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Performance evaluation of the particle swarm optimization for clustering based on different parameter selection

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ABSTRACT

Particle Swamp Optimization (PSO) is an effective method for solving a wide range of problems. However, the most existing PSO algorithms easily trap into local optima when solving complex multimodal function optimization problems. In this paper, we explain the importance of PSO algorithm's general purposes to optimize strategy which has various parameters that decide its conduct and viability in advancing a given issue. This study gives a rundown of the best selections of parameters for different advancement situations which should enable the specialist to accomplish better outcomes with less exertion. In this paper, we define an important in the PSO algorithm, the parameters and how to apply this algorithm to different type of datasets online and offline. Repeat Consumption Matrices Dataset has been tested with PSO algorithm to define the number of clusters using selection of parameters. The results are then having been compared with the Genetic Algorithm (GA) where the algorithms have been tested based on the number of cluster and DB index for each of the data. Based on the results, it is shown that the PSO algorithm gives good and efficient results compared to GA algorithm. The output of the research is a PSO-based clustering algorithm that can be used in data mining by providing accurate and robust results in clustering, which can be realized in web search engines and automatic doc-ument organization.

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1. INTRODUCTION

Data clustering is a data-driven, unsupervised classification approach to determine homogeneous groups in a given dataset [1]. "Unsupervised" means that there is no predefined information about the form of the dataset. Generally, there are two ways to conduct the division of data into groups [2]: the deterministic approach, and the optimization approach. The former approach includes partitioned clustering, hierarchical clustering, density-based clustering, grid-based clustering, and model-based clustering[3]. However, these approaches cannot handle all kinds of data [4], [5]. There are many problems in the field of engineering and science. In order to solve these problems, there are two methods used; one of which is called classical and heuristics. Programming methods, both linear and non-linear are not enough to solve the problems of improvement because they need pre-requisites to start the process of improvement. For example, continuity and the extent of difference in target posts [6], [7]. The methods of curriculum are always being taken from the vital, for example, genetic algorithm and strategies of development and differentiation development. Heuristics do not expose most of the drawbacks of classical and technical approaches. Among heuristics, particle swarm optimization (PSO) has shown more promising behavior. PSO is a stochastic, population-based optimization technique introduced by Kennedy and Eberhard in 1995.

Particle swarm optimization (PSO) is an effective method for solving a wide range of problems. However, the most existing PSO algorithms easily trap into local optima when solving complex multimodal function optimization problems [8]–[10]. The PSO based clustering parameters tuning as offline strategy, where the value of the parameter statically initialized by use before each algorithm run. This kind of initialized is unrobustness because each problem at hand (dataset) has it's unique parameter setting [11]. Thus, this strategy has no more useful and the algorithm needs to reinitialize its parameter dynamically during the search algorithm. This drawback effect on measuring the performance of PSO in clustering datasets. This is the whole problem statement of this research.

One of the important issues in the PSO algorithm is by having different parameters that can lead to distinct mathematical behaviors in a clear and noticeable manner. In this case, it can work with some parameter and on the hand, treats the parameters in an undesirable manner. The PSO algorithm is considered as a sensitive algorithm for parameter, although the sensitivity of PSO variables is different in relation to its parameter. Therefore, there is an effort to get the best parameters of the algorithm and this effort leads to the best computer behavior. This is considered very important. There are several strategies in clusters, the algorithm needs to tune the parameters where the accuracy of the result is affected for each different dataset. However, the existent in using parameter based on tuning strategy where all parameters are tuning before the algorithm run. Thus, clustering accuracy for each dataset.

This search contains two of Research Questions attempts to answer the following questions: the first questions Can PSO be implanted in optimizes clusters. And another research question Can PSO-based data clustering algorithm produced move improvement result. This research also contains two kind of research objective. The first adjective to propose a PSO-based data clustering algorithms. And also have another objective to evaluate the proposed method with Repeat Consumption Matrices Data Set. This type of research will address the solution of the comprehensively analyzed algorithm PSO (practical swarm optimization. The most existing PSO algorithms easily trap into local optima when solving complex multimodal function optimization problems [8]. The PSO based clustering parameters tuning as offline strategy, where the value of the parameter statically initialized by use before each algorithm run. This kind of formatting consider not suitable and not secure; therefore, the algorithm should carefullybe selected based onthe best result and show how they evaluate the performance the result. To solve this problem, this article aims to develop the work on the different dataset by measurement the performanceof thisalgorithm compared withanother algorithm (Genetic Algorithm) to identify the DB index and to improve the work of the algorithm [12], [13]. The output of the research is a PSO-based clustering algorithm that can be used in data mining by providing accurate and robust results in clustering, which can be realized in web search engines and automatic document organization.

2. RELATED WORK

In this part, different studies on the different type of the parameter have been shown. Table 1 shows the type of the parameter and the article review for each type. There are six types of parameter in the PSO algorithm. The first type,calledthe Initialization technique [14]. This study investigates and made a comparison about the effects of low-discrepancy sequences used in the PSO. It also shows the PSO advantage and behave better in the search for optimal result and use off-line parameter strategy [15]. Many studies show that nonlinear dynamic hysteretic models used in nonlinear dynamic analysis contain generally lots of model parameters which need to be identified accurately and effectively. One of the important of this studyis Control algorithm performance has been improvedand have the disadvantage like number of search space parathion need to be known by the researcher and use online parameter strategies. It is also in this kind of parameter have another study that usesa novel approach to effectively initialize particle swarm optimization [16].

The second type of parameter isMaximum velocity. The value of maximum velocity is directly showing the performance of the algorithm in the term of exploration and exploitation. If the value is too high, the algorithm produce results without enough exploration of the search space [17]. The studyillustrated a mechanism of the dynamic change of value Vm which improve the performance of PSO algorithm. Erik Magus Pruderies in 2011 do not use the regression problem to be optimally, it helps user achieved better results with the less effort and use online strategy [18]. Another study in their studies improve dependent strategieson transformative learning. It has demonstrated their solid viability in unscrambling ideal arrangements in complex spaces and utilized disconnected procedure for the execution precision of PSO and also use offline parameter strategy.

The third type of parameter is Inertia weight. Inertia weight is one of the most important parameters in PSO algorithm which directly effects the performance of the algorithm. The inertia weight parameter affects one the trade-off between exploration and exploitation process, thus the accuracy of the algorithm also significantly affected. Study like [19] show that the suitable values for a met heuristic's parameters depend on relative ruggedness and smoothness of this hyperspace and used off-line strategy of parameter. Another study [20] in the study used to identify a complex non-linear relationship between input and output parameters of the SSHS, and to obtain the optimized estimating ANN model use on-line parameter strategy.

There are another study work in the same field use fuzzy adaptive [21]. The result shows that AHPSO has faster convergent speed and use off-line parameter strategy. Another study in this kind of parameter improve accuracy of structural dynamic information and use off-line parameter strategy [14].

The fourth type of parameter is Adaptive inertia-weight variants. The hunt procedure of PSO calculation is non-direct, consequently systems, for example, straightly that dependent on diminishing the esteem if inactivity weight isn't powerful in light of the fact that it cannot change the calculation seek from worldwide to neighborhood look. This kind of parameter has been studied by many researchers such as in 2015 [22]. They used three-diodes for large area (~154.8cm2) industrial silicon solar cell. This kind of parameter used in the offline strategy. There are another study [15] in this case the PSO used non-linear dynamic, as showin by Liu and Ouyang in 2010 where that study has actualized a fuzzy versatile PSO by utilizing a fuzzy inactivity weight and furthermore a fuzzy position control use the off-line parameter strategy [21].

The fiveth type of parameter is Acceleration coefficient. The value of acceleration coefficient C1 and C2 are so important in the PSO performance. The value acceleration coefficientforce particles towards$P_{best}$and g_{best}. Those constants values effects on algorithm convergence and trapped in local optima. If the value set as too high, particles may moveabruptly and the algorithm traped in local optima where algorithm solution produce same results, while if the value is too low, the particles movement in the search space is too slowly. In this type of parameter have many study to explain how can parameter work like the value has a proved as acceptable value and can be used for the most of problems [24]. The study done by Bao and Mao in 2009 has use clustering K-means to adapt acceleration coefficient [25]. There are also another study of [26] using non-linear dynamic and use the off-line parameter type strategy.There are another study of [22] used optimization techniques based on evolutionary. The study of Guo and Chen in 2009 has proposed to adaptiveinertia weight and social acceleration coefficient [28] shows the results indicated that the accuracy of the proposed method is increased significantly using particle swarm optimization.

The final type of parameter Neighborhood topology. PSO algorithm has two neighborhood topologies which can be classified into global best $\mathbf{g_{best}}$ and local best $\mathbf{l_{best}}$. Both neighborhood topologies are directly affects on exploration and exploitation process. In PSO, many topologies are proposed to balance between both $\mathbf{g_{best}}$ and local best $\mathbf{l_{best}}$. As example, the study of [8] used balance local and global search. While other study proposed in 2009 used different stages includes exploration, exploitation, convergence and jumping [29]. Parameters controlling are used automatically during the search of the algorithm to improve the search efficiency and convergence speed.

3. PROPOSED METHDOLOGY

In this paper, the PSO algorithm was tested on the basis of two axesnumber of cluster and DB index where the algorithm was used and operated by the Matlab program. The algorithm was restarted 10 run times with 1000 attritions means 10 times every 1000 times attritions. The rate is calculated each time from the first run down to the run for the 10th time, where the rate was taken for the first set. It is depending on the PSO algorithm, the lowest values are chosen from the total number of times the algorithm is run. GA algorithm used the same number of times as the operation PSO algorithm. The rate is chosen based on its DB index values and number of clusters. This is also the case for the five-digit data contained in the datasets Repeat Consumption Matrices.The rate is also extracted based on the number of operations performed on the dataset which represents the lowest value depending on the DB index and number of clusters and same with the rest of all dataset.

4. BENCHMARK DATASET

The datasets Repeat Consumption Matricesis one of the special data set that specialize in clustering of the specifications that characterize theMultivariate. Add to it, this data set isunlabeleddata set and used unsupervised parameter. This is a major reason that we has been using this type of data set that contains a number of properties [30]. There are 6 datasets from Reddit, Twitter, Gowalla and Lastfm. Each matrix contains how many times a user 'consumed' and item. Items can be locations, artists, or subreddits. The details about each dataset are presented below. (In the parenthesis is the number of Users x Items). The dataset Repeat Consumption Matrices contains two sub-data segments, as mentioned above were making a high possibility of getting results is easy because it has given different values. DataSet results will be selected depending on the number of clusters and on DB index. As well as the nature of the work depends on running the PSO algorithm and comparing it with the GA algorithm. The following table1.1 shows the properties of each dataset it contains in the Repeat Consumption Matrices.

Table 1. Benchmark characteristics of each dataset in the inrepeat consumption matrices

Dataset	Distribution
tw_oc	tweets with geolocation from Orange County CA area. Items are locations a user visits in this case.
tw_ny	Same as tw_oc but from the New York area.
go_sf	Check-ins from the app Gowalla, from the San Fransisco area.
go_ny	Same as go_sf, but from the New York area.
reddit_sample	How many times a user posted in a subreddit. These are the 130k most active users from 2015 and 20k most subscribed subreddits. This dataset is very large and can take a lot of time to load/use.
lastfm	How many times, a user listened to each artist. Covers 3 years of listening habbits

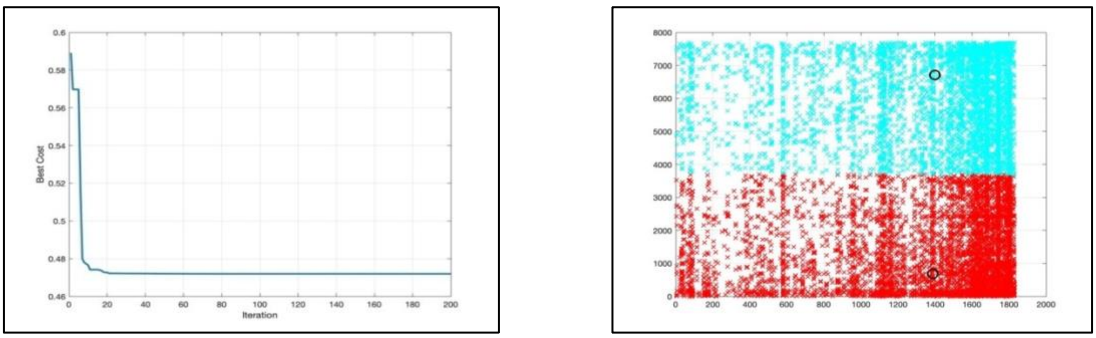
5. RESULTS AND DISCUSSION

This part explains the PSO algorithm work and test it on DataSet (Repeat Consumption Matrices) and compares it with dataset results, which are proven by PSO algorithm and GA based on the number of clusters. Consider this DataSet is a numerical type where its ratings are not well. It will encounter challenges in running the algorithm to determine the number of cluster where this test depends on DB index. Through which the number is known the number of clusters depending on the changes you get the number of cluster where the lower the value, the higher it means. In this paper the PSO algorithm was tested for operation based onRepeat Consumption Matrices DataSet and then compare the results with the GA algorithms. Based on the observation between thesetwo algorithms, PSO gives good results compared to the GA algorithm as shown in the table1 2.

Table 2. Comparison results between the PSO and GA algorithm

Dataset	PSO Algorithm		PSO Algorithm	
	Number of clusters	DB fitness	Number of clusters	DB fitness
go_ny	2	0.47196	2	0.47197
go_sf	2	0.50064	2	0.50072
lastfm	2	0.49807	2	0.49807
reddit_sample	3	0.68756	3	0.69713
tw_ny	6	0.68962	2	0.51026
tw_oc	2	0.70362	2	0.70363

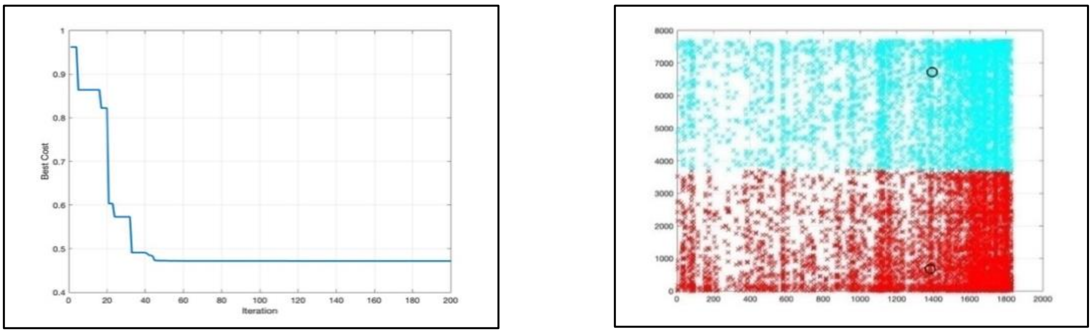
Note that the Repeat Consumption data set contains six typesof data set. That will test each type separately. The following diagrams illustrate the run of the data set on the PSO algorithm, and a number of different clusters are added the accuracy. As shown in the Figure1.1, the Repeat Consumption Matrices dataset was run by the PSO algorithm and gives good results depending on the number of clusters. Figure 1.1(a) represent the flow of the data set depending on the color while the Figure 1.1(b) red and blue color repre-sents the number of clustersbyusing DB index as evolution.



(a) (b)

Figure 1.1 (a) Best cost founded during iterations process forgo_ny dataset using DB index as evolution criteria (b) Number of clusters cost founded forgo_ny dataset using DB index as evolution criteriafor PSO algorithm

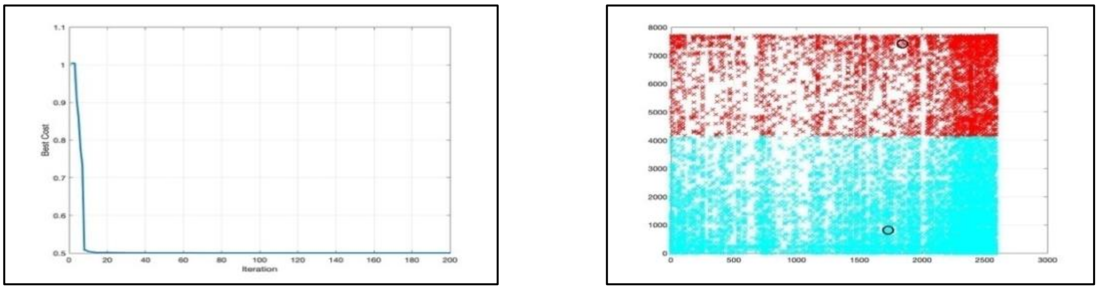
If that test the same data on another algorithm, then it will give different results depending on the flow of dataset and also the number of the cluster as shown in Figure 1.2 by using DB index as evolution.



(a) (b)

Figure 1.2 (a) Best cost founded during iterations process forgo_ny dataset using DB index as evolution criteria (b) Number of clusters cost founded forgo_ny dataset using DB index as evolution criteria for GA algorithm

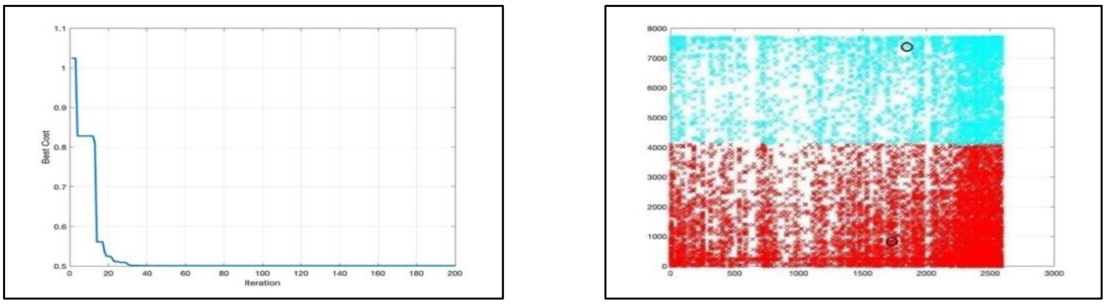
When the PSO algorithm is rerun on its own species, different results will be invoked compared to the first dataset as well as a difference in the number of clusters. It is possible to drill on as shown in the following Figure 2.1.



(a) (b)

Figure 2.1 (a) Best cost founded during iterations process forgo_sf dataset using DB index as evolution criteria (b) Number of clusters cost founded forgo_sf dataset using DB index as evolution criteriafor PSO algorithm

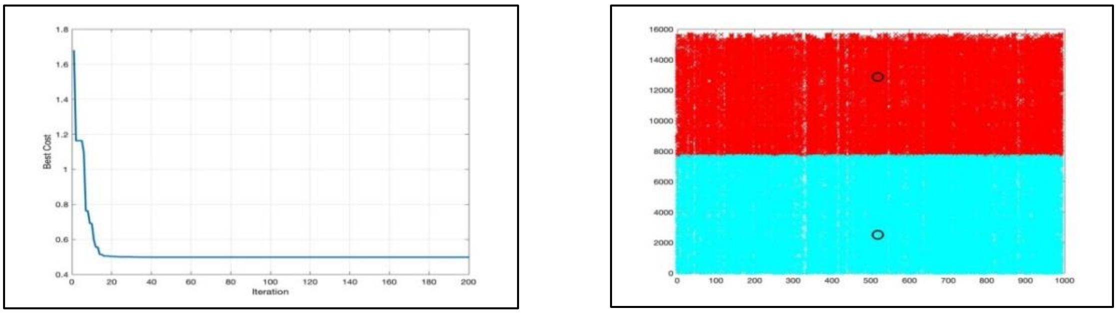
The same is true when we run the second type of data set as mentionedin Table1.1 using the geneticalgorithm and showing the results are uneven but are considered to be of less quality compared with the PSO and depending on the same as in the Figure 2.2.



(a) (b)

Figure 2.2 (a) Best cost founded during iterations process forgo_sf dataset using DB index as evolution criteria (b) Number of clusters cost founded forgo_sf dataset using DB index as evolution criteria for GA algorithm

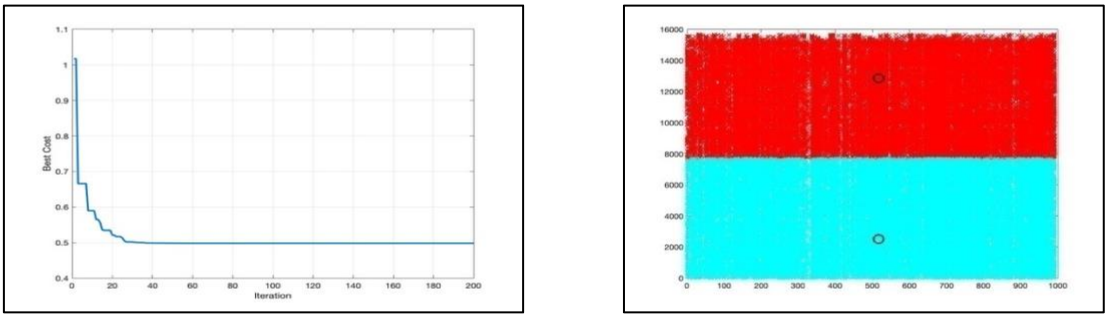
The Repeat Consumption DataSet also contains a third type called forlastm dataset. This type has been tested with PSO algorithm. A number of results have been shown based onDB index and the number of clusters in the Figure 3.1.



(a) (b)

Figure 3.1 (a) Best cost founded during iterations process forlastm dataset using DB index as evolution criteria (b) Number of clusters cost founded forlastfm dataset using DB index as evolution criteriafor PSO algorithm

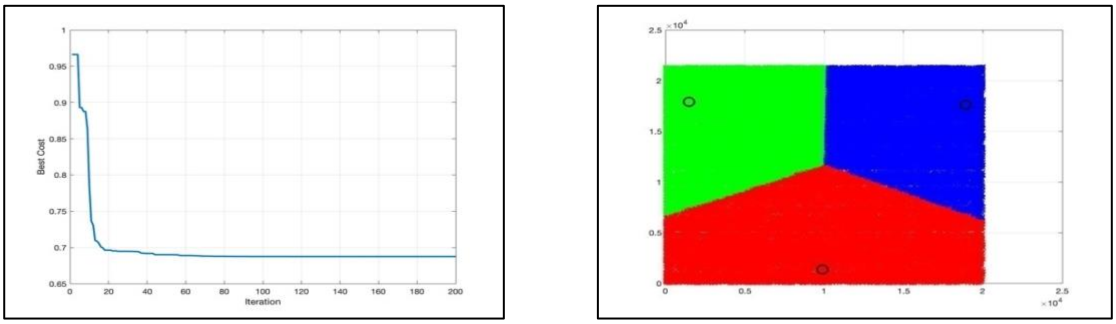
When the genetic algorithm is used on the same dataset (forlastm dataset), it has beenproduced results of less quality compared to the PSO algorithm. It represents good results through iterations process as shownFigure 3.2 where the part (a)represents the data flow while the segment(b) represents the number of the clusters.



(a) (b)

Figure 3.2 (a) Best cost founded during iterations process forlastfmdataset using DB index as evolution criteria (b) Number of clusters cost founded forlastfm dataset using DB index as evolution criteria for GA algorithm.

There is also another dataset (forreddit_sample data set) contains in the Repeat Consumption Dataset. In the previous, DataSet was tested by the PSO algorithm, and the results were compared usingGA algorithm. The data for this dataset and can be observed in Figure 4.1. It can be observed in the following figure based onbest cost founded during iterations process the number of cluster and are considered to be different compared to the other datas where the number of clusters become 3.

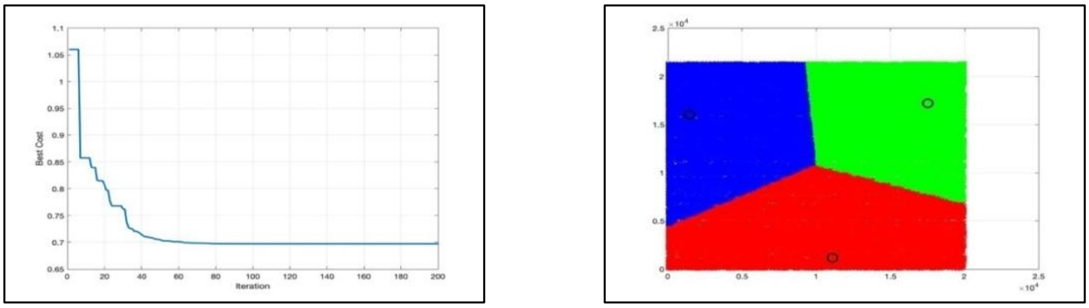


(a) (b)

Figure 4.1 (a) Best cost founded during iterations process forreddit_sample dataset using DB index as evolution criteria (b) Number of clusters founded forreddit_sampledataset using DB index as evolution criteriafor PSO algorithm

The purpose of demonstrating the PSO algorithm of the results by relying on DB index as evolution. The forreddit_sample dataset will be tested by a genetic algorithm (GA)to compare the results. It also turned out that the PSO algorithm does provide advanced results compared to its counterpart. As shown in Figure

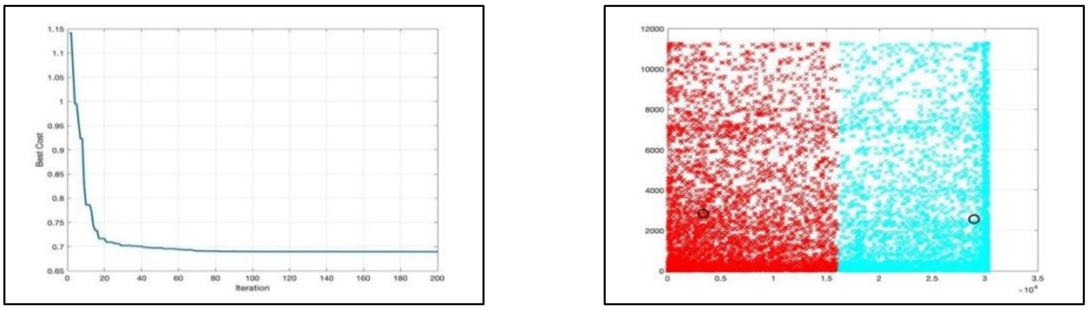
4.2. the form of the first penalty (a)represents the flow of DataSet of the ratio while the (b) represents the number of clusters.



(a) (b)

Figure 4.2 (a) Best cost founded during iterations process forreddit_sample dataset using DB index as evolution criteria (b) Number of clusters founded forreddit_sampledataset using DB index as evolution criteriafor GA algorithm

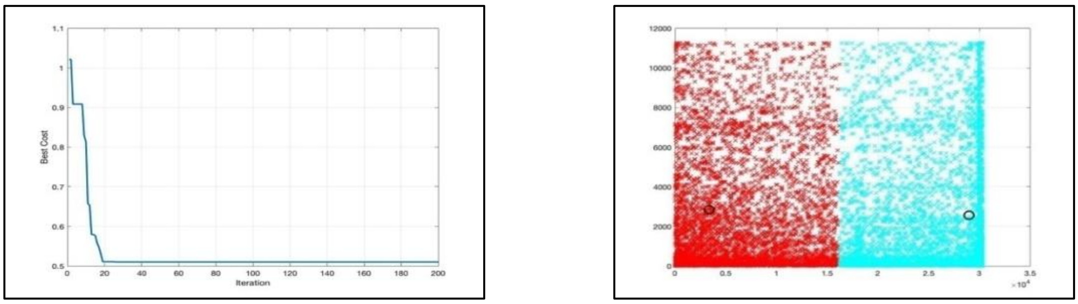
The Repeat Consumption DataSet contains fifth types of the data set(fortw_nydataset). When activated by the PSO algorithm, the results are well demonstrated by dependence on DB index. The results can be observed by the Figure 5.1. where the first part of the figure(a) represents best cost founded during iterations process fortw_nydataset using DB index as evolution criteria. While the other part(b), number of clusters cost founded fortw_nydataset using DB index as evolution criteria for PSO algorithm.



(a) (b)

Figure 5.1(a) Best cost founded during iterations process fortw_nydataset using DB index as evolution criteria (b) Number of clusters cost founded fortw_nydataset using DB index as evolution criteriafor PSO algorithm

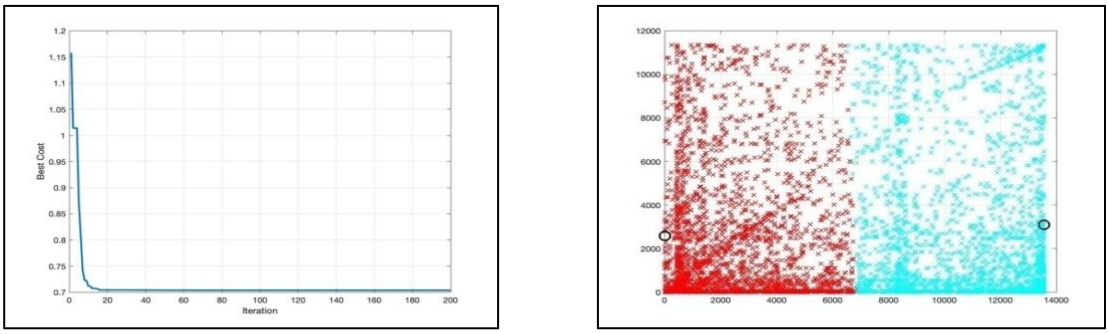
This type of dataset (fortw_nydataset) is tested by a GA algorithm. The results show that the PSO algorithm gives a better comparison to the GA algorithmas shown in the figure5.2. This shows that two parts where the first part(a) is represented best cost founded during iterations process fortw_nydataset using DB index as evolution criteria while the other part(b), number of clusters cost founded fortw_nydataset using DB index as evolution criteria for GA algorithm.



(a) (b)

Figure 5.2 (a) Best cost founded during iterations process fortw_nydataset using DB index as evolution criteria (b) Number of clusters cost founded fortw_nydataset using DB index as evolution criteriafor GA algorithm

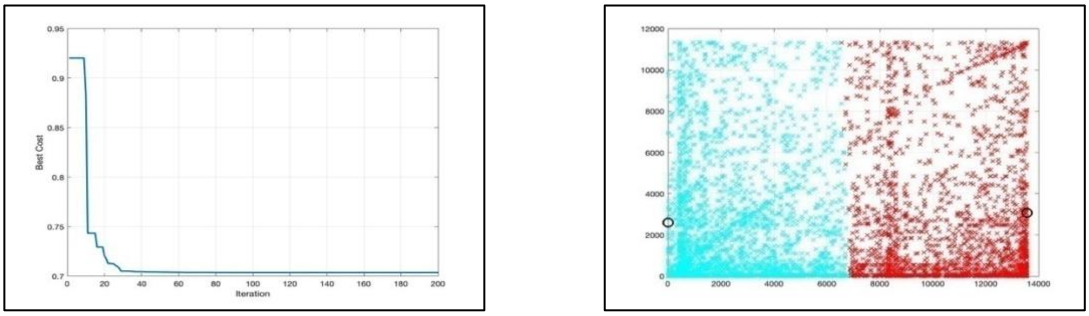
The Repeat Consumption Dataset have a sixth dataset(fortw_ocdataset) and will also be tested and output results by the PSO algorithm where it can be observed through the Figure 6.1, it also shows good results by relying on DB index evolution criteria. It can be observed in the Fig. Despite the possibilities of the PSO algorithm to give good results, it has a different number of clusters.



(a) (b)

Figure 6.1 (a) Best cost founded during iterations process fortw_ocdataset using DB index as evolution criteria (b) Number of clusters founded fortw_ocdataset using DB index as evolution criteria for PSO algorithm

Here the genetic algorithm(GA) is also used to detect the best possible results in comparison with the product demonstrated by the PSO algorithm.But as appeared in the Figure 6.2, the results reflect a bad comparison as given by the PSO algorithm where the figure can be seen representing the first part(a), best cost founded during iterations process fortw_ocdataset using DB index as evolution criteria of the other part(b) while representing number of clusters founded fortw_ocdataset using DB index as evolution criteria for GA algorithm.



(a) (b)

Figure 6.2(a) Best cost founded during iterations process fortw_ocdataset using DB index as evolution criteria (b) Number of clusters founded fortw_ocdataset using DB index as evolution criteriafor GA algorithm

6. CONCLUSION

The PSO algorithm is based on the previous tests in its work on six types of datasets and extract the best results by It best cost founded during iterations process fortw_ocdataset using DB index as evolution criteria. The results are extracted in this research based on two axeswhere it represents the first axis; best cost founded during iterations process using DB index as evolution criteria and the second axis represents number of clusters founded using DB index as evolution criteria for algorithm. The tests proved by comparing the PSO algorithm and GA algorithm that the PSO algorithm does give good results compared to the GA algorithm.

In the PSO algorithm, there is no immediate recombination of hereditary material between people during the hunt. The PSO calculation takes a shot at the social conduct of particles in the swarm. Hence, it gives the worldwide best arrangement by basically altering the direction of every person toward its own best area and toward the best molecule of the whole swarm at each time step. The PSO strategy is winding up extremely well known because of its straightforwardness of execution and capacity to rapidly combine to a sensibly decent arrangement.

Specifically, PSO algorithm maintains a population of particles, each of which represents a potential solution to an optimization problem. The position of the particle denotes a feasible, if not the best, solution to the problem. The optimum progress is required to move the particle position in order to improve the value of objective function. The convergence condition always requires setting up the move iteration number of particles.

The algorithm was able to identify the number of clusters, which is the best algorithm PSO in the field of improvement. In the latter, the number of clusters and the finger differed. It is difficult to identify the number of clusters as a result of progress and evolution, but the PSO algorithm compares with the other algorithms, such as GA, gives good result.

The particle swarm optimization (PSO) algorithm was introduced and improved, the new definition and update rule of velocity and position vector were proposed, and the improvement approach about generating a random velocity was adopted to avoid particle swarm into local optimal solution. Then an actual case study was calculated to check its feasibility in practical use. The results show that the PSO algorithm can be more preferably solve the number of clusters problem than GA algorithm.

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