Enhancing the performance of social spider optimization with neighbourhood attraction algorithm

K Tamilarasi¹, M Gogulkumar² and K Velusamy³

¹Department of Computer Science, Srim Jayajoithi Arts and Science College for Women, Tharamangalam, Tamilnadu, India
²Mu Sigma, Bangalore, India
³Department of Computer Science, Sri Vasavi College, Erode, Tamilnadu, India

E-Mail: ¹kta_gk@yahoo.co.in, ²gogulkumar97@gmail.com, ³kvelusamy85@gmail.com

Abstract. Data clustering is a well-known problem in order to identify the inherent structures and extracting the useful information. Recently, social spider optimization (SSO) algorithm is applied to solve a clustering problem. But, it may fall into premature convergence due to find improper nearest spiders in order to achieve the global solution. In this research paper, the neighbourhood attraction (NA) method is used to enhance the performance of the SSO clustering algorithm. In the experimental results, the proposed NA+SSO clustering method is producing better performance when compared with other conventional clustering algorithm.

1. Introduction
Data mining is a famous data analysis tool that the aim is the mining of unknown predictive knowledge from enormous databases. It is used to forecast future behaviors that propose businesses to build knowledge-driven decisions [1]. Clustering is well-known unsupervised data mining techniques for extracting an useful pattern in a collection of unlabeled data [2]. Clustering is used to segregating the huge data objects into smaller groups based similarity.

The similar data objects are in the same groups and dissimilar data objects are in different groups [3]. Building an efficient clustering techniques is a demanding task due to NP-complete when the number of clusters is more than three clusters [4]. The clustering problem is applied to solve many real world problems including image segmentation [5], document clustering [6], Disease prediction [7], wireless sensor networks [8], social network analysis [9], network traffic identification [10], information retrieval [11], marketing [12].

The k–means algorithm is a well-known partitioned clustering algorithm, due to its straightforward and easy to use [13]. However, the traditional k-means algorithm is improper for real data sets in which there are no specific boundaries between the clusters. The k-means is an algorithm which is failure to find a global optimum [14]. The swarm intelligence (SI) and evolutionary algorithm (EA) based clustering algorithm is a more attentions in the researchers and applied to solving a data clustering such as genetic algorithm (GA) [15], artificial bee colony algorithm (ABC) [16], particle swarm optimization (PSO) [17], Ant Colony Optimizations (ACO) [18], bacterial foraging optimization (BFO) [19], bacterial colony optimization (BCO) [20]. However, the conventional SI
and EV based algorithms have some demerits including local optima, premature convergence and high convergence rate [3].

Recently, the SSO algorithm has been applied to solve data clustering problem and it has produced higher clustering accuracy compared with some conventional clustering algorithm [21]. However, the convergence rate is very high due to failure for finding nearest optimum solutions. Hence, the enhancing the convergence rate of machine learning algorithm is a challenging task. In this research paper, the NA algorithm is used to enhance the performance SSO algorithm method. The proposed NA+ SSO has applied eight different datasets in order to analyze performance. The scope of this research work is to enhance the performance of conventional SSO. In the NA scheme, each individual of the population is only fascinated by the most excellent solution achieved in a small neighborhood rather than the complete population. The following contributions are made in this research work.

- The NA based SSO is to make stronger the global search capability
- An enhance the convergence speed of the SSO
- Avoiding the premature convergence

The remaining part of the paper is organized as follows, the definition of data clustering problem shows in section 2. The fundamental SSO algorithm discusses in section 3. The section 4 shows the details of neighbourhood algorithm. In section 5, discusses details of the proposed NA+SSO data clustering model. The experimental analysis and discussion demonstrated in section 6. Finally, the conclusion of the research work shows in section 7.

2. **Data clustering**

Given data samples \( X = \{x_1, x_2, \ldots, x_n\} \) find out a partition of the data samples \( N \) into \( K \) cluster \( C_1, C_2, \ldots, C_K \). The objective of the clustering algorithm is to reduce Sum of Squared Error (SSE) [3] and it can be defined as follows

\[
SSE = \sum_{k=1}^{K} \sum_{i \in C_k} \|x_i - c_k\|^2
\]  

(1)

Where, \( \|x_i - c_k\|^2 \) denotes the distance between data points \( x_i \) and center point of \( c_k \), in this research work, the Euclidean distance function is used for measuring the SSE. The low SSE value is considered as best optimal cluster group. In the optimization based data clustering algorithms, the SSE (Equation 1) is required to specify the fitness function as an objective function that defined as follows,

\[
J_m(w, z) = \sum_{c=1}^{K} \sum_{i=1}^{n} \sum_{d=1}^{D} w_{tp} \|x_i - z_{cd}\|^2
\]  

(2)

\( D \) is the dimension of search space. \( z \) is the cluster center. \( w \) is the weight matrix \( n \times K \). \( w_{tp} \) is associated weights of data sample \( x_t \) with cluster \( c \) that can be assigned as follows,

\[
w_{tp} = \begin{cases} 1 & \text{if } x_t \text{ is labelled cluster } c \\ 0 & \text{otherwise} \end{cases}, t = 1, 2, \ldots n; c = 1, 2, \ldots K
\]  

(3)

3. **Social Spider Optimization**

SSO algorithm is a well-known population based optimization algorithm for solving real world applications based on co-operative behavior of the social- spider. SSO was developed by E. Cuevas et al. in 2013 [22]. The SSO algorithm guesses optimal solution by an interacting with each others on the communal web. The weight value of the every social spider is computed according to the fitness value of the given solutions. A fitness value of each spider is calculating the weights for deciding the ability of spiders.
3.1 Initialization of the spiders

The female spider $N_f$ is randomly determined from total population $N$ which range between 65-90% of the total population. Hence, $N_f$ is calculated as follows,

$$N_f = \text{floor}(0.9 \times \text{rand} \times 0.25) \times N$$  \hspace{1cm} (4)

Where, $\text{rand}$ - denote the random number between 0 and 1, $N$ - denote is the total population and floor $(.)$ is convert a real value to an integer value. The number of male spiders $N_m$ is calculate between ' $N_f$ ' and $N$. It can be defined as follows

$$N_m = N_f - N$$  \hspace{1cm} (5)

The whole population is divided into female $F$ and male $M$. The group of female $F$ is brings together as a set of female entity $F = \{f_1, f_2, ..., f_{N_f}\}$. Likewise, male individual spiders are determined as $M = \{m_1, m_2, ..., m_{N_m}\}$. Hence, the total population is denoted by $S = F \cup M (S = \{s_1, s_2, ..., s_N\})$.

3.2 Assignation of the Fitness values

The weights of the each spider are performing major responsibility in order to find a fittest element of the colony. The weight associated with each spider which is defined based on the following fitness functions,

$$W(i) = \frac{\text{worst}_f - J_m(S_i)}{\text{worst}_f - \text{best}_f}$$  \hspace{1cm} (6)

Where, $J_m(S_i)$-denote the fitness value. $\text{best}_f$ - denote least fitness value and $\text{worst}_f$ - denote the highest fitness value.

3.3 Vibrations

The vibration is used to make communication with each spider on the communal web. The vibration of the each spider value is considered with the help of distance function. The following formula is defining the vibration process.

$$\text{Vib}_j = W_j e^{-d_{ij}^2}$$  \hspace{1cm} (7)

Here, $\text{Vib}_j$ - denotes the vibration established from $i^{th}$ spider and send by the $j^{th}$ spider and $d_{ij}$ is the distance function value between $i^{th}$ spider and $j^{th}$ spider. The Euclidean distance function is used in this paper.

3.4 Cooperative operators

In SSO, social spiders are interactive with each other on the communal web based on their gender. In which, two kinds of cooperative operators process are performing including female cooperative operator and male cooperative operator.

3.4.1 Male cooperative operator process

The attraction actions are designed over the other spiders according to their vibration process.

$$S_{F}^{k+1}(i) = \begin{cases} 
S_{F}^{k}(i) + a_{F}(i) \times \frac{\beta_{F}^{k}(i)}{S_{F}^{k}(i) - S_{F}^{k}(i)} & \text{if rand} \leq 0.5 \\
S_{F}^{k}(i) - a_{F}(i) \times \frac{\beta_{F}^{k}(i)}{S_{F}^{k}(i) - S_{F}^{k}(i)} & \text{if rand} > 0.5 \\
S_{F}^{k}(i) & \text{otherwise}
\end{cases}$$  \hspace{1cm} (8)
Where, $\alpha$, $\beta$, rand and $\otimes$ are selected by random from the uniform distribution function between 
\[
\begin{bmatrix}
0, \frac{P}{N_F + N_M}
\end{bmatrix},
\]

3.4.2 Male cooperative operator process
Male population is separated into two different kinds such as dominant male and non-dominant male. The dominant male exhibits better fitness compares with non-dominant male. It is more paying attention with a female spider in the communal web. In the Dominant male position updates, the major responsibility of the dominant male is moving to the female spiders for reproduction process. The position update process can determined as follows,
\[
S_{DM}^{k+1} = S_{DM}^k + \alpha \cdot \nabla F_i + \theta (\text{rand} - 0.5)
\]
(9)
In the Non-dominant male position update process, the objective of non-dominant male is into bringing mutually in the middle of the dominant male spider to acquire the gain of the left over. This result of weight means is based on their behavior which is made as follows,
\[
S_{NM}^{k+1} = S_{NM}^k + \alpha (X_w - S_{NM}^k)
\]
(10)
The weighted mean values is acquires by the male population weights which is denoted by $X_w$.

3.5 Mating process
The mating process is a major role in the SSO algorithm in order to adjust the search agents. The dominant males are necessary to mating process with female spider certain radius to produce new offspring spiders. The following formula is used to calculate the radius values of each dominant male.
\[
\text{Radius} = \frac{R_{\text{max}} - R_{\text{min}}}{2D}
\]
(11)
Where, $D$ - denote the dimensionality of the given datasets. '$R_{\text{min}}$' and '$R_{\text{max}}$' are the minimum and maximum value of the datasets respectively.

4. Neighborhood attraction (NA) algorithm
Searching the nearest individual in any SI or EA is helpful to find the best possible solution. In this way, the NA scheme is a very powerful technique in order to find the best possible solution. Neighborhood attraction model inspired by the k-neighborhood concept [23]. In this method, each individual is attracted by the most excellent solution found in the k-neighborhood rather than the whole population. Hence, the NA method is can be expressed as follows,
\[
X_i(k+1) = X_i(k) + r \cdot X_{i,\text{neigh}}(k) - X_i(k)
\]
(12)
Where, $r$ is the random number between 0 and 1. $X_{i,\text{neigh}}$ is the best individual in the neighborhood of $X_i$.

5. Proposed NA+SSO data clustering algorithm
The each spider communicates with a certain number of neighbours rather than the total population, which helps to make stronger the capability of exploration. Hence, The spiders are communicating with each other in order to find a matching colleague for the mating process in order to enhance the populations. The most of the spider populations are collected by females. The female spider will choose the male spider based on some constraints like weight and growth. In this situation, the conventional SSO algorithm takes more computation time for accomplishes the given solution. Hence, the NA algorithm used to find a nearest partner to perform the mating operation in order to enhance the search ability [24]. In the proposed method, the nearest female spider is searched with the help of NA algorithm that attracted with a dominant male spider in order to make the mating
process [25]. The analysis of the attraction of the each spider $S_{ij}$ is sorted at the beginning and the k-neighborhood of $S_{if}$ is the number of spiders attracted with $S_{id}$. Algorithm 1 shows the step by step process of proposed NA+SSO.

### Algorithms 1: Proposed NA+SSO clustering algorithm

**Begin FSSO**

- **Step 1:** Initialize the population $S'$.
- **Step 2:** initialize the parameter $\alpha, \beta, \delta, r_m$, Max_Iter, Iter and $PF$
- **Step 3:** Compute centroid values
- **Step 4:** Compute distance between data samples and centroid values
- **Step 5:** For all $S'$
  - **Step 5.1:** Compute the fitness values
  - **Step 5.2:** Allocate the weights for each spider
- **Step 6:** End
- **Step 7:** While (Iter < Max_Iter)
- **Step 8:** Update the female spiders location using equation 12
- **Step 9:** Update the male spiders location using equation 12
- **Step 10:** Compute radius value
- **Step 11:** if distance < $r$
  - **Step 11.1:** The dominant male and female spider mate to create new spiders
- **Step 12:** If ($f(S_{new}) > f(S_{worst})$)
  - **Step 12.1:** The new spider are substituted with the worst spiders
- **Step 13:** Compute the objective function
- **Step 14:** Achieve best solutions
- **Step 15:** Iter=Iter+1
- **Step 16:** End while
- **Step 17:** if achieve the best solution or arrive at the Max_Iter, then stop the process; otherwise, go to back step 3.

**End SSO**

6. **Experimental results and discussions**

The data clustering are implemented by using MATLAB 2015b. The outcome of every clustering algorithm is achieved from the average values of 50 independent runs. The performance of the proposed NA+SSO clustering algorithm is compared with some benchmark algorithms such as k-means, PSO and SSO.

#### 6.1 Dataset collections

In this research work, different standard UCI machine learning datasets are used and details are shown in Table 1.

- **Artificial datasets 1** is a 2 different features problem with four different classes [3]. An entire 600 patterns were drawn from four independent bivariate normal distributions. The classes were distributed according to,
  \[
  N_2(\mu = \begin{pmatrix} m_1 \\ 0 \end{pmatrix}, \Sigma = \begin{pmatrix} 0.5 & 0.05 \\ 0.05 & 0.5 \end{pmatrix}), \quad i = 1, 2, 3, 4, m_1 = -3, m_2 = -5, m_3, m_4 = 6
  \]
- **Artificial dataset 2** is a three features problem with five different classes, in each class, the features were distributed according to the following manner [3]. Such as Class 1—Uniform (85, 100), Class 2—Uniform (70, 85), Class 3—Uniform (55, 70) Class 4—Uniform (40, 55), Class 5—Uniform (25, 40).
- **Balance data set** is created based on weight of the balance scale and distance. It contains six hundred and twenty five data samples with 4 features and 3 unique classes.
- **Fisher’s iris dataset** has three different species of the iris flower, one fifty data sample and four different features were collected in each species.
Glass datasets have two hundred and four data points with six classes with 9 features in each type.

The Heart data set is based on the heart disease diagnosis. It has seventy six attributes for each data sample with 303 data sample and 2 unique classes.

Wisconsin Breast Cancer (WBC) data set has 683 data samples and two classes with 9 features.

The wine dataset has 178 data objects and three kinds of class with 13 features.

Contraceptive Method Choice (CMC) dataset has 1473 data samples with 3 categories and 9 different features.

The vowel data set contains 871 Indian vowels and 3 features with 6 classes.

### 6.2 Parameter settings

The maximum iteration is set to \( \text{Max\_Iter} = 200 \) for each clustering algorithm and the population size is set equal to 100. \( \alpha, \beta, \delta, r_m \) and \( PF \) are random number which ranges between \([0,1]\). The parameter values are set as a best parameter setting for the proposed clustering algorithms based on the reference \([22, 26]\). In this paper, the following parameter settings are considered and it can be produced higher clustering efficiency. In \( k\)-means, the maximum iterations are set as 100. In PSO, \( c_1 = c_2 = 2 \), \( P = 100 \), \( w = 0.9 \rightarrow 0.1 \). In BFO, \( s = 100 \), \( N_c = 100 \), \( N_s = 4 \), \( N_{re} = 4 \), \( N_{ed} = 2 \) and \( P_{ed} = 0.25 \).

### 6.3 Performance indicators

The performance indicators are very significant which is used to investigate the performance of clustering algorithms. We can classify how many data samples are properly classified to the related groups. In this research work, the objective function (Equation 2) is used for analyzing the performance of the proposed NA-SSO clustering algorithm. In which, three parameters are considered such as worst, average and best. The highest value of the objective function value is called worst value. The lowest value of objective function values is called best value. The average value is computed from the both highest and lowest values of the objective function. The goal of the objective function is used to decrease the SSE between the data samples and cluster centroid [27]. The lowest value of the objective function \( J_m \) values is measured as the best values.

### 6.4 Discussions

The experimental results are computed over 10 independent runs for PSO, SSO and proposed NA+SSO clustering algorithm and 100 independent runs for FCM. The simulation results shows in
Table 1. From the Table 1, the outcome of clustering algorithm is estimated by using objective function. The Figure 1 shows the average performance of the proposed NA+SSO data clustering model which is obtained from average values of all datasets of the best value. The lowest value of the objective function is considered as a best optimal solution which is highlighted in bold letters. The proposed NA+SSO clustering algorithm attained higher efficiency compared with k-means, PSO and SSO clustering algorithm.

Table 2. Performance comparisons of proposed NA+SSO data clustering model

| Datasets | Methods | Objective function values | Best | Average | Worst |
|----------|---------|---------------------------|------|---------|-------|
| Art 1    | K-Means | 692.57                    | 736.56 | 780.56 |
|          | PSO     | 618.45                    | 633.82 | 649.19 |
|          | SSO     | 589.71                    | 595.62 | 601.54 |
|          | NA+SSO  | 564.91                    | 579.31 | 593.71 |
|          | K-Means | 2372.18                   | 2615.59 | 2859.01 |
|          | PSO     | 2239.51                   | 2365.17 | 2490.84 |
|          | BFO     | 2196.89                   | 2243.53 | 2290.17 |
|          | OBL+BFO | 2016.47                   | 2101.70 | 2186.93 |
| Art 2    | K-Means | 764.18                    | 873.68 | 983.18 |
|          | PSO     | 683.61                    | 704.43 | 725.26 |
|          | SSO     | 645.19                    | 666.71 | 682.59 |
|          | NA+SSO  | 634.92                    | 663.89 | 641.63 |
| Balance  | K-Means | 107.86                    | 128.75 | 149.64 |
| Iris     | PSO     | 96.63                     | 98.06  | 99.49  |
| BFO      | 645.19  | 666.71                    | 682.59 |
|          | SSO     | 645.19                    | 666.71 | 682.59 |
| Glass    | K-Means | 107.86                    | 128.75 | 149.64 |
|          | PSO     | 96.63                     | 98.06  | 99.49  |
|          | SSO     | 645.19                    | 666.71 | 682.59 |
|          | NA+SSO  | 634.92                    | 663.89 | 641.63 |
| Heart    | K-Means | 4963.67                   | 5156.72 | 5492.01 |
|          | PSO     | 4293.84                   | 4562.37 | 4830.91 |
|          | SSO     | 4129.49                   | 4188.44 | 4247.39 |
|          | NA+SSO  | 4028.83                   | 4110.29 | 4191.75 |
|          | K-Means | 2917.28                   | 3206.11 | 3494.94 |
|          | PSO     | 2750.24                   | 2847.07 | 2943.90 |
|          | SSO     | 2647.07                   | 2698.29 | 2749.52 |
|          | NA+SSO  | 2632.57                   | 2663.03 | 2693.49 |
|          | K-Means | 16527.98                  | 17265.97 | 18003.95 |
| WBC      | PSO     | 16411.06                  | 16464.06 | 16517.06 |
|          | SSO     | 16291.62                  | 16344.42 | 16397.22 |
|          | NA+SSO  | 16273.48                  | 16282.15 | 16290.82 |
|          | K-Means | 5821.60                   | 5879.27 | 5936.93 |
|          | PSO     | 5780.76                   | 5795.52 | 5810.28 |
|          | SSO     | 5680.70                   | 5710.30 | 5739.89 |
|          | NA+SSO  | 5615.22                   | 5643.84 | 5672.46 |
| Wine     | K-Means | 149562.96                 | 155226.17 | 160889.38 |
|          | PSO     | 148976.68                 | 149048.65 | 149120.62 |
|          | SSO     | 147006.60                 | 147262.65 | 147518.70 |
|          | NA+SSO  | 146730.54                 | 146835.13 | 146939.73 |

Table 1. From the Table 1, the outcome of clustering algorithm is estimated by using objective function. The Figure 1 shows the average performance of the proposed NA+SSO data clustering model which is obtained from average values of all datasets of the best value. The lowest value of the objective function is considered as a best optimal solution which is highlighted in bold letters. The proposed NA+SSO clustering algorithm attained higher efficiency compared with k-means, PSO and SSO clustering algorithm.
Conclusions
In this research paper, the SSO clustering algorithm is combined with NA for enhancing the clustering quality and speed up of the convergence rate. The experimental result shows that the proposed NA+SSO clustering algorithm produces enhanced outcome when compared with SSO, PSO and k-means clustering algorithm.

References
[1] Mohanty P P, Nayak S K, Mohapatra U M and Mishra D 2019 A survey on partitional clustering using single-objective metaheuristic approach Int. J. of Inn. Comp. and Appl. 10, 207-226.
[2] Abraham A, Das S and Roy S 2008 Swarm intelligence algorithms for data clustering,” in Soft computing for knowledge discovery and data mining Springer.
[3] Niknam T and Amiri B 2010 An efficient hybrid approach based on PSO, ACO and k-means for cluster analysis Appl soft comp. 10 183-197.
[4] Sahoo G 2017 A two-step artificial bee colony algorithm for clustering Neural Comp. and Appl. 28 537-551.
[5] Nithya A, Appathurai A, Venkatadri N, Ramji D and Palagan C A 2020 Kidney disease detection and segmentation using artificial neural network and multi-kernel k-means clustering for ultrasound images Measurement 149 106952.
[6] Christy A and Gandhi G M 2020 Feature Selection and Clustering of Documents Using Random Feature Set Generation Technique Advances in Data Science and Management Springer Springer.
[7] Ramasamy S and Nirmala K 2020 Disease prediction in data mining using association rule mining and keyword based clustering algorithms Int. J. of Comp. and Appl. 42 1-8
[8] Kotary D K and Nanda S J 2020 Distributed robust data clustering in wireless sensor networks using diffusion moth flame optimization Eng. Appl. of Art. Intell. 87, 103342.
[9] Curiskis S A, Drake B, Osborn T R and Kennedy P J 2020 An evaluation of document clustering and topic modelling in two online social networks: Twitter and Reddit Information Processing & Management 57 102034.
[10] Yang J, Han Y, Wang Y, Jiang B, Lv Z and Song H 2020 Optimization of real-time traffic network assignment based on IoT data using DBN and clustering model in smart city Future Generation Computer Systems 108 976-986

[11] Bedi P and Chawla S 2010 Agent based information retrieval system using information scent Journal of Artificial Intelligence 3 220-238

[12] Yue B 2020 Topological Data Analysis of Two Cases: Text Classification and Business Customer Relationship Management J. of Phy.: Conf. Ser.

[13] Hartigan J A and Wong M A 1979 Algorithm AS 136: A k-means clustering algorithm Journal of the Royal Statistical Society. Series C (Applied Statistics) 28 100-108

[14] Kanungo T, Mount D M, Netanyahu N S, Piatko C D, Silverman R and Wu A Y 2002 An efficient k-means clustering algorithm: Analysis and implementation IEEE Transactions on Pattern Analysis & Machine Intelligence, 881-892.

[15] Maulik U and Bandyopadhyay S 2000 Genetic algorithm-based clustering technique Pattern recognition 33 1455-1465.

[16] Zhang C, Ouyang D and Ning J 2010 An artificial bee colony approach for clustering Exp. Sys. with Appl. 37 4761-4767.

[17] Cui X, Potok T E and Palathingal P 2005 Document clustering using particle swarm optimization Swarm Intelligence Symposium 2005 SIS 2005 Proceedings 2005 IEEE.

[18] Shelokar P, Jayaraman V K and Kulkarni B D 2004 An ant colony approach for clustering Analytica Chimica Acta 509 187-195.

[19] Wan M, Li L, Xiao J, Wang C and Yang Y J 2012 Data clustering using bacterial foraging optimization 38 321-341

[20] Revathi J, Eswaramurthy V and Padmavathi P 2019 Bacterial Colony Optimization for Data Clustering 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT) IEEE.

[21] Padmavathi P, Eswaramurthy V and Revathi J 2018 Fuzzy Social Spider Optimization Algorithm for Fuzzy Clustering Analysis in 2018 International Conference on Current Trends towards Converging Technologies (ICCTCT) IEEE

[22] Cuevas E, Cienfuegos M, Zaldívar D and Pérez-Cisneros M 2013 A swarm optimization algorithm inspired in the behavior of the social-spider Exp. Sys. with Appl. 40 6374-6384.

[23] Wang H, Wang W, Zhou X, Sun H, Zhao J, Yu X and Cui Z 2017 Firefly algorithm with neighborhood attraction Information Sciences 382 374-387.

[24] Cuevas E and Cienfuegos M 2014 A new algorithm inspired in the behavior of the social-spider for constrained optimization Exp. Sys. with Appl. 41 412-425.

[25] Wang H, Sun H, Li C, Rahnamayan S and Pan J-S 2013 Diversity enhanced particle swarm optimization with neighborhood search Information Sciences 223 119-135.

[26] Shukla U P and Nanda S J 2016 Parallel social spider clustering algorithm for high dimensional datasets Eng. Appl. of Art.Intl. 56, 75-90.

[27] Borgelt C 2013 Objective functions for fuzzy clustering Computational Intelligence in Intelligent Data Analysis Springer.