International Research Journal of Mechanical Engineering Vol. 2 (12) pp. 268-279, December, 2014. Available online at www.Internationalscholarsjournals.org © International Scholars Journals

Full Length Research paper

Reconciliation of thermo mechanical strains into ideal resilience configuration of mechanical Assembly utilizing NSGA II and FE Simulation

***M. H. Ansari, Vishnu Mittal and E. A Singh**

Department of Mechanical Engineering, University of Calicut, Malappuram, India.

Accepted 28 November, 2014

In the design of mechanical assembly, the dimension-chain tools take into account the manufacturing dispersion of the parts and assembly defects. This ensures the interchangeability of the different components and guarantees that an assembly can carry out different service functions, as it is modeled in infinitely rigid solids. However, this approach does not take thermo-mechanical effects and deformation due to inertia effects like gravity, angular velocity etc., into account. Most materials change length as they change temperature. As a result of this change, the dimensions and tolerances of a product become at variance with the design values. Hence, thermal effects must be taken into account when designing a product that will undergo temperature cycling and yet, the different operating regimes of an assembly make it indispensable that the effects caused by the thermodynamic cycle should be integrated. In this regard, a finite element model of a machine assembly is created in order to determine the deformation due to change in temperature and inertia effects. The aim of this article is to include the deformation determined by Finite element analysis in the dimension chain thereby controlling clearances in the mechanical assembly. The approach first generates a Cost-tolerance model using neural network where the inputs are parameters and tolerance levels. Then, Finite element analysis of the machine assembly is carried out. The deformation obtained by FEA is then included in the dimension chain. Finally, optimization is done using Non-dominated sorting genetic algorithm II (NSGA II). The results provide designers with optimal component parameters and tolerance values, and the critical components and the manufacturing cost. The approach can also guarantee that the parameter and tolerance values found remain within tolerance for the temperature variation. Then, the product can function as intended under a wide range of temperature conditions for the duration of its life.

Key words: Dimension chain, thermo mechanical tool, finite element analysis, neural network and NSGA II.

INTRODUCTION

Both the performance and reliability of products are strongly influenced by temperature (Bejan et al., 1996; Sergent and Krum, 1998). Hence, exposure to a temperature that is higher or lower than the product is designed to withstand, may result in the failure of the product to perform to specification, or in total failure. As demands for product quality continually increase, the problem of temperature impact becomes an important and challenging issue. A survey shows that the impact of temperature on a product contributes to a substantial portion of product failures. Unfortunately, the effects of temperature impact are often ignored during the design process or are considered too late; consequently, design changes are limited and become very costly. Hence, integration of thermal impact into the early design cycle will ultimately lead to more robust and reliable products which undergo temperature changes during their application. The detrimental effects of excessive

*Corresponding author. E-mail: ansari.mh@yahoo.co.in.

temperatures may be divided into two categories. The first category is soft failures which are caused by the tendency of the parameters and tolerances of components to exhibit a degree of sensitivity to temperature variation.

As the temperature increases or decreases, the cumulative effects of component parameter drift and tolerance variation may eventually cause the output variables of interest to deviate from the design specifications. The second category is hard failures, which occur as a result of component breakdown resulting from temperature variation. This deviation of temperature from the acceptable operating temperature established by the design specification creates mechanical stresses in components, which may cause fatigue, cracking, fracture, or displacement. One possible way to reduce temperature impact is through thermal control by reducing or adding heat to the product, so that the temperature remains within an acceptable range.

However, thermal control results in a dramatic increase in cost owing to the required cooling or heating equipment and the increase in size, weight, and cost. Robust design should be employed to find the appropriate parameter and tolerance values for each component of a product, so that the output quality of interest is resistant to extreme temperature variation. As is known, quality engineering uses robust design to improve product or process quality by reducing the effects of variation. The variation of output can be reduced by two methods (Kacker, 1985; Nair, 1992; Padke, 1989). One is parameter design which adjusts the parameter value so that the output is less sensitive to causes of variation. The other is tolerance design which reduces the tolerance value to control the variation (Evans, 1974). There is usually no cost associated with changing parameter values. However, reducing tolerance values always leads to additional costs. Hence, parameter design is normally carried out prior to tolerance design for economic reasons.

Generally, there are two types of input variables in product or process design: 1) those with a tolerance requirement and 2) those without a tolerance requirement. As a result of the fact that the values of these input variables do not influence product application and manufacturing operation, only the nominal values need be determined. Hence, for the first type of input variable in product or process design, if the quality determined by measuring the output variables which result from parameter and tolerance design have the same unit, optimization of the parameter and tolerance design may be completed in one step (Jeang, 2001; Jeang and Chang, 2001). For product or process design, the quality function describing the relationship between the output quality of interest and the input variable of the design may or may not be available. For the former situation, well-known methods such as root-sum- square (RSS), worse-case (WC), and numerical simulation can be applied directly for design analysis; however, the latter situation requires a physical experiment (Nigam and Turner, 1995). This paper considers a situation where the quality function is known. A distinct advantage over the situation where the quality function is not available is that costly physical experimentation can be replaced by numerical simulation (Welch et al., 1990).

Furthermore, the computation of design analysis will be more accurate because the quality function is not estimated in this case. A measurement score which is converted from the values found through numerical simulation will be used. The measurement score (or total cost) includes quality loss, manufacturing cost, and failure cost. This score is also called the response value in the statistical analysis presented. Normally, it is efficient to proceed with the design activities if a functional relationship (or response function) exists between the measured score (or response value) and the set of design input variables. In addition to finding the best component design values during the design process, it is necessary to locate the critical components of product or process design, particularly by a repeated application under uncertain design conditions.

Traditional tolerance analysis methods assume that all objects have rigid geometry. The variance is increasingly stacked up as components are assembled. The geometric variation of assembly is always assumed to be larger than those of its subassemblies and components. This rigid body analysis overlooks the role of deformation of flexible parts of the assembly due to inertia effects like gravity, angular velocity, etc. The conventional addition theorem of tolerances has to be suitably modified to accommodate deformation due to the inertia effects. Several studies have been carried out to manage compliant structure (Jack and Camelio, 2006; Stewart and Chase, 2005; Soderberg et al., 2006; Xie et al., 2007). The finite element (FE) simulation is used to predict the influence of geometric tolerances on the part distortions for complex part-forms and assembly designs (Manarvi and Juster, 2004). Tolerance analysis of hull is done considering thermo mechanical effect (Pierre, 2009), where the effect of thermal flux in modifying the contacts and distortion the geometry of parts are studied. In this paper, a finite element model of a machine assembly is created in order to determine the deformation due to change in temperature and inertia effects. The aim of this article is to include the deformation determined by Finite element analysis in the dimension chain thereby controlling clearances in the mechanical assembly.

NEURAL NETWORK-BASED COST-TOLERANCE FUNCTIONS

Neural networks have received a lot of attention in many research and application areas. One of the major benefits

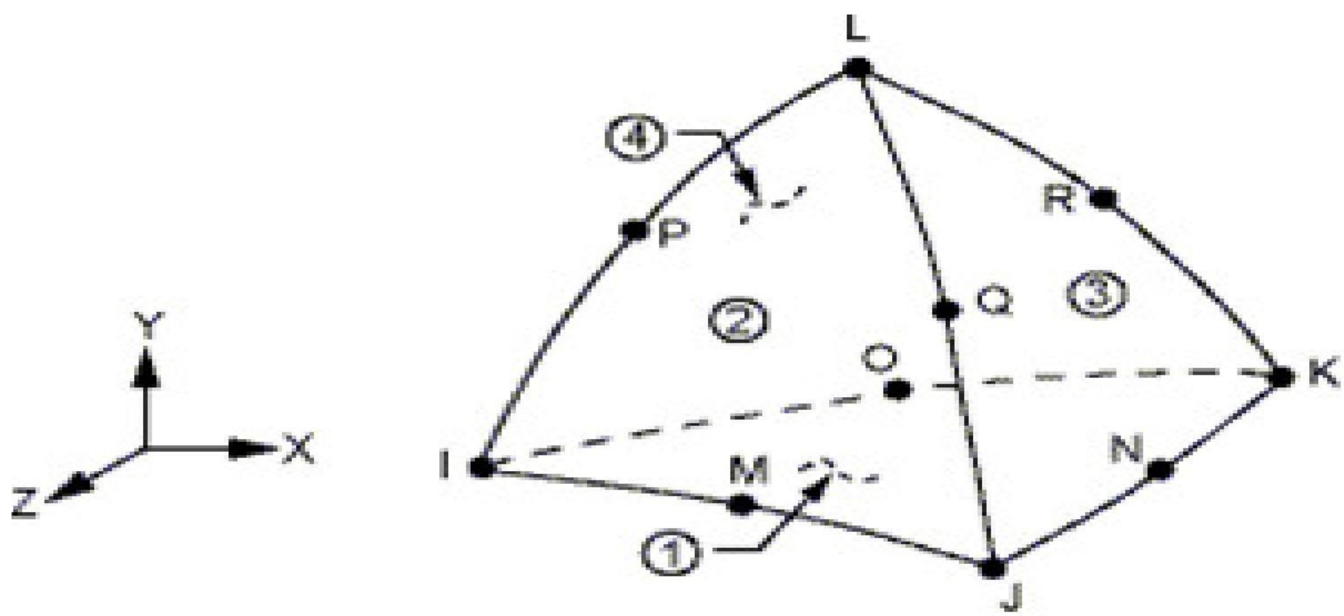

Figure 1. Element geometry.

of neural networks is the adaptive ability of their generalization of data from the real world. Exploiting this advantage, many researchers apply neural networks for nonlinear regression analysis and have reported positive experimental results in their applications (Stern, 1996). Recently, neural networks have received a great deal of attention in manufacturing areas. Zhang and Huang (1995) presented an extensive review of neural network applications in manufacturing. Neural networks are defined by Rumelhart and McClelland (1989) as `massively parallel interconnected networks of simple (usually adaptive) elements and their hierarchical organizations which are intended to interact with objects of the real world in the same way as biological nervous systems do.

The approach towards constructing the cost-tolerance relationships is based on a supervised back-propagation (BP) neural network. Among several well-known supervised neural networks, the BP model is the most extensively used and can provide good solutions for much industrial application (Lippmann, 1987). A BP network is a feed-forward network with one or more layers of nodes between the input and output nodes. An imperative item of the BP network is the iterative method, that propagates the error terms required to adopt weights back from nodes in the output layer to nodes in lower layers. The training of a BP network involves three stages: 1) the feed forward of the input training pattern, 2) the calculation and BP of the associated error, and 3) the adjustment of the weights. After the network reaches a satisfactory level of performance, it will learn the relationships between input and output patterns and its weights can be used to recognize new input patterns.

Figure 1 depicts a BP network with one hidden layer. The hidden nodes of the hidden layer perform an important role in creating internal representation. The following nomenclatures are used for describing the BP learning rule:

net_{pi} = net input to processing unit i in pattern p (a pattern corresponding to a vector of
factors),
w_{ij} = connection weight between processing unit I and processing unit j,
a_{pi} = activation value of processing unit i in pattern p,
δ_{pi} = the effect of a change on the output of unit I in pattern p,
g_{pi} = target value of processing unit
i, ε = learning rate.

The net inputs and the activation values of the middle processing nodes are calculated as follows:

$$net_{pi} = \sum_{j} w_{ij} a_{pj}, \tag{1}$$

$$a_{pi} = \frac{1}{1 + \exp\left(net_{pi}\right)} \tag{2}$$

The net input is the weighed sum of activation values of the connected input units plus a bias value. Initially, the connection weights are assigned randomly and are varied continuously. The activation values are in turn used to calculate the net inputs and the activation values of the output processing units using the same Equations (1) and (2). Once the activation values of the output units are calculated, we compare the target value with activation value of each output unit. The discrepancy is propagated using

$$\delta_{pi} = \left(g_{pi} - a_{pi}\right) f_i^{'}\left(net_{pi}\right) \quad (3)$$

For the hidden processing units in which the target values are unknown, instead of Equation (3), the following equation is used to calculate the discrepancy. It takes the form

$$\delta_{pi} = f_i^{'}\left(net_{pi}\right) \sum_k \delta_{pk} w_{ki} . \quad (4)$$

From the results of Equations (3) and (4), the weights between processing units are adjusted using

$$w_{ij} = \varepsilon \delta_{pi} a_{pj} . \quad (5)$$

In this paper, neural network is used to generate a Cost-tolerance model, the inputs being parameters and tolerance levels.

FINITE ELEMENT ANALYSIS

The finite element method (FEM) is a numerical technique for finding approximate solutions of partial differential equations (PDE) as well as of integral equations. The solution approach is based either on eliminating the differential equation completely (steady state problems), or rendering the PDE into an approximating system of ordinary differential equations, which are then numerically integrated using standard techniques.

The Finite Element Method is a good choice for solving partial differential equations over complicated domains (like cars and oil pipelines), when the domain changes (as during a solid state reaction with a moving boundary), when the desired precision varies over the entire domain, or when the solution lacks smoothness.

FEM allows detailed visualization of structures bend or twist, and indicates the distribution of stresses and displacements. FEM software provides a wide range of simulation options for controlling the complexity of both modeling and analysis of a system. Similarly, the desired level of accuracy required and associated computational time requirements can be managed simultaneously to address most engineering applications. FEM allows entire designs to be constructed, refined, and optimized before the design is manufactured.

In this paper, we have chosen the finite element analysis method to find the deformation in the machine assembly due to change in temperature and inertia effects .This analysis is done by using the ANSYS11.0 software. The analysis of the machine assembly is carried out by commercial FEM code ANSYS 11.0 with SOLID 98 element**.** SOLID98 is a 10-node tetrahedral element with quadratic displacement behavior and is well suited to model irregular meshes (such as produced from various CAD/CAM systems). When it is used in structural and piezoelectric analyses, SOLID98 has large deflection and stress stiffening capabilities. The element is defined by ten nodes with up to six degrees of freedom at each node.

ELITIST NON-DOMINATED SORTING GENETIC ALGORITHM (NSGA-II)

Kalyanmoy Deb proposed the NSGA-II algorithm (2002). Essentially, NSGA-II differs from non-dominated sorting Genetic Algorithm (NSGA) implementation in a number of ways. Firstly, NSGA-II uses an elite-preserving mechanism, thereby assuring preservation of previously found good solutions. Secondly, NSGA-II uses a fast non-dominated sorting procedure. Thirdly, NSGA-II does not require any tunable parameter, thereby making the algorithm independent of the user. Initially, a random parent population P_o is created. The population is sorted based on the non-domination. A special book-keeping procedure is used in order to reduce the computational complexity to $O(MN^2)$. Each solution is assigned a fitness equal to its non-dominated level (1 is the best level). Thus, minimization of fitness is assumed. Binary tournament selection, recombination, and mutation operators are used to create a child population Q_o of size N, thereafter; the algorithm that follows is used in every generation.

$R_t=P_tUQ_t$

F=fast-non-dominated-sort(R_t)
P_{t+1} = φ and i=1
Until P_{t+1} + F_i ≤N
P_{t+1}= P_{t+1}U F_i

crowding-distance-assignment(F_i)
i=i+1
Sort($F_i \propto_n$)
P_{t+1}= P_{t+1} U P_{t+1}[1:(N- P_{t+1}
)] Q_{t+1} = make-new-
pop(P_{t+1}) t=t+1

First, a combined population $R_t=P_tUQ_t$ is formed. This

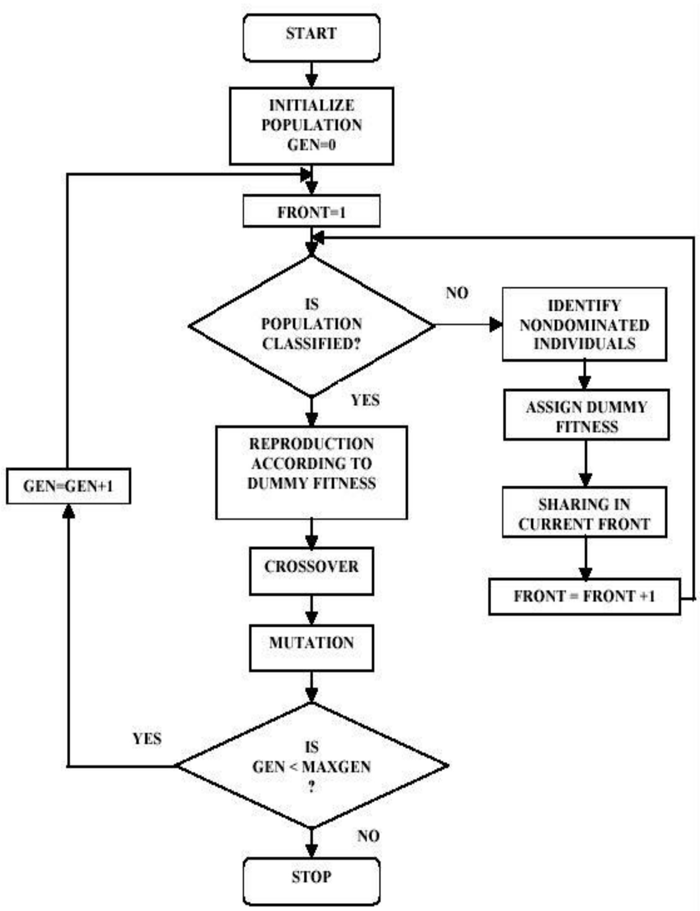

Figure 2. An iteration procedure of the NSGA-II algorithm.

allows parent solutions to be compared with the child population, thereby ensuring elitism. The population R_t is of size 2N. Then, the population R_t is sorted according to non-domination and non-dominated fronts F1, F2, and so on are found. The algorithm is illustrated in the following:

The new parent population P_{t+1} is formed by adding solutions from the first front F_1 and continuing to other fronts successively till the size exceeds N. Individuals of each front are used to calculate the crowding distance – the distance between the neighboring solutions. Thereafter, the solutions of the last accepted front are sorted according to a crowded comparison criterion and a total of N points are picked. Since the diversity among the solutions is important, the crowded comparison criterion uses a relation α_n as follows: solution i is better than solution j in relation α_n if ($i_{rank} < j_{rank}$) or (($i_{rank} = j_{rank}$) and ($i_{distance} > j_{distance}$)). That is, between two solutions with differing non-domination ranks, the preference is the point with the lower rank.

Otherwise, if both the points belong to the same front then the preference is the point, which is located in a region with smaller number of points (or with larger crowded distance). This way solutions from less dense regions in the search space are given importance in deciding which solutions to choose from R_t. This constructs the population P_{t+1}. This population of size N is now used for selection, crossover and mutation to create a new population Q_{t+1} of size N. A binary tournament selection operator is used but the selection criterion is now based on the crowded comparison operator α_n. The aforestated procedure is continued for a specified number of generations. It is clear from the earlier description that NSGA-II uses (i) a faster non-dominated sorting approach, (ii) an elitist strategy, and no niching parameter. It has been proved that the aforementioned procedure has $O(MN^2)$ computational complexity. The outline of the proposed optimization strategy is shown in Figure 2.

THE APPLICATION EXAMPLE

Assembly is the process by which various parts and subassemblies are brought together to form a complete assembly or product which is designed to fulfill a certain

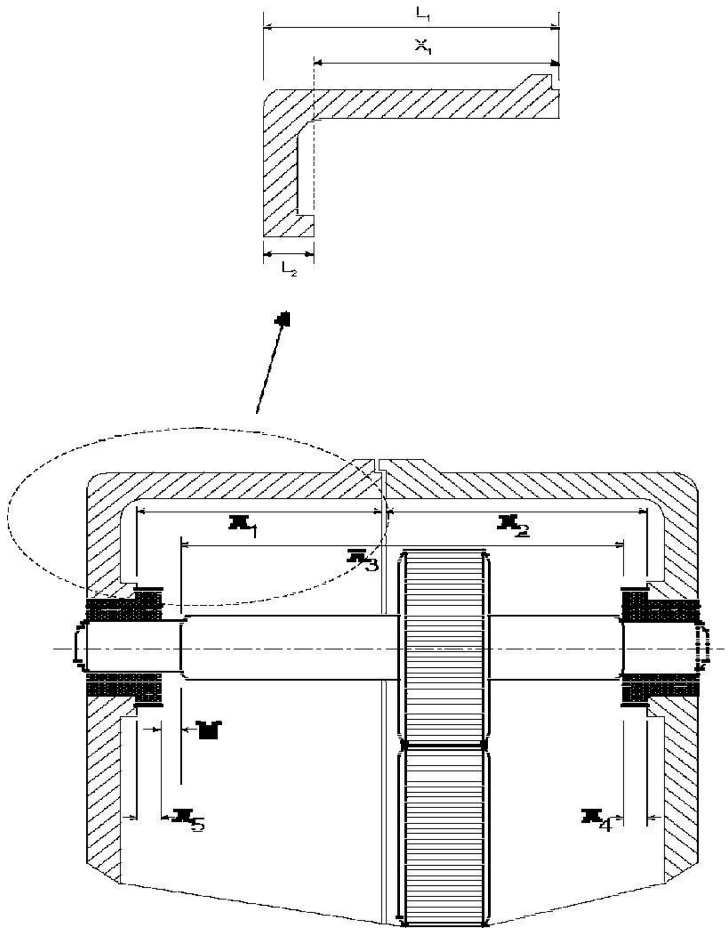

Figure 3. The gear box assembly.

mechanical function. A proper allocation and analysis of tolerance among the assembly components is important that the functionality and quality of the designs are met. Figure 3 is a classic Bjorke gearbox assembly (Bjorke, 1992). The gearbox assembly is the application example for the proposed tolerance design. The gearbox assembly consists of components X_1, X_2, X_3, X_4 and X_5. The assembly function that describes the quality value is:

$$Y = -X_3 - X_4 + X_2 + X_1 - X_5 \quad (6)$$

The associated component dimensions and tolerances, U_1, U_2, U_3, U_4, U_5; t_1, t_2, t_3, t_4 and t_5, must be determined so that the gap Y, between the bushing and hub fall within the functionality limits, T ± S, where T is 0.900 mm and S is 0.200 mm. Table 1 shows process capability limits for each component. The associated low, middle and high levels for input factors U_i and t_i are decided as shown in Table 2 and 3. Table 4 shows the parameter level for each component. The tolerance design involves following stages. Initially a neural network model of cost-tolerance function is developed based on the experimental results (Chase.K.W et al, 1990). The response variable in this study is Total cost which is sum of manufacturing cost and quality losses and it is expressed as

$$TC_i = \sum_{j=1}^{Q} k_j \left[\left(U_{ij} - T_j \right)^2 + \sigma_{ij}^2 \right] + \sum_{k=1}^{m} C_M(t_{ik}), \quad (7)$$

Where m is the total number of components from q assembly dimensions in a finished product, K_j the cost coefficient of the jth resultant dimension for quadratic loss function, U_{ij} the jth resultant dimension from the ith experimental results, σ_{ij} the jth resultant variance of statistical data from the ith experimental results, T_j the design nominal value for the jth assembly dimension, t_{ik} the tolerance established in the ith experiment for the kth component, and $C_M(t_{ik})$ the manufacturing cost for the tolerance t_{ik}.

Then neural network model of cost-tolerance function is developed as follows. The 2/3rd of experimental results drawn randomly are used to train the neural network. Before applying the neural network for modeling, the

Table 1. Process capability limits for each component.

Component I	Lower limit (mm)	Upper limit (mm)
t_1	0.014	0.042
t_2	0.018	0.052
t_3	0.024	0.072
t_4	0.009	0.027
t_5	0.010	0.030

Table 2. Feasible design space for each component.

Component I	Lower limit (mm)	Upper limit (mm)
X_1	15.9879	16.0121
X_2	17.9850	18.0150
X_3	28.9792	29.0208
X_4	1.7922	1.8078
X_5	2.2913	2.3087

Table 3. Tolerance and cost for each component.

Component I	Lower level $(mm)	Middle level $ (mm)	Upper limit $ (mm)
t_1	733.7(0.014)	579.8(0.028)	517.5 (0.042)
t_2	674.8(0.018)	541.7(0.035)	497.4 (0.052)
t_3	1385.8(0.024)	975.0(0.048)	899.3 (0.072)
t_4	541.2(0.009)	436.5(0.018)	403.6 (0.027)
t_5	522.8(0.010)	425.6(0.020)	398.7 (0.030)

Table 4. Parameter levels U_i for each component.

Component I	Lower level (mm)	Middle level (mm)	Upper level (mm)
X_1	15.9879	16.0000	16.0121
X_2	17.9850	18.0000	18.0150
X_3	28.9792	29.0000	29.0208
X_4	1.7922	1.80000	1.8078
X_5	2.2913	2.3000	2.3087

architecture of the network has been decided; that is the number of hidden layers and the number of neurons in each layer. As there are 10 inputs and 1 output, the number of neurons in the input and output layer has to be set to 10 and 1 respectively. Also, the back propagation architecture with one hidden layer is enough for majority of the applications. Hence only one hidden layer has been adopted. A procedure was employed to optimize the number of neurons in the hidden layer. Accordingly, an experimental approach was adopted, which involves testing the trained neural networks against the remaining 1/3rd of experimental results. Experimental and predicted outputs for different number of neurons have been compared. The regression statistics for different architecture are determined. The training function used in this research is Gradient descent with momentum back-propagation. The transfer function used in this research is tan-sigmoid and gradient. Descent w/momentum weight/bias learning function has been used. The learning rate = 0.7, momentum = 0.65 and training epochs = 2000. The weights (and biases) are randomly initialized between -0.5 and 0.5.Once the neural network gets trained, it can provide the result for any arbitrary value of input data set. Thus the neural

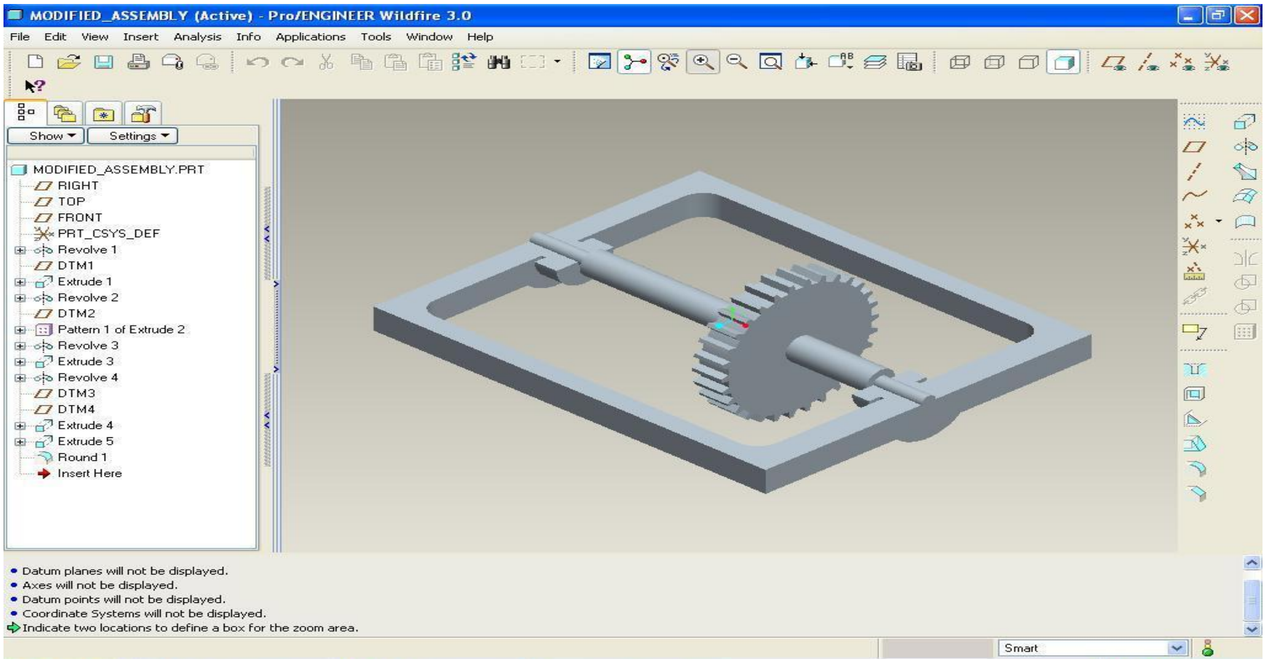

Figure 4. The Pro/E model.

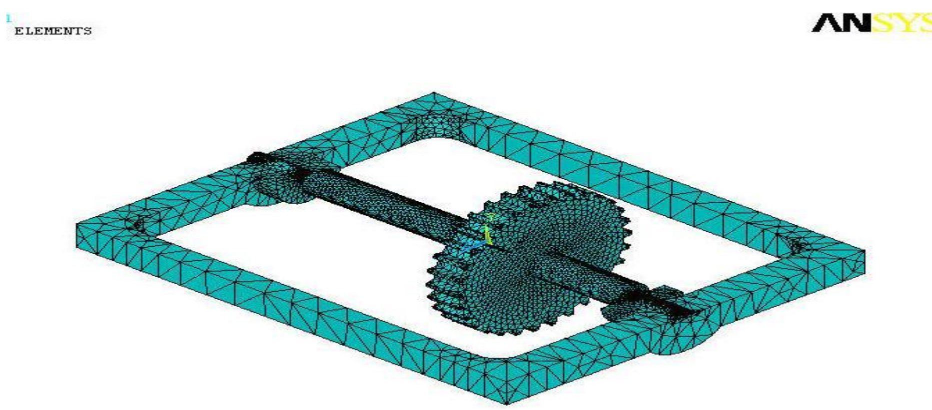

Figure 5. The meshed model.

network model for the above problem is developed as per the approach discussed previously. Once the neural network model of the cost-tolerance function is developed, than Finite element analysis of the assembly is done.

The major constraints in the presented design are variation of thermal environment both within and among various application categories and inertia effects. Hence the design which withstands temperature variation and inertia must be considered in the present case. If the temperature is 25°C when the gearbox is assembled and then varies between 10°C and 40°C during application; if the self weight of the shaft is considered and inertia effect due to angular velocity of the shaft is considered, then the deformation is determined using Finite Element Analysis. First, a 3D model of the gearbox assembly is created using Pro/E wildfire 3.0 software (Figure 4). Then it is converted into a file type (.sat) suitable for importing the same in the Ansys software version 11.0. Once the model is imported, material properties for the three components, shaft, bushing and casing is given. Then the model is meshed with SOLID98, which is a 10-node tetrahedral element with quadratic displacement behavior and it is well suited to model irregular meshes (such as produced from various CAD/CAM systems). The meshed model has 71223 elements and 107,726 nodes as shown (Figure 5). Then the loads and constraints are applied as shown (Figure 6). In order to account for inertia effects

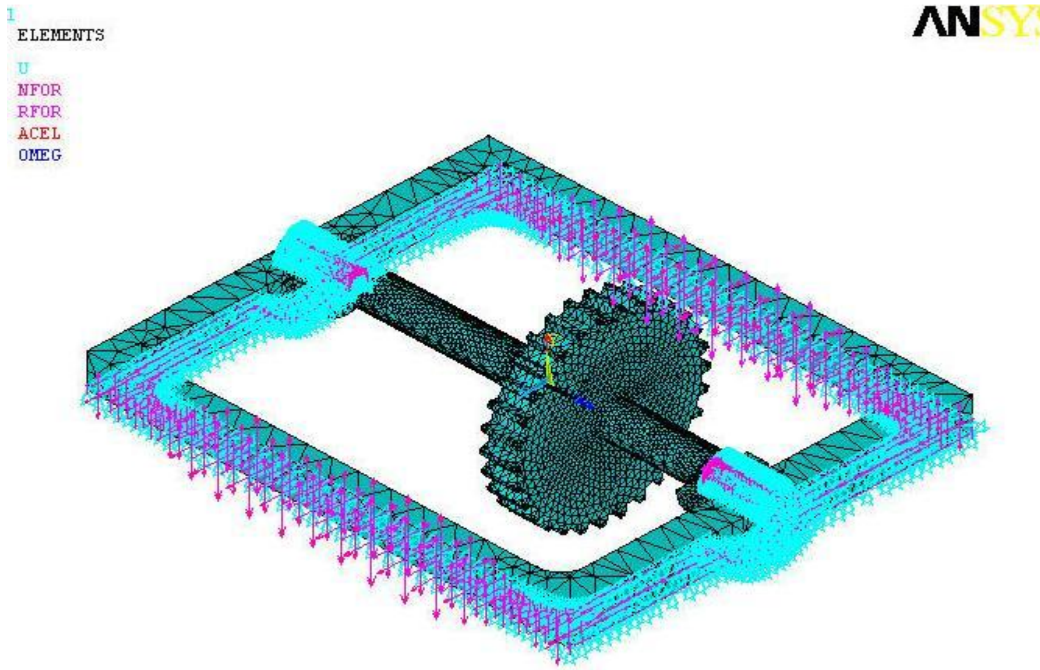

Figure 6. Applied loads and constraints.

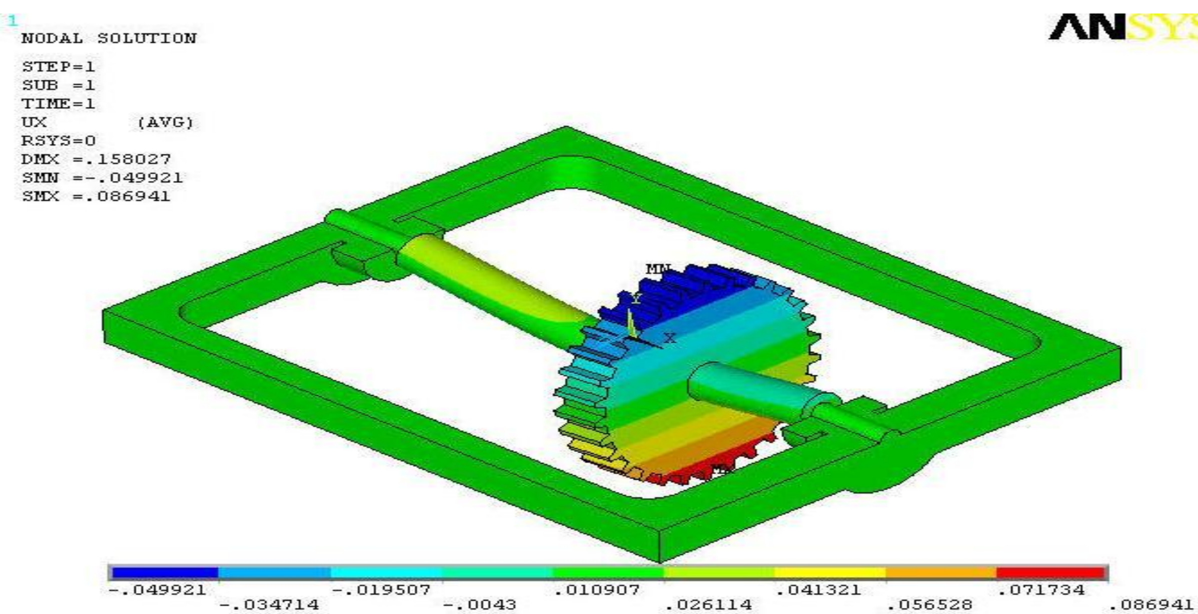

Figure 7. Deformation plot for 10°C.

like gravity, angular velocity, etc., appropriate values for g (9.81 m/s^2) and ω (rad/sec) are given. Then the deformation is calculated for three levels of temperature within the operating range (that is 10°C, 25°C and 40°C). Figure 7 shows the deformation pattern for 10°C. The variation of deformation along the length of the shaft is determined for all the three values of temperature (Figure 8 to 10). The deformation due to thermal and inertia effect for various temperatures is plotted (Figure 11). Table 5 has deformation values for different levels of temperature. It is observed that the deformation has a linear relationship with the temperature and the same is

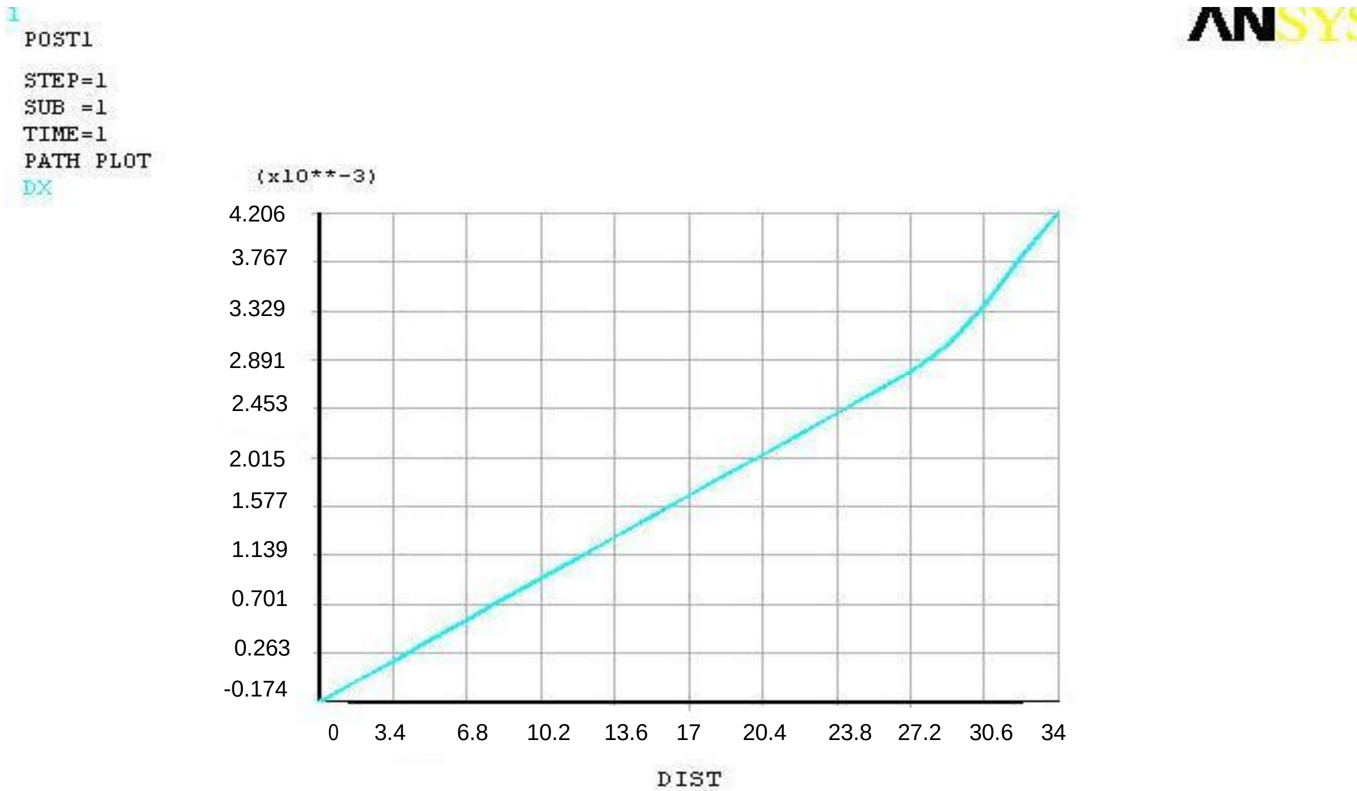

Figure 8. Deformation vs length plot (10°C).

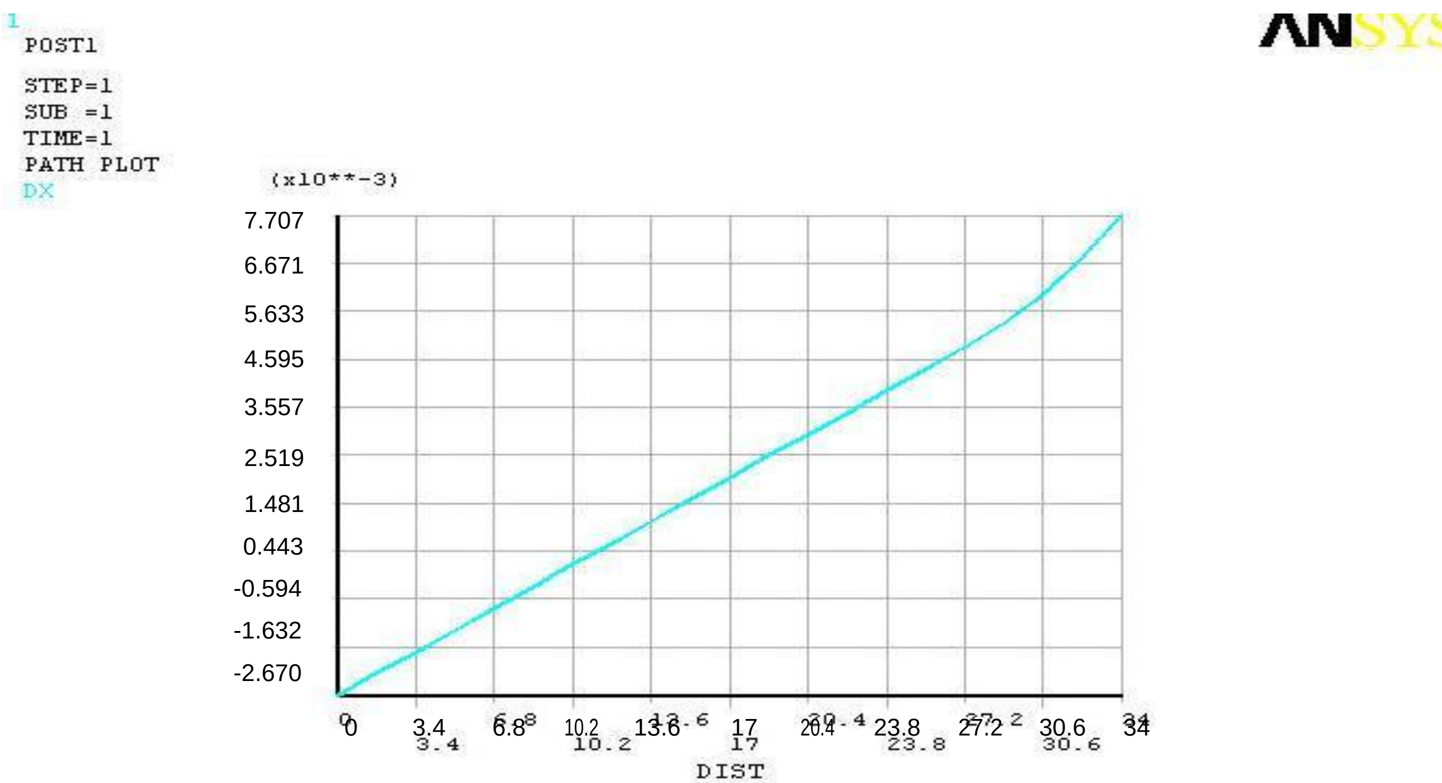

Figure 9. Deformation vs length plot (25°C).

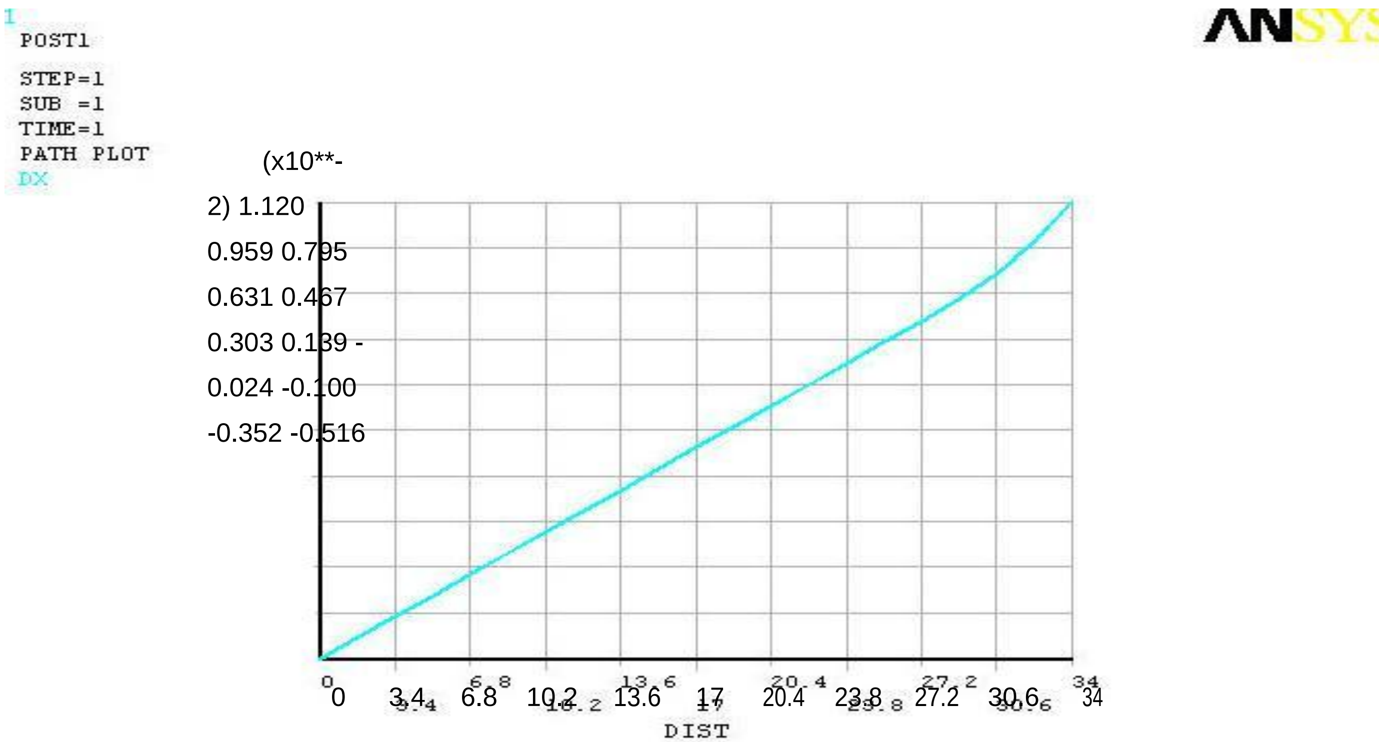

Figure 10. Deformation vs length plot (40°C).

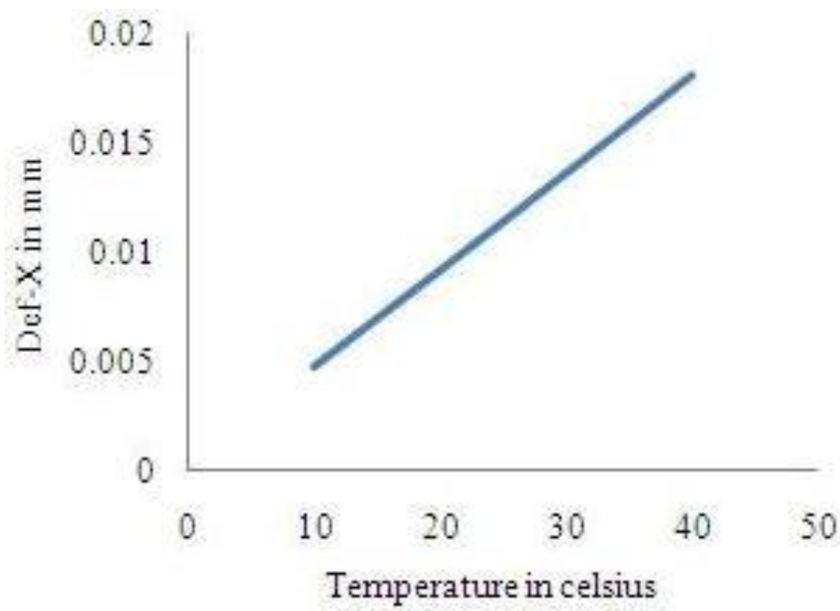

Figure 11. Deformation vs Temperature.

determined.

Once the deformation is determined and linear relationship between the deformation and the process variable (temperature) is determined, then the optimal values of the component dimensions and tolerances are determined by using NSGA II. Table 6 shows the NSGA II specific data. The solution of the gearbox assembly case can be found by solving the following mathematical

Table 5. Deformation for various temperatures.

S/No	Temperature (°C)	Deformation (mm)
1	10	0.4791E-2
2	25	1.1395E-2
3	40	1.18115E-2

Table 6. Optimal values U_i and t_i for TC at various temperatures T.

Temperature	10°C	25°C	40°C
Optimal values	**TC**	**TC**	**TC**
t_1	0.0276	0.0278	0.0282
t_2	0.0243	0.0245	0.0254
t_3	0.0256	0.0257	0.0264
t_4	0.0215	0.0218	0.0219
t_5	0.0295	0.0297	0.0298
X_1	15.9882	16.0000	16.0121
X_2	17.9923	18.0000	18.0150
X_3	28.9792	29.0000	29.0208
X_4	1.7922	1.80000	1.8078
X_5	2.3086	2.3000	2.3087
Optimal response value	$ 2535.52	$2531.25	$2528.12

Table 7. The NSGA II specific data.

Variable type	Real variable
Population size	100
Cross over probability	0.7
Real parameter mutation probability	0.2155
Real parameter SBX parameter	10
Real parameter mutation parameter	100
Total no of generation	100

models:

$$\text{Minimize}\,TC = F(t_1, t_2 \ldots t_5, U_1, U_2 \ldots\ldots U_5) \text{ subjectedto :}$$
$$U_1 + U_2 - U_3 - U_4 - U_5 \le 0.900$$
$$\sqrt{t_1^2 + t_2^2 + t_3^2 + t_4^2 + t_5^2} \le 0.200 + \delta \qquad (8)$$
$$\text{where } \delta = f\,(\text{temperature})$$

A clearance of 0.9 mm has to be maintained, between the bushing and hub should be 0.900 mm. Another functional constraint is the constraint equation developed using statistical tolerance design method, where δ is the deformation determined using FEA. The deformation δ (Figure 11) is found to have a linear relationship with the variable temperature while the inertia effects like gravity and angular velocity are constant. The Problem (7) is solved by the proposed NSGA II discussed previously. The outline of the proposed optimization strategy is shown in Figure 2. The optimization strategy is explained

as follows. Initially, the cost-tolerance function is established by the neural network model. Once the neural network based cost – tolerance function is established, and then optimization of the problem (Equation 7) is carried out using NSGA II. The optimization program determines the set of tolerance and component dimensions with minimum cost. The least cost is found for all the three values of temperature (Table 7).

DISCUSSION

Once a customer starts using a product, the quality of that product can vary for many reasons. Temperature impact and gravity effects have been found to be one of the reasons for variation in quality of the product. Product specifications must be perfectly fulfilled in order to manufacture a quality product. Furthermore, products may consist of a few components which are associated with various materials, grades, and tolerances. The cost involved for each component varies due to selected materials or assigned tolerance values. Hence, product design that considers the thermal impact and inertia effects is required to design those products successfully. The customer's perception of the quality of a design is closely related to the sensitivity of the design to environmental impact, which is the temperature and inertia effect. Design engineers must minimize the effects of the previously discussed factors on performance of the product; that is, a robust design regulating thermal impact is required. There are three ways to minimize quality variation caused by thermal impact:

1) Eliminate the reality of the thermal impact and inertia effects.
2) Design a product with a feature and parameter which can eliminate the deformation.
3) Have a robust design that enables to reduce deformation due to thermal and inertia effects.

It can be very costly, inconvenient, and inefficient to realize the first and second ways of eliminating temperature impacts, because some thermal impacts cannot be controlled and others are too expensive or difficult to control. A product or process is said to be robust when it is insensitive to the effects of sources of variation, even when the sources have not been eliminated. This leads to the third way which is a robust design - a process that results in a product performance which is minimally affected by temperature impact. Robust design focuses on minimizing variation or creating a system less sensitive to variation, making it possible to decrease cost, because expensive means for controlling quality are no longer necessary. Hence, this third method of eliminating temperature impact should be attempted before the first and second ways are tried. The objective of this study is to develop a robust product or process design that functions as intended under a wide range of temperatures for the duration of the design stage.

Conclusion

Using neural network, FEA and NSGA II, a statistical optimization of parameter and tolerance determination for assembly under various temperature and inertia effects have been developed. With the presented approach, critical component parameters and tolerances can be identified,and optimal component parameter and tolerance values can be determined. The component parameter and tolerance values found are the most robust to withstand temperature variation during the products application. Benefits also include low failure related costs and high product reliability. These benefits make it possible to create high-quality and cost effective parameter and tolerance design at the earliest stages of product development.

REFERENCES

Bejan A, Tsatsaronis G, Moran M (1996) Thermal Design and Optimization, John Wiley.

Evans DH (1974). "The State of Art: Part 1 - Background", J. Qual. Technol., 6: 188-195.

Hu J, Camelio J (2006). Modeling and control of compliant assembly systems. CIRPAnn. Manuf. Technol. 55-1,19-22.

Jeang A (2001), "Combined optimization of parameter and tolerance design for quality and cost", Int. J. Production Res., to appear in 2001.

Jeang A, Chang CL (2001). "Concurrent optimization of parameter and tolerance design via computer simulation and statistical method", Int. J. Adv. Manuf. Technol., to appear in 2001.

Kacker RN (1985). "Off-line quality control, parameter design, and Taguchi method", J. Qual. Technol., 17: 176-209.

Kalyanmoy D (2002) Optimization for engineering design. (Prentice-Hall), New York.

Lippmann RP (1987). An introduction to computing with neural nets, IEEE ASSP Magazine 4: 4-22.

Manarvi IA, Juster NP (2004). Framework of an integrated tolerance synthesis model and using FE simulation as a virtual tool for tolerance allocation in assembly design, J. Mater. process Technol., 150: 182 - 193.

Nair VN (1992). "Taguchi's parameter design: a panel discussion", Technometrics, 34: 127-161.

Nigam SD, Turner JU (1995). "Review of statistical approaches to tolerance analysis", Computer-Aided Design, 27(1): 6-15.

Padke MS (1989). Quality Engineering Using Robust Design, Prentice-Hall. Englewood Cliffs, New Jersey.

Pierre L, Teissandier D, Nadeau JP (2009). Integration of thermo mechanical strains into tolerancing analysis, Int. J. Interact. Des. Manuf., 3(4): 247-263.10.1007/s 12008-009-0058-8.

Rumelhart DE, McClelland JL (1989). Parallel Distributed Processing Explorations in the Microstructure of Cognition: Vol. I, MIT Press, Cambridge MA, USA.

Sergent J, Krum A (1998). Thermal Management Handbook, McGraw-Hill.

Soderberg R, Lindkvist L, Dahlstorm S (2006). Computer aided robust analysis for compliant assemblies. J. Eng. Des.17: 411-428.

Stern HS (1996). Neural networks in applied statistics (with discussion), Technometrics, 38: 205-220.

Stewart ML, Chase KW (2005). Variation simulation of fixture assembly for compliant structures using piece wise- linear analysis. Am. Soc. Mech. Eng. 16-1, 591-600.

Welch WJ, Yu TK, Kang SM, Sacks J (1990). "Computer experiments for quality control by parameter design", J. Qual. Technol, 22: 15-22.

Xie K, Wells L, Camelio JA, Youn BD (2007). Variation propagation analysis of compliant assemblies considering contact interaction. J. Manuf. Sci. Eng., Trans, ASME 129-5, 934-942, 2007.

Zhang HC, Huang H (1995). Applications of neural networks in manufacturing: A-state-of-the-art survey, Int. J. Production Res. 33(3): 705-728.