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SELECTIVE ASSEMBLY TO MINIMIZE CLEARANCE VARIATION IN COMPLEX ASSEMBLIES USING FUZZY EVOLUTIONARY PROGRAMMING METHOD

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ABSTRACT

Selective assembly is an economic method to obtain perfect precision assemblies by using the components manufactured with wide tolerance specifications. The mating component's tolerances are divided into equal number of groups. The manufactured components are segregated according to these groups and the components from the corresponding groups are assembled interchangeably in the conventional method. The required clearance can be achieved at this assembly method that is tighter than those achieved at the normal fabrication method with lowest total cost. Still there are more variations in the clearance range. In this paper, a new optimization method is proposed to find the best combination of the selective groups to minimize assembly variation for the complex assemblies. A case example is analyzed for piston, cylinder and piston ring assembly. Fuzzy evolutionary programming (EP) method is used to obtain the best combination of the selective groups to control the assembly variation. Selective assembly is successfully applied for a piston and cylinder assembly using fuzzy EP method to achieve minimum clearance variation without sacrificing the benefit of wider tolerance in manufacturing.

Keywords: selective assembly, assembly clearance, piston and cylinder assembly, fuzzy evolutionary programming method.

1. INTRODUCTION

Variation in either side of the target is natural in any manufacturing process. The allowable amount of variation that will not affect the functional requirements of the component is called tolerance. Due to the allowable tolerance limits on the components, the assembled product will get the clearance. When a product consists of two or more components being assembled, the cumulative amount of clearances will affect the functional performance of the assembled product. Manufacturing the components with tight tolerance may reduce the clearance, but it will increase the manufacturing cost. Components with wider tolerances increase the clearance and affect the functional performance. For high volume production, there are two types of assembly system: interchangeable assembly and selective assembly. In interchangeable assembly, the components are assembled by selecting them randomly from the lots produced. Due to the random selection, this system of assembly is desirable for speeding up the assembly process and reducing cost. But the assembled product can not be obtained with the required clearance range. If the variation acceptable is less than the sum of the available component tolerances, it is not possible to assemble interchangeable assembly system. Selective assembly is the only solution to achieve the required clearance range.

Selective assembly is a method of obtaining high precision assemblies from relatively low precision components at the lowest manufacturing cost. In selective assembly, the mating components are manufactured with wider tolerances. Each mating component tolerances are partitioned into equal number of selective groups, and the components from the corresponding groups are assembled. This economic method is very much useful where the process variation is too large, and the required clearance variation for the assemblies is too small. The assembly products used in the selective assembly method can be classified into two groups: linear assembly and radial assembly. The dimensional variation (tolerance variation) is parallel to the axis of the assembly in linear assembly as in the case of gears assembled in an automobile gear box. In radial assembly, the dimensional variation under consideration is radial like in shaft and hole (pin and bush) assembly. The tolerance variation is called as clearance variation or interference in radial assemblies. When the number of components in an assembly is more than two and if the clearance variation is depending on the quality characteristics contributed by the components, then is it called a complex assembly. It can be linear (valve train assembly - clearance between cam and tappet), or radial (piston, piston ring and cylinder assembly - clearance between piston rings and cylinder walls), or both (turbine rotor assembly).

Research in the area of selective assembly has been focused on several key aspects. Kannan and Jayabalan (2001a) described a method for designing the required dimensional mean when manufacturing mating components to minimize surplus parts and grouping for selective assembly. Kannan and Jayabalan (2001b) analyzed a complex assembly with three mating parts and proposed a method of partitioning the lots to obtain lesser assembly variation with minimum surplus parts by selective assembly. Fang and Zhang (1995) proposed a method of making groups with equal probabilities. In the proposed method, the parts are manufactured within the tolerance specifications and the grouping is planned after manufacturing. This method is suitable when the clearance specifications are greater than the difference in standard

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deviations of the mating parts. Allen Pugh (1992) presented a method to truncate the component's dimensional distribution with large variance. The resulting components variances are equal the components produced at the extremes of the distribution are discarded during the assembly process. This method has limitations in minimizing the surplus parts and in meeting the closer clearance specifications. Allen Pugh (1986) suggested a method (computer program) of partitioning the mating parts population for selective assembly. The limitation given in this method is the number of groups. Mansoor (1961) classified the selective assembly problem based on the natural process tolerance and their relationship to the tolerance on the fit. Desmond and Setty (1962) recommended a method to determine the relationship between size and performance and to establish limits for the assembly, which will satisfy performance requirements. Shan and Satywadi (1989) described a procedure for one-to-one pairing of component parts to be assembled. To improve the selective assembly process Zhang and Fang (1999) developed an analytical model involving PCI-based tolerance to predict and assure the matcheable degree. Arne Thesen and Akachai Jantayavichit (1999) proposed and evaluated the design of a high-speed station for the selective assembly of certain high precision automotive components. David Kern *et al*. (2003) proposed an approach to forecast the manufacturing quality of a product and optimize its robustness while it is being designed. David Mease *et al*. (2004) defined selective assembly as a cost effective approach for reducing the overall variation and thus improving the quality of an assembled product. The authors described the statistical formulation of the population and developed optimal binning strategies under several loss functions and distributional assumptions.

Selective assembly can be used for the fabrication of high precision assemblies with minimum clearance and less surplus parts by using the best combination of selective groups. This best combination can be obtained using various optimization tools. Kannan *et al.* (2003 and 2008) proposed new selective assembly methods that are selecting the matting components form the best combination rather than from corresponding groups. The methods are proposed for linear and radial assemblies and the assembly variation and surplus parts are minimized using best combination obtained through genetic algorithm. But for a complex assembly where the matting components are having mare than one quality characteristics and more than one objective, it is not possible with genetic algorithm. In this paper, a new fuzzy evolutionary programming (EP) method is proposed to obtain the best combination for selective assembly that involves more objective functions as well as more than one quality characteristics in matting component (complex assembly).

2. PROBLEM BACKGROUND

The quality of an assembly depends on the quality of the mating parts being assembled. The mating parts are manufactured in different processes and in different machines. So the standard deviation (σ) of the mating parts will be different. The dimensional distribution of the components is not uniform. It results more surplus parts at selective assembly process. The dimensional distribution of the components is equivalent to the process capability (6σ) of the process. So the process capability 6σ (±3σ) of the process is considered for analysis. The assembly clearance depends on the tolerance of the individual components. To minimize the assembly clearance variation, it is vital to minimize the individual component tolerance. It may require an improved process or an improved machine to manufacture the parts with small tolerances. It is not possible under economical consideration. In some high precision complex assemblies, it may not be possible to have a closer assembly clearance variation with interchangeable system. The proposed new method of selective assembly meets the above requisite and gives an enhanced solution. In conventional selective assembly, the corresponding groups are assembled resulting in higher clearance variation. Here the probability areas of all components are same. Minimum clearance can be obtained through the best combination of selective assembly groups.

3. THE PROBLEM

In the assembly of two components (simple assembly), the clearance variation is very high with interchangeable system and slightly reduced within the groups in conventional selective assembly. However in selective assembly, the clearance variation of the population is the same (Kannan *et al*., 2003). If a better combination, instead of assembling corresponding groups is used, the clearance variation of the population can be reduced largely. In complex assemblies, the clearance variation is very high, as it is contributed by the tolerances of all the components. A complex assembly of piston and cylinder assembly is considered for analysis as shown in Figure-1. It consists of the matting components as piston, piston ring and cylinder.

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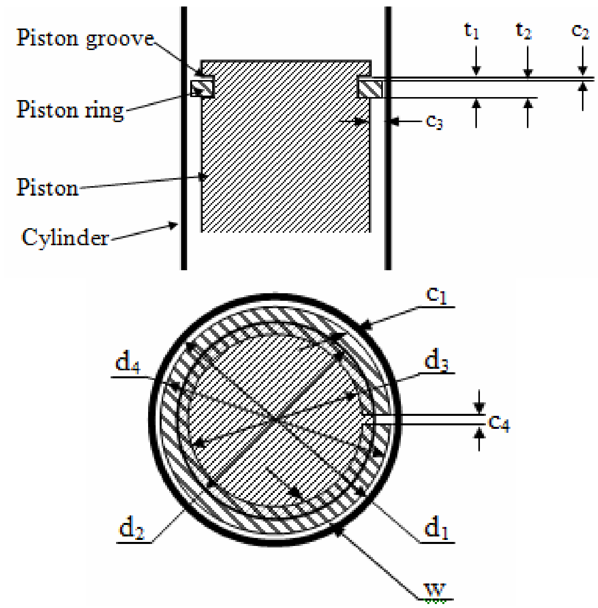

Figure-1. Piston, piston ring and cylinder assembly.

In Figure-1, the quality characteristics of the piston and cylinder assembly are cylinder inner diameter (d_1), piston diameter (d_2), piston groove diameter (d_3), piston groove thickness (t_1), piston ring thickness (t_2), piston ring width (w) and circumferential area of the piston ring (A_R). The dimensions of the above quality characteristics are considered as follows:

Cylinder inner diameter	(d_1)	$50^{\pm 0.028}_{0.004}$ mm
Piston diameter	(d_2)	$50^{\pm 0.012}_{0.000}$ mm
Piston groove diameter	(d_3)	$42^{\pm 0.000}_{0.018}$ mm
Piston groove thickness	(t_1)	$3.2^{\pm 0.000}_{0.012}$ mm
Piston ring thickness	(t_2)	$3^{\pm 0.000}_{0.006}$ mm
Piston ring width	(w)	$4^{\pm 0.000}_{0.018}$ mm

Circumferential area of the piston ring (A_R) $156^{\pm 0.008}_{0.008}$ mm

The tolerances for these quality characteristics are considered as the natural tolerances of the manufacturing process. But, this complex assembly consists of more than one quality characteristics in a matting component. Piston consists of the important quality characteristics as d_2, d_3 and t_1. Piston ring consists of the quality characteristics as d_4, t_2 and w. By considering all the above quality characteristics of the matting components, there are three important assembly clearances in between piston groove and piston ring (δ_1), piston ring and cylinder wall (δ_2), piston and cylinder wall (δ_3) and the gap between the piston ring ends at its open end position (δ_4). These clearances of piston and cylinder assembly are calculated as follows:

δ_1 $= d_1 - (d_3 + 2w)$

δ_2 $= t_1 - t_2$

δ_3 $= d_1 - d_2$

δ_4 = circumferential are of cylinder-circumferential area of piston ring

$= \pi d_1 - A_R$

The gap between the piston ring ends at its closed position in the cylinder is most critical parameter for the piston and cylinder assembly. For the cylinder dimension of $50^{\pm 0.028}_{0.004}$ mm, its circumferential area varies as $157.13^{\pm 0.038}_{0.038}$ mm. The allowable specification for the piston ring circumferential area (at cold condition) is $156^{\pm 0.008}_{0.008}$ mm.

Based on the most important dimensional distributions like cylinder inner diameter (d_1), piston diameter (d_2) and piston ring circumferential area (A_R) the corresponding matting components cylinder (C), piston (P) and piston ring (R) are divided into six groups for selective assembly method. For a combination of selective groups, in one assembly set, the maximum assembly clearance (δ^{max}) is the sum of the maximum limits of the component's group tolerances. So δ^{max} can be obtained by the sum of multiplications of group number (n_a) and group tolerance (δ_a), where 'a' is the matting component. Here, 'a' defines the matting components cylinder (C), piston (P) and piston ring (R). The minimum assembly clearance (δ^{min}) is the sum of the minimum limits of the component's group tolerances. It can be obtained by the sum of multiplications of (n_a–1) and δ_a. Therefore maximum and minimum assembly clearances for a combination are,

$$\delta^{max} = (n_C \times \delta_C) + (n_P \times \delta_P) + (n_R \times \delta_R)$$

$$\delta^{min} = ((n_C - 1)\delta_C) + ((n_P - 1)\delta_P) + ((n_R - 1)\delta_R)$$

Consider an example combination with six selective groups (n=6) as shown in Figure-2. Table-1 shows their δ_1 clearance calculation. The assembly clearance δ_1 involves three quality characteristics of the matting components cylinder, piston and piston ring as cylinder inner diameter, piston groove diameter and piston ring width respectively. Tolerance for the cylinder is given as 32 μm. For the selective group size (n) of 6, the group tolerance becomes 5.3 μm. Similarly for the matting components piston and piston ring with the tolerances of 18 μm results the group tolerances of 3 μm. The assembly clearance range for the assembly sets is calculated as follows. In Table-1, the first assembly set 4_C, 2_P and 2_R (first column in the combination) is considered as an example. It means that, the component C (cylinder) is from the fourth selective group, the component P (piston) is from the second selective group and the component R (piston ring) is from the second selective group. The maximum assembly clearance is the sum of multiplications of selective groups and corresponding group tolerances [$(4_C \times 5.3\mu m) + (2_P \times 3\mu m) + (2_R \times 3\mu m) = 28\mu m$]. Similarly, the minimum assembly clearance is

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the sum of multiplications of initial limits of the selective groups and their corresponding group tolerances [((4_C–1) ×5.3µm) + ((2_P–1) ×3µm) + ((2_R–1) ×3µm) =18µm]. For each 'n' number of selective group combination, 'n' number of assemblies can be produced. Each assembly will have different assembly clearances that lead assembly variations. Then the clearance range (δ^{range}) for the assemblies of a combination is the subtraction of the minimum of δ^{min} from the maximum of δ^{max}.
i.e., δ^{range} = max (δ^{max}) - min (δ^{min}).

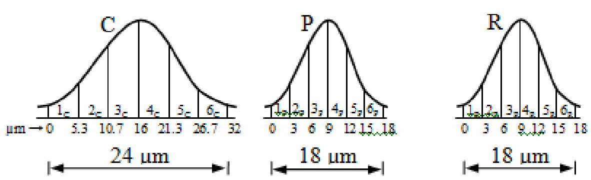

Figure-2. Dimensional distribution of the quality characteristics for piston and cylinder assembly with n = 6 for δ_1.

Table-1. Assembly variation of δ_1 calculation for the piston and cylinder assembly.

Matting component (a)		Combination					
C		4_C	2_C	3_C	5_C	6_C	1_C
P		2_P	1_P	6_P	3_P	4_P	5_P
R		2_R	6_R	4_R	3_R	1_R	5_R
Assembly clearance variation (µm)	δ_1^{max}	33.3	31.7	46	44.7	47	35.3
	δ_1^{min}	22	20.4	34.7	33.4	35.7	24
Clearance range (δ_1^{range}) (µm)		46 - 20.4 = 25.6					

The maximum and minimum clearance values for each assembly set of the combination are calculated. The assembly clearance variation for the first set is 33.3 - 22 = 11.3 µm. But δ_1^{range} (25.6 µm) for the entire sets (one combination) is the difference between the maximum value of δ_1^{max} (46µm) and minimum value of δ_1^{min} (20.4 µm). For this same combination, the second clearance δ_2 involves only the matting components piston groove and piston ring with their quality characteristics of thickness of piston groove and thickness of piston ring respectively. Figure-3 shows its dimensional distribution and the clearance (δ_2) calculation is shown in Table-2.

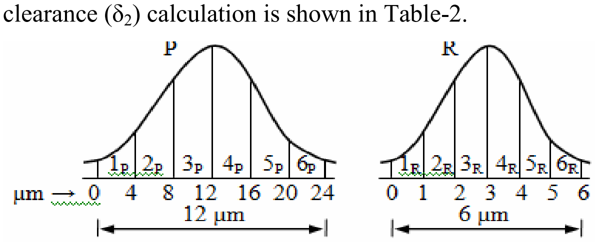

Figure-3. Dimensional distribution of the quality characteristics for piston and cylinder assembly with n = 6 for δ_2.

Table-2. Assembly variation of δ_2 calculation for the piston and cylinder assembly.

Matting component (a)		Combination					
P		2_P	1_P	6_P	3_P	4_P	5_P
R		2_R	6_R	4_R	3_R	1_R	5_R
Assembly clearance variation (µm)	δ_2^{max}	8	8	16	9	9	15
	δ_2^{min}	3	5	13	6	6	12
Clearance range (δ_2^{range}) (µm)		16 - 3 = 13					

The best combination is to be selected such that it results in the minimum assembly clearances in each assembly sets as well as minimum assembly variation in the entire sets of the combination. But this complex assembly has more numbers of assembly clearances with different quality characteristics in the matting components. The example calculation shown in Table-1 involves the first clearance (δ_1) calculation with three matting components. But for the same combination, the clearances δ_2 δ_3 and δ_4 involve different matting component combination with different quality characteristics. It involves different dimensional, group tolerance considerations regarding to their clearance calculation. This complex process of finding the best combination for minimum overall assembly clearance variation is obtained through the fuzzy evolutionary programming method.

4. FUZZY EP METHODOLOGY

For solving this problem, fuzzy EP method is used as a tool to find the optimal combination of selective groups for obtaining minimum assembly clearance range. Dr. Lotfi Zadeh introduced the term fuzzy logic in 1965 at his seminal work in the journal of information and control (Timothy J. Rose, 1997). Fuzzy logic provides the opportunity for modelling conditions that are inherently imprecisely defined. It poses the ability to mimic the human mind to effectively employ modes of reasoning that are approximate rather than exact. The aim of such logic is to formalize the approximate reasoning that is used in everyday life. This formalization is carried out by the predicates as big, near or slow which are vague in nature. These predicates are interpreted by the notion of fuzzy set. Fuzzy sets are generalized sets introduced by Prof. Zadeh as a mathematical way to represent and deal with vagueness in everyday life (Paolo Dadone, 2001). Elements of a fuzzy set are taken from a universe of discourse or universe (*U*) in short. The universe contains all elements that can come into consideration. Every element (*x*) in the universe of discourse (*U*) is a member of the fuzzy set to some grade. The function that ties a number to each element *x* of the universe is called the membership function *μ(x)*. Each fuzzy set is completely and uniquely defined by one particular membership function. The membership function is a relationship between the fuzzy set and the degree of satisfaction. The degree of satisfaction can vary from zero to one.

A fuzzy set A on a universe of discourse U is characterized by a membership function $\mu_a(x)$ that takes values in the interval [0, 1]. That is, every function $\mu: U \rightarrow [0, 1]$ is a fuzzy set. The higher the number indicates the higher value of membership. The grade of membership is a precise, but subjective measure that depends on the context. A fuzzy set expresses the degree to which an element belongs to a set. If U is a collection of objects denoted generically by x, then a fuzzy set A in U is defined as a set of ordered pairs,

$$A = \{(x, \mu_a(x)) \mid x \in U\}$$

where, $\mu_a(x)$ is called the membership function for the fuzzy set A.

Evolutionary algorithm (EA) is an umbrella term used to describe computer based problem solving and search methods that take their inspiration from natural selection and survival of the fittest in the biological world. EA differs from more traditional optimization techniques in that they involve a search from a population of solutions, not from a single point (Kalyanmoy Deb, 2003). Each iteration of an EA involves a competitive selection that weeds out poor solutions. The solutions with high fitness are recombined (crossed) with other solutions by swapping parts of a solution with another. Solutions are also mutated by making a small change to a single element of the solution. These cross over and mutation operators are used to generate new solutions that are biased towards regions of the space for which good solutions have already been seen. Several different types of evolutionary search methods were developed independently. These include (i) genetic programming (GP), which evolve programs, (ii) evolutionary programming (EP), which focuses on optimizing continuous functions without cross over operation, (iii) evolutionary strategies (ES), which focuses on optimizing continuous functions with recombination and (iv) genetic algorithm (GA), which focuses on optimizing general combinatorial problems.

Evolutionary programming (EP) was first proposed by Lawrence J. Fogel in 1960, as an approach to artificial intelligence and it has been recently applied with success to many numerical and combinatorial optimization problems (Xin and Yong, 1999). The primary difference between evolutionary programming and the other approaches (GA, GP, and ES) is that no exchange of material between individuals in the population is made (Fogel D.B., 1995). Only mutation operators are applied within the materials of an individual that varies in the severity of their effect on the behaviour of the individual. Optimization by EP can be summarized into two major steps: (i) mutate the solutions in the current population and (ii) select the next generation from the mutated and the current solutions. An initially random population of N number of individuals (trial solutions) is created. Mutation is applied to each N number of individual. For each individual, a new offspring is generated, and it results in $2N$ number individuals in the population. A typical selection method is applied on these $2N$ numbers of individuals, to test which of the newly generated best N numbers of solutions should survive to the next generation (Venkatesh *et al*., 2004). Fuzzy concepts are used for the selection process in fuzzy EP method.

5. BEST COMBINATON THROUGH FUZZY EP METHODOLOGY

For this complex linear assembly of valve train assembly, fuzzy evolutionary programming (EP) method is used to find the best combination of mating components for achieving minimum assembly clearance variation. The combination of selective groups is considered as solution string (X) for this method. The fuzzy membership function is employed to choose best solution string that results minimum assembly clearance variation. The solution string for the proposed fuzzy EP method consists of numbers of elements. Figure-4 shows the example solution string for the piston and cylinder assembly.

1_C	2_C	3_C	4_C	5_C	6_C	1_P	2_P	3_P	4_P	5_P	6_P	1_R	2_R	3_R	4_R	5_R	6_R

↑
Element

Figure-4. Example for solution string 'X'.

A set of solutions X^1, X^2, X^3,…… X^N are generated at first. N is the number of such generated solutions. Thereafter the process generates another set of an equal N numbers of solutions randomly. Among these two sets of $2N$ individuals, the EP process chooses N best solutions. This process continues until the optimum is reached. Thus, the evaluation of the objective function for each of the $2N$ solutions and their ranking is done in each EP iteration. Keeping these $2N$ numbers of solutions X^1, X^2, X^3,…… X^N, X^{N+1}, X^{N+2}, X^{N+3},…… X^{2N}, the fuzzy objective functions and membership functions are modelled as below:

First objective and its membership function

Through this complex assembly of piston and cylinder, this paper addresses four objective functions which are the minimization of assembly clearances. The first objective is to minimize the clearance between piston groove and piston ring (δ_1). For a solution string X, it is termed as $\delta_1(X)$.

$$\delta_1(X) = d_1 - (d_3 + 2w)$$

Upon evaluating all the solutions [X^1, X^2, X^3,…… X^{2N}], the corresponding values of [$\delta_1(X^1)$, $\delta_1(X^2)$, $\delta_1(X^3)$, ….. $\delta_1(X^{2N})$] are obtained.

It forms the fuzzy set E as,

$$E = \{[\delta_1(X), \mu_e[\delta_1(X)]] \mid \delta_1(X) \in \text{[set of all permissible values]}\}$$

The membership function $\mu_e(\delta_1(X))$ is defined as,

$$\mu_e[\delta_1(X)] = \frac{e^{\max} - \delta_1(X)}{e^{\max} - e^{\min}}$$

Where e^{max} and e^{min} are the maximum and minimum values of δ_1^{max} and δ_1^{min}, respectively.

Second objective and membership function

The second objective is to minimize the clearance between piston ring and cylinder wall (δ_2). For a solution string X, it is termed as $\delta_2(X)$.

$\delta_2(X) = t_1 - t_2$

All the solutions [X^1, X^2, X^3,…… X^{2N}] are evaluated and the corresponding values of [$\delta_2(X^1)$, $\delta_2(X^2)$, $\delta_2(X^3)$,….. $\delta_2(X^{2N})$] are obtained. It forms the fuzzy set F as,

F = {[$\delta_2(X)$, μ_f [$\delta_2(X)$]] | $\delta_2(X) \in$ [set of all permissible values]}

The membership function $\mu_f(\delta_2(X))$ is defined as,

$$\mu_f[\delta_2(X)] = \frac{f^{\max} - \delta_2(X)}{f^{\max} - f^{\min}}$$

Where f^{max} and f^{min} are the maximum and minimum values of δ_2^{max} and δ_2^{min}, respectively.

Third objective and membership function

The third objective is to minimize the clearance between piston and cylinder wall (δ_3). For a solution string X, it is termed as $\delta_3(X)$.

$\delta_3(X) = d_1 - d_2$

All the solutions [X^1, X^2, X^3,…… X^{2N}] are evaluated and the corresponding values of [$\delta_3(X^1)$, $\delta_3(X^2)$, $\delta_3(X^3)$,….. $\delta_3(X^{2N})$] are obtained. It forms the fuzzy set G as,

G = {[$\delta_3(X)$, μ_g [$\delta_3(X)$]] | $\delta_3(X) \in$ [set of all permissible values]}

The membership function $\mu_g(\delta_3(X))$ is defined as,

$$\mu_g[\delta_3(X)] = \frac{g^{\max} - \delta_3(X)}{g^{\max} - g^{\min}}$$

Where g^{max} and g^{min} are the maximum and minimum values of δ_3^{max} and δ_3^{min}, respectively.

Fourth objective and membership function

The fourth objective is to minimize the gap between the piston ring ends at its open end position (δ_4). For a solution string X, it is termed as $\delta_4(X)$.

$\delta_4(X) = \pi d_1$ - circumferential area of the piston ring

All the solutions [X^1, X^2, X^3,…… X^{2N}] are evaluated and the corresponding values of [$\delta_4(X^1)$, $\delta_4(X^2)$, $\delta_4(X^3)$,….. $\delta_4(X^{2N})$] are obtained. It forms the fuzzy set H as,

H = {[$\delta_4(X)$, μ_h [$\delta_4(X)$]] | $\delta_4(X) \in$ [set of all permissible values]}

The membership function $\mu_h(\delta_4(X))$ is defined as,

$$\mu_h[\delta_4(X)] = \frac{h^{\max} - \delta_4(X)}{h^{\max} - h^{\min}}$$

Where h^{max} and h^{min} are the maximum and minimum values of δ_4^{max} and δ_4^{min}, respectively.

Overall objective function

Then all the membership functions that are related to the individual objectives are combined, and the over all objective function is developed. It requires a method to combine the four objectives using a fuzzy intersection operator. In this paper simple product is chosen as the intersection operator. Thus the over all objective function is defined as below:

$\mu_x(X) = \mu_e[\delta_1(X)] \times \mu_f[\delta_2(X)] \times \mu_g[\delta_3(X)] \times \mu_h[\delta_4(X)]$

The overall objective function defined above quantifies the satisfaction with the solution string X and is used to evaluate a best string X^J from among the $2N$ solutions X^J to X^{2N} in the proposed evolutionary programming method. The flowchart of the proposed fuzzy EP method is shown in Figure-5. The steps in the proposed fuzzy EP method are explained below:

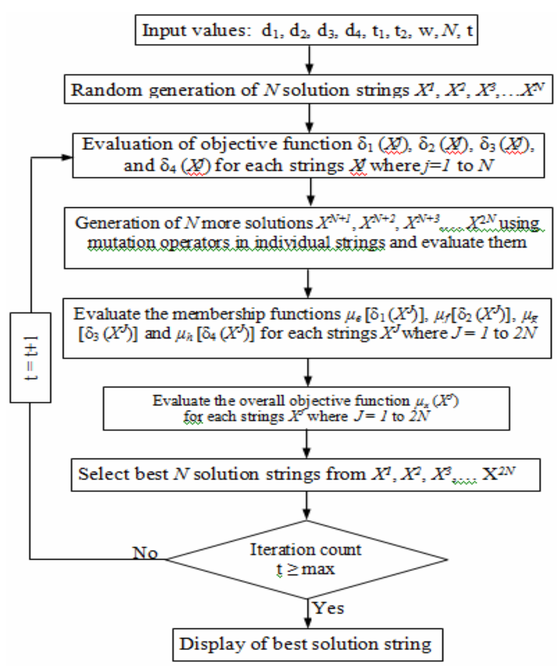

Figure-5. Structure of proposed fuzzy EP method.

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Step-1:

The input data and example for the first stage are as follows:

a) $d_1 = 50^{\pm^{0.028}_{0.004}}$ mm
b) $d_2 = 50^{\pm^{0.012}_{0.000}}$ mm
c) $d_3 = 42^{\pm^{0.000}_{0.018}}$ mm
d) $t_1 = 3.2^{\pm^{0.000}_{0.012}}$ mm
e) $t_2 = 3^{\pm^{0.000}_{0.006}}$ mm
f) $w = 4^{\pm^{0.000}_{0.018}}$ mm
g) Population size $N = 5$
h) Iteration t = 50

Step-2:

The numbers of solution strings equal to population size (N) are randomly generated based on the information given in the first step. Figure-6 shows the example for the 5 number of randomly generated solution strings as per in information given in step-1.

4_C	2_C	3_C	5_C	6_C	1_C	2_P	1_P	6_P	3_P	4_P	5_P	2_R	6_R	4_R	3_R	1_R	5_R

2_C	6_C	3_C	1_C	4_C	5_C	4_P	6_P	3_P	5_P	2_P	1_P	3_R	2_R	6_R	5_R	1_R	4_R

6_C	5_C	2_C	1_C	3_C	4_C	5_P	3_P	4_P	2_P	1_P	6_P	6_R	1_R	4_R	3_R	2_R	5_R

4_C	2_C	3_C	1_C	6_C	5_C	2_P	1_P	6_P	4_P	5_P	3_P	4_R	6_R	5_R	3_R	2_R	1_R

6_C	3_C	5_C	1_C	2_C	4_C	3_P	5_P	1_P	6_P	2_P	4_P	1_R	5_R	2_R	6_R	4_R	3_R

Figure-6. Random generation of N number of combinations.

Step-3:

The objective function values δ_1, δ_2, δ_3 and δ_4 for each of the combinations X^j for j = 1 to N is evaluated. For the randomly generated combinations in the step-2 (Figure-6), the objective function is evaluated and presented in Table-3.

Table-3. Objective function evaluation for N numbers of combinations.

Solution string (X^j)	δ_1 (X^j)	δ_2 (X^j)	δ_3 (X^j)	δ_4 (X^j)
X^1	26.5	13	34.6	68
X^2	37	12	36	70.6
X^3	56	16	40	71.3
X^4	38	13	36	75.9
X^5	28.6	17	30.6	65.3

Step-4:

Each individual combination X^1, X^2, X^3,…… X^N is considered as a parent. The mutation operator is applied in each parent strings and N more solutions X^{N+1}, X^{N+2}, X^{N+3},… X^{2N} are generated. Mutation is the process of exchange of genes within the substring of one combination. In a combination, the selective groups of a component are considered as a substring. The parameter covering the mutation operation is called probability of mutation (p_mut), which is assigned as 0.75. A random number 'r' is generated for each element. If the random number r is less than the probability of mutation (r ≤ p_mut), that particular element is mutated with previous one. From Figure-4 the first combination X^1 is selected to explain the mutation process and random numbers are generated for each element as shown in Table-4. The mutated offspring X^{N+1} is shown in Figure-7.

Table-4. Mutation for the parent string X^1 (* selected gene for mutation operation).

4_C	2_C	3_C	5_C	6_C	1_C	2_P	1_P	6_P	3_P	4_P	5_P	2_R	6_R	4_R	3_R	1_R	5_R
0.865	0.926	0.761	0.664*	0.356*	0.091*	0.878	0.045*	0.189*	0.257*	0.597*	0.965	0.017*	0.541*	0.101*	0.336	0.243*	0.984

4_C	2_C	5_C	6_C	1_C	3_C	1_P	6_P	3_P	4_P	2_P	5_P	6_R	4_R	5_R	1_R	3_R	2_R

Figure-7. Mutated offspring X^{N+1}.

Step-5:

All the combinations from step-2 and offspring from step-4 are combined. The membership functions for all $2N$ number of solution are evaluated. For example, 5 numbers of combinations from step 2, and 5 numbers of newly generated combinations from step 4 are combined. For 2×5 number of combinations, membership functions μ [$\delta(X)$] are evaluated and presented in Table-5.

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Table-5. Membership evaluation for *2N* numbers of combinations.

X^J	$\delta_1(X^J)$	e^{max}	e^{min}	$\mu_e[\delta_1(X^J)]$	$\delta_2(X^J)$	f^{max}	f^{min}	$\mu_f[\delta_2(X^J)]$	$\delta_3(X^J)$	g^{max}	g^{min}	$\mu_g[\delta_3(X^J)]$	$\delta_4(X^J)$	h^{max}	h^{min}	$\mu_h[\delta_4(X^J)]$
X^1	26.5	65	9	0.6875	13	18	1	0.2941	34.6	44	2	0.22381	68	92	5.4	0.277136
X^2	37			0.5	12			0.3529	36			0.190476	70.6			0.247113
X^3	56			0.160714	16			0.1176	40			0.095238	71.3			0.23903
X^4	38			0.482143	13			0.2941	36			0.190476	75.9			0.185912
X^5	28.6			0.65	17			0.0588	30.6			0.319048	65.3			0.308314
X^6	41.7			0.416071	12			0.3529	30.7			0.316667	73.3			0.215935
X^7	32			0.589286	15			0.1765	32.6			0.271429	69.5			0.259815
X^8	29			0.642857	14			0.2353	38.6			0.128571	66			0.300231
X^9	46			0.339286	12			0.3529	34			0.238095	68.2			0.274827
X^{10}	38.6			0.471429	16			0.1176	36.8			0.171429	71.9			0.232102

Step-6:

The overall objective function is obtained for all the *2N* solution strings. Table-6 shows the overall objective function value for the ten numbers of solution strings.

Table-6. Overall objective function evaluation for *2N* numbers of combinations.

X^J	$\mu_e[\delta_1(X^J)]$	$\mu_f[\delta_2(X^J)]$	$\mu_g[\delta_3(X^J)]$	$\mu_h[\delta_4(X^J)]$	$\mu_x(X^J)$
X^1	0.6875	0.2941	0.22381	0.27713	0.01254
X^2	0.5	0.3529	0.19047	0.24711	0.00830
X^3	0.160714	0.1176	0.09523	0.23903	0.00043
X^4	0.482143	0.2941	0.19047	0.18591	0.00502
X^5	0.65	0.0588	0.31904	0.30831	0.00376
X^6	0.416071	0.3529	0.31666	0.21593	0.01004
X^7	0.589286	0.1765	0.27142	0.25981	0.00733
X^8	0.642857	0.2353	0.12857	0.30023	0.005839
X^9	0.339286	0.3529	0.23809	0.27482	0.007835
X^{10}	0.471429	0.1176	0.17142	0.23210	0.002206

Step-7:

The higher value of overall objective function value indicates the highly fittest solution. From steps-6, all the *2N* numbers of solutions strings are ranked. The first *N* numbers of fittest solutions are selected and others are omitted. In Table-7, the rank for the ten combinations are allotted and the best 5 number combinations X^1, X^9, X^2, X^4 and X^7 are selected orderly and renamed as X^1, X^2, X^3, X^4 and X^5.

Table-7. Ranking and choosing the best *N* numbers of combinations from *2N* numbers of combinations.

X^J	$\mu_x(X^J)$	Rank
X^1	0.01254	I
X^2	0.00830	III
X^3	0.00043	X
X^4	0.00502	VII
X^5	0.00376	VIII
X^6	0.01004	II
X^7	0.00733	V
X^8	0.00583	VI
X^9	0.00783	IV
X^{10}	0.00220	IX

Step-8:

If $t <$ maximum, the iteration count is increased as $t = t+1$ and the loop is connected at step-3. The steps are repeated number of times for the predefined number of iterations that leads the proposed fuzzy EP method to find the optimal combination with minimum assembly clearance range.

Step-9:

When iteration exceeds the iteration count, the process will be completed and the best combination is displayed.

RESULTS

The best combinations for the piston and cylinder assembly are obtained and presented in Table-8.

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Table-8. Best combination for the piston and cylinder assembly.

Component	Best combination						δ_1 (μm)	δ_2 (μm)	δ_3 (μm)	δ_4 (μm)
C	6	2	1	3	4	5	13.8	14	27.8	65.3
P	2	6	5	3	4	1				
R	1	4	6	5	2	3				

6. CONCLUSIONS

Selective Assembly is useful in improving the quality of assembly particularly in high precision assemblies. Selective assembly is more effective only when the combination of selective groups is appropriate to get minimum clearance. In this paper, the objective is to minimize the assembly clearance variation in piston and cylinder assembly. The component population is divided in to six groups. The best combination of assembling the components for selective groups is obtained using fuzzy EP method. A computer program in advanced package of MATLAB 7 (R14) is written to obtain the best combination of selective groups using fuzzy EP method. This methodology can be extended for any other complex assemblies having more than three components and more objective functions. Fuzzy evolutionary programming method is applied in the complex assembly analysis successfully.

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