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Best Design Selection Using Particle Swarm Optimization Algorithm and Hybrid Pareto Technique: Case Study

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Abstract: The aim of this study is to select the best design of polyethylene pipe to produce and then comparing the traditional and Meta heuristic methods with each other. In concurrent engineering, design processes are often complicated with multiple conflicting criteria and discrete sets of feasible alternatives. So this paper proposes a design framework governed by MCDM technique, which are in conflict in the sense of competing for common resources to achieve variously different performance objectives such as financial, functional, environmental, etc. The Pareto MCDM model and PSO algorithm are applied to polyethylene pipe concurrent design governed by four criteria (Density, Tensile strength, Impact strength and Time) to determine the best alternative design to Pareto-compromise design. Since, we want to select the best design among twelve designs and Pareto gives a local optimized solution, we used PSO algorithm to solve the model and find the best alternative. A model proposed to select the design and solved by PSO algorithm. The PSO algorithm showed the best efficient solution and design 3 is selected in comparison to Pareto method. At the end, applicable suggestions were proposed for future studies.

Key words: Concurrent engineering · Pareto MCDM · Pareto data · Pareto-Compromise design · Pareto-competitive equilibrium · Particle Swarm Optimization.

INTRODUCTION

Nowadays, global competition in providing new products is very intensive. The time needed for providing product is an important distinction between successful and unsuccessful companies. Successful companies learn how to manage time and technological advances. Concurrent Engineering, one of the tangible progress in this field and has evolved as a technique. In this technique, engineering product design and engineering process design are performed, simultaneously. The implementation of CE is based on teamwork to increase the efficiency of an organization. A specialized team normally is responsible for performing conceptual thinking, product design and production planning, simultaneously. The aim of this method requires individuals to consider all product life cycle factors which include customers and suppliers' requirements such as performance, quality, cost, program implementation, maintenance [1]. A successful teamwork needs to incorporate people from different departments such as design, marketing, construction, purchase, financial engineers. The team begins its work from the first stage and continues the teamwork until the end of the project [2]. A good communication plays an important role for success of teamwork and it involves the relationship between human and computer and both. There are some disadvantages on the implementation of CE when different people gather and wish to reach the same objective. For instance, it is difficult to overcome the barriers between design and manufacturing just by gathering people. Concurrent design also requires communication and flexibility, which is difficult in some cases to achieve. One alternative to overcome to such

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difficulties is to use MCDM techniques to find a good trade-off among various objectives [3]. Agrell [4] used MCDM technique to form a modern methodology for collaborating among various departments in the product development process. He presented a non-linear compromise programming algorithm with simplified operation as a support for his proposed methodology. Qi *et al.* [5] proposed a case retrieval technique combined with similarity measurement and MCDM techniques for concurrent design. In their implementation, they used a hybridization of fuzzy similarity measurement (FSM) and fuzzy MCDM for case retrieval from historical cases for concurrent design. During the first stage, FSM uses triangular function to represent various fuzzy requirements, respectively and measures the similarity, which helps remove less valuable cases. Then fuzzy MCDM is incorporated for the assessment of the most similar cases in terms of product criteria to pick out the most suitable case. They also implemented the proposed model to power transformer concurrent design and reported that the proposed model could be useful for case retrieval. Liu [6] used quality deployment function (QFD) and fuzzy MCDM for product design and development. In this study, Liu integrates fuzzy QFD and the prototype product selection system to present a product design and selection (PDS) approach. In fuzzy QFD, the α-cut operation is used to measure the fuzzy set of each component. The method also uses engineering characteristics and the factors involved in product development for prototype product selection. The method also uses a fuzzy MCDM method to select the best prototype product.

Valle and Vasquez-Bustelo [7] analyzed the link between the use of CE and success in new product development (NPD) under different circumstances of uncertainty and complexity, radical versus incremental innovations. They concluded that overlapping activities, inter-functional integration and teamwork positively could affect NPD performance based on development time and new product superiority for the case of incremental innovations and based on development cost in the case of radical innovations. They also concluded that CE should be used in the context or particular conditions, which characterize each innovation process. Grierson and Khajehpour [8] used genetic algorithm as a meta-heuristic method for design of office buildings. Koski [9] used heuristic method to select an appropriate design method. Grierson [10] developed a new method for NPD using multiple objective criteria, which are conflicting in the sense of competing for common resources to achieve variously different performance objectives such as financial, functional, environmental, etc. The proposed MCDM strategy employs a tradeoff-analysis method to identify compromise designs for which the competing criteria are met in a Pareto-optimal sense. Grierson's MCDM technique was initially developed for the case of design governed by two objective criteria. It is then extended to design governed by more than two objective criteria, by presenting the concept of primary and aggregate criteria. There are some evidences to believe that from infinite number of feasible designs forming the Pareto front for a design problem governed by *n* independent objective criteria, there is a unique Pareto-compromise design which represents a mutually agreeable tradeoff among all *n* criteria. Grierson demonstrated this idea for a flexural plate design governed by two criteria, a bridge maintenance-intervention protocol design governed by three criteria and a media centre envelops design governed by eleven criteria. Alem Tabriz [21] also has applied the Pareto-MCDM technique and CE to design pipes.

In this paper, we present an empirical method for the case study of concurrent engineering for designing the pipes based on the implementation of the method proposed by Grierson. The presentation of this paper first proposes Grierson's method and PSO algorithm in section 2 and the implementation of the case study is demonstrated in section 3. Finally, concluding remarks are given in section 4 to summarize the contribution of the paper.

Pareto Optimal Method

Pareto Optimal Definition: In Multi-objective problems, a feasible solution, A, is called Pareto optimal if there is another feasible solution which is better than *A* at least in terms of another objective. An optimal troubleshooting issue Pareto with *n* objective functions can be demonstrated as follows:

$$\begin{aligned} &\min\{f_1(z),\cdots,f_n(z)\} \\ &\text{subject to} \\ &\quad z \in \omega. \end{aligned} \qquad (1)$$

Where f_i (z) to f_I (z) are design objective functions based on different variables shown as technical vector topics as *z*. Let z^*be the Pareto optimal solution then there exists *k* objective functions such that we have,

$$f_i(z) \le f_i(z^*), \qquad i = 1,\cdots,k \le n \qquad (2)$$

Two Criteria Pareto Technique: Let A and B be two designers who are completely in conflict with each other. Obviously, increasing on one objective function could result on losing optimality in other one, i.e.

$$f_1^* = (f_1^{\min}, \cdots, f_1^{\max})' \rightarrow f_2^* = (f_2^{\max}, \cdots, f_2^{\min})' \quad (3)$$

In other words, let $f_i^*, i = 1, \cdots m$ be the vector of Pareto optimal solutions, therefore we have,

$$f_{1,j}^* \le f_{1,j+1}^*, \;\; f_{2,j}^* \le f_{2,j+1}^* \quad j = 1, \cdots, m \quad (4)$$

Once the Pareto optimal solutions are determined, we may scale them using the following,

$$x_i = \frac{f_i^* - f_i^{\min}}{f_i^{\max} - f_i^{\min}}; \quad i = 1, \cdots, n \quad (5)$$

The Grierson's Two-dimensional Method: The first step of the proposed method developed by Grierson is to normalize all design alternatives using Eq. (5) and transfer the resulted normalized data into a two dimensional space by introducing the following,

$$y_i = \frac{\sum_{k=1}^{n} x_k - x_i}{n-1}; \quad i = 1, \cdots, n \quad (6)$$

Next, we calculate x^* and y^* using the following,

$$x^* = \frac{x + \delta_x}{1 + \delta_x} \;\; y^* = \frac{y + \delta_y}{1 + \delta_y}, \quad (7)$$

Where $\delta_x = \sqrt{2}(x_{\max} - x_{\min}) - x_{\max}$ and $\delta_y = \sqrt{2}(y_{\max} - y_{\min}) - y_{\max}$. Based on Grierson's method, the efficient design yields equal values for x^* and y^*. The relative importance of each attribute is calculated as follow,

$$\Delta x_0 = \Delta y_0 = 0.5 - \frac{(x_j^* + x_{j+1}^*)(y_j^* + y_{j+1}^*)}{x_j^* + x_{j+1}^* + y_j^* + y_{j+1}^*}, \quad (8)$$

$$\Delta r_0 = \sqrt{2}\Delta x_0 = \sqrt{2}\Delta y_0 \quad (9)$$

$$f^0 = f^{\max} - (f^{\max} - f^{\min})(\Delta r_0 + \frac{\sqrt{2}}{2}). \quad (10)$$

In real-world case studies, we choose the alternatives with relatively close amount of values for x^* and y^*. For more details on Grierson's method, the interested readers are referred to read his article.

Particle Swarm Optimizations (PSO): PSO is a powerful evolutionary algorithm used for finding global solution to a multidimensional problem. PSO is a population based optimization tool, where the system is initialized with a population of random particles and the algorithm searches for optima by updating generations [11]. Suppose that the search space is D-dimensional. The position of the i-th particle can be represented by a D-dimensional vector $Xi = (x_{i1}; xi2; \ldots ; x_{iD})$ and the velocity of this particle is $Vi = (vi1; vi2; \ldots ; viD)$. The best previously visited position of the i-th particle is represented by $Pi = (pi1; pi2 \ldots ; piD)$ and the global best position of the swarm found so far is denoted by $Pg = (pg1; pg2 \ldots ; pgD)$. The fitness of each particle can be evaluated through putting its position into a designated objective function. The particle's velocity and its new position are updated as follows:

$$v_{id}^{t+1} = \omega^t v_{id}^t + c_1 r_1^t (p_{id}^t - x_{id}^t) + c_1 r_2^t (p_{gd}^t - x_{id}^t) \quad (11)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad (12)$$

Where $\in \{1,2,...D\}$, $I \in \{1,2,...N\}$ N is the population size, the superscript t denotes the iteration number, w is the inertia weight, $r1$ and $r2$ are two random values in the range [0 1], $c1$ and $c2$ are the cognitive and social scaling parameters which are positive constants.

Pseudocode for PSO algorithm is as below:

```
FOR each particle i
FOR each dimension d
Initialize position xid randomly within permissible range
Initialize velocity vid randomly within permissible range
End FOR
END FOR
Iteration t=1
DO
FOR each particle i
Calculate fitness value
IF the fitness value is better than p_best_id in history
Set current fitness value as the p_best_id
END IF
END FOR
Choose the particle having the best fitness value as the g_bestd
FOR each particle i
FOR each dimension d
Calculate velocity according to the equation
v_id^{t+1} = ω^t v_id^t + c1 r1^t (p_id^t − x_id^t) + c1 r2^t (p_gd^t − x_id^t)
Update particle position according to the equation
x_id^{t+1} = x_id^t + v_id^{t+1}
END FOR
END FOR
t=t+1
WHILE maximum iterations or minimum error criteria are not attained
```

Fig. 1: Pseudocode for PSO algorithm

It should be noted that there are plethora of researches in the field of Meta-heuristics. For example Alem-Tabriz *et al* [12] have used *Simulated Annealing Algorithm* in flow shop scheduling. Kulkarni and Venayagamoorthy [13] have used *Particle Swarm Optimization* for distribution estimation. Also Khorshidian *et al.* [14] has used Genetic Algorithm (GA) for JIT single machine scheduling. Mohammed Arafa *et al* [15] used Neural Network Models for Predicting Shear Strength. Khamis *et al* [16] used neural networks for Oil Palm Modeling. Hernane *et al.* [17] measured the performance of an asynchronous algorithm of Particle Swarm Optimization for Scheduling Problem. For more case studies refer to [18-20].

Case Study: The case study of this paper is a real-world application of one of Iranian pipe production called Vahid Industrial Group (VIG) and it is located in one of Northern provinces of Iran, Mazandaran. The company produces polyethylene pipes in various diameters up to 250 mm size and the factory maintains a capacity of 500 tones. The firm's management considers the technological capabilities and competitive factors for producing polyethylene pipes. Therefore, a team composed of design staff, marketing and production is gathered to select an appropriate design of the pipe in a concurrent engineering process.

Since the concurrent team members were from different fields, it was important to establish a synergy among these people such that we could end up having common criteria to be measured for our study. Three groups of criteria are considered as the most important affecting factors which are cost, quality and capacity. Quality factor is considered by marketing and design sectors and cost is considered by production and financial sectors and production rate is considered by marketing and production sectors. A comprehensive review on all influencing factors reveals that there are different important factors influencing the selection of our final design. This includes flammable, color, density, tensile strength, yield stress, coefficient of flexibility, elongation, impact strength, thermal conductivity, hardness and PH range. Since there is a limit on the budget of this research study, we have selected density, two pressure factors and the amount of time needed to one meter in each design alternative as the most essential factors. Table 1 summarizes the input data of these four attributes for twelve design alternatives.

Note that the first objective, density, is on the form of the maximization and the other three are of the forms of minimization. Therefore, we need to consider a negative sign for them.

For the case study of our proposed model we first normalize all four criteria based on Eq. (5) and transfer them into two dimensional space using Eq. (6) and Eq. (7) which are summarized in Table 2.

The relative importance of each attributes is calculated based on Eq. (8-10) as follows,

$$f_1^0 = 0.938705,\ f_2^0 = 18.3545,\ f_3^0 = 15.7324,\ f_4^0 = 7.48865.$$

As we can observe, design number 8 is the preferred one based on density characteristic, design number 5 is the preferable one based on tensile strength, design numbers 9 and 7 are also considered the best based on impact strength and production rate, respectively.

Table 1: Input data

	Product features			
Designs #	Density (gr/cm^3)	Tensile strength (20^0)(N/mm^2)	Impact strength (Kg/mm^2)	Time
1	92.0	22	25	11
2	925.0	8.22	23	2.10
3	93.0	1.23	5.21	8.9
4	937.0	3.23	19	9
5	941.0	9.23	18	3.8
6	944.0	3.24	5.17	7
7	946.0	25	16	9
8	95.0	3.26	2.15	5.9
9	956.0	4.27	5.14	10
10	958.0	28	8.13	5.10
11	961.0	1.29	13	11
12	9635.0	30	12	6.11

Table 2: The coordinate PC curve in two dimensional spaces

Density (gr/cm^3)			Tensile strength (20^0)(N/mm^2)			Impact strength (Kg/mm^2)			Time		
D#	X*	Y*	D#	X*	Y*	D#	X*	Y*	D#	X*	Y*
12	0.292893	1	1	0.292893	1	12	0.292893	1	1	0.292893	1
1	0.385125	0.891688	2	0.372443	0.679555	11	0.401679	0.674116	2	0.385125	0.722596
11	0.385125	0.832476	3	0.46967	0.629183	10	0.483268	0.62941	3	0.385125	0.699253
10	0.461984	0.813892	4	0.522703	0.616491	9	0.61925	0.623517	4	0.461984	0.680668
2	0.5081	0.757903	5	0.61993	0.57818	8	0.673643	0.58022	5	0.5081	0.6503
9	0.538843	0.716241	6	0.734835	0.548303	7	0.700839	0.553063	6	0.538843	0.624009
3	0.569587	0.658173	7	0.796707	0.510859	6	0.782429	0.52219	7	0.569587	0.576189
8	0.615703	0.600558	8	0.832062	0.491545	5	0.825943	0.473641	8	0.615703	0.528822
4	0.692562	0.534646	9	0.885095	0.458042	4	0.864018	0.42586	9	0.692562	0.478282
7	0.692562	0.446021	10	0.902773	0.387095	3	0.902093	0.382563	10	0.692562	0.415277
5	0.800165	0.386415	11	0.929289	0.359899	2	0.945607	0.350153	11	0.800165	0.355672
6	1	0.292893	12	1	0.292893	1	1	0.292893	12	1	0.292893

D#: Design number, Bold numbers are used in Eq. (9) for the calculation of the relative importance of each attribute.

Table 3: The MSE results

D#	1	2	3	4	5	6	7	8	9	10	11	12
MSE	81	5004	68	5160	5183	5227	5260	55	5379	5377	5443	550945

One important question is to find the best possible alternative based on four attributes. There are different methods to choose the appropriate alternative design is to use mean square error (MSE) as follows,

$$\mathrm{MSE}_j = \frac{1}{n}\sum_{i=1}^{n}(1-\frac{f_i}{f^0}), j=1,\cdots,m \tag{13}$$

Where f_i are the attributes associated with different design alternatives given in Table 1 and f^0 is the result of the implementation of Grierson . Table 3 summarizes the results of our MSE for all twelve alternative designs.

As we can observe from Table 3, alternative 8 represents the minimum MSE and it is chosen as the best design alternative and alternative 3 and 1 come after with relatively small MSE difference.

For entering the data to PSO algorithm we define the proposed model as below:

$$\begin{aligned} MaxZ &= \sum_{i=1}^{12}\ \sum_{j=1}^{4} D_j x_i \\ MinZ &= \sum_{i=1}^{12}\ \sum_{j=1}^{4} Tn_j x_i \\ MinZ &= \sum_{i=1}^{12}\ \sum_{j=1}^{4} \mathrm{Im}_j\, x_i \\ MinZ &= \sum_{i=1}^{12}\ \sum_{j=1}^{4} Ti_j x_i \end{aligned} \tag{14}$$

St:

$$\sum_{1}^{12} x_i = 1 \tag{15}$$

So the results of proposed model will be as below:

$f_1^0 = 0.998971,\ f_2^0 = 7.1045,\ f_3^0 = 5.6512,\ f_4^0 = 1.00876.$

Table 4 Is Showing the Mse for Proposed Model:

And for designs we have:

$x_3 = 1, x_{1,11} = 0$

According to proposed model, the design number 3 will be selected. As compared to Grierson's model, we see that this approach is more efficient than Grierson's method.

In this paper, we have presented an empirical method for case study of polyethylene pipes. The primary aim of this research was to choose an alternative design among various available one. In our study, we gathered different team members in a concurrent engineering team who were actively working for a pipeline production and chose the most important factors involved in designing pipeline.

We have also used Grierson's two-dimensional MCDM method and PSO algorithm to find the most appropriate design alternative based on various attributes and used a mean square error to rank different alternatives based on all existing criteria. As it is shown in table3 the MSE for proposed model (Eq.14) that is solved by particle swarm optimization is less than Grierson's method.

The first function is to maximize the *density* and other functions are minimizing *tensile strength, impact strength and time* respectively.

```
FOR each particle i
FOR each dimension d
Initialize position x_id randomly within permissible range
Initialize velocity v_id randomly within permissible range
End FOR
END FOR
Iteration t=1
DO
FOR each particle i
Calculate fitness value
IF the fitness value is better than p_best_id in history
Set current fitness value as the p_best_id
END IF
END FOR
Choose the particle having the best fitness value as the g_best_d
FOR each particle i
FOR each dimension d
Calculate velocity according to the equation
```

$$v_{id}^{t+1} = \omega^t v_{id}^t + c_1 r_1^t (p_{id}^t - x_{id}^t) + c_1 r_2^t (p_{gd}^t - x_{id}^t)$$

```
Update particle position according to the equation,
```

$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}$ get *d*th dimension of PSO-particle

```
Compute weights if Gaussian functions in kernel wi
Select a Gaussian function gi from kernel according to pi
Sample gi to get dth dimension of Hybrid Pareto-particle
END FOR
END FOR
FOR each particle i
Evaluate fitness of ith PSO-Particle
Evaluate fitness of ith Hybrid Pareto -Particle
IF fitness(PSO-Particle) < fitness (Hybrid Pareto -Particle)
x(t+1) = PSO-Particle
ELSE
x(t+1) = Hybrid Pareto -Particle
END IF
END FOR
t=t+1
WHILE maximum iterations or minimum error criteria are not attained
```

Fig. 2: Pseudocode for Hybrid Pareto Algorithm

Table 4: The MSE results

D#	1	2	3	4	5	6	7	8	9	10	11	12
MSE	54	2000.34	13	3890	2870	4310	1700.43	30	3294	1843.2	4620	230439.4

CONCLUSIONS

The PSO-Algorithm and corresponding Pareto-MCDM computational procedure resolve an important issue related to multi-criteria decision making, that of rigorously selecting a compromise design from among a potentially large number of alternative feasible designs.

The results indicated that proposed method (Equation 14) could be easily used for problems with various alternative designs, successfully. The Particle Swarm Optimization procedure is applicable for solving all mathematical models of design from conceptual to detailed, across the entire spectrum of engineering disciplines. Beyond engineering, the procedure can be applied for any tradeoff/bargaining scenario that involves multiple conflicting criteria and parties. PSO algorithm have successfully ran and developed for this study.

For future study we suggest to apply other Meta-heuristic methods, as *Genetic Algorithm, Bee Colony and Ant Colony* and compare the result with this method to extend the research.

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