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Hybrid of Hunting Search and Modified Simplex Methods for Grease Position Parameter Design Optimisation

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***Abstract*—This study proposes a multi-response surface optimization problem (MRSOP) for determining the proper choices of a process parameter design (PPD) decision problem in a noisy environment of a grease position process in an electronic industry. The proposed models attempts to maximize dual process responses on the mean of parts between failure on left and right processes. The conventional modified simplex method and its hybridization of the stochastic operator from the hunting search algorithm are applied to determine the proper levels of controllable design parameters affecting the quality performances. A numerical example demonstrates the feasibility of applying the proposed model to the PPD problem via two iterative methods. Its advantages are also discussed. Numerical results demonstrate that the hybridization is superior to the use of the conventional method. In this study, the mean of parts between failure on left and right lines improve by 39.51%, approximately. All experimental data presented in this research have been normalized to disguise actual performance measures as raw data are considered to be confidential.

***Keywords*—Grease Position Process, Multi-response Surfaces, Modified Simplex Method, Hunting Search Method, Desirability Function Approach.

I. Introduction

Electronic industries are growing up continuously including in Thailand. According to the expansion of markets, the traders need to amplify their productive forces with more investments on especially the bearing production process that consists of turning, heat treatment, grinding, washing and assembly [1]. In assembly process, there is a grease position process (GPP) that is an operation of filling the grease in a bearing (Fig. 1 and 2). During uses the grease is degraded in rolling bearings and as a result there is the deterioration in lubrication performance. Under severe operating conditions this brings a lubrication failure and, thus, the grease life will effectively decrease the bearing life. Filling grease in bearing is an important process of an assembly. It protects direct touching of metal ball and metal race way and defends worming out. In addition, it can prevent corrosion cross-contamination from environment. At present there is a lack of useful information regarding the designed changes that occur in the grease and the way in which this degradation affects lubrication performance and failure [2].

It is very important to be able to predict the grease service life. This study aims to develop systematic procedures based on intelligent design optimisation that can be used in practice to predict different aspects of grease life [3]. As a first step, the conventional experimental design and analysis forces on the sequential simplex based algorithm is studied. The authors present a desirability function approach that can be used to predict the increase in a grease life as a desirability level function of across all two lines. To provide some design modifications for this improvement, stochastic mechanisms based on two metaheuristics of the hunting search and ant colony optimisation are carried out. There are three design parameters affecting the quality measures on the GPP which consist of the lower grease supply distance (x_1), speed (x_2) and removal pressure speed (x_3). This process brings a lot of failed parts and wrong positioned filling which are called grease no-go parts (Fig. 3).

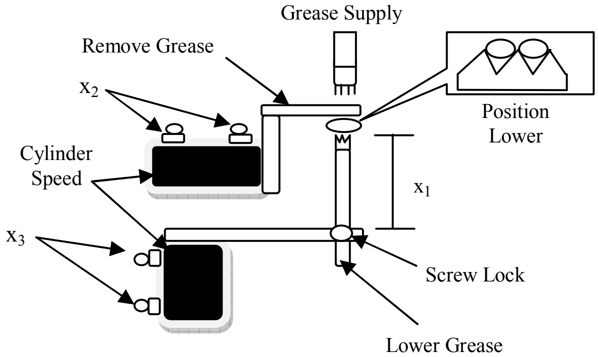

Fig. 1 Side View of the GPP

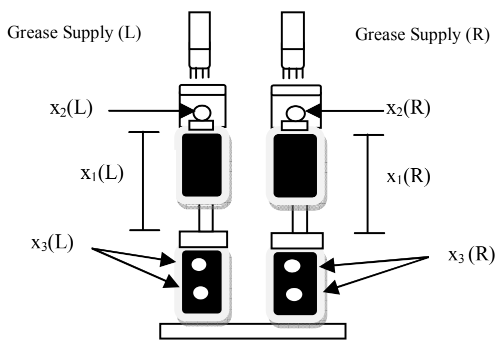

Fig. 2 Front View of the GPP

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These parts are then sent to a reworking process. In this research, the tooling ball position is designed and its aim is to reduce failed products. However, during a quality development of this process the life time of tooling is impractical to determine directly. This brings an uncontrollable situation of the grease no-go parts effectively and also affects the purchasing department of tooling ball position unit grease supplies of an A-model. Nowadays, the grease position process forms a double line system of grease check process. At current operating condition the tooling life times or design responses on both left (y_1) and right (y_2) lines are at 9236 on average. To dissolve this problem, the parameter settings of the GPP should be optimised. There are three GPP parameters affecting to this dual responses that are revised by the design expert system. The aim of this study is to study the hybrid of efficient optimisation algorithms based on the modified simplex and hunting search methods to achieve the maximal responses or life time of tooling ball position.

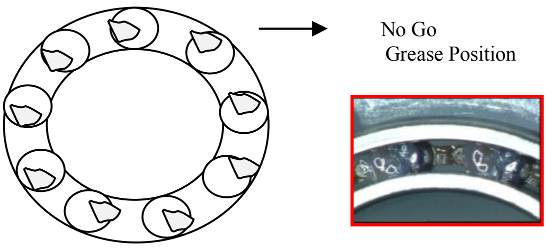

Fig. 3 No-Go Part Characteristics

The objective of this paper is to investigate the performances of the algorithmic approaches with an intelligence and inspiration, adopted into the iterative searching process called as meta-heuristics, on the multi-response surface optimisation problem (MRSOP) of the GPP. A simulation study is based on the data from a Thai firm. It aims to enhance the efficiency of the grease service life and pay more attention to the harmonious balance between various responses and noisy environments. This paper is organised as follows. Section II describes the multi-response surface problem of the GPP. Sections III, IV and V are briefing about the desirability function approach, the modified simplex method and the hunting search algorithm, respectively. Section VI shows design and analysis of computational experiments for comparing the performance of the hybrid methods. The conclusion is also summarised and it is followed by acknowledgment and references.

II. Multi-Response Surface Optimisation Problem

Response surface methodology (RSM) has a wide range of applications in the designed experiments on various systems such as engineering processes. RSM is an association of statistical and mathematical tools which is useful for optimising processes [4, 5]. However, the performance measures of a process often characterised by correlated multi-objectives or multi-responses. Consequently, a decision maker(DM) must determine the process parameter design (PPD) problem to optimise each response. This problem is formulated as a multi-response surface optimisation model (MRSOP) subject to various requirements controllable process parameters. Many response surface problems involve the analysis of several objectives of product specifications.

Suppose that there are M responses of $\mathbf{y} = (y_1, y_2, ..., y_i, \ldots, y_M)$, which are determined by the process parameters. The problem is formally defined as

Optimise $\{ \hat{y}_1, \hat{y}_2, ..., \hat{y}_i, ..., \hat{y}_M \}$

subject to

$$Y_i^{MIN} \leq \hat{y}_i \leq Y_i^{MAX} ;\ i = 1, 2, \ldots, \text{M and } \mathbf{x} \in \Omega \qquad (1)$$

; where $\hat{y}_i$ is the ith estimated response model, Ω is the experimental region, Y_i^{MIN} and Y_i^{MAX} are the minimal and maximal acceptable values of the ith response, respectively. In this research, the objective are to focus on the mean of parts between failure of left and right processes and subject to some related constraints of process parameters that needs to be controllable on their acceptable ranges.

III. Desirability Function Approach (DFA)

The desirability function is a useful and flexible technique to analyse a multi-response surface optimisation problem in practical application. The desirability function value represents the degree of achieving the target or overall satisfaction. It lies in the interval of [0, 1] and it can be viewed as the transformation value of the estimated response of the observation[6, 7]. There are three forms of the desirability function according to response characteristics which consist of the-nominal-the best (NTB), the-smaller-the best (STB) and the-larger-the best (LTB). Firstly, the NTB is used when the estimated response of $\hat{y}_i$ is to achieve a particular target. When the estimated response equals to the target, the desirability function value equals to 1.

If the departure of the estimated response excesses a particular range from the target or the worst case, the desirability function value equals to 0. For the STB, the value of estimated response is required to be minimal. When the estimated response is less than a particular criteria value, the desirability function value equals to 1. If the estimated response excesses a particular criteria value, the desirability value equals to 0. For the LTB, the aim is to maximise the value of estimated response. When the estimated response excesses a particular criteria value or the requirement, the desirability function value equals to 1. If the estimated response is less than a particular criteria value, which is unacceptable, the desirability function value equals to 0. In this research the related responses are to be maximised and the desirability function of the LTB can be written as follows.

$$d_i(\hat{y}_i)=\begin{cases}0 & \text{if } \hat{y}_i \le Y_i^{MIN},\\ \left[\dfrac{\hat{y}_i - Y_i^{MIN}}{Y_i^{MAX}-Y_i^{MIN}}\right]^{P_i} & \text{if } Y_i^{MIN} < \hat{y}_i \le Y_i^{MAX},\\ 1 & \text{if } \hat{y}_i \ge Y_i^{MAX}\end{cases} \qquad (2)$$

The power coefficient of P_i is the parameters that determine the shape of $d_i(\hat{y}_i)$ and they are defined according to the requirement of the decision's maker. The individual optimisation value of $d_i(\hat{y}_i)$, whose value are scaled between zero and one, increases as the "desirability" of the corresponding response is improved. In a multi-response system, the ideal case is that all desirability function values of responses equal 1 and the overall response's desirability function value also equal 1. If any response cannot reach the target, the ideal case of the overall response cannot achieve and it turns to be the unacceptable scenario.

Moreover, if the desirability function value of any response equals to 0, the overall response will be also viewed as the extremely unacceptable scenario. The individual desirability is then aggregated using the geometric mean to provide the overall assessment of the desirability of the combined response levels or $D=(d_1(\hat{y}_1)d_2(\hat{y}_2)...d_M(\hat{y}_M))^{1/M}$. D provides a value less than or equal to the lowest individual optimisation desirability function value and will increase as the balance of the properties is more favourable. That is, the D equals 1 when all responses reach the target and the D equals 0 when any one response cannot achieve the target.

IV. Modified Simplex Method (MSM)

The MSM by Nelder and Mead is one among direct search methods which have been usually applied to any optimisation problems in terms of the RSM with k parameters. It has been revised from the important class of the direct search method based on simplex designs or the rigid simplex method by Spendley and his colleagues [8, 9]. Later on it returns to be the most popular simplex-based search method. An original simplex method constructs an evolving pattern of k+1 design points that are viewed as the vertices of a simplex. A simplex in two dimensions is a triangle and a simplex in three dimensions is a tetrahedron. In the MSM a sequence of changing simplex designs is created, but the design is deliberately modified so that the simplex adapts itself to the local surface.

At each iteration one of these design points is dropped after a comparison of the values of the objective function at the (k+1) vertices of a general simplex and a new design point is generated a new simplex in the opposite face [10]. The direction of a new design point follows the line that joints the centroid of the k best simplex design points and the worst design point in order to select a new design point. The basic idea of reflection in the conventional simplex method is to move the simplex gradually toward the optimum during the iterative process. The MSM adds two more operations of contraction and expansion to increase the speed of convergence. As a consequence, the simplex adjusts its shape and size during iterative processes.

This work incorporated the MSM into the same manner of the first algorithm based on the rigid simplex method. As before, the simplex design is first applied at an arbitrary design point within the safe region of operation. The response is evaluated for each of the design points. In a maximisation process with three process parameters or a tetrahedron simplex, the vertex corresponding to the worst yield (W) is identified and reflected in the opposite hyper-face to obtain the reflected vertex (R) via the centroid ($\overline{P}$) obtained by other vertices in the simplex consists [11]. The new design point can be extended (E) in the direction of more favorable conditions, contracted (C- or C+) if a move is taken for least favorable conditions and shrunk toward the best vertex if a contracted vertex is still the least but not less than the rejected trial condition. The next design point is carried out with process parameters set at values corresponding to this new design point. This algorithmic process iterates until the volume of the simplex is sufficiently small or any other stopping rule is met. The pseudo code is used to briefly explain to all the procedures of MSM shown in Fig. 4.

```
Procedure of MSM()
While (termination criterion not satisfied)– (line 1)
Schedule activities
Reflection of least yield W is processed;
Compute R and f(R);
Compare response function;
If f(R) is highest then
      Extension E will be processed;
Else
            If  R and f(R) continue to be the least then
                Reflect backward to prior point;
                Recalculate W and f(W);
                or
                Contraction C or shrinking S will be processed;
                Recalculate f(C) or f(S);
            Else
      Go to line 3;
            End if;
      End if;
End schedule activities;
End while;
End procedure;
```

Fig. 4 Pseudo Code of the MSM

V. Hunting Search Algorithm (HuS)

The HuS is a probabilistic metaheuristic for solving the global optimisation problems and is derived from a model of group hunting of creatures when searching for food [12]. An aim is to approximate an acceptably good candidate solution, rather than the best possible candidate solution, of a problem of interest in a large domain space with a fixed amount of computational time. Its inspiration comes from a process in catching a prey in the group hunting of animals. Members in the group or hunters cooperate to enclose a prey and hopefully catch it in the final. The specific hunter chance to finally catch the prey depends on the distance of each hunter and prey position. That real hunting process is analogous with the iterative engineering optimisation processes to search a global optimum via an objective function. The current solution from the HuS is replaced by generating random neighborhood solutions with a preset probability. However, it depends on the difference in objective function values assigned to each candidate solution of the problem or an artificial hunter.

There are some differences between the real and artificial group hunting processes. Firstly, in real group hunting, hunters can see or sense the smell of their prey. The prey position can be obviously determined by the hunter. However, in artificial hunting process of optimization problems there is no indication of the optimum. Secondly, in real group hunting, there is a movement or dynamic nature of the prey but in optimisation problems, there is no change in the optimum. Finally, in real group hunting the position of the prey will be corrected from time to time to escape the hunters, but in artificial hunting process of optimisation the optimum stand its own position all the times during the searching process. From the difficulty reasons above, the dynamic nature of the real group hunting needs to be modified when applied in the HuS. During the real movement of other hunting animals towards their leader, candidate solutions or artificial hunters move towards the current leader or the current best candidate solution via the operator of the maximal movement toward the best solution or leader (MML). The new artificial leader can be changed from time to time if any of them finds a better solution when compared to the current leader.

During the real group hunting process close to the prey, the real hunters correct their position with a consideration on both the position of other hunting animals and the prey. During the movement toward the previous leader, the HuS follows by correcting the artificial hunter position based on other member positions with the hunting group consideration rate (HGCR) parameter. HGCR is the probability of choosing one value from the hunting group stored in the hunting group and (1-HGCR) is the probability of doing a position correction. In the real group hunting, if the prey can flee from the ring hunters will reorganize themselves to enclose the prey. In the HuS, the capability of artificial hunters can be used to seek the onslaught ring to avoid a chance to be trapped in a local optimum of artificial hunters within the certain number of searches or one epoch. Even too close to each other or no difference between the objective function values of the leader and the worst in the group, the artificial hunters are also reorganised to find the optimum in the next iteration.

VI. Computational Results and Analyses

Grease or a solid to semi-fluid product in a liquid lubricant is often not able to ensure a sufficiently thick lubricant film throughout the entire fatigue life of the bearing [2]. The service life is restricted by what is referred to as the grease life. Relubrication by supplying fresh grease to the bearing to extend the grease life is not an efficient option. The grease life or reinterchange interval is then used to predict a function of lower grease supply distance, speed and removal pressure speed. The aims of this work therefore were to examine the interchanges that occur to grease in a bearing. Two greases (left and right lines) have been operated in bearing tests under different conditions of load, speed and temperature. Due to the poor knowledge on design parameters' influence on all the design responses of average life times of tooling in the grease position process. Consequently, it is desirable for the DM to determine an overall optimal design condition or a best compromise of the problem characteristics simultaneously.

Based on the screening experiments via an expert system there are three design parameters affecting such design responses on the left (y_1) and right (y_2) lines for the grease supply. Three uncontrollable factors of a protection equipment height, cycle time and pallet lock speed will be fixed at 1, 2.1 and (4.5, 4), respectively. The design parameter levels of x_1, x_2 and x_3 currently depending on the left and right lines are set at (82, 80), (4.5, 4.8) and (4.5, 4.0), respectively. The lower and upper bounds of operation on x_1, x_2 and x_3 is given as [78, 82], [4.3, 5.0] and [3.8, 4.7], respectively. The aim of this study is to introduce the new optimization algorithm based on the modified simplex method, desirability function approach, and the hunting search method called the novel hunting search on modified simplex method (HSMS) with desirability function approach. This novel algorithm is applied to the GPP. An aim is to simultaneously optimise all requirements of responses via the proper levels of process parameters.

Within the hybrid algorithm the MSM remains the sequential procedures until another solution better than the incumbent is found and then jumps there. Firstly, the starting treatments from the simplex will be applied to determine dual responses or the life times of tooling ball position measured by the mean of parts between failures. The overall desirability level of D is used to moves toward the optimum. The new vertices of the conventional MSM such as R, C+ and C- are generated in order to achieve the better desirability level. The hybrid, without forbidden moves, then escapes from the current solution to a new one. The new treatments from the MML operator are then applied in such a way that intensification of the survey around the current solution is naturally followed by diversification controlled by a set of parameters (Fig. 5).The proper choices of a process parameter design (PPD) from the HSMS will be applied at the pilot stage.

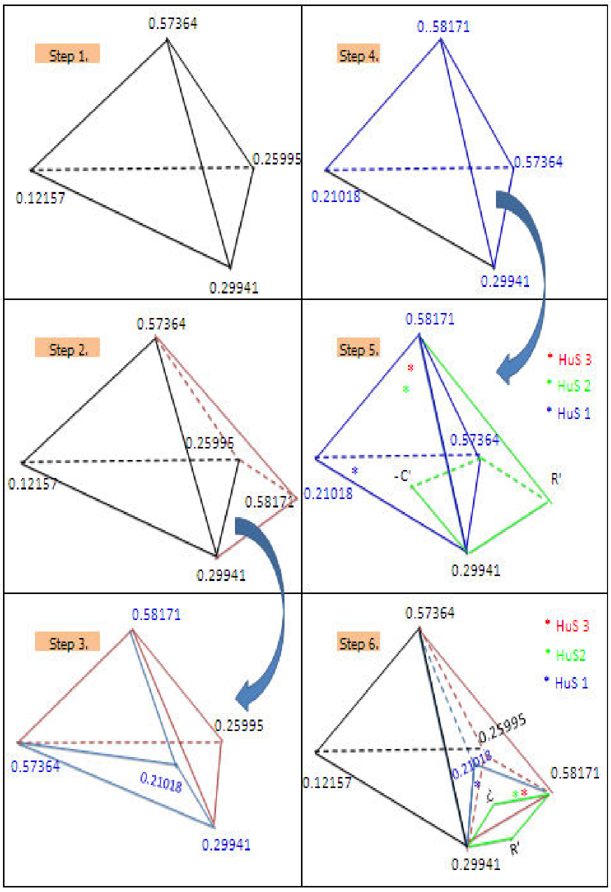

Fig. 5 Moving schemes in the HSMS

The mechanism of the MML of the HSMS can be enhanced the new design points with some level of desirability. As expected, process parameter levels show little variations in the course of the simplex evolution. Indeed narrow level ranges should be selected for all parameters in order to avoid physical drifting of the whole process. After some iterations as shown in Table I and Fig. 6 the best so far solution (BSF) is **x*** = (x_1*, x_2*, x_3*) = (81, 4.6, 4.4). At the BFS corresponding desirability levels of $d_1(\hat{y}_1)$ and $d_2(\hat{y}_2)$ are 0.8886 and 0.3808, respectively and the responses of the left and right lines of about 24880 and 10663, respectively. To validate the achieved levels of process parameters, confirmation experiments were carried out with GPP operating conditions chosen from analytical results of the HSMS and the new design point would lead to maximal responses of the left and right lines of about 25835 and 8184, respectively, on average. Initially, by increasing the levels of x_2 and $x_3$the effective design response on the left line is reduced (Fig. 7). In contrast increasing the levels of x_2 and x_3, the effective design response on the left line is enhanced (Fig. 8).

TABLE I
ITERATIVE PROCEDURES OF PROCESS IMPROVEMENT VIA THE HSMS

Vertex	X_1	X_2	X_3	d_1	d_2	D
	80	4.5	4.5	0.4376	0.1544	0.25995
	80	4.5	4.0	0.6414	0.5131	0.57364
	80	4.8	4.5	0.1307	0.6860	0.29941
	82	4.5	4.5	0.1326	0.1114	0.12157
R	78	4.8	4.3	0.1262	0.0663	0.09146
R	78	4.8	4.3	0.1262	0.0663	0.09146
C-	81	4.6	4.4	0.8886	0.3808	0.58171
C+	79	4.7	4.3	0.2521	0.1050	0.16270
R	81	4.3	4.2	0.4379	0.0337	0.12144
C-	80.5	4.6	4.5	0.4459	0.0991	0.21018
C+	81	4.7	4.3	0.2538	0.0436	0.10520
HuS1	80.5	4.8	4.3	0.2533	0.0580	0.12123
HuS2	80.5	4.5	4.1	0.9060	0.2461	0.47219
HuS3	80.5	4.6	4.0	0.9265	0.2780	0.50749

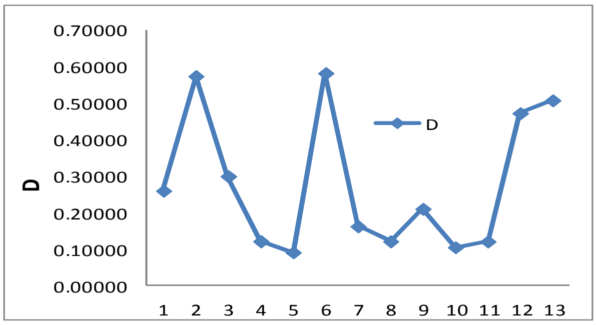

Fig. 6 Sequential Performance of the HSMS on the GPP

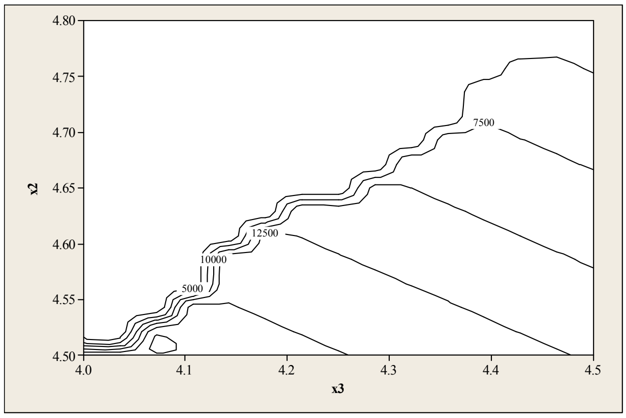

Fig. 7 Contour Plot of the Design Response on the Left Line when x_1 Fixed at 80

A confirmation technique of analysis of variance or ANOVA is applied for analysing experimental data in which design responses on the left (y_1) and right (y_2) lines are measured under two operating scenarios from the previous and the HSMS. It can also be seen that these experimental results on all scenarios categorised by two operating conditions, were not statistically significant with a 95% confidence interval (Tables II and III). The numerical results suggested that the HSMSscenario provided the slightly better performance in terms of the average the grease life (Fig. 9 and 10). As the results, the HSMSscenario is then implemented to the manufacturing system.

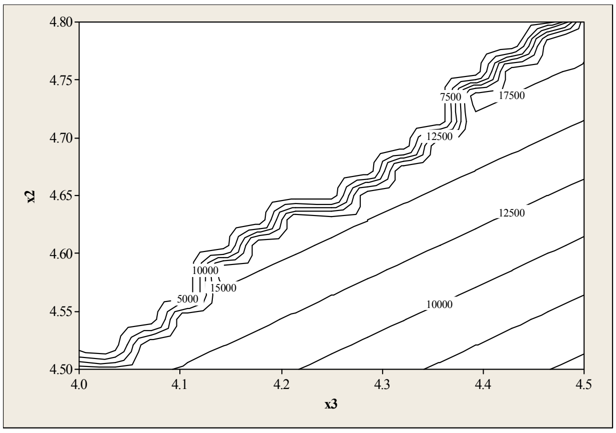

Fig. 8 Contour Plot of the Design Response on the Right Line when x_1 Fixed at 80

TABLE II
ONE-WAY ANOVA: DESIGN RESPONSE ON THE LEFT LINE VERSUS SCENARIOS

Source of Variation	SS	df	MS	F	P-value
Between Groups	76348068	1	76348068	2.724	0.174166
Within Groups	112092683	4	28023171		
Total	18844075	5			

```
                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  ------+---------+---------+---------+---
Current   3  25517    579           (-----------*-----------)
HSMS      3  18382   7464  (-----------*-----------)
                           ------+---------+---------+---------+---
                             14000     21000     28000     35000
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Fig. 9 Graphical Comparison for Two Scenarios of Design Response on the Left Line

TABLE III
ONE-WAY ANOVA: DESIGN RESPONSE ON THE LEFT LINE VERSUS SCENARIOS

Source of Variation	SS	df	MS	F	P-value
Between Groups	1215000	1	1215000	0.263	0.634705
Within Groups	18435941	4	4608985		
Total	19650941	5			

```
                       Individual 95% CIs For Mean Based on
                       Pooled StDev
Level     N  Mean  StDev  --+---------+---------+---------+-------
Current   3  9010   1512  (----------------*----------------)
HSMS      3  9910   2633      (-----------------*----------------)
                          --+---------+---------+---------+-------
                          6000      8000     10000     12000
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Fig. 10 Graphical Comparison for Two Scenarios of Design Response on the Right Line

VII. CONCLUSIONS AND DISCUSSIONS

This experiment integrates the DFA, MSM and HuS to find influential parameters and suitable levels of these parameters in the GPP affecting the life time of tooling ball position on the left and right lines. The experimental results show that with the increased desirability level of 0.251 three parameters of the lower grease supply distance, speed and removal pressure speed should be set at 81, 4.6 and 4.4, respectively. It performed much better with approximate percentage of 39.51%. Therefore, this way is able to enhance the life time of tooling ball position effectively, fast and economically. The operator of MML with care can search further feasible levels of influential design parameters on the process improvement. However, the MML levels are sensitive to different problems. The reorganizing operator from the HuS including other metaheuristics could be surveyed to improve the speed of convergence or escape from a local optimum or to get another opportunity to find the optimum point.

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