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Line Search, Genetic Algorithm and Simulated Annealing approaches for Fuzzy Natured Problem in Manufacturing Environment

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Abstract: This paper discusses the findings of simulation and computational results to compare the performance of two different novel hybrid optimization techniques with respect to the famous real world industrial engineering problems on production planning. The best optimal solution obtained for the fitness function, decision variables respect to vagueness factor, level of satisfaction, and computational time of CPU been investigated in detail. The results reported here are exactly obtained from the real world problem in manufacturing industry under fuzzy nature. The intelligent performance analysis is reported for the convenience of decision maker and implementer to select the best-preferred and strategic solution and methods under uncertain and turbulence environment.

Keywords: Fuzziness, Line Search, Genetic Algorithm, Simulated Annealing, Production Planning.

1. Introduction

1.1. Hybrid Line Search and Genetic Algorithms (HLSGA)

In this paper, the simulation and computational results on the hybridization techniques of merging Line Search (LS) and Genetic Algorithm (GA) presented for the industrial production planning problems is propounded. LS techniques utilized for the searching of best initial points to start the optimization process, and GA [1] techniques are used for finding the best global close to the optimal solutions. GAs are in a class of biologically motivated optimization methods that evolve a population of individuals where individuals who are more fit have a higher possibility of surviving into subsequent generations. Line search method is a type of gradient-based method that uses derivative of objective function and constraints for the continuous functions. Its' suggested that this hybrid method would be a good candidate to find best global near optimal value for the fitness function and feasible solution for the decision variables as well as a reasonable computational CPU time.

1.2. Hybrid Line Search and Simulated Annealing (HLSSA)

This paper discusses a novel optimization technique of simulated annealing been merged in the hybridization with line search approach. The main reason for incorporating SA (Simulated Annealing) in this hybridization process are: it is very easy to implement with few lines of algorithmic code, SA [2] can conveniently handle continuous optimization problems, lastly SA can possibly provide high quality solution for the objective function and outstanding computational efficiency in running CPU time. Thus, the features of SA, which been described, make SA a very useful tool for the operational research practitioner especially in industrial engineering.

2. Model Development

Optimization techniques are primarily used in production planning problems in order to achieve optimal profit, which maximizes certain objective function by satisfying a number of constraints.

The first step in an optimal production planning problems is to formulate the underlying nonlinear programming (NLP) problem by writing the mathematical functions relating to the objective and constraints.

Given a degree of satisfaction value μ, the fuzzy constrained optimization problem can be formulated [3, 4, 5] as the non linear constrained optimization problem shown below.

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Maximize $\sum_{i=1}^{8} (c_i x_i - d_i x_i^2 - e_i x_i^3)$

Subject to:

$$\sum_{i=1}^{8}\left[a_{ij}^{l}+\left(\frac{a_{ij}^{h}-a_{ij}^{l}}{\alpha}\right)\ln\frac{1}{C}\left(\frac{B}{\mu}-1\right)\right]x_i-b_j\le 0,\quad j=1,2,...,17 \tag{1}$$

$$\sum_{i=7}^{8} r_i x_i - 0.15\sum_{i=1}^{6} r_i x_i \le 0$$

$$x_1 - 0.6x_2 \le 0$$

$$x_3 - 0.6x_4 \le 0$$

$$x_5 - 0.6x_6 \le 0$$

$$0 \le x_i \le u_i,\quad i = 1,2,...,8$$

In the above non-linear programming problem, the variable vector x represents a set of variables x_i, i = 1, 2,…, 8. The above optimization problem contains eight continuous variables and 21 inequality constraints. A test point x_i satisfying constrains is called feasible, if not infeasible. The set satisfying constrains is called the feasible domain. The aim of the optimization is to maximize the total production profit for the industrial production planning problems. The formulation of the new non-linear cubic function for this particular problem has been refereed in [6]. The cubic objective function has 24 coefficients for eight decision variables. This problem considered one of the most challenging problems in the research area of industrial production planning [7].

3. Simulation and Computational Analysis of Hybrid Algorithm LS and GA

The hybrid algorithm for LS and GA in the program is as follows:

- Step 1: Start
  Line search [8]
- Step 2: Genetic algorithms [9]
- Step 3: End
- The Parameter setting for GA is available in [7].

Table 1 indicates the feasible solution for the decision variables with $\gamma = 0.001$ to $\gamma = 0.99$ and objective function values at $\alpha = 13.813$.

Table 1: Optimal value for Objective Function

γ	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	f	LS_t (s)	GA_t (s)
0.001	246.8	411.4	205.7	342.8	134.3	223.9	120.6	0.00	147712.9	2.8205	2.8210
0.1	284.8	474.7	239.2	398.7	148.8	248.0	150.4	0.00	163731.6	0.5864	0.5869
0.2	292.5	487.6	246.1	410.1	151.8	253.0	156.7	0.00	166763.3	0.0303	0.0306
0.3	297.9	496.5	250.8	418.0	153.8	256.4	161.2	0.00	168830.5	0.0267	0.0269
0.4	302.5	504.1	254.8	424.7	155.6	259.3	165.1	0.00	170548.7	0.0286	0.0289
0.5	306.8	511.7	258.6	431.0	157.2	262.1	168.8	0.00	172146.4	0.0795	0.0797
0.6	311.2	518.6	262.5	437.5	158.9	264.9	172.6	0.00	173763.9	0.0264	0.0267
0.7	316.1	526.9	266.9	444.8	160.8	268.1	176.9	0.00	175548.3	0.0559	0.0562
0.8	322.4	537.4	272.4	454.1	163.3	272.1	182.4	0.00	177754.9	0.0277	0.0279
0.9	332.3	553.9	281.2	468.6	167.1	278.5	191.3	0.00	181132.7	0.0679	0.0682
0.99	414.3	690.6	354.0	590.0	200.0	333.4	200.0	54.5	200116.4	0.0375	0.0377

LS_t(s): CPU time for LS technique and GA_t(s): CPU time for GA technique

From Table 1, it is observed that the average CPU time running LS and GA is 0.3443 s and 0.3446 s respectively. Even though the best optimal objective function value same as the best objective function value for LS method alone but the superiority of hybrid LS and GA method lies on the computational CPU time supremacy. Total CPU time for running LS and GA for $\gamma = 0.001$ to $\gamma = 0.99$ is 3.7874 s and 3.7907 s respectively. This CPU time extremely lower compare to LS method alone and Hybrid GA with LS method. This is the major contribution of novel techniques of GA in helping LS to achieve the best optimal objective function value of 200116.4 with average CPU time 0.3446 s. However, the major drawback of HLSGA techniques is on the inability of obtaining non-zero solution for the decision variable x_8 for $\gamma = 0.001$ to $\gamma = 0.90$. There is a possibility of obtaining non-zero solution for the decision variable x_8 at $\gamma = 41$.

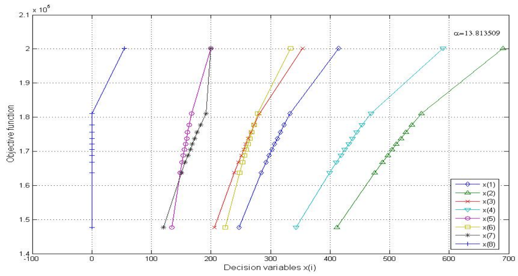

Fig. 1: Objective value versus decision variables

Figure 1 depicts the objective function values versus feasible solution of decision variables at $\alpha = 12.813$. Unfortunately, there is no any improvement in the feasible values for decision variables compare to LS method alone and hybrid GA with LS. This is the major set back of incorporating GA with LS in this hybridization approach. Moreover, similar tragedy occurs for the hybrid GA with LS approach. These techniques fail to produce a productive solution for the decision variable x_8 while they are capable to produce a reasonable best solution for x_2 and x_4 feasible decision variables.

Figure 2 depicts the simulation and computational results for objective function respect to α and γ via 3D mesh plot. Total CPU time for running this result is 7.61 seconds. This CPU time is extremely low compare to CPU time for LS techniques and hybrid GA with LS techniques. Computational efficiency is one of the novel characteristic of GA techniques when it's incorporated in the hybridization process. This is one of the major achievements in these research case studies.

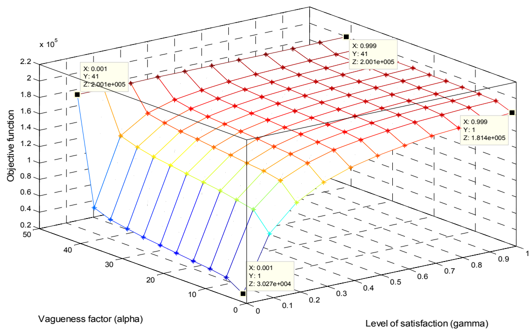

Fig. 2: Objective value versus α and γ

Table 2 describe the superiority of computational efficiency in finding the best optimal objective function respect to $\alpha = 1$ to $\alpha = 41$ at $\gamma = 0.99$ respect to CPU time. This lowest CPU time reveal the major significant contribution of superb techniques of GA in these research findings. The findings also indicate that GA is the best quality approach as far as CPU time concern in this research work.

Table 2: Best CPU time for objective function at $\gamma = 0.99$

α	*f*	*LS CPU time (s)*	*GA CPU time (s)*
1	200116.44	0.03104	0.03129
5	200116.44	0.05659	0.05685
9	200116.44	0.02970	0.02995
13	200116.44	0.15890	0.15917
17	200116.44	0.01922	0.01947
21	200116.44	0.02525	0.02550
25	200116.44	0.02510	0.02535
29	200116.44	0.18363	0.18389
33	200116.44	0.02599	0.02625
37	200116.44	0.02660	0.02685
41	200116.44	0.02620	0.02645

The strength of GA in this hybridization process lies in great contribution of computational efficiency of CPU time. This clearly indicated in Table 2. The average CPU time for running LS and GA for $\alpha = 1$ to $\alpha =$

41 at γ = 0.99 is 0.0553 s and 0.0555 s respectively. In fact, GA has contributed for his own CPU running time as well as great help in CPU running time for LS techniques. The major contribution of LS is in finding the benchmark solution for the best global near optimal value for the cubic objective function of industrial production planning problems. On the other hand, the great contribution of GA is on the quality of computational efficiency and robust convergence computing CPU time in this particular hybridization approach.

4. Experimental Results for Hybrid Line search and Simulated annealing (HLSSA)

The hybrid algorithm for LS and SA in the program is as follows:

- Step 1: Start
  Line search
- Step 2: Simulated Annealing [10]
- Step 3: End
- The Parameter setting for SA is available in [6]

Table. 3: Optimal value for Objective Function

γ	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	f	LS_t (s)	**SA_t (s)**
0.001	246.8	411.4	205.7	342.8	134.3	223.9	120.6	0.00	147712.9	0.2269	0.2273
0.1	284.8	474.7	239.2	398.7	148.8	248.0	150.4	0.00	163731.6	0.0606	0.0608
0.2	292.5	487.6	246.1	410.1	151.8	253.0	156.7	0.00	166763.3	0.0638	0.0640
0.3	297.9	496.5	250.8	418.0	153.8	256.4	161.2	0.00	168830.5	0.0258	0.0261
0.4	302.5	504.1	254.8	424.7	155.6	259.3	165.1	0.00	170548.7	0.0285	0.0287
0.5	306.8	511.7	258.6	431.0	157.2	262.1	168.8	0.00	172146.4	0.0272	0.0275
0.6	311.2	518.6	262.5	437.5	158.9	264.9	172.6	0.00	173763.9	0.0425	0.0427
0.7	316.1	526.9	266.9	444.8	160.8	268.1	176.9	0.00	175548.3	0.0244	0.0246
0.8	322.4	537.4	272.4	454.1	163.3	272.1	182.4	0.00	177754.9	0.0563	0.0565
0.9	332.3	553.9	281.2	468.6	167.1	278.5	191.3	0.00	181132.7	0.0308	0.0311
0.99	414.3	690.6	354.0	590.0	200.0	333.4	200.0	54.5	200116.4	0.0852	0.0855

LS_t(s): CPU time for LS technique and SA_t(s): CPU time for SA technique

Table 3 describe the experimental results for the simulation and computational of eight decision variables with optimal objective function and CPU time. The average CPU time for running LS and SA techniques is 0.0611 s and 0.0613 s respectively. This CPU time far better than CPU time obtained by hybrid LS with GA techniques. The main reason for this great achievement in the computational efficiency is due to fast convergence rate of SA approach. In this case, a SA algorithm has helped the LS techniques to achieve a tremendous computational CPU time. These hybrid optimization techniques of LS with SA work extremely well in the computational of CPU time. This is the major contribution of SA optimization approach in solving a non-linear optimization problem of industrial production planning. On the other hand, this hybrid approach could not able to solve the productive decision variable x_8 while they have produced a very high productive solution for the decision variables x_2 and x_4.

Table 4 reports a very import findings of simulation and computational results for objective function value respect to CPU time for LS and SA techniques at γ = 0.99.

Table 4: Best CPU time for objective function at γ = 0.99

α	f	*LS CPU time (s)*	*SA CPU time (s)*
1	200116.44	0.04347	0.04372
5	200116.44	0.02914	0.02939
9	200116.44	0.02400	0.02424
13	200116.44	0.07037	0.07062
17	200116.44	0.02493	0.02518
21	200116.44	0.02458	0.02482
25	200116.44	0.08689	0.08714
29	200116.44	0.02496	0.02521
33	200116.44	0.06627	0.06653
37	200116.44	0.02568	0.02593
41	200116.44	0.03151	0.03176

An average CPU time running LS and SA techniques for $\alpha = 1$ to $\alpha = 41$ at $\gamma = 0.99$ is 0.04107 s and 0.04132 s respectively. This result completely outperformed against the CPU running time for hybrid approach of LS with GA. It has shown clearly that the main strength of SA techniques is on the superiority of computational time of CPU. Again, it has proven that a SA technique has helped tremendously LS techniques in reducing the computational time for LS as well. This is one of the great contributions of SA techniques in this research studies.

Figure 6 exhibits the outcome for the objective function respect to α and γ. CPU time for running this simulation results is 7.53 seconds. This CPU time is far better than LS (alone) CPU time and slightly improved compared with hybrid LS and GA approach.

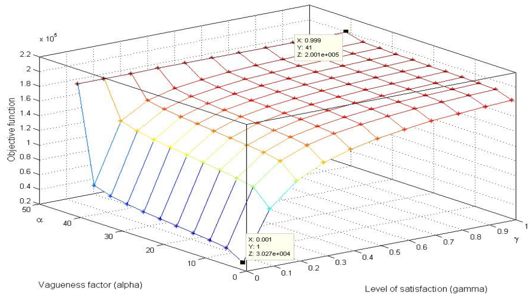

Fig. 3: 3D mesh plot for objective value versus α and γ

5. Conclusion

In conclusion, it is highly recommended that SA technique is one of best option to be considered for the hybrid optimization techniques as far as computational efficiency (CPU time) is concern particularly in this research work. The novel innovative of hybridization of soft computing techniques such as GA and SA with classical optimization technique such as LS provides a great future especially in solving complex problems of industrial engineering and other real world applied optimization manufacturing problems.

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7. References

[1] K. Deb: Multi-objective Optimization Using Evolutionary Algorithms (John Wiley & Sons, New York 2001.

[2] R. W. Eglese: Simulated Annealing: A tool for Operational Research. *European Journal of Operational Research* Vol. 46 (1990), pp. 271-281.

[3] P. Vasant: Fuzzy decision making of profit function in production planning using S-curve membership function. *Computers and Industrial Engineering* Vol. 51 (2006), pp. 715 – 725.

[4] B. W. Wah and T. Wang: Tuning strategies in constrained simulated annealing for nonlinear global optimization. *International Journal on Artificial Intelligence Tools*, vol. 9 (2000), pp.3–25.

[5] K. P. Wong and S. Y. W. Wong: (1997). Hybrid genetic/simulated annealing approach to short-term multiple-fuel-constrained generation scheduling, *IEEE Transactions on Power Systems* Vol. 12 (1997), pp.776–784.

[6] P. Vasant: Hybrid simulated annealing and genetic algorithms for industrial production management problems. *International Journal of Computational Methods* Vol. 7(2010), pp. 279-297.

[7] P. Vasant and N. Barsoum: Hybrid genetic algorithms and line search method for industrial production planning with non-linear fitness function. *Engineering Applications of Artificial Intelligence* Vol. 22 (2009), pp. 767-777.

[8] S. J. Chapman: *MATLAB programming for engineers* (Brooks & Cole, USA 2002).

[9] A. Gilat: *MATLAB An introduction with applications* (John Wiley & Sons, Inc., USA 2005)

[10] MATLAB user's Guide. The MathWorks (2007).