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Cluster based Approach of Student's Employment Prediction using PSO & EP

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Abstract: In the present era of globalization where the geographical boundaries are no bar in terms of job opportunities, there is need of understanding and analyzing the students profile in terms of probable job offers. This work presents the cluster based concept in developing the easy and handy approach to define the possible job category for the engineering undergraduate students. The limitation of K-means has been explored in terms of their initialization and can't consider in practice without re-verification. The optimal level of clustering has been developed using a hybrid approach of swarm intelligence and evolutionary computation. The dynamic approach of inertia weight in particle swarm optimization has been applied to provide the more suitable change with iteration while self-adaptive strategy in the evolutionary programming delivered the faster exploration. The proposed approach ensures the better balance between explorations vs. exploitation and delivered the optimal solution with high value of reliability.

Keywords: *Job category prediction, cluster, PSO, EP, Self-adaptive*

1. Introduction

Employment Programs for young people seeking job might be transformed by artificial intelligence (AI). Several instances of how AI may increase the availability, applicability, and effectiveness of youth programmes in developing nations are provided in a recent IFC report. According to research, the worldwide market for AI in learning and education is predicted to increase at a pace of 38% annually and reach $2 billion by 2023. The demand for more effective technological solutions for young employment, such as training, job matching, access to financing, etc., is projected to rise as a result of the decline in work options and mobility issues brought on by COVID-19. These cutting-edge technologies may reach more vulnerable populations as there is growth in rates mobile penetration to remote areas. The transition to competency-based profile and job matching systems can be aided by AI technologies. Instead of only gathering data on a job seeker's formal education and professional experience, a competence-based matching technique takes a more comprehensive approach by identifying talents, life experiences, and aspirations. AI may also assist in the analysis of skills assessment data to pinpoint a young person's ability gap and offer personalized recommendations for skill improvement and career advancement. AI is used by online education providers like Coursera and Andela to assess student test results and provide skill-building recommendations. Other companies, like the Brazilian company Revelo, aggregate information from work and school platforms online to provide upskilling recommendations on demand. Latent abilities and entrepreneurial potential in young people can also be discovered via the use of comprehensive psychometric evaluation. For instance, KnackApp measures 2,500'micro-behaviors', such as active and passive decisions, responses, or exploration, using a game based on neurological and behaviour research. Then, it pairs young people with suitable skill-development programmes in a variety of industries, including sales, retail, construction, hospitality services, and data science. Identifying the particular job abilities that will be required in the future is challenging. Traditional demand assessment techniques like surveys, focus groups, and industry consultations take time and are not always in-depth. It can often take up to 10 years for labor market systems to adapt to new trends and information, which causes nations to lag. Utilizing unstructured data from a variety of sources, including job listings, social media, and official websites, AI programmes may quickly forecast the demand for positions in the near future. For instance, Singapore's government-sponsored job-matching portal MyCareersFuture uses AI to evaluate real-time online labor market data from a

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variety of job boards in order to forecast impending opportunities and skill needs. Access to market trends at the right moment may thus assist educational and training institutions in adjusting their curricula to meet employer demands, influence governmental funding and policies, and enhance the overall effectiveness of the workforce development system. It is crucial to keep in mind that any AI integration on young employment solutions should take gender and occupational biases in the labor market into account while maintaining data privacy. Lack of sufficient data is a significant issue when adopting AI solutions, particularly in poor nations. Effective local relationships across the public, corporate, and academic sectors will be essential to the success of these initiatives.

Predicting student performance has gotten harder as a result of the vast amount of data in educational databases. The lack of a developed system for assessing and monitoring student achievement is also not being taken into account. There are mainly 2 causes for this type of scenario. First of all, there is presently inadequate study on the various prediction techniques to choose the ones that will best forecast students' success in academic settings. Second, in the lack of research into particular courses, it may be possible to more effectively enhance student performance and advancement using machine learning techniques in education.

As a key indicator of educational institutions' success, student employability is essential. But because of globalization, automation, and recent developments in artificial intelligence, the employment market environment is more dynamic than ever. All stakeholders can benefit greatly from being aware of the key elements influencing employability as well as the demands of the new job market. Students could better plan their careers if they are aware of their areas of strength and weakness. To address the demands of quickly changing job markets, instructors might put more of an emphasis on skill sets that are more applicable. Program directors can plan ahead and enhance their curricula to develop new capabilities for instructing and training. Certainly the cumulative efforts of all these initiatives can improve employability. Numerous disciplines of educational data mining have made substantial use of data-driven and machine learning approaches.

The work in this paper carried the number of subdivision where different aspects of work have been discussed. In the section 2 related works has been discussed while section 3 carried the discussion over the proposed work. The experimental results and analysis has been presented in section 4 and conclusion is at the end.

2. Literature Survey

Academic achievement and academic motivation are interconnected. Both early identification of pupils who lack academic desire and early identification of students who exhibit high levels of academic drive are crucial for instructors. To create a classification model for categorizing student academic motivation based on how they behave in learning management system (LMS) courses, [1] aims to create connections between expected academic motivation of students and how they behave in the LMS course. In order to enhance career counseling and career advising, there is a data-driven methodology for predicting students' profession choices after graduation based on their behaviour on and around campus [2]. [3] has employed a multi-layered neural network (NN) to categories students' degrees into either a good or basic degree class in order to forecast students' performances using a mix of institutional, academic, demographic, psychological, and economic characteristics. In [4], XGBoost classifier is used to study, research, and incorporate external factors in order to forecast student achievement. The ability of traditional statistical evaluations to accurately forecast the standard of higher education is restricted. [5] has described a method for modeling and predicting student performance using neural networks in addition to traditional statistical analyses. [6] has attempted to use machine learning to predict the placement and ranking outcomes of programming competitions without doing a thorough analysis. Different kinds of explanatory variables are used in machine learning. Numerous factors, including the economy and public policy, have an impact on college students' employment, which increases the prediction error of this statistic. A gray system-based employment rate prediction approach for college students was created in [7] to address this issue. A significant area of the development of education data mining is the establishment of student accomplishment prediction models to forecast student success in academic institutions. With the use of their 10th, 12th, and prior semester grades, a prediction method has been put out in [8]. Binomial logical regression, a decision tree, an entropy and KNN classifier, and binomial regression were used to assess the study. Big data analytics and artificial intelligence are rarely used in underdeveloped nations, and this is especially true in the education sector. Developing nations like Bangladesh must adopt online learning at the same rate as students and teachers worldwide do. While we might not be able to transfer an entire student's educational experience from the classroom to the Internet, we can take steps to use the data we already store to develop efficient monitoring systems, like the student performance monitor (SPM) that can inform students about their strengths and weaknesses and point them in the right direction [9]. The purpose of the study in [10] was to determine the significance of artificial intelligence (AI) in human resources (HR), particularly in the wake of the Corona Virus (19) epidemic. Other functional modules include management, course management, exam room management, and performance management. [11] Investigated how computer technology is used to supervise university students. Every aspect of the administration of students' whole lifecycle, from enrollment to employment, was covered in the design material, which included a variety of functions with student management at their heart, such as student.

3. Proposed solution

3.1 Dynamic weighted PSO

Under swarm intelligence domain PSO has been considered as a very efficient approach because of its simplicity and faster convergence along with satisfactory solution for number of applications. The functional characteristics defined by a population under the social inspirational concept where an individual member updates its current position by updating its change in the previous velocity. The velocity change is inspiration approach based on differences from best member along with its own self-best has been achieved in the past. The control over change mainly defined through the inertia weight associated with the previous velocity. The difference values from best member and previous self-best to current value also controlled through the social constant and cognition factor. The mathematical formulation can be represented by the Eq1 and Eq.2

(i)Velocity up gradation of k th dimension

$$V_k' = \chi\,[w \times V_K + C1 \times R1 \times (M_{best,k} - P_k) + C2 \times R2 \times (M_{SB,k} - P_k)] \quad \textbf{(1)}$$

(ii) Solution member up gradation for k th dimension

$$P_k' = P_k + V_k'; \quad (2)$$

Where , χ represents a constriction factor, w defined inertia weight, C1 & C2 are social and cognition constants, R1 &R are random number $\epsilon[0\ 1]$.The dynamic nature of 'w' was given by

Linear change with iteration as shown in Eq3.

$$w = w_{max}\frac{(w_{max}-w_{min})}{iter_{max}} \times iter \quad (3)$$

3.2 Evolutionary programming (EP)

EP has been considered as the part of the evolutionary computation which carried the Genetic algorithm and Evolutionary Strategy as the other forms of approach which has the genetic evolution nature for the fitness improvement. In the EP , an individual member get mutated to create the offspring and later a combined pool of parents and offsprings are form from which the best member are selected through selection process in forming the new generation population. To make the selection unbiased rather than directed fitness based selection, tournament selection has been applied which provide the opportunity to everyone in more fair manner. The mutation generally supported by Gaussian distributed random number whose spread has been controlled in self-adaptive manner.

(i) Mutation strategy

$$M'_k = M_k + \eta_k . N\,(0,1) \quad (4)$$

(ii) Self-adaptive strategy for Gaussian spread

$$\eta'_k = \eta_k \exp\,[\tau' N(0,1) + \tau N_k(0,1)] \quad (5)$$

$N(0,1)$ represents a random number generated through Gaussian distribution having zero mean with unity as standard deviation while $N_k(0,1)$ is a random number generated through Gaussian distribution for each component . η_k is the standard deviation for k th component. τ and τ' are constant and $\tau = \left(\sqrt{2\sqrt{n}}\right)^{-1}$; $\tau' = \left(\sqrt{2n}\right)^{-1}$.where n is dimension of problem.

3.3 Hybrid approach Carried Social & Genetic evolution (HPSOEP)

There are number of applications where PSO and EP both have shown efficient exploration of solution space at the same time fundamental limitations also inherited with these algorithms. In PSO there is high probability of diversity loss at the early stage because of influential characteristics of algorithm and cause of end with suboptimal solution. The EP carried the large amount of genetic variations and doesn't utilize the information having by other members available in the population. To overcome the both issues, a hybrid approach has been proposed which carried the PSO and EP sequential manner. The EP has been used in the probabilistic mode so that there will not the genetic dominancy occurred over the social evolution. The complete detail of the proposed solution has shown in Fig.1.

Initially a population set for three centroids have been defined randomly carried out from data set. After estimating the fitness value of each member, best member (having maximum fitness) decision has taken place. The initial population for self-best population is same as initial solution population. The velocity up gradation has taken place for each individual member from population using Eq1. and the position update has been provided through Eq2. The new position solution has become the starting population for the EP or replace the old population of PSO depends upon the condition of random number against the threshold value. In the EP, corresponding to each member a new offspring has been created using Eq.4 and later through tournament selection population for next generation declared. There were update of new spread of Gaussian function have done and generated new population passed to the PSO for further iteration if permitted else process terminated while considering the best member in the population as the final solution. Under each iteration the inertia weight 'w' were updated using Eq.3

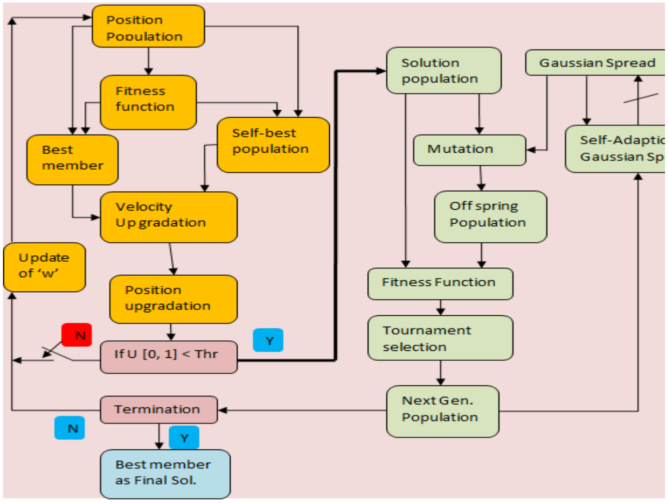

Fig.1. working flow of HPSOEP

4. Experimental Results

The prediction of the obtaining the jobs by the undergraduate engineering students have been considered for the experimental purpose. The marks of past seven semester results and personality index (PI) parameters have been considered to define the probable category of obtain job. There were three categories of job considered as the very good, good and average depends upon their salaries. There were total 300 undergraduate engineering students data have been considered from different streams and their placement was considered for the core companies involved in the corresponding domain. For training purpose 150 students have been considered carried the 50 students from each category of job and remaining 150 students data have been used to test purpose. A sample set of data containing 4 students details have shown in Table1.

Table 1: a sample data set for 4 students

	Semester Marks							
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	6^{th}	7^{th}	PI
1	80.5839	82.1696	82.4924	89.2653	84.9770	89.9548	81.1241	9.0
2	83.6828	82.6309	88.9713	84.1719	85.6089	86.0430	89.2911	3.0
3	70.1289	75.0963	65.0944	71.5032	70.0603	77.1920	72.8968	10.0
4	60.3216	63.3744	73.9925	73.1312	79.2229	75.1201	70.6927	1.0

The prediction of jobs landing has been considered using the cluster development where each cluster center represents the reference for prediction. There were total 3 different jobs categories existed hence needed three centroids where each centroid carried the dimension of 8 in result the total 24 parameters needed. The parameter values were estimated under different algorithm environments and their benefits versus limitations have been analyzed. The performances have been evaluated in terms of number of true member belongs to that cluster (as R) and number of members existed in the cluster but actually belongs to other clusters (as W). The frequently used cluster algorithm in practice K-Means approach have been considered for the reference and later meta-heuristic based on swarm intelligence and evolutionary computation have been considered to explore the solution space. The performances of K-Means algorithms were very good but a major limitation existed in terms of initialization. The poor initialization caused of either suboptimal solution or may not end with the desired number of needed clusters. The obtained performances under 10 independent trials have shown in Table2 where it can observe that there were two trials where convergences were not proper. To overcome such issue meta-heuristic approach based on PSO and EP have been considered with population size of 50 and allowed numbers of iteration were 200. In the PSO, dynamic weights with iteration have been considered where the values change from high to low from 1.2 to 0.1 with iteration. This approach has applied the large change at the beginning while small change appeared later stage when the solution is towards convergence.

The value of constriction factor was considered as 0.72 while social and cognition constant were 0.5. The obtained intra cluster distance fewer than 10 different trials have shown in Table3 .It can observe that for all cases there were proper convergence as shown in Fig.2 and mean intra cluster distance of 15251.431 was achieved with standard deviation of 383.07281 It can observe that there were very faster convergence happen because of loss of diversity. The Gaussian mutation based self –adaptive mutation strategy for the EP has been considered. The obtained performances in terms of total intra cluster distance have shown in Table4 while convergence under 10 independent trials has shown in Fig.3. it can observe that there were lesser intra cluster distance of 14485.909 with variability of 130.88189 in compare to PSO .The proposed solution HPSOEP has also applied over the 10 independent trials and obtained performances in terms of total intra cluster distances and obtained centroids under each trail have shown in Table 3 and Table 4.The convergence characteristics have shown in Fig.4.

It can observe that HPSOEP not only has deliver the minimum intra cluster distance of 14074.699 but also the variability in performance under different trials were very less equal to 0.01244. The comparison of convergence have shown in Fig.5 and observe that PSO had the diversity loss early hence could not explore the solution space efficiently. The EP was able to maintain good diversity but quality of convergence rate were poor. The proposed HPSOEP has shown both faster and optimal convergence.

Table 2: performances of K-Means algorithms under 10 independent trials over training/ test data

Trail	**Centroids values**	**JC1 JC2 JC3 R/W R/W R/W**	**Efficiency (%)**
1	68.4674 69.5687 69.5573 75.0014 74.5397 74.9445 75.0609 5.8182	[46/9 ; 41/0; 50/4]	91.33
	65.2962 64.2532 65.3597 65.4419 65.1757 65.2329 64.9423 5.6341	[41/4; 50/9; 46/0]	91.33
	85.6414 84.6985 85.0775 84.8780 84.6060 85.3307 85.6511 5.5370		
2	68.4674 69.5687 69.5573 75.0014 74.5397 74.9445 75.0609 5.8182	[46/9; 50/4; 41/0]	91.33
	85.6414 84.6985 85.0775 84.8780 84.6060 85.3307 85.6511 5.5370		
	65.2962 64.2532 65.3597 65.4419 65.1757 65.2329 64.9423 5.6341	[41/4; 46/0; 50/9]	91.33
3	67.1130 67.2985 67.7646 70.9187 70.5405 70.7968 70.7394 5.7396	[50/46; 26/4; 24/0]	66.66
	85.1324 86.6043 84.3186 83.6175 84.7795 85.5178 84.7672 4.9000		
	86.2776 82.3163 86.0262 86.4536 84.3890 85.0968 86.7559 6.3333	[50/54;26/0; 20/0]	64
4	65.2962 64.2532 65.3597 65.4419 65.1757 65.2329 64.9423 5.6341	[41/0 ;46/9; 50/4]	91.33
	68.4674 69.5687 69.5573 75.0014 74.5397 74.9445 75.0609 5.8182	-----------------------	
	85.6414 84.6985 85.0775 84.8780 84.6060 85.3307 85.6511 5.5370	[50/9;41/4; 46/0]	91.33
5	68.4674 69.5687 69.5573 75.0014 74.5397 74.9445 75.0609 5.8182	[46/9 ;50/4; 41/0]	91.33
	85.6414 84.6985 85.0775 84.8780 84.6060 85.3307 85.6511 5.5370	----------------------	
	65.2962 64.2532 65.3597 65.4419 65.1757 65.2329 64.9423 5.6341	[41/4; 46/0; 50/9]	91.33
6	68.4674 69.5687 69.5573 75.0014 74.5397 74.9445 75.0609 5.8182	[46/9;41/0; 50/4]	91.33
	65.2962 64.2532 65.3597 65.4419 65.1757 65.2329 64.9423 5.6341	------------------------	
	85.6414 84.6985 85.0775 84.8780 84.6060 85.3307 85.6511 5.5370	[41/4;50/9; 46/0]	91.33
7	68.4674 69.5687 69.5573 75.0014 74.5397 74.9445 75.0609 5.8182	[46/9;50/4; 41/0]	91.33
	85.6414 84.6985 85.0775 84.8780 84.6060 85.3307 85.6511 5.5370	---------------------	
	65.2962 64.2532 65.3597 65.4419 65.1757 65.2329 64.9423 5.6341	[41/4 ;46/0; 50/9]	91.33
8	65.2962 64.2532 65.3597 65.4419 65.1757 65.2329 64.9423 5.6341	[41/0 ; 46/9;50/4]	91.33
	68.4674 69.5687 69.5573 75.0014 74.5397 74.9445 75.0609 5.8182	[50/9 ;41/4; 46/0]	91.33
	85.6414 84.6985 85.0775 84.8780 84.6060 85.3307 85.6511 5.5370		
9	81.2905 85.2688 83.2026 82.0567 83.5400 82.2522 83.6699 5.2000	[11/4 ;49/45;39/2]	66
	67.0061 67.0696 67.5316 70.7672 70.3879 70.6694 70.6357 5.7340	[12/1 ;50/53;34/0]	64
	86.5744 84.1659 85.4532 85.5767 84.6598 86.0402 85.8864 5.6829		
10	65.2962 64.2532 65.3597 65.4419 65.1757 65.2329 64.9423 5.6341	[41/0;50/4;46/9]	91.33
	85.6414 84.6985 85.0775 84.8780 84.6060 85.3307 85.6511 5.5370	[50/9;46/0; 41/4]	91.33
	68.4674 69.5687 69.5573 75.0014 74.5397 74.9445 75.0609 5.8182		

Table 3. Intra cluster distance by different algorithms under 10 trials

Trials	DyPSO	EP	K-Means	HPSOEP
1	15314.09884256722	14406.00814761508	14074.63835900428	14074.72240347680
2	15143.13349828371	14394.74894034479	14074.63835900428	14074.72240347680
3	15405.24752423060	14459.85867874995	23722.62200919252	14074.69289876332
4	15223.92867989508	14375.01250441380	14074.63835900428	14074.69289876332
5	15575.57908557794	14609.47635106524	14074.63835900428	14074.69289876332
6	14755.64273920212	14439.07314638814	14074.63835900428	14074.69289876332
7	15145.57285728273	14704.54429207667	14074.63835900428	14074.69289876332
8	14545.60659110686	14372.07538701724	14074.63835900428	14074.69289876332
9	15622.19026658063	14691.06399702991	23644.46197864506	14074.69289876332
10	15783.31169070246	14407.23793629089	14074.63835900428	14074.69289876332
Mean (Std.DEV)	15251.43117754293 (383.07281)	14485.90993809917 (130.88189)	15996.41908598718 (4051.511)	14074.69879970602 (0.01244)

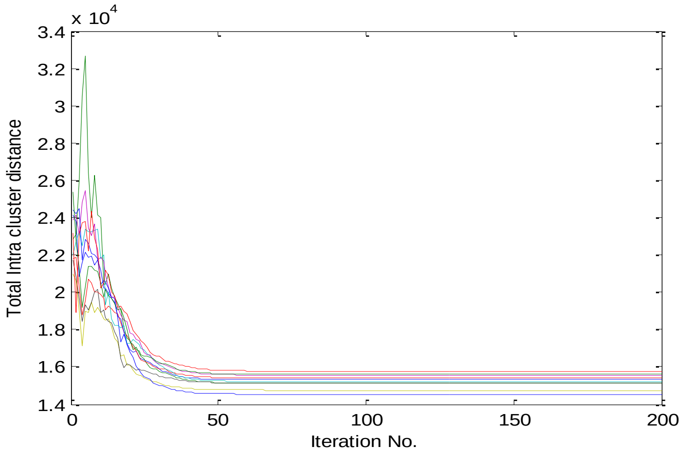

Fig.2. Convergence of DyPSO under 10 trials

Table4: performances of HPSOEP algorithms under 10 independent trials over training/ test data

Trials	**Centroids values**								**JC1 JC2 JC3 Efficiency W/R W/R W/R (%)**
1	85.6377	84.7016	85.0639	84.8826	84.6044	85.3284	85.6510	5.5389	[50/4; 46/9; 41/0] 91.33
	68.4661	69.5656	69.5423	75.0094	74.5408	74.9498	75.0525	5.8291	------------------------
	65.2961	64.2636	65.3747	65.4537	65.1678	65.2236	64.9614	5.6413	[46/0; 41/4; 50/9] 91.33
2	85.6473	84.6913	85.0699	84.8867	84.6001	85.3305	85.6451	5.5424	[50/4 ;46/9; 41/0] 91.33
	65.2988	64.2482	65.3592	65.4501	65.1814	65.2241	64.9429	5.6437	-------------------------
	68.4644	69.5625	69.5590	75.0072	74.5447	74.9446	75.0472	5.8140	[46/0 ;41/4; 50/9] 91.33
3	85.6364	84.6942	85.0753	84.8817	84.6072	85.3251	85.6502	5.5464	[50/4;46/9; 41/0] 91.33
	68.4666	69.5753	69.5554	75.0002	74.5347	74.9604	75.0651	5.8217	-------------------------
	65.3031	64.2517	65.3579	65.4401	65.1582	65.2405	64.9291	5.6309	[46/0; 41/4; 50/9] 91.33
4	85.6436	84.7017	85.0758	84.8776	84.5982	85.3315	85.6550	5.5416	[50/4;46/9; 41/0] 91.33
	68.4703	69.5684	69.5572	74.9929	74.5438	74.9378	75.0603	5.8165	-------------------------

	65.3050	64.2522	65.3524	65.4365	65.1780	65.2371	64.9555	5.6372	[46/0; 41/4; 50/9] 91.33
5	85.6394	84.6966	85.0807	84.8783	84.6062	85.3315	85.6448	5.5253	[50/4 ;46/9; 41/0] 91.33
	68.4713	69.5678	69.5546	75.0054	74.5380	74.9456	75.0585	5.8174	--------------------------
	65.2976	64.2524	65.3649	65.4388	65.1771	65.2490	64.9505	5.6421	[46/0 ;41/4; 50/9] 91.33
6	85.6391	84.7029	85.0765	84.8650	84.6014	85.3324	85.6501	5.5449	[50/4 ;46/9;41/0] 91.33
	68.4673	69.5732	69.5578	75.0065	74.5458	74.9487	75.0692	5.8164	------------------------
	65.2947	64.2498	65.3562	65.4416	65.1812	65.2309	64.9418	5.6245	[46/0; 41/4;50/9] 91.33
7	85.6477	84.7004	85.0803	84.8831	84.6042	85.3282	85.6511	5.5311	[50/4 ;46/9;41/0] 91.33
	68.4645	69.5736	69.5587	74.9983	74.5318	74.9372	75.0628	5.8155	------------------------------
	65.2951	64.2541	65.3608	65.4393	65.1720	65.2403	64.9396	5.6390	[46/0; 41/4; 50/9] 91.33
8	85.6432	84.6978	85.0732	84.8825	84.6129	85.3241	85.6674	5.5350	[50/4;46/9; 41/0] 91.33
	68.4646	69.5699	69.5582	75.0084	74.5405	74.9455	75.0549	5.8171	------------------------
	65.2958	64.2619	65.3633	65.4515	65.1772	65.2255	64.9395	5.6383	[46/0;41/4; 50/9] 91.33
9	85.5679	84.6251	85.1902	84.9421	84.6416	85.3012	85.7864	5.4867	[50/4;46/9 ; 41/0] 91.33
	68.4157	69.5304	69.5448	75.0000	74.5771	74.8708	75.0986	5.9347	--------------------------
	65.3507	64.2681	65.4323	65.5329	65.1827	65.2613	65.0023	5.6621	[46/0;41/4; 50/9] 91.33
10	85.6410	84.7046	85.0770	84.8810	84.6029	85.3337	85.6514	5.5322	[50/4 ;46/9;41/0] 91.33
	68.4696	69.5704	69.5638	74.9998	74.5433	74.9458	75.0609	5.8198	-------------------------
	65.3018	64.2560	65.3670	65.4443	65.1801	65.2311	64.9400	5.6387	[46/0;41/4; 50/9] 91.33

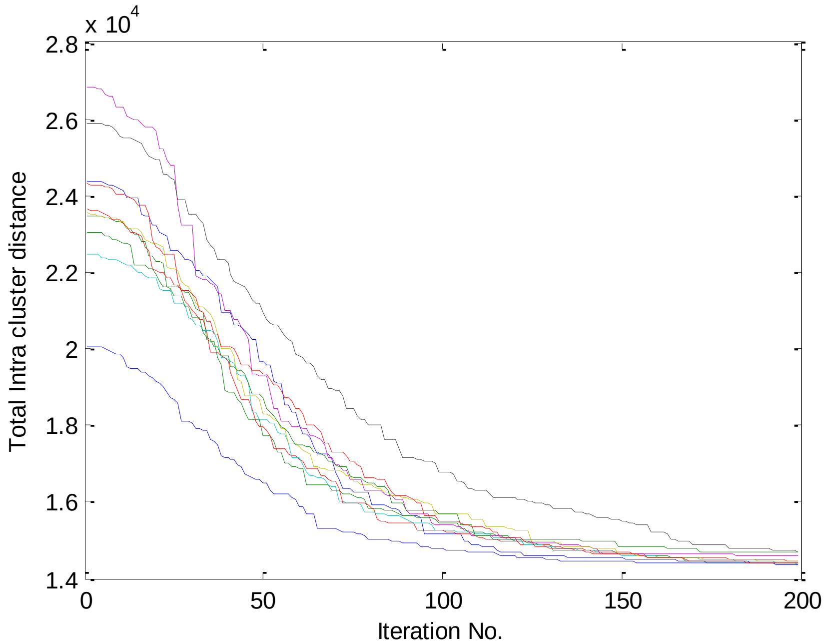

Fig.3. Convergence of EP under 10 trials

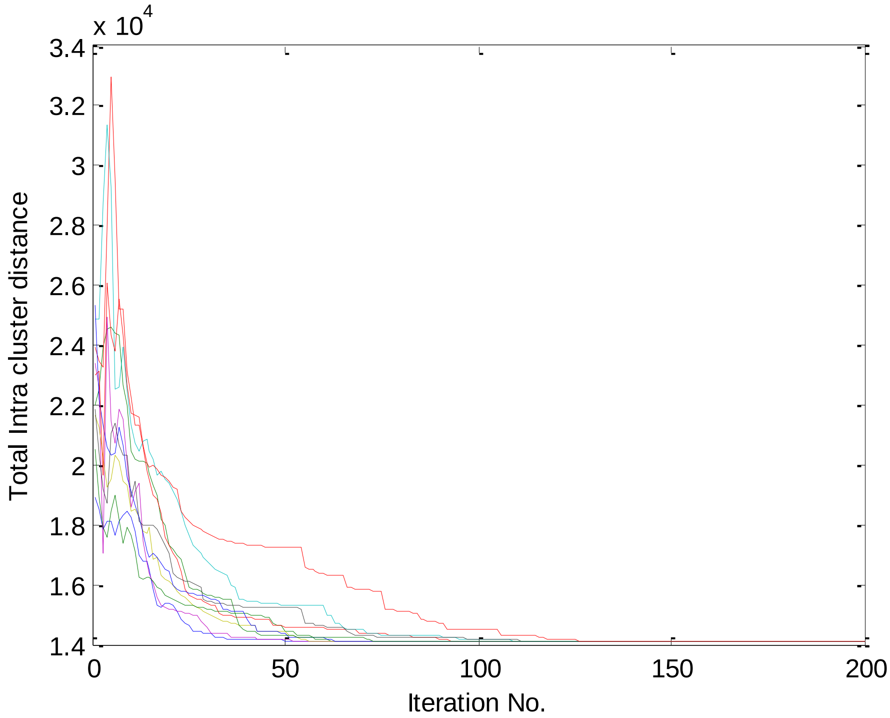

Fig.4. Convergence of HPSOEP under 10 trials

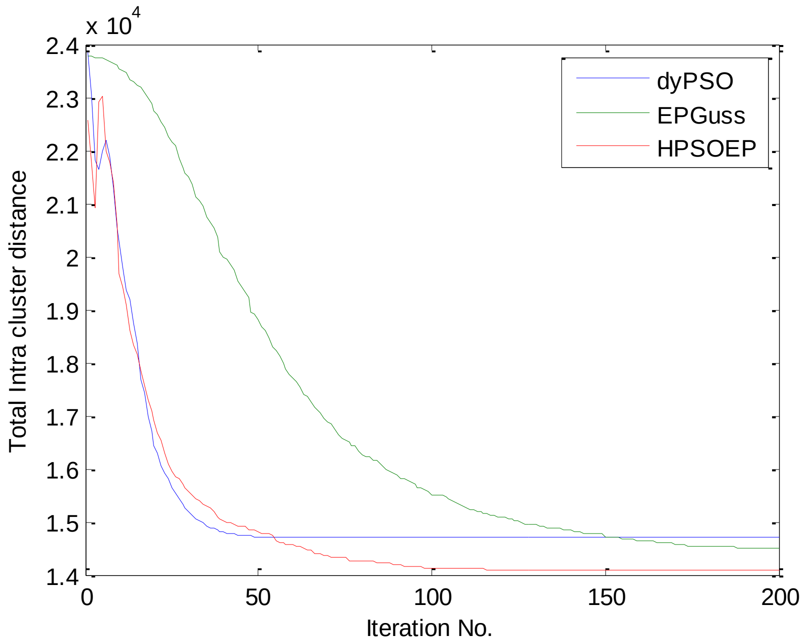

Fig.5. Mean Convergence of different algorithms under 10 trials

5. Conclusion

The use of AI in education and job employment environment have been attended a lots of attention by the researchers. The proposed work has applied the cluster concept to develop the easy and handy approach in finding the possible job opportunity for the students. The combination of PSO and EP has ensured the quality of exploration of solution space and delivery of optimal solution with faster convergence rate. From real time application point of view the reliability of outcomes is very important. The K-Means algorithm has shown the failure over that while proposed solution HPSOEP has maintain the very level of reliability. The benefit of proposed approach can be use as very handy tool in predicting the job category with minimal computation cost. In future, to make the predictability more handy, rule based approach will apply to define the job category.

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