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Convergency Analysis of Some Estimation of Distribution Algorithms in Detail

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1 Introduction

Although the previous EDAs are promising to solve hard problems when we have no knowledge about the problems, the researchers want to know how to design an effective EDAs or revise an existing EDAs. In addition, there are two cruxes of EDAs. First of all, EDAs may cause the problem of overfitting the search space and cannot represent the general information [3]. Most importantly, due to the premature convergence of EDAs [1], the probabilistic models no longer generate diversified solutions resulted in poor performance.

This technical report investigates the convergency speed of EA/G and ACGA in solving the NP-Hard single machine scheduling problems with earliness/tardiness considerations, which is used in the just-in-time production environment. We found the convergency speed of EA/G is rather fast; however, the probabilistic models no longer generates diversified individuals which causes a problem of premature convergency. Although ACGA may not converge fast, it outperforms the EA/G significantly when we have sufficient computation time. After the analysis of convergency speed, we discover interesting connections between intensification and diversification effects of EDAs and that alternatives with other algorithms. Because these results are interesting, the authors further illustrate the guidelines for designing effective EDAs in another paper based on this technical report. The detail results is shown in the following section.

2 Convergency Progress Analysis of EDAs

In this section, ACGA and EA/G are analyzed by running the instances of single machine scheduling problems with the minimization of earliness/tardiness cost. When we observe the convergency progress of the two EDAs, simple Genetic Algorithm (SGA)

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with elitism is also adopted into the comparisons. The stopping criteria are based on the number of examined solutions, which are 50000, 75000, 100000, and 125000 solutions. The four examined solutions stand for the different implementation environments which allow lower, medium, high, and higher level of computational time. When taking a close look of the convergency behavior, we attempt to discover whether there is any difference among the three algorithms when the stopping criteria are different. The analysis is done by Design-of-Experiment to distinguish the difference of these algorithms. And the parameter settings are the same, such as the population size is 100, the crossover rate is 0.9, and mutation rate is 0.5 across all experiments. And when we use 50000 solutions, it means that the algorithms stop at generation 500.

There are numerous data sets published in the literature [4] for the single machine scheduling problems, including 20, 30, 40, 50, 60, and 90 jobs. Each data set of 20 jobs up to 50 jobs contains 49 instances (problems) whereas there are 9 instances in the data set of 60 jobs and 90 jobs. We carried out our experiments on these total 214 instances. Each algorithm will replicate every instance 30 times. The following subsections are the empirical results of solving the single machine scheduling problems.

2.1 Empirical Results of Different Stopping Criteria

In Table 1 to Table 4, they illustrate the minimum, average, and maximum objective values for the SGA, ACGA, and EA/G respectively. It is clearly that ACGA and EA/G outperform the SGA. In order to test the significance between ACGA and EA/G, Analysis of Variance (ANOVA) is used. When the P-Value is less than 0.05, it means there is a significance of the factor. The detailed information of the ANOVA analysis is in [2].

Table 1 Selected results of these algorithms employ 50000 Examined Solutions

	SGA			ACGA			EA/G		
instance	Min	Avg.	Max	Min	Avg.	Max	Min	Avg.	Max
sks222a	5286	5357.2	5504	5286	5289.3	5298	5286	5290.8	5298
sks255a	2372	2413.8	2508	2372	2382.7	2388	2372	2380.0	2388
sks288a	3421	3471.2	3576	3421	3421.0	3421	3421	3421.0	3421
sks322a	11574	11874.7	12760	11568	11578.9	11622	11568	11574.6	11622
sks355a	6090	6430.1	6930	6056	6056.9	6058	6056	6065.7	6212
sks388a	11317	11345.1	11517	11317	11317.0	11317	11317	11318.5	11340
sks422a	25769	26177.6	26971	25656	25666.6	25704	25656	25661.8	25697
sks455a	6797	7409.1	8415	6405	6443.5	6545	6405	6435.2	6667
sks488a	16910	17600.0	18431	16862	16862.9	16888	16862	16862.0	16862
sks522a	29564	30388.7	31799	29309	29327.0	29398	29309	29343.7	29398
sks555a	10338	11903.9	13510	10187	10233.9	10456	10187	10208.6	10264
sks588a	25469	26143.1	26931	24844	24846.5	24861	24844	24846.4	24861
sks622a	44150	45269.9	46818	43048	43098.0	43369	43048	43107.1	43286
sks655a	17565	19996.8	22313	16158	16224.8	16716	16158	16196.4	16640
sks688a	34886	36366.7	38108	33551	33638.5	33797	33551	33600.3	33686
sks922a	92619	95766.7	99835	88853	89085.8	89549	88841	88870.8	89082
sks955a	36733	41872.8	47525	30606	30828.9	31235	30582	30648.2	30804
sks988a	89034	92361.9	97193	82099	82279.9	82531	81984	81985.3	81990

In [2], the factor Method is very significant in the all ANOVA tables, Duncan Grouping test is used to further distinguish the performance of the two algorithms. In Duncan Group test, when the algorithms share the same alphabet, it means they are in the same group so that there is no difference between/among these algorithms.

Table 2 Selected results of these algorithms employ 75000 Examined Solutions

	SGA			ACGA			EA/G		
instance	Min	Avg.	Max	Min	Avg.	Max	Min	Avg.	Max
sks222a	5286	5356.9	5604	5286	5289.2	5298	5286	5289.2	5298
sks255a	2372	2428.6	2712	2372	2381.1	2388	2372	2382.9	2388
sks288a	3421	3472.0	3648	3421	3421.0	3421	3421	3421.0	3421
sks322a	11568	11880.5	12358	11568	11574.6	11622	11568	11570.6	11622
sks355a	6056	6430.3	7061	6056	6057.0	6058	6056	6072.1	6242
sks388a	11317	11334.4	11534	11317	11317.0	11317	11317	11320.1	11340
sks422a	25755	26245.1	27044	25656	25660.5	25704	25656	25663.9	25697
sks455a	6613	7202.4	7916	6405	6428.0	6545	6405	6428.4	6545
sks488a	17013	17490.0	18128	16862	16865.5	16888	16862	16862.9	16888
sks522a	29588	30294.6	31365	29309	29318.3	29396	29309	29320.8	29398
sks555a	10625	11933.9	13957	10187	10217.6	10368	10187	10210.5	10267
sks588a	24992	25863.0	26348	24844	24844.6	24861	24844	24846.4	24861
sks622a	43543	44858.5	46690	43048	43089.8	43369	43048	43095.7	43286
sks655a	17645	19304.3	21366	16158	16175.1	16570	16158	16241.2	16640
sks688a	34872	35966.8	37579	33551	33612.8	33665	33551	33590.1	33686
sks922a	92013	94714.1	98407	88842	88940.7	89631	88842	88884.5	89078
sks955a	34538	40738.2	48650	30582	30710.3	31435	30582	30649.4	30769
sks988a	87099	91698.7	97224	81984	82037.5	82198	81984	81989.6	82112

Table 3 Selected results of these algorithms employ 100000 Examined Solutions

	SGA			ACGA			EA/G		
instance	Min	Avg.	Max	Min	Avg.	Max	Min	Avg.	Max
sks222a	5286	5352.3	5603	5286	5288.9	5298	5286	5289.9	5298
sks255a	2372	2459.3	2936	2372	2380.0	2388	2372	2380.4	2388
sks288a	3421	3480.1	3684	3421	3421.0	3421	3421	3421.0	3421
sks322a	11568	11857.1	12211	11568	11577.1	11622	11568	11575.5	11622
sks355a	6100	6335.4	7083	6056	6065.4	6193	6056	6062.1	6212
sks388a	11317	11323.9	11413	11317	11317.0	11317	11317	11320.1	11340
sks422a	25662	26169.9	27138	25656	25659.2	25704	25656	25661.1	25712
sks455a	6575	7298.5	9472	6405	6426.7	6666	6405	6424.6	6545
sks488a	17126	17528.5	18059	16862	16862.9	16888	16862	16862.9	16888
sks522a	29477	30232.9	31574	29309	29312.2	29396	29309	29325.5	29398
sks555a	10667	11910.3	15024	10187	10215.8	10299	10187	10224.1	10299
sks588a	25004	25836.3	26580	24844	24844.9	24861	24844	24849.3	24870
sks622a	43401	44786.5	45863	43048	43119.9	43479	43048	43103.2	43273
sks655a	17728	19389.5	22617	16158	16218.0	16635	16158	16222.4	16617
sks688a	34517	35775.6	37418	33551	33638.6	33665	33551	33596.6	33686
sks922a	92425	94684.9	99061	88841	88894.2	89067	88841	88875.5	89188
sks955a	35558	39495.4	43256	30582	30682.8	31312	30590	30643.2	30768
sks988a	86422	90895.5	96954	81984	82001.5	82053	81984	81985.2	81989

On the other hand, as soon as they are not in the same group (or to share the same alphabet), there is significant difference between/among them.

The Duncan grouping results show that when EA/G outperforms the ACGA under the stopping criterion of using 50000 and 75000 solutions. There is no difference between EA/G and ACGA when they both apply 100000 solutions. Finally, ACGA outperforms the EA/G statistically significant in the case of employing 125000 solutions. A performance transition is occurred at the stopping criterion of using 100000 solutions.

In order to show the results clearly, we demonstrate the interaction plots of the algorithms together with the different examined solutions in Fig. 2.1. Through the interaction plots, it shows that the EA/G indeed outperforms the ACGA very much. However, the performance of EA/G doesn't be improved with the number of examined solutions increased after the level of 75000. ACGA, nonetheless, is improved gener-

Table 4 Selected results of these algorithms employ 125000 Examined Solutions

	SGA			ACGA			EA/G		
instance	Min	Avg.	Max	Min	Avg.	Max	Min	Avg.	Max
sks222a	5286	5352.3	5603	5286	5288.9	5298	5286	5289.9	5298
sks255a	2372	2459.3	2936	2372	2380.0	2388	2372	2380.4	2388
sks288a	3421	3480.1	3684	3421	3421.0	3421	3421	3421.0	3421
sks322a	11568	11857.1	12211	11568	11577.1	11622	11568	11575.5	11622
sks355a	6100	6335.4	7083	6056	6065.4	6193	6056	6062.1	6212
sks388a	11317	11323.9	11413	11317	11317.0	11317	11317	11320.1	11340
sks422a	25662	26169.9	27138	25656	25659.2	25704	25656	25661.1	25712
sks455a	6575	7298.5	9472	6405	6426.7	6666	6405	6424.6	6545
sks488a	17126	17528.5	18059	16862	16862.9	16888	16862	16862.9	16888
sks522a	29477	30232.9	31574	29309	29312.2	29396	29309	29325.5	29398
sks555a	10667	11910.3	15024	10187	10215.8	10299	10187	10224.1	10299
sks588a	25004	25836.3	26580	24844	24844.9	24861	24844	24849.3	24870
sks622a	43401	44786.5	45863	43048	43119.9	43479	43048	43103.2	43273
sks655a	17728	19389.5	22617	16158	16218.0	16635	16158	16222.4	16617
sks688a	34517	35775.6	37418	33551	33638.6	33665	33551	33596.6	33686
sks922a	92425	94684.9	99061	88841	88894.2	89067	88841	88875.5	89188
sks955a	35558	39495.4	43256	30582	30682.8	31312	30590	30643.2	30768
sks988a	86422	90895.5	96954	81984	82001.5	82053	81984	81985.2	81989

ation by generation and this algorithm is superior to EA/G when we apply longer computational time.

This phenomenon can be explained by Fig. 2.1 which utilizes the instance sks952a. EA/G converges faster than ACGA and SGA. After the generation 150, EA/G is converged and the performance is not improved. As a result, it could be a problem of premature convergency belonged to EA/G. So we may increase the diversity of the generated solutions for the EA/G or the EDAs completely sample new individuals from probabilistic models.

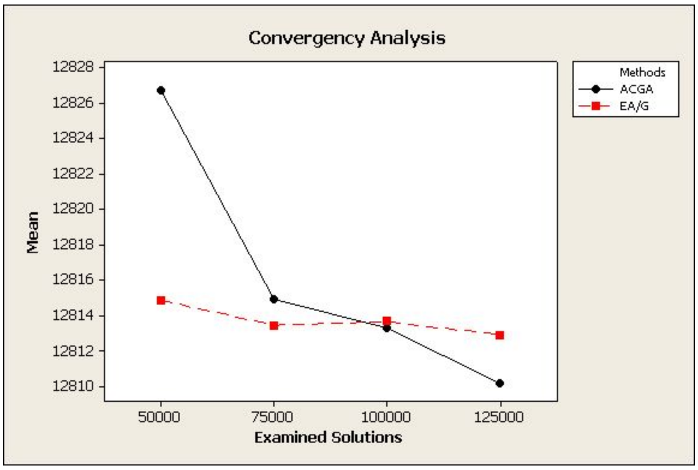

Fig. 1 ACGA and EA/G evaluate different examined solutions

To conclude the comparison results, these experiments reveal interesting points when the three algorithms are ran under the various stopping criteria. EA/G outperforms the ACGA statistically significant when it stops under lower computational time

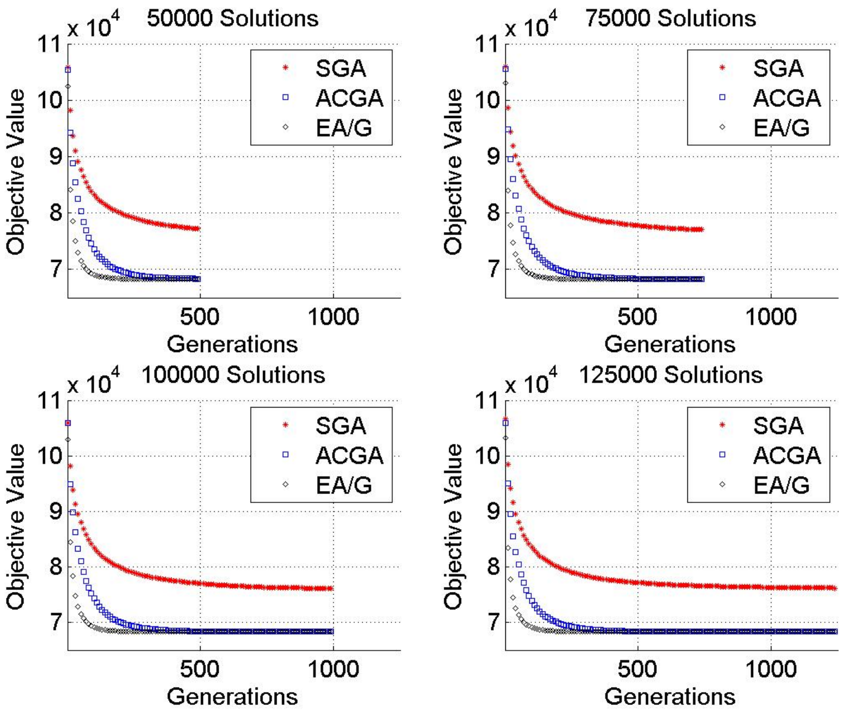

Fig. 2 Convergency analysis of the algorithms in different stopping criteria (instance-sks952a)

whereas ACGA performs well when we apply higher level of stopping criterion. It shows EA/G might converge faster than ACGA; however, when we concern on the solution quality and we are able to employ higher level computing time.

3 Conclusions

EA/G and ACGA sample new solutions from probabilistic models completely and periodically. Due to this difference and through the analysis of EA/G and ACGA, EA/G may converge faster than ACGA when few computational time is available while ACGA outperforms EA/G when we apply more computational time. The main reason causes the difference is the intensification effect and diversification effect. Because EA/G completely samples new solution from probabilistic models, it likely preserves the salient genes in the population so that EA/G has better intensification effect. However, we discover that the EA/G no longer generate diversified solutions resulted in poor performance when we use longer computational time. As a result, the authors will give some guidelines of taking the intensification and diversification effect into considerate when researchers want to develop an effect EDAs in another paper.

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