MAXIMIZATION OF WIND ENERGY CONVERSION USING SLIDING MODE CONTROL TUNED BY LINEARIZED BIOGEOGRAPHY-BASED OPTIMIZATION

Tarek A. BOGHDADY*,i Mahmoud M. SAYED*,ii

*Electrical Power and Machines Dept., Faculty of Engineering, Cairo University, Giza, Egypt. iPhone: +2010 2044 3386 Email: engtarek82@gmail.com, iiphone: +2010 9345 6422 Email: Fecu.MSayed@Gmail.com

Essam E. ABOUELZAHAB*,iii

*Electrical Power and Machines Dept., Faculty of Engineering, Cairo University, Giza, Egypt. iii Phone: +20100 145 9334 Email: zahab0@yahoo.com

Abstract: A sliding mode controller (SMC) is applied in this paper to control a grid-connected Doubly Fed Induction Generator (DFIG) wind turbine for maximization the wind energy conversion and hence reducing the generator losses, the sliding mode controller is a nonlinear controller that implemented here with two Proportional Integral Derivative (PID) controller. The chattering problem of SMC is rejected here by using a minimum discontinuous controller term for ensuring disturbance rejection. PID controller is a commonly used controller in many industrial applications, while PID controller parameter tuning is a challenging issue which had been done here using a new version of Biogeography-Based Optimization (BBO) which is called Linearized Biogeography-Based Optimization (LBBO) algorithm. BBO is one of the latest evolutionary optimization algorithm based on mathematical model of Biogeography; it permits recombination among candidate solutions (habitats) by migration and immigration also a mutation process is being used. The objective function to be minimized is chosen to be the overall copper losses of the DFIG using MATLAB/SIMULINK. The simulation results are compared with Tyreus-Luyben tuning method, Genetic Algorithm (GA), and Biogeography-Based Optimization (BBO). Simulation results shows that the LBBO is an effective tuning method and has better performance compared with GA, and BBO.

Key words: Biogeography-Based Optimization (BBO), Evolutionary Algorithm (EA), PID control, and Sliding Mode Control.

1. Introduction.

Developing wind energy generation has an increasing interest in the last decade. A lot of objectives can be achieved by using electrical controller especially in variable speed operations [1-3]. Due to the improvement and cost reduction of micro controllers and AC drives, the classical controllers can be replaced by modern controllers such as fuzzy control [4], robust control [5], and adaptive control [6]. One of the modern controllers is the Sliding Mode (SM) control which it is useful when dealing with a variable speed process as it has a merits:

reduced-order, robustness against disturbances and system parameters variation with time [7-9], but In SMC, there is an undesirable oscillations, which is known as "chattering" [10]. By using PID controllers in SMC implementation, finding its parameters values problem is risen. We can't often tune PID parameters at its optimum values due to the difficulties of the conventional techniques that being used like frequency response. Ziegler-Nichols rules based on loop testing was used in the past [11, 12], but today intelligent control has become a focus of research as Artificial Neural Network (ANN) controller, fuzzy control, and evolutionary algorithms based controller [13].

Dan Simon introduced Biogeography-Based Optimization (BBO) Algorithm [14], many searches focused on that new algorithm to develop its ability of getting the global optimum value, to increase its variance, and to reduce its optimization time as; Biogeography-Based Optimization with Blended Migration for Constrained Optimization Problem [15], A Hybrid Differential Evolution with Biogeography-Based Optimization (DE/BBO) for Global Numerical Optimization [16], Equilibrium Species Counts and Migration Model Tradeoffs for Biogeography-Based Optimization [17], a Modified Biogeography-Based Optimization (MBBO) [18], and Linearized Biogeography-Based Optimization with Re-initialization and Local Search [19].

This paper is organized as follows: Section 2 presents sliding mode control. Section 3 presents the dynamic model of the wind energy conversion system. Section 4 reviews Biogeography-Based Optimization. Section 5 presents the Linearized Biogeography-Based Optimization. In Section 6 discussion and comparison of GA, BBO, and LBBO Finally, the conclusions are stated in section 7.

2. Sliding Mode Control.

A sliding mode control is a nonlinear controller that

modifies the dynamics of a system using application of a discontinues control signals which coerces the system to slide a cross-section of the system's normal behavior [20]. Consider a MIMO nonlinear system, modeled by the following:

$$\dot{X} = f(x) + G(x)U + \zeta = f(x) + \sum_{i=1}^{m} g_i(x)u_i + \zeta$$
 (1)

Where f is the drift vector, and g_i of the input distribution matrix are smooth vector fields, $\hat{\zeta} =$ $[\zeta_1, \zeta_2, ..., \zeta_n]^T$ is an unknown disturbance vector. We should select m individual sliding variables $s_i(x)$, it is also assumed that the system is hyperbolically minimum phase [20]. The controller will be a summation of three terms as follow:

$$U(x) = U_{I}(x) + U_{II}(x) + U_{III}(x)$$
 (2)

By using Lyaponouv theory with variable structure and geometric concepts.

$$V(x) = \frac{1}{2}S^T S \tag{3}$$

$$\dot{V}(x) = S^T \frac{\partial S}{\partial x} \dot{x} = S^T \frac{\partial S}{\partial x} (f(x) + G(x)U) \tag{4}$$

 $\dot{V}(x) = S^{T} \frac{\partial S}{\partial x} \dot{x} = S^{T} \frac{\partial S}{\partial x} (f(x) + G(x)U)$ With $S = [s_{1}, s_{2}, ... s_{m}]^{T}$ and $\frac{\partial S}{\partial x} = [\frac{\partial s_{1}}{\partial x} \frac{\partial s_{2}}{\partial x} ... \frac{\partial s_{m}}{\partial x}]_{m \times n}^{T}$ To design the drift cancellation controller U_{I} assuming the system is initially at S=0, our aim is to force $\dot{V}(x) = 0$, by substituting in equation 4, we get

$$U_{I}(x) = -\left[\frac{\partial S}{\partial x}G(x)\right]^{-1}\left[\frac{\partial S}{\partial x}f(x)\right]$$
 (5)
While U_{II} is the reaching mode controller, its target

if the system wasn't initially at S = 0, is to ensure reaching the intersection manifold.

$$U_{II}(x) = -\left[\frac{\partial S}{\partial x}G(x)\right]^{-1}\Gamma S \tag{6}$$
 Where Γ is a diagonal positive matrix. By

assuming that the derivative of Lyaponouv equation

$$\dot{V}(x) = -\sum_{i=1}^{m} \gamma_i u_i^2 \tag{7}$$

Where the m is positive design parameters γ_i correspond to the diagonal elements of Γ . To avoid chattering, a discontinuous control term U_{III} should be able to cancel any projection of ζ bounded by $\zeta_M =$ $[\zeta_{M1}, \zeta_{M2}, ..., \zeta_{Mn}]^T$ on the orthogonal subspace with m dimensions. ζ can be assumed as it is actually unknown. The orthogonal projection onto the basis vector $\partial S_1/\partial x$ is bounded by using:

$$\left| \frac{\partial \check{S}}{\partial X} \right| \zeta_M = \left[\left| \frac{\partial \check{S}_1}{\partial X^T} \right| \zeta_M, \dots, \left| \frac{\partial \check{S}_m}{\partial X^T} \right| \zeta_M \right]^T$$
So the discontinuous control term will be:

$$U_{III}(x) = -\left[\frac{\partial S}{\partial X}G(X)\right]^{-1} \Lambda \, sgn(S) \tag{9}$$
Where $\Lambda = diag\left(\left|\frac{\partial S}{\partial X}\right|\zeta_M\right)$.

3. Wind Energy Conversion System Modeling.

The stator is directly connected to the grid, also the

rotor is connected to the utility through bidirectional converter as shown in fig. 1. By selecting the d-q frames and the q-axis of the stator will be selected as a reference frame ($V_{qs}=V_L$ and $V_{ds}=0$). The dynamic model can be described by the following equations:

$$\dot{\varphi}_{qs} = -R_s i_{qs} - \omega \varphi_{ds} + V_L \tag{10}$$

$$\dot{\varphi}_{ds} = -R_s i_{ds} + \omega \varphi_{qs} \tag{11}$$

$$\dot{\varphi}_{qr} = -R_r i_{qr} - (\omega - \omega_r) \varphi_{dr} + v_{qr} \tag{12}$$

$$\dot{\varphi}_{dr} = -R_r i_{dr} + (\omega - \omega_r) \varphi_{qr} + v_{dr} \tag{13}$$

$$\varphi_{qs} = L_s i_{qs} + L_m i_{qr} \tag{14}$$

$$\varphi_{ds} = L_s i_{ds} + L_m i_{dr} \tag{15}$$

$$\varphi_{qr} = L_r i_{qr} + L_m i_{qs} \tag{16}$$

$$\varphi_{dr} = L_r i_{dr} + L_m i_{ds} \tag{17}$$

$$\varphi_{dr} = L_r i_{dr} + L_m i_{ds}$$

$$T_e = \frac{3}{2} P L_m (i_{qr} i_{ds} - i_{dr} i_{qs})$$

$$(17)$$

Where R_s and R_r are the stator and rotor resistances, L_s and L_r are the stator and rotor inductances, L_m is the mutual inductance. The $v_{qs},\ v_{ds},\ v_{qr},$ and v_{dr} are the quadrature-direct components of the stator and rotor maximum voltages, i_{qs} , i_{ds} , i_{qr} , and i_{dr} are the components of the stator and rotor currents, while ϕ_{qs} , ϕ_{ds} , ϕ_{qr} , and ϕ_{dr} are the components of the stator and rotor concentrated flux. Te is the generator torque and P is the number of pair poles.

By applying the Newton's equation and neglecting the friction term, the dynamic equation will be

$$\dot{\omega}_{rm} = \frac{\dot{\omega}_r}{P} = \frac{1}{J} (T_t - T_e) \tag{19}$$

$$T_t = \frac{1}{2} \rho \pi r^3 C_t(\lambda) v^2 \tag{20}$$

$$C_t = \frac{\bar{a}}{\lambda} \left(\frac{b}{\lambda} - 1 \right) e^{-\frac{c}{\lambda}} \tag{21}$$

Where J is the inertia of the rotating parts, $\omega_{rm} =$ ω_r/P is the mechanical rotation, v is the average wind speed, Tt is the turbine torque, ρ is the air density, r is the blade length, Ct is the coefficient of performance, and λ is the Tip-Speed Ratio (TSR), which TSR= $\omega_{rm} * r/v$, with a, b, and c are constants related to the turbine under consideration.

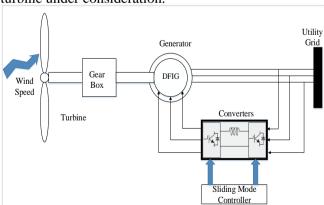


Fig. 1. Schematic diagram of the wind energy conversion system with DFIG.

The maximum extractable power could be obtained at λ_{ont} . By substituting equations (10)-(21) in equation (1), we get:

$$\dot{X} = \begin{bmatrix} f_{1}(x) \\ f_{2}(x) \\ f_{3}(x) \\ f_{4}(x) \\ f_{5}(x) \end{bmatrix} + \frac{1}{L_{eq}^{2}} \begin{bmatrix} -L_{m} & 0 \\ 0 & -L_{m} \\ L_{s} & 0 \\ 0 & L_{s} \\ 0 & 0 \end{bmatrix} U + \zeta \tag{22}$$
Where the states are $X = [i_{qs}, i_{ds}, i_{qr}, i_{dr}, \omega_{r}]^{T}$, and the control input $U = [v_{qr}, v_{dr}]^{T}$, and $L_{eq}^{2} = L_{s}L_{r} - L_{m}^{2}$

$$f_1 = \frac{{}^{R_SL_ri_{qS}-\left(\omega L_{eq}^2+\omega_r L_m^2\right)i_{dS}-R_rL_mi_{qr}+L_rV_L-\omega_rL_mL_ri_{dr}}}{L_{eq}^2},$$

control input
$$U=[V_{qr}, V_{dr}]^T$$
, and $L_{eq} = L_s L_r - L_m$

$$f_1 = \frac{R_s L_r i_{qs} - (\omega L_{eq}^2 + \omega_r L_m^2) i_{ds} - R_r L_m i_{qr} + L_r V_L - \omega_r L_m L_r i_{dr}}{L_{eq}^2},$$

$$f_2 = \frac{\omega L_{eq}^2 i_{qs} + \omega_r L_m^2 i_{qs} + R_s L_r i_{ds} + \omega_r L_m L_r i_{qr} - R_r L_m i_{dr}}{L_{eq}^2},$$
 and
$$f_5 = \frac{1}{JP} \left(T_t - \frac{3}{2} P L_m \left(i_{qr} i_{ds} - i_{dr} i_{qs} \right) \right)$$
To maximize the wind energy conversion, we

$$f_5 = \frac{1}{JP} \left(T_t - \frac{3}{2} P L_m \left(i_{qr} i_{ds} - i_{dr} i_{qs} \right) \right)$$

should operate at λ_{opt} with the variation of the wind speed. To achieve the maximization object and reducing the copper losses, we should track T_{ref} and Q_{ref} through the individual sliding manifold S_1 and S_2 .

$$T_{ref} = K_{opt}\omega_r^2 = \frac{\rho \pi r^5 C_t(\lambda_{opt})}{2\lambda_{opt}^2 P^2} \omega_r^2$$
 (23)

$$T_{ref} = K_{opt}\omega_r^2 = \frac{\rho\pi r^5 C_t(\lambda_{opt})}{2\lambda_{opt}^2 P^2}\omega_r^2$$

$$Q_{ref} = \frac{3}{2}P\frac{\omega L_s R_r \varphi_{ds}^2}{L_m^2 R_s + L_s^2 R_r}$$
(23)

$$S_1(x) = K_{opt}\omega_r^2 - \frac{3}{2}PL_m(i_{qr}i_{ds} - i_{dr}i_{qs})$$
 (25)

$$S_2(x) = Q_{ref} \frac{3}{2} P(v_{qs}i_{ds} - v_{ds}i_{qs}) = Q_{ref} - \frac{3}{2} P V_L i_{ds}$$
 (26)
By assuming that the DFIG is connected to a

constant voltage constant frequency utility and hence $\phi_{qs}=0$ and $\dot{\phi}_{ds}=0$ also we will neglect the resistive voltage drop in the stator winding to be more suitable for implementation. The controller terms in a simplified form will be:

$$U_{I} = \begin{bmatrix} \frac{L_{eq}^{2}}{L_{m}} (f_{1} + \frac{4K_{opt}\omega_{r}f_{5}}{3P\varphi_{ds}}) \\ \frac{L_{eq}^{2}}{L_{m}} f_{2} \end{bmatrix}$$
 (27)

Simplified form will be:
$$U_{I} = \begin{bmatrix} \frac{L_{eq}^{2}}{L_{m}} (f_{1} + \frac{4K_{opt}\omega_{r}f_{5}}{3P\varphi_{ds}}) \\ \frac{L_{eq}^{2}}{L_{m}} f_{2} \end{bmatrix}$$

$$U_{II} = \begin{bmatrix} \frac{2L_{eq}^{2}\gamma_{1}S_{1}}{3PL_{m}\varphi_{ds}} \\ -\frac{2L_{eq}^{2}\gamma_{2}S_{2}}{3L_{m}V_{L}} \end{bmatrix}$$

$$U_{III} = \begin{bmatrix} \frac{L_{eq}^{2}}{L_{m}} (\zeta_{1M} + \frac{4K_{opt}\omega_{r}\zeta_{5M}}{3P\varphi_{ds}}) \operatorname{sgn}(S_{1}) \\ \frac{L_{eq}^{2}}{L_{m}} \zeta_{2M} \operatorname{sgn}(S_{2}) \end{bmatrix}$$
(29)

$$U_{III} = \begin{bmatrix} \frac{L_{eq}^{2}}{L_{m}} (\zeta_{1M} + \frac{4K_{opt}\omega_{r}\zeta_{5M}}{3P\varphi_{ds}}) \operatorname{sgn}(S_{1}) \\ \frac{L_{eq}^{2}}{L_{m}} \zeta_{2M} \operatorname{sgn}(S_{2}) \end{bmatrix}$$
(29)

4. Biogeography-Based Optimization (BBO)

BBO is based on the biogeography science, which is the study of the distribution of organisms over time and space. Biogeography was first studied by Alfred Wallace [22] and Charles Darwin [23]. In BBO every possible solution of the optimization problem can be presented by an island. Each island H has a number of

features called a suitability index variable (SIV). The number of SIV in each solution H is proportional to the problem dimension. The fitness of each solution is called its habitat suitability index (HSI), where a high HSI of an island means good performance on the optimization problem, and a low HSI means bad performance on the optimization problem. Improving the population is the way to solve problems in heuristic algorithms. The method to generate the next generation in BBO is by emigrating solution features to other islands, and receiving solution features by immigration from other islands. The algorithm assumes high species' count in island having high HSI (i.e., for island corresponding to good solutions). The high species' count encourages species to leave the island sharing their good SIV with other island. Hence, islands with good HSI have high emigration rate and low immigration rate. Bad solutions (islands with low HSI) have small species count, low emigration rates and high immigration rates. Mutation is performed for the whole population in a manner similar to mutation in GAs.

5. Linearized Biogeography-Based Optimization (LBBO) [18].

As BBO has limitations that it deals with one variable at a time in each solution, and it has weakness of its local search ability so a gradient descent will be The gradient descent is one of some modifications applied to conventional BBO. Some of the modifications as boundary search, global grid search strategy, restart, and re-initialization will be discussed below:

5.1. LBBO Migration.

The immigration rate λ_k is used to probabilistically decide whether a solution zk to immigrate or not, where $k \in [1, N]$ is a randomly-selected parameter. The solution z_k is linearly combined with the k emigrating solutions such that z_k moves towards each emigrating solution y_i with an amount that is proportional to its emigration rate μ_i :

$$z_k \leftarrow z_k + \mu_j (y_j - z_k) \tag{30}$$

The linearized migration method is described in Algorithm 1.

For each solution zk

Use λ_k to probabilistically decide whether to immigrate to z_k

If immigrating then

For i = 1 to κ

Use $\{\mu_i\}$ (i = 1, ..., N) to probabilistically select the emigrating solution y_i

$$z_k \longleftarrow z_k + \mu_j (y_j - z_k)$$

Next i

End if

Probabilistically decide whether to mutate $z_{k,s}$

5.2. Gradient Descent.

LBBO is combined with several local search operators to improve its performance as it nears the global optimum. Gradient descent is implemented as shown in Algorithm 2.

If FE >
$$\alpha$$
 FE_{max} or $(f_{min}(g+1) - f_{min}(g)) / f_{min}(g) < \varepsilon_1$ then

Perform gradient descent on the N_g best individuals End if

Where FE is the current number of function evaluations by LBBO that have been performed, and FE_{max} is the maximum function evaluation limit. Gradient descent is activated according to α value where $\alpha \in [0, 1]$. It is typically used $\alpha = 1/2$. $f_{min}(g)$ is the minimum function value obtained by LBBO during the g-th generation. The quantity $f_{min}(g+1) - f_{min}(g)$ / $f_{min}(g)$ indicates the relative improvement in the best function value found by LBBO from the g-th generation to the (g+1)-st generation. ϵ_1 is a threshold that determines when gradient descent is activated.

5.3. Boundary Search.

As many real-world optimization problems have their solution on the boundary of the search space so a boundary search is applied. If the best individual in the population are within a certain threshold of the search space boundary, then it is moved to the search space boundary and perform gradient descent on the other dimensions.

5.4. Global Grid Search.

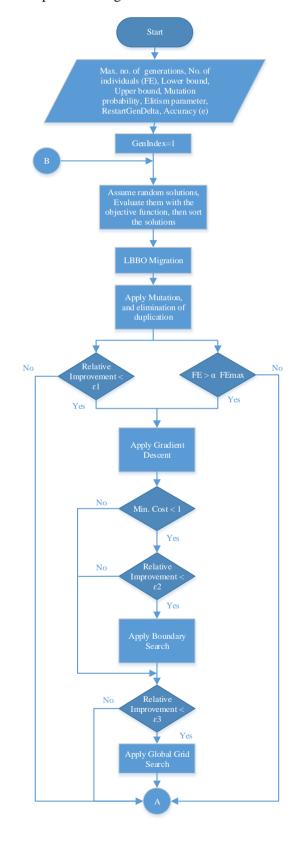
The global grid search systematically covers the search space, the global grid search is implemented under similar conditions as gradient descent and boundary search stated previous. Global grid search is implemented if the best individual is improved by a factor of less than the computer precision so that global grid search is implemented only if the best individual does not improve at all from one generation to the next. Global grid search is implemented for the best No individuals, which it is typically equal to 2.

5.5. Re-initialization.

Re-initialization is performed every Nr (Nr is set typically equal to 1000) function evaluations. We generate N (population size) new random individuals, along with two individuals at each extreme of the search domain. This gives us a temporary population size of 2N+2. The best N individuals are then selected out of these 2N+2 individuals for the next generation.

5.6. Restart.

If there is no improving in the population, we start over, a randomly-generated population will be started, and discard the entire population. The LBBO flow chart is shown in Fig. 2. As with standard BBO, elitism is typically used where the best two solutions are kept from one generation to the next.



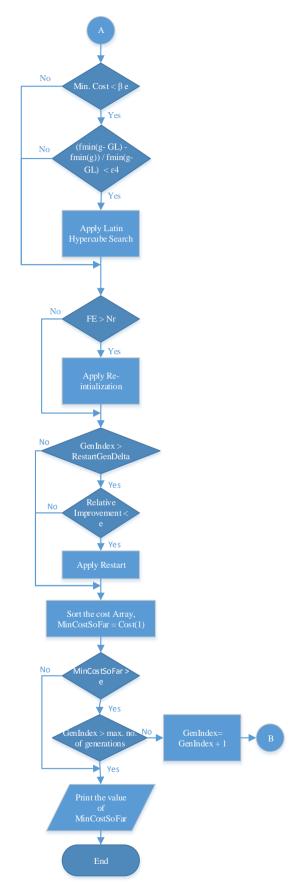


Fig. 2. LBBO Flow Chart.

6. Simulation, Discussion, and Comparison.

The aim of this part is to test the performance of Linearized Biogeography-Based Optimization algorithm and hold a comparison among its performance with GA, BBO, and Tyreus-Luyben tuning method. The total copper losses in equation (31) is the objective function to be minimized for the Wind Energy Conversion System (WECS) with a PID and PI controllers.

$$P_{cu} = \frac{3}{2} (i_{qs}^2 + i_{ds}^2) R_s + \frac{3}{2} (i_{qr}^2 + i_{dr}^2) R_r$$
(31)
By tuning the proportional gain (K_{p1}), integral

By tuning the proportional gain (K_{p1}) , integral constant (τ_{i1}) , and differential constant (τ_{d1}) for the first PID controller and the proportional gain (K_{p2}) , integral constant (τ_{i2}) for the PI controller, using MATLAB/SIMULINK the total simulation time is 7290 seconds to test all the wind speed from 7 m/sec. to 15 m/sec, each speed will be simulated for 90 sec,. The transfer function of the controller is given as:

$$G_c(s) = K_p(1 + \frac{1}{\tau_i S} + \tau_d S)$$
 (32)

The simulation constants are a=19.346, b=9.4117, c=20, r=3.8 m, R_s =0.082 Ω , R_r =0.228 Ω , L_s =0.0355 H., L_r =0.0355 H., L_m =0.0347 H., J=3.362 Kg.m², V_L =380, frequency=60 Hz, P=4 poles, and Gear ratio=16:1. Tyreus–Luyben, GA, BBO, and LBBO are tested with WECS_DFIG. The tuned gains obtained by the algorithms are given in Table 1. Table 2 gives the optimization function, which it is the integration of the copper losses over the simulation period, the LBBO shows the best result.

Table 1
PID tuned Parameters obtained by GA, BBO, LBBO and Tyreus–Luyben (T-L) tuning method.

Algorithm	Kp1	τil	τd1	Kp2	τi2
T–L	0.06909	0.09533	0.006878	0.00017	0.12
GA	0.91472	0.99995	0.5598	0.6969	0.681
BBO	0.20887	0.91548	0.5250	0.99624	0.936
LBBO	0.96204	0.9145	0.5173	0.92688	0.997

Table 2
The optimized value obtained by GA, BBO, LBBO and Tyreus–Luyben tuning method (Best result is shown in boldface.

Algorithm	Optimization value		
Tyreus-Luyben	3.49 e+06		
GA	3.38 e+06		
BBO	3.28 e+06		
LBBO	3.25 e+06		

Figure 3 shows the power losses in the DFIG at speed of 10.7 m/sec. as a sample of the overall simulation period, it is clear that Genetic Algorithm has a better result than the Tyreus–Luyben, but LBBO gives the best result of all algorithms used in this

paper. LBBO reduces the power losses by average value of 8 % over all the available working speed range.

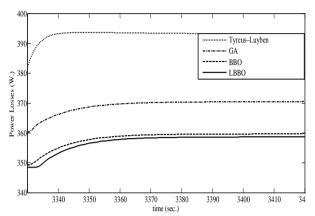


Fig. 3. Power losses curves at speed 10.7 m/sec obtained by T-L, GA, BBO, and LBBO.

7. CONCLUSIONS

In this paper, a Sliding mode controller, WECS-DFIG, Biogeography-Based Optimization, and linearized biogeography-based optimization had been presented, then Tyreus-Luyben, GA, BBO, and LBBO are tested and compared. It was clear that the LBBO has a better performance than BBO, and GA; which it has the lowest cost value for the tested plant. LBBO reduces the power losses by an average value of 8% and hence it increased the generated power.

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