Multi-Objective Optimisation of Rolling Rod Product Design using Meta-Modelling Approach

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Abstract

Traditional solution methods such as search and sort for optimising complex real life engineering problems can be very expensive in terms of computational time. The considerable execution time tends to inhibit elaborate exploration of the design space and often results to sub-optimal solutions. This paper reports on an engineering optimisation approach designed to bridge the gap between traditional solution methods in the industry and state-of-the-art techniques from the research community. A modelling and optimisation technique has been developed using Design of Experiment (DoE) and meta-modelling approach to approximate expensive finite element (FE) runs. An evolutionary computational technique (NSGAII) is used for solving the optimisation problem. This solution technique was applied for multi-objective optimisation of a rod rolling design problem. The results showed NSGAII converge to the Pareto optimal front. The multiple optimal solutions help the designer in delivering a variety of optimal designs.

1 INTRODUCTION

Finite element analysis (FEA) and genetic algorithm (GA) often used as an integrated optimisation process paradigm is an increasingly important component of engineering research and product development. Finite element solver is used as the fitness function within GA in order to exploit GA's global searching capability and the modelling strength of the FE solvers. Since GA requires a large number of function evaluations, it follows that large number FE runs are also required. This can be computationally expensive for solving complex engineering problems.

In rod rolling design optimisation problems, conventional methods such as search and sort are often used to solve complex optimisation problems. This approach relies on the use of the analyst's qualitative knowledge to explore the design space (Roy, 1997; Oduguwa and Roy, 2001). Expensive FE analyses are often invoked repeatedly during the process making multi-objective optimisation and concept exploration time consuming. This search method can inhibit elaborate exploration of the design space and often results to sub-optimal solutions. The use of evolutionary multi-objective optimisation techniques for improving the search for this class of real life engineering problems is proposed in this paper. Even though this approach can be an improvement from the conventional method, literature reveals that integrating FE and GA incurs quite an expensive computational cost.

Cerrolaza and Annicchiarico, (1999) solved a bi-dimensional shape optimisation problem using GA and FEA as the fitness function. In the test results presented in their paper, the optimisation process stopped after 5000 FE evaluations and took about 150 minutes. If the same number of evaluations were used in rod rolling optimisation problem (such as the case presented in this paper, where one FE run last about 17 minutes) the process would be completed after 52 days. Clearly this time scale is not acceptable for engineering applications.

Statistical meta-modelling approach is proposed to address expensive FE runs in the context of multi-objective optimisation for rod rolling problems. Statistical techniques are becoming widely used in engineering design to construct approximations of meta-models- 'a model of a model' of these analysis codes; these serve as surrogate models of the analysis codes (Myers and Montgomery, 1995; Kleijnen and Sargent, 2000). An evolutionary multi-objective optimisation technique is also proposed as above, for improving the search for this class of real life engineering problem.

This paper reports on the application of design of experiment (DoE) to create meta-models for FE models and evolutionary computational techniques (NSGAII) for the multi-objective optimisation of a rod rolling design problem.

The remainder of the paper is organised as follows. Section 2 states the formal definition on multi-objective optimisation. Section 3 reviews the literature on approaches to address the computational cost of FE runs and also the recent multi-objective techniques. Section 4 presents the rod rolling design problem. Section 5 covers the meta-modelling approach consisting of 6 main steps. Section 6 and 7 presents the application of the meta-modelling approach to the rod rolling design problem. Section 8 contains future research activities and finally, section 9 concludes.

2 MULTI-OBJECTIVE OPTIMISATION

Most real world problems are characterised by several non-commensurable, conflicting objectives. Multi-objective optimisation seeks to minimise the n components $f(x) = (f_1(x), \ldots, f_n(x))$, of a possibly non-linear vector function f of a decision variable x in the search space. Each of these objectives has a different optimal solution. There is no unique, (Utopian) solution to a multi-objective problem but a set of non-dominated solutions referred to as Pareto-optimal set. A solution to this class of problem is Pareto-optimal if from a point in the design space, the value of any other solution cannot be improved without deteriorating at least one of the others. The objective for a complex multi-objective optimisation problem is to find different solutions close and well distributed on the true Pareto-optimal front. The conditions for a solution to become dominated with respect to another solution are described as follows.

For a problem having more than one objective function (say, f_j, where $j = 1, \ldots., M$ and $M > 1$), A solution $x^{(1)}$ is said to dominate solution $x^{(2)}$ if the following conditions are satisfied:

a) The solution $f_j(x^{(1)})$ is no worse than $f_j(x^{(2)})$ for all $j = 1, 2, \ldots., M$ objectives.

b) The solution $x^{(1)}$ is strictly better than $x^{(2)}$ in at least one objective.

3 LITERATURE REVIEW

In this section, related research in optimisation for solving real life problems is reviewed, with focus on the solution approaches to address the expensive computational cost of large FE runs. Recent solution techniques on multi-objective optimisation are also reviewed.

3.1 FEA AND GA COMPUTATIONAL COST

There are several approaches proposed to address computational cost of large FE runs. Deb and Gulati, (2001) in their work on design of truss-structures, introduced the concept of basic and non-basic node to emphasise creation of user-satisfactory trusses and reduce computational time by avoiding expensive FEA for unsatisfactory trusses. Quagliarella and Vicini, (2001) proposed a hierarchical approach for the fitness evaluation. This involves using several solvers with different levels accuracy, in order to use the more computationally expensive models only when needed. These approaches can be regarded as “good house keeping measures” that improves on the computational expense of large FE runs, however they fall short of alleviating the problem in the context that makes them applicable to complex real life problems. A second classification is the solution approximation approach. This occurs when numerical solution of the FE solver is approximated, using different techniques. Chen and Lin (2000) in optimisation of design space topology used artificial neural network as an approximation to replace the structural analyses of the FE. Although this gives quick results, the approach still requires substantial data to train and validate the neural network Chen, (2001) applied design of experiment to approximate FE analysis and created a response surface for single objective optimisation of impact structure and crashworthiness problem. The author used classical full factorial experimental designs. This is considered expensive. Sacks et al, (1989) argued that since deterministic computer experiment lacks random error, classical experimental designs are not suitable for sampling them. This implies that computer experiments can be run with less sample points. Greiner et. al. (2001) also reported, using least square approximation for FE runs in optimising frame structures. Approximate models even though are not as accuracy as the actual numerical solutions, can give a reasonable representation of the design landscape, and speed up the search procedure. They can achieve significant savings in computational cost and can be used for solving complex real-life optimisation problems.

3.2 MULTI-OBJECTIVE METHODS

The challenge facing most solution methods is to ensure convergence of well-dispersed solutions close to the true optimal front. Some of the most recent evolutionary search algorithms for multi-objective optimisations are reviewed as follows.

3.2.1 Strength Pareto Evolutionary Algorithm (SPEA)

SPEA is an elitist evolutionary algorithm (Zitzler and Thiele, 1998). The algorithm maintains an external population for storing elite solutions from beginning of the initial population. At each generation, the external and current population is combined and fitness assigned. All non-dominated solutions are assigned fitness equal to the number of solutions they dominate and dominated solutions are assigned fitness worse than the worst solution of any non-dominated solution. Clustering technique is used to maintain diversity.

3.2.2 Pareto-Archived Evolutionary Strategy (PAES)

PAES is a multi-objective evolutionary algorithm (Knowles, Watson, et al., 2000) based on evolutionary strategy. Deb et al (2000) described PAES with one parent and one child. Both are compared, and if the child dominates the parent, it becomes the new parent and the iteration continues. If the parent dominates the child, the child is discarded and a new child created by mutation. However if either of them dominates each other the choice is made by comparing them with the archived best solutions found so far. If the child dominates any member of the archive, it becomes the new parent and the dominated solution eliminated from the archive. If the child does not dominate any member of the archive, both parent and child are compared for their proximity, with archive solutions. If the child resides in the least crowded region in the parameter space among the archived member it becomes the parent and a copy added to the archive.

3.2.3 Elitist Non-Dominated Sorting Genetic Algorithm (NSGAII)

NSGAII(Deb, Agrawal et al., 2000) is a fast elitist solution algorithm that uses explicit–preservation strategy to maintain diversity among solutions in the non-dominated front. In the elitist strategy, the population is sorted into different non-domination levels and each solution assigned a fitness equal to its non-domination level (where 1 is the best level). Binary tournament selection, crossover and mutation operators are used to create offspring population. Other features of the algorithm include crowding distance assignment procedure (for estimating the distance between two points in the solution space) and the crowded tournament selection operator (guides the selection process towards a uniformly dispersed Pareto-optimal front). The algorithm has been shown to demonstrate better performance than most of other contemporary algorithms (Deb, Agrawal et al., 2000). NSGAII can generate some non-Pareto-optimal solutions if the first non-dominated set is larger than the population (Deb, 2001). This problem was experienced in the current study. It is referred to as "generational elitist problem".

3.2.4 Generalised Regression GA (GRGA)

GRGA is one of the most recent multi-objective GA developed by Tiwari et. al (2001) to handle complex multi-objective optimisation problems having high degrees of inseparable function interaction. An interaction occurs when the effect a variable has on the objective function depends on the values of other variables in the function. The author suggests in his paper that "inseparable function interaction in objective functions may augment one or more of the following features that obstruct convergence to the true (or global) Pareto-optimal front", multi-modality, deception, collateral noise and isolated optimum. GRGA works by attaching a non-linear multi-variable regression analysis module to other optimisation algorithm. The author used NSGAII in their paper, but other optimisation algorithm can be used. The algorithm use regression coefficient to guide the search towards the Pareto front and determine termination conditions for the algorithm. One of the main advantages of this algorithm is that it can be used with different multi-objective solution algorithm. GRGA demonstrates better performance than NSGAII in solving the inseparable function interaction problem present in most complex multi-objective optimisation problems. See (Tiwari, Roy et al., 2001) for more details.

4 ROD ROLLING DESIGN PROBLEM

The Rod rolling process considered is a continuous manufacturing process whereby a square billet (dimension ranging from 100mm to 150mm) referred to as the stock is deformed into a rod size ranging between 5mm to 12mm. The rolling operation is a high speed, high production process in which a pair of rolls rotates at the same peripheral speed in opposite directions. The stock is continuously deformed by passing it through a series of high rolling mill stands. During the rolling process, the stock undergoes changes in the mechanical and thermal characteristics and after final cooling the metallurgical properties. Design of the rolling system involves consideration of the mechanical, thermal and thermo-mechanical behaviour of the process (Sun, Yun , et al., 1998), and the optimisation of roll pass design (Farrugia, 2000). Modelling of the rolling process is used to predict mill parameters (roll separating force, torque) and deformation characteristics such as the lateral spread and the evolution of metallurgical properties. These predictions were obtained using design variables related to the rolls and stock such as geometrical and material characteristics: temperature, friction etc.

Ovality in rod rolling is a geometrical property defined as the percentage difference between the stock height and the width. Ovality is considered important because it helps in forming the rod during rolling process, however it is not desirable in the end product. In this study a different definition of ovality is adopted. Ovality is defined as the difference between the maximum and minimum radial distance of the rod profile. This definition is chosen to mimic its application in the plant. In this work, ovality and the load required for rod deformation is modelled using a meta-modelling technique, and the minimisation of both responses is treated as a multi-objective problem. The problem is considered multi-objective in nature because ovality tends to vary inversely with load. In practice a minimum rod ovality condition requires high contact of the stock with the roll, which results in high loads.

5 META-MODELLING

A meta-model is defined as a model of an underlying simulation model (Kleijnen, 1975; Friedman, 1996). It is an approximation of the simulation program's input/output transformation referred to as a response surface. A typical meta-model approach is the design of experiment (DoE) using regression analysis, also known as analysis of variance (ANOVA). DoE involves making several designs at once and investigating the joint effects of these changes on a response variable. Meta-models offer the following benefits: (1) Insight into the relationship between output responses y, and the input design variables, x. (2) Fast analysis tools for optimisation and design space exploration since the surrogate models are used in lieu of the expensive computer, and (3) the integration of discipline dependent analysis codes.

The basic meta-model framework adopted in this research is shown in figure 1. A brief discussion of some of the main steps is given below.

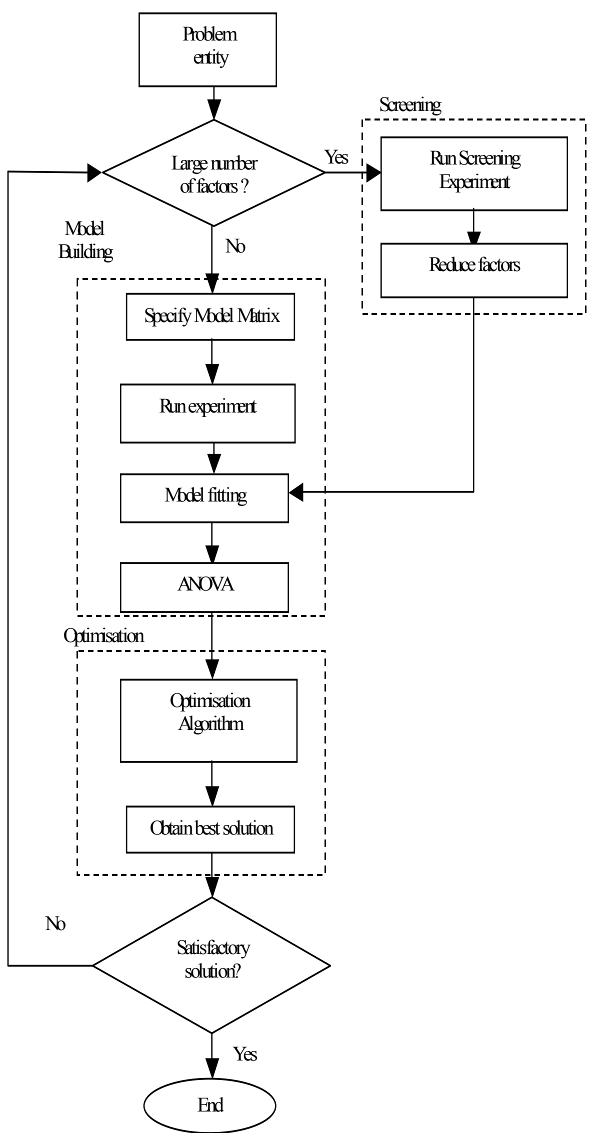


Figure 1: Meta-model approach

Step 1: Problem formulation

This is the first stage of the simulation effort where the problem is defined. The aim at this stage is to understand the nature of the problem, and to define the experimental region (Zeigler, 1976). This is achieved by identifying the candidate parameters and the boundaries that characterise the design space. Existing knowledge is required to identify all the possible parameters involved in the problem space. The output of this stage is a list of inputs and responses with their respective range.

Step 2: Definition of Objective

Defining the objective indicates the question to be answered by the simulation study. The options available in this methodology are screening and optimisation. Screening is based on the '*principle of parsimony'* or *Occam's razor*(Banks, 1998). The aim is to derive a short list of the most important factors from a large number of potentially important factors. In optimisation, the meta-model can be used to determine the set of problem entity input values that optimises a specific objective function.

Step 3: Specification of model matrix

Model matrix implies the type of DoE design (for example 2^{k-p}). The choice of design type is dependent on the objective and the number of factors. This decision is simplified by using existing designs.

Step 4: Fitting meta-model

The simulation run (is define as a single path with fixed values for all its inputs and parameters) is performed to obtain the input and output. This data set is used to estimate the parameter values of the meta-model using least squares. Typically a regression meta-model belongs to one of the following three classes:

Main effects model: (a first-order polynomial):

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k$$

Main effects + interaction effects (a first-order polynomial augmented with two factor interactions)

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_k x_k + \beta_{12} x_1 x_2 + \ldots + \beta_{k-1,k} x_{k-1} x_k$$

Quadratic model with quantitative factors (a second-order polynomial, which includes purely quadratic effects)

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \beta_{12} x_1 x_2 + \ldots + \beta_{k-1,k} x_{k-1} x_k + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \ldots + \beta_{kk} x_k^2$$

Step 5: Validation

The data set is validated by carrying out the statistical tests using the Analysis of Variance (ANOVA) table. This tests the hypothesis that each parameter significantly influences the response.

Step 6: Post-processing

Post-processing implies the interpretation and display of the results. The following are options available for displaying the results: Main effect plot, interaction plot, and half normal probability plot (Daniel plot).

6 APPLICATION OF META-MODELLING APPROACH FOR THE ROD ROLLING DESIGN PROBLEM

6.1 EXPERIMENTAL METHOD

The example described in this paper deals with the multi-objective optimisation (load and load) of oval to round pass. The factors affecting ovality in the rod rolling process can be categorised as; (a) geometrical parameters such as height, width, roll gap, roll radius. (b) Related metallurgical parameters such as strain values, stress components and bulk temperature, (c) process parameters such as friction, roll speed etc. The independent variables especially relevant to the present ovality simulation are height (he), width (w), roll gap (rg), arc radius, roll radius, rolling speed and the bulk temperature. It is important to understand the overall effects and interactions of these parameters on ovality. Roll designers can use this knowledge to design the optimum required ovality that satisfies the conflicting objectives of the process plant (e.g. minimum load) and the product specification (e.g. minimum ovality).

Existing knowledge was used to define region of interest, 5 variables were identified and their operating range specified. A two level fractional factorial DoE augmented with centre points (to test for curvature) was applied to the design problem. The meta-modelling approach was applied as described below:

Table 1:Factors and factor levels used in simulations

Level	Factors				
	Width (W)	Roll Gap (Rg)	Arc Radius (Ar)	Pass Depth (Pd)	Angle (Ar)
1	18	4	66	20	30
-1	16	2	64	18	28.5

Step 1: Fractional factorial (DoE) design

A low cost resolution V design for a two-level 5 factor, fractional factorial design is shown in Table 2. This was augmented with one centre point to test for curvature. Each factor was run at two levels. Resolution V designs are types of designs where no main effect or two-factor interaction is aliased with any other main effect or two factor-interactions (Montgomery, 1997).

FEA simulations were performed using the set-up in Table 2 and the settings in Table 3 as the input value for the FE runs. For each run, values of the measured ovality (O_v) and load (L) were recorded as shown in Table 3.

Table 2:A 2^{5-1} Design

Run	A	B	C	D	E
1	-1	-1	-1	-1	1
2	1	-1	-1	-1	-1
3	-1	1	-1	-1	-1
4	1	1	-1	-1	1
5	-1	-1	1	-1	-1
6	1	-1	1	-1	1
7	-1	1	1	-1	1
8	1	1	1	-1	-1
9	-1	-1	-1	1	-1
10	1	-1	-1	1	1
11	-1	1	-1	1	1
12	1	1	-1	1	-1
13	-1	-1	1	1	1
14	1	-1	1	1	-1
15	-1	1	1	1	-1
16	1	1	1	1	1
17	0	0	0	0	0

Table 3:Input settings and response values from simulation study

Run	W (A)	Rg (B)	Ar (C)	Pd (D)	An (E)	Ov	L
1	16	2	64	18	30	1.17	238.5
2	18	2	64	18	28.5	4.69	299.5
3	16	4	64	18	28.5	3.17	178.0
4	18	4	64	18	30	1.15	232.0
5	16	2	66	18	28.5	1.28	241.0
6	18	2	66	18	30	4.6	293.0
7	16	4	66	18	30	3.2	167.0
8	18	4	66	18	28.5	1.24	226.3
9	16	2	64	20	28.5	3.17	169.3
10	18	2	64	20	30	1.15	222.8
11	16	4	64	20	30	6.55	129.7
12	18	4	64	20	28.5	3.93	159.1
13	16	2	66	20	30	3.22	171.4
14	18	2	66	20	28.5	1.25	233.5
15	16	4	66	20	28.5	6.52	122.2
16	18	4	66	20	30	3.99	154.4
17	17	3	65	19	29.2	1.74	217.3

Step 2: Model Fitting

Regression models of both responses are generated by fitting the model types shown in section 5 step 4 (main effects and interaction effects). The fit with the lowest sum of squares error (highest R^2) was selected, this resulted in the following experimental model as predicted using ANOVA for ovality (O_v) and load (L) as functions of the inputs,

$$f(x_{Ov}) = 3.06 - 0.3925x_1 + 0.5762x_2 + 0.02x_3 + 0.58x_4 - 0.0138x_5 - 0.75x_1x_2 - 0.75x_1x_4 + 0.95x_2x_4 + 0.0175x_2x_5 + 0.604\,x_3x_5 + 0.019x_4x_5 \quad (1)$$

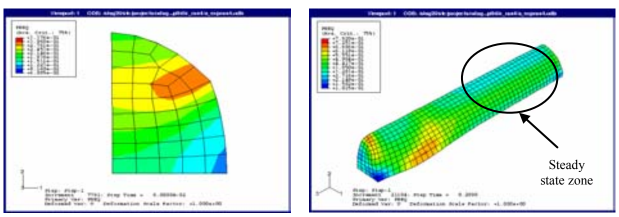
$f(x_L) = 203.28 + 25.21x_1 - 31.29x_2 - 1.25x_3 - 32.05x_4 - 1.25x_5 - 3.35x_1x_2 - 3.07x_1x_4 - 0.77x_1x_5 - 2.36x_2x_3 + 2.32x_2x_4 + 0.95x_2x_5 + 1.33x_3x_4 - 3.4x_3x_5$ (2)

With the inputs expressed in coded [-1,1] units (useful for comparing experimental models). The input was also expressed in engineering units as shown in equation 3 and 4. This can be useful for engineering decision making.

$O_v = 1314.263 + 16.1W - 4.7R_g - 23.53A_r + 9.75P_d - 52.82A_n - 0.75WR_g - 0.75WP_d + 0.95R_gP_d + 0.805A_rA_n + 0.025P_dA_n$ (3)

$L = -8246.94 + 123.7W + 97.74R_g + 113A_r - 73P_d + 306.1A_n - 3.35WR_g - 3.1WP_d - 1.03WA_n - 2.36R_g A_r + 2.32R_gP_d + 1.27R_gA_n + 1.33 A_r P_d - 4.52A_rA_n$ (4)

This model was used to perform the multi-objective optimisation problem.



(a) (b)

Figure 2: Finite Element contour plots of rod profile (a) Transverse section (b) Full view showing SS zone

Table 4: Parameters used in simulation study

Geometrical parameters		Material specification
Height	30.6 mm	0.08% Carbon steel C 0.087, Si 0.003, Mn 0.34, P 0.025 S 0.02. Hot rolled and annealed Suzuki (4.22)
Roll Radius	250 mm	
Pass Radius	20 mm	
Width (W)	Factor	
Roll Gap (Rg)	Factor	
Arc Radius (Ar)	Factor	
Pass Depth (Pd)	Factor	Process Parameters
Arc Angle (An)	Factor	
Ovality (O_v)	Response	Temperature: 1000 º C
Load (L)	Response	Roll Speed: 1000 m/s

6.2 Process conditions used in experiment

The choice of geometrical parameters and material properties is discussed in this section. The choice of parameters was driven by the need to mimic the real design problem experienced on the plant in the study. The results obtained can then be validated using existing domain knowledge.

Geometrical parameters:

Expert domain knowledge was used to select the geometrical parameters and the region of interest defined according to the ranges shown in Table 1. These five factors are varied in the simulation runs. Other parameters such as height roll radius and pass radius are kept constant to make the simulations comparable. A summary of these geometrical parameters is shown in Table 4.

Material specification

The material specification used in the study is shown in Table 4. The specification was identical for all runs.

Process parameters

The same loading conditions were applied in all the simulations so that the response could be obtained under similar conditions.

Finite Element Analysis and Data Extraction

The finite element runs were performed using Abaqus version 6.2.2. The mesh was generated using Patran software. A contour plot of PEEQ (equivalent plastic strain) for a typical run is shown in figure 2a. Results showing the deformation characteristics are taken in the steady state (SS) zone of the rod. The SS is defined as the region where the deformation characteristics is assumed to be uniform. This zone is identified by using a qualitative judgement to identify region along the rod (figure 2b) where the contour profiles are parallel.

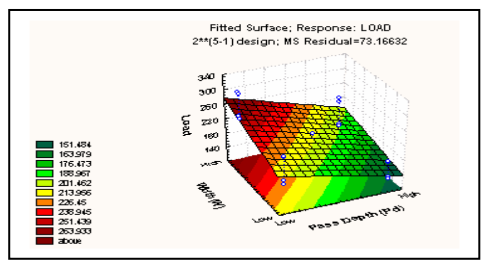


Figure 3: Interaction effects on Ovality Response

6.3 MULTI-OBJECTIVE OPTIMISATION OF ROD DESIGN PROBLEM USING NSGAII

NSGAII (Deb, Agrawal, et al., 2000) was considered suitable for optimising the response function described in section 6.1. (Equations 3 and 4). This is because NSGAII has been shown to perform well on equations with low-level inseparable function interaction (Deb, 2001). If the model were developed with higher order interaction terms, then GRGA would have being used. The models shown in section 6.1 (equations 3 and 4) were used as the fitness function in NSGAII. The parameters were represented using binary coding. The crowded tournament selector operator was used to select new offsprings. The experiment was run with a population of size 100 for 1000 generation with a crossover probability of 0.8 and a mutation probability of 0.05.

7 DISCUSSION AND RESULTS

7.1 METAMODELS

The response ovality and load from the simulation results were recorded as shown in Table 3 and the data used to perform the ANOVA shown in Table 5. The result suggests that for the ovality response, the most significant terms are A (W), B (Rg), D (Pd), AB, AD, BD and CE. The sum of square of these terms accounts for over 96% of the total variability in the response. Figure 3 shows interaction effect plots of pass depth and roll gap. These response surface have been generated whilst the third variable has been held constant. This plot indicates that pass depth has a much stronger effect on ovality when the roll gap is at high level. For minimum ovality, the roll gap should be at the low level and pass depth at high level. For the load response, factors A, B and D show the most significant effect on the load response. These three factors explain 98% of the variation in the load. Interaction effect of pass depth and width is plotted in figure 4. Again the plot indicates that pass depth has a much stronger effect on ovality where minimum ovality occurs at high pass depth level and low width level.

Table 5: Analysis of Variance (ANOVA) associated with regression model in equations 3 and 4

Ovality			Load		
Term	DoF	SSq	Term	DoF	SSq
A (W)	1	2.465	A (W)	1	10175.9
B (Rg)	1	5.313	B (Rg)	1	15664.4
C (Ar)	1	0.0064	C (Ar)	1	25.0
D (Pd)	1	5.382	D (Pd)	1	16432.0
E (An)	1	0.003	E (An)	1	24.9
AB	1	8.97	AB	1	179.1
AD	1	9.0	AD	1	151.2
BD	1	14.4	AE	1	9.5
AE	1	0.005	BC	1	89.0
CE	1	5.832	BD	1	86.4
DE	1	0.006	BE	1	14.4
Model	11	51.38	CD	1	28.2
Error	5	1.85	CE	1	184.3
Total	16	53.23	Model	13	43064.3
SSq: Sum of Squares			Error	3	220
DoF: Degree of Freedom			Total	16	43284.3

7.2 MULTI-OBJECTIVE OPTIMISATION (NSGAII)

The result in figure 5 shows the plots of solution results obtained by running the NSGAII algorithm. NSGAII was used to minimise both load and ovality using the GA parameters described in section 6.3 and equation 3 and 4 as the objective function. NSGAII was run ten times with different random number seeds. The best convergence is presented in figure 5. Seven out of ten runs obtained similar results. Therefore it is likely that NSGAII has converged to the global Pareto front. It can also be seen from figure 5 that NSGAII converges to the Pareto optimal front with a good spread of multiple optimal solutions. Table 6 shows decision variable values at two optimal solution points picked at one and two in figure 5, the extreme ends of the Pareto front. This demonstrates how multiple optimal solution can help produce a variety of optimal solutions.

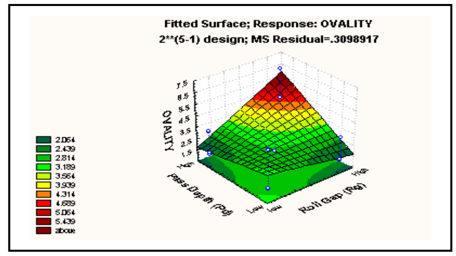


Figure 4: Interaction effects on Load Response

Table 6:Variable values for optimal solutions

Point	W	Rg	Ar	Pd	An	O_v	Load
1	16	2.4	64.7	18.7	30	2.2	216.9
2	16	4	66	20	30	7.7	130.5

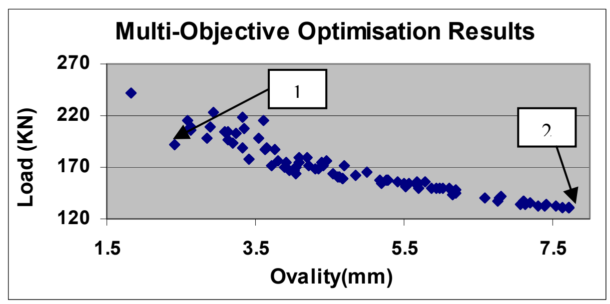


Figure 5: Multi-Objective Optimisation Solution Plot

8 FUTURE RESEARCH ACTIVITIES

The limitations in the current modelling and optimisation approach and the corresponding research activities are listed below.

- Qualitative (QL) knowledge cannot be used within the optimisation phase of the current methodology. It will be very useful to develop a framework explore the effect of QL variables on quantitative variables. This information can be used to guide the search in the optimisation process.
- The GA runs differ in results when different parameter settings and scaling for the decision variable space are used. The choice of the best parameter settings is difficult as it depends on the nature of the problem. Developing parameter-less GA's provides a challenging research area.

9 CONCLUSION

Traditional solution methods for optimising complex real life engineering problems can be very expensive and often results in sub-optimal solutions. A multi-objective optimisation approach is presented to address expensive computational cost of large FE runs using meta-models. This technique is effective in approximating FE runs and exploring complex search spaces for achieving multiple global optimal solutions. NSGAII was applied to a rod-rolling problem. NSGAII converged to the Pareto optimal front showing good results. Multiple optimal solutions give the opportunities to deliver variety of optimal designs in the presence of existing qualitative knowledge.

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