated using equation (7) by substituting Eq. (3) into (2) [25, 26]:

$$I_D = I_s \left[\exp\left(\frac{q(V_{\mathrm{PV}} + I_{\mathrm{PV}} R_S)}{N_S T_{\mathrm{act}} K A}\right) - 1\right] \quad (3)$$

$$I_{\mathrm{RS}} = \frac{I_{\mathrm{SC}}}{\left[\exp\left(\frac{q V_{\mathrm{OC}}}{N_S T_{\mathrm{act}} K A}\right) - 1\right]} \quad (4)$$

$$I_{\mathrm{SC}} = I_{\mathrm{RS}} \left(\frac{T_{\mathrm{act}}}{T_{\mathrm{ref}}}\right)^3 \exp\left[\frac{q E_G\left(\frac{1}{T_{\mathrm{ref}}} - \frac{1}{T_{\mathrm{act}}}\right)}{K A}\right] \quad (5)$$

$$V_{\mathrm{ph}} = V_{\mathrm{oc}} = \frac{N K T_{\mathrm{act}}}{q} \ln\left(\frac{I_{\mathrm{Sh}} - I_{\mathrm{PV}}}{I_{\mathrm{PV}}}\right) + 1 \quad (6)$$

$$I_{\mathrm{pv}} = I_{\mathrm{ph}} - I_s \left[\exp\left(\frac{q(V_{\mathrm{PV}} + I_{\mathrm{PV}} R_S)}{N_S T_{\mathrm{act}} K A}\right) - 1\right] \quad (7)$$

where I_{SC} is the short circuit current, T_{act} is the actual temperature of the PV cell, T_{ref} reference temperature (25°), ? is solar irradiation (W/m^2), K_i is the cell short circuit current temperature coefficient (K_i= 0.0017A/°C), $V_{\mathrm{ph}} = V_{\mathrm{oc}}$ open circuit voltage, q is the electron charge constant (q = 1.602×10^{-19} coulomb), K is the Boltzmann constant (K =1.380649×10^{-23}m^2·kg·s^{-2}·k^{-1}), N_S is the number of connected series PV cells, A is the ideality factor which in this paper, 1.5 was used as an average value to represent typical solar cells to account for non-ideal effects in solar cells, and finally, E_G is the Energy Band Gap of Solar cells. In this paper, an Energy Band Gap of 1.1 eV is taken for maximum sunlight absorption.

B. Mathematical Modeling of Wind Turbine(WT)

Similar to other sources of production technology, wind turbines also produce electricity. There is a linear relationship between wind speed and the production of wind energy. That is, when the wind speed is in its nominal state, the wind turbine will produce nominal power and vice versa. Based on the above-mentioned conditions, the mathematical model of the wind turbine in this work considered these constraints as indicated in Eq. (8) [15].

$$P_W(v)=\begin{cases}\frac{P_n(V-V_{ci})}{(V_r-V_{ci})} & (V_{ci}\le V\le V_r)\\ P_n & (V_r\le V\le V_{co})\\ 0 & (V\le V_{ci}\text{ or }V_{co}\le V)\end{cases} \tag{8}$$

where P_W is the wind power (kW), P_n is the nominal power (kW) of a wind turbine, V_{ci}, V_{co} and V_r are cut-in, cut-off, and rated wind speeds, respectively, and V is the wind speed (m/s). Eqs. (9) [27] to (13) were used to model the wind turbine mathematically. The mechanical power produced by a wind turbine was estimated based on the following equations used for the mathematical modeling [15, 26]:

$$P_m=\frac{1}{2}xC_p(\lambda,\beta)A_T\rho V^3 \tag{9}$$

$$T_m=\frac{P_m}{\omega_t} \tag{10}$$

$$C_P(\lambda,\beta)=C_1\cdot\left(\frac{C_2}{\lambda_i}-C_3\beta-C_4\beta^2-C_5\right)e^{-\left(\frac{C_6}{\lambda_i}\right)} \tag{11}$$

$$\lambda_i^{-1}=(\lambda+0.008\beta)^{-1}-0.0035(1+\beta^3)^{-1} \tag{12}$$

$$\lambda_T=\frac{\omega_t R_T}{V} \tag{13}$$

where P_m is the power extracted by the wind turbine or the mechanical power, V indicates the wind speed(m/s), A_T is the rotor area of the turbine (m^2) = πr^2 with r being the radius of the wind turbine blades, ρ indicates air density(kg/m^3), C_P is the power coefficient, β represents the pitch angle, λ_T is the optimal pitch speed ratio, λ the tip speed ratio, ω_t is the relational speed of the wind turbine(rad/sec), λ_i is the intermittent tip speed ratio (TSR), and is related to λ_T and β as shown in equation (12). C_P is defined in terms of the turbine coefficients from C_1 to C_6 as indicated in Eq. (11). The values of the turbine coefficients used in this paper are tabulated in Table I [15, 28–30] while the rated wind turbine power, rated wind speed, pitch angle, optimal pitch speed ratio, and air density of the proposed wind turbine are tabulated in Table II.

TABLE I: WIND TURBINE (WT) COEFFICIENTS

Coefficients	C_1	C_2	C_3	C_4	C_5	C_6
Values	0.956	116	0.4	0	5	21

TABLE II: PROPOSED WIND TURBINE (WT) SPECIFICATIONS

Parameters	Ratings
Rated power	4MW
Rated wind speed(V)	12m/s
Pitch angle (β)	0
Optimal pitch speed ratio(λ_T)	8.1
Air density (ρ)	1.225kg/m^3

Using the values in the above Table I and Table II, it was realized that the intermittent tip speed ratio (TSR) was calculated to be 11.4, the radius of the turbine was 27.493 m, and the wind turbine speed ω_t was obtained to be 3.4665 rad/sec, the power coefficient (C_P) was calculated to be 0.784. Fig. 2 shows the complete model of the proposed Wind Turbine.

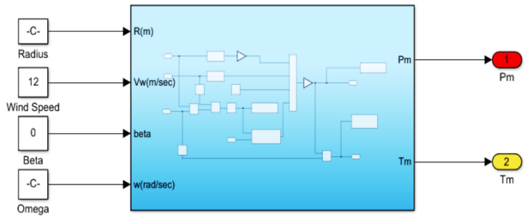

Fig. 2. Modeled wind turbine subsystem

C. Mathematical Modeling of Battery Energy Storage System(BESS)

The basic dynamics of the battery's state of charge (SoC) were modeled using equation (14) [31–33] while the state of charge constraint is presented in Eq. (15) to maintain the battery lifespan.

$$\mathrm{SoC}_{\mathrm{batt}}=100\left[1-\left(\frac{1}{Q_{\mathrm{batt}}}\int_0^t i_{\mathrm{batt}}(t)dt\right)\right] \tag{14}$$

$$\mathrm{SoC}_{\min}\le \mathrm{SoC}\le \mathrm{SoC}_{\max} \tag{15}$$

where $\mathrm{SoC}_{\mathrm{batt}}$ is the battery state-of-charge (%), i_{batt} is the battery current, and Q_{batt} is the maximum battery capacity (Ah). The proposed battery's SoC is limited to between 30% and 95% of its power in ampere-hour capacity. To prevent undercharging or overcharging of the battery, the charging restrictions were placed on the charging and discharging control system of the battery using Eq. (15).

D. Design of the Proposed ANFIS Controller.

ANFIS has both high-level reasoning ability and low-level computational proficiency with an adaptive network used for complicated and nonlinear systems using parameters as output and a minimal amount of input [4]. ANFIS uses a hybrid learning approach to create input-output relationships based on input-output data of the fuzzy interference system. The ANFIS layered structure is depicted in Fig. 3 where the nodes for input, fuzzification, product, normalization, and defuzzification, among other functional nodes, are shown. In the ANFIS structure, the adaptive nodes are the first and fourth layers whereas the fixed nodes (nonadoptive nodes) are layers 2, 3, and 5 respectively. The instantaneous power generation $P_{MG}(t-1)$ from microgrid distributed energy sources, the load power demand $P_{LD}(t)$ within a given time t was used as inputs. The output of the trained ANFIS is the power reference (P_{MGRef}) to be supplied by the microgrid at time t.

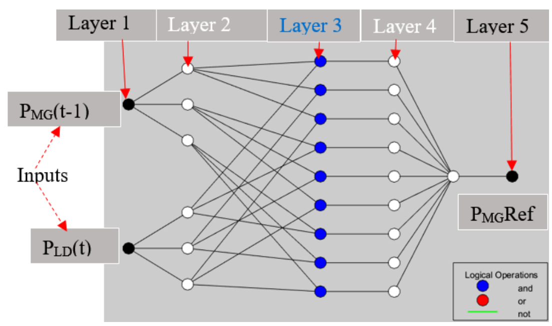

Fig. 3. Proposed ANFIS structure.

Eqs. (16), and (17) are rule sets used in the first-order Takagi-Sugeno interference system with two fuzzy layers

[11, 20]. The relation $W_i = X_i(a)Y_i(b)$ was used to determine the activation levels in connection with fuzzy rules, with the logical operator "AND" being optimized by a permanent t-norm. Where X_i (a) and Y_i (b) are fuzzed values for each input data, and W_i is the actual value for every "IF-Then" rule while a and b are the membership function (MF) parameters for the linear signal. Equation (18) is the output of each rule, which is generated as a linear equation or variable between the parameters of each rule's antecedents, while Eq. (19) is the generalized formula for the output of each rule.

Rule 1: If $P_{MG}(t-1)$ is E_1 and $P_{LD}(t)$ is H_1 then

$$f_1 = m_1 P_{\mathrm{MG}}(t-1) + n_1 P_{\mathrm{LD}}(t) + Z_1 \quad (16)$$

Rule 2: If $P_{MG}(t-1)$ is E_2 and $P_{LD}(t)$ is H_2 then

$$f_2 = m_2 P_{\mathrm{MG}}(t-1) + n_2 P_{\mathrm{LD}}(t) + Z_2 \quad (17)$$

$$f_n = m_n P_{\mathrm{MG}}(t-1) + n_n P_{\mathrm{LD}}(t) + Z_n \quad (18)$$

$$f_i = m_i P_{\mathrm{MG}}(t-1) + n_i P_{\mathrm{LD}}(t) + Z_i, i = 1,2 \quad (19)$$

where m_1, m_2, n_1, n_2, Z_1, and Z_2 are linear parameters, while E_1, E_2, H_1, and H_2 are non-linear parameters, $m_i P_{\mathrm{MG}}(t-1)$, $n_i P_{\mathrm{LD}}(t)$, and Z_i are the design parameters calculated during the ANFIS training, and E_i and H_i are the fuzzy sets in the antecedent. To create a well-designed ANFIS, training is required for the premise parameters E_i and H_i as well as the result parameters $m_i P_{\mathrm{MG}}(t-1)$, $n_i P_{\mathrm{LD}}(t)$, and Z_i whereas i and j = 1, 2, 3... are used to define the rule base of the fuzzy inference system (FIS) for a given node. Fig. 3 shows the proposed ANFIS layer framework [4, 11].

The output of the model "f" was derived by multiplying the individual output of each rule by the standardized activation degrees of the rules as in equation (20).

$$f = \frac{\sum W'_i f_i}{\sum W_i},\ i=1, 2, \ldots \quad (20)$$

where W'_i denotes the normalized value of the parameters used, which is made up of the weight W_1 and W_2 added together and W_i is the actual value for every 'IF-Then' rule with f_i, the model function at the ith node, and f is the model output predicted value of a given node function.

1). Layer of fuzzification

The input variable of each input layer is sent to the fuzzification layer. In this paper, both the load demand $P_{LD}(t)$ and the generated power or available power energy P_{MG}(t-1) at a given instant of the nodes represented as E_1, E_2, H_1, and H_2 where the E_1, E_2, H_1, and H_2 are the linguistic fuzzy theory for various membership functions. Equations (21) and (22) represent the output of the fuzzy layer [23].

$$F_{\mathrm{L1},i} = \dot{x}E_i[P_{\mathrm{MG}}(t-1)],\ i = 1,2,3,\ldots \quad (21)$$

$$F_{\mathrm{L1,j}} = \dot{x}H_j[P_{\mathrm{LD}}(t)],\ j = 1,2,3,\ldots \quad (22)$$

where, $F_{\mathrm{L1},i}$ and $F_{\mathrm{L1,j}}$ are the output of the fuzzy layer, $\dot{x}E_i[P_{\mathrm{MG}}(t-1)]$ and $\dot{x}H_j[P_{\mathrm{LD}}(t)]$ are the fuzzy layer membership functions.

2). Product layer ($\dot{x}$)

Logic "AND" or the product of the input membership functions are carried out by the product layer. The output from the product layer denotes the nodes and subsequent nodes' input weight function. Eqs. (23) and (24) are used to explain the output layer [23] while the outputs of the product layers are represented by W_1 and W_2, $\dot{x}$ coefficient of the input parameters.

$$W_1 = F_{\mathrm{L2},i} = (\dot{x}E_i[P_{\mathrm{MG}}(t-1)])(\dot{x}H_i[P_{\mathrm{LD}}(t)]),\ i = 1,2,\ldots \quad (23)$$

$$W_2 = F_{\mathrm{L2},j} = \left(\dot{x}E_j[P_{\mathrm{MG}}(t-1)]\right)\left(\dot{x}H_j[P_{\mathrm{LD}}(t)]\right),\ j = 1,2,\ldots \quad (24)$$

3). Normalization layer (N)

The third layer is represented by the normalized layer (N), where each permanent node characterizes the "IF" section of a fuzzy rule. Both the normalizing of the input weights and the fuzzy "AND" operations are normalized at this point. The outputs of this layer are stated in Eq. (25).

The normalized layer outputs are, using W'_1, and W'_2:

$$\begin{bmatrix} W'_1 = F_{\mathrm{L3},i} = \frac{W_i}{W_1+W_2}, i = 1,2,\ldots\ldots \\ W'_2 = F_{\mathrm{L3},j} = \frac{W_j}{W_1+W_2}, j = 1,2,\ldots\ldots \end{bmatrix} \quad (25)$$

4). Defuzzification Layer (DL)

This layer carries out an adaptive function that provides an output membership function in line with predetermined fuzzy rules. Eqs. (26) and (27) are used to provide mathematical expressions of the defuzzification layer outputs. The de-fuzzy layers weight membership functions are represented with $W'_1 f_i$ and $W'_2 f_j$ respectively:

$$W'_1 f_i = \frac{W_i}{W_1+W_2}[m_1 P_{\mathrm{MG}}(t-1) + n_1 P_{\mathrm{LD}}(t) + z_1] \quad (26)$$

$$W'_2 f_j = \frac{W_j}{W_1+W_2}[m_2 P_{\mathrm{MG}}(t-1) + n_2 P_{\mathrm{LD}}(t) + z_2] \quad (27)$$

5). The output layer (Σ)

The fuzzy rule "THEN" section is determined by the output layer. The input signal was determined as $\sum W'_i f_i$, hence, the total output of the layers is then calculated using Eq. (28).

$$f = \sum W'_i f_i = \frac{\sum W_i f_i}{\sum W_i} = \sum f_i \quad (28)$$

where f, or $\sum W'_i f_i$ or $\sum f_i$ is the total output or the predicted value.

After training the ANFIS, the power reference value was obtained for energy management in grid-connected microgrids. The ANFIS-trained data was imported into the Fuzzy model and incorporated into the microgrid control systems. The power source reference control formulations are presented in Table III.

TABLE III: PROPOSED POWER SOURCES CONTROL REFERENCE

Power Sources	**Power Control**
BES	$P_{BES\_Ref}(t) = V_{BES\_Ref} I_{BES\_Ref}$
PV	$V_{PV\_Ref}(t) = \frac{P_{PV\_MPPT}}{I_{PV}}$ or $\frac{P_{PV\_LIMIT}}{I_{PV}}$
Wind Turbine	$WT_{V\_Ref}(t) = \frac{P_{WT\_MPPT}}{I_{WT}}$ or $\frac{P_{WT\_LIMIT}}{I_{WT}}$
Grid Power	$Grid_{V\_Ref}(t) = \frac{P_{GRID}}{I_{GRID}}$ or $\frac{P_{GRID\_LIMIT}}{I_{GRID}}$

In this paper, the ANFIS controller was used because it has the ability to adapt and learn from the system dynamics and can adjust its parameters based on the changes in the operating conditions, making it well-suited for environments with varying renewable energy sources and load patterns. Again, the integrating nature of ANFIS also allows for control strategies to achieve optimal operation of distributed generators within the microgrid configurations that may change over time due to the addition or removal of distributed generators, hence its use in this paper.

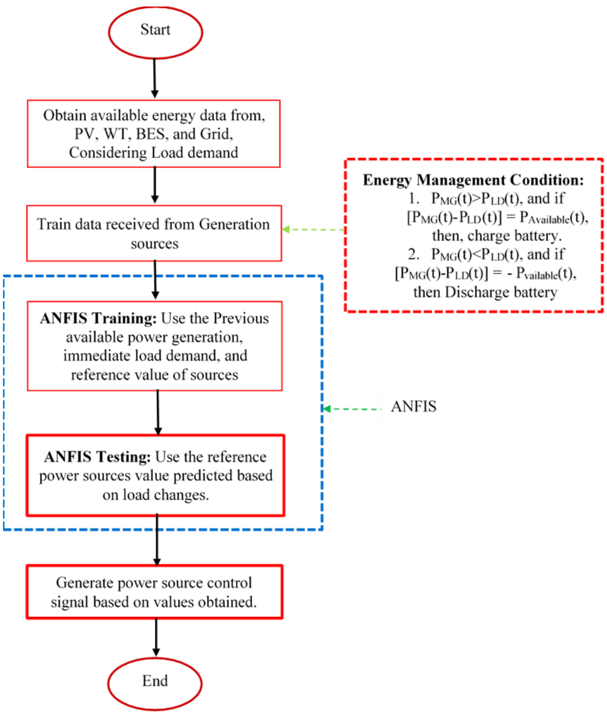

Fig. 4. Training procedure of ANFIS controller and various energy management conditions.

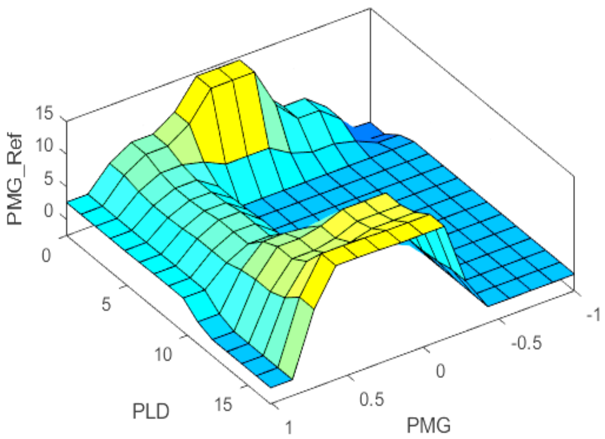

Fig. 5. ANFIS surface structure.

The general procedure for training the ANFIS controller is presented in Fig. 4. Fig. 5 represents the ANFIS structure of the power dispatched while Fig. 6 is the set of the membership function rules used during the training. Fig. 7 represents the model of the ANFIS Power Sharing System.

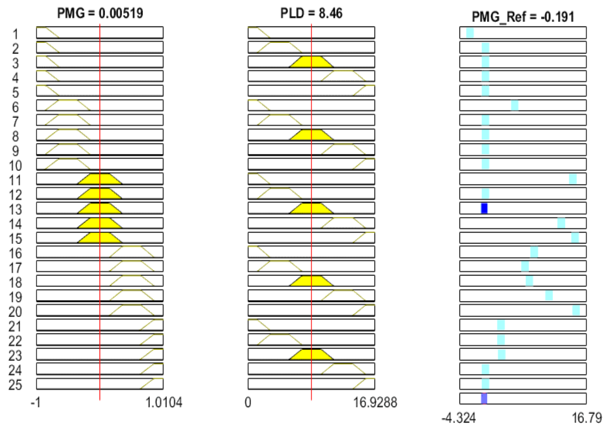

Fig. 6. ANFIS membership function rules.

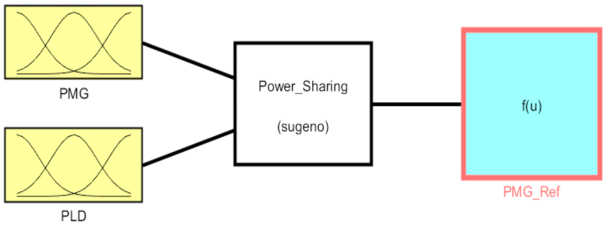

Fig. 7. ANFIS power sharing system.

E. ANFIS Data Training and Testing

The training dataset was obtained from the simulation work and was collected using to workspace model in MATLAB/SIMULINK. The obtained data is then used to train the ANFIS model. The training dataset consists of a large portion of the available data and is used to adjust the parameters of the ANFIS model to accurately capture the underlying patterns and relationships in the data. The training process involves presenting input-output pairs to the ANFIS model and adjusting its parameters iteratively to minimize the difference between the predicted output(s) and the actual output(s). After the ANFIS model had been trained on the training dataset, it was evaluated using the testing dataset to assess its generalization performance. This helps to determine how well the model can make accurate predictions on new, unseen data and whether it has learned the underlying patterns without overfitting the training data.

F. Configuration of Proposed Grid-Connected Microgrids

In this paper, the proposed grid-connected microgrid distributed generator sources were modeled in MATLAB/SIMULINK, and the configuration of the various components that were used. The grid-connected microgrid consists of four microgrids with each microgrid made up of a photovoltaic (PV) plant, a wind turbine (WT) plant, a battery energy storage system (BESS), and an ANFIS controller. The architecture of the proposed grid-connected microgrid is presented in Fig. 8. Fig. 9 shows the proposed distribution network modeled in MATLAB/SIMULINK with the integrated microgrids and loads.

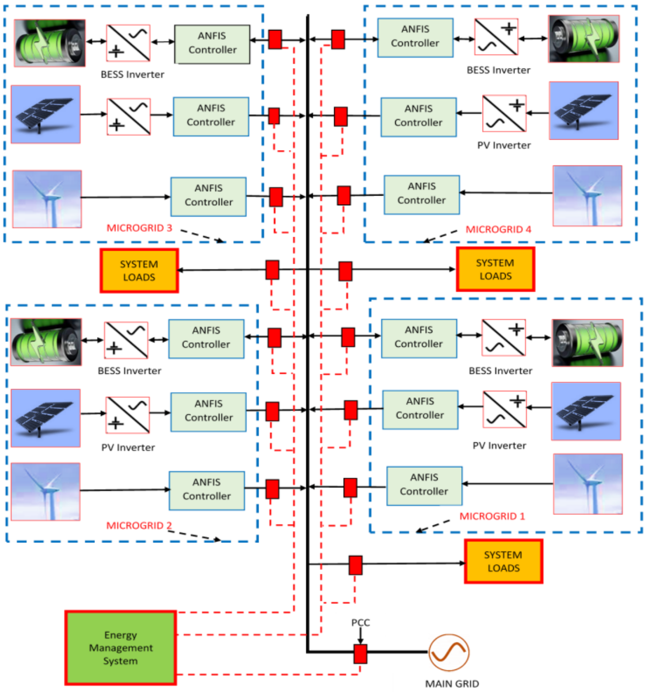

Fig. 8. The architecture of the proposed grid-connected microgrid.

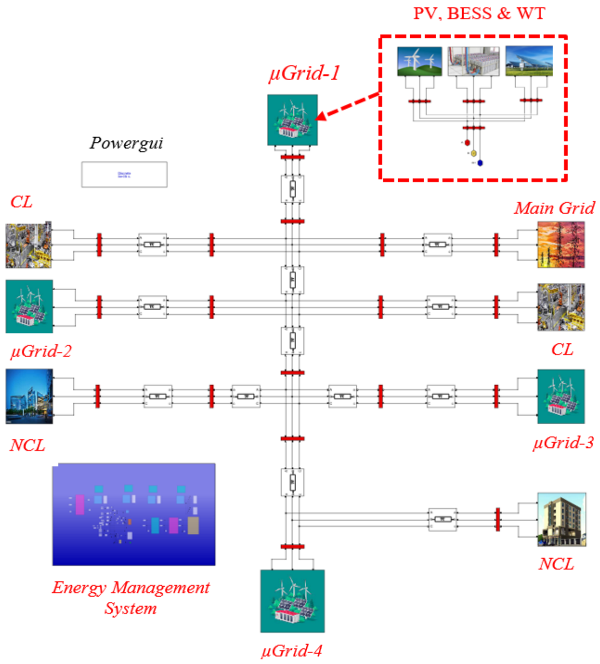

Fig. 9. MATLAB/SIMULINK model of distribution network with microgrids.

III. Results and Discussion

The suggested system was modeled and simulated in MATLAB/SIMULINK as discussed in the previous sections. In testing the performance effectiveness of the proposed method of distributed generators energy harvest control and power dispatch, the ANFIS controller was applied to the battery control system, PV plant control system, and Wind Turbine control system of all four microgrids integrated into the distribution network. The energy management system in this paper was used as the main system for controlling and dispatching available power source(s). A 24-hour energy harvest control and power dispatch were used in this paper for the simulation. For charging the battery, any available source supplying power from the distribution network with excess power is then stored in the battery and utilized during peak demand. Two scenarios were used; (i) the main grid was used as the main power supply; (ii) a distributed generator, that is wind turbine was used as the main source of supply with the grid power as a backup source during peak period from 06:00 to 10:00 and 18:00 to 20:00 respectively.

In Fig. 10, the state of charge of the battery occurs between 00:00 to 06:00, 09:00 to 18:00, and 20:00 upwards, while the change occurs between 06:00 to 09:00, and 18:00 to 20:00 respectively. 95% of the SoC of the storage system is considered with at least 10% of power discharge of about 4000 kW power, voltage 218 V, and current approximately 55,000 A. The graph of state-of-charge (SoC) and discharge is shown in Fig. 11. This is in line with an outcome from reference [20], yet the proposed method outperforms that result.

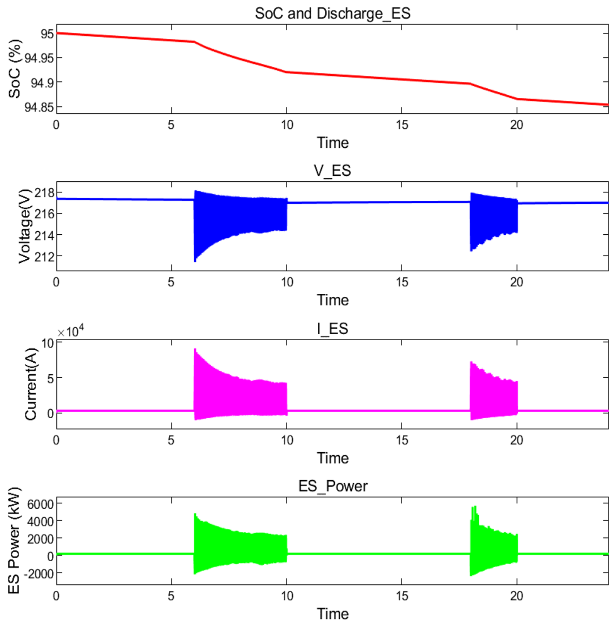

Fig. 10: Battery Storage (SoC).

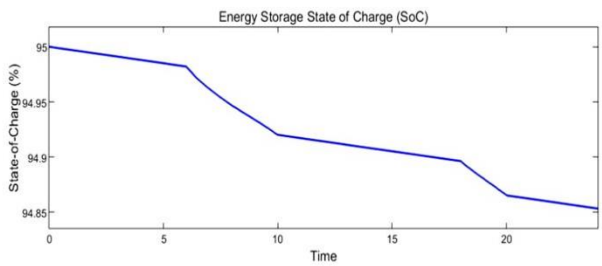

Fig. 11. Characteristics of battery with initial SoC.

Controlling the wind turbine in harvesting maximum wind power is important in wind energy technology, hence in this paper, the pitch angle controller of the wind turbine and the two mass drive system was designed using ANFIS to control the generator to enhance maximum wind power generation. The control simulation results of the characteristics of the rotor speed (RS) and the electromagnetic torque(Te) are shown in Fig. 12. The results show that with a rotor speed of 300 rad/s, the maximum electromagnetic torque or electrical power generated is around 2000 Nm during the peak hours between the hours of 06:00 to 10:00 after which a constant 1800 Nm is maintained at a rotor speed of 200 rad/s. It was envisaged that with the adaptive control system proposed, the wind turbine could harvest a large amount of electrical energy with a small wind speed due to the adaptive nature of ANFIS. Again, the proposed controller has an improved signal of electromagnetic torque (Te) and the Rotor Speed with fewer ripples as presented in Fig. 12, compared to the result in Fig. 13 where ANFIS was not applied.

The effect of variation in wind speed was analyzed and it was realized that variation in wind speed has a great impact on rotor voltage, rotor current, and power generation. The result of this analysis is presented in Fig. 14 showing the various fluctuations in rotor speed, phase-to-phase voltage, phase-to-phase current, and AC power generated. It was realized that 1000A of current was recorded during the time that more power was supplied with a reduced wind turbine voltage below 500V and rotor speed operating at 300 rad/s. When ANFIS was not applied, the root mean square (Voltage and Current) and the AC power supply had increased ripples as depicted in Fig. 15 as compared to when ANFIS was applied as shown in Fig. 14 and this can affect power quality delivery. In general, it can be concluded that an increase in rotor speed increases the various electrical parameters and vice versa. The simulation results obtained are in line with research conducted in reference [15, 16], however, there is an improved performance in this proposed work due to the implementation of ANFIS in designing the pitch angle controller and the two mass drive system that coupled the generator to the wind turbine. It must be emphasized that the proposed intelligent adaptive controller (ANFIS) method helps in improving the control of wind power generation. Hence, developing an adaptive controller for the pitch angle of a wind turbine is essential for adequate harvesting of wind power and controlling the wind generator in wind speed variation conditions.

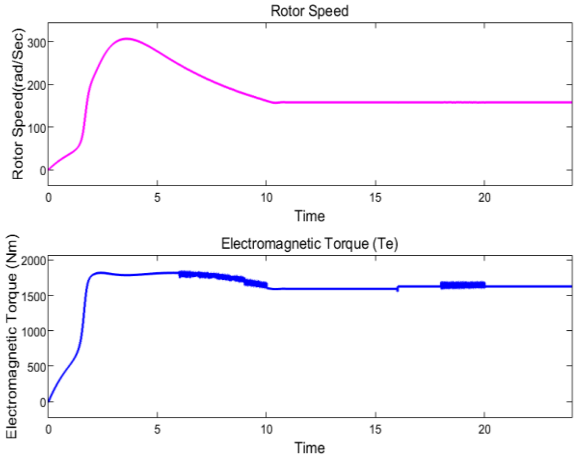

Fig. 12. Characteristics of rotor speed and electrical power with ANFIS.

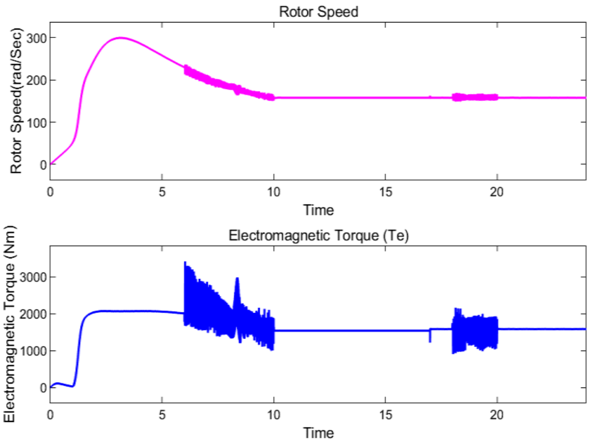

Fig. 13. Characteristics of rotor speed and electrical power without using ANFIS.

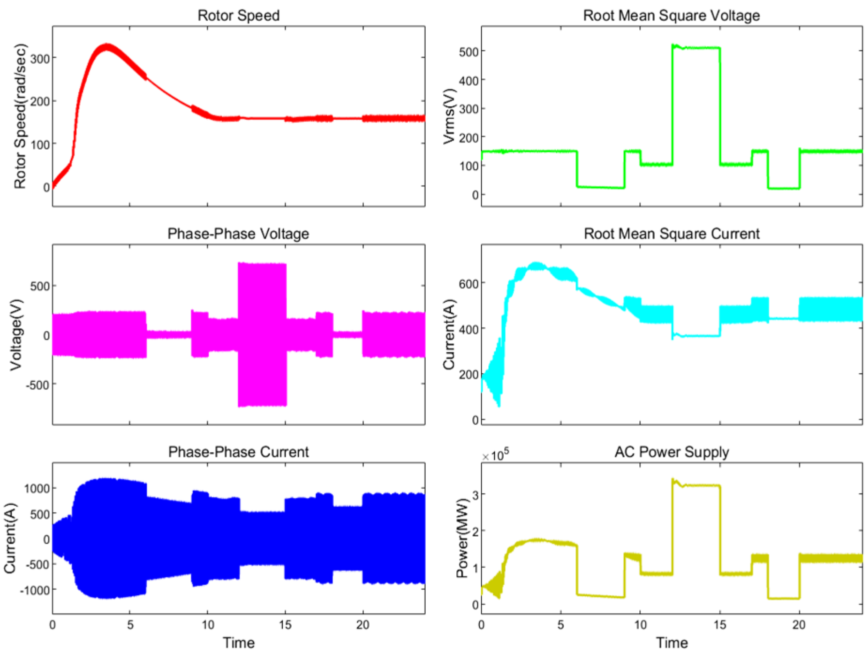

Fig. 14. Rotor speed effect on generator electrical parameters with ANFIS.

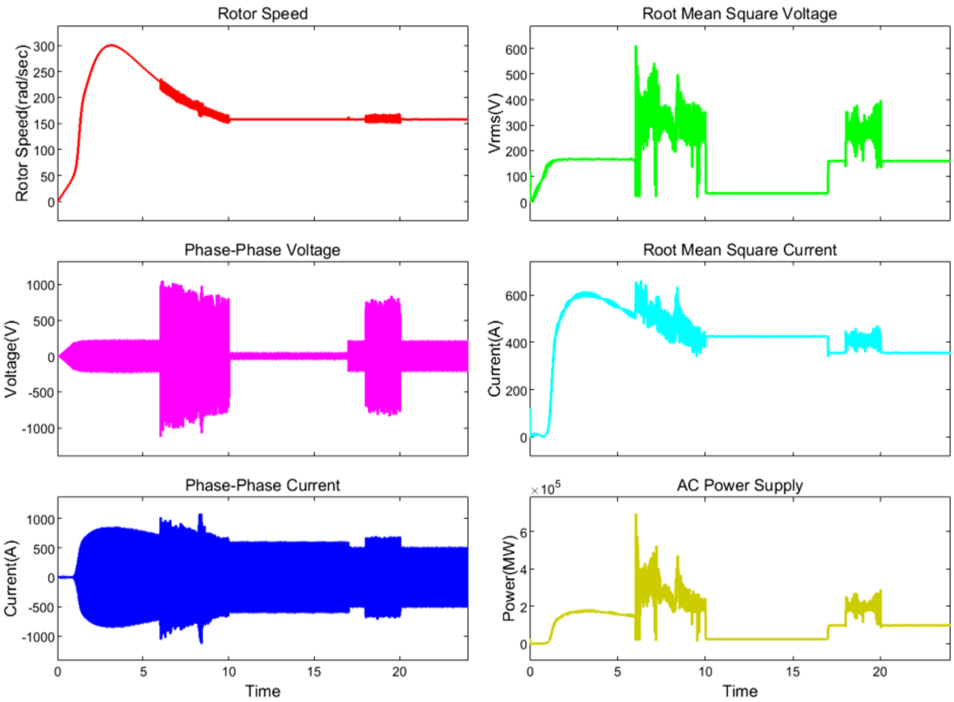

Fig. 15. Rotor speed effect on generator electrical parameters without ANFIS.

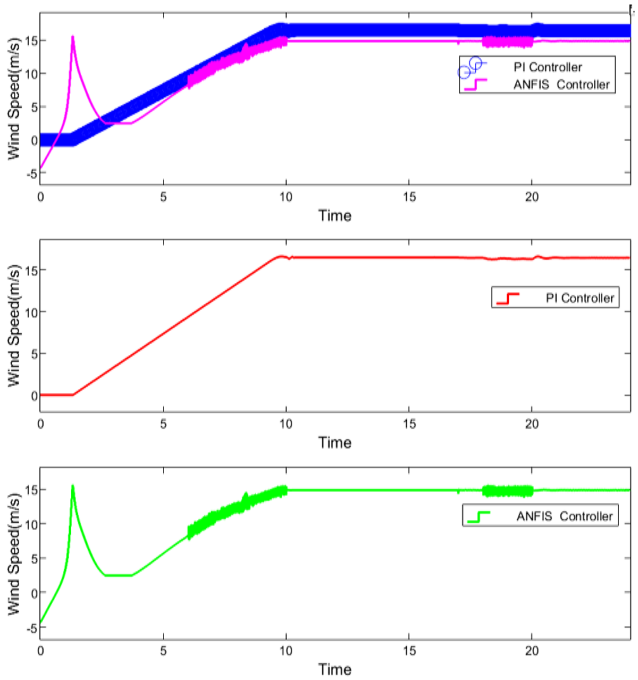

Fig. 16. Rotor speed control.

To prove that the proposed ANFIS controller is effective, two different controllers were used, namely, PI and ANFIS, and the results were compared as shown in Fig. 16. The results show that the ANFIS controller has a better performance in controlling pitch angle based on variations in wind speed to maintain 12m/s wind speed. In Fig. 16, the wind turbine speed increased significantly when using the ANFIS controller to set the wind turbine into motion faster while the PI controller could not around the time of 00:00h to 02:00h. However when the wind speed rises until 10:00h, the generator attained its full speed (12 m/s), meanwhile, PI controller could not maintain 12 m/s rather 15 m/s was maintained. However, the ANFIS controller maintained 12 m/s of wind speed, which indicates that an ANFIS controller is effective to be used to control the pitch angle of a wind turbine.

The result in Fig. 17 shows how the proposed intelligent control system assigns a power source to an additional load connected to the distribution network during active engagement of the power supply network during the day which requires immediate power supply without interruption of system power flow. This proves that the controller can assign a power source when an additional load is connected to the distribution network without affecting power delivery.

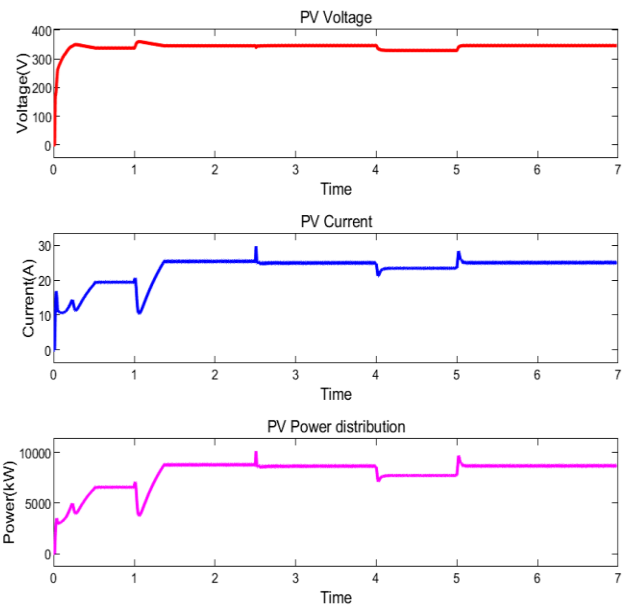

Fig. 17. Result of PV plant supplying additional connected load.

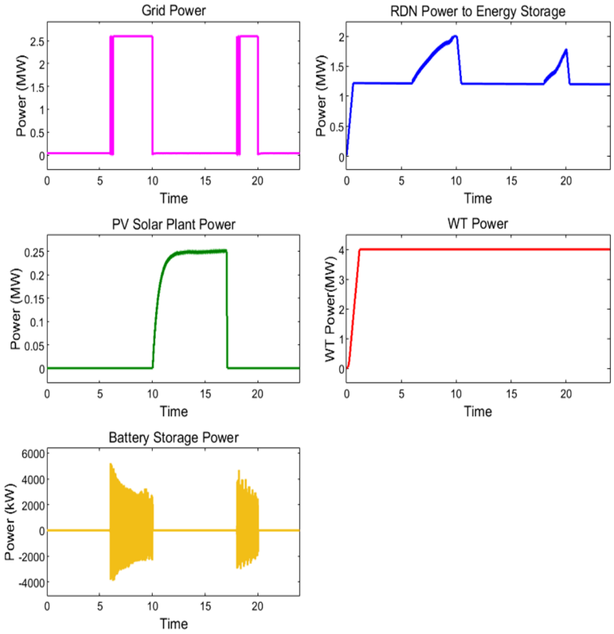

Fig. 18. Power dispatch of the generating sources in a distribution network.

A. *Evaluating the Effectiveness of the Proposed Energy Harvest and Power Scheduling*

In this paper, a reliable power supply with minimal downtime and the use of renewable energy resources (REs) due to the environmental benefits of REs were taken into consideration. With this, about 80% of the power supply was based on renewable energy sources (PV and Wind) where the main grid and battery energy stored were used to aid demand supply during peak hours in the first simulation scenario as shown in Fig. 18. In this case, the wind plant is made to generate a constant power supply of 4 MW throughout the 24-hour period with the PV supplying approximately 0.28 MWp power between the hours of 09:00 to 17:00 during the day. During peak hours, the main grid supplies 2.5 MW of power, and the battery storage system supplies between 4000 kW and 5,000 kW based on load demand. Again between 00:00 to 05:50 and 06:00 to 23:00, 1 MW to 1.3 MW and a constant 1.3 MW power is supplied from the distribution network to the storage system respectively. This proposed method has a better performance than the result presented in [15].

In Fig 18, generation sources complement each other in that the grid power and the battery storage power supply power at peak hours only to complement system power demand that cannot be met by the renewable power source(s). In Fig 18, when renewable power is/are available, there will be enough power to meet the system demand of power supply thereby minimizing or eliminating load scheduling by the power supply authority and vice versa. Any time a generating plant supplies power, a microgrid with more storage system initiates charging using some of the power supply available. During such period(s), the battery storage system acts as a load and the power stored is discharged during the peak hours when power demand is high to maintain constant power supply in the distribution network. In Fig. 18, power is taken from the grid only at peak hours.

In Fig. 19, the main grid was used as the main power source to supply power from the hours of 00:00h to 06:00h, 09:00h to 18:00h, and 20:00h to 24:00h respectively while the distributed generators, the wind turbine were used as backups to supply power at peak hours (06:00h to 09:00h and 18:00 to 20:00h) with the PV plant supplying power between 10:00h to 16:00h during the day. Utilizing the ANFIS control mechanism, any excess power realized in the distribution network is sent to the battery storage system. In this scenario, the wind plant supplies 2.5MW power during the peak hours of 06:00h to 09:00h and 18:00 to 20:00h likewise the battery storage also supplies about 0.17MW power to the grid network during peak hours to help in power balancing. In addition, the PV plant also supplies about 1.6MWp power between the hours of 10:00h to 16:00h during the day when the grid is supplying around 1MW power as shown in Fig. 19.

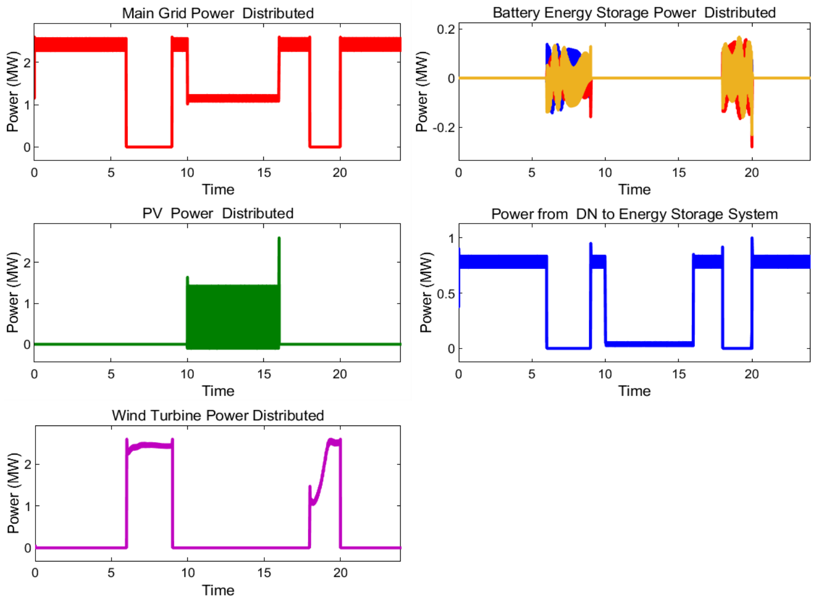

Fig. 19. Power dispatch in a distribution network.

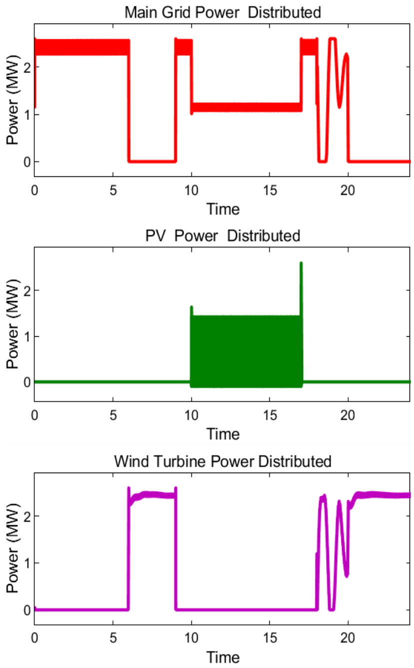

Fig. 20. Validating the performance of the proposed controller power dispatch.

In validating the performance of the proposed controller on the harvest of renewable energy and power dispatching, the wind plant and the battery storage system distributed power from 18:00 to 24:00, it was observed that the wind plant was supported by the grid power when varied wind speed occurs from 18:00 to 20:00. The wind turbine control system was able to adapt to system changes and maintained the wind plant power supply of 2.5 MW till 24:00h as shown in Fig. 20. In comparison with similar works in references [6, 12], it is proving that the proposed intelligent ANFIS controller is capable of maintaining reliable power supply by adapting to system changes thereby mitigating losses of power supply in distribution network.

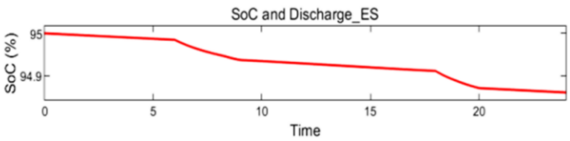

Fig. 21. Proposed battery energy storage (SoC).

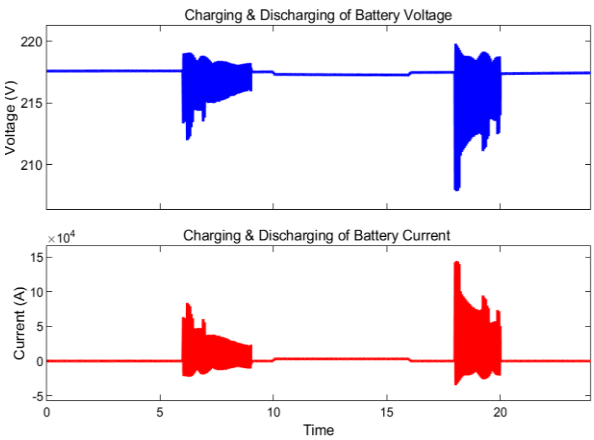

Fig. 22. Charging and discharging of proposed battery current and voltage.

B. *Comparison of the Proposed Control System with Other Work*

The proposed ANFIS Controller works effectively in controlling and dispatching available energy sources based on an increase or decrease in load demand. With the renewable energy sources and battery storage system, the battery can discharge the desired power when necessary proving that the controller works better as compared with work done in [25, 26] where a PSO-ANFIS MPPT, ANFIS-PID controller was used. Fig. 21 and Fig. 22 show the results of the proposed battery energy storage state of charge (SoC) and charging and discharging of battery current and voltage respectively, having smooth and clear breaking points without ripples as compared to the result presented in Fig. 6 and Fig. 10 of [25, 26] during charge and discharge periods of the battery.

In reference [3, 16, 27], the ANFIS control scheme using a heuristic algorithm for energy management was proposed for power sharing of PV, WT, and BESS, it can also be mentioned that their result shows that their system works well, yet it cannot be compared to the power scheduling results obtained in this manuscript as presented in Fig. 17–20, respectively. Again, the results of controlling the wind turbine pitch angle and two mass drive model using the ANFIS Controller aided in harvesting a constant wind power of 4MW as presented in Fig. 18. It is also therefore important to emphasize that the Adaptive neuro-fuzzy inference system (ANFIS) control mechanism used for the control and dispatch of energy sources in this paper, works effectively for effective power supply and demand balance.

IV. Conclusion

A proper energy management and control system plays an important role in the integration of microgrids with distributed generators (DGs) energy sources into a distribution network. In the paper, an ANFIS controller is utilized for controlling and dispatching distributed generators as well as scheduling the main grid supply, and allocating a power source to any additional load(s) connected to the active distribution network without disrupting system power flow. The ANFIS controller was applied to four microgrids with available power sources and load demand as input signal while reference power was used as the output during the training of the ANFIS. The results obtained show that the performance of the ANFIS Controller proposed is better than the conventional PID controller in terms of regulating the pitch angle of the wind turbine and also the dispatching of power among distributed generator (DG) units. The simulation was done under different power dispatch scenarios and the results demonstrated that the ANFIS controller has the potential as a good solution for an efficient energy management system for distribution networks with multiple grid-connected microgrids due to its adaptive nature. The proposed controller was designed to work only with low-voltage systems, it was therefore not tested on a high-voltage network (transmission network) to compare its performance to the low-voltage network outcome. As a result, future research should concentrate on applying certain optimization techniques to the proposed controller and applying it to a transmission network as well. The outcomes should be compared with the results obtained from the distribution networks.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, design, modeled, simulation, evaluation of system performance, writing, and visualization have been done by Ebenezer Narh Odonkor. Peter Musau Moses and Aloys Oriedi Akumu supervised, analyzed, and edited the paper.

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