Optimized PI Controller Tuning for reactive power control of Stand-Alone DFIG Wind Energy Systems Utilizing Grey Wolf Optimization with Simplex Algorithm

Hatem Seoudy[1]*

ABSTRACT

Abstract— Wind energy is an essential element of the global shift towards renewable energy, providing clean and sustainable electricity generation. The Doubly Fed Induction Generator (DFIG) is extensively utilized in variable-speed wind turbine systems owing to its efficiency and controllability. This research introduces a comprehensive control approach for a stand-alone Doubly Fed Induction Generator (DFIG) utilizing a Proportional-Integral (PI) controller optimized via the integration of Grey Wolf Optimization and the Simplex algorithm (GWO-SM). A laboratory prototype has been created, including a Brushless DC (BLDC) motor that simulates wind fluctuations and a wound rotor induction machine operating as the Doubly Fed Induction Generator (DFIG). System identification techniques are utilized to describe the reactive power and speed control loops using input-output data. The new GWO-SM method is evaluated against traditional Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) across several test settings, including abrupt alterations in speed and load. The results indicate that GWO-SM surpasses both PSO and GWO by attaining quicker transient responses, reduced steady-state error, and enhanced resilience. The results confirm the efficacy of GWO-SM as a superior tuning technique for PI controllers in independent wind energy applications.

Keywords: DFIG, GWO, GWO-SM, BLDC

I. INTRODUCTION

Wind energy generation has emerged as one of the fastest-growing and most significant sources of renewable energy globally due to substantial electricity demands. The variable-speed wind turbine (VSWT) employing a doubly fed induction generator (DFIG) has recently attracted significant interest owing to its benefits [1, 2].

DFIG systems are extensively utilized in large variable-speed wind power generation applications. This study applies a DFIG to a stand-alone configuration. In contrast to grid-connected systems, wind turbines in stand-alone and islanding operations must regulate and sustain both active and reactive power while aligning generation with load, irrespective of fluctuations in rotor speed caused by variations in wind speed and load changes [2-4].

[1] High Institute of Engineering – Shorouk city

* Corresponding Author

Conventional PI control cannot achieve satisfactory transient performance for DFIG as a result of its time-varying and nonlinear control features.

This study is dedicated to the development of an advanced control methodology for DFIG in stand-alone applications. Various control strategies, including adaptive, neural network-based, and fuzzy logic approaches, have been explored in the literature. Among these, PI controller remains the most widely adopted technique, primarily due to its simplicity in design and ease of implementation. The conventional PI controller is frequently utilized in wind energy conversion systems for these reasons. Attaining the desired control performance is challenging in the absence of appropriate controller tuning. The parameterization of the PI controller is a critical aspect of its design, as these settings have a direct and significant impact on the overall system performance. In recent years, heuristic optimization techniques have been increasingly employed to enhance PI controller tuning. Furthermore, many graduate-level engineering programs now emphasize the study of intelligent algorithms, such as neural networks and their associated mutation strategies, highlighting the growing importance of these advanced methodologies in control system design. [5-7].

The selection of controller gains ((Kp) and (Ki)) is performed to satisfy specific performance criteria, such as rise time, settling time, overshoot, and steady-state error (ess) following a step change in demand [8]. Over time, a variety of heuristic optimization techniques have been proposed to enhance the tuning of PI controllers. While considerable research has focused on advanced PI controllers, including those incorporating fuzzy logic or variable gain algorithms, the effective optimization of the associated fuzzy rules and gain scheduling mechanisms remains essential [9, 10]. To address these challenges, biologically inspired optimization methods, such as evolutionary computation and swarm intelligence, have been widely adopted to further improve the tuning of PI controller parameters [8,11, 12].

Section 2 delineates the system modeling. Section 3 presents the validation of the identified model and elucidates the application of optimization approaches. Section 4 provides a comparative analysis of the simulation results obtained using the proposed GWO-SM method against those achieved with alternative stochastic optimization techniques, namely PSO and the standard GWO.

II. SYSTEM MODELING

A. Implemented a wind turbine and Doubly Fed Induction Generator (DFIG) system.

The system comprises a Doubly Fed Induction Generator (DFIG), BLDC, a drive circuit, an inverter, a speed measurement unit, a reactive power measurement unit, and a data acquisition card. Optimization methods are utilized for the PI controller in MATLAB/Simulink, alongside the integration of the data collection card with MATLAB/Simulink through the Data Collection Toolbox. The technical specifications of the system are outlined as follows [2].

B. Modeling of Wind Turbine Laboratory-scale

The identification of transfer functions for the Doubly Fed Induction Generator (DFIG) in VAR control and the Brushless DC (BLDC) motor in speed control is conducted using the MATLAB System Identification Toolbox, as described in references [13, 14]. For the DFIG's VAR control, a step input with a voltage range of 0 to 0.6 V is applied, and the resulting output is collected as test data. Analysis reveals that the optimal transfer function contains 4 poles and between 2 and 3 zeros, providing the best fit to the validation data. Alternatively, a lower-order transfer function with 4 poles and 2 zeros delivers a similar accuracy, achieving a fit of 91.5%. The identified transfer function of the variable frequency drive loop for the DFIG is expressed as follows:

$$\boldsymbol{G_Q(S) = \frac{8134\,S^2 + 2.101e04\,S + 411.6}{S^4 + 26.4\,S^3 + 215.5\,S^2 + 508.4\,S + 7.229}} \quad (1)$$

The BLDC motor's speed control transfer function comprises poles ranging from 1 to 3 and zeros from 1 to 3, utilizing a descending step input with a voltage range of 2.5 to 1 V, with the output serving as test data. The optimal fit for the data validation is achieved with a transfer function with three poles and two zeros, yielding a fitting percentage of 95.131%. For a brushless DC motor and its drive circuit, the transfer function of the speed control loop is:

$$\boldsymbol{G_{Speed}(S) = \frac{1279\,S^2 + 5.867e05\,S - 1.053e04}{S^3 + 50.21\,S^2 + 915\,S + 2.506e - 12}} \quad (2)$$

C. Experimental Model Validation

The transfer function of the models is delineated in equations (1) and (2); Figure 1 illustrates the response of both identified models and the practical system to a step input.

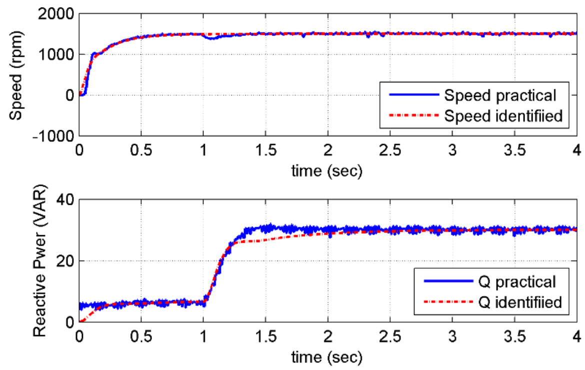

Figure 1. Empirical and Identified Model VAR and Speed Responses

Figure 1 shows that the response of the identified model closely matches the actual system's response, demonstrating that the model obtained from equations (1) and (2) is appropriate for simulation studies. The structure of the PI tuning algorithm is depicted in Figure 2.

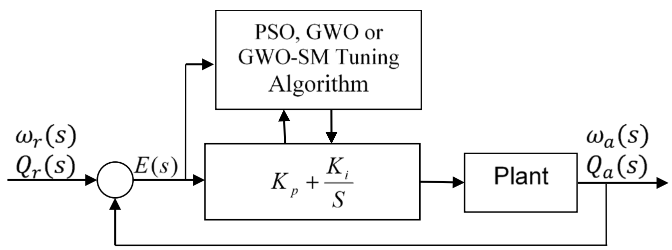

Figure 2. Structure of system with pi tuning algorithms.

In the Wind Power Generator System, the turbine is modeled as a variable torque source that responds to changes in wind speed. BLDC motor, along with its associated drive circuits, is utilized to emulate the dynamic behavior of the wind turbine. Due to the inherently fluctuating torque and power outputs characteristic of wind energy, a dedicated speed control system has been implemented to regulate the BLDC motor's rotational speed. The controller receives feedback on the generator speed via an encoder mounted on the shaft of DFIG. The encoder provides an output voltage ranging from 0 to 2 volts, corresponding linearly to shaft speeds between 0 and 2000 revolutions per minute (r.p.m.). The BLDC motor drive circuit is powered by a 220-volt AC mains supply, which is first rectified to produce a DC voltage. This DC output is subsequently processed through an IGBT inverter to drive the BLDC motor. The control input voltage to the inverter ranges from 0 to 5 volts, thereby determining the output voltage supplied to the motor. A 0.27 kW wound rotor induction machine, functioning as the DFIG, is mechanically coupled to the emulated wind turbine and is energized through a dedicated converter system.

III. MATERIALS AND METHODS

A. Fitness Function and PI Controller Modeling

The tuning of PI controller parameters is closely related to the inherent characteristics of the system. As a result, careful calibration of these parameters is essential to achieve the desired control performance. The transfer function of a proportional-integral (PI) controller is typically given by [15]:

$$\boldsymbol{G_c(s) = K_p + \frac{K_i}{s}} \tag{3}$$

where, K_p, and K_i denotes the proportional, and integral gains respectively.

In this study, PSO, GWO, and GWO-SM techniques are utilized to optimally determine the controller constraints for both VAR regulation in DFIG and speed control of BLDC motor. The optimization process is guided by multi-objective performance indices, specifically WGAM1 and WGAM2 (Weighted Goal Attained Method 1 and 2), as defined in equations (4), and (5) [13].

$$\mathrm{WGAM1} = \frac{1}{[c_1(t_r - t_{rd})^2 + c_2(M_p - M_{pd})^2 + c_3(t_s - t_{sd})^2 + c_4(e_{ss} - e_{ssd})^2]} \tag{4}$$

$$\mathrm{WGAM2} = \frac{1}{(1 - e^{-\beta}) \cdot (M_p + e_{ss}) + (e^{-\beta}) \cdot (t_s - t_r)} \tag{5}$$

Where, r is the required output, e is the error signal, β weighting factor, $c_1 : c_4$ are positive constants, t_{rd} , M_{pd} , e_{ssd} , and t_{sd} are the desired rise time, maximum overshoot, steady state error, and settling time respectively.

In WGAM1, the definitive closed-loop specifications of the system, including the controller t_r, M_p, t_s, *and* e_{ss}, are utilized to assess the fitness function. This is accomplished by aggregating the squares of discrepancies between actual and desired parameters, t_{rd}, M_{pd}, t_{sd}, and e_{ssd}, as delineated in the equation (4).

The WGAM2 satisfy the requirements using β value as given in equation (5). The factor β is set higher than 0.7 to reduce the overshoot and ess. On the other hand β is set smaller than 0.7 to reduce the rise time and settling time [5].

B. Simplex Algorithm (SM)

This method utilizes a derivative-free line search strategy, relying on the evaluation of the objective function at the N + 1 vertices of a polytope (simplex) within an N-dimensional space. The optimization process advances by systematically moving the simplex toward the minimum point through a sequence of geometric transformations: reflection, contraction, and expansion [16-19]. The procedure begins with the selection of an initial starting point, followed by the construction of an initial simplex comprising this point and additional points generated in each coordinate direction. The objective function is then evaluated at each vertex of the simplex.

Subsequently, the vertex corresponding to the highest function value is replaced by a new point derived from the application of simplex operators. These steps, evaluation and replacement, are iteratively repeated until a predetermined termination criterion is met.

C. Grey Wolf Optimization Simplex Method (GWO-SM) Algorithm

The Grey Wolf Optimizer–Simplex Method (GWO-SM) is a hybrid optimization approach that integrates the stochastic search capabilities of GWO with the deterministic refinement of the Simplex Method. This combination is specifically designed to address two common issues in optimization: the tendency of deterministic algorithms to become trapped in local minima, and the relatively slow convergence and suboptimal refinement associated with purely stochastic methods. In the GWO-SM algorithm, the GWO is initially employed to explore the solution space and identify a promising global minimum. Subsequently, the final solution obtained by the GWO serves as the starting point for the Simplex Method, which is then utilized to refine the solution and accelerate convergence toward the optimum. This sequential integration leverages the strengths of both algorithms to achieve efficient and robust optimization performance [16-18].

D. PI Tuning With GWO-SM (GWO-SM-PI):

The step response of the system under the influence of GWO-SM-PI controller using the fitness function of WGAM1 and WGAM2 are shown in Figure 3 for Reactive Power Loop, and Figure 4 for Speed Loop. The optimum PI controller parameters and the response parameters of the Reactive Power Loop are summarized in Table I and for Speed Loop are summarized in Table **II**.

TABLE I. RESPONSE PARAMETERS OF VAR LOOP SYSTEM UTILIZING A GWO-SM-PI CONTROLLER WITH WGAM-BASED FITNESS FUNCTIONS

Response	*Performance Criteria*	
	WGAM1	*WGAM2*
Value of fitness function	0.0435	0.6623
Rising time(sec), tr	0.1631	0.164
Overshoot percentage, Mp	0.0042	0.0042
Settling time (sec), ts	0.9206	0.9045
Error, e	6.89E-04	6.86E-04
Kp	0.0206	0.0192
Ki	0.1693	0.1649

TABLE II. RESPONSE PARAMETERS OF THE SPEED LOOP SYSTEM UTILIZING A GWO-SM-PI CONTROLLER WITH WGAM-BASED FITNESS FUNCTIONS

Response	*Performance Criteria*	
	WGAM1	*WGAM2*
Value of fitness function	5.22E-04	0.0395
Rising time(sec), tr	0.2766	0.0803
Overshoot percentage, Mp	-0.0034	0.0142
Settling time (sec), ts	0.514	0.1223
Error, e	0.0365	-0.0012
Kp	1.66E-04	0.0011
Ki	0.0095	0.0273

It can be noticed that for reactive power loop the influence of GWO-SM-PI controller using the fitness function WGAM1 and WGAM2 is almost the same but WGAM2 is relatively better meanwhile for speed loop WGAM2 have relatively better response than WGAM1.

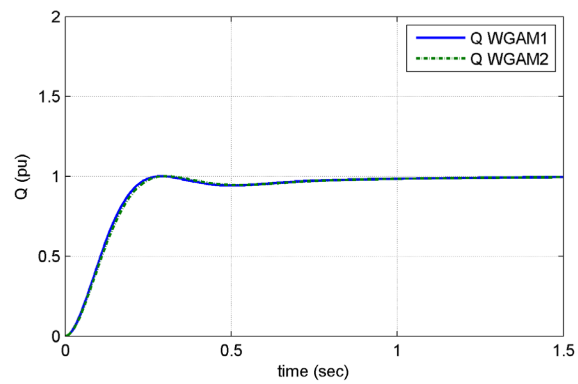

Figure 3. Reactive Power Loop step response with GWO-SM-PI controller and WGAM fitness functions

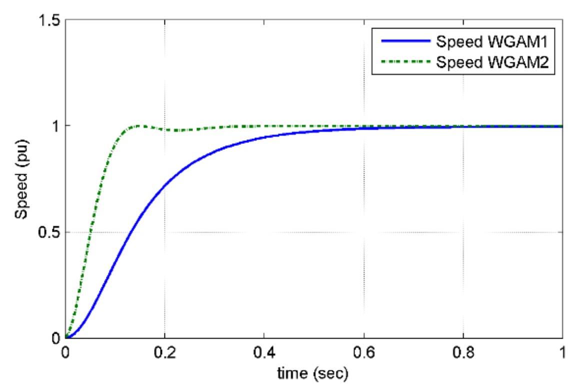

Figure 4. Speed Loop system step response with GWO-SM-PI controller and WGAM fitness functions.

IV. RESULTS

The optimal PI parameters for the transfer function of the identified models, derived from equations (1) and (2), are determined based on the performance indices outlined in equations (4), and (5). For WGAM1, the investigated parameters are: $t_{rd} = 0.3$, $M_p\% = 0$, $t_{sd} = 0.5$, $e_{ss}\% = 0$, and $c_1 = c_2 = c_3 = c_4 = 0.25$. For WGAM2, the examined parameter is $\beta = 0.1$. The performance of the identified model is evaluated using PSO, GWO, and GWO-SM controllers and is presented in Table III and Table IV. The values of the PI parameters are presented in Table V and Table VI. Furthermore, the response times are illustrated in Figure 5 and Figure 6.

TABLE III. PERFORMANCE OF PSO, GWO, AND GWO-SM FOR PI CONTROLLERS IN SIMULATION OF THE REACTIVE POWER LOOP

Response	*Optimization Methods*	*Performance Criteria*	
		WGAM1	*WGAM2*
fitness function value	*PSO*	1.5392	1.4392
	GWO	0.048917	0.67034
	GWO-SM	0.0435	0.6623
Rising time(sec)	*PSO*	0.087399	1.4055
	GWO	0.04855	0.164
	GWO-SM	0.1631	0.1640
Overshoot percentage	*PSO*	0	0
	GWO	28.12	0.004235

	GWO-SM	0.0042	0.0042
Settling time (sec)	*PSO*	2.9721	2.9962
	GWO	0.50076	0.90447
	GWO-SM	0.9206	0.9045
Steady state error	*PSO*	0.001282	0.00201
	GWO	0.000205	0.000686
	GWO-SM	6.8946e-04	6.8630e-04

TABLE IV. PERFORMANCE OF PSO, GWO, AND GWO-SM FOR PI CONTROLLERS IN SIMULATION OF SPEED LOOP

Response	*Optimization Methods*	*Performance Criteria*	
		WGAM1	*WGAM2*
fitness function value	*PSO*	0.11515	0.86391
	GWO	0.000482	0.10963
	GWO-SM	5.2238e-04	0.0395
Rising time(sec)	*PSO*	0.60787	0.58724
	GWO	0.27678	0.16767
	GWO-SM	0.2766	0.0803
Overshoot percentage	*PSO*	0.046845	0.01337
	GWO	0.033398	0.13483
	GWO-SM	0.0365	0.0142
Settling time (sec)	*PSO*	1.103	1.5402
	GWO	0.51626	0.27438
	GWO-SM	0.5140	0.1223
Steady state error	*PSO*	-0.00578	-0.00357
	GWO	-0.00311	-0.00247
	GWO-SM	-0.0034	-0.0012

TABLE V. REACTIVE POWER LOOP: PI CONTROLLER PARAMETERS

PI Gains	*Optimization Methods*	*Performance Criteria*	
		WGAM1	*WGAM2*
Kp	*PSO*	0.061582	0.027787
	GWO	0.02041	0.019792
	GWO-SM	0.0206	0.0192
Ki	*PSO*	0.076026	0.054485
	GWO	0.16455	0.16529
	GWO-SM	0.1693	0.1649

TABLE VI. SPEED LOOP: PI CONTROLLER PARAMETERS

PI Gains	*Optimization Methods*	*Performance Criteria*	
		WGAM1	*WGAM2*
Kp	*PSO*	0.000296	0.003862
	GWO	0.000307	0.000131
	GWO-SM	1.6604e-04	0.0011
Ki	*PSO*	0.005508	0.008898
	GWO	0.010311	0.013
	GWO-SM	0.0095	0.0273

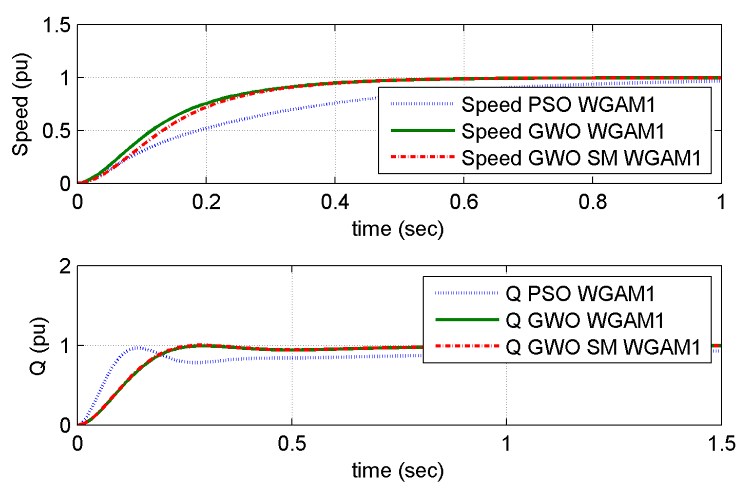

Figure 5. Simulation with respect to WGAM1

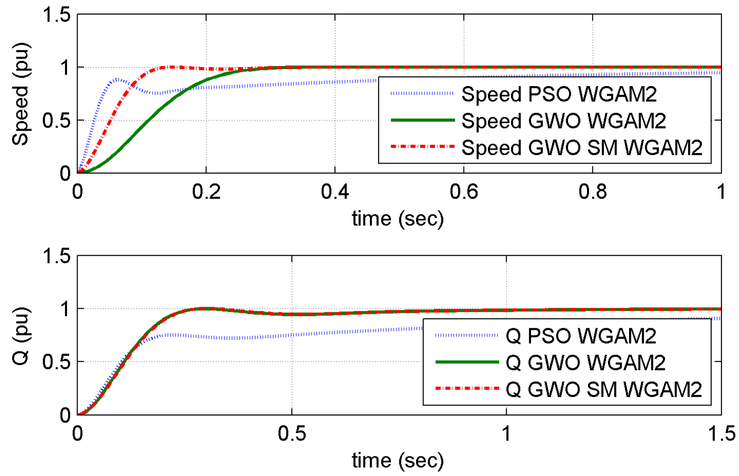

Figure 6. Simulation with respect to WGAM2

It is concluded from the above comparison that WGAM1 objective function with GWO-SM-PI for reactive power loop has been proven to be more efficient than the other optimization algorithms and objective functions. However, WGAM2 objective function with GWO-SM-PI for speed loop has been proven to be more efficient than the other optimization algorithms and objective functions. Thus, the system performs better time response with GWO-SM-PI controller.

V. CONCLUSION

Wind energy continues to play a pivotal role in the global transition to clean and sustainable power sources. This study has presented a robust control strategy for stand-alone Doubly Fed Induction Generator (DFIG) wind energy systems, utilizing a Proportional-Integral (PI) controller tuned through a hybrid optimization approach combining Grey Wolf Optimization with the Simplex algorithm (GWO-SM). A laboratory-scale prototype was developed to emulate realistic wind conditions using a BLDC motor and a wound rotor induction machine acting as a DFIG. System identification techniques were employed to accurately model the reactive power and speed control loops based on input-output data.

Comprehensive performance evaluations under varying operational scenarios, including sudden changes in rotor speed and electrical load, demonstrate that the proposed GWO-SM algorithm significantly outperforms conventional GWO and PSO methods. Specifically, GWO-SM achieved faster transient responses, lower steady-state errors, and greater robustness across all test conditions. These findings validate the effectiveness of the GWO-SM approach as a superior PI tuning method for enhancing the performance and reliability of off-grid wind energy systems.

REFERENCES

[1] W. Qiao, G. K. Venayagamoorthy, and R. G. Harley, "Design of optimal PI controllers for doubly fed induction generators driven by wind turbines using particle swarm optimization," in *Neural Networks, 2006. IJCNN'06. International Joint Conference on*, pp. 1982-1987: IEEE.

[2] H. M. Seoudy, M. A. Saadeldin, and W. A. Mohamed, "Design and implementation of optimal controller for DFIG-WT using autonomous groups particle swarm optimization," *International Journal of Power Electronics Drive Systems,* vol. 13, no. 3, pp. 1813-1821, 2022.

[3] "Control of Variable Speed Wind Turbines with Doubly Fed Asynchronous Generators for Stand-Alone Applications," *Energies,* vol. 11, no. 1, 2017.

[4] M. M. Reda, M. I. Elsayed, M. A. Moustafa Hassan, and H. M. Seoudy, "Enhancing microgrid renewable energy integration at SEKEM farm," *Global Energy Interconnection,* vol. 7, no. 6, pp. 761-772, 2024/12/01/ 2024.

[5] A. S. E.-W. Al-Said Abd ElAziz Osman, A.kamel and H. M. Seoudy, "Optimal tuning of PI Controllers for Doubly-Fed Induction Generator using Grey Wolf Optimizer," *Journal of American Science,* vol. 11, no. 11, pp. 154-164, 2015.

[6] R. Kumar and N. Sinha, "Modeling and Control of Dish-Stirling Solar Thermal Integrated With PMDC Generator Optimized by Meta-Heuristic Approach," *IEEE Access,* vol. 8, pp. 26343-26355, 2020.

[7] S. Ekinci and B. Hekimoglu, "Improved Kidney-Inspired Algorithm Approach for Tuning of PID Controller in AVR System," *IEEE Access,* vol. 7, pp. 39935-39947, 2019.

[8] M. E.-S. El-Telbany, "Employing Particle Swarm Optimizer and Genetic Algorithms for Optimal Tuning of PID Controllers: A Comparative Study," *ICGST-ACSE Journal,* vol. Volume 7, no. Issue 2, November 2007.

[9] D. Nangru, D. K. Bairwa, K. Singh, S. Nema, and P. K. Padhy, " Modified PSO based PID Controller for Stable Processes," presented at the PDPM Indian Institute of Information Technology Design and Manufacturing, Jabalpur-482005 (M.P.), India,,IEEE, 2013. .

[10] Z.-L. Gaing, "A Particle Swarm Optimization Approach for Optimum Design of PID Controller in AVR System," IEEE Tran. Energy Conversion, Vol.19(2)Jun. 2004.

[11] G. Huang, D. Wu, W. Yang, and Y. Xue, " Self-tuning of PID Parameters Based on the Modified Particle Swarm Optimization," presented at the Proceedings of the 8th World Congress on Intelligent Control and Automation, Jinan, China, IEEE,, 2010.

[12] J.Kennedy and R.Eberhart, "Particle Swarm Optimization," presented at the IEEE International Conf. in Neural Networks, 1995.

[13] A. S. El-Wakeel, F.Hassan, A.Kamel, and A. Abdel-hamed, "OPTIMUM TUNING OF PID CONTROLLER FOR A PERMANENT MAGNET BRUSHLESS DC MOTOR," *International journal of electrical engineering &Technology (IJEET),* vol. 4, no. 2, pp. 53-64, 2013.

[14] A. S. El-Wakeel, A. E.-E. Kamel, and A. Abdel-hamed, "A Hybrid Bacterial Foraging-Particle Swarm Optimization Technique for Optimal Tuning of Proportional-Integral-Derivative Controller of a Permanent Magnet Brushless DC Motor," *Electric Power Components and Systems,* vol. 43, no. 3, pp. 309-309, 2-2015 2015.

[15] M. R. Alrashidi; and M. E. El-Hawary, "A Survey of Particle Swarm Optimization Applications in Power System Operations," *Electric Power Components and Systems,* vol. 34, no. 12, pp. 1349–1357, 2006.

[16] A. S. El-Wakeel, "Design optimization of PM couplings using hybrid Particle Swarm Optimization-Simplex Method (PSO-SM) Algorithm," *Electric Power Systems Research,* vol. 116, pp. 29-35, 2014.

[17] A. S. El-Wakeel and A. C. Smith, "Hybrid Fuzzy-particle Swarm Optimization-simplex (F-PSO-S) Algorithm for Optimum Design of PM Drive Couplings," *Electric Power Components and Systems,* 2015.

[18] A. El-Wakeel, " Design Optimisation for Fault Tolerant Switched Reluctance Motors," Doctor of Philosophy thesis in Department of Electrical Engineering and Electronics. , Manchester: UMIST, 2003.

[19] M. A. Tawhid, A. F. J. N. A. Ali, Control, and Optimization, "A simplex grey wolf optimizer for solving integer programming and minimax problems," vol. 7, no. 3, pp. 301-323, 2017.