

Research Article

A Cost-aware QFD Decision-making Problem using Guided Firefly Algorithm

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Abstract: Satisfaction of customers is one of the ultimate goals of most companies and industries that may lead to increasing the amount of sales and earning revenue. Quality Function Deployment (QFD) as a well-known process for reaching this goal is applied in the literature. To apply QFD, it is necessary to solve QFD Decision-Making Problem (QFDDMP) in which using house of quality; engineers try to find the best solution among all possible solutions that satisfies customer requirements with minimal budget and time. In real problems, because of the abundant number of customers, customer requirements and constraints QFDDMP is known as an NP-hard optimization problem. Hence, it is required to apply efficient heuristic algorithms to solve the problem. In this study, by applying virtual attractiveness an improved version of Firefly Algorithm is proposed for solving QFDDMP. Virtual attractiveness is actually an attractiveness larger than the real amount to be given some fireflies to attract more fireflies and faster, to increase the speed of local search around them. Comparison of the obtained result to genetic algorithm, Particle Swarm Optimization and classic version of firefly algorithm it is proved that Guided Firefly Algorithm (GFA) could reach better solutions for QFDDMP with focus on minimizing the cost of the solutions.

Keywords: Firefly algorithm, NP-hard problem, QFD, quality function deployment

INTRODUCTION

Quality Function Deployment (QFD) as a process of satisfaction of customers on the basis of their requirements is introduced, described and developed by Yoji Akao (Akao, 2004). 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” (Akao, 1966).

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 (The-QFD-Institute, 2013). 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 (Chan and Wu, 2002).

One of the most popular and effective tools for implementation of QFD in an organization is the House of Quality (HOQ) (Hauser and Clausing, 1988) in which customer attributes, engineering characteristics, relative importance, relationships and objective measure should be prepared accurately in several steps. HOQ for a car 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 (MBASKool-Community, 2013).

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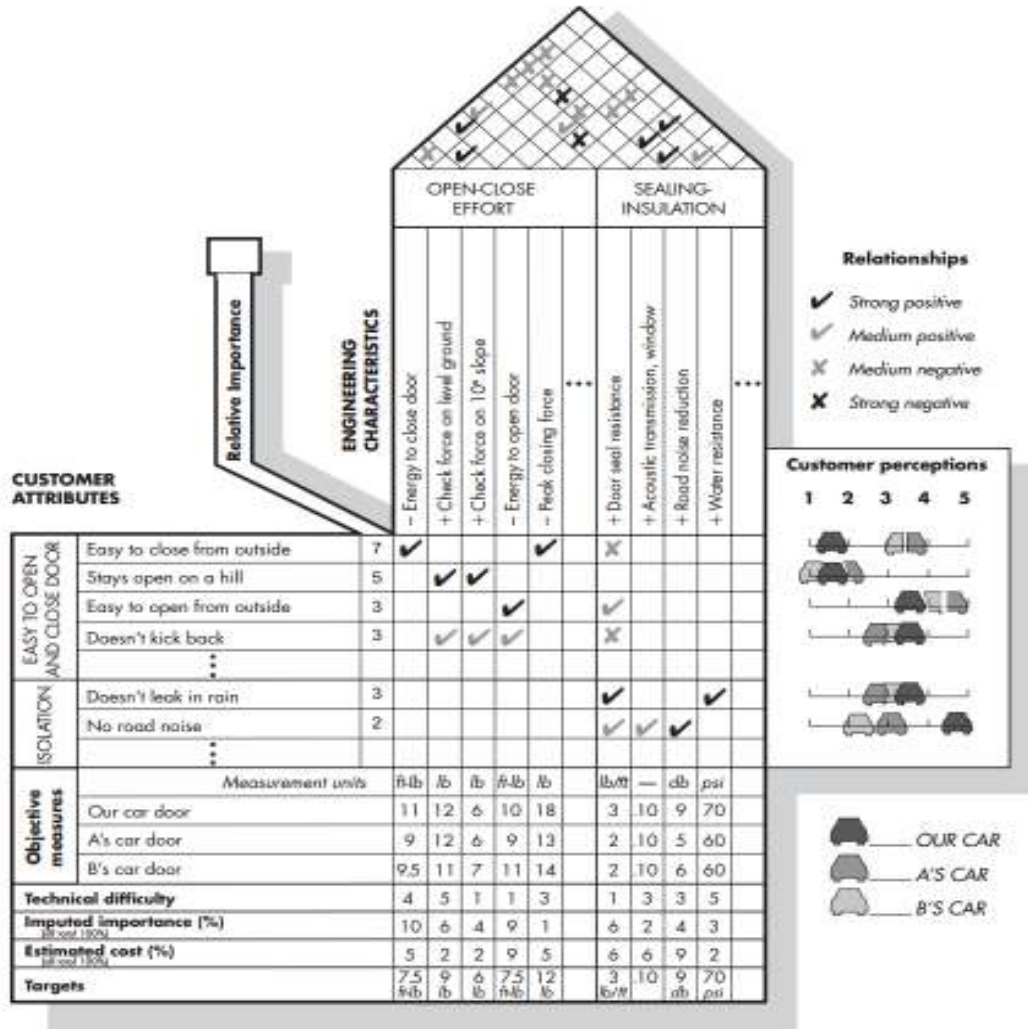


Fig. 1: HOQ for a car (Hauser and Clausing, 1988)

In this study, by applying a new parameter in Firefly Algorithm called Virtual Attractiveness, it was possible to guide fireflies to search more around more appropriate positions in the search space of the problem for reaching more proper solutions. Utilizing proposed improvement will lead to increase customer satisfaction in the generated problems along with a significant decrease in budget and time consumption.

MATERIALS AND METHODS

QFD decision-making problem: 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 (Liu, 2010). 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. To reach this goal different approaches are introduced in the literature. Using Genetic Algorithm (Tian and Che, 2007; Bai and Kwong, 2003; Huang *et al.*, 2005) and applying fuzzy logic (Li, 1999; Ching-Hsue, 1999; Liu, 2010; Kahraman *et al.*, 2006) are the important efforts in this area.

Evaluation function: One of the most important parts of a method for solving optimization problem is designing an accurate evaluation function or objective function for calculating the validity and value of the produced solutions and selection of the best ones. As it is proposed in Tian and Che (2007), Eq. (1) can be considered as the objective function of QFDDMP we called it merit function:

$$Merit(sol_i) = \frac{1}{\sum_{i=1}^m w_i v_i + \frac{1}{k} \sum_{k=1}^k d_k} \quad (1)$$

where,

w_i = The weight of the i^{th} customer requirement
 y_i = The under achievement of the i^{th} customer requirement
 $deck =$ The k^{th} constraint penalty factor while d_k defines as Eq. (2):

$$d_k = \begin{cases} 0; & \text{if } sol_i \text{ satisfies constraint } k \\ \text{large positive number;} & \text{otherwise} \end{cases} \quad (2)$$

Based on Eq. (1), solution with highest merit value will be the best solution among all generated solutions.

Firefly Algorithm (FA):

Fireflies behavior: It is obvious that fire fly flashing light is an appealing natural event can be seen in the tropical areas. Most of fireflies can produce rhythmic flashes. The flashing light is produced by a bioluminescence process and for each particular kind of fireflies the pattern of these flashes is unique.

Fireflies use the flashing for three aims including mating partner attraction, potential prey attraction and protective warning mechanism. The flashing rate and the amount of time of flashing form different parts of signal system that attract both sexes together. A female firefly responds to a male’s unique pattern of flashing if the male is in the same kind. On the basis of physic laws the light intensity at distance r from the light source follows the inverse square law. This reality leads most fireflies to be seen only in limited distances from their position, usually a few hundred meters at nights. The flashing light patterns can be used to design new heuristic optimization algorithm (Yang, 2010).

Firefly algorithm: Inspired by fireflies flashing behavior, FA is introduced by Xin-She Yang as a heuristic algorithm to be used in solving optimization problems (Yang, 2010). In order to simplify firefly behavior for formulation three rules are assumed as follows:

- All fireflies are considered unisexual, hence each firefly can be attracted to all other fireflies.
- Attractiveness is defined proportional to the fireflies brightness, hereupon, for every two fireflies, brighter insect will attract firefly with less bright and it leads to its movement; according to physical law the brightness will decrease as the distance increases.
- Each firefly can move randomly if there are no other fireflies brighter than it.

For each problem, brightness of fireflies should be calculated using objective function. It means that using FA it is possible to find the optimal value of the objective function by finding the brightest firefly.

Firefly’s attractiveness is proportional to the light intensity that seen by neighbor insects. Hence, with respect to the inverse square law and absorption, attractiveness of firefly i from distance r can be defined as Eq. (3):

$$Attractiveness_i(r) = \frac{Attractiveness_i(0)}{1+\gamma r^2} \quad (3)$$

where, γ is a fixed coefficient of light absorption.

The distance between two fireflies that are in the positions x_i and x_j can be considered as Cartesian distance and for D -dimensional space will be as Eq. (4):

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{d=1}^D (x_i^d - x_j^d)^2} \quad (4)$$

The movement of firefly i that is located in x_i toward brighter firefly j located at x_j with distance r_{ij} will lead to changing its position. New position of firefly i can be calculated by Eq. (5):

$$x_i = x_i + \frac{Attractiveness_i(0)}{1+\gamma r_{ij}^2} (x_j - x_i) + \alpha (rnd - 0.5) \quad (5)$$

where, α is a uniform random number in (0, 1).

Guided Firefly Algorithm (GFA):

Firefly structure: To simplify the implementation of the fireflies and their positions that compose the solutions a vector as Eq. (6) is designed in which x_i^d means the position of firefly x in dimension d . In order to save the merit value of solutions another vector is defined in which $merit(i)$ is the merit value of firefly i and n is the number of fireflies in the search space. Merit vector is shown in Eq. (7):

$$x_i = [x_i^1, x_i^2, \dots, x_i^d] \quad (6)$$

$$Merit = [merit(1), \dots, merit(i), \dots, merit(n)] \quad (7)$$

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 Eq. (1). To reach this goal, if the cost that technical characteristics TC_l can meet the customer requirement CR_m is $cost_{lm}$, so, the cost of solution i will be as what is shown in Eq. (8):

$$cost[i] = \sum_{l=1}^{N_{tc}} \sum_{m=1}^{N_{cr}} cost_{lm} \times b_{lm} \quad (8)$$

where, b_{lm} is a binary value that is 1 if TC_l and CR_m should meet and is 0 otherwise. Hence, Eq. (1) can be changed to Eq. (9) to be aware of the cost:

$$Merit(sol_i) = \frac{1}{\sum_{i=1}^m w_i y_i + cost[i]} \quad (9)$$

Virtual attractiveness: Because each firefly moves toward more lighter fireflies and in order to apply more search around best solutions with the goal of finding better solutions and escaping of local optima it is proposed to apply virtual attractiveness that is bigger

than real attractiveness on k better solutions. This helps the proposed algorithm to search more around better solutions by attracting them. Based on Eq. (10), whatever the real attractiveness is higher, the rate of increasing in the virtual attractiveness will be higher. In order to keep the random characteristics of the algorithm, k is calculated by roulette wheel algorithm as it is defined in (Jula *et al.*, 2010):

$$VirtualAttr(i) = Attractiveness(i) \times \left(\alpha + \left(1 - \frac{rank(i)}{k} \right) \right) \quad (10)$$

where,

α = A random number in (0, 1)

$rank(i)$ = The rank of solution i in the descending sorted list of solutions

RESULTS AND DISCUSSION

In order to evaluate the GFA, it has been implemented in Visual C#.Net 2010 and executed to optimize a different type of cost-aware QFD optimization for a combination of customer requirements and objective measures. To ensure the accuracy of the results, it is important to use a comprehensive dataset. To reach this goal, a complete dataset is generated randomly including 100 numerical-value customer requirements, 1000 customer responses each of them determined all customer requirements, technical characteristics and their costs. Using above-mentioned dataset, three different problems are generated with different size of parameters, randomly.

For the first evaluation, a cost-aware QFD optimization was generated randomly based on requiring 15 numerical-value customer requirements and 100 customer responses. The number of fireflies was 100. The problem is solved 15 times for each method, using classic Firefly Algorithm (FA), Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and PFA and the final average results of calculated cost for the best found solutions are inserted in Table 1. The information analysis of Table 1 shows that GFA could reach the best solution in the view of the cost among four implemented algorithms and has had a better merit value than those found by GA, FA and PSO. The percentage of the optimality of GFA than other algorithms is also presented in Table 2.

Second generated problem on the basis of 30 numerical-value customer requirements and 200 customer responses. The number of fireflies was 100. Each method of four is executed 15 times and the final average results of calculated cost for the best found solutions are mentioned in Table 3. The obtained results show that the GFA has a tangible advantage over other algorithms. It is also observed that the percentage of the optimality of the GFA than the other algorithms

Table 1: The final average results of calculated cost for the best found solutions for the first problem

	GA	PSO	FA	PFA
Calculated cost (\$)	563	524	537	507

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

	PFA/GA	PFA/PSO	PFA/FA	PFA
Optimality percentage	9.94%	3.24%	5.58%	-

Table 3: The final average results of calculated cost for the best found solutions for the second problem

	GA	PSO	FA	PFA
Calculated cost (\$)	921	851	872	817

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

	GA	PSO	FA	PFA
Optimality percentage	11.29%	3.99%	6.30%	-

Table 5: The final average results of calculated cost for the best found solutions for the third problem

	GA	PSO	FA	PFA
Calculated cost (\$)	2434	2155	2229	1974

Table 6: The percentage of the optimality of GFA than other algorithms for the third problem

	PFA/GA	PFA/PSO	PFA/FA	PFA
Optimality percentage	18.89%	8.39%	11.44%	-

that is shown in Table 4 is increased compared to the first problem.

In order to evaluate the efficiency of the GFA in solving very large QFDDMPs and comparing its optimality percentage to other methods third problem is generated for with big values for effective parameters. The problem is including 90 numerical-value customer requirements and 600 customer responses. The number of fireflies was 100. Each of the methods is executed 15 times and the final average results of calculated cost for the best found solutions are mentioned in Table 5. The optimality percentage is also mentioned in Table 6. Based on the obtained information it is quite clear that GFA increases its quality and optimality whatever the size of the problem extends.

CONCLUSION

Solving QFDDMP may lead to increase in the amount of sales and consequently the rate of company profits. Finding the optimal solution of the problem causes reaching maximal benefit because of achieving the maximum amount of customer satisfaction with the lower cost. In order to reach this aim, an improved firefly algorithm called GFA is proposed in which using virtual attractiveness and designing a cost-aware merit function, reaching better solutions comparing to GA, PSO and FA has been possible. Solving different-size problems proved that the optimality and efficiency of the GFA increases with extension in the size of the problem.

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