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A Hybrid Cuckoo-Gravitation Algorithm for Cost-optimized QFD Decision-Making Problem

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Abstract

Utilizing QFD in the process of manufacturing and service performing is confronted with an optimization problem called QFD decision-making problem (QFDDMP). Facing many customer constraints and requirements, and huge number of customers in the target market have made QFDDMP a complex planning problem. Achieving optimal solution by which the products satisfy customers with lowest costing budget and minimum time requires employing House of Quality (HoQ). In this paper, by hybridizing the Gravitational Search Algorithm (GSA) as a local search technique and the Cuckoo Optimization Algorithm (COA) a new memetic algorithm (COGSA) is proposed and applied for solving QFDDMP. Using GSA part, COGSA can search more around best solutions found by COA and get more near to optimal. Comparing obtained results of COGSA, COA, genetic algorithm and particle swarm optimization has showed that COGSA is significantly stronger than other investigated algorithms in solving QFDDMP.

Keywords: Quality function deployment, QFD, House of Quality, QFD decision-making problem, Cuckoo Optimization, Gravitational Search, memetic algorithm.

1. Introduction

Quality function deployment (QFD) as a process of satisfaction of customers on the basis of their requirements is introduced, described and developed by YojiAkao[1]. He also presented a formal description of QFD as a “method to transform user demands into design quality, to deploy the functions forming quality, and to deploy methods for achieving the design quality into subsystems and component parts, and ultimately to specific elements of the manufacturing process” [2].

The most important goals of QFD are true identification of customer requirements and accurate understanding of value in the view of the customers, assessment and recognition of what leads to users' satisfaction, true selection of the parameters that the customers are interested to and determining their value levels, establishing a smart linkage between the requirements of the customers with design, development, engineering, manufacturing, and service functions [3]. Remarkable impact of applying QFD on the process of production and increasing the number of customers and their satisfaction has led to an growing trend in the management of industries in different countries to apply it to reach higher sale in the market in comparison to their commercial competitors [4].

One of the most popular and effective tools for implementation of QFD in an organization is the House Of Quality (HOQ) [5] in which customer attributes, engineering characteristics, relative importance, relationships and objective measure should be prepared accurately in several steps. HOQ for a system is shown in Fig. 1.

The skeleton of a HOQ can be constructed as follows: house ceiling shows the technical descriptors that are provided through engineering design constraints, requirements and various parameters. House roof indicates the interrelationship between different technical descriptors. Customer attributes can be listed on the left side wall while on the right side wall the prioritized customer attributes that reflects the importance of the requirements of the customer are located.

The interior of the house gives interrelationship between what the customers want and the technical descriptions can implement. The foundation of the house consists of the prioritized technical descriptions. It also gives factors as technical benchmarking, target values and technical descriptors importance [7].

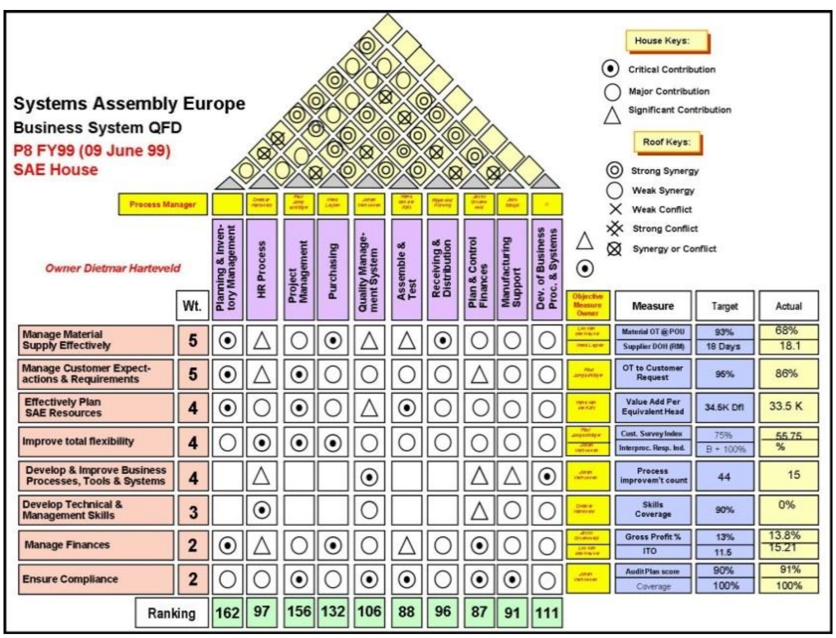

Fig.1 House of Quality, a sample [6]

In this paper, Cuckoo Optimization Algorithm (COA)[8] is used for exploring the search space of the problem to find proper solutions. Then, as a local search method, Gravitation Search Algorithm (GSA)[9] is applied to exploit the space around the found solutions by COA due to reach better solutions. As it is proved in the literature, memetic algorithms can obtain better solutions in lower time comparing pure evolutionary or local search algorithms [10-13]. Successful applying COA in solving problems similar to QFDDMP [14-16]and proved capabilities of GSA [13, 17, 18]are the strongest motivation for the authors to utilize them in solving QFDDMP. Hybridization of above-mentioned algorithms could also enhance the abilities of searching process because of getting benefits of them in simultaneously exploring and exploiting the search space. The final achievement of applying the proposed algorithm is increasing the customer satisfaction and companies' revenue with the lowest time and budget consumption.

The reminder of the paper is organized as follows. After the introduction, QFDDMP, Cuckoo Optimization and Gravitation Search Algorithms are described in part 2. The proposed improvements and structure of COGSA are discussed in part 3. Experimental results and achievements of the research are discussed in part 4. Finally, part 5 includes conclusion.

2. Preliminary Description

2.1. Cuckoo Optimization Algorithm (COA)

All After several months unremitting efforts to recognize Cuckoo natural behavior, COA as a novel heuristic and nature-based algorithm has been introduced by RaminRajabioun[8] for solving optimization and NP-hard combinatorial problems. COA starts with initialization the cuckoos' first population in which each cuckoo lays in other birds' nest. Host birds will kill cuckoos' eggs if they can recognize them; else the eggs will become mature cuckoos. The more eggs survive in each nest, the more proper solution (with highest profit) is achieved in that nest. The position of a cuckoo in search space that is a solution in COA is called habitat. For an n-dimensional problem, ith solution is represented as it is shown in (1)

$$habitat\,(i) = [x_1, x_2, ..., x_n] \tag{1}$$

where x_j means the value of *j*th element of the solution.

The profit of habitats must be calculated by an objective function. The objective function is actually a function with n different variables as inputs and an output value. How to calculate the amount of profit, is absolutely dependent on the type of problem and user requirements. Generally, the objective function can be represented as is in (2).

$$profit = f_{obj}(x_1, x_2, ..., x_n) \tag{2}$$

After becoming mature, cuckoos try to emigrate toward better habitats to provide more proper citations for laying. To reach this goal, each cuckoo should select a target habitat among all. If the distance between current and target habitats is d and flight angle is φ ,the displacement of the cuckoo in *j*th dimension can be obtained using (3)

$$dis(i) = d \times \lambda \times \cos(\varphi) \tag{3}$$

while λ is a normal random number in (0,1] and φ is a normal random selected radian in $(-\frac{\pi}{6}, \frac{\pi}{6})$. Executing of the algorithm will continue in next iterations until the predefined termination conditions are met.

2.2. Gravitational Search Algorithm (GSA)

GSA is a local search algorithm which is inspired from physics laws of gravitation [19]. In GSA, each solution is represented by a particle in the search space and better solutions have greater mass. Based on what occurs in the real world, heavier objects attract lighter ones. In the process of displacement, a lot of points of search space will be searched for finding optima; solution. Thus, after a sufficient number of iterations, it can be expected that the best solution or a solution very close to the best be found. Particle representation for D dimensions, resultant of exerted forces, acceleration, velocity and displacements can be observed in (4), (5), (6), (7) and (8) respectively. A complete description of GSA can be found in [17, 20].

$$X_i = (x_i^1, ..., x_i^d, ..., x_i^D) \tag{4}$$

$$F_i^d(t) = \sum_{j=1, j \neq i}^{m} r_j F_{ij}^d(t) \tag{5}$$

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{6}$$

$$V_i^d(t+1) = r_i \times V_i^d(t) + a_i^d(t) \tag{7}$$

$$x_i^d(t+1) = x_i^d(t) + V_i^d(t+1) \tag{8}$$

2.2. QFD Decision-Making Problem (QFDDMP)

The most important role of the applying the process of producing the HOQ is maximizing satisfaction of customers by selecting optimal technical characteristics with respect to time and budget limitation and some other constraints [21]. Hence, there is an optimization problem called QFD decision-making problem (QFDDMP) that needs to be solved by efficient algorithms for finding the best solution among all possible solutions can be generated by a combination of different options of values of customer requirements, budget and time[21, 22]. To reach this goal different approaches are introduced in the literature. Using Genetic Algorithm [22-24] and applying fuzzy logic [21, 25-27] are the important efforts in this area.

2.3.1 Objective Function

Designing a reliable evaluation or objective function is one of the most important parts of a method for solving optimization problem. The objective function is used for calculating the validity of generated solutions and selecting the best one. As it is proposed in [22], (9) can be considered as the objective function of QFDDMP we called it merit function.

$$Merit(Sol_i) = (\sum_{i=1}^{m} w_i y_i + \frac{1}{K}\sum_{k=1}^{K} d_k)^{-1} \tag{9}$$

where w_i is the weight of the ith customer requirement, y_i is the underachievement of the ith customer requirement and d_k is the kth constraint penalty factor and is defined as (10).

$$d_k = \begin{cases} 0; & if\ sol_i\ satisfies\ constrnt\ k \\ +\infty; & otherwise \end{cases} \tag{10}$$

Based on equation 10, solution with highest merit value will be the best solution among all generated solutions.

3. Hybrid Cuckoo Optimization-Gravitational Search Algorithm (COGSA)

COGSA is a memetic algorithm in which COA must to explore the search space and try to find global optima whereas GSA as a local search algorithm is responsible to search near some better solutions that are achieved by COA to reach the benefits of exploiting the space. Hence, COGSA includes two separated parts identified CO-part and GS-part.

3.1. CO-part

CO-part is executed exactly as it is defined in part 2.1. After generating a suitable number of first generation cuckoos based on number of customer constraints and variables, the process of executing starts and the merit value of the solutions is calculated at the end of each iteration. For simple access to the best solution, solutions should be sorted ascending due to reach the solution with the lowest value of constraint violation at the first position of the list of solutions.

Thereafter, using roulette wheel selection algorithm [28], 10% of CO-part generated solutions are selected for doing local search.

3.2. GS-part

After selecting proper solutions for local search, GS-part of COGSA starts and using a suitable number of particles generated in the neighborhood of the giving solutions, tries to look for better solutions and replace them with previous ones. At the end of GS-part performance, it is expected to reach that the solutions would have been better.

3.3. Merit Function

For making the method aware of the cost of meeting the technical characteristics with customer requirements it is necessary to apply some changes in equation 10. To reach this goal, if the cost that technical characteristics *TCl* can meet the customer requirement *CRm* is *costlm*, so, the cost of solution *i* will be as what is used in (11)

$$\cos t(i) = \sum_{l=1}^{Ntc}\sum_{m=1}^{Ncr} \cos tlm \times blm \tag{11}$$

where*blm* is a binary value that is 1 if *TCl* and *CRm* should meet and is 0 otherwise. Hence, equation 10 can be changed to (12) to be aware of the cost.

$$Merit(Sol_i) = (\sum_{i=1}^{m} w_i y_i + \cos t(i))^{-1} \tag{12}$$

4. Experimental results and discussion

In order to evaluate the COGSA, the algorithm is implemented in Visual C#.Net 2013 and executed for optimizing different types of cost-aware QFDDMP to reach a suitable combination of customer requirements and objective measures. Ensuring the accuracy of the results, it is essential to use a reliable complete dataset. To reach this aim, a complete dataset is generated randomly including 150 numerical-value customer requirements, 2000 customer answers each of them determined all customer requirements, technical characteristics and their costs. Using this dataset, three different problems are randomly generated with different size of parameters.

For the first evaluation, a cost-aware QFDDMP is generated randomly based on requiring 20 numerical-value customer requirements and 150 customer responses. The number of cuckoos was 200. The problem is solved 10 times using COA, Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and COGSA. The final average results of calculated cost for the best achieved solutions are entered in table 1. The information analysis of Table 1 shows that COGSA could reach the most appropriate solution in the view of the cost among four applied algorithms and has had a better merit value than those resulted by GA, COA and PSO. The optimality percentage of COGSA than other algorithms for solving first problem is also inserted in Table 2.

Table 1.the final average results of calculated cost for the best achieved solutions for the first problem

	GA	*PSO*	*COA*	*COGSA*
Calculated Cost ($)	**595**	**574**	**559**	**521**

Table 2. The percentage of the optimality of GFA than other algorithms for the first problem

	COGSA /GA	*COGSA /PSO*	*COGSA /COA*	*COGSA*
Optimality percentage	**12.44%**	**9.23%**	**6.80%**	**--**

The second problem was on the basis of 40 numerical-value customer requirements and 300 customer responses. The number of cuckoos was kept constant and equal to 100. All four algorithms are executed 10 times and the final average results of calculated cost for the best achieved solutions are entered in table 3. The achieved results show that the COGSA has a tangible advantage over other algorithms. It is observed that the optimality percentage of the COGSA than the other algorithms in solving second problem that is shown in Table 4 is enhanced in comparing to the first problem.

Table 3. The final average results of calculated cost for the best achieved solutions for the second problem

	GA	*PSO*	*COA*	*COGSA*
Calculated Cost ($)	**1015**	**973**	**931**	**855**

Table 4. The percentage of the optimality of GFA than other algorithms for the first problem

	COGSA /GA	COGSA /PSO	COGSA /COA	COGSA
Optimality percentage	**15.76%**	**12.15%**	**8.15%**	**--**

To evaluate the performance of the COGSA in solving very large QFDDMPs and comparing its percentage of optimality with other methods, the third problem is randomly generated with big values for effective parameters. The problem is including 100 numerical-value customer requirements and 1000 customer responses. The number of Cuckoos was 100 as it was for last two problems. Each method is executed 10 times and the final average results of calculated cost for the best achieved solutions are mentioned in table 5. The optimality percentage is mentioned in Table 6 as well. On the Basis of the gained information, it is completely clear that COGSA increases its quality and optimality whatever the size of the problem extends. The obtained optimality utilizing COGSA comparing to other considered algorithms in solving the three problems are shown in Fig. 2.

Table 5. The final average results of calculated cost forthe best achieved solutions for the third problem

	GA	PSO	COA	COGSA
Calculated Cost ($)	**2755**	**2634**	**2493**	**2209**

Table 6. The percentage of the optimality ofGFA than other algorithms for the third problem

	COGSA /GA	COGSA /PSO	COGSA /COA	COGSA
Optimality percentage	**19.81%**	**16.12%**	**11.41%**	**--**

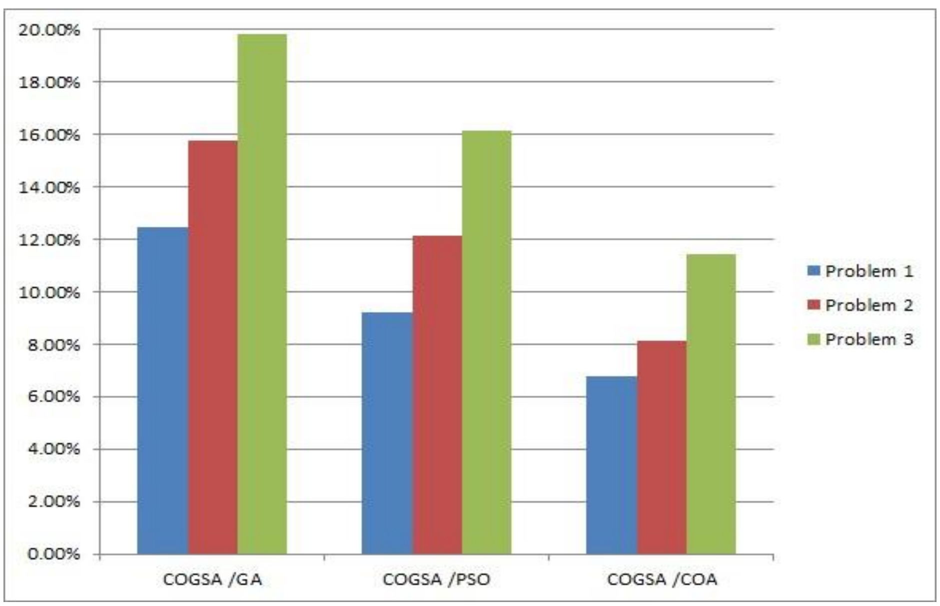

Fig. 2 Achieved optimality percentage using COGSA comparing to other investigated algorithms

5. Conclusion

Increase in the amount of sales and consequently the rate of company profits as an important and vital goal is reachable by solving QFDDMP. Gaining the maximum rate of customer satisfaction with the lower cost and eventually reaching maximal benefit would be achieved by finding the optimal solution of the problem. Reaching this goal, a hybrid Cuckoos Optimization-Gravitation Search Algorithm called COGSA is proposed. Applying local search capabilities of GSA in 10% solutions of COA-generated solutions that are selected by roulette wheel algorithm, along with designing a cost-aware objective function, has led to obtain better solutions comparing to GA, PSO and COA. Solving different-size problems proved that the optimality and efficiency of the COGSA increases with extension in the size of the problem.

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