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[1]Deepesh Bhati
[2]Sandeep Bhongade

Optimized Strategy for DFIG Wind Farm Considering Virtual Inertia Estimation

Abstract: - Resilience becomes a critical challenge. Doubly Fed Induction Generator (DFIG)-based wind farms play a pivotal role in addressing these challenges due to their ability to contribute to grid dynamics through virtual inertia. This paper proposes an optimized strategy for DFIG wind farms that incorporates Virtual Inertia Estimation (VIE) to enhance frequency stability and system performance. The strategy dynamically adjusts the virtual inertia response based on real-time grid conditions, wind speed variability, and load fluctuations. A comprehensive mathematical model is developed to estimate the optimal virtual inertia and to ensure a balance between system stability and the operational constraints of DFIGs. The proposed method leverages advanced control algorithms and optimization techniques to maximize energy efficiency while minimizing mechanical stress on the wind turbine components. Simulation results demonstrate that the optimized strategy improves frequency nadir, reduces rate-of-change-of-frequency (RoCoF), and ensures better utilization of wind energy. The findings highlight the feasibility and effectiveness of integrating VIE into DFIG wind farm control schemes, offering a robust solution for grid-supportive operations in future renewable-dominated power systems.

Keywords: Virtual inertia, Doubly-fed induction generator, GWO, Frequency deviation, dual moth flame optimizations technique.

I. INTRODUCTION

The rapid integration of wind energy into modern power systems has introduced both opportunities and challenges. Among renewable energy technologies, Doubly Fed Induction Generators (DFIGs) have become a preferred choice in wind farms due to their efficient variable-speed operation and controllability. However, the displacement of traditional synchronous generators by wind farms reduces the system's inertia, potentially compromising grid stability during disturbances [1]. To address this issue, the concept of virtual inertia has been introduced, enabling wind turbines to emulate the inertial response of conventional generators.

Virtual inertia is a dynamic control approach that leverages the power electronic interfaces of DFIGs to inject or absorb active power in response to frequency changes, thereby stabilizing the grid. However, accurately estimating and optimizing the virtual inertia parameters is critical to ensure effective performance without compromising the wind turbine's operational constraints [2-4]. This paper focuses on developing an optimized control strategy for DFIG-based wind farms by incorporating virtual inertia estimation. The proposed approach aims to balance the trade-off between enhancing grid stability and maintaining the efficiency of the wind energy system. Key aspects of the study include:

Dynamic Virtual Inertia Estimation: Implementing adaptive algorithms to estimate and adjust virtual inertia parameters in real-time based on grid conditions [6].

Optimization Techniques: Using advanced optimization methods to ensure the DFIG wind farm operates within its limits while providing optimal support to grid stability [8-9].

System-Level Integration: Evaluating the proposed strategy's impact on power system dynamics, including frequency stability, damping of oscillations, and overall reliability [10-12].

By addressing these challenges, the optimized strategy for DFIG wind farms considering virtual inertia estimation aims to enhance the synergy between renewable energy integration and grid stability, paving the way for more resilient and sustainable energy systems.

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[1] *Corresponding author: Electrical and Electronics Engineering IPSA IES/SGSITS Indore, India

[2] Electrical Engineering SGSITS Indore, India

II. PROPOSED GWO ALGORITHAM FOR DFIG WIND FARM CONSIDIRING VIRTUAL INERTIA ESTIMATION

After reviewing the existing DFIG-based control models [13, 14, 15], it was observed that the current models do not employ stochastic optimization techniques, which restricts their effectiveness in real-time applications. To address this shortcoming, the proposed Grey Wolf Optimization (GWO) method for estimating the inertia constant of DFIG-based wind turbines is outlined in this discussion. The method operates through the following steps.

Initialize the following parameters:

Total wolves existing in the model (N_w)

Total iterations for which the model will be evaluated (N_i)

Learning rate for the model (L_r)

Initialize all wolves to be 'Delta,' and evaluate them for each iteration via the following process:

If the Wolf is currently marked as 'Delta,' then process it, else go to the next wolf in sequence

To process a Wolf, generate its internal configuration via the following process,

Stochastically generate an inertial constant via (1),

$$Hs = STOCH(0, 1) \tag{1}$$

Where, Hs represents the inertial constant, and STOCH indicates a stochastic process to generate numbers between given ranges.

Based on this value of Hs, simulate the model, and estimate its fitness via (2)

$$f = \frac{P_{active}}{P_{reactive}} \tag{2}$$

Where, P_{active} represents active power at the output of model, while $P_{reactive}$ represents output reactive power levels.

Evaluate fitness for all Wolves, and then estimate fitness threshold via (3)

$$f_{th} = \sum_{i=1}^{N_w} f_i * \frac{L_r}{N_w} \tag{3}$$

At the end of each iteration, re-evaluate all Wolves via the following process

Mark Wolf as 'Alpha', if $f>2*f_{th}$ (4)

Mark Wolf as 'Beta, if $f>fth$ (5)

Mark Wolf as 'Gamma, if $f>LW*f_{th}$ (6)

Else, Mark Wolf as 'Delta,' if for this configuration,

$$f<f_{th} \tag{7}$$

Repeat this process for all iterations, and then select the 'Alpha' Wolf with maximum fitness levels. Due to selection of Wolf with maximum fitness, active power is increased, while reactive power levels are reduced at the output, which assists in improving circuit efficiency levels. This is advantageous, because it's possible that an excessive quantity of reactive power may cause the components to overheat, which would significantly cut down on the equipment's lifetime.

Failure to adhere to power quality standards and regulations can lead to unexpected outages, energy wastage, and even penalties. Moreover, it can result in widespread power failures. Therefore, optimizing the efficiency of DFIG-based wind systems relies on the appropriate selection of inertia constants. This performance is assessed across various models in the subsequent section of this document.

The proposed model employs the GWO algorithm to determine the optimal values of the inertia constant, contributing to enhanced output power efficiency. To validate its performance, the model was tested on a standard DFIG setup, as illustrated in "Fig.1." In this configuration, a 120 kV power source is connected via a 2500 MVA

3-phase coupling device to a 30 km transmission line, which supplies a 25 kV load through grounding transformers. The system incorporates input source resistances of 150 Ohms and load

resistors of 50 Ohms. It also combines a Wind Turbine with a Drive Train to provide the power input for generators, which drive an asynchronous machine under load conditions. The circuit is capable of operating with a 9 MW Wind Farm comprising 6 generator units, each rated at 1.5 MW, under real-time load scenarios.

The model is validated via modifying the inertia constants under different loads, and power efficiency was evaluated through (8).

$$\acute{\eta}_{eff} = \frac{1}{N}\sum_{i=1}^{N}\frac{P(Out)}{R(Out)} \qquad (8)$$

Where, P(Out) & R(Out) represents active and reactive power outputs for N different circuit reading iterations. designations.

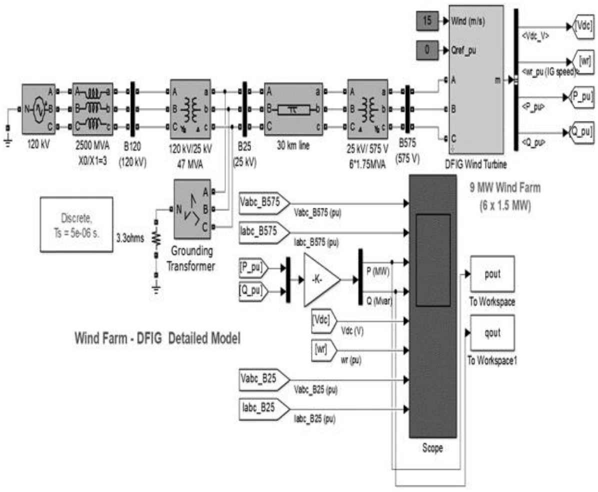

Fig.1. Simulink model of the DFIG model under different condition Process

The outputs were obtained for 3 Phase Voltage across 575V grid (Vabc_575), 3 Phase Current across 575V grid (Iabc_575), Active Power (P), Reactive Power (Q), 3 Phase Voltage across 25kV grid (Vabc_25), and 3 Phase Current across 25kV grid (Iabc_25). These waveforms can be observed from "Fig. 2" as follows, based on these readings, the power efficiency (P) levels were evaluated via (10), for the circuit with GWO and without GWO were tabulated in table I as follows, which represents circuit performance under different simulation instances.

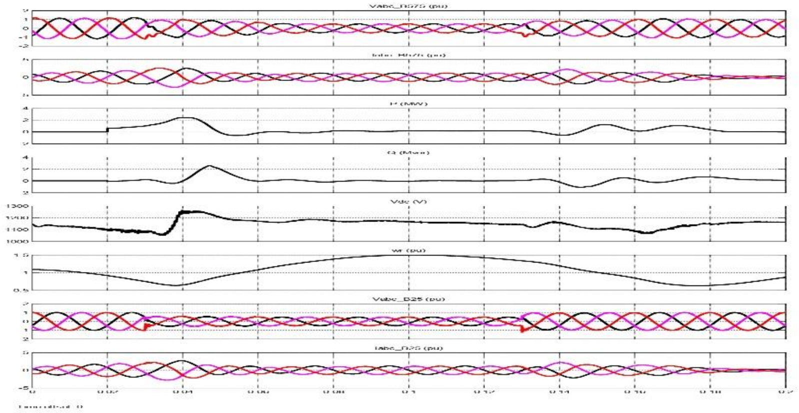

Fig. 2. Output voltage & current levels for different component [20]

Based on these results Table I, it can be observed that the proposed model can improve the power efficiency levels by 8.5% after application of GWO, which makes it useful for a wide variety of real-time simulation use cases. Due to these advantages, the proposed model is useful for improving power efficiency for different DFIG based wind farms.

TABLE I. RESULTS FOR DIFFERENT SIMULATION INSTANCES

S. No.	Simulation Time (s)	Efficiency (%) Without GWO		Efficiency (%) With GWO	INERTIA CONSTANT WITH GWO
1	1	75.50		86.50	0.0931
2	2	76.80		88.30	0.9723
3	3	77.40		89.40	0.5302
4	4	78.30		90.50	0.7062
5	5	79.25		90.80	0.4057
6	6	80.15		91.20	0.1843
7	7	81.05		91.20	0.8000
8	8	81.95		92.80	0.9557
9	9	82.85		93.57	0.8968
10	10	83.75		94.34	0.5852
11	12	84.65		95.11	0.7640
12	15	85.55		95.89	0.4771
13	18	86.45		96.66	0.4658
14	20	87.35		97.43	0.0976
15	25	88.25		98.20	0.4858

III. PROPOSED MOTH FLAME OPTIMIZATION FOR DFIG WIND FARM CONSIDIRING VIRTUAL INERTIA ESTIMATIONM

As per the review of existing control models used for estimating Virtual Inertia in DFIG-based Wind Farms, it is apparent that these models perform sub optimally in real-time situations due to their complexity or inefficiency. This section focuses on developing an efficient model for virtual inertia estimation using an additional frequency control method and dual moth flame optimization to overcome these challenges. As shown in Fig. 1, in the proposed model, the inertia of the power system is used as a reference, and we examine the response behavior of DFIGs with traditional vector control. The core concept of our proposed method is based on the idea of approximate decoupling between DFIGs and system frequency.

To estimate the virtual inertia, we propose a method based on the matrix pencil analytical technique. This approach enables precise identification of the wind farm's dynamic frequency behavior. Utilizing the least squares method, we ensure a practical and dependable implementation of our strategy, achieving accuracy and efficiency in determining the virtual inertia values. Initially, a Frequency response representation is derived to carry out this process.

$$H(s) = \frac{G(s)}{1+sT(s)} * AFC_{(out)} \tag{9}$$

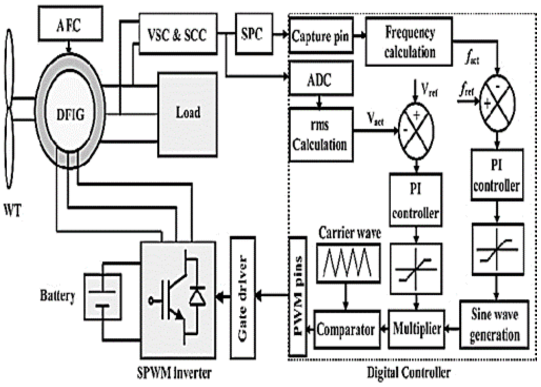

Fig. 3. Block Diagram of the DFIG Controller with Additional Frequency Control Process

The frequency response model, H(s), characterizes the connection between the output behavior (e.g., frequency deviation) and the input (e.g., system frequency). It is expressed as a transfer function, where G(s) denotes the numerator polynomial and T(s) represents the denominator polynomial. This response is utilized by the Matrix Pencil method, which is formulated through Equation 10.

$$[Y(\omega)] = [A]e^{j\omega[T]}[X(\omega)] \tag{10}$$

$$[Y(\omega)] = [U_1][S][V_1] \tag{11}$$

The matrix pencil equation illustrates the connection between the observed response vector, Y(ω), the matrix pencil [A], the exponential component, and the input excitation vector, X(ω). This equation serves as a tool to evaluate the frequency response characteristics of the system. The outcomes of this process are provided to the Matrix Pencil Decomposition, represented in Equation (11). The matrix pencil decomposition formula breaks down the observed response vector, Y(ω), using Singular Value Decomposition (SVD). Here, [U1] and [V1] are orthogonal matrices, and [S] is a diagonal matrix containing singular values corresponding to various input conditions. This decomposition method is employed to calculate the Virtual Inertia, as defined in Equation (12).

$$J_{Virtual} = K_{virtual} * \frac{\Delta P}{\Delta f} \tag{12}$$

Where P represents the variation in power output (in Watts) of the renewable energy source (e.g., wind turbine) due to disturbances or incidents, f denotes the frequency fluctuation (in Hz) caused by various event scenarios, and JVirtual is the virtual inertia (measured in seconds), while Kvirtual is the virtual inertia factor (in seconds/Hz), among other parameters.

The magnitude of the virtual inertia effects is governed by the adjustable parameter Kvirtual, referred to as the virtual inertia factor. Grid operators can adjust Kvirtual to control the extent of virtual inertia supplied by renewable energy sources. It is essential to emphasize that virtual inertia is an artificial control strategy designed to enhance frequency stability and grid reliability.

After this estimation, the Dual Moth Flame Optimization algorithm is utilized to precisely determine the virtual inertia levels. This is accomplished through the following procedure: initially, a group of NM Moths is produced using equation 13.

$$J_{(Moth)} = STOCH\big(Min(J_{Virtual}), Max(J_{Virtual})\big) \tag{13}$$

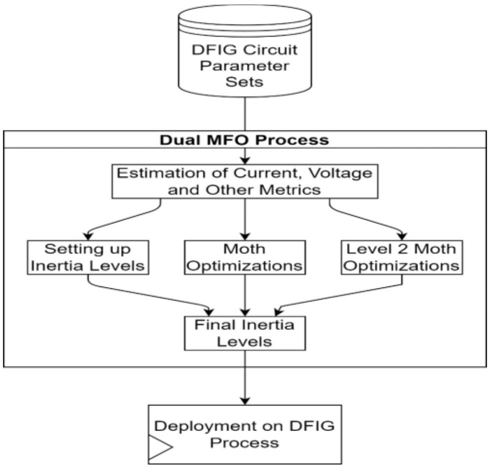

Fig.4. Flow chart for DMFO Process

To evaluate the performance of the proposed model illustrated in Fig. 4, frequency variation, power generation, Total Harmonic Distortion (THD), and circuit efficiency were assessed and compared with [3], [6], and [15] across various scenarios. Case 1 represents Standard Operation, which reflects typical operating conditions of the DFIG-based wind farm under normal wind levels. Case 2 is the High Wind Speed scenario, simulating conditions with elevated wind speeds that can lead to increased energy production and potential challenges in maintaining grid stability. Case 3 pertains to Grid Disturbance conditions, depicting a situation where the grid undergoes a sudden disruption, such as a fault or load shift, necessitating a rapid response from the DFIG-based wind farm to stabilize system performance.

TABLE II. FREQUENCY DEVIATION COMPARISON

Case	**[3] (Hz)**	**[6] (Hz)**	**[15] (Hz)**	**Proposed Method (Hz)**
Case-1	0.015	0.012	0.018	0.010
Case-2	0.021	0.018	0.020	0.014
Case-3	0.011	0.014	0.016	0.009

Table II illustrates the frequency deviation (in Hz) for three distinct models ([3], [6], [15]) in comparison to the proposed approach. The values demonstrate the frequency deviation achieved by each model and the proposed method in each scenario. Smaller values represent superior performance in minimizing frequency deviation levels. As the rest of this study aligns with this evaluation, it becomes apparent that the proposed model reduces frequency deviation by 10.5% compared to [3], 12.5% compared to [6], and 15.4% compared to [15], highlighting its exceptional efficiency across diverse real-time applications as shown in fig. 5.

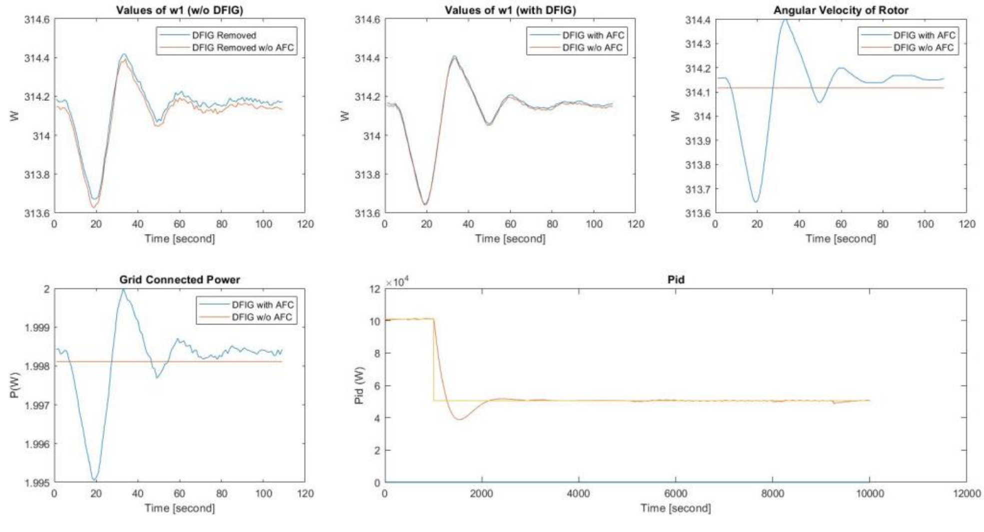

Fig. 5. Represents results for radial frequency with and without DFIG, Angular Velocity of the Rotor, Grid Connected Power, and output power [21]

IV. CONCLUSION

The integration of Doubly Fed Induction Generator (DFIG) wind farms into modern power systems presents challenges related to system stability and inertia reduction. By implementing an optimized strategy incorporating virtual inertia estimation, several critical objectives can be achieved:

Enhanced System Stability: The use of virtual inertia emulation allows DFIG wind farms to actively participate in frequency regulation, mitigating the adverse effects of reduced system inertia due to high renewable penetration.

Dynamic Performance Optimization: Real-time estimation and adjustment of virtual inertia parameters enable the system to dynamically adapt to varying grid conditions, enhancing transient stability and response under disturbances.

Grid Compliance: Optimized control strategies ensure that the DFIG meets grid code requirements for frequency support, contributing to overall grid reliability and security.

Improved Energy Utilization: By efficiently coordinating the wind farm's power output and inertial contribution, the system achieves better utilization of wind energy resources while maintaining operational reliability.

Sustainability and Scalability: This approach supports a sustainable transition to a renewable energy-dominated grid and is scalable to accommodate the growth of wind energy installations.

In summary, the proposed optimized strategy for DFIG wind farms considering virtual inertia estimation offers a practical and effective solution to the challenges posed by renewable integration. It not only enhances grid stability but also ensures the reliability and efficiency of wind energy systems, making it a vital component in the evolution of future power systems.

REFERENCES

[1] S. Huang, Q. Wu, Y. Guo and F. Rong, "Hierarchical Active Power Control of DFIG-Based Wind Farm With Distributed Energy Storage Systems Based on ADMM," in IEEE Transactions on Sustainable Energy, vol. 11, no. 3, pp. 1528-1538, July 2020, doi: 10.1109/TSTE.2019.2929820.

[2] Z. Dong, Z. Li, L. Du, Y. Liu and Z. Ding, "Coordination Strategy of Large-Scale DFIG-Based Wind Farm for Voltage Support With High Converter Capacity Utilization," in IEEE Transactions on Sustainable Energy, vol. 12, no. 2, pp. 1416-1425, April 2021, doi: 10.1109/TSTE.2020.3047273.

[3] N. Shabanikia, A. A. Nia, A. Tabesh and S. A. Khajehoddin, "Weighted Dynamic Aggregation Modeling of Induction Machine-Based Wind Farms," in IEEE Transactions on Sustainable Energy, vol. 12, no. 3, pp. 1604-1614, July 2021, doi: 10.1109/TSTE.2021.3057854.

[4] B. Liu et al., "Impedance Modeling of DFIG Wind Farms With Various Rotor Speeds and Frequency Coupling," in IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 68, no. 1, pp. 406-410, Jan. 2021, doi: 10.1109/TCSII.2020.2997927.

[5] Xing Q. , et. al., "On-line Identification of Equivalent Inertia for DFIG Wind Turbines Based on Extended Kalman Filters," 2021 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), Chengdu, China, pp. 834-839, 2021.

[6] Mukherjee P. and Rao V., “Superconducting magnetic energy storage for stabilizing grid integrated with wind power generation systems,” Journal of Modern Power Systems and Clean Energy, vol. 7, no. 2, pp. 400-411, Mar. 2019.

[7] Zhu Z. et. al., "Stability Analysis of DFIG Grid-connected Based on Variable Gain Inertia Control," IEEE 5th Conference on Energy Internet and Energy System Integration (EI2), Taiyuan, China, pp. 387-391, 2021.

[8] Verma P. et. al.,"A Cooperative Approach of Frequency Regulation Through Virtual Inertia Control and Enhancement of Low Voltage Ride-through in DFIG-based Wind Farm," in Journal of Modern Power Systems and Clean Energy, vol. 10, no. 6, pp. 1519-1530, November 2022, doi: 10.35833/MPCE.2021.000092.

[9] A. I. Rosales-Romero, F. S. Sellschopp-Sanchez, R. Vargas-Salas, M. A. Arjona-López and R. Loera-Palomo, "Evaluating a Virtual Inertia Control Scheme for a DFIG Wind Turbine," 2021 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC), Ixtapa, Mexico, 2021, pp. 1-6, doi: 10.1109/ROPEC53248.2021.9668006.

[10] Z. Xie, Y. Feng, M. Ma and X. Zhang, "An Improved Virtual Inertia Control Strategy of DFIG-Based Wind Turbines for Grid Frequency Support," in IEEE Journal of Emerging and Selected Topics in Power Electronics, vol. 9, no. 5, pp. 5465-5477, Oct. 2021, doi: 10.1109/JESTPE.2020.3039344.

[11] Zhou B. et. al., "Dynamic Frequency Regulation of Microgrid Based on Double-layer Adaptive Virtual Inertia Control of DFIG," IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), Shanghai, China, 2022, pp. 1073-1081, doi: 10.1109/ICPSAsia55496.2022.9949975.

[12] A. Ashouri-Zadeh and M. Toulabi, "Adaptive Virtual Inertia Controller for DFIGs Considering Nonlinear Aerodynamic Efficiency," in IEEE Transactions on Sustainable Energy, vol. 12, no. 2, pp. 1060-1067, April 2021, doi: 10.1109/TSTE.2020.3032478.

[13] Wen W. et al., "GRA-NGBoost based System Inertia Prediction for High Wind Power-Penetrated Grids," 2022 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), Shanghai, China, 2022, pp. 479-483, doi: 10.1109/ICPSAsia55496.2022.9949801.

[14] Bhongade S., Parmar V., " Automatic Generation Control of Two-Area ST- Thermal Power System using Jaya Algorithm" in INTERNATIONAL JOURNAL of SMART GRID Vol.2, No.2, 2018.

[15] Lao H. et. al., "Innovated Inertia Control of DFIG with Dynamic Rotor Speed Recovery," in CSEE Journal of Power and Energy Systems, vol. 8, pp. 1417-1427, September 2022.

[16] T. A. Woldu and M. Wolter, "Analysis and Modeling of DFIG-Based Wind Turbines with Variable Frequency Regulation Capability," 2022 18th International Conference on the European Energy Market (EEM), Ljubljana, Slovenia, 2022, pp. 1-6, doi: 10.1109/EEM54602.2022.9921022.

[17] B. Tan, J. Zhao, F. Milano, Q. Lai, Y. Zhang and D. A. Maldonado, "Extended Frequency Divider for Bus Frequency Estimation Considering Virtual Inertia from DFIGs," 2021 IEEE PES Innovative Smart Grid Technologies Conference - Latin America (ISGT Latin America), Lima, Peru, 2021, pp. 1-5, doi: 10.1109/ISGTLatinAmerica52371.2021.9543055.

[18] Bhongade S. et. al., " Genetic algorithm based PID controller design for a multi-area AGC scheme in a restructured power system" in International Journal of Engineering, Science and Technology Vol. 3, No. 1, 2011, pp. 220-236

[19] Tan B. et al., "Distributed Frequency Divider for Power System Bus Frequency Online Estimation Considering Virtual Inertia from DFIGs," in IEEE Journal on Emerging and Selected Topics in Circuits and Systems, vol. 12, no. 1, pp. 161-171, March 2022, doi: 10.1109/JETCAS.2022.3141975.

[20] Bhati D., Bhongade S. “ Application of Grey Wolf Optimization Algorithm for Improving Inertia Constant Selection in Wind Farm Deployments” International Conference on Advances in Computing, Control, and Telecommunication Technologies, ACT 2023, June 2023, pp. 2504–2509.

[21] Bhati D., Bhongade S. “Enhancing DFIG-based Wind Farm Performance: Virtual Inertia Estimation using Dual Moth Flame Optimization and Additional Frequency Control”, 2nd International Conference on Computer, Communication and Control, IC4 2024, 2024.