New Challenges for Density-Based Clustering (NCDBC)

Archana Tomar, Deepshikha Patel, Nitesh Gupta
Department of Information Technology
Technocrats Institute of Technology
Bhopal, India
Archana.simmy@gmail.com
Department of Information Technology
Technocrats Institute of Technology
Bhopal, India
23.deepshikha@gmail.com
Department of Information Technology
Technocrats Institute of Technology
Bhopal, India
gupta_neetesh81@yahoo.com

Abstract

This thesis is concerned with Data Mining and clustering: extracting useful insights from large and detailed collections of data. With the increased possibilities in modern society for companies and institutions to gather data cheaply and efficiently, this subject has become of increasing importance. This interest has inspired a rapidly maturing research field with developments both on a theoretical, as well as on a practical level with the availability of a range of commercial tools. Unfortunately, the widespread application of this technology has been limited by an important assumption in mainstream Data Mining approaches.

In this thesis, our aim is to advance the state of the art clustering, especially density based clustering by identifying novel challenges for density based clustering and proposing innovative and solid solutions for these challenges. A hierarchical clustering algorithm can be applied to these interesting subspaces in order to compute a Latitude and Longitude of different cities of world using, density based clustering algorithm..

Keywords: data mining; data clustering; density based clustering algorithm; DBSCAN;

I.INTRODUCTION

This thesis is concerned with Data Mining: extracting useful insights from large and detailed collections of data. With the increased possibilities in modern society for companies and institutions to gather data cheaply and efficiently, this subject has become of increasing importance. This interest has inspired a rapidly maturing research field with developments both on a theoretical, as well as on a practical level with the availability of a range of commercial tools. Unfortunately, the widespread application of this technology has been limited by an important assumption in mainstream Data Mining approaches. This assumption – all data resides, or can be made to reside, in a single table – prevents the use of these Data Mining tools in certain important domains, or requires considerable massaging and altering of the data as a pre-processing step. This limitation has spawned a relatively recent interest in richer Data Mining paradigms that do allow structured data as opposed to the traditional flat representation.

Over the last decade, we have seen the emergence of Data Mining techniques that cater to the analysis of structured data. These techniques are typically upgrades from well-known and accepted Data Mining techniques for tabular data, and focus on dealing with the richer representational setting. Within these techniques, which we will collectively refer to as Structured Data Mining techniques, we can identify a number of paradigms or 'traditions', each of which is inspired by an existing and well-known choice for representing and manipulating structured data. For example, Graph Mining deals with data stored as graphs, whereas Inductive Logic Programming builds on techniques from the logic programming field.

This thesis specifically focuses on a tradition that revolves around relational database theory: New Challenges for Density-Based Clustering (NCDBC).

Building on relational database theory is an obvious choice, as most data -intensive applications of industrial scale employ a relational database for storage and retrieval. But apart from this pragmatic motivation, there are more substantial reasons for having a relational database view on Structured Data Mining. Relational database theory has a long and rich history of ideas and developments concerning the efficient storage and processing of structured data, which should be exploited in successful Multi-Relational Data Mining technology. Concepts such as data modeling and database

Normalization may help to properly approach an NCDBC project, and guide the effective and efficient search for interesting knowledge in the data. Recent developments in dealing with extremely large databases and managing query-intensive analytical processing will aid the application of NCDBC in larger and more complex domains.

To a degree, many concepts from relational database theory have their counterparts in other traditions that have inspired other Structured Data Mining paradigms. As such, NCDBC has elements that are variations of those in approaches that may have a longer history. Nevertheless, we will show that the clear choice for a relational starting point, which has been the inspiration behind many ideas in this thesis, is a fruitful one, and has produced solutions that have been overlooked in 'competing' approaches.

II. REVIEW

DBSCAN-DBSCAN, proposed by Ester et al. in 1996 [2], was the first clustering algorithm to employ density as a condition.

DBSCAN: Density Based Spatial Clustering of Applications with Noise:

In this section, we present the algorithm DBSCAN (Density Based Spatial Clustering of Applications with Noise) which is designed to discover the clusters and the noise in a spatial database according to definitions 5 and 6. Ideally, we would have to know the appropriate parameters Eps and MinPts of each cluster and at least one point from the respective cluster. Then, we could retrieve all points that are density-reachable from the given point using the correct parameters.

But there is no easy way to get this information in advance for all clusters of the database. However, there is a simple and effective heuristic (presented in section section 4.2) to determine the parameters Eps and MinPts of the "thinnest", i.e. least dense, cluster in the database. Therefore, DBSCAN uses global values for Eps and MinPts, i.e. the same values for all clusters. The density parameters of the “thinnest” cluster are good candidates for these global parameter values specifying the lowest density which is not considered to be noise.
DBSCAN does not require you to know the number of clusters in the data a priori, as opposed to k-means. DBSCAN can find arbitrarily shaped clusters. It can even find clusters completely surrounded by (but not connected to) a different cluster. Due to the MinPts parameter, the so-called single-link effect (different clusters being connected by a thin line of points) is reduced.DBSCAN has a notion of noise.DBSCAN requires just two parameters and is mostly insensitive to the ordering of the points in the database.DBSCAN can only result in a good clustering as good as its distance measure is in the function getNeighbors(P,epsilon). The most common distance metric used is the euclidean distance measure. Especially for high-dimensional data, this distance metric can be rendered almost useless. DBSCAN does not respond well to data sets with varying densities (called hierarchical data sets)

DBSCAN ALGORITHM:

Density-Based Spatial Clustering and Application with Noise (DBSCAN) was a clustering algorithm based on density. It did clustering through growing high density area, and it can find any shape of clustering (Rong *et al.*,2004). The idea of it was:
1. ε-neighbor: the neighbors in ε semi diameter of an object
2. Kernel object: certain number (*MinP*) of neighbors in ε semi diameter
3. To a object set *D*, if object *p* is the ε-neighbor of *q*, and *q* is kernel object, then *p* an get “direct density reachable” from *q*.
4. To a ε, *p* can get “direct density reachable” from *q*; *D* contains *Minp* objects; if a series object $p_1,p_2,...,p_n$, $p_1=q, p_n=p$, then p_{i-1} can get “direct density reachable” from p_i, $p_i \in D$, $1\leq i\geq n$.
5. To ε and *MinP*, if there exist a object $o(o \in D)$, *p* and *q* can get “direct density reachable” from *o, p* and *q* are density connected.

Explanation of DBSCAN Steps:

1. DBSCAN requires two parameters: epsilon (eps) and minimum points (minPts). It starts with an arbitrary starting point that has not been visited. It then finds all the neighbor points within distance eps of the starting point.
2. If the number of neighbors is greater than or equal to minPts, a cluster is formed.The starting point and its neighbors are added to this cluster and the starting point is marked as visited. The algorithm then repeats the evaluation process for all the neighbors recursively.
3. If the number of neighbors is less than minPts, the point is marked as noise.
4. If a cluster is fully expanded (all points within reach are visited) then the algorithm proceeds to iterate through the remaining unvisited points in the dataset.

Advantages

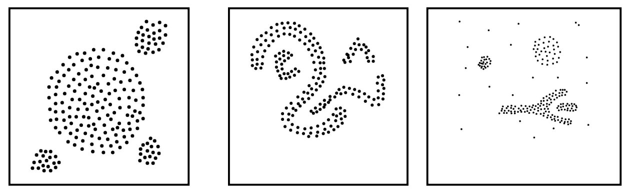
1. DBSCAN does not require you to know the number of clusters in the data a priori, as opposed to k-means.
2. DBSCAN can find arbitrarily shaped clusters. It can even find clusters completely surrounded by (but not connected to) a different cluster. Due to the MinPts parameter, the so-called single-link effect (different clusters being connected by a thin line of points) is reduced
3. DBSCAN has a notion of noise.
4. DBSCAN requires just two parameters and is mostly insensitive to the ordering of the points in the database.

Disadvantages:

1. DBSCAN can only result in a good clustering as good as its distance measure is in the function getNeighbors(P,epsilon). The most common distance metric used is the euclidean distance measure. Especially for high-dimensional data, this distance metric can be rendered almost useless.
2. DBSCAN does not respond well to data sets with varying densities (called hierarchical data sets)

A Density Based Notion of Clusters

When looking at the sample sets of points depicted in figure 1, we can easily and unambiguously detect clusters of points and noise points not belonging to any of those clusters.



database 1 database 2 database 3

figure 1: Sample databases

The main reason why we recognize the clusters is that within each cluster we have a typical density of points which is considerably higher than outside of the cluster. Furthermore, the density within the areas of noise is lower than the density in any of the clusters. In the following, we try to formalize this intuitive notion of “clusters” and “noise” in a database *D* of points of some k-dimensional space *S*. Note that both, our notion of clusters and our algorithm DBSCAN, apply as well to 2D or 3D Euclidean space as to some high dimensional feature space. The key idea is that for each point of a cluster the neighborhood of a given radius has to contain at least a minimum number of points, i.e. the density in the neighborhood has to exceed some threshold. The shape of a neighborhood is determined by the choice of a distance function for two points p and q, denoted by *dist(p,q).* For instance, when using the Manhattan distance in 2 space, the shape of the neighborhood is rectangular. Note, that our approach works with any distance function so that an appropriate function can be chosen for some given application. For the purpose of proper visualization, all examples will be in 2D space using the Euclidean distance.

Definition 1: (Eps-neighborhood of a point) The *Epsneighborhood* of a point p, denoted by NEps(p), is defined by NEps(p) = $\{q \in D \mid dist(p,q) \leq Eps\}$. A naive approach could require for each point in a cluster that there are at least a minimum number (*MinPts*) of points in an Eps-neighborhood of that point. However, this approach fails because there are two kinds of points in a cluster, points inside of the cluster (*core points*) and points on the border of the cluster (*border points*). In general, an Epsneighborhood of a border point contains significantly less points than an Eps-neighborhood of a core point. Therefore, we would have to set the minimum number of points to a relatively low value in order to include all points belonging to the same cluster. This value, however, will not be characteristic for the respective cluster - particularly in the presence of noise. Therefore, we require that for every point p in a cluster C there is a point q in C so that p is inside of the Epsneighborhood of q and NEps(q) contains at least MinPts points. This definition is elaborated in the following.

Definition 2: (directly density-reachable) A point p is *directly density-reachable* from a point q wrt. Eps, MinPts if
1) $p \in NEps(q)$ and
2) $|NEps(q)| \geq MinPts$ (core point condition).

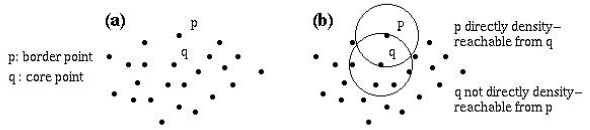


figure 2: core points and border points

Definition 3: (density-reachable) A point p is *densityreachable* from a point q wrt. Eps and MinPts if there is a chain of points $p_1, ..., p_n$, $p_1 = q$, $p_n = p$ such that p_{i+1} is directly density-reachable from pi. Density-reachability is a canonical extension of direct density-reachability. This relation is transitive, but it is not symmetric. Figure 3 depicts the relations of some sample points and, in particular, the asymmetric case. Although not symmetric in general, it is obvious that density-reachability is symmetric for core points. Two border points of the same cluster C are possibly not density reachable from each other because the core point condition might not hold for both of them. However, there must be a core point in C from which both border points of C are density-reachable. Therefore, we introduce the notion of density-connectivity which covers this relation of border points.

Definition 4: (density-connected) A point p is *densityconnected* to a point q wrt. Eps and MinPts if there is a point o such that both, p and q are density-reachable from o wrt. Eps and MinPts. Density-connectivity is a symmetric relation. For density reachable points, the relation of density-connectivity is also reflexive (c.f. figure 3). Now, we are able to define our density-based notion of a cluster. Intuitively, a cluster is defined to be a set of densityconnected points which is maximal wrt. density-reachability. Noise will be defined relative to a given set of clusters. Noise is simply the set of points in *D* not belonging to any of its clusters.

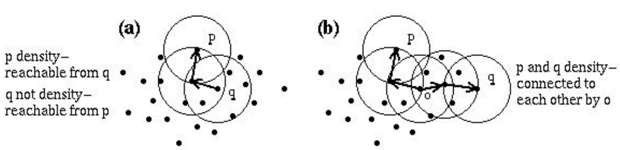


Figure3: density-reachability and density-connectivity

Definition 5: (cluster) Let *D* be a database of points. A *cluster C* wrt. Eps and MinPts is a non-empty subset of *D* satisfying the following conditions:

1) $\forall$p, q: if p $\in$C and q is density-reachable from p wrt. Eps and MinPts, then q ⋅ C. (Maximality)

2) $\forall$p, q $\in$ C: p is density-connected to q wrt. EPS and MinPts. (Connectivity)

Definition 6: (noise) Let $C_1 ,. . ., C_k$ be the clusters of the database *D* wrt. parameters Epsi and MinPtsi, i = 1, . . ., k. Then we define the *noise* as the set of points in the database *D* not belonging to any cluster C_i , i.e. noise = {p $\in D$ | $\forall$ i: p$\notin Ci$}.

IDBSCAN ALGORITHM :

IDBSCAN is a density-based data clustering scheme developed by Borah et al. in 2004 [3]. This method applies a Marked Boundary Object to determine the data point of an expansion seed when searching for neighborhood to add in expansion seeds. Assuming that the core point is P(O,O), the eight marked objects may be defined as: A(0,0), B(0 /√2, Ɛ /√2), C(Ɛ, 0), D(Ɛ /√2, -Ɛ /√2}), E(0, - Ɛ), F(-Ɛ /√2, - 0 /√2), G(-Ɛ, 0), H(-Ɛ /√2}, Ɛ /√2)

If P indicates the core point, and it satisfies the set density condition, then the algorithm finds within the neighborhood the closest point to these eight marked boundary objects, and sets these data points as the expansion seeds. Since these seeds may be selected using multiple marked boundary objects, the algorithm requires only one instance of input is needed. The number of seeds added is below (3d_i), where d represents the dimension of the database.

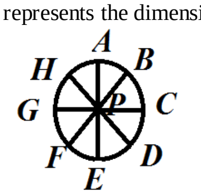


figure3: eight marked boundary object of IDBSCAN

KIDBSCAN ALGORITHM:

KIDBSCAN is a density-based clustering method presented by Tsai and Liu in 2006[4]. They searched for marked boundary objects with IDBSCAN, and found that inputting data sequentially from low-density database causes remnant seed searching, resulting in poor expansion results.

To decrease the number of sample instances, KIDBSCAN performs expansion by inputting elite points. It has three parameters, elite point, radius and MinPts. The execution steps are as follows.

(1) Adopt K-means algorithm to find the K numbers of the centroid within the database, then find the K data points closest to these centroid and define them as elite points, because K-means can discover these elite points quickly.

(2) Move the K elite points to the very front of the database.

(3) Execute the IDBSCAN algorithm. Experimental results prove that KIDBSCAN performs data clustering quickly.

DBSCALE ALGORITHM

"Density-BaSed Clustering Algorithm for Large databasEs" (DB SCALE), algorithm that reduces the number of searches for neighbors and reduce the number of expansion seed approaches. The improved method and concept Searching for neighborhood data in density-based clustering algorithms is time-consuming.

The DBSCALE redefines the eight Marked Boundary Objects from IDBSCAN algorithm. This proposed data points exclude the expansion seeds from the data near P. Because these seeds have large coverage, adding expansion seeds increases the cost of search time; these seeds then join the expansion list according to far centrifugal force. [7]

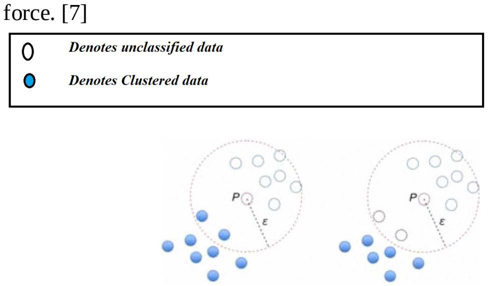


Figure 1. The concept of neighbor search processing.
(a) The traditional search for neighborhood data contains unclassified data and clustered data. (b) DBSCALE was not includes in clustered data to search neighborhood data.

CLUSTER VALIDATION

A large number of clustering algorithms have been developed to deal with specific applications. Several questions arise: which clustering algorithm is best suitable for the application at hand? How many clusters are there in the studied data? Is there a better cluster scheme? These questions are related with evaluating the quality of clustering results, that is, cluster validation. Cluster validation is a procedure of assessing the quality of clustering results and finding a fit cluster strategy for a specific application. It aims at finding the optimal cluster

ISSN 2229-5518

scheme and interpreting the cluster patterns [6].

Cluster validation is an indispensable process of cluster analysis, because no clustering algorithm can guarantee the discovery of genuine clusters from real datasets and that different clustering algorithms often impose different cluster structures on a data set even if there is no cluster structure present in it. Cluster validation is needed in data mining to solve the following problems [6]:

1. To measure a partition of a real data set generated by a clustering algorithm.
2. To identify the genuine clusters from the partition.
3. To interpret the clusters.

Generally speaking, cluster validation approaches are classified into the following three categories Internal approaches, Relative approaches and External approaches. We give a short introduction of cluster validation methods as follows.

INTERNAL CRITERIA

Internal cluster validation is a method of evaluating the quality of clusters when statistics are devised to capture the quality of the induced clusters using the available data objects only . In other words, internal cluster validation excludes any information beyond the clustering data, and only focuses on assessing clusters' quality based on the clustering data themselves.

The statistical methods of quality assessment are employed in internal criteria, for example, root-mean-square standard deviation (RMSSTD) is used for compactness of clusters [6]; R-squared (RS) for dissimilarity between clusters; and S Dbw for compound evaluation of compactness and dissimilarity . The formulas of RMSSTD, RS and S_Dbw are shown below.

$$RMSSTD = \sqrt{\frac{\sum_{\substack{i=1\ldots nc \\ j=1\ldots d}} \sum_{k=1}^{n_{ij}} \left(x_k - \overline{x}_j\right)^2}{\sum_{\substack{i=1\ldots nc \\ j=1\ldots d}} \left(n_{ij} - 1\right)}}$$

where, $\overline{x}_j$ is the expected value in the jth dimension; n_{ij} is the number of elements in the ith

cluster jth dimension; n_j is the number of elements in the jth dimension in the whole data set;

n_c is the number of clusters.

$$RS = \frac{SS_t - SS_w}{SS_t}$$

Where,

The formula of S_Dbw is given as:

S_Dbw = Scat(c) + Dens_bw(c)

where Scat(c) is the average scattering within c clusters. The Scat(c) is defined as:

t

$$Scat(c) = \frac{\frac{1}{c}\sum_{i=1}^{c} \left\|\sigma\left(v_i\right)\right\|}{\left\|\sigma\left(X\right)\right\|}$$

$\sigma(X)$

The value of Scat(c) is the degree of the data points scattered within clusters. It reflects the compactness of clusters. The term is the variance of a data set; and the term is the variance of cluster c_i.

Dens_bw(c) indicates the average number of points between the c clusters (i.e., an indication of inter-cluster density) in relation with density within clusters. The formula of Dens_bw is given as:

$$Dens\_bw = \frac{1}{n_c\left(n_c - 1\right)} \sum_{i=1}^{n_c} \left(\sum_{\substack{j=1, \\ i \neq j}}^{n_c} \frac{density(u_{ij})}{\max\left\{density(v_i), density(v_j)\right\}} \right)$$

where u_{ij} is the middle point of the distance between the centres of the clusters v_i and v_j. The

density function of a point is defined as the number of points around a specific point within the given radius.

RELATIVE CRITERIA

Relative assessment compares two structures and measures their relative merit. The idea is to run the clustering algorithm for a possible number of parameters (e.g., for each possible number of clusters) and identify the clustering scheme that best fits the dataset , i.e., they assess the clustering results by applying an algorithm with different parameters on a data set and finding the optimal solution. In practice, relative criteria methods also use RMSSTD, RS and SDbw to find the best cluster scheme in terms of compactness and dissimilarity from all the clustering results. Relative cluster validity is also called cluster stability, and the recent works on research of relative cluster validity are presented in [6].

EXTERNAL CRITERIA

The results of a clustering algorithm are evaluated based on a pre-specified structure, which reflects the user's intuition about the clustering structure of the data set . As a necessary post-processing step, external cluster validation is a procedure of hypothesis test, i.e., given a set of class labels produced by a cluster scheme, and compare it with the clustering results by applying the same cluster scheme to the other partitions of a database, as shown in the Figure 1- 4.

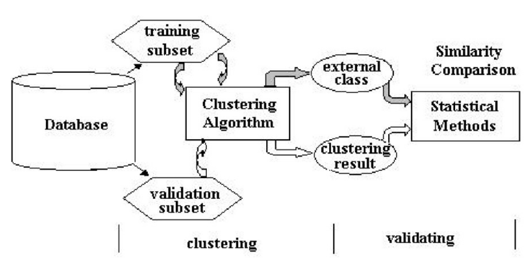


Figure 1-4 External criteria based validation

External cluster validation is based on the assumption that an understanding of the output of the clustering algorithm can be achieved by finding a resemblance of the clusters with existing

classes
The statistical methods for quality assessment are employed in external cluster validation, such as Rand statistic , Jaccard Coefficient, Folkes and Mallows index, Huberts Γ statistic and Normalized Γ statistic, and Monte Carlo method

ANALYSIS CLUSTERING
By the survey of cluster analysis above, it is clear that there are two major drawbacks that influence the feasibility of cluster analysis in real world applications in data mining.

The first one is the weakness of most existing automated clustering algorithms on dealing with arbitrarily shaped data distribution of the datasets.

The second issue is that, the evaluation of the quality of clustering results by statistics-based methods is time consuming when the database is large, primarily due to the drawback of very high computational cost of statistics-based methods for assessing the consistency of cluster structure between the sampling subsets. The implementation of statistics-based cluster validation methods does not scale well in very large datasets. On the other hand, arbitrarily shaped clusters also make the traditional statistical cluster validity indices ineffective, which leaves it difficult to determine the optimal cluster structure [6].

In addition, the inefficiency of clustering algorithms on handling arbitrarily shaped clusters in extremely large datasets directly impacts the effect of cluster validation, because cluster validation is based on the analysis of clustering results produced by clustering algorithms.
Moreover, most of the existing clustering algorithms tend to deal with the entire clustering process automatically, i.e., once the user sets the parameters of algorithms, the clustering result is produced with no interruption, which excludes the user until the end. As a result, it is very hard to incorporate user domain knowledge into the clustering process. Cluster analysis is a multiple runs iterative process, without any user domain knowledge, it would be inefficient and unintuitive to satisfy specific requirements of application tasks in clustering.

III. CONCLUSION AND FUTURE SCOPE

This dissertation introduces a new challenge cluster optimization approach for the solution of ED problem with Artificial Immune System.
The cluster technique can be implemented for solving real life, multi-objective problems where the objectives are conflicting in nature. The Technique approach may be extended to provide solution for larger systems and losses may be considered.

IV. ACKNOWLEDGMENT

The authors would like to thank the National Science Council of the Republic of China, Taiwan for financially supporting this research under Contract No. NSC-96-2221-E-020-027.

V. REFERENCES

[1]. I.J. Nagrath and D.P. Kothari, “Modern Power System Analysis” Tata McGraw hill 6th Edition, 2009.

[2]. Leandro dos Santos Coelho, Viviana Cocco Mariani, “Chaotic artificial immune approach applied to economic dispatch of electric energy using thermal units” Chaos, Solutions and Fractals 40, pp 2376–2383, Dec2009.

[3]. Saumendra Sarangi, ”Particle swarm optimization applied to economic load dispatch problem” NIT Rourkela, M.E. Dissertation, June 2009, pp 1-88.

[4]. Krishna Teerth Chaturvedi, Manjaree Pandit and Laxmi Srivastava, ”Particle swarm optimization with crazy particles non convex economic dispatch” Applied Soft Computing, volume 9, Issue 3June2009, pp. 962-968.

[5]. A. Rajoriya, N. Khatri,and L. Srivastava, “Application of genetic algorithm in power system: a review”, Proceedings of National Conference, Ujjain, 21-22 Apr 2007, pp156-162.

[6]. Titik Khawa, Abdul Rahman, Saiful Izwan Suliman, and Ismail Musirin, “Artifical immune based optimization technique for solving economic dispatch in power system” B. Apolloni et al. (Eds.): WIRN/NAIS 2005, LNCS 3931, pp. 338 – 345, Sep2006.

[7]. C.L.Wadhwa, “Electrical power systems”, New Age International Publishers, 4th Edition, 2004.

[8]. Scholarpedia, http://www.scholarpedia.org/wiki/index.php?title=Ant_colony_optimization.

[9]. J. G. Damousis, A.G. Bakirtzis and P.S. Dokopoulos, “Network-constrained economic dispatch using real-coded genetic algorithm”, IEEE Trans. Power Syst., vol.18, pp. 198 – 205, Feb 2003.

[10]. B. N. S. Rahimullah, E.I. Ramlan and T.K.A. Rahman, “Evolutionary approach for solving economic dispatch in power system”, In proceedings of the IEEE/PES National Power Engineering Conference, vol.1, pp. 32 – 36, Dec 2003.

[11]. Zwe-Lee Gaing, “Particle swarm optimization to solving the economic dispatch considering the generator constraints”, IEEE Transaction on Power SystemVol18, pp.1187-1195, August 2003.

[12]. Wikipedia: http://en.wikipedia.org/wiki/simulated_Annealing.

[13]. J.Tippayachai, W. Ongsakul and I. Ngamroo, “Parallel micro genetic algorithm for constrained economic dispatch”, IEEE Trans. Power Syst., vol.17, pp. 790 – 797, Aug 2002.

[14]. P. Attavriyanupp, H. Kita, T. Tanaka and J. Hasegawa, “A hybrid EP and SQP for dynamic economic dispatch with non smooth fuel cost function”, IEEE Trans. Power Syst., vol.17, pp. 411 – 416, May 2002.

ISSN 2229-5518

[15]. L. N. de Castro and J. Timmis, "Artificial Immune Systems : A novel paradigm to pattern recognition", In Artificial Neural Networks in Pattern Recognition, SOCO-2002, University of Paisley, UK, pp. 67-84, Aug 2002.

[16]. L.N. de Castro and F.J. Von Zuben. "Learning and optimization using the clonal selection principle", IEEE Trans. Evolutionary Computation., vol.6, pp. 239 –251, June 2002.

[17]. Su CT, Lin CT., "New approach with a hopfield modeling framework to economic dispatch " ,IEEE Trans on Power System;15(2):541-545, May2000.

[18]. Wikipedia,http://en.wikipedia.org/wiki/Particle_swarm_optimization.

[19]. L.N. de Castro and F.J. Von Zuben. "Artificial immune system : part 1 – basic theory and applications", Technical Report, TR-DCA 01/99, Dec 1999.

[20]. Y. Matsumura, K. Okhura and K. Ueda, "Evolutionary Programming with non-coding segments for real valued function optimization", In proceedings of the IEEE International conference on Systems, Man and Cyber-Matics 1999, vol.4, pp. 242 – 247, Oct 1999.

[21]. Hadi Sadat, Power System Analysis, Tata McGraw Hill, Economic dispatch neglecting losses and including generators limit, pp.27, International edition,1999.

[22]. D. Dasgupta and N. A. Okine, "Immunity-based systems: a survey", In proceedings of the IEEE International conference on systems, Man and Cyber-Matics, vol.1, pp. 369 – 374, Oct 1997.

[23]. X.Yao and Y. Liu, "Fast evolutionary programming", Proc. of the 5th annual conference on evolutionary programming, pp 451 – 460, MIT press, June1996.

[24]. K.P. Wong and Y.W. Wong, "Genetic and genetic/simulated – annealing approaches to economic dispatch ", Proc. IEE Gen. Trans. Dist., vol.141, no. 5, pp. 507 – 513, Sept 1994.

[25]. A.G. Bakirtzis, V. Petridis and S. Kazarlis, "Genetic algorithm solution to the economic dispatch problem", Proc. IEE Gen. Trans. Dist., vol.141, no. 4, pp. 377 – 382, July 1994.

[26]. F.N. Lee and A.M Breipohl, "Reserved constrained economic dispatch with prohibitive operating zones", IEEE Trans. Power Syst, vol. 8, pp. 246 – 254, Feb 1993.

[27]. Walters DC, Sheblé GB. "Genetic algorithm solution of economic dispatch with valve-point loading". IEEE Trans Power Syst1993; 8(3), pp 1325-32, July1993.

[28]. D.N. Wilke, M.E. Thesis, University of Pretoria, "Analysis of particle swarm optimization algorithms", http://upetd.up.ac.Za/thesis/available/etd-01312006/5743/unrestricted 01/chapters1-3.pdf .