International Journal of Advanced Science and Technology
Vol.115 (2018), pp.45-52
http://dx.doi.org/10.14257/ijast.2018.115.05

Employee Ranking Application using Univariate Marginal Distribution Algorithm (UMDA)

Ch. Viswanathsarma[1], Debnath Bhattacharyya[2] and Tai-hoon Kim[3*]

[1,2]Department of Computer Science and Engineering,
Vignan's Institute of Information Technology,
Visakhapatnam-530049, India
[3]Department of Convergence Security, Sungshin Women's University,
249-1, Dongseon-dong 3-ga, Seoul 136-742, South Korea
*[1]vissu.viit@gmail.com, [2]debnathb@gmail.com, [3]*taihoonn@daum.net*

Abstract

In powerful conditions, it is critical to track changing ideal arrangements after some time. Univariate Marginal Distribution Algorithm (UMDA) which is a class calculation of estimation of conveyance calculations pulls in more consideration lately. In this paper another multi-population UMDA (MDUMDA) is proposed for dynamic multimodal issues. This approach utilizes both the data of current population and the part history data of the ideal arrangements. The exploratory outcomes demonstrate that the MDUMDA is successful for the capacity with moving ideal and can adjust to the dynamic conditions quickly. Employee ranking application gives ranking of every employee in light of various characteristics.

Keywords: *Univariate Marginal Distribution Algorithm, Optimization, Ranking*

1. Introduction

Albeit the vast majority of the enhancement issues examined in the logical writing is static, some true issues are dynamic for example, information mining in persistently refreshing databases, booking issues with dynamic accessible assets [1,2]. In these dynamic improvement issues, the assessment capacity (or wellness work) and the requirements may change after some time. So for these issues the improvement calculation needs to track a moving ideal as nearly as could be expected under the circumstances, as opposed to simply finds a solitary decent arrangement. This structures a genuine test to customary transformative calculations since they can't adjust well to a changed situation once united [3]. Typically, the dynamic condition expects EAs to keep up adequate decent variety for a constant adjustment to the evolving scene.

Notwithstanding, much of the time, the learning about past pursuit space might be useful to quicken the inquiry in the recently changed condition. So great adjustment for dynamic enhancement calculations should keep up and increment the assorted variety and make full utilization of learning of past condition. There are numerous techniques that have been proposed for dynamic advancement issues [5].

1.1. Employee Ranking Application

The current application proposed in the article concentrates on the performance of employees in both work as well as other fields to select best performer of the employee in an academic year. This system deals with ranking of the employee based on multiple

Received (December 18, 2017), Review Result (March 11, 2018), Accepted (March 20, 2018)
* Corresponding Author

ISSN: 2005-4238 IJAST

activities like Academic performance, Awards received, Personal achievements, and publication of books & Journals in a particular organization. The priorities for different parameters (performance, achievements, awards, book publications) are taken as input and then optimize this multi objective function based on UMDA algorithm [6].

The residual division of the article is alienated as various sections. Part 2 of the article discusses about optimization problem. Part 3 of the article reviews Univariate Marginal Distribution Algorithm (UMDA).

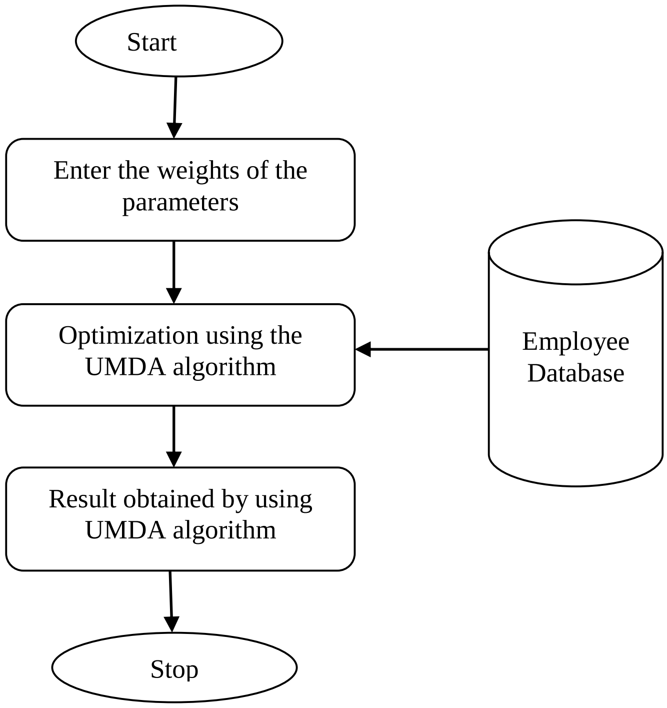

Figure 1. Steps for Processing ERA Application

2. Optimization

Optimization technique deals with the issue of minimizing or maximizing a specific work in a restricted dimensional Euclidean space over a subset of that space [8]. When all is said in done it could be a strategy to pick the main plan (regarding a few criteria) from an arrangement of feasible courses of action Developmental computations can deal with colossal look spaces, multi target limits, multimodal limits. They use randomized techniques to reach at game plan speedier which may something different take lifetime. They perform all around in fact when there's little or no space specific data roughly the look space. They are favored for issues with giant course of action space, little or no space specific data and where little piece of error, imprecision and insecurity is an agreeable exchange off for snappier, moo brought, sensible and vivacious figuring. Regardless of the way that randomized these counts use information from past cycles and advances the course of action space to guide it towards the perfect plan. Developmental calculations are stochastic hunt predicated procedure which purposely incorporates aimlessness to test procedure to sidestep being gotten at nearby optima.

3. Univariate Marginal Distribution Algorithm (UMDA)

UMDA is a probability model-based evolutionary algorithm and attracts more and more attentions in recent years. UMDA works on the idea of the probability methods and the performance or the behavior of the method can be observed and analyzed by using mathematical equations and with some graphical representations.

The Univariate Marginal Distribution Algorithm fit in to the ground of Estimation of Distribution Algorithms (EDA), withal alluded to as Population Model-Building Genetic Algorithms (PMBGA), an augmentation to the field of Evolutionary Computation. It utilizes a likelihood vector and people of the populace are made through the testing.

Like other EA, the populace loses the assorted variety when UMDA merges. In such a case, UMDA should be adjusted for ideal outcomes on unique advancement issues. The multi populace and dissemination UMDA (MDUMDA) for dynamic advancement issues in order to expand the assorted variety with manage mold after a change. The accompanying is the proposed calculation. Keeping in mind the end goal to test the execution of the proposed calculation, the moving pinnacles benchmark (MPB) is utilized. The MPB has as of late turned into the standard testing issue for dynamic advancement.

3.1. Algorithm

The information dispensation approach of the algorithm is to make use of the occurrence of the machinery in a populace of contender resolutions in the building of original applicant resolutions. This is attained by primarily calculate the occurrence of every constituent in the populace (the univariate insignificant likelihood) and by means of the likelihood to manipulate the probabilistic collection of mechanism in the component-wise structure of novel applicant explanations.

UMDA works as follows:

Step1 : Initialize a population $\{y_i\}$, i ε [1,M]
Each y_i includes n bits yi(1)…………yi(n)

Step 2 : While termination criterion meets

i. Select P individuals as {yi} according to fitness where P<M
ii. Index the P selected individuals as $\{y_k\}$, for k ε [1,M]
iii. Calculate the probability function as follows for each individual selected.

$$\Pr ob(y(k)=1)=\sum_{i=1}^{P}\frac{\delta(y_i(k)-1)}{P}$$

Step 3: For i=1toM (Size of the population taken at step 1)

For k=1 to n (no of bits in each candidate solution)
s ← U[0,1]
If (r < Prob (y (k) =1))
y_i (k)← 1
Else
y_i (k)← 0
End if
Next bit
Next individual
Next Generation

Where,

1. $\delta(y)=\begin{cases}1, y=0\\0, y\neq 0\end{cases}$
2. y_i (k) denotes k^{th} bit in the i^{th} individual
3. s can be considered as a random point among 0 and 1

3.2. Procedure:

The Procedure of Univariate Marginal Distribution Algorithm is as follows:

Initialize Population
Evaluate Population
Get the Best Solution (Population)
While (termination condition)
    Select best Fit Solutions (Population)
    Calculate probability function of Components (Selected Population)
    Generate Offspring
For (To)
    Probabilistically Construct Solution for Offspring
    End
Evaluate Population of Offspring
Get Best Solution of Offspring
Population Offspring
End
Return

Example : Consider a sample population of size 3

y1	0 1 0 0 1 0 1
y2	1 1 0 1 0 1 0
y3	0 0 0 1 1 0 1

Where $y_1(1) = 0$, $y_1(2) = 1$, $y_1(3) = 0$, $y_1(4) = 0$, $y_1(5) = 1$, $y_1(6) = 0$ and $y_1(7) = 1$

$$\delta(y) = \begin{cases} 1 & y = 0 \\ 0 & y \neq 0 \end{cases} \qquad k€[1,n]$$

Finding the Probability function:

$$\mathrm{Prob}(y(k)=1) = \sum_{i=1}^{n} \frac{\delta(y_i(k)-1)}{P}$$

$$\mathrm{Prob}(y(1)=1) = \sum_{i=1}^{3} \frac{\delta(y_i(1)-1)}{P} = \frac{\delta(y_1(1)-1)+\delta(y_2(1)-1)+\delta(y_3(1)-1)}{3}$$
$$= \frac{\delta(0-1)+\delta(1-1)+\delta(0-1)}{3}$$
$$= \frac{\delta(-1)+\delta(0)+\delta(-1)}{3}$$
$$= \frac{0+1+0}{3} = 0.333$$

$$\mathrm{Prob}(y(2)=1) = \sum_{i=1}^{3} \frac{\delta(y_i(2)-1)}{P} = \frac{\delta(y_1(2)-1)+\delta(y_2(2)-1)+\delta(y_3(2)-1)}{3}$$
$$= \frac{\delta(1-1)+\delta(1-1)+\delta(0-1)}{3}$$
$$= \frac{\delta(0)+\delta(0)+\delta(-1)}{3}$$
$$= \frac{1+1+0}{3} = 0.666$$

$$\mathrm{Prob}(y(3)=1) = \sum_{i=1}^{3} \frac{\delta(y_i(3)-1)}{P} = \frac{\delta(y_1(3)-1)+\delta(y_2(3)-1)+\delta(y_3(3)-1)}{3}$$
$$= \frac{\delta(0-1)+\delta(0-1)+\delta(0-1)}{3}$$
$$= \frac{\delta(-1)+\delta(-1)+\delta(-1)}{3}$$
$$= \frac{0+0+0}{3} = 0$$

Similarly, we get

$$\Pr ob(y(4)=1)=\sum_{i=1}^{3}\frac{\delta(y_i(4)-1)}{P}=\frac{2}{3}=0.666$$

$$\Pr ob(y(5)=1)=\sum_{i=1}^{3}\frac{\delta(y_i(5)-1)}{P}=\frac{2}{3}=0.666$$

$$\Pr ob(y(6)=1)=\sum_{i=1}^{3}\frac{\delta(y_i(6)-1)}{P}=\frac{1}{3}=0.333$$

$$\Pr ob(y(7)=1)=\sum_{i=1}^{3}\frac{\delta(y_i(7)-1)}{P}=\frac{2}{3}=0.666$$

4. Experimentation and Results

The experimentation of the current work or the current method was performed by using Java platform (jdk 1.8). To test the current method, we had collected a dataset of data from Vignan‟s Institute of Information Technology, Visakhapatnam which consists of various employee records. The dataset contains 50 employee records.

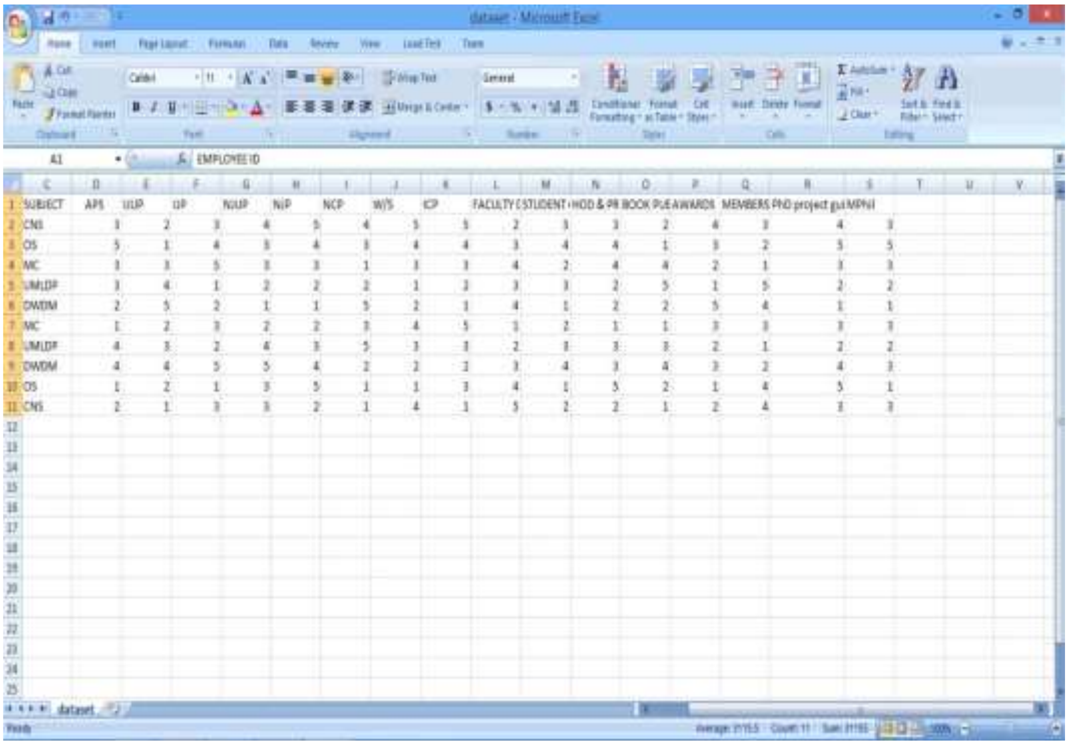

Figure 2. Data Set of Employee Records

a) Here the data set consists of the multiple activities like Academic performance, Awards received, Personal achievements, and publication of books & Journals in a particular organization.

Each activity scaled on between the ranges 0-5 based on the parameters it consists of. For example consider the research activity which is scaled between 0-5 based on the following parameters

a) No Paper publications/workshops/seminars/conferences in an academic year : 0

b) Papers published in national journals : 1-2

c) Papers published in International journals (if The article/paper must be HIndexed /SJR indexed/Scopus / Thomson Reuters indexed journal) : 3-5

d) Books published : 3-5

e) Conferences/Seminars/Workshops attended : 3-5

f) Conferences/Seminars/Workshops Conducted : 3-5

Like the above all actives will be scaled between 0-5(max) based on different parameters.

b). Once the database created like above then it will be normalized to get the values between the ranges from 0-1 by using standard normal distribution.

c) After getting the values the between 0-1 we applied the optimization algorithm Univariate Marginal Distribution Algorithm (UMDA) to the above database, by which the database optimized and after 30-50 iterations it outputs the final database with rankings each faculty.

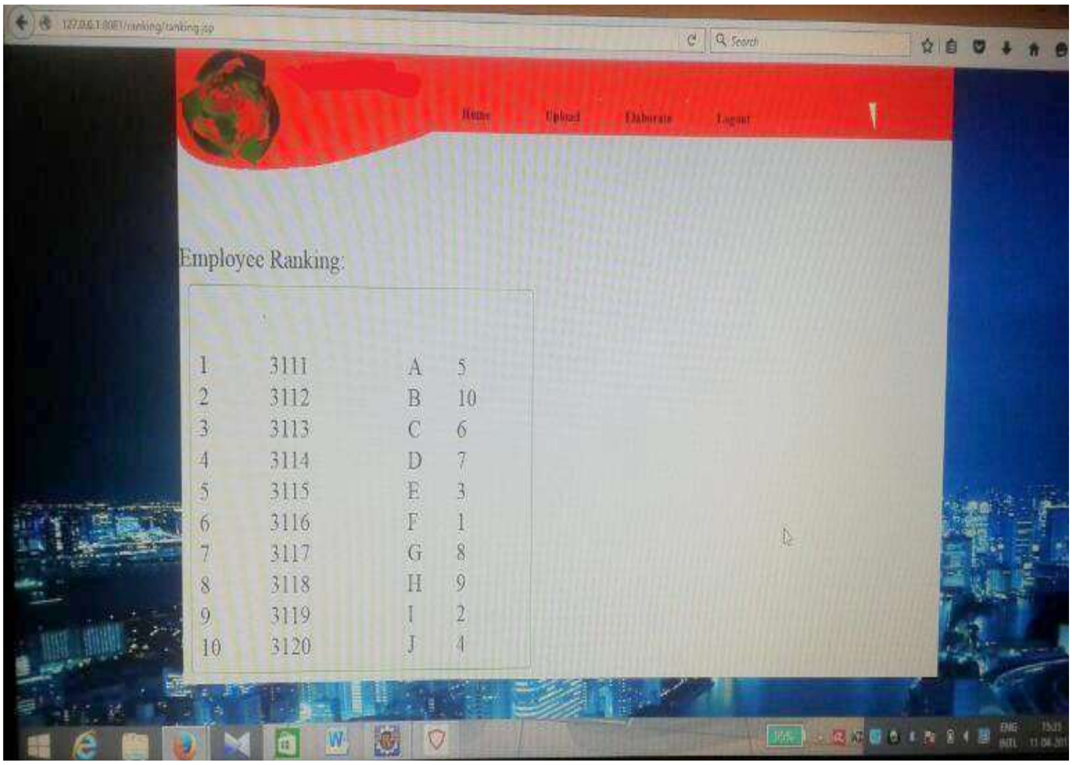

Figure 3. Result of Employee Ranking System using UMDA Algorithm

d) The following figure gives us the information about the various field selected and also count of each label which are represent in the graph

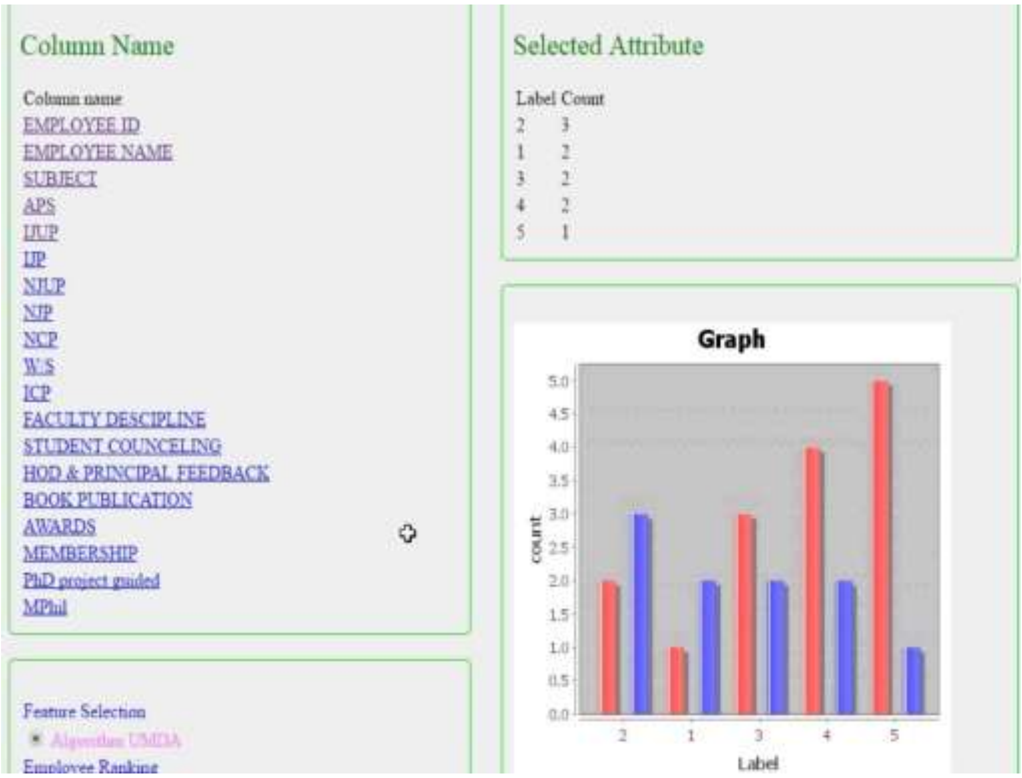

Figure 4. Graphical Representation Journals Count

Figure 5. Graphical Representation Employee ID Count

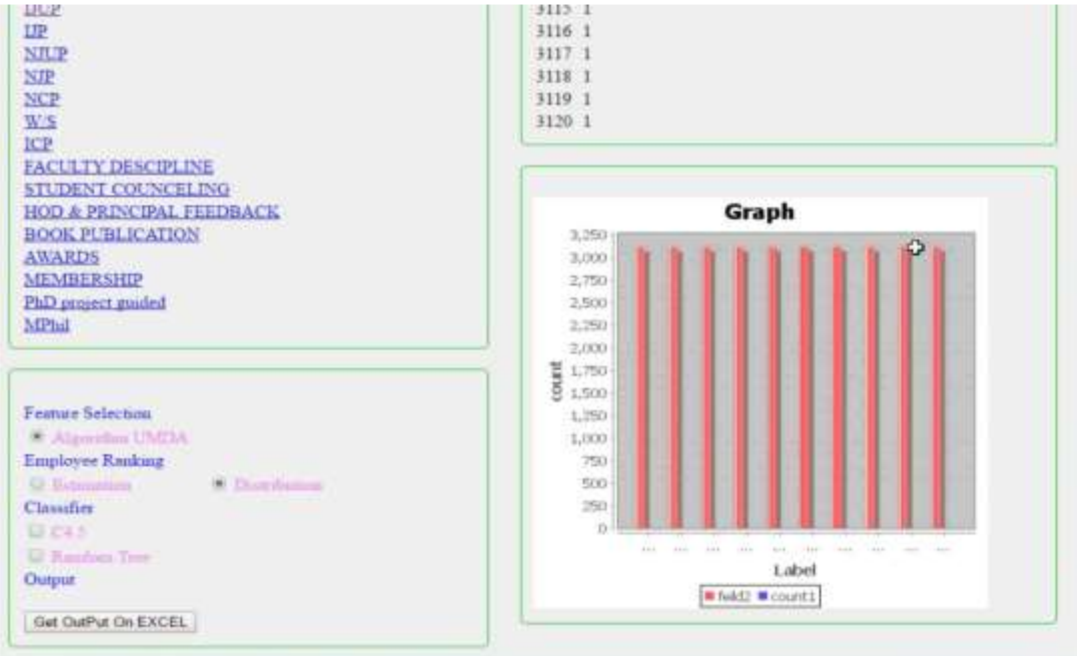

Figure 6. Graphical Representation Employee ID Count

5. Conclusion

In a dynamic multimodal condition, it is essential for calculations to discover various optima in parallel and persistently track the moving ideal after some time. In this paper we explore and enhance UMDA to handle dynamic situations. This approach is constituted by the multi populace and dispersion show. The inspiration of utilizing multi-populace approach is to find various pinnacles. The principle thought of the dispersion demonstrate is to build the assorted variety in a guide mold after a change and develop the hunt space slowly from past ideal arrangement.

References

[1] Y. Leung and Y. Wang, "An orthogonal genetic algorithm with quantization for global numerical optimization", IEEE Trans. on Evolutionary Computation, vol. 5, no. 1, **(2001)**, pp. 41-53.
[2] Y. Jin and J. Branke, "Evolutionary optimization in uncertain environments-a survey", IEEE Trans. on Evolutionary Computations, vol. 9, no. 3, **(2005)**, pp. 1-15.
[3] H. G. Cobb, "An investigation into the use of hypermutation as an adaptive operator in genetic algorithms having continuous, time-dependent nonstationary environment", Washington: Naval Research Laboratory, **(1990)**, pp. 1-6.
[4] R. W. Morrison and K. A. de Jong, "Triggered hypermutation revisited", Proc. of Congress on Evolutionary Computation, Piscataway: IEEE Service Center, **(2000)**, pp. 1025-1032.
[5] J. J. Grefenstette, "Genetic algorithms for changing environments", Parallel Problem Solving from Nature, **(1992)**, pp. 137-144.
[6] D. E. Goldberg and R. E. Smith, "Nonstationary function optimization using genetic algorithms with dominance and diploidy", Proc. of the 2nd Int. Conf. on Gene tic Algorithms, **(1987)**, pp. 59-68.
[7] S. Yang, "Memory-enhanced univariate marginal distribution algorithms for dynamic optimization problems", IEEE Congress on Evolutionary Computation, **(2005)**, pp. 2560-2567.
[8] Y. Wu, Y. Wang and X. Liu, "Multi-population univariate marginal distribution algorithm for dynamic optimization problems", Control and Decision, vol. 23, no. 12, **(2008)**, pp. 1401-1406.
[9] T. Blackwell and J. Branke, "Multiswarms, exclusion, and anticonvergence in dynamic environments", IEEE Trans. on Evolutionary Computation, vol. 10, no. 4, **(2006)**, pp. 459-472.
[10] P. Larra˜naga, R. Etxeberria and J. A. Lozano, "Optimization by learning and simulation of Bayesian and Gaussian Networks", Department of Computer Science and Artificial Intelligence, University of the Basque Country, **(1999)**, pp. 2254–2265.
[11] Q. Zhang, "On stability of fixed points of limitmodels of univariate marginal distribution algorithm and factorized distribution algorithm", IEEE Trans. on Evolutionary Computation, vol. 8, no. 1, **(2004)**, pp. 80-93.

