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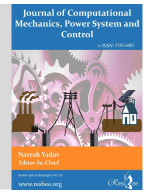

Frequency Control in PhotoVoltaic -based Microgrid System using Jarratt-Butterfly Optimization Algorithm-based Deep Learning Model

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Abstract: In a power system, one of the main complexities is the integration of the Distributed Generators that balance the power and also regulate the frequency and the voltage. The speed frequency of the rotor and the PhotoVoltaic (PV) panel pulse are assorted during the varied electric motors linked with the PV. Therefore, the main aim of this work is to develop a Fuzzy logic control and Deep learning Controller. This model is exploited for controlling the rotor speed frequency and PV panel pulse concurrently to develop the performance of the power system. One of the major criteria explained in the adopted model is to control output waveform, therefore reducing error among reference and control signals. In adopted fuzzy controller in adopted model, the membership function is optimized using the "Jarratt-Butterfly optimization algorithm (J-BOA)". Finally, the developed technique performance is calculated by varying the controllers concerning the switching time.

Keywords: Distributed Generator, Fuzzy Controller, Microgrid, Photovoltaic, Power System

1. Introduction

The multi-objective functions are possessed by the energy management systems which require pact with several commercial, technical, and environmental problems. In order to handle such problems, the hierarchical control models were developed and extensively exploited as satisfactory standard solutions for effectual microgrid management. In a microgrid, the supervisory energy and control management system model can be either decentralized, centralized, or maybe a hybrid model. The centralized control system with the communication amid the diverse units performs the management to have appropriate continuous energy management amid the connected loads and the generation units. This is absolutely not possible in many existing power systems specifically with the rise of the size of the power system. It augments additional costs and difficulty to control the entire power system. In addition, the power system expansion can be affected by communication. If communication amid diverse units is not utilized the model of an effective coordination scheme tends to be challenging scheme since there will be either a central energy management model or direct communication amid the diverse units. Conversely, decentralized control models to manage Photo voltaic and battery units in droop-controlled microgrids are not extensively utilized in state-of-the-art methods. Conventionally, for an island microgrid, the energy management system lies on the battery or the Energy Storage Systems (ESS) generally to take up extra power from Renewable Energy Sources (RES) once tracking their Maximum Power Points (MPPs) separately. Nevertheless, substantial additional energy can remain unused thus running hybrid RES that can lead to damage or overcharging of the batteries.

The main idea behind the microgrid (MG) was developed by various researchers. In addition, because of the stochastic nature of both the power utilized and renewable sources by the load in an MG case, the enclosure of WSS for example flywheels, batteries, ultracapacitors, and EMS is extremely suggested to enhance the stability of the system and its performance. Generally, MGs can work in both grid-connected and stand-alone modes. They are described as low-voltage systems consisting of DG units, loads, and storage devices that are linked to the mains at a single Point of Common Coupling (PCC). The major contribution of this paper is to develop a new optimized fuzzy controller, wherein membership functions are optimally tuned utilizing the Jarratt-Butterfly optimization algorithm (J-BOA) technique.

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2. Literature Review

In [1], Wei Dong *et al.,* developed an adaptive optimal fuzzy logic on the basis of the energy management solution. In the operation uncertainties presence, suitable day-ahead fuzzy rules were developed for the real-time energy dispatch adaptively. The optimal fuzzy inference system for instance the inference rule set and membership function shape set were determined by the solution. It was on the basis of the predicted information with a particular period via an offline meta-heuristic optimization model. On the basis of the attained optimal fuzzy logic rules the real-time energy dispatch was performed to convene several operational criteria for instance minimum operational cost and power fluctuation. In [2], Bhukya Laxman *et al.,* adopted an Adaptive Fuzzy Logic Controller (AFLC) based MPPT model. Here, by exploiting the Grey Wolf Optimization (GWO) technique, the membership functions (MFs) were optimized to produce the optimal duty cycle for MPPT. To experiment with the AFLC model performance, four shading patterns were employed. For all shading circumstances, this model follows the global MPPT. Additionally, it enhances the tracking effectually and speeds with reduced oscillations. The efficiency and robustness of the AFLC-based tracker outcomes over conventional techniques were examined by utilizing the Matlab/Simulink environment. In [3], Rashid AlBadwawi *et al.,* modeled a supervisory controller based on fuzzy logic. This method was utilized to guarantee that the battery power and energy, which do not go beyond their design restrictions and maintained a stable power flow. Here, the microgrid was comprised of a battery, PV, load, and auxiliary supplementary unit. The AC bus frequency was altered by the fuzzy logic controller that was employed by the local controllers of the parallel units. To limit the power generated by the PV or to enhance the power from the auxiliary unit. In [4], Diego Arcos-Aviles *et al.,* worked on the microgrid. Here, the main aim was to reduce the grid power profile fluctuations when keeping the Battery State of Charge (SOC) within protected limits. Rather than utilizing a forecasting-based approach, the developed technique exploits both the microgrid energy rate-of-change and the battery SOC to augment, minimize or preserve the power absorbed or delivered by the mains. To optimize a pre-defined set of the quality criterion of the microgrid behavior the controller design parameters such as rule-base and membership functions were adjusted. In [5], Deepesh Sharma intended to develop Fuzzy with an adaptive membership function and Deep learning (DL) Controller model. This model was exploited to control the rotor speed frequency and the PV panel pulse concurrently to develop the performance of the power system. The most important principle stated in the adopted model was to adjust the waveform of output. Therefore, the error was minimized among the reference and control signals. In the adopted Fuzzy controller, the Sorted Position based GWO (SP-GWO) was exploited to optimize the membership function. The developed model performances were calculated over varied controllers concerning switching time.

3. Modeliing the Elements in Microgrid

3.1 Modeling of PV Array Modeling

Eq. (1), (2) and (3) states the conventional numerical technique of a PV array when disregarding inside shunt resistance. In Eq. (1) as well as Eq. (2), K represents "Boltzmann constant", C_O and V_O indicates the solar arrays output current and voltage, p represents electron charge, C_g represents insolation current, C_{sat} represents reverse saturation current, B represents ideal constraint, D represents temperature, R_S represents solar array series resistance, C_{or} represents "saturation current at reference temperature" D_r, F_G represents "band-gap energy of semiconductor", K_C represents "short-circuit current temperature coefficient" as well as ω represents isolation in mW/cm2. Additionally, PC execution of the PV array is stated in Eq. (1) to Eq. (3).

$$C_O = C_g - C_{sat}\left\{\exp\left[\frac{p}{BKT}\left(V_O + C_O R_S\right)\right] - 1\right\} \tag{1}$$

$$C_{sat} = C_{or}\left[\frac{D}{D_r}\right]\exp\left[\frac{pF_G}{KD}\left(\frac{1}{D_r} - \frac{1}{D}\right)\right] \tag{2}$$

$$C_g = \left[C_{sc} + K_C\left(D_c - 25\right)\right]\frac{\omega}{100} \tag{3}$$

3.2 Designing of Solid Oxide Fuel Cell (SOFC)

In this work, SOFC is considered as a benchmark technique. The rate of natural gas flow is stated as (mol/s), V_{fc} represents output voltage stack (V). P_{fc} and P_{d-r} represents output and reference power demand of SOFC. From the exterior current load, the interruption starts, and it is stated as C_{fc} (A). Moreover, τ_{H-O} illustrates proportion of hydrogen (H_2) and oxygen (O_2) and the input flow rate of O_2, $p_{H_2}^{in}$, which is equivalent to (H_2), reformer generates the $p_{O_2}^{in}$. The partial pressure of steam (Pa), H_2, and O_2 in a cell was represented as pH_2O, pO_2, and pH_2 correspondingly. Eq. (4) to (7) determines the nonlinearity of the system primarily occurs from "Nernsts formulation". Eq. (8) and (9) states SOFC voltage, which is stated as a total of Nernsts formulation and Ohms law.

$$V_o = N_0\left[F_0 + \frac{R_0 D_0}{2E_0}\ln\frac{pH_2 p_{O_2}^{0.5}}{pH_2O}\right] \tag{4}$$

$$pH_2 = \frac{1/K_{H_2}}{1+\tau H_2 S}\left(\frac{1}{1+\tau_f S}p_f - 2K_r I\right) \tag{5}$$

$$pO_2 = \frac{1/K_{O_2}}{1+\tau O_2 S}\left(\frac{1/\tau_{H-O}}{1+\tau_f S}p_f - K_r I\right) \tag{6}$$

(7)

$$V_{cell} = V_0 - V_{ohmic} \tag{8}$$

$$V_{ohmic} = I_{fc}\tau \tag{9}$$

Fuel utilization factor (u_f) is stated as the ratio amid fuel flow reacted as well as input fuel flow, it can be stated regarding fuel cell current I_{fc}" as stated in Eq. (10).

$$u_f = \frac{p_{H_2}^{in} - p_{H_2}^{o}}{p_{H_2}^{in}} = \frac{p_{H_2}^{\tau}}{p_{H_2}^{in}} = \frac{2K_\tau I_{fc}}{p_{H_2}^{in}} \tag{10}$$

3.3 PV Controller

From a PV array, power generated changes regarding solar radiation and temperature. Thus, the purpose of regulating a PV array is to remove maximal power in varied states.

When controlling the voltage, "reference dc bus voltage" is obtained at MPPT from output voltages. The previous step of voltage control is exploited to evaluate the inverter current reference. Hence, output power taken from the PV array follows higher power. The inverter duty cycle is balanced regarding current variations [5].

3.4 SOFC Controller

In an attempt to avoid more fuel utilization of SOFC, a divergence of reference power command to SOFC must be minimized to an immense degree. By performing this, the pressure on SOFC will be minimized [5].

In [5], by attaining the error amid ΔP as well as reference power demand, P_{d-r} of SOFC is generated, then input fuel (P_f) quantity is exposed by deploying feedback.

4. Adopted Fuzzy logic control and Deep Learning Controller

4.1 Fuzzy logic control

The FLC [7] is designed to distribute power between the fuel-cell system as well as the ultra-capacitor to avoid power concerns under dynamic restrictions such as demand of fuel power, SOC of UC, and consumption rate. Additionally, SOFC output must be varied economically and the functioning point difference in SOFC should be minimized and maintained in the necessary bounds. By the FLC controller, the output is associated with inputs with a list of "if-then statements" called rules. The "if part" of rules represents the adjectives that show the input constraint areas. A definite value of input is owned by these areas to an exact degree that is identified as degree of membership function, DMF . The "then-part" of rules indicates the output parameters value. To obtain controller output, DMF of "if-part" of whole rules is computed and weighted by membership degrees.

4.2. Deep Belief Network (DBN)

"DBN [8] is a famous intellectual method that involves several layers, each comprises of hidden neurons and visible neurons". In Eq. (12), output $\overline{PO}$ based on the probability function $\overline{P_q}(\zeta)$. The DBN is stated in Eq. (13), in that t^P represents "pseudo-temperature". The numerical method discloses "Boltzmann machine energy to configure binary state bi " as described in eq. (14) & (15), in that, $L_{a,l}$ stipulates weights amid neurons and θ_a indicates biases.

$$\overline{P}_q(\zeta) = \frac{1}{1+e^{\frac{-\zeta}{t^P}}} \tag{11}$$

$$\overline{PO} = \begin{Bmatrix} 1 & \text{with } 1-\overline{P}_q(\zeta) \\ 0 & \text{with } \overline{P}_q(\zeta) \end{Bmatrix} \tag{12}$$

$$\lim_{t^P \to 0^+} \overline{P}_q(\zeta) = \lim_{t^P \to 0^+} \frac{1}{1+e^{\frac{-\zeta}{t^P}}} = \begin{cases} 0 & \text{for} \quad \zeta < 0 \\ \frac{1}{2} & \text{for} \quad \zeta = 0 \\ 1 & \text{for} \quad \zeta > 0 \end{cases} \tag{13}$$

$$EN(bi) = -\sum_{a<l} bi_a L_{a,l} - \sum_a \theta_a bi_a \tag{14}$$

$$\Delta EN(bi_a) = \sum_l bi_a L_{a,l} + \theta_a \tag{15}$$

The energy description of joint compositions of visible and hidden neurons (x,y) is indicated as eq. (16), (17) and (18), in that k_a and C_l states biases, x_a and y_a indicates "binary state of a visible and hidden unit l" and $L_{a,l}$ signifies weight among them. The distributed probabilities are acquired by RBM training, as well as ensuing weight allotment is indicated as Eq. (19). Eq. (20) describes the hidden and visible vectors pair $(\vec{x},\vec{hi})$, in that PR^F indicates partition function as in Eq. (21).

$$EN(x,y) = -\sum_{(a,l)} L_{a,l} x_a y_l - \sum_a k_a x_a - \sum_l C_l y_a \tag{16}$$

$$\Delta EN(x_a, \bar{y}) = \sum_l L_{al} y_l + k_a \tag{17}$$

$$\Delta EN(\vec{x}, y_a) = \sum_l L_{al} x_a + C_l \tag{18}$$

$$\hat{L}(\hat{G}) = \max_{\hat{L}} \prod_{\vec{x} \in N} c(\vec{x}) \tag{19}$$

$$c(\vec{x}, \vec{hi}) = \frac{1}{PR^F} e^{-EN(\vec{x},\vec{y})} \tag{20}$$

$$PR^F = \sum_{\vec{x},\vec{y}} e^{-EN(\vec{x},\vec{y})} \tag{21}$$

Subsequent to MLP learning process, "presume $\left(K^{\hat{G}}, W^{\hat{G}}\right)$ training pattern, in that, $\hat{G}$ signifies number of training pattern, $1 \le \hat{G} \le \overline{P}$, $K^{\hat{G}}$ and $W^{\hat{G}}$ indicates input vector beside with essential output vectors, respectively. Eq. (22) indicates each neuron error in l of output layer. As a result, eq. (22) exhibits squared error of $\hat{M}$ pattern is stated in eq. (23) and (24), in that, $\widetilde{P}$ indicates number of training patterns".

$$e_l^{\hat{G}} = K^{\hat{G}} - W^{\hat{G}} \tag{22}$$

$$SE^{mean}_{\hat{G}} = \frac{1}{\tilde{o}_y}\sum_{l=1}^{\tilde{o}_y}\left(e_l^{\hat{G}}\right)^2 = \frac{1}{\tilde{o}_y}\sum_{l=1}^{\tilde{o}_y}\left(K^{\hat{G}} - W^{\hat{G}}\right)^2 \tag{23}$$

$$SE_{avg} = \frac{1}{\tilde{P}} SE^{mean}_{\hat{G}} \tag{24}$$

4.3. Objective Function

In microgrid system for improved frequency controller, it is intended to optimize the restrictions of membership function, (LMF) of the fuzzy controller. "LMF involves 5 values such as, 0.8, 0.9, 1, 2 and 2.2". Amid these values of limit, the limits at 0.9, 1 and 2 are fed to optimization. Along with that, the weights of DBN(L) are also optimally selected, by which accurate outcomes could be obtained. Here, for optimization reasons, J-BOA algorithm is used which is an enhanced version of BOA model. The main purpose of adopted technique attempts to minimize the error between the predicted and targeted control pulse of fuzzy as well as DBN as stated in Eq. (25), wherein Err indicates the error.

$$\text{Objective function} = \text{Min} \quad \text{Err of (DBN and fuzzy)} \tag{25}$$

4.4. Proposed JBOA Model

The conventional BOA [8] is a robust optimization model, which has been effectively used for numerous applications. Nevertheless, as explained in the No Free Lunch (NFL) theorem, to solve the issues no approach is ideal. Moreover, the BOA might ensnare at local optima or occur divergence issues while resolving Non linear System of Equation (NSE). Thus, integrating Jaratta's and BOA models in JBOA [9] has considerably enhanced the JBOA performance to solve the NSE. In each iteration of BOA, Jaratta's approach is used.

Initially, the optimal position of butterfly is ascertained by the BOA, and that are considered as a candidate position. Subsequently, candidate position is exploited as input to Jarratt approach that enhances the butterfly position in numerous scenarios. After that, the candidate position is subjected into the Jarratt approach that most of time enhances butterfly position. At last, outcome of Jarratt's approaches is evaluated with the candidate positions, as well as one with optimal fitness is selected. Jarratt's technique can create highly precise solutions in fewer iterations because of its high order of convergence. Consequently, search method of JBOA to solve NSE is enhanced. The global search formulation is stated as below:

$$y_i^{t+1} = y_i^t + \left(r^2 \times h^* - y_i^t\right) \times f_i \tag{26}$$

Where, y_i^t indicates the solution vector, f_i indicates the fragrance, h^* indicates the optimal solution of the current iteration, r indicates the arbitrary number among 0 and 1. Conversely, butterflies in the local search begin to move arbitrarily in their potential areas, following eq. (3) as below:

$$y_i^{t+1} = y_i^t + \left(r^2 \times y_j^t - y_k^t\right) \times f_i \tag{27}$$

Finally, the perfect position which measures the optimal fitness is chosen as the best solution.

5. Result and Discussion

This section describes the experimentation analysis of the proposed Jarratt BOA and conventional models. The adopted model was evaluated with the conventional models such as fizzy controller, DBN and PID controller, and the related consequences were attained.

Figure 1 demonstrates the mean analysis of proposed model with conventional models for four varying fault intervals. Figure 2 shows the standard deviation attained with respect to faulty intervals, which must be negligible. From noticed results, the mean and standard deviation for presented Jarratt BOA model is much insignificant than conventional models. For that reason, the proposed system has shown its effectiveness in attaining enhanced FC in the Microgrid system.

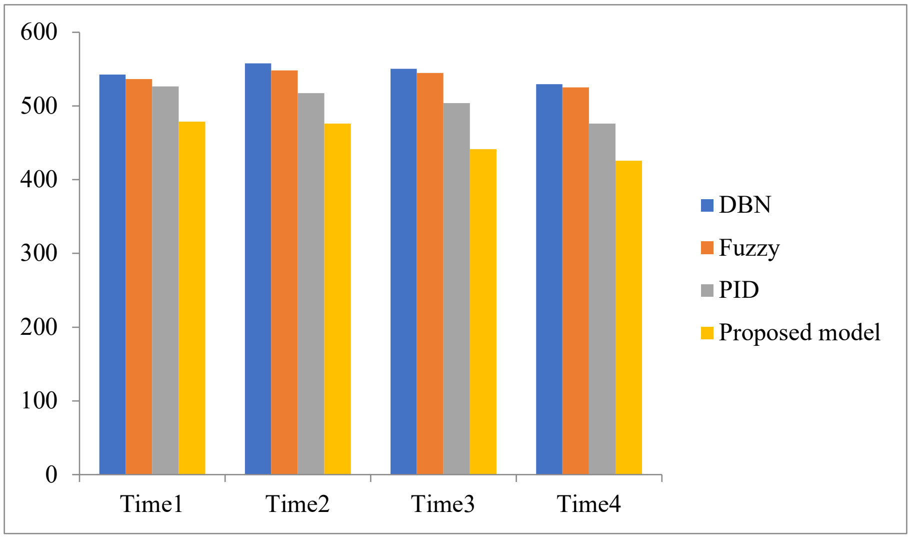

Fig. 1. *Graphical representation of proposed model and Conventional Models regarding time for Mean analysis*

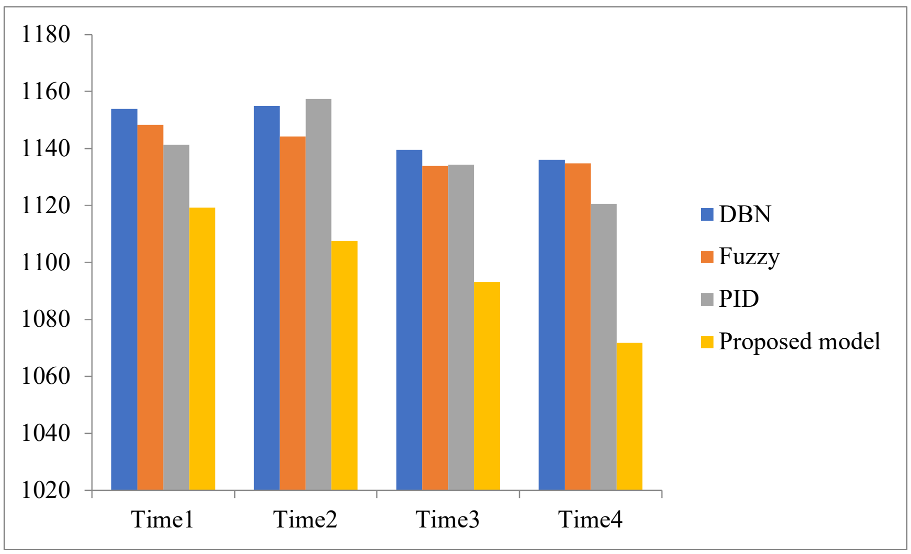

Fig. 2. *Graphical representation of proposed model and Conventional Models regarding time for standard deviation analysis*

6. Conclusion

This work has adopted Fuzzy with adaptive membership function and DL approach to regulate rotor speed as well as PV panel pulse concurrently to model power systems performances. As a result, the major aim of proposed model lies in controlling the output signal. Therefore, reducing the error between reference as well as control signal was possible. In the adopted Fuzzy controller, membership function was optimized by improved BOA algorithm. As the adaptation was performed by sorting the location, the developed model was called as J-BOA. From the experimental evaluation, conservative techniques had practised the quick trigger at specific faulty intervals, however, the adopted J-BOA technique didn't practised more trigger and have ensued as an acquired control pulse. Consequently, the supremacy of adopted J-BOA technique was shown from experimented outcomes.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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