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# Survey on Biogeography Based Optimization Algorithm and Application of Biogeography Based Optimization to determine Parameters of PID Controller

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**Abstract:** Biogeography is the study of the distribution of species over space and time. Naturists and biologists have studied this for few decades. Recently, the theory of biogeography has been applied to solve difficult engineering optimization problems. The algorithm that is popularly used is biogeography based optimization (BBO). In this paper, a brief survey on biogeography based optimization is carried out. The system model of immigration and emigration of organisms in an island biogeography system is used as the basis of BBO to find unknown parameters of PID controller because it is difficult to achieve the proper values of the parameters $K_p$, $K_i$ and $K_d$ in PID controller. The approach is based on the search for global optimum value for the PID control parameters with the help of cost functions which converges to minimum value having minimum error. Finally the time and frequency domain responses are founded with the help of simulation and compared.

**Keywords** : Biogeography Based Optimization (BBO), Immigration, Emigration, Habitat Suitability Index (HSI), PID Controller.

## I. INTRODUCTION

Biogeography is the study of the geographical distribution of biological organisms. Biogeography based optimization (BBO) algorithm is a optimization algorithm based on Biogeography [1,9]. It is designed based on the migration strategy of animals to solve the problem of global optimization. The mathematical equations that govern the distribution of organisms were first discovered and developed during the 1960s. The researchers can learn from nature and can use the concept in the application of biogeography to optimization problem [1]. This paper considers the mathematics of biogeography as the basis for the development for finding out the unknown parameter of PID controller using the biogeography-based optimization (BBO). The application of biogeography to engineering is similar to what has occurred in the past few decades with other evolutionary algorithm like genetic algorithm (GA), neural networks, fuzzy logic, particle swarm optimization (PSO) and other areas of computer intelligence.

The BBO migration strategy is similar to the global recombination approach of evolutionary strategies (ES) (B¨ack, 1996), (B¨ack et al., 1997), in which many parents can contribute to a single offspring. Global recombination has also been adapted to GA (Eiben, 2003), (Eiben, 2000) but BBO differs from GAs in one important aspect. In GA recombination is used to create new solutions, while in BBO migration is used to change existing solutions. Global recombination in ES is a reproductive process, which creates new solutions, while BBO migration is an adaptive process that modifies existing solutions. A quantitative comparison between BBO and other EAs is included in Simon (2008), where 14 benchmark functions, each with 20 dimensions, were studied [1].

The control system is used to obtain desired static and dynamic characteristics of closed loop systems. PID (Proportional Integral Derivative) control is one of the earlier control strategies which are used for controlling any plant transfer function. Now to get better efficiency, the actual output should be matched with the set output. Hence some control action should be carried out. Since many control systems using PID controller gives satisfactory result and it helps to tune the control parameters to the optimum values, it is used in industrial control. Now there are various methods to obtain optimum values of the parameters of PID controller for the purpose of tuning [10]. The classical methods are Ziegler Nichols method, Ziegler Nichols reaction curve method [11], Cohen Coon reaction curve method [12] etc. But recently the use of Evolutionary algorithm for tuning the parameters has increased drastically. Genetic Algorithm (GA), Biogeography Based Optimization (BBO) , Particle Swarm Optimization (PSO), Differential Evolutionary (DE) Algorithm, Ant Colony Optimization (ACO) etc are generally used to tune the unknown parameters.

In this paper three types of transfer functions (Type 0, Type 1 and Type 2) are taken and the PID controller block is attached before these transfer function blocks. The tuning of parameters of the PID controller is carried out by

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using Biogeography Based Optimization. Finally the time domain and frequency domain responses are generated after fitting all the tuned parameters and comparisons are made. The main objective of this paper is to show that a system can be optimized by using Biogeography Based Optimization.

## II. SURVEY ON BIOGEOGRAPHY BASED OPTIMIZATION

The mathematical model of biogeography describe how species migrate from one island to another, how new species arise and how species become extinct [1-3]. Geographical areas that are well suited as residences for biological species are said to have a high habitat suitability index (HSI). Features that correlate with HSI are rainfall, diversity of vegetation, diversity of topographic features, land area and temperature. The variables that characterize habitability are called suitability index variables (SIV). SIVs are the independent variables of the habitat and HSI can be considered as the dependent variable. Habitats with a high HSI tend to have a large number of species and those with a low HSI have a small number of species. Habitats with a high HSI have many species that emigrate to nearby habitats. Habitats with a high HSI have a low species immigration rate because they are already nearly saturated with species. Therefore, high HSI habitats are more static in their species distribution than low HSI habitats. The high HSI habitats have a high emigration rate. Hence the large number of species on high HSI islands will tend to emigrate to neighbouring habitats. The species is not completely disappears from its home habitat. Only a few representatives emigrate. Habitats with a low HSI have a high species immigration rate. This immigration of new species to low HSI habitats may raise the HSI of the habitat, because the suitability of a habitat is proportional to its biological diversity.

A good solution is analogous to an island with a high HSI, and a poor solution represents an island with a low HSI. High HSI solutions resist change more than low HSI solutions. The high HSI solutions tend to share their features with low HSI solutions. Hence new features are appearing in the low HSI solutions. The model of species for a single habitat is shown in Figure 1. The immigration rate λ and the emigration rate μ are functions of the number of species in the habitat.

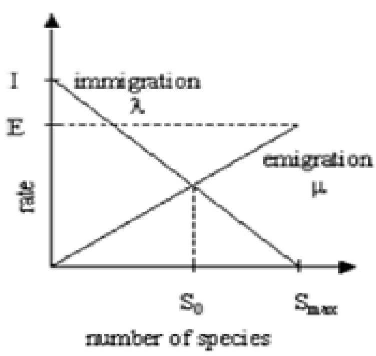


Figure.1. Species model of a single habitat based on biogeography

From the immigration curve, the maximum possible immigration rate to the habitat is I and this occurs when there are zero species in the habitat. As the number of species increases, the habitat becomes more crowded, fewer species are able to successfully survive immigration to the habitat, and the immigration rate decreases. The largest possible number of species that the habitat can support is $S_{max}$, at which point the immigration rate becomes zero. From the emigration curve if there are no species in the habitat then the emigration rate must be zero. As the number of species increases, the habitat becomes more crowded. The maximum emigration rate is E, which occurs when the habitat contains the largest number of species that it can support.

The immigration and emigration curves is shown in Figure 1 as straight lines but, in general, they might be more complicated curves [1, 4-5].

The probability $P_s$ is the habitat contains exactly S species. Ps changes from time t to time (t + Δ t) and denoted as ,

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

where $\lambda_s$ and $\mu_s$ are the immigration and emigration rates when there are S species in the habitat. This equation holds because in order to have S species at (t + Δt) time, one of the following conditions must hold:

- There were S species at time t, and no immigration or emigration occurred between t and (t + Δt);
- There were (S - 1) species at time t, and one species immigrated;
- There were (S + 1) species at time t, and one species emigrated.

It is assumed that Δ t is small enough so that the probability of more than one immigration or emigration can be ignored.

Taking the limit of (1) as Δ t → 0 gives equation (1) shown as follows:

$$\mathring{P}_s = \begin{cases} -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1} & S = 0 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_{s+1}P_{s+1}, & 1 \le S \le S_{max} - 1 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} & S = S_{max} \end{cases} \quad \text{------} \quad (2)$$

Say, $n = S_{max}$ and $P = [P_0 P_1 P_2 ......... P_n]^T$

Now, we can arrange the equations of equation (2) into the single matrix equation

$$\mathring{P} = AP \quad \text{------} \quad (3)$$

Where the matrix A is given in the following equation:

$$A = \begin{bmatrix} -(\lambda_0 + \mu_0) & \mu_1 & 0 & \dots & 0 \\ \lambda_0 & -(\lambda_1 + \mu_1) & \mu_2 & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \lambda_{n-2} & -(\lambda_{n-1} + \mu_{n-1}) & \mu_n \\ 0 & \dots & 0 & \lambda_{n-1} & -(\lambda_n + \mu_n) \end{bmatrix} \quad \text{-------} \quad (4)$$

For the straight-line curves shown in Figure 1, we have

$$\mu_k = \frac{Ek}{n} \quad \text{---------------------------} \quad (5)$$

$$\lambda_k = I\left(1 - \frac{k}{n}\right)$$

Now for special case E= I, then

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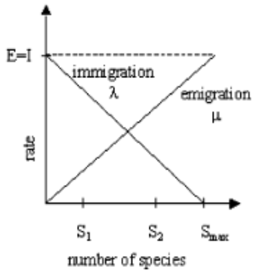
$$\lambda_k + \mu_k = E \quad ------------------------(6)$$

According to the simplified form stated in equation (6), the species model will be the following type.




(Figure 2: $S_1$ is relatively a poor solution and $S_2$ relatively a good solution)

***Formulation of the Algorithm:***

***a) Migration:*** Generally each integer in the solution vector is considered to be an SIV. The assessment for the goodness of the solutions has to be done. The solutions that are good are considered to be habitats with a high HSI and those that are poor are considered to be habitats with a low HSI. HSI is analogous to "fitness" in other population-based optimization algorithms (GAs, BBOs for example).

$S_1$ in Figure 2 represents a low HSI solution (i.e. habitat with only a few species) while $S_2$ represents a high HSI solution (i.e. habitat with many species).

The immigration rate $\lambda_1$ for $S_1$ will be higher than the immigration rate $\lambda_2$ for $S_2$.
The emigration rate μ1 for $S_1$ will be lower than the emigration rate μ2 for $S_2$.

The emigration and immigration rates of each solution probabilistically share information between habitats. With probability $P_{mod}$, each solution is modified based on other solutions. If a given solution is selected to be modified, then the immigration rate λ to probabilistically decide whether or not to modify each SIV in that solution. If a given SIV in a given solution $S_i$ selected to be modified, then the emigration rates μ of the other solutions to probabilistically decide which of the solutions should migrate to solution $S_i$. To retain the best solutions in the population, some sort of elitism is incorporated to prevent the best solutions from being corrupted by immigration [1, 4-5].

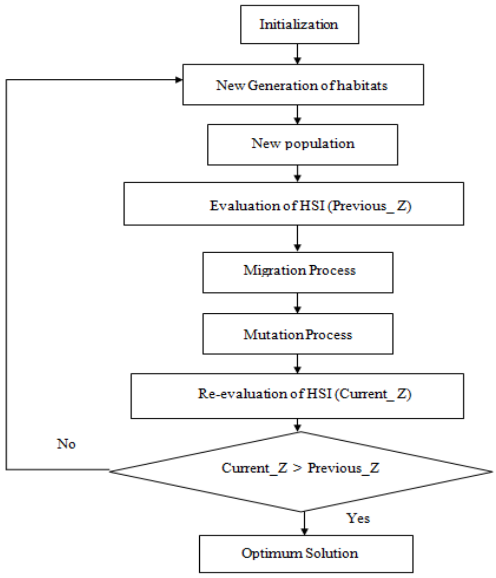
***b) Mutation:*** A habitat's HSI can change suddenly due to apparently random events (unusually large flotsam arriving from a neighbouring habitat, disease, natural catastrophes etc.). The model of BBO as SIV mutation and species count probabilities is used to determine mutation rates.

The probabilities of each species count will be governed by the differential equation given in (3). From Figure 2, it is observed that low species counts and high species counts both have relatively low probabilities and medium species counts have high probabilities because they are near the equilibrium point.

Each population member has an associated probability on to the given problem. Very high HSI solutions and very low HSI solutions are equally improbable. Medium HSI solutions are relatively probable. If a given solution S has a low probability $P_s$, then it is surprising that it exists as a solution. It is, therefore, likely to mutate to some other solution. Conversely, a solution with a high probability is less likely to mutate to a different solution. The mutation rate and given by,

$$m_i = m_{\max}\left(1 - \frac{P_i}{P_{\max}}\right) ------------(7)$$

where $m_{max}$ is a user-defined parameter, and $P_{max}$ = argmax$P_i$,
i = 1,...NP .




(Flowchart of the algorithm)

## III. MODELLING OF CONTROL SYSTEM

In Control Engineering, any model is represented by transfer function. Mathematically the transfer function is a function of complex variables. In this paper three types of transfer functions (Type 0, Type 1 and Type 2) are taken and the PID controller block is attached before these transfer function blocks. The popularity of PID controllers in industry has increased due to their applicability, functional simplicity and reliability in performance. Moreover, there is a wide conceptual understanding of the effect of the three terms involved amongst non-specialist plant operators. In general, the synthesis of PID can be described by,

$$u(t) = K_p e(t) + K_i \int_0^t e(t)dt + K_d \frac{de(t)}{dt} ---------(8)$$

where e(t) is the error and e(t) = r(t) – y(t) , r(t) is the reference input, u(t) is the controller output, and $K_p$, $K_i$, and $K_d$ are the proportional, Integral and derivative gains.
For a simple feedback control system with PID controller, the transfer function of the PID controller is described by,

$$G_{pid}(s) = K_p + \frac{Ki}{s} + sK_d --------------(9)$$

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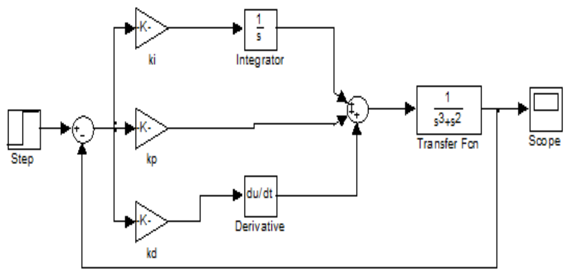
The proportional term provides an overall control action which is proportional to the error signal through the constant gain factor. The integral term is the action which is to reduce steady-state errors through low-frequency compensation by an integrator. The derivative term improves transient response through high-frequency compensation by a differentiator. The system is designed at SIMULINK toolbox and represented in **Figure 3**




(Figure 3 Simulink model of a PID controller with a system)

The tuning of the parameters is applied for modelling the system. In this paper optimization method is introduced for the purpose of tuning the PID parameters. These methods utilize offline numerical optimization methods for a single composite objective with the help of evolutionary algorithm to search the best solution. Further the rise time, maximum overshoot, settling time, gain margin, phase margin are measured to check the stability of the system.

A set of performance indicators may be used as a design tool to evaluate tuning method [13]. The performance indicators which are generally used for tuning are Integral Squared Error (ISE), Integral Absolute Error (IAE), Integral Time-Weighted Absolute Error (ITAE) and Integral Time-Weighted Squared Error (ITSE). In this paper Integral Absolute Error (IAE) is taken as performance indicator [8] and it is denoted by,

$$J_{IAE} = \int_0^t |e(t)|dt \text{ ------------------------ } (10)$$

## IV. SIMULATED RESULTS OF CONTROL SYSTEM PARAMETERS BY USING BBO

The BBO should be provided with a population of PID sets. The initial population for choosing PID parameters are derived from the trial and error method where the following specifications are maintained: Population Size=50, Chromosome Length=20, Crossover Rate=0.5 and Mutation Rate=0.05. With the given specifications, the PID parameters are obtained using BBO programming as $K_p$ = 8.15, $K_d$= 0.084 and $K_i$ = 0.00854. After tuning the PID parameters Using BBO, the transfer function of the controller becomes,

$$G_{pid}(s) = 8.15 + \frac{0.00854}{s} + 0.084s \text{ ---------------- } (11)$$

All the plots after tuning the PID parameters are given below.

With the optimized PID parameters the fitness distributions are plotted in **Figure 4(a)-4(c)**.From the fitness distribution with respect to the number of generation plot, we can see that the near optimal values of feedback gains can obtain with in 50 generations.

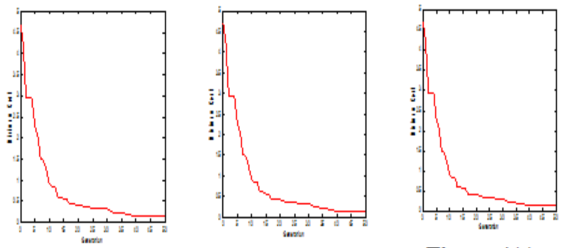


**Figure 4(a)** **Figure 4(b)** **Figure 4(c)**

**Figure 4(a)-(c):** Fitness value w.r.t. the no. of generation for tuning $K_p$,$K_d$ and $K_i$ respectively)

For **Type 0, Type 1 and Type 2** transfer functions, the time domain response curves and frequency domain response curves for the closed loop system (Figure 3) are plotted in **Figure 5(a)-5(f)**.

Using Type 0 System

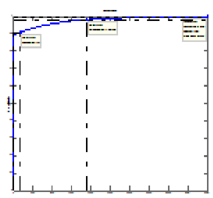


Figure 5(a)

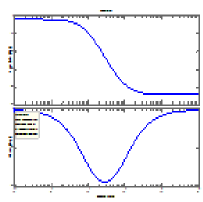


Figure 5(b)

Using Type 1 System

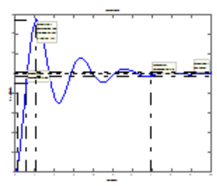


Figure 5(c)

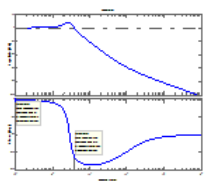


Figure 5(d)

Using Type 2 System

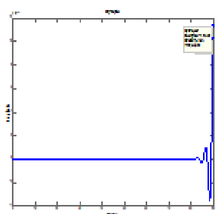


Figure 5(e)

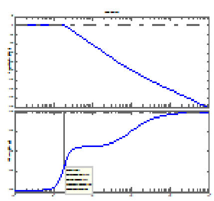


Figure 5(f)

In Figure 5(a), (c), (e) all the time domain step responses are shown and in Figure 5(b), (d), (f) all the frequency responses are shown.

The comparative study of the obtained parameters are made and shown in the table 1.

Comparative study of time domain parameters and frequency domain parameters after tuning PID parameters using BBO for Type 0, Type 1 and Type 2 systems

| Parameters | **Using BBO Algorithm** | | |
|---|---|---|---|
| | **Type 0** | **Type 1** | **Type 2** |
| Rise time | 181 | 0.498 | N.A. |
| Settling time | 1910 | 6.86 | N.A. |
| Peak amplitude | 0.999 | 1.5 | $1.14*10^{12}$ |
| Percentage Overshoot | 0% | 49.7% | Very high |
| Gain Margin | Infinity | Infinity | Infinity |
| Phase Margin | -180˚ | 38.1323˚ | -122.49˚ |
| Stability of the system | Stable | Stable | Unstable |

(Table 1)

The results obtained from the step response and frequency response of the systems is shown in Table 1. It is clear that rise time and settling time are better when Type 1 system is used. Hence the system response will be faster. The performance of BBO in case of Type 1 system is better than Type 0 and Type 2 systems because most of the parameters have small values. Phase margin is also less for Type 1 system. But in case of Type 2 system , the peak amplitude rises very much and most of the other parameters become uncontrollable and hence stability is decreased.

## IV. CONCLUSION

This paper presents the brief idea of Biogeography Based Optimization (BBO).The mathematical expression for species migration and immigration are surveyed and expressed in this paper. Also the application of optimization method on PID control parameters for the purpose of tuning the parameters of PID controller rather than using classical method of tuning the parameters is discussed. Biogeography Based Optimization (BBO) is used as search techniques to find the optimum values of the parameters $K_p$, $K_d$ and $K_i$ with the help of cost function. From the obtained results, it is obvious that the performance of BBO is better in case of Type 1. It is observed that with the increase of type of the transfer function, the system stability is decreased which is the major disadvantage of this approach. It seems to be easy to adapt the method presented here to tune other controller types, where optimization is involved.

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