Distributed Fault Estimation of Complex System Using Improved Biogeography-Based Optimization

Chenyu Xiao
School of Electrical and Automation Engineering
Hefei University of Technology
Hefei, China
xcyhfut@163.com

Ming Yu, Xin Liu, Xiaozheng Jin, Canghua Jiang
School of Electrical and Automation Engineering
Hefei University of Technology
Hefei, China
mltrym@163.com

***Abstract*—This paper deals with distributed fault estimation of complex system using bond graph and improved biogeography-based optimization. Firstly, a system decomposition method is used where the complex system is decomposed into several minimal subsystems. Then, distributed analytical redundancy relations and distributed fault signature matrix derived from subsystems diagnostic bond graphs are used for distributed fault detection and isolation respectively. When a set of possible faults are obtained through distributed fault isolation, an improved biogeography-based optimization is proposed for distributed fault estimation. Finally, taking a complex circuit system as an example, numerical simulations are performed to illustrate the effectiveness of the developed method.**

Keywords-Distributed fault estimation; system decomposition; improved biogeography-based optimization;

I. Introduction

Nowadays, in the process of modern industrial production, a lot of complex systems have been produced, such as large-scale integrated circuits, electromechanical systems and so on. With the increase of system complexity, the importance of system health management becomes more and more prominent. However, for complex systems, the global fault diagnosis has become difficult to achieve, to solve this problem, it is required a model-based distributed fault diagnosis approach.

Model-based diagnosis method can be classified into two approaches: qualitative way and quantitative way. In [1] and [2], a qualitative distributed fault diagnosis method is studied, where system decomposition algorithm is used in temporal causal graphs (TCG), fault detection and isolation (FDI) are implemented by qualitative analysis. After that, fault parameters identification is accomplished by Kalman filter (KF). Qualitative methods can detect and isolate possible faults by observing sensor changes without precise numerical calculations. However, because of the imprecision of qualitative method, it is difficult to detect and isolate incipient faults, such as drift faults. Due to the limited discrimination ability of the qualitative method, there are also some difficulties on the ability to deal with multiple faults [3]. Compared with qualitative method, quantitative method has more advantages in dealing with multiple faults and incipient faults because it links closely the fault with the parameter change [4]. Therefore, a model-based quantitative diagnosis method is proposed.

Model-based quantitative distributed fault diagnosis consists of three steps: subsystem models generation using system decomposition algorithm, distributed fault detection and isolation, and distributed fault parameters estimation. The first two steps have been studied in detail in previous work [5]. In this paper, distributed fault estimation will be discussed detailly. Firstly, the global system model is established via bond graph (BG), and subsystems diagnostic bond graphs (SDBGs) are obtained via system decomposition. Then, distributed analytical redundancy relationships (DARRs) can be derived for subsystems fault detection, and distributed fault signature matrix (DFSM) based on DARRs is used to isolate the possible faults. Finally, a set of potential faults (SPF) of each subsystem can be obtained after fault isolation, which corresponds to the estimator of each subsystem. The estimation of possible faults in the estimator is realized by the optimization algorithm. The SPF is updated according to the estimation results, and a set of true faults (STF) is obtained [6]. Compared with the global estimation method, it is not necessary to consider all system parameters in the distributed method, but only to estimate one or more subsystems that may fail [7]. This is the main advantage of distributed fault estimation.

For distributed fault estimation purpose, an improved biogeography-based optimization (IBBO) is proposed in this paper, which modifies the original BBO migration model. The simulation results show that IBBO is an effective method in distributed fault estimation [8][9].

The paper is organized as follows. Section II constructs the SDGBs, DARRs and DFSM of subsystems through system decomposition method, taking a complex circuit system as an example. Section III introduces the principle of IBBO and its implementation method in fault parameters estimation. In section IV, the proposed method is verified by simulation results. Section V concludes this work and puts forward the direction of future research.

II. Distributed Fault Detection and Isolation

In previous work, the system decomposition based on bond graph (BG) model has been introduced in detail, so the specific process of global system decomposition will be omitted in this paper. In this section, we will take a complex circuit system as an example, use system decomposition method to get SDBGs, then deduce DARRs to detect faults, and construct DFSM to

This work was supported by the National Natural Science Foundation of China under Grant 61673154 and Grant 61773149, and the Fundamental Research Funds for the Central Universities under Grant JZ2018YYPY0293.
978-1-7281-0860-5/19/$31.00 ©2019 IEEE

isolate faults. The complex circuit system used in this paper is shown in Fig. 1, and its global diagnostic bond graph (GDBG) is shown in Fig. 2.

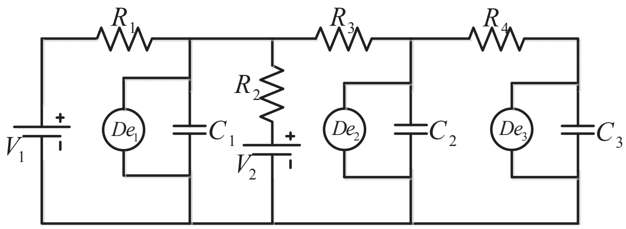


Figure 1. A complex circuit system.

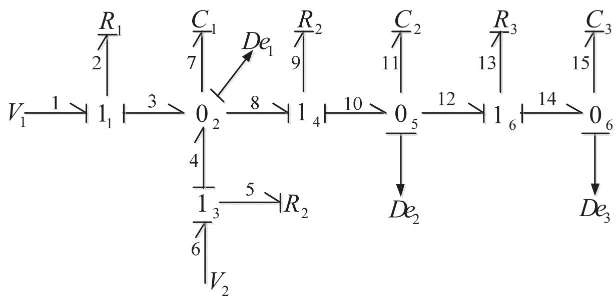
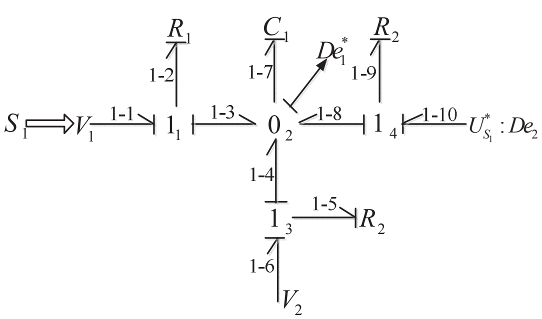


Figure 2. The GDBG of Figure 1.

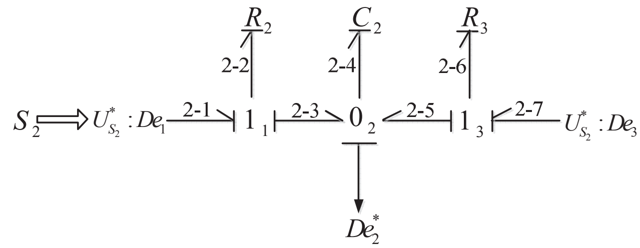
A. System Decomposition and SDBGs

The main idea of the system decomposition method is as follows: The sensor is the core of system decomposition. Through using the nominal measurement of each sensor as the local output of subsystems, each subsystem can be decomposed from the global system. For example in Fig. 2, De_1 is a voltage sensor in global system, and in subsystem 1 (S_1), De_1 is the local output, according to the method mentioned above, the S_1 can be obtained. By the same way, De_2 is the local output of the subsystem 2 (S_2), De_3 is the local output of the subsystem 3 (S_3). Therefore, two other subsystems can be obtained, namely, S_2, and S_3 [5].

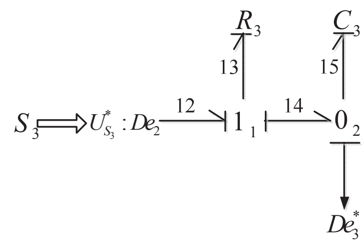
According to the above descriptions, the GDBG shown in Fig. 2 can be decomposed into three subsystems, $S_1, S_2$and S_3, respectively, where S_i represents the *i*th subsystem. The SDBGs obtained after decomposition is shown in Fig. 3.



(1) S_1



(2) S_2



(3) S_3

Figure 3. The SDBGs after system decomposition.

B. DARRs and Fault Detection

After all SDBGs are obtained by system decomposition method, each subsystem can derive a relatively independent analytical redundancy relationships, which is called $DARR_s$. Taking S_1 as an example, $DARR_1$ can be established from junction 0_2 as:

$$DARR_1: i_{1-3} + i_{1-4} + i_{1-8} - i_{1-7} = 0 \tag{1}$$

where

$$i_{1-3} = \frac{V_1 - De_1^*}{R_1} \tag{2}$$

$$i_{1-4} = \frac{V_2 - De_1^*}{R_2} \tag{3}$$

$$i_{1-8} = \frac{(U_{S_1}^*: De_2) - De_1^*}{R_3} \tag{4}$$

$$i_{1-7} = C_1 \frac{d}{dt} De_1^* \tag{5}$$

If one combines (1)~(5), the $DARR_1$ equation can be reformulated as equation (6):

$$DARR_1 = \frac{V_1 - De_1^*}{R_1} + \frac{V_2 - De_1^*}{R_2} + \frac{(U_{S_1}^*: De_2) - De_1^*}{R_3} - C_1 \frac{d}{dt} De_1^* \tag{6}$$

Similarly, other $DARR_s$ can be deduced respectively in this way, as shown in equation (7) and (8). Distributed fault detection can be accomplished by calculating the residuals of each $DARR_s$.

$$DARR_2 = \frac{\left(U_{S_2}^*: De_1\right) - De_2^*}{R_3} + \frac{\left(U_{S_2}^*: De_3\right) - De_2^*}{R_4} - C_2 \frac{d}{dt} De_2^* \tag{7}$$

$$DARR_3 = \frac{\left(U_{S_3}^{*} : De_2\right) - De_3^{*}}{R_4} - C_3 \frac{d}{dt} De_3^{*} \tag{8}$$

C. DFSM and Fault Isolation

Based on the $DARR_s$ obtained in previous section, the DFSM which represents the cause and effect relation between faults and residuals can be established in Table I.

TABLE I. DFSM

θ/dr	dr_1	dr_2	dr_3
R_1	1	0	0
R_2	1	0	0
R_3	1	1	0
R_4	0	1	1
C_1	1	0	0
C_2	0	1	0
C_3	0	0	1
De_1	1	0	0
De_2	0	1	0
De_3	0	0	1

When the system is running, the fault detection can be carried out according to whether the residual values of $DARR_s$ exceed the given threshold. If any subsystem is detected to have faults, a SPF is judged and isolated by DFSM. When the SPF is obtained, it is necessary to collect a piece of data from the corresponding fault subsystem (under fault conditions) for fault estimation to correct the SPF, in order to obtain a STF. Therefore, distributed fault estimation is an essential part of distributed fault diagnosis.

III. IBBO FOR DISTRIBUTED FAULT ESTIMATION

When a set of possible faults is obtained through distributed fault isolation, a swarm intelligence algorithm called IBBO is proposed for distributed fault estimation. BBO is a newly developed bionic algorithm, which is first proposed by D. Simon in 2008. It has some features in common with other heuristic algorithms, such as genetic algorithm (GA) and particle swarm optimization (PSO) [10]. In this decade, BBO has been widely used in many fields and many significant results have been achieved, such as model parameters identification problems and multi-objective optimization problems. BBO has also been proved by many related studies to be an effective method in fault estimation domains, with high adaptive ability and global search ability [11].

BBO is the application of mathematical algorithms for studying the geographical distribution of organisms in optimization problems. An island is any habitat that is geographically isolated from other habitats. A habitat represents a solution with a habitat suitability index (HSI) which indicates the quality of the habitat. Suitability index variables (SIV), which characterize habitability, represent the variables of each solution. Those high HSI habitats mean good solutions, whereas low HSI habitats are deemed to be poor-quality solutions that need to be changed, thus two main steps in BBO is introduced, migration and mutation.

BBO uses migration operations to exchange information between habitats. For the habitat, immigration rate is λ_k and emigration rate is μ_k. The migration mathematical model is shown in Fig. 4, then immigration rate λ_k and emigration rate μ_k can be computed from Fig. 4 as follows:

$$\lambda_k = I\left(1 - \frac{k}{S_{max}}\right) \tag{9}$$

$$\mu_k = \frac{Ek}{S_{max}} \tag{10}$$

where k is the number of species, S_{max} is the size of the habitat, I is the maximum possible immigration rate, E is the maximum possible emigration rate. Suppose that $E=I$, then $\lambda_k + \mu_k = E$.

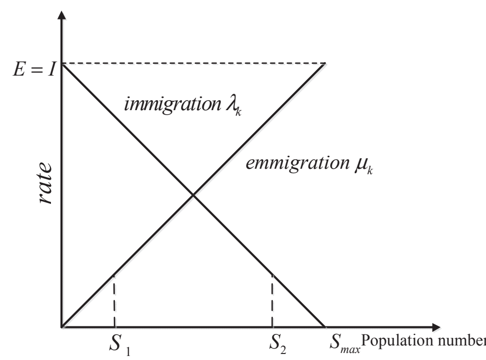


Figure 4. Migration model of BBO.

The HSI of habitat can change suddenly due to random emergencies. This phenomenon can be modeled SIV mutation in BBO algorithm, and the mutation rate m is determined by species count probability called P_s. The solutions with high or low HSI tend to mutate, while the solutions with medium HSI are relatively probable which has low probabilities rate of mutation.

Before calculating the mutation rate m, the P_s should be available. Now, consider the $P_s(t)$ that the habitat contains S species at t. P_s changes from t to $t + \Delta t$ as follows:

$$P_s(t + \Delta t) = P_s(t)(1 - \lambda_s \Delta t - \mu_s \Delta t) + P_{s-1}(t)\lambda_{s-1}\Delta t + P_{s+1}(t)\mu_{s+1}\Delta t \tag{11}$$

where λ_s and μ_s are the immigration and emigration rates when there are S species in this habitat. Similarly, $P_{s-1}(t)$ and $P_{s+1}(t)$ represent the probabilities when there are $S-1$ and $S+1$ species respectively at time t. For the same reason, λ_{s-1} and μ_{s+1} represent the immigration rate for $S-1$ species and emigration rate for $S+1$ species respectively.

Suppose Δt is small enough, we can take the limit of (11) as $\Delta t \to 0$, thus

$$\dot{P}_s(t) = \lim_{\Delta t \to 0} \frac{P_s(t + \Delta t) - P_s(t)}{\Delta t} = -(\lambda_s + \mu_s)P_s(t) + \lambda_{s-1}P_{s-1}(t) + \mu_{s+1}P_{s+1}(t) \tag{12}$$

$$\dot{P}_s = \begin{cases} \Delta_1, & S = 0 \\ \Delta_2, & 1 \le S \le S_{max} \\ \Delta_3, & S = S_{max} \end{cases} \tag{13}$$

where

$$\begin{aligned} \Delta_1 &= -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1} \\ \Delta_2 &= -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_{s+1}P_{s+1} \\ \Delta_3 &= -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} \end{aligned}$$

According to the calculation results of $P_s(t+\Delta t)$, the mutation rate m can be expressed as follows:

$$m = m_{max}\left(\frac{1-P_s}{P_{max}}\right) \tag{14}$$

where m_{max} is a user-defined parameter which is called maximum mutation rate, and P_{max} is the maximum value of P_s.

The migration model of the original BBO is a fairly idealized linear model, which is a simplification of species migration law. However, in the actual process of species migration, migration process more likely to be non-linear. When the number of species in the habitat is large or small, the change of immigration rate and emigration rate tends to be gentle, when the number of species is in the middle, the migration probability changes greatly [11]. According to the above description, a typical function model called cosine function can be associated, as shown in Fig. 5.

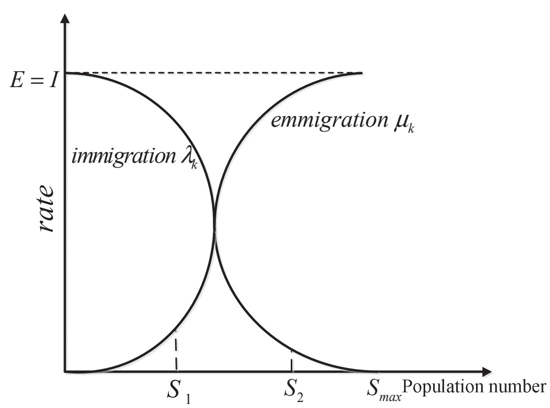


Figure 5. Improved migration model of BBO.

The improved immigration and emigration probabilities can be expressed by the following equations:

$$\lambda_k = \frac{I}{2}\left(\cos\left(\frac{k}{S_{max}}\pi\right)+1\right) \tag{15}$$

$$\mu_k = \frac{E}{2}\left(-\cos\left(\frac{k}{S_{max}}\pi\right)+1\right) \tag{16}$$

In order to apply IBBO in the distributed fault estimation problem, objective function (or fitness function) is required to define for optimization purpose. It can be described as follows:

$$F_{fit} = 1\Big/\sum_{j=1}^{m}\left(\left|DARR_i^j\right| + \varepsilon\right) \tag{17}$$

where ε is a small positive constant, and is used to avoid singular solutions in the search process of IBBO. $DARR_i$ represents the $DARR_s$ of the ith subsystem which requires fault estimation.

IV. Simulation Results

In simulation studies, the nominal values of parameters of the complex circuit system in Fig. 1 are:

$$R_1 = 670\Omega, R_2 = 215.6\Omega, R_3 = 67.5\Omega, R_4 = 215.4\Omega.$$
$$C_1 = 0.001F, C_2 = 0.0047F, C_3 = 0.001F.$$
$$V_1 = \sin(t), V_2 = \sin(t).$$

where sampling time T is T=0.05 second. The operation time of this circuit system is 20 seconds.

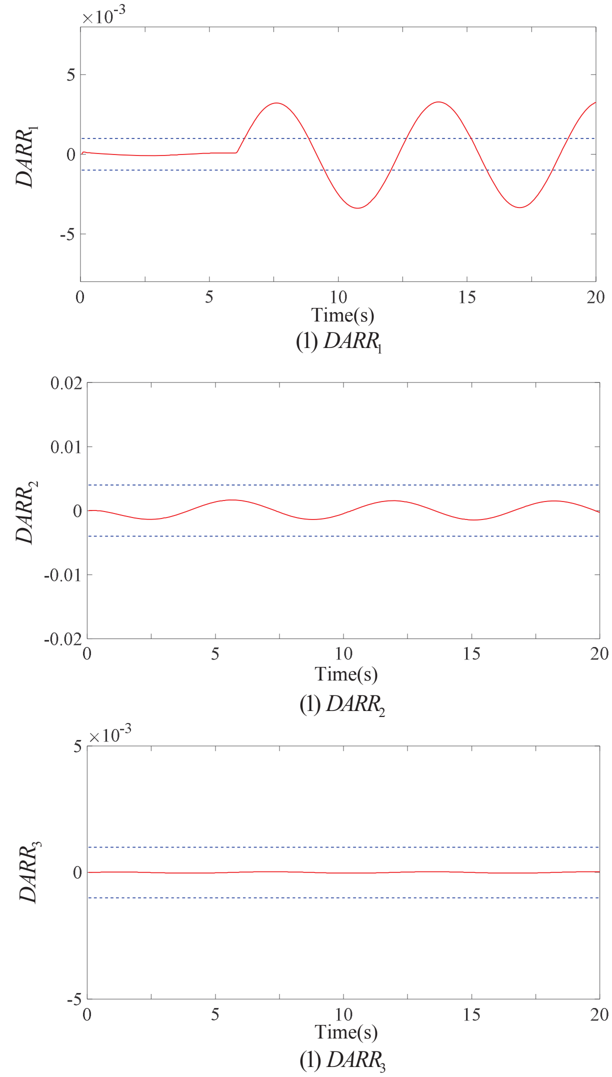


Figure 6. $DARR_s$ of each subsystem.

Faults occur in resistor R_1 from 670Ω to 1000Ω and in resistor R_2 from 215.6Ω to 600Ω at the same time when the system runs to 6s. According to the DFSM, the fault signature should be [1 0 0], and the SPF can be obtained, which is {R_1 R_2}(only resistance faults are considered for the time being in this research). The simulation results of $DARR_s$ are shown in Fig. 6, from the Fig. 6, R_1 and R_2 belong to S_1, therefore, the residual of $DARR_1$ exceeds the threshold. After fault detection and isolation, the subsystems which need fault parameter estimation are identified. The fitness function is given in (17), according to it, $DARR_1$ is required to be written into the objective function, and IBBO is used to identify the set of possible faults, the estimation results are shown in Fig. 7 and Fig. 8. Where the identified R_1 is 998.67Ω, R_2 is 601.2Ω. Through fault estimation process, it is found that the STF is $\{R_1$ $R_2\}$, The simulation results show that it is an effective method proposed in this paper.

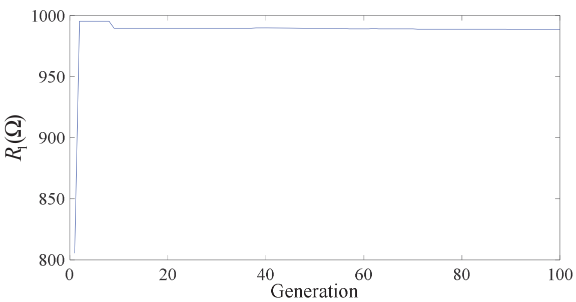


Figure 7. Estimation of parameter R_1.

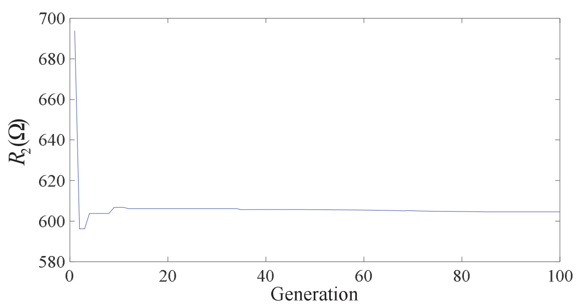


Figure 8. Estimation of parameter R_2.

V. CONCLUSION

In this paper, a distributed fault estimation method based on BG and IBBO is proposed. First, the SDBG is obtained via system decomposition method, DARRs and DFSM are used for distributed fault detection and isolation. Then, IBBO, as a new swarm intelligence optimization algorithm, is used to accomplish distributed fault estimation. Finally, the simulation results show the feasibility of the proposed method. In the future work, the method will be used in a more complex system and the related experiment will be carried out further.

REFERENCES

[1] A. Bregon, G. Biswas, and B. Pulido, "A decomposition method for nonlinear parameter estimation in TRANSCEND," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: System and Humans*, vol. 42, no. 3, pp. 751-763, 2012.

[2] F. Boem, R. M.G. Ferrari, T. Parisini, and M. M. Polycarpou, "Distributed fault diagnosis for continuous-time nonlinear systems: The input-output case," *Annual Reviews in Control,* vol. 37, pp. 163–169, 2013.

[3] M. J. Daigle, I. Roychoudhury, and A. Bregon, "Qualitative event-based diagnosis applied to a spacecraft electrical power distribution system," *Control Engineering Practice,* vol. 38, pp. 75-91, 2015.

[4] Z. W. Gao, C. Cecati, and S. X. Ding, "A survey of fault diagnosis and fault-tolerant techniques—Part I: Fault diagnosis with model-based and signal-based approaches," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 6, pp. 3757–3766, 2015

[5] A. Bregon, G. Biswas, B. Pulido, "A decomposition method for nonlinear parameter estimation in TRANSCEND," *IEEE Transactions on Systems, Man, and Cybernetics—Part A: Systems and Humans*, vol. 42, no. 3, pp. 751–763, 2012.

[6] N. Chatti, B. O. Bouamama, A. L. Gehin, and R. Merzouki, "Signed bond graph for multiple faults diagnosis," *Engineering Applications of Artificial Intelligence,* vol. 36, pp. 134-147, 2014.

[7] M. Yu, D. W. Wang, and M. Luo, "An intergrated approach to prognosis of hybrid systems with unknown mode changes," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 1, pp. 503-515, 2015.

[8] D. Simon, "Biogeography-based optimization," *IEEE Transactions on Evolutionary Computation,* vol. 12, no. 6, pp. 702-713, 2008.

[9] A. Ando, S. Dirk, and K. Ralf, "An auto-deployed model-based fault detection and diagnosis approach for Air Handling Units using BIM and Madelia," *Automation in Construction,* vol. 96, pp. 508-526, 2018.

[10] F. Van den Bergh and A. P. Engelbrecht, "A cooperative approach to particle swarm optimization," *IEEE Transactions on Evolutionary Computation,* vol. 8, no. 3, pp. 225–239, 2004.

[11] D. Simon, R. Rarick, M. Ergezer, and D. Du, "Analytical and numerical comparison of biogeography-based optimization and genetic algorithms," *Information Sciences,* vol. 18, pp. 1224-1248, 2011.