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Advanced Design and Dynamic Simulation of an MPPT based FUZZY PI &ANN Controlled Grid-Connected PV-Wind-Battery System for Intelligent Load Management

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***Abstract* - In this paper an energy management system designed based on Fuzzy PI & Artificial Neural Network (ANN) is presented to optimize power sharing amongst Wind-PV-Battery DC microgrid and to ensure steady operation of DC bus for microgrid under numerous operating conditions. Proposed approach is an ANN to control operation of power flow between PV system, Wind and Battery for optimal energy utilization and for system stabilization. The developed model is implemented in MATLAB/Simulink and tested using various operating conditions. Simulated results illustrate that proposed ANN-based strategy is capable of effectively improving dynamic response of microgrid by successfully reducing settling time of DC-link voltage from 0.2923 s to 0.0038 s, ripple of DC-link voltage from 1.70% to 0.19%, PV power ripple from 3.10% to 0.57%, and wind power ripple from 2.95% to 0.89%. Results show that proposed energy management system based on ANN method has better response speed, voltage regulation, and operation reliability of hybrid DC microgrid.**

Keywords - ANN, Renewable Energy Integration, DC Microgrid, Energy Management Control, Bidirectional

DC-DC Converter (BDC).

I.INTRODUCTION

The demand for electricity has been increasing continuously, conventional fossil fuel resources are becoming exhausted, concern about environment has been rising, and renewable energy technologies have been quickly integrated into modern power systems. Among different renewable energy resources, together PV and wind energy have been captivating a lot of attention for their high availability, clean generation and their potential reduction of greenhouse gas (GHG) emissions.

However, fluctuations in these Renewable Energy Resources (RES) make a constant and stable power generation, voltage stability and continuous power supply difficult to achieve for various environmental conditions [1]-[2]. To overcome problem of each non-renewable source's limitation, which integrate PV, wind and battery have been recently developed as an effective solution to improve operational flexibility and energy reliability.

In such systems, batteries, could be used to compensate for variability of renewable energy supply and demand in these systems, by storing energy when supply remains high and discharging energy when demand is high.

This is a cooperative operation which can help to stabilize system and improve power quality, it will also enable increased use of renewable energy sources and make Wind–PV–Battery systems suitable for residential, commercial and microgrid applications [3]-[5].

When compared to other microgrid architectures, DC microgrids have gained much research interest because of their higher efficiency, simpler control structure and direct links with proposed system. The benefits of DC Microgrid over traditional AC Microgrid are that there is no redundant AC/DC conversion stage, which decreases amount of energy lost in conversion process and increases efficiency of system.

Furthermore, development of DC loads, Power Electronics conversions, EV and battery storage systems has increased application of DC microgrids in current distributed energy systems [6]-[8]. These advantages notwithstanding, hybrid DC microgrid operating successfully is still a challenging task because of fluctuations of renewable energy

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production based on irradiation and wind speed, variation of load demand from consumers during day. Therefore, an efficient Energy Management System (EMS) is necessary to manage power movement among PV arrays, wind generation, battery storage and load.

The well-designed EMS guarantees that DC-link voltage stays within DC-link voltage range, optimizes power generation and load consumption, minimizes number of charging and discharging cycles of batteries and helps to stabilize and keep microgrid reliable [9]-[11]. Various control strategies have been reported in literature to improve performance of renewable energy powered microgrid. Conventional proportional-integral (PI) controllers have been popular due to their easy implementation and acceptable steady state performance.

In the field of renewable energies, this revealed constraints of fixed parameter PI controllers and has led to use of several intelligent control methods such as Fuzzy Logic Controllers (FLC), ANN, optimization techniques and others based on artificial intelligence. These clever techniques offer better learning efficiency, nonlinear mapping properties, adaptability and better dynamic performance in uncertain operating situations [12]-[15].

ANN is an attractive solution for energy management applications, because of its ability to model complex nonlinear relationships without need to have an accurate mathematical model of system. Controllers are trained from data obtained from system operating conditions using ANN to control system to effectively coordinate renewable energy sources and battery storage under various operating conditions. Traditional rule-based controllers [16]-[19] may not achieve stable microgrid operation, effective power sharing, voltage regulation and response time as well as that of ANN controllers.

Considering the above merits, this paper proposes an EMS using ANN approach for a hybrid Wind-PV-Battery DC Microgrid (MG). Proposed method uses ANN as a substitute for conventional Fuzzy–PI energy management controller, which enhances coordination of PV generation, wind generation, battery energy storage and load demand. Various operating conditions are designed and synthesized in MATLAB/Simulink with proposed controller.

The simulations results highlight advantages of proposed controller in terms of improved DC-link voltage regulation, reduced power ripple, reduced voltage ripple and quick transient response when compared with conventional Fuzzy–PI controller presented in [20]– [22]. Remaining part of this paper will be structured as follows. Suggested EMS for hybrid Wind–PV–Battery DC microgrid is proposed and subsequently, modelling and control of different components of microgrid are considered. Next, implementation of ANN controller and its operation in DC-link voltage regulation and power coordination is discussed. Finally, results of simulations and performance comparison are presented to show effectiveness of proposed approach.

II. STRUCTURE DESCRIPTION

Fig 1 shows overall configuration of proposed hybrid Wind–PV–Battery DC microgrid. Its purpose is to be interconnected with an energy storage system, a wind and PV generation system through a common DC bus, to supply uninterrupted power to various loads.

The interface between each renewable source and DC bus is provided with an appropriate power electronic converter that enables power to flow between different renewable sources to be controlled independently of each other and DC bus maintained at a regulated voltage. Auxiliary source is BESS that can store energy when renewables are generating excess energy, and discharge energy when renewable Sources are generating not enough energy to meet load demand.

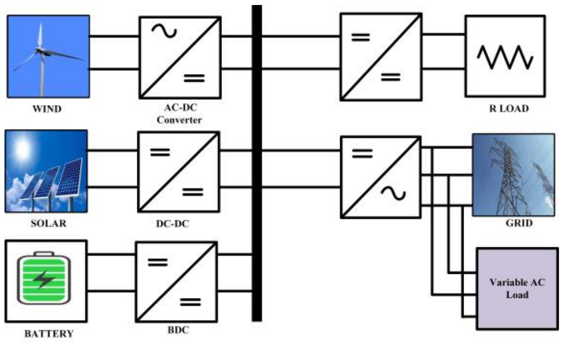

Fig .1 Configuration of the Hybrid Wind-PV-Battery DC Microgrid

WECS module transforms wind energy into electrical energy and after passing through AC-DC converter, electrical energy is transferred to common DC bus. Similarly, solar irradiation is converted to DC power by PV array and Boost Converter is used to control PV array before it is associated with dc link. Battery is charged in both directions by Bidirectional Converter based on balance of system power.

This is a coordinated operation to maintain a balance between energy consumptions and energy production for microgrid and voltage regulation for DC-link. A regulated DC power source provides necessary DC power at common DC bus to power DC loads, and a DC–AC inverter connects microgrid to utility grid and AC power sources that require DC power.

Inverter takes regulated DC and transforms it to AC with proper voltage and frequency, thus allowing for reliable connection to grid and functionality of AC loads. Proposed hybrid microgrid is controlled by Energy Management Controller based on ANN

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which senses power contribution from wind, PV and battery subsystems and tunes their parameters based on operating condition to keep DC bus voltage stable and renewables used efficiently.

III. SYSTEM MODELLING AND CONTROL STRATEGY

3.1 PV System Modeling

PV system is one of major renewable energy resources of proposed hybrid Wind–PV–Battery DC micro-grid. It generates electricity directly from sun's energy in a process known as photovoltaic effect, generating clean and sustainable electricity. PV array output characteristics depend on environmental conditions (solar radiation and PV cell temperature) and hence are non-linear voltage-current (VI) and power-voltage (P V) characteristics. Therefore, a proper control strategy is needed to obtain most efficient energy extraction in different weather conditions.

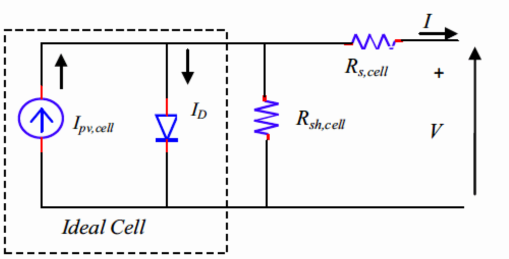

Fig. 2 equivalent Circuit of Solar panel

The most common equivalent circuit model of PV cell is single diode model of Fig. 2, consisting of a photocurrent source, diode, shunt resistance (R_sh), and series resistance (R_s). Current due to solar irradiance incident on solar cell is termed as photocurrent and diode model represents p–n junction characteristics of solar cell. Series resistance includes losses of conduction inside cell and shunt resistance represents path of leakage current across junction.

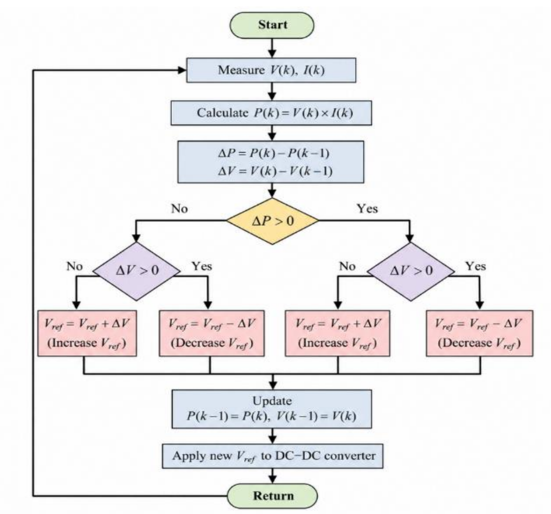

Fig .3 Flowchart of the Perturb & Observe (P&O) Algorithm

Algorithm of P&O MPPT algorithm is shown in Fig3. Algorithm continuously measures PV voltage, current and calculate PV output power. Variations in power and voltage changes reference voltage, so that PV system can operate near Maximum Power Point under different environmental conditions

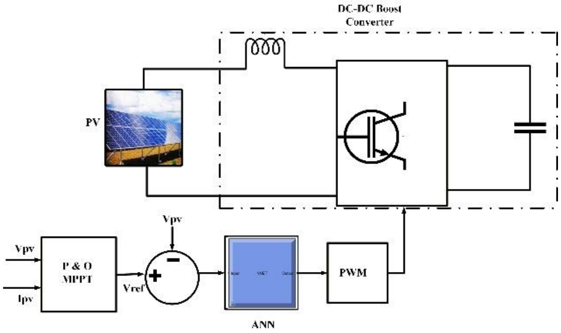

Fig .4 Control Architecture of Solar

Fig 4 shows control architecture of photovoltaic generation structure employed in proposed hybrid Wind–PV–Battery DC microgrid. PV array generates electrical power based on available solar irradiance and supplies measured photovoltaic voltage (V_{pv}) and current (I_{pv}) to P&O MPPT algorithm. MPPT block continuously evaluates operating condition of PV array and determines optimum reference voltage (V_{ref}) corresponding to maximum power point.

Desired voltage is evaluated against with measured PV voltage to produce an error signal, which is applied as input to ANN controller. Based on voltage error, ANN generates an appropriate control signal that is supplied to PWM generator. PWM unit converts control signal into gate pulse for boost converter, thereby regulating converter duty cycle. Consequently, step up converter maintains panel at its optimum operating point while ensuring efficient power transfer to common DC bus under varying solar irradiance conditions.

3.2 Wind System Modeling

Proposed hybrid DC microgrid includes wind energy conversion system as one of renewable energy sources.

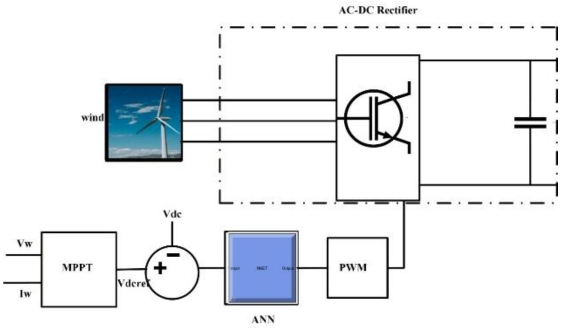

Fig .5 Control Architecture of Wind System

Fig5 shows control architecture of wind energy conversion system. Wind turbine captures energy

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carried by moving air and converts mechanical power which is subsequently transformed into electrical energy through generator. Generated three-phase AC power is processed through a controlled AC–DC rectifier, which converts it into regulated DC power before supplying it to common DC bus [17].

$$P = \frac{1}{2}\rho A v^3 \tag{3}$$

Tip speed ratio

$$\lambda = \frac{\omega - R}{\vartheta} \tag{4}$$

$$\tau = \frac{P}{\omega} \tag{5}$$

ANN is used to control DC-link voltage and ensure stability of operation. first block in MPPT block is a wind system variable processor block, which computes a reference DC-link voltage V_{dcref} from wind system variables. reference voltage that is created is compared with measured DC-link voltage V_{dc}, and difference between them is given as error signal to ANN controller. voltage error signal is fed into ANN controller which produces a control signal for PWM generator. Then PWM pulses are given to controlled AC-DC rectifier switches, controlling power flow from wind generation system to DC bus. Switching pulses are continuously adjusted so that proposed ANN controller maintains stability of DC-link voltage and enhances power capture under different wind conditions.

3.3 Battery Modeling

Battery is united to maintain balancing power supply and steady process of hybrid DC microgrid under various renewable energy generation and load conditions. This battery is associated to common DC bus via a BDC that can charge and discharge battery as needed.

$$e_v = V_{dcref} - V_{dc} \tag{6}$$

$$e_i = I_{batref} - I_b \tag{7}$$

$$P_b = v_b * I_b \tag{8}$$

$$SOC(t) = SOC(t_o) + \frac{1}{C_{rated}} \int I_{bat}(\tau) d\tau \tag{9}$$

Battery power flow is controlled by using cascaded control strategy. measured vdc is evaluated against vdc reference to get voltage error signal in outer control loop. This error is used by controller to calculate reference battery current to be used for stabilizing DC-bus voltage.

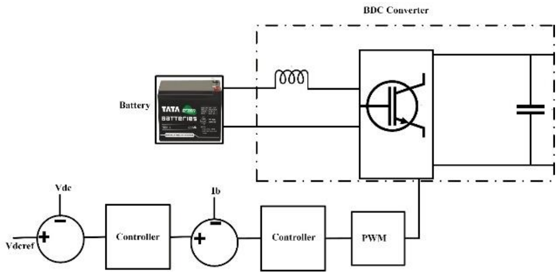

Fig .6 Control Architecture of Battery

Fig 6 shows inner control loop; desired battery current is compared with measured battery current. current error is fed back to current controller which then delivers necessary control signal to PWM generator. PWM pulses produced by command signal control switching operation of bidirectional DC-DC converter, and thus charging and discharging characteristics of battery [18]. converter is connected to battery during power surplus periods when renewable energy generation is high, enabling excess power to be stored. If renewable energy sources are not adequate to meet load demands, then converter will discharge necessary power to DC microgrid [19]. This control approach leads to better voltage regulation, higher system reliability, and ensures power continuity during dynamic operating situations.

3.4 Conventional Fuzzy–PI Energy Management Strategy

In this section, traditional Fuzzy–PI Energy Management Strategy is discussed. Hybrid Wind–PV–Battery DC microgrid with a conventional energy management strategy is implemented by using a FLC and a PI controller. Predefined fuzzy rules and membership functions are used to process FLC system variables such as: DC-link voltage error and rate of change of DC-link voltage and a proper supervisory control signal is generated. This signal then goes to PI controller that regulates power electronic converters to stabilize voltage of DC link, and balances PV system, wind energy conversion, BESS and connected loads.

Although Fuzzy–PI controller has good steady-state performance, performance of this controller is still sensitive to experts' careful design of membership functions and rules. Hence, it is not very flexible to changing renewable electricity generation and load demand, making it worthwhile to explore an energy management strategy using an ANN.

3.5 Proposed ANN-Based Energy Management Strategy

ANN is intelligent computation models that were inspired by learning and decision-making process of human brain. ANNs have been widely used for renewable energy systems, power electronics, and microgrid control applications, intelligent model to

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their capability of learning complex nonlinear relationships from input data. Their adaptability ensures successful operation in varying environmental conditions and uncertainties of systems.

Neuron output

$$Z = \sum_{i=1}^{n} \omega_i x_i + b \qquad (10)$$

Where:

- x_i= input signals
- w_{ij}= connection weights
- b_j= bias term
- $f(\cdot)$= activation function
- y_j= neuron output

Hidden Layer Output

$$a_j = \sigma(\sum_{i=1}^{n} w_{ji} x_i + b_j \qquad (11)$$

Where:

- h_j= hidden layer output
- x_i= ANN inputs
- w_{ij}= weights connecting input and hidden layers

Output layer

$$u - f(\sum_{j-1}^{m} v_j \, h_j + b_o \qquad (12)$$

Where:

- u= ANN control output
- v_j= hidden-to-output layer weights
- h_j= hidden layer outputs
- b_o= output layer bias

Conventional fuzzy logic controller is replaced by ANN in proposed hybrid Wind–PV–Battery DC microgrid. system error signals from PV system, wind, and battery are fed to ANN network then calculates what control action to take, based on these inputs, to adjust power flow and keep system stable.

ANN has three layers: input layer, processing layers, and output layer. input layer is connected to measured system variables and control errors, and hidden layers are connected to each other by various neurons to process information. output layer creates control signal which will be fed to PWM generator for switching control of converter.

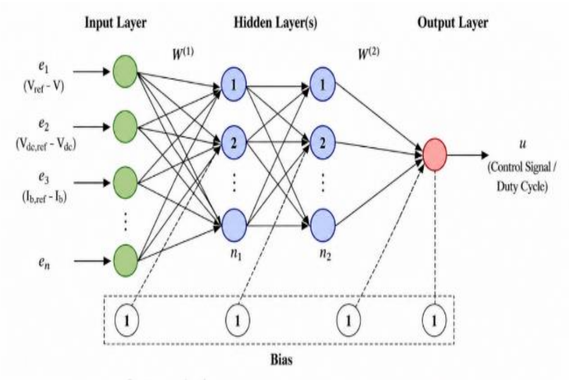

Fig .7 Structure of ANN controller

Fig7 shows ANN, it is used to create a nonlinear mapping between values of operating conditions in system and value of required control action in this structure. network is trained with historic operating data taken for various renewable generation and load scenarios.

ANN continuously optimizes its internal parameters throughout training to minimize prediction errors and enhance control accuracy. After training, network can quickly generate appropriate control signals without need of detailed mathematical modeling of system.

trained ANN controller also constantly observes and adjusts operation of microgrid in response to changes in solar power input, wind speed, battery state of charge, and load demand. This ability allows controller to be adaptive, providing DC-link voltage stability, power-sharing performance and overall energy management efficiency.

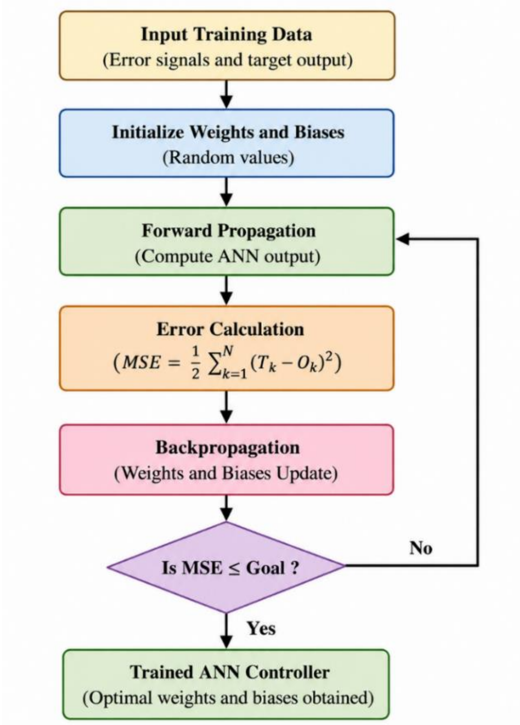

Fig .8 ANN Training process with back propagation Algorithm

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Fig8 shows ANN training algorithm starts by supplying input training data, which includes error signals and target outputs. Random values are used for initial weights and biases of network. In forward propagation part, ANN operates on data fed into it, and produces an output. Generated output is evaluated against output target and Mean Square Error (MSE) to assess performance. weights and biases are adjusted using back-propagation algorithm to minimize error. This is repeated until MSE is less than or equal to target value. Last, trained ANN controller with optimized parameters is generated with an accurate control performance.

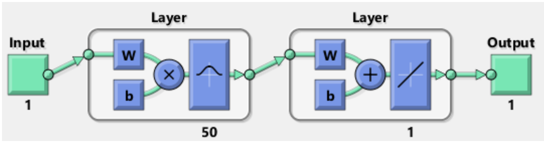

Fig. 9 Radial bias ANN

Radial Basis Network (RBN) used in EMS is shown in Fig 9. Network comprises of an input layer and a hidden layer containing 50 radial basis neurons and one output neuron. Each hidden neuron receives input signal through a set of weighted connections, and activation of each hidden neuron is determined by a radial basis function that is based on distance between input signal and center of hidden neuron. Bias values can be used to determine response width of each neuron which can make nonlinear system characteristic to be approximated effectively. In output layer, all outputs from hidden layers are linearly combined with some weights and bias to generate output control signal. This configuration also exhibits rapid learning, superior nonlinear mapping and superior control performance in dynamic energy management of Hybrid DC microgrid.

IV. PERFORMANCE EVALUATION

Developed ANN- EMS for hybrid DC micro grid was simulated and tested in MATLAB/Simulink. overall simulation model is comprised of PV source, wind, Battery, BDC, DC link, multilevel inverter and grid interface.

Table 1. Simulation Parameters

Parameter	value
Wind Power	10000W
Windspeed	12m/s
Battery Voltage,	240v
SOC	80%
Grid Voltage	415V,50Hz
PV Power	2950W
Inductance	3mH
Dc Link Voltage	240V

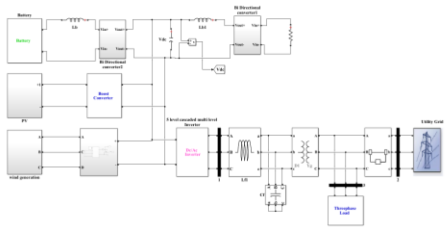
Fig .10 Simulation Diagram of the proposed system

Proposed hybrid Wind–PV–Battery DC microgrid is shown in Fig.10. System comprises of panel, wind system, battery, DC bus, BDC, inverter, filter, grid and load. Boost converter is used to increase panel voltage. wind energy system is connected via an AC–DC converter to common DC bus. Battery is coupled with a BDC that allows battery to be charged or discharged for energy balancing. voltage stability of DC bus is ensured by DC bus capacitor. inverter converts generated DC to AC, which then goes through a filter to grid and local load. This setup facilitates stable transmission of power, efficient management of energy resources, and delivery of a consistent load supply even amidst changing conditions of renewable energy.

Case 1: Step Variation in Wind Speed

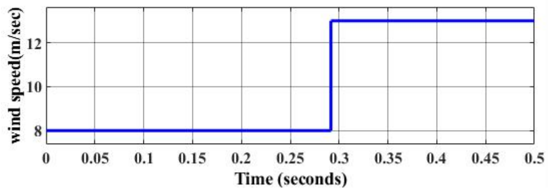

Fig .11 wind speed

ANN-based controller controls process of RES and Battery to confirm a steady power flow and control DC-link voltage in various operating conditions. observed wind speed varies from step to step. In case 1, wind speed is variable at each step. To check dynamic performance of proposed control strategy, wind speed varies from 8 m/s to 13 m/s with an interval of 0.3 s as shown in Fig. 11. This variation was added to study ability of ANN controller in controlling system when sudden variations occur in renewable power generation.

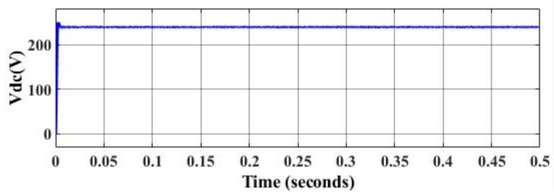

Fig .12 Dc link Voltage

Fig12 shows Even though wind speed increases abruptly, operation of DC-link voltage is almost constant throughout simulation period, which shows that proposed energy management strategy, based on ANN, is effective in maintaining system stability. regulated DC-link voltage is used to ensure coordination between wind system, PV source and battery energy storage unit.

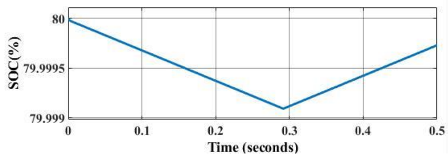

Fig. 13 SOC

Fig13 shows during transient interval battery State of Charge (SOC) varies slightly. battery serves to provide support to maintain a balance of power at first. Since wind energy generation has increased, charging condition of battery also gets better, which leads to gradual recovery of charging profile of SOC. This behaviour confirms effectiveness of proposed controller in managing exchange of energy in an efficient and optimal way without overusing battery.

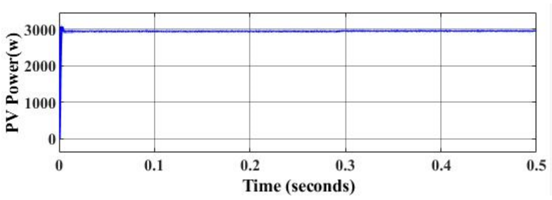

Fig. 14 PV Power

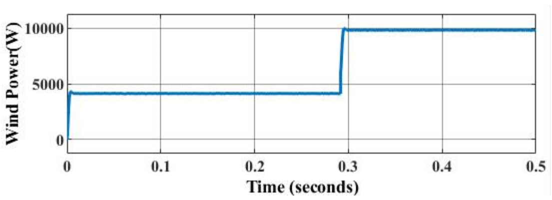

Fig .15 Wind power

Fig 14,15 shows power profiles of renewable energy sources show that power from PV is almost constant since operating parameters of PV are not changing in this case study. But, when wind speed crosses 0.3 s, wind power rises tremendously. This results in more renewable energy available in microgrid. generated power is distributed according to energy management system with stable operation of DC bus.

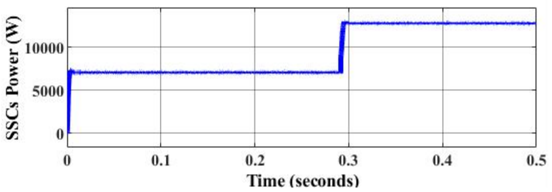

Fig .16 SSC Power

Fig 16 shows SSC power also rises with growth of wind power, which reflects correct coordination of energy among storage elements.

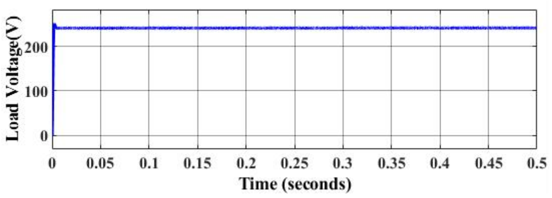

Fig .17 Load Voltage

Fig17 shows load voltage is kept constant during entire duration of simulation, indicating inverter and its control system's capability towards sustain decent voltage quality under varying conditions of renewable energy sources.

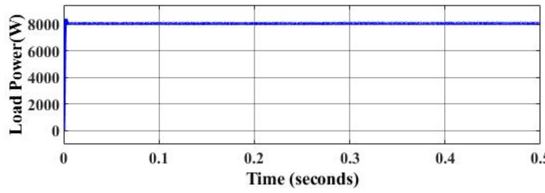

Fig .18 Load power

Fig18 shows Same applies to load power, which does not change significantly, suggesting that power is being passed on to load without significant disturbances. Due to renewable generation, battery mode of operation is altered and takes over surplus energy from wind subsystem. This is a transition showing successful control of charging and discharging operations based on requirements of system by ANN controller.

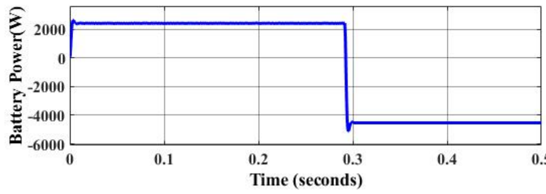

Fig .19 Battery Power

Fig 19 shows battery power response is clearly showing operation of energy management system. Up to wind speed rise, battery supplies power to meet load demand.

Case2: Dynamic Changes in Wind Speed

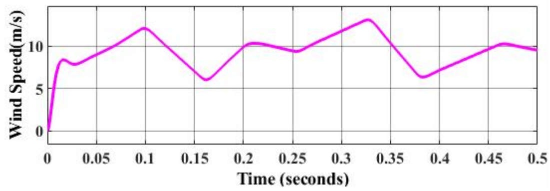

Fig .20 Variable Wind Speed

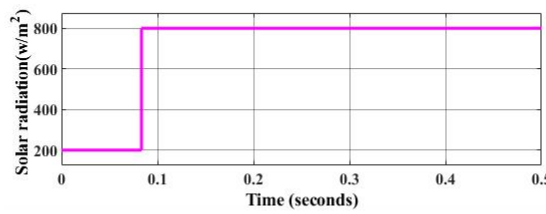

Fig .21 Irradiance

Fig 21 and 22 shows Fluctuation of both wind speed and solar irradiance to evaluate performance of proposed hybrid Wind–PV–Battery DC microgrid. wind speed is dynamically varied throughout duration of simulation, from about 6m/s to 13m/s, indicating varying environmental conditions. Similarly, for other conditions, at 0.1 s, Sun

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irradiation remains set to 800 W/m² after which it is maintained constant throughout simulation period. These differences are responsible for differences in renewable energy production and, for testing performance of proposed energy management strategy under realistic working conditions.

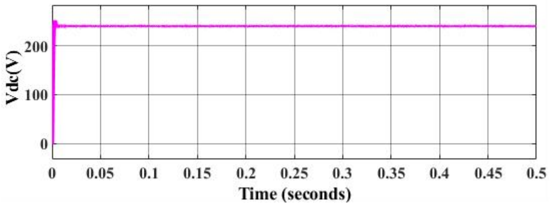

Fig .22 Dc link voltage

Proposed controller has been found to have even better performance under conditions of variable renewables. Fig22 shows DC-link voltage is well controlled even under wide fluctuations of wind power and solar irradiance.

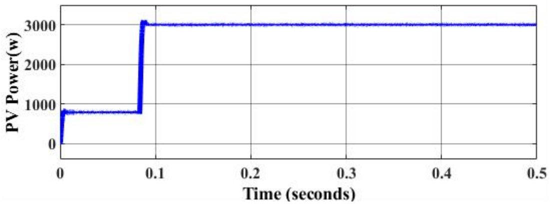

Fig .23 Panel power

Fig23 shows PV power response illustrates how PV power is utilized during changes in irradiance.

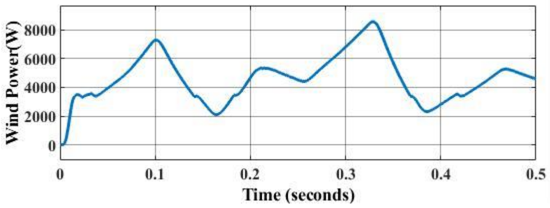

Fig. 24 Wind power

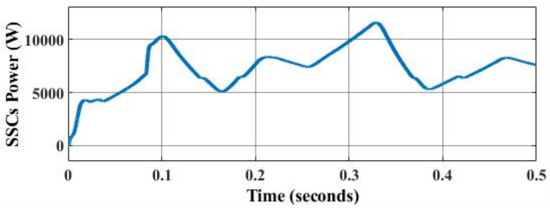

Fig .25 ssc power

Similarly, Fig24,25 shows wind power and SSC power waveforms closely follow changes in renewable energy, but provide smooth running of system. operating conditions are dynamically changed with ANN controller, and optimised.

Comparative Analysis of FUZZY& PI and Proposed ANN Controller

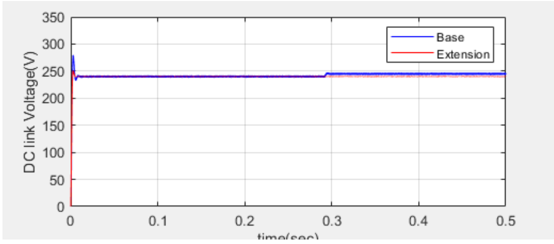

Fig .26 Dc Link Voltage Comparison

Table. 2 Dc Link Voltage Comparison

Controller	Settling Time(s)	Peak Value(V)	Overshoot (%)	Ripple (%)
Fuzzy & PI	0.2923	279.73	14.22	1.70
ANN	0.0038	250.56	4.40	0.19

Fig 26 and table 2 shows responses of proposed energy management system (ENMS) implemented as ANN are compared with conventional (Fuzzy & PI) controller based on responses of DC link voltage, PV power, Wind power, and load voltage. Comparison performed based on settling time, peak value, overshoot and ripple percentage. Response of ANN controller is much faster as compared to Fuzzy & PI controller from DC-link voltage results. Settling time is reduced from 0.2923 s to 0.0038 s, while overshoot decreases from 14.22% to 4.40%. ripple is also reduced from 1.70% to 0.19%, indicating improvement of dc link voltage stability.

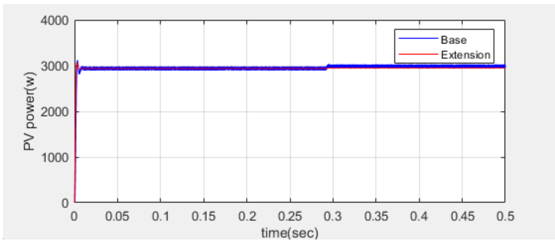

Fig .27 Panel Power Comparison

Table.3 Pv Power Comparison

Controller	Settling Time(s)	Peak Value(V)	Overshoot (%)	Ripple (%)
Fuzzy & PI	0.2927	3122.45	4.70	3.10
ANN	0.0028	3070	3.24	0.57

Fig 27 and table3 shows as far as power response of PV is concerned, ANN controller improves performance of system by decreasing settling time from 0.2927 s to 0.0028 s. overshoot decreases from 4.70% to 3.24%, and ripple is reduced from 3.10% to 0.57%. This means that proposed controller can extract power from PV system smoothly.

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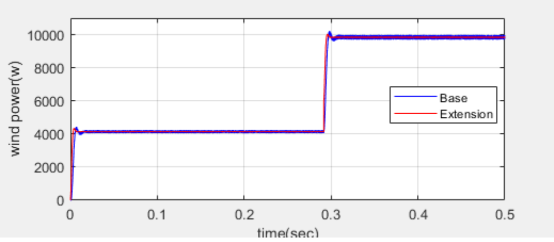

Fig 28 Wind Power Comparison

Table.4 Wind Power Comparison

Controller	Settling Time(s)	Peak Value(V)	Overshoot (%)	Ripple (%)
Fuzzy & PI	0.3041	10217.72	3.84	2.95
ANN	0.2956	10038	2.02	0.89

Fig 28 & Table. 4 shows wind power comparison shows a better performance with ANN controller. Overshoot is lowered from 3.84% to 2.02%, and the ripple is lowered from 2.95% to 0.89%. This will give a more constant wind power production when operating condition changes.

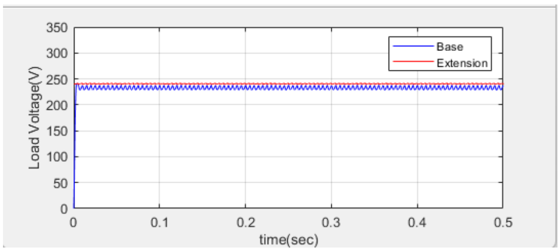

Fig 29 Load Voltage Comparison

Table. 5 Load Voltage Comparison

Controller	Settling Time(s)	Peak Value(V)	Overshoot (%)	Ripple (%)
Fuzzy & PI	0.0048	248.79	3.67	1.23
ANN	0.0033	251.37	4.11	0.32

As shown in fig 29 and table 5 load voltage response has a quicker settling time of 0.0033s using ANN controller. Ripple is minimised from 1.23% to 0.32% which reduces voltage ripple at load. Comparison indicates that proposed ANN controller is suitable for hybrid Wind–PV–Battery DC micro-grid applications as it has faster response, less overshoot, less ripple and better energy management compared to conventional Fuzzy & PI controller.

V. CONCLUSION

This paper introduced predictive energy management system based on ANN for hybrid DC microgrid system for improving stability and power management of system. Proposed ANN controller was implemented and tested with conventional Fuzzy & PI controller with same operating condition. Simulation results showed a tremendous improvement in efficiency of system. Settling time of DC-link voltage was lowered by 98.7% and voltage ripple was lowered by 88.8%. Likewise, power ripple of PV system, wind system and load voltage was decreased by 81.6%, 69.8% and 74.0% respectively. Results exhibited improvements resulted in a faster dynamic response, power transfer smoothness and voltage regulation. Based on this, it is concluded that proposed energy management strategy using ANN provides better performance, and is suitable for implementing in a hybrid Wind–PV–Battery DC microgrid.

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