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A New Grouping Method in Selective Assembly for Minimizing Clearance Variation Using TLBO

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Abstract: Allowable variation from the nominal dimension that's tolerance of a component plays a vital role in selecting manufacturing process and functioning of the product while mating with other sub components and its manufacturing cost. Closer tolerance required secondary process which increases manufacturing cost in considerable amount. Selective assembly is a method where components are manufactured with wider tolerance, measured and partitioned into groups and the components in their corresponding groups are assembled together to form precision assemblies. This method reduces the cost involved in secondary operation but in the mean time the cost of measuring the components in additions with the existing random assembly process. A trade off between measuring cost of each components and secondary operation cost is the deciding factor in implementing the selective assembly techniques. Existing method mostly focuses on equal group numbers and equal group width either surplus parts or reducing the clearance variation or both. A new technique of variable group numbers according to their tolerance is suggested in this work and the precision assemblies are produced using the best bin combinations obtained using teaching-and learning-based optimization algorithm. The proposed method has been implemented on the existing problem and can able to produce close precision assemblies without any surplus parts with less manufacturing cost. It is established that the TLBO algorithm minimizes the clearance variation from 17.5 ym to 15ym in a linear assembly that consists of three gears in a gear box and from 17 m to 16 m in a ball bearing assembly in a single stage with zero surplus parts.

Keywords: Selective assembly, clearance variation, surplus parts, Teaching Learning Based Optimization

1 Introduction

Customer mostly focuses on trouble free, high quality, low cost and long life in any products. In this aspect, manufactures are looking for different kinds of methods/processes to make the products as per the market demand. Due to invariability existing in all manufacturing methods it is highly difficult to produce any components as per the exact dimension. This may require some allowable variation from the nominal dimension. Manufacturing of the quality products is necessarily to ensure the geometry, shape, size and dimensional accuracy of the products. Most of the products consist of two or more than two components assembled together through fitted assembly, random or interchangeable assembly and selective assembly method. In fitted assembly, mating parts are manufactured for each other components. In random or interchangeable assembly, components are manufactured under mass production and mated or assembled by selecting randomly from the entire lot. In selective assembly, the entire components are classified based on their measured dimension and the components are assembled from their corresponding classified group. The manufacturer has to go for secondary operation or closer tolerance components to avoid scrap in both fitted and random assembly methods where as in selective assembly, because of classification/partitioning, the components may be manufactured with wider tolerance. Tolerances of a product considered as a mechanical assembly have a strong relationship with its manufacturing cost, quality and functional performance. Design of tolerance plays a

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vital role as it links between design and manufacturing phases. Design engineers normally specify stringent tolerance to ensure the fits, performance and functionality of a product. In manufacturing phase, the engineers prefer wider tolerance to manufacture the components economically. Selective assembly method meets both design and manufacturing engineers requirements.

The present study, enumerates the systematic procedure of minimization of total cost of manufacturing in the environment of any assemblies consisting of number of components. The present work differs from the existing work in the aspect of introducing two things namely different group numbers for each component according to their tolerance and introducing repeated group number based on their availability of number of components in the group. Whereas earlier studies considered only equal group numbers for all components and multiple stages of assemblies. The proposed work has been described with the problem environment and definition, methodology, TLBO algorithms in a sequential way after brief discussion on literature review in the related area. A numerical illustration with the aid of a gear box assembly consists of three various gears and a ball bearing assembly consists of inner race, balls and outer race. They are presented to explain the step-to-step implementation of the proposed methodology. Further, brief discussions on results have been followed by numerical illustration with conclusion.

2 Literature survey

Many researchers reported and discussed minimization of clearance variation and surplus parts in selective assembly techniques. Different heuristic and meta-heuristic algorithms have been implemented in literature to obtain the best combination of selective groups. Kannan et al. [1] illustrated that the mating part with smaller standard deviation is manufactured at shifted means for corresponding lots and the resulting standard deviation matches with the other mating part. The mating part in selective assembly is partitioned to a certain number having almost equal number of mating parts in corresponding group. Kern et al. [2] introduced a general approach to selective assembly when the distribution variations were different and also developed closed form equations for various selective assembly techniques. David et al. [3]developed optimal binning strategies using squared error loss function and compared the results with two commonly-used heuristic methods. Matsuura et al. [4] described on mathematical algorithms that require substantial gradient information. Various truss examples with fixed geometries are presented to demonstrate the effectiveness and robustness of the new method. The results indicate that the new technique is a powerful search and optimization method for solving structural engineering problems compared to conventional mathematical methods or genetic algorithm-based approaches. Vijayan et al. [5] described a new harmonic search meta-heuristic algorithm-based approach for engineering optimization problem with continuous design variable and it has been successfully used in areas such as function optimization. Xianying et al. [6] studied an optimal mean shift that minimizes the clearance variation when the component with smaller variance is manufactured at two shifted means. Rajeshbabu et al. [7] made the first attempt to study the optimal binning strategies with respect to squared error loss function, under the assumption that the dimensions of two respective components were followed by the same normal distribution. Cong et al. [8] introduced a new method of selective assembly and demonstrated the method on a linear assembly consists of three gears to minimize clearance variation without surplus parts using genetic algorithm. Manickam et al. [9] derived an optimal mean shift that minimizes the number of surplus components for equal width partitioning schemes when the component with smaller variance is manufactured at three shifted means. Rajeshbabu et al. [10] used genetic algorithm for obtaining the best combination of selective groups to have minimum clearance variation in hole and shaft assembly with four stages to use entire population of mating parts. The clearance variation of interchangeable assembly was 30m. With the best combination which was obtained by genetic algorithm, the minimized clearance variation for the first stage was 9m, 7.5m for second stage, 6m for third stage and in the last stage for 4.5m for the fourth stage. Geem et al. [11] obtained a best combination of selective group in the assembly tolerance with minimum variation. They also evaluate the deviation from mean using Taguchis loss function and also analysed the selection of number of groups for selective assembly.Lee et al. [12] made a study on two component assembly system with unreliable Bernoulli machine and finite buffers. They developed analytical methods based on a two-level decomposition procedure to analyze the system performance. Lee et al. [13] was developed to propose a novel selective assembly strategy which can improve profitability by reducing the variation of components in the final product assemblies and achieving the target performance. Two theorems of Discarding theorem and Binning theorem are formulated to guide the selective assembles strategy. This theorem provide the rules for discarding inferior components before assembly and for selecting matching pairs of components to prevent producing overqualified product. Geem et al. [14] has developed a selective assembly approach with genetic algorithm to increase the assembly success rate and to reduce the surplus parts, considering the different tolerance ranges of the mating parts. A new grouping method is proposed by which different parts are assembled at random. Based on the grouping method, a genetic algorithm is proposed with a specially-designed 2D structure of the chromosome, with the crossover, mutation, and the constraint satisfaction mechanism, to achieve the objective of the selective assembly. Finally, the proposed selective assembly approach is improved to adapt to the product assembly with multiple dimension chains. Wang et al. [16] has developed the best group size and its combination for very small batch size quantity with wider tolerance, MAT Lab genetic algorithm tool was used for analysing the best combination. The mating selection from corresponding selective groups is assembled so that similar clearance can be obtained in a better manner than those achieved in the interchangeable level at lower total cost. Radhakrishnan et al. [17] proposed a symmetrical interval which is based on Taguchi loss function and applied in selective assembly method to evaluate the assembly loss. Also, an improvement in sheep flock heredity algorithm to obtain the best combination of selective group with minimum clearance variation and the least assembly loss value was proposed.

Feng ju et al. [18] made a study of selective assembly system switch two component machine, two finite buffers and one assembly machine. Hai-yan et al. [19] discussed about the remanufacturing which is a sustainable strategy and the number of groups and the range of each group are changeable in this the high added value parts which are remanufactured and for the adder value new parts are adopted. Chu Xuyang et al. [20] developed the method for gear reducer by using a new method of selective assembly based on genetic algorithm for RV reducer. This method of selective assembly is proposed to meet the RV reducer back lash requirements through the genetic algorithm analysis. Shaogang Liu et al. [21] introduced meta-heuristic method to reduce clearance variation in a complex assembly. Ball bearing assemblies are made in three stage to minimize clearance variation. Kwon et al. [22] developed a new TLBO method for optimization mechanical design problems. In this work several mechanical assemblies were considered. The TLBO and ABC algorithms were developed and the results compared with different bench mark problems with different characteristics. The success rate of TLBO was 24.1% higher than that of ABC. Saravanakumar et al. [23] developed a new TLBO method. The experimentation was carried out for constrained and unconstrained benchmarking functions. The findings of TLBO were presented quantitatively and qualitatively through code-reviews. Weimin wang et al. [24] developed a TLBO algorithm for multi-pass turning operation optimization. The single and multi-objective problem was considered to produce low-cost products by selecting optimum speed, feed rate, depth of cut and number of passes. Asha et al. [25] introduced a TLBO algorithm of a linear mechanical piston and cylinder assembly. The optimum design of manufacturing tolerances with stack up condition was determined. The results indicated that the TLBO technique provided better results than GA, SA and SS algorithms. Rao et al. [26] developed an Orthogonal Teaching Learning Based Optimization (OTLBO) for investigating a set of 20 benchmark problems taken from existing study in order to test and compare the performance of the PSO, DE, and TLBO with OTLBO. It was evident that OTLBO outperformed all other approaches including basic TLBO for all benchmark problems. Rao et al. [27] developed an improved teaching-learning-based optimization (I TLBO) and TLBO algorithm and tested against 23 bench mark problems and the results were compared with ABC algorithm, along with its improvised versions (I-ABC and GABC) and hybrid version (PS-ABC). The results proved that I-TLBO outperforms the basic TLBO and PS-ABC algorithms. Matej et al. [28] developed a TLBO algorithm for optimal selection of design and manufacturing tolerances with an alternative manufacturing process to obtain the optimal solution for over running clutch assembly and knuckle joint with three arms. The developed results were compared with various algorithms and it was noted that TLBO algorithm gave better results in less computational time [30], [31]. Godwin et al. [29] presented detail review about TLBO and application of TLBO for beginners for solving unconstrained and constrained optimisation problems. It is inferred from the above literature survey that a good number of attempts have been made by different authors with various optimization techniques and algorithms in order to obtain minimum clearance variation in an assembly and also to reduce surplus parts. However, the manufactures are looking for a novel method to cut down their manufacturing cost in turn to get considerable profit in order to survive in globalization context by the way of minimizing the clearance variation in order to get precision assemblies [32].

3 Problem Environment and Definition

In general, components of an assembly are made by different machines, materials and tools which create dissimilar distribution among the dimension of the components. Moreover, the product is assembled by combining the components together where the tolerance of the components is cumulative in effect. For example, a component i is manufactured with Timax and Timin tolerance using a process and the maximum and minimum clearance of an assembly consists of n number of components which can be computed using equations (1) and (2) whereas the clearance variation is estimated through equation (3).

$$Tamax = \sum_{i=1}^{n} Timax \tag{1}$$

$$Tamin = \sum_{i=1}^{n} Timin \tag{2}$$

$$CV = Tamax - Tamin \tag{3}$$

In an interchangeable assembly, for getting a close clearance variation that is to make a precision assembly, it is necessary to produce each component to closer tolerance. This may cause additional expenses due to secondary operation. Due to global completion in the market, manufactures cant afford the high cost of making a component. In this situation, selective assembly method can help manufacturers to solve the above problem. It is understood from the literature that the traditional selective assembly techniques could help to minimize clearance variation in some extent and reduce surplus parts. Even though, the manufacturers seek new method in this area to get better improvement in both clearance variation and surplus parts.

In this work, the problem of minimizing the manufacturing cost for an assembly and increasing of its performance is addressed by obtaining the nominal dimension selection with tolerance allocations by selection of alternate manufacturing process. A complex assembly consists of N components with the nominal dimensions, tolerances, alternative manufacturing processes and cost model constant values, which are considered. The langrage Multiplier (LM) method is used for generating initial feasible solution. The evolutionary algorithm of TLBO is used for further minimization the manufacturing cost. Randomly a process is selected for each component from the alternative processes and then nominal dimension of the components is selected from the given range without affecting the critical dimension. Further, the tolerance of each component is selected from the process tolerance range corresponding to the process and the nominal dimension of the component to meet out the tolerance on the critical dimension. The other parameters related to the problem environment considered in the present study are listed below. or identifying the intrusion in network intrusion detection is proposed. This methodology can be applied to detect terrorists and their supporters using legal ways of Internet access and also unseen attack [8]. Back-propagation neural network with all features of KDD data is employed and the classification rate for experiment result for normal traffic is 100%, known attacks are 80%, and unknown attacks are 60% [9].The application of some Neural Networks (NNs) to identify and categorize intrusions is discussed and determination of which NN classifies well the attacks and produces the higher detection rate of each attack which is performed. Resilient back propagation for detecting each type of attack along is suggested with the accurse detection rate of 95.93 [10]. Back propagation neural network with many types of learning algorithm is employed and the performance of the network is 95.0 [11]. Studies convey that Single Instance Single-Label (SISL) Learning mechanisms are faster and converge for better results but the percentage of false positive and false negative alarms are of concerns. Learning mechanisms are linear in nature in most of the proposed algorithms.Evolution of supervised training mechanisms has helped more accurate decision making however it failed to incorporate the dynamism of new instances which are in early stages and non-overlapping with current training/data sets.Machine learning algorithms are proven to be highly convergent and give true normalized data sets. However, the increase in internet/intranet traffic and applications makes Cloud-based virtual infrastructure demands even highly convergent results and more accurate decision-making mechanisms in IDS to prevent multiple threats.

4 Methodology

Existing selective assembly method shown in figure 1 has produced precision assemblies in multiple stages with different clearance variation in each stage with similar group/partition number irrespective of different dimensional distribution of components. In the present work, according to the dimensional distribution that is tolerance range, the components are classified into different number of groups rather than similar number of groups, and that is shown in figure 2. A particular group is repeated again for making assembly based on the probability of total components available in that particular group number. Number of repetition of the group (RNij)is calculated using equation (5) where the length of selective assembly group L is computed by equation (4).

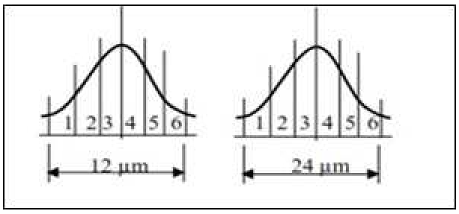

Fig. 1: Traditional Selective Assembly Methode

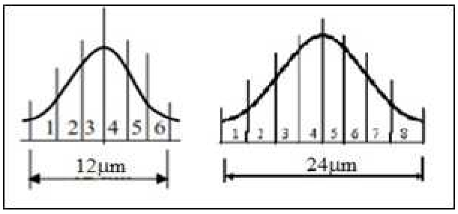

Fig. 2: Proposed Selective Assembly Method

$$L = n * max(gni)_{i=1}^{n} - 2 \tag{4}$$

$$RNij = \frac{L * Nij}{Nt} \tag{5}$$

The methodology of the proposed work is explained in a step-by-step procedure. Step 1: Normally-distributed one thousand components dimensions are generated using randn(mean,std,1000,1) Matlab function. Step 2: Compute gni of ith component using equation (6) which makes the group width of each components is nearly equal.

$$gni = \frac{Timax + Timin}{gwi} \tag{6}$$

Step 3: Count Numbers of parts in each group of components (Nij) Step 4: Compute number of repetition of group number (RNij) using equation (4) where RNij is rounded to nearest integer. Step 5: Determine length of selective group L using equation (5). The possible selective group combination (PLi) is determined using both group number and repetition group number. Step 6: Randomly generate a combination of selective group for each components RLi within combination of PLi Step 7: Mate the components in the corresponding group of RLik and compute maximum clearance (CXk), minimum clearance (CMk) and clearance variation (CVk) using equations (7) (9). Number of assemblies (NAk) and surplus parts (Sij) are calculated using equations (10) (11). The clearance variation (C) of the entire assembly based on the combination of selective groups and total number of assemblies (TA) made are determined using equations (12) (13).

$$CXk = gwi * RLik + gwi + 1 * RLi + 1k + . + gwn * RLnk \tag{7}$$

$$CMk = gw_i * (RLik - 1) + gwi + 1 * (RLi + 1k - 1) + \\ + gwn * (RLnk - 1) \tag{8}$$

$$CVk = CXk - CMk \tag{9}$$

$$NAk = min(Nik)_{i=1}^{n} \tag{10}$$

$$Sij = Nik - NAk \tag{11}$$

$$C = max(CVk) - min(CVk) \tag{12}$$

$$TA = \sum_{k=1}^{L} NAk \tag{13}$$

Different possibilities of combination of selective group are possible in this case; hence, this problem is treated as NP-hard problem. Teaching learning based optimization algorithm has been implemented to obtain the best combination of selective groups. The various steps involved in TLBO algorithm is given below. 1. Initialization of student population 2. Evaluation of initial population. Determination of mean and best teacher and Teachers phase 1. Learners phase 2. Replacing criteria and stopping criteria

5 TLBO Algorithm

The minimization or maximization of the objective value is achieved based on teaching-learning environment happening in a class room. The number of students in a class room is considered as a size of the initial population. The performance of the student is treated as objective value and it is improved either by learning from the teacher or among themselves or from both processes. The group number (RLik) is considered as a subject and the number of subjects of each student is equal to the product of L and n. The total or average mark of students is considered as fitness/objective value in teaching-learning environment whereas in the proposed method the clearance variation of the assembly C is considered as fitness/objective value. The initial population is considered as a batch of students. The performance of each student is evaluated for its objective value. The next population elements are generated in two phases namely teachers phase and learners phase subsequently that are briefed below. Teacher Phase: In this phase, the best student is selected from the population based on the performance and considered as teacher. The revised performances of the student in the specific subject is carried out using the equation (14).

$$RL_{ik}^{n} = R_L ik + \phi(RL_{bk}^{b} - TF * RL_{ik}^{m}) \tag{14}$$

Where,

$$TF = 1 + \phi \tag{15}$$

Learner Phase: In this phase, the performance of the student is improved by sharing their knowledge among themselves. Randomly two students (x and y) are selected based on the condition that they should not have the same performance (C(x)C(y)). The new value of RLik is calculated using the following equations (15) (16).

if C(x)¡ C(y)

$$RL_{ik}^{n} = R_{Lik}(x) + \phi(RL_{ik}(x) - TF * RL_{ik}(y)) \tag{16}$$

if C(y)¡ C(x)

$$RL_{ik}^{n} = R_{Lik}(x) + \phi(RL_{ik}(y) - TF * RL_{ik}(x)) \tag{17}$$

The results from the learner phase is identified as the best performer and considered for next iteration. Further, the process continues for improving the results of the student iteratively. After reaching the predetermined termination criteria such as the number of iterations or obtaining same results consecutively for a specific number of iterations. Finally, the best performance of the student is identified with respect to minimized C. The various stages involved in TLBO algorithms have been briefed in problem environment section and the same for the proposed methodology in predicting the C and its hierarchy is illustrated in Figure 3. A linear assembly of gears in a gear box assembly and a ball bearing assembly are taken as an example problem to demonstrate the proposed method using TLBO. In the next

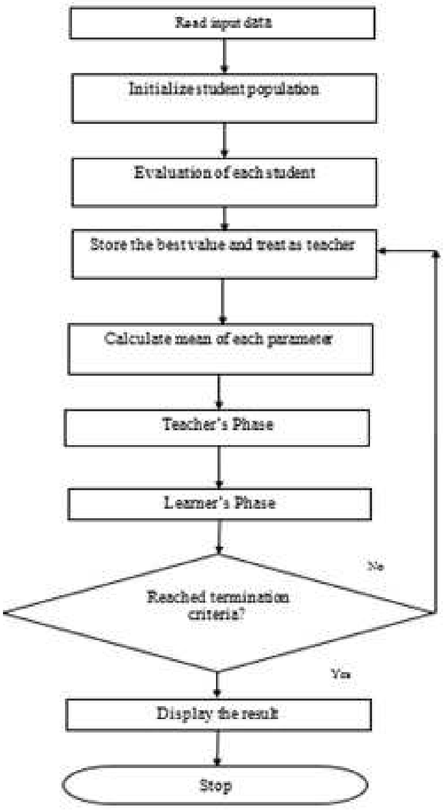

Fig. 3: General structure of TLBO algorithm

section a numerical illustration is briefed using the proposed TLBO methodology.

6 Numerical Illustration

6.1 Case 1: Linear Assembly

Three gears A, B and C are manufactured using different process and machines. These gears are assembled linearly in a gear box which is shown in Figure 4. The dimension of the components A, B and C are $\phi^{-0.00}_{+0.012}$, $\phi 12^{-0.000}_{0.015}$ and respectively. If the components are assembled interchangeably, the dimension of the assembly will be considered. Selective assembly techniques are used to reduce the assembly clearance variation from 0.045 to 0.0175. TLBO algorithm has been demonstrated in reducing the clearance variation of gear box assembly in the next section.

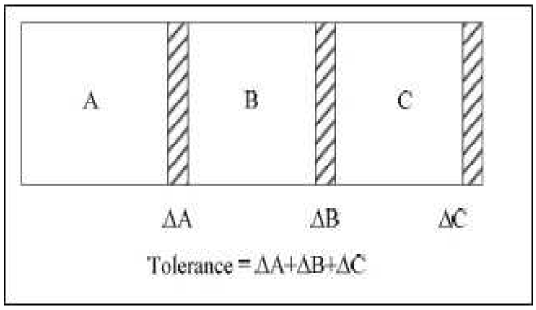

Fig. 4: Linear Assembly

One thousand parts of components A, B and C are randomly generated in Matlab using randn() function based on the mean and tolerance of the components given in Table 1. Parts of components A, B and C are classified into 4, 5 and 5 groups (gni) respectively. The number of parts fall into each group of components that are determined and listed in Table 2. All dimensions are in mm and the tolerance in m.

The group width of each component is estimated using the following equation (17).

$$gw_i = \frac{T_i}{gn_i} \tag{18}$$

For example group width of component A is

$$gw_a = \frac{T_A}{gn_A} = \frac{12}{4} = 3 \tag{19}$$

Table 3 illustrates group width of component A, B and C. Using equation (4), the length of the combination of selective group of each component is calculated.

$$\begin{aligned} L &= n * max(gn_i)_{i=1}n - 2 \\ &= 3 * max(4,5,5) - 2 \\ &= 3 * 5 - 2 = 13 \end{aligned} \tag{20}$$

The repeated group number (RNij) is estimated using equation (5). For example RNA2 is

$$\begin{aligned} RN_A 2 &= \frac{L * N_i j}{N_t} \\ &= \frac{13 * 522}{1000} \\ &= 6.78 \simeq 6 \end{aligned} \tag{21}$$

Table 1: Manufacturing details of Components

Component Name	Dimension	Tolerance (m)
A	10	12
B	12	15
C	14	18

Table 2: Manufacturing details of Components

G.No	Nij (A)	Nij (B)	Nij (C)
1	131	18	16
2	522	169	250
3	316	483	531
4	31	291	188
5	Nil	39	15

Table 3: Group width of each component

Component Name	Group width (m)
A	3
B	3
C	3.6

6.2 Implementation of TLBO Algorithm

The implementation of TLBO algorithm with the numerical illustration is presented in this section.

6.3 Initializing the Student Population

For demonstration purpose, the numbers of students is considered as 10 and the random combination of selective groups of each component is shown Table 5.

$$\begin{aligned} CX_1 &= gw_A * RL_A 1 + gw_b * RL_B 1 + gw_c * RL_C 1 \\ &= 3*2+3*5+3.6*3 \\ &= 31.8 \end{aligned} \tag{22}$$

$$\begin{aligned} CX_1 &= gw_A * (RL_A 1 - 1) + gw_b * (RL_B 1 - 1) + gw_c * (RL_C 1 - 1) \\ &= 3*1+3*4+3.6*2 \\ &= 25.8 \end{aligned} \tag{23}$$

6.4 Evaluation of Each Student

In evaluation phase, the corresponding groups parts are assembled together to make assemblies. For example, the first student combination of selective groups is considered for demonstration purpose. The maximum and minimum clearance values are calculated using equations (7) and (8).The number of assemblies made using the first position of selective group is calculated using equation (10). Table 6 represents the number of assemblies produced for each combination selective groups. The surplus parts of the components are estimated using equation (11). The total number of assemblies made using the first student is calculated using equation (12). The fitness/objective function ie. the assembly clearance variation of each student is shown in Table 7.

6.5 Determination of Mean and Best Teacher

The mean value of each selective group is computed and presented in Table 5. The student holds the minimum clearance variation of the assembly that is considered as a teacher and it is highlighted as a bold letter in Table 7.

6.6 Teachers Phaser

In this phase, a scenario of learning of students through knowledge sharing from the teacher has been dealt. The

Table 4: Possible selective groups of each component

RLA	1	2	2	2	2	2	2	3	3	3	3	4	1
RLB	1	2	2	3	3	3	3	3	3	4	4	4	5
RLC	1	2	2	2	3	3	3	3	3	3	4	4	5

Table 5: Manufacturing details of components

RLAK	2	2	3	3	1	3	4	2	3	2	2	1	2
RLBK	5	2	3	3	4	2	4	3	3	3	3	1	4
RLCK	3	5	3	3	3	2	3	2	4	3	2	4	1

best learner in the entire student population is considered as a teacher based on the performance. New values of the selective groups are calculated using equation (14). The value generated for each student and each component is listed in Table 8. Table 8 represents the new values of selective group in teachers phase. The above values are verified for satisfying the condition that the selective group must be within the maximum group number of corresponding component. Table 9 represents the data after verifying the satisfaction of the above conditions. The student performance, before and after teachers phase has been compared and the best is selected as teachers phase output of an individual student. The output of teachers phase is presented in Table 10 and it is considered as input for learners phase.

6.7 Learners Phase

In this phase, the performance of the student is improved by sharing their knowledge among themselves. Randomly two students (x and y) are selected based on the condition that they should not have the same performance (C(x) C(y)). The new value of the selective groups, are calculated using the equations (15) and (16). Randomly selected two students x and y and generated random number less than 1 for each student are presented in Table 11. The new values of selective group of each student are calculated and listed in Table 11. Similar to teachers phase, the new values are verified. The verified new values and its corresponding calculated C of the assembly is presented in Table 12. The outcome of the learners phase is given in Table 13. The values of combination of selective groups corresponding to the minimum C of the assembly is considered as the best one in the first iteration.

6.8 Replacement Strategy

The strategy of 100% replacement is considered in this work. The values of combination of selective groups presented in Table 5 are replaced by the outcome values of combination of selective groups of learners phase.

6.9 Termination Criteria

After reaching a specific number of iterations or no change in the objective value for a specified number of iterations are considered as termination criteria in this work.

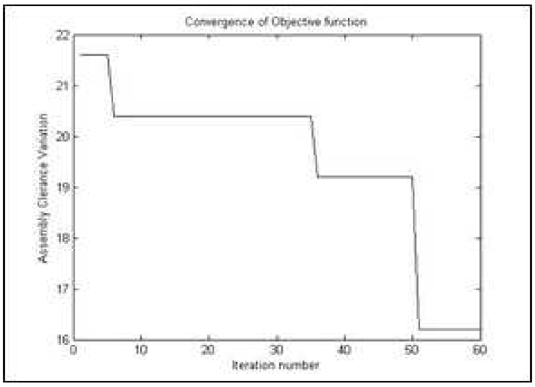

Fig. 5: Output of TLBO from Matlab for linear assembly Group number of A, B and C are 4, 5 and 5l

6.10 Case 2: Ball Bearing Assembly

Inner race, outer race and balls are the components of a ball bearing assembly (Figure 6) which is considered as an example problem in case 2. The dimensional distribution or the manufacturing tolerance of inner race, ball and outer race are 1m, m, and m respectively.

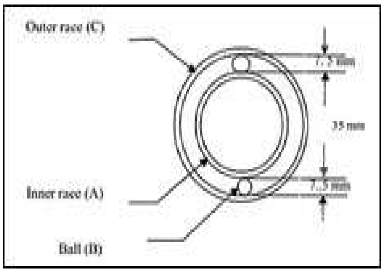

Fig. 6: Ball bearing assembly

7 Results and Discussion

A linear assembly consists of three gears in a gear box assembly considered for minimizing objective of the clearance variation that is carried out using TLBO algorithm. Seven different combination of group number of components A, B and C have been tried out to demonstrate the effectiveness of the proposed method. The dimensional distribution, group number combination and the clearance variation of the linear assembly have been shown in Table 14. It is observed that it is possible to obtain 15Ym 16.5Ym as compared with existing clearance variation of 17.5Ym. Because of wider tolerance components are partitioned into more group numbers which reduce the group width, hence the close clearance variation in assembly is possible. There are no surplus parts due to using repetition of group number again for making assemblies. Table 15 illustrated that the number of assemblies made in each selective group combination. The best combination of selective groups of components A, B and C is listed in Table 16. Similar details are presented in Tables 17 19 for ball bearing assembly.

8 Conclusion

A systematic procedure for minimization of clearance variation in a linear assembly consists of three gear of a gear box assembly which has been addressed in this paper. Existing papers minimize the clearance variation in multiple stages with similar group number for all the components. The proposed method introduces different group number for the necessary components according to their tolerance level with single stage to minimize the clearance variation of the assembly. Based on number of parts existing in the selective group, the number of repetition of the particular group is considered for single stage assembly. The proposed method improved the clearance variation of a linear assembly from 17.5 Ym to 15Ymm and in the case of ball bearing from 17 Ym to 16Ymm. TLBO algorithm has been adopted to obtain the best combination of selective group. The minimized clearance variation of the assembly certainly reduces the cost of making assembly by the way of eliminating the secondary operation. It is expected that the manufacturing sectors benefit by the above work. The present work is suitable for an assembly which consists of any number of components with dissimilar dimensional distribution. The work can be extended further by adding tolerance cost to estimate the manufacturing cost of the assembly with or without quality loss function.

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