An Approach to optimize ANN Meta model with Multi Objective Genetic Algorithm for Multi-disciplinary Shape optimization

Ram Krishna Rathore, Amit Sarda, Rituraj Chandrakar

Abstract*— In several design cases, designers need to optimize a number of responses concurrently. A general approach for the multiple response cases optimization start with using the regression models to calculate the correlations between response functions and control factors. Then, a system for collecting various response functions together into a one quantity, such as an objective function, is engaged and, at last, an optimization technique is used to calculate the best combinations for the control functions. A different method proposed in this paper is to use an artificial neural network (ANN) to calculate the parameter response functions. At the optimization stage, a multi objective genetic algorithm (MOGA) is used in combination with an objective functions to establish the optimum conditions for the control functions. A crane hook example has been taken to optimize multiple shape parameter responses to with stand a new loading condition. The results estimate the reduction in mass and sufficient factor of safety to show the proposed approach for the optimization of multi- disciplinary shape optimization problems.

***Index Terms*— ANN, MOGA, Shape optimization, Meta modeling**

I. INTRODUCTION

A lifting hook is a device for grabbing and lifting up the loads by means of a device such as a hoist or crane. Crane Hooks are the components used for most of the material handling environments and are most of the time subjected to failure due to accretion of large amount of stresses, which can ultimately lead to the failure. To study the failure of the crane hook in its new loaded condition, a solid model of crane hook is prepared. By predicting the stress concentration area, the shape of the crane is modified to increase its working life and reduce the failure rates. In this paper a new high loading condition is applied to the existing design, due to this load the component is failed. To make the design changes to sustain the new condition, we will use a Design of Experiment analysis which will gives the parameters variation over given ranges and the performance of the hook is examined over these ranges. Some promising candidates for best design will be determined with the help of response surface created trough artificial neural network Meta model. Then after checking the responses of the various parameters, Multi Objective Genetic Algorithm will be applied to find the best suitable shape optimization for the objective functions.

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II. LITRATURE REVIEW

Different approaches have been projected in the literature for the optimization of multiple-response problems. Reference [1] shows implementation of an artificial neural network (ANN) to estimate the quantitative and qualitative response functions. In the optimization phase, a genetic algorithm (GA) is considered in conjunction with an unconstrained desirability function to determine the optimal settings for the control factors. The main difficulty with this approach is that it cannot recognize the most dominant solution. Reference [2] describes the response surface methodology (RSM), based on Moving Least-Square (MLS) approximation and adaptive moving region of interest, and is presented for shape optimization problem. To avoid a local optimum and to obtain an accurate solution at low cost, an efficient strategy which allows improving the RSM accuracy in the vicinity of the global optimum is presented. During the progression of the optimization procedure, the region of interest is moving and the search space is reduced by half around each local optimum. The clinch forming process is considered as an application example using the ABAQUS finite element code. The geometries of both the punch and the die are optimized to improve the joints resistance to tensile loading. Reference [3] shows a study of shape design of a crane-hook. In order to improve the performance of the crane-hook, we formulate a multi-objective optimization problem based on a FEM analysis. The displacement at the usual force applied point, the ratio between the total displacement against various load conditions and an H2-norm of the dynamic behavior are adopted as the objective functions to be minimized. The crane-hook dealt with in this study has a typical cross-section of so-called T-shape. The cross-section and the contour shape are adopted as the design variables. Continuous change of these design variables is expressed in terms of orthogonal polynomials and the Fourier series. The Particle Swarm Optimization (PSO) is used as the optimization procedure. The obtained crane-hook design has a typical tapered shape similar to those of existing designs. The result shows the basic applicability of the proposed objective functions as well as the optimal design approach. Reference [4] shows the study of Crane Hooks failure due to accumulation of large amount of stresses which can eventually lead to its failure. To study the stress pattern of crane hook in its loaded condition, a solid model of crane hook is prepared with the help of CMM and CAD software. Real time pattern of stress concentration in 3D model of crane hook is obtained. The stress distribution pattern is verified for its correctness on an acrylic model of crane hook using Diffused light Polariscope set up. By predicting the stress concentration area, the shape of the crane is modified to increase its working life and reduce the failure rates. Reference [5] Describes the Response surface methodology (RSM) explores the relationships between several explanatory variables and one or more response variables. The main idea of RSM is to use a set of designed experiments to obtain an optimal response. RSM tries to simplify the original problem through some polynomial estimation over small sections of the feasible area, elaborating on optimum provision through a well known optimization technique, say Gradient Method. As the real world problems are usually very complicated, polynomial estimation may not perform well in providing a good representation of the objective function. Also, the main problem of the Gradient Method, getting trapped in local minimum (maximum), makes RSM at a disadvantage, while defining sub-sections of the feasible area is also a problem faced by analyst. In this article, neural networks are used as a means to improve the estimation in the RSM context. This approach leads to reducing the calculations. Furthermore, it is proposed to use simulated annealing in maximizing the estimated objective function in reaching a suitable point. Three examples of different complexities are solved to shed light on the merits of the proposed method. The comparison results indicate that the proposed algorithm outperforms the classical method.

III. THE PROPOSED APPROACH

Now days for function approximations Artificial Neural Network models have been widely used. An artificial neural network technique is an extremely comparable distributed processor that has a natural tendency for accumulate experimental information and creating it available for different utilization purposes. Neural networks are mostly used for parameter approximation and pattern identification. On the basis of which type of Artificial Neural Network we employ, there are various parameters to setup, but the conception that they all contribute to common that they all require to be defined. The intent of an ANN may ensue as follows. Firstly, a suitable structural design is chosen for the ANN. Secondly, it need proper learning. Third, the generalization process needs to define. The proposed method follows essentially the similar three steps. It uses ANN to calculate the correlation between control function as inputs parameter and responses as outputs parameter at the first stage and, finally, a multi objective genetic algorithm as a parameter optimization tool at the optimization stage. This step allow us to get benefited of artificial neural networks' capabilities in function parameter approximation, the probability of objective function in individual responses, and as well the fitness of MOGA in optimizing extremely nonlinear, complex functions. The main purpose of this paper is to identify the relationship between the performance of the product and the design variables. Based on these results, we will be able to influence the design so as to meet the product's requirements and able to identify the key parameters of the design and how they influence the performance.

The cross-section and the contour shape are adopted as the design variables. Continuous change of these design variables is expressed in terms of orthogonal polynomials and the Fourier series. With the help of these variables, various Modern Optimization Techniques are available to optimize the overall working conditions of the crane hook.

The process flow chart is given below:

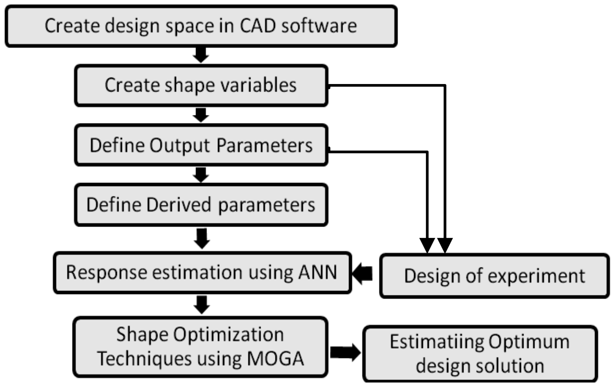

Fig.1 flow charts of proposed approach

A. *Design of Experiments*

Design of Experiments is a technique used to determine the location of sampling points and is included as part of the Response Surface, Goal Driven Optimization, and Six Sigma systems. There are several versions of Design of Experiments available in engineering literature. These techniques all have one common characteristic: they try to locate the sampling points such that the space of random input parameters is explored in the most efficient way, or obtain the required information with a minimum of sampling points. Sample points in efficient locations will not only reduce the required number of sampling points, but also increase the accuracy of the response surface that is derived from the results of the sampling points. By default the deterministic method uses a central composite design, which combines one center point, points along the axis of the input parameters, and the points determined by a fractional factorial design

1. *Design of experiment: central composite design*

In Central Composite Design (CCD), a Rotatable (spherical) design is preferred since the prediction variance is the same for any two locations that are the same distance from the design center. However, there are other criteria to consider for an optimal design setup. Among these criteria, there are two commonly considered in setting up an optimal design using the design matrix. The degree of non-orthogonality of regression terms can inflate the variance of model coefficients. The position of sample points in the design can be influential based on its position with respect to others of the input variables in a subset of the entire set of observations. The location of the generated design points for the deterministic method is based on a central composite design. If N is the number of input parameters, then a central composite design consists of:

- One center point.
- 2*N axis point located at the $-\alpha$ and $+\alpha$ position on each axis of the selected input parameters.
- 2(N-f) factorial points located at the -1 and +1 positions along the diagonals of the input parameter space.

B. *Response Surface System*

Response Surface Methods are based on the fundamental assumption that the influence of the random input variables on the random output parameters can be approximated by mathematical function. Hence, Response Surface Methods locate the sample points in the space of random input variables such that an appropriate approximation function can be found most efficiently; typically, this is a quadratic polynomial. In this case the approximation function $\hat{Y}$ is described by

$$\hat{Y} = c_o + \sum_{i=1}^{NRV} c_i X_i + \sum_{i=1}^{NRV} c_{ij} X_i \cdot X_j$$

where c_0 is the coefficient of the constant term, c_i, i = 1,...NRV are the coefficients of the linear terms and c_{ij}, i = 1,...NRV and j = i, ...,NRV are the coefficients of the quadratic terms. To evaluate these coefficients a regression analysis is used and the coefficients are usually evaluated such that the sum of squared differences between the true simulation results and the values of the approximation function is minimized.

C. Artificial Neural Network System

An artificial neural network (ANN) is a system composed of many simple processing elements operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing element or nodes. A network is a system with many elements connected together. A neural network is a network with neurons as the basic elements. A neuron is a simple processing unit in artificial neural networks.
This mathematical technique is based on the natural neural network in the human brain.
Weighted functions are issued from the algorithm which minimizes the distance between the interpolation and the known values (design points) – learning process.
The error is check in every iteration.

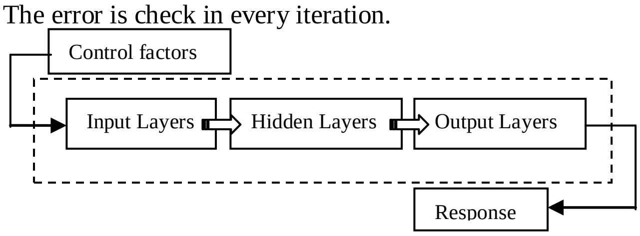

Fig.2 Topology of Artificial neural network model

Each arrow is associated with a weight (W) and each ring is called a cell (like a neural). If the inputs are xi, the hidden level contains function gj (X_i) and the output solution is also:

$$F_k (X_i) = K (\Sigma\, W_{jk}\, g_j(X_i))$$

where K is a predefined function, such as the hyperbolic tangent or an exponential based function, in order to obtain something similar to the binary behaviour of the electrical brain signal (like a step function). The function is continuous and differentiable.

D. MOGA (Multi-Objective Genetic Algorithm) System

1. Pareto Dominance in Multi-Objective Optimization

The concept of Pareto dominance is of extreme importance in multi-objective optimization, especially where some or all of the objectives are mutually conflicting. In such a case, there is no single point that yields the "best" value for all objectives (i.e., the Utopia Point). Instead, the best solutions, often called a Pareto or non-dominated set, are a group of solutions such that selecting any one of them in place of another will always sacrifice quality for at least one objective, while improving at least one other. Formally, the description of such Pareto optimality for generic optimization problems can be formulated as in the following equations.

Taking a closer, more formal look at the multi-objective optimization problem, let the following denote the set of all feasible (i.e., do not violate constraints) solutions:

$$X := \{x \in \Re^{n} : g(x) \geq 0, h(x) = 0, x_i \leq x \leq x_u\}$$

The problem can then be simplified to:

$$\min_{x \in X} f(X)$$

If there exists x'ϵ X such that for all objective functions x* is optimal. This, for i = 1, ..., k, is expressed:

$$f_i(X^*) \leq f_i(X) \forall X \in X, \forall$$

This indicates that x* is certainly a desirable solution. Unfortunately, this is a utopian situation that rarely exists, as it is unlikely that all f1(x) will have minimum values for X at a common point (x*). The question is left: What solution should be used? That is, how should an "optimal" solution be defined? First, consider the so-called ideal (utopian) solution. In order to define this solution, separately attainable minima must be found for all objective functions. Assuming there is one, let x'1 be the solution of the scalar optimization problem:

$$\min_{x \in X} f_i(X) = f_i^*$$

Here f_1' is called the individual minimum for the scalar problem i; the vector $f^* = (f_i^*, \ldots, f_k^*)i$ is called ideal for a multi-objective optimization problem; and the points in X which determined this vector is the ideal solution.
It is usually not true that below equation holds, although it would be useful, as the multi-objective problem would have been solved by considering a sequence for scalar problems. It is necessary to define a new form of optimality, which leads to the concept of Pareto Optimality. Introduced by V. Pareto in 1896, it is still the most important part of multi-objective optimization.

$$f^* = (f_i^*, \ldots, f_k^*)i$$

A point x'ϵ X is said to be Pareto Optimal for the problem if there is no other vector xϵX such that for all i = 1, ..., k,

$$f_i(X) \leq f_i(X^*)$$

and, for at least one i ϵ {1, ..., k}: $f_i(X) < f_i(X^*)$

This definition is based on the intuitive conviction that the point x* ϵ X is chosen as the optimal if no criterion can be improved without worsening at least one other criterion. Unfortunately, the Pareto optimum almost always gives not a single solution, but a set of solutions. Usually Pareto optimality is spoken of as being global or local depending on the neighborhood of the solutions X, and in this case, almost all traditional algorithms can at best guarantee a local Pareto optimality. However, this MOGA-based system, which incorporates global Pareto filters, yields the global Pareto front.

2. MOGA

The MOGA is a hybrid variant of the popular NSGA-II (Non-dominated Sorted Genetic Algorithm-II) based on controlled elitism concepts. Currently, only continuous problems can be solved. The Pareto ranking scheme is done by a fast, non-dominated sorting method that is an order of magnitude faster than traditional Pareto ranking methods.
The multi-objective genetic algorithm is used to solve multi-objective optimization problems by identifying the Pareto front—the set of evenly distributed non-dominated optimal solutions.
This also ensures that the feasible solutions are always ranked higher than the infeasible solutions. The objective of the NSGA algorithm is to

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improve the adaptive fit of a population of candidate solutions to a Pareto front constrained by a set of objective functions. The algorithm uses an evolutionary process with surrogates for evolutionary operators including selection, genetic crossover, and genetic mutation. The population is sorted into a hierarchy of sub-populations based on the ordering of Pareto dominance. Similarity between members of each sub-group is evaluated on the Pareto front, and the resulting groups and similarity measures are used to promote a diverse front of non-dominated solutions.

IV. OPTIMIZATION PROCESS FOR CRANE HOOK

The crane hook which, we want to change is the existing one, which were used for the material handling purpose for various products. Now we want to make a suitable optimization process for redesign the crane hook to carry the load of 6000N. At this condition the previous crane hook was failing, so we wants a crane hook design which sustain the load of 6000N and the mass should be minimized and one of most enviable property is that the design should be manufacturable. The hook should be strong enough so as to resist scattering of the load and unavoidable variations of its dimensions (manufacturing variations). The schematic diagram of the existing crane hook is shown in the figure 3.

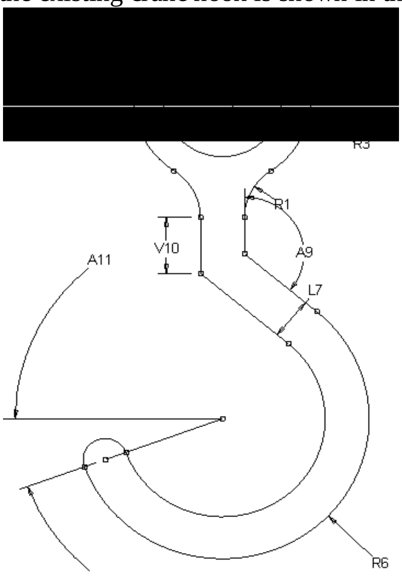

Fig.3 Schematic diagram

The crane hook is made of structural steel and the material is same for the creation of the new design of the crane hook. Now the boundary conditions are the hook is mounted through the 'eye' of the hook. The cylindrical support applied to restrict radial and axial motion of the crane hook. A 6000N load is applied downward on the inside surface of the hook. This has to be lifted by the crane hook in the future. The result of the initial finite element analysis (Static Structural analysis) for the crane hook, with the given conditions shows when the 6000N load is applied on the existing crane hook design and the hook failed to lift the load. The minimum safety factor value is 0.54, indicating a failing design (yield stress is exceeded). In this stage the weight of the crane hook is 752gms.

Input Parameters: Input or shape parameters are those parameters that define the geometry for the analysis. Input Parameters have predefined ranges that may be changed. These include CAD parameters and Simulation parameters. Here we have taken the input variables as, thickness of the hook (P1), the depth of the hook (P2), the lower radius (P3), and the hook angle (P4).

Initial values are:

Thickness P1 = 15mm Depth P2 = 20mm

Lower radius P3 = 50mm Hook angle P4 = 130°

Response Parameters: Response Parameters are those parameters which representing the outputs (responses) from the analysis. In this paper it is taken as mass (P5) and safety factor (P6).

The initial values of output parameters are:

Mass P5 = 0.752kg Safety factor P6 = 0.54

The first thing to the optimization process is the creation of the solid model of the crane hook. The crane hook is made of structural steel material, and cad model is created with the existing parameters. The structural steel properties are given as: Density 7850kg m-3, tensile yield strength 2.5e8pa, Compressive yield strength 2.5e8pa, and tensile ultimate strength 4.8e8pa. When the 6000N load is applied on the existing crane hook design and the hook failed to lift the load. The initial analysis shows that the minimum safety factor value is 0.54, indicating a failing design (yield stress is exceeded). In this stage the weight of the crane hook is 752gms. The optimal values of the design variables in crane hook are acquired by using the ANN and MOGA. At the beginning, the sampling points are calculated by considering the upper/lower bounds of design variables and they are used for optimization. With the help of the upper and lower limits of the input parameters the sampling points are created with the help of design of experiments as the Central composite design method.

i: Design of experiment (central composite design)

S.no	P1	P2	P3	P4	P5	P6
1	20.000	20.000	50.000	132.500	0.897	0.981
2	15.000	20.000	50.000	132.500	0.756	0.546
3	25.000	20.000	50.000	132.500	1.018	1.496
4	20.000	15.000	50.000	132.500	0.664	0.701
5	20.000	25.000	50.000	132.500	1.129	1.245
6	20.000	20.000	45.000	132.500	0.828	1.075
7	20.000	20.000	55.000	132.500	0.966	0.889
8	20.000	20.000	50.000	115.000	0.872	0.975
9	20.000	20.000	50.000	150.000	0.964	0.974
10	16.479	16.479	46.479	120.176	0.609	0.569
11	23.521	16.479	46.479	120.176	0.741	1.128
12	16.479	23.521	46.479	120.176	0.883	0.852
13	23.521	23.521	46.479	120.176	1.070	1.688
14	16.479	16.479	53.521	120.176	0.672	0.495
15	23.521	16.479	53.521	120.176	0.832	1.019
16	16.479	23.521	53.521	120.176	0.974	0.741
17	23.521	23.521	53.521	120.176	1.202	1.504
18	16.479	16.479	46.479	144.824	0.645	0.567
19	23.521	16.479	46.479	144.824	0.792	1.150
20	16.479	23.521	46.479	144.824	0.935	0.849

21	23.521	23.521	46.479	144.824	1.144	1.684

S.no	P1	P2	P3	P4	P5	P6
22	16.479	16.479	53.521	144.824	0.714	0.498
23	23.521	16.479	53.521	144.824	0.892	1.009
24	16.479	23.521	53.521	144.824	1.034	0.746
25	23.521	23.521	53.521	144.824	1.288	1.503

On the basis of the sampling data the parameters parallel charts are shown below:

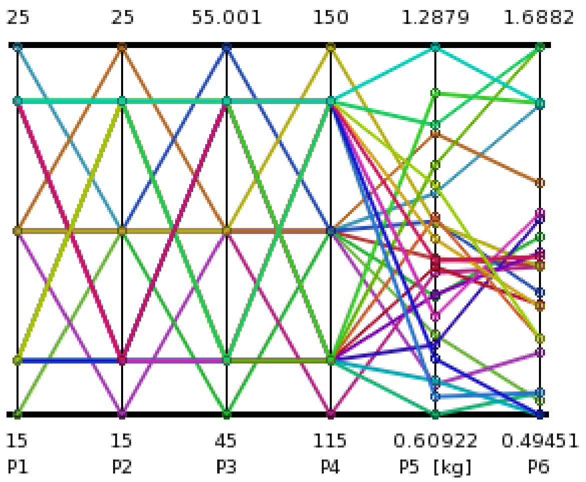

Fig.5 Parameter Parallel chart

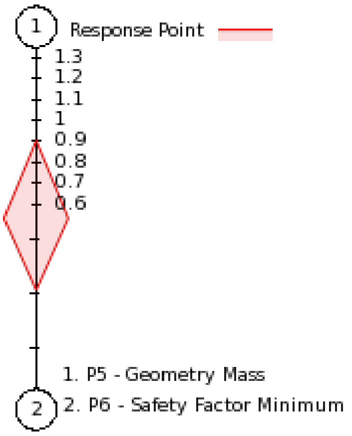

Fig.6 Spider chart

On the basis of the DOE data the Response Surface are created with the help of ANN tool. For ANN Meta model 10 cells are selected for generation of response surface. The Min-Max search table is created to know the minimum and the maximum value of the various output parameters.

ii: Min-Max Search

Output Parameter Minimums						
Name	P1	P2	P3	P4	P5	P6
P5	15	15	45	135.8	0.524	0.490
P6	15	15	55	137.8	0.614	0.306
Output Parameter Maximums						
P5	25	25	55	144.86	1.333	1.62
P6	25	25	45	125.66	1.129	1.872

From table 2, we can read that the safety factor ranges from 0.306 to 1.872 and the mass from 524grams to 1333 grams. This indicates a pretty wide variation for both parameters.

We need to further investigate to find interesting design points. Response surfaces for factor of safety Vs input parameter are shown in figure 7 and 8.

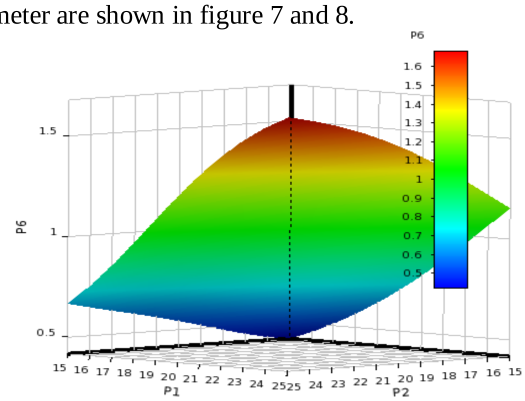

Fig.7 Response chart for thickness Vs Depth

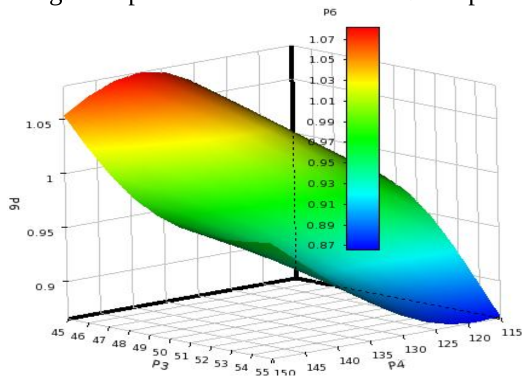

Fig.8 Response chart for Lower radius Vs angle

Response surfaces for Mass of geometry (P5) Vs input parameter are shown in figure 9 and 10.

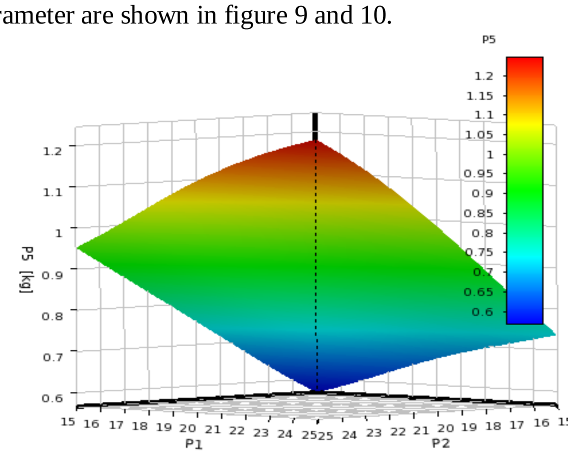

Fig.9 Response chart for thickness Vs Depth

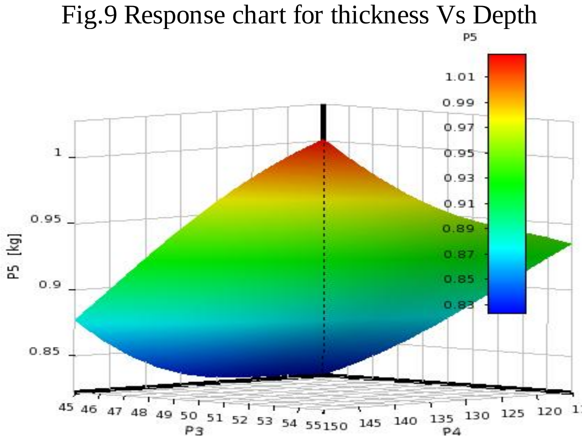

Fig.10 Response chart for Lower radius Vs angle

Here, we see that the safety factor is mostly influenced by the thickness and depth of the hook, and then by the lower radius and angle has no

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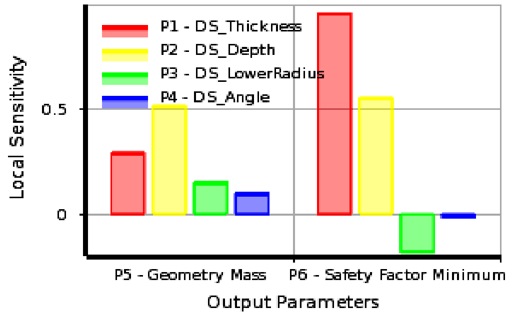
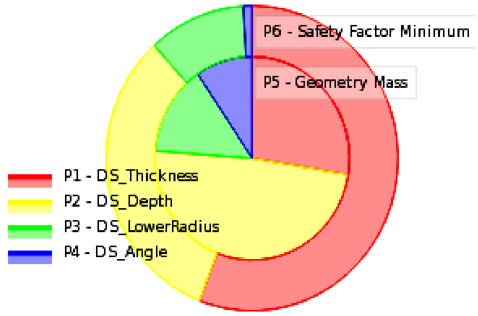
effect on it. Thickness or depth increase will increase the safety factor, while the radius will lower it. The parameter sensitivity for the output functions are shown in figure below. The mass is influenced by all parameters –any increase of the parameters increases the mass.



(a.) Bar Chart



(b.) Pie chart

Fig.11 Local sensitivity of input parameter vs. output parameter

Now after checking all the parameters from the Response surface of ANN, we have to optimize the ANN response surface with the help of MOGA optimization technique.

Optimization Method	MOGA
Number of Initial Samples	100
Number of Samples per Iteration	100
Maximum Allowable Pareto percentage	70
Maximum number of Iterations	20
Size of Generated sample set	100

From the above shown optimization method configuration, the various candidate points are created. The goal has been set as the mass has to minimize and the factor of safety has to be around 1.1. For satisfying these conditions MOGA generates the various candidate points. Then, for confirming the candidate points verification has been done, which is shown in the figure 12.

According to the MOGA verification point the candidate A is the suitable candidate, which satisfies the goal. A trade off plot is a representation of the sample set we used for the goal driven optimization. From the trade off chart we come to know that which point is feasible.

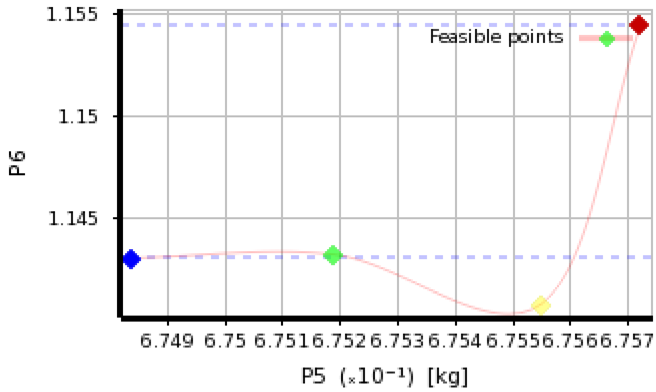


Fig.13 trade off chart

The values given for candidate A may not represent a design that can be manufactured. We have to use the values of the dimensions to something that can be manufactured.

V. RESULTS AND DISCUSSION

From the above suggested methodology, the analysis has been performed and the Artificial Neural Network Meta model is created with 10 cells, which is further optimized by Multi Objective Genetic Algorithm. The results of the method are given below.

iii: Design iterations output

	P1	P2	P3	P4	P5 (kg.)	P6
Initial design	15	20	50	130	0.75244	0.54
New design	24	15	45	127	0.66916	1.10

From the above table and the figure shown, we compare the new design and the one we started with, we have raised the safety factor from .54 to 1.1 and the mass has been reduced from 752 grams to 669 grams (-11%). Now after performing this analysis we comes to know that the implementation of Multi Objective Genetic Algorithm on Response surface Artificial Neural Network Meta model gives the more optimized results. This simple, yet realistic, engineering example of the design of an crane hook has been utilized to demonstrate the use of Multi Objective Genetic Algorithm on Response surface Artificial Neural Network Meta models as an alternative approximation technique for multidisciplinary design optimization.

Candidate Points	P1	P2	P3	P4	P5	P6
Candidate A	24.261	15.109	45.038	126.96	0.67484	1.143
Verification A					0.67841	1.1183
Candidate B	24.65	15.12	45.092	128.62	0.67776	1.1928
Verification B					0.68741	1.1459
Candidate C	23.583	15.031	46.164	137.91	0.67975	1.1098
Verification C					0.69708	× 1.0351

Fig.12 MOGA candidate point verification

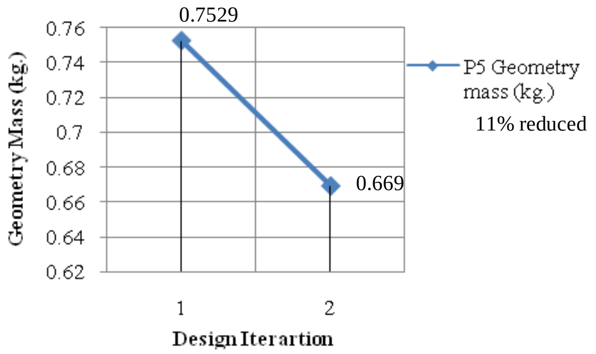


Fig.14 geometry mass reduction in design

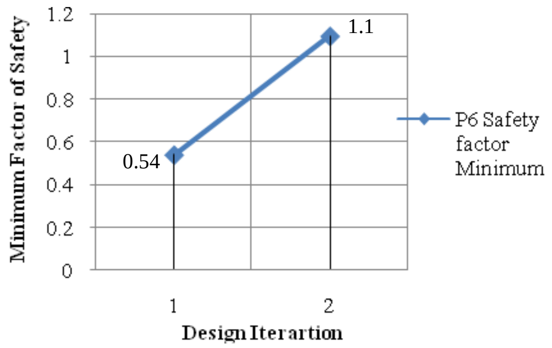


Fig.15 safety factor changes in design

From the above table and the figure shown, we compare the new design and the one we started with, we have raised the safety factor from .54 to 1.1 and the mass has been reduced from 752 grams to 669 grams (-11%). Now after performing this analysis we comes to know that the implementation of Multi Objective Genetic Algorithm on Response surface Artificial Neural Network Meta model gives the more optimized results. This simple, yet realistic, engineering example of the design of an crane hook has been utilized to demonstrate the use of Multi Objective Genetic Algorithm on Response surface Artificial Neural Network Meta models as an alternative approximation technique for multidisciplinary design optimization.

VI. CONCLUSIONS

This paper proposes a method for the optimization of multi-response. The approach considers a artificial neural network for every response function to calculate its relation with control functions, unrestrained objective functions to combine diverse responses into single, and a multi objective genetic algorithm (MOGA) to perform the multi disciplinary optimization. The projected method is novel because of three things. First, it utilizes design of experiment with central composite design method. Second, it usage artificial neural networks to calculate the responses for every parameter with respect to the output function. Finally, it utilizes the multi objective genetic algorithm for optimize the responses created with artificial neural networks. This has been shown with the help of the crane hook example through which the shape responses are estimated for the mass and the factor of safety. Especially, the projected optimization method only involves estimating outcome of the responses. Therefore, one can extend the proposed method to include the more number of parameters for the responses. In this condition, manufacturable constraints are needed to estimate the different responses at various settings of the control factors.

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