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Neuro-Fuzzy Modeling of Design Parameters of Connecting Rod

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Abstract: Finite element analysis is frequently used for the simulation of complex shaped mechanical systems, under the complicated loading conditions; however, it is usually time consuming and difficult for the parametric design. To overcome this problem, Neuro-Fuzzy technique is used for modeling the design parameters of a component based on FEA results. In the present work, an attempt has been made to develop Neuro-Fuzzy model for predicting the maximum stresses generated in I section connecting rod (CR) at critical locations (node), based on FEA results. The three design parameters such as fillet radius, diameter and height of the big end of CR, obtained from FEA, are used as input for Neuro-Fuzzy model based on full factorial design. The Neuro-Fuzzy model is most efficient as regards to the accuracy achieved. Moreover, Neuro-Fuzzy modeling reduces the time as well as cost incurred for FE analysis of the component. It is concluded that Neuro-Fuzzy model may be preferred for modeling the design parameters of CR, under the fully reversible cyclic loading.

Keywords: Connecting Rod, Neuro-Fuzzy, Fuzzy, ANN, FEA.

I. INTRODUCTION

In recent years, the Neuro-Fuzzy modeling has received attention in the area of manufacturing processes, electrical power drive systems, electronics systems and mechanical design systems. This is based on the combination of Neural Networks and Fuzzy Logic (FL) techniques for modeling the design parameters of a component based on FEA results [1, 2]. The idea is to lose the disadvantages of the two and gain the advantages of both modeling techniques. Neural networks bring into this union the ability to learn. Fuzzy logic brings into this union a model of the system based on membership functions and a rule base.

Neuro-Fuzzy approach combines two powerful computing disciplines: Neural networks and Fuzzy set theory. Neural networks are well known for its ability to learn and adapt to unknown or changing environment to achieve better performance [1, 2]. The effectiveness in handling linguistic information makes Fuzzy set theory to incorporate human knowledge, to deal with imprecision and uncertainty, and to clarify the relations between input and output variables. A Neuro-Fuzzy model can be used to study both neural as well as FL systems. A neural network can approximate a function, but it is impossible to interpret the result in terms of the natural language. The fusion of neural networks and FL in Neuro-Fuzzy models provides learning as well as readability. The engineers find this useful because the model can be interpreted and supplemented by the process operators [1].

Reddy et al. [2] develop the Neuro-Fuzzy model for the prediction of surface roughness. The predicted and measured values are found fairly close to each other. The developed model is used to predict the surface roughness in the machining of aluminum alloys. The Neuro-Fuzzy results are superior as compared to the response surface methodology results. An on-line monitoring and prediction of surface roughness in grinding is introduced with experimental verification by Murad et al. [4]. A Neuro-Fuzzy system [4] is used to monitor and identify the surface roughness online. Different Neuro-Fuzzy parameters are adopted during the training process of system to improve the on-line monitoring and prediction of accuracy of surface roughness. The comparison shows that the adoption of bell-shaped membership function achieved a satisfactory on-line accuracy of 91%.

A connecting rod works in variably complicated conditions, and is subjected to not only the pressure due to the connecting rod mechanism, but also due to the inertia forces. When repetitive tensile and compressive stresses are developed due to the reversible cyclic loadings it leads to fatigue phenomenon which can cause dangerous ruptures and damages [5, 6, 7]. Lal et al. [5] performed finite element fatigue analysis (FEFA) of I section CR to study the effects of design parameters on the mass of CR and stresses generated at the critical point, under the fully reversible cyclic loading. Tevatia et al. [6, 7] performed FEFA of + section, I section, H section, rectangular section and circular cross-section CR and predicted the fatigue life using Coffin-Manson, Morrow and Smith-Watson-Topper (SWT) strain life theories. Coffin-Manson strain life theory is found to be conservative compared to Morrow and

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SWT strain life theories.

It is difficult to utilize the FEA results many times for the parametric design. Keeping in view; the author have developed a Neuro-Fuzzy system, which combines reasoning ability of FL and learning ability of ANN for modeling the design parameters of CR, to make it more useful for the stress-strain analysis. The present work is focused on the development of Neuro-Fuzzy model for predicting the maximum stresses generated at the critical locations (node) of CR without performing the FEFA. Based on FEA results, the stresses are calculated corresponding to the three design parameters (fillet radius, diameter and height of the big end) of I section CR. The FEA results are used as input for Neuro-Fuzzy modeling.

II. PROBLEM FORMULATION

More recently, fatigue analysis of connecting rods of different cross-sections has been carried out, under the fully reversible cyclic loading conditions in virtual environment [5, 6, 7]. In these works, the modeling of different cross-sections is carried out in parametric *Pro/E* software, followed by FEFA on *ANSYS workbench*. The forged steel I section (optimized shape) CR is found to be the best when elastic and plastic strains together are considered (Coffin-Manson theory) for estimating the fatigue life [7]. The readers are requested to refer above cited papers for the detail analysis.

A. *Finite Element Analysis*

The FEA of forged steel I section CR is carried out to study the effect of three critical design parameters such as fillet radius, diameter and height of big end. The analysis is based on the full factorial design where all possible combinations of design parameters are realized [8]. The minimum, optimum and maximum values of each design parameters [5] are considered as the three parametric levels for modeling, as shown in Table 1. The twenty seven sets of FEA are performed using full factorial design [8]: $N^a = 3^3 = 27$ where N is the number of design parameters and a is the number of levels. Fig. 1 shows the Von Mises stresses distribution in different parts of CR, subjected to a tensile/compressive load of 9500 N.

Table 1: The levels of each design parameter of connecting rod

Designing Parameters	Parametric levels (mm)		
	Level 1	Level 2	Level 3
Radius, R_f	45.0	48.5	52.0
Diameter, D	75.0	80.2	85.0
Height, H	45.0	49.3	54.0

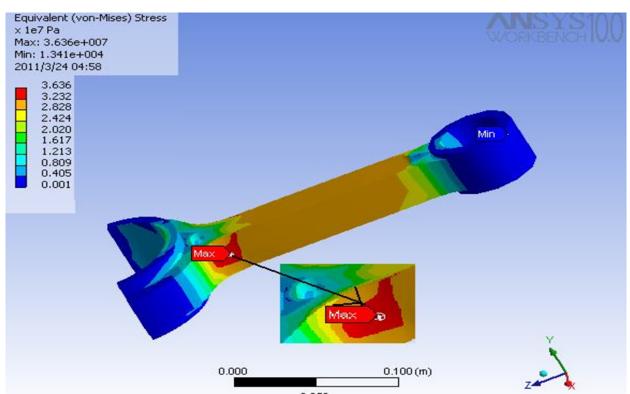

Figure 1: FE model of I section CR

B. *Neuro-Fuzzy Modeling*

Neuro-Fuzzy inference system is a fuzzy inference system implemented in the framework of an artificial neural network (Fig. 2). By using a hybrid learning procedure, Neuro-Fuzzy model is constructed on *MATLAB* by mapping an input-output design parameters, based on both the human-knowledge as well as fuzzy IF-THEN rules; and approximate membership functions from the stipulated input/output data pairs for neural network training. A back propagation topology with least squares estimation is used for learning

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the Neuro-Fuzzy input and output membership functions. Consequently, the training error decreases, at least locally, throughout the learning process. Finally, the crisp output is obtained from the Neuro-Fuzzy model.

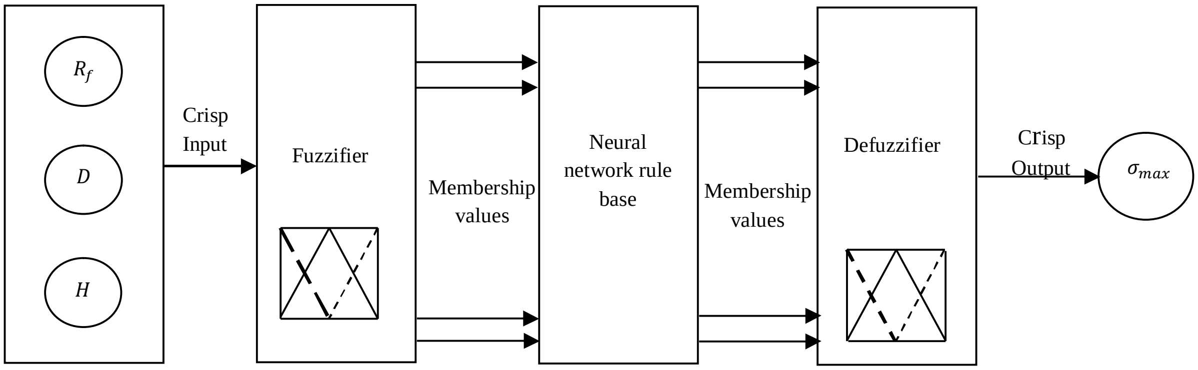

Figure 2: Neuro-Fuzzy based hybrid intelligent system

To measure the accuracy of Neuro-Fuzzy model, the error is calculated as [4]

$$\emptyset_j = \left|\frac{(\sigma_{max})_{FEA} - (\sigma_{max})_P}{(\sigma_{max})_{FEA}}\right| \times 100\,\% \qquad (1)$$

where $\emptyset_j$ is the percentage error and suffix *P* corresponds to the stresses calculated from Neuro-Fuzzy model. The effectiveness of Neuro-Fuzzy model is determined and compared by calculating the average percentage error as [4]

$$\overline{\emptyset} = \frac{\sum_{j=1}^{z} \emptyset_j}{z} \qquad (2)$$

where $\overline{\emptyset}$ is the average percentage error and *z* is the total number of sets.

III. RESULTS AND DISCUSSION

Twenty seven sets of design parameters (based on full factorial design) are considered for FE analysis, and for each set, the maximum stresses at critical location of CR are calculated under the fully reversible cyclic loading. Three design parameters shown in FEA data sheet (Table 2) are used into Neuro-Fuzzy model. The Neuro-Fuzzy model estimate the average percentage error of 1.98%.

The capabilities of Neuro-Fuzzy model is compared with the actual model (in present case, FEA model). Fig. 3 shows the variation of maximum stresses generated corresponding to Neuro-Fuzzy modeling techniques for the entire range of parametric sets. For example, for first set, the difference between maximum stresses obtained from Neuro-Fuzzy model with the actual model is 1.43%. Similarly, for thirteenth set, the differences become 0.71%. For the last set, the differences is limited up to 1.13%. Thus, from eqns. (1) & (2), the overall accuracy achieved by Neuro-Fuzzy modeling 98.02%, as regards to the maximum stresses generated at the critical location.

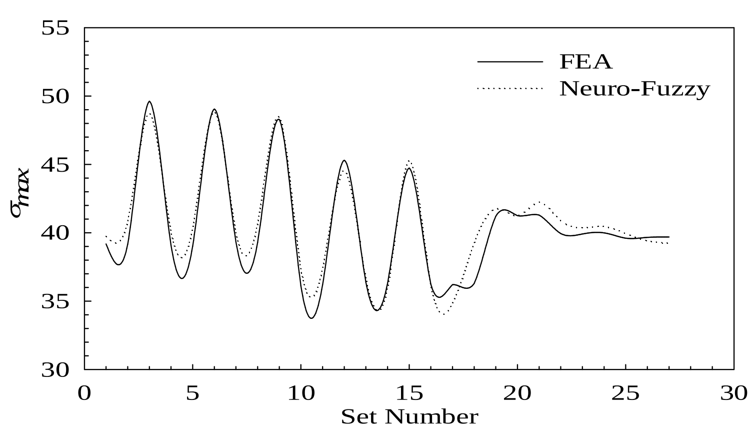

Figure 3: Variation of maximum stresses with number of sets for FEA and Neuro-Fuzzy model

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IV. CONCLUSION

The present analysis provide an effective and accurate way for estimating the maximum stresses at the critical location of CR based on the three design parameters. Three design parameters from FEA are used as input for Neuro-Fuzzy model. For the entire range of design parameters, the analysis reveals that Neuro-Fuzzy model is 98.02% accurate compared to FEA model. Thus, Neuro-Fuzzy intelligent system may be preferred for modeling I section CR, under the fully reversible cyclic loading.

Table 2: Maximum stresses calculated from finite element analysis

Set number	Radius, R_f (mm)	Diameter, D (mm)	Height, H (mm)	Maximum stresses, σ_{max} (MPa)
1	45.0	75.0	45.0	39.18
2	45.0	80.2	45.0	39.16
3	45.0	85.0	45.0	49.62
4	45.0	75.0	49.3	39.09
5	45.0	80.2	49.3	39.02
6	45.0	85.0	49.3	49.05
7	45.0	75.0	54.0	39.33
8	45.0	80.2	54.0	39.29
9	45.0	85.0	54.0	48.28
10	48.5	75.0	45.0	36.12
11	48.5	80.2	45.0	36.19
12	48.5	85.0	45.0	45.30
13	48.5	75.0	49.3	36.39
14	**48.5**	**80.2**	**49.3**	**36.30**
15	48.5	85.0	49.3	44.73
16	48.5	75.0	54.0	36.24
17	48.5	80.2	54.0	36.20
18	48.5	85.0	54.0	36.29
19	52.0	75.0	45.0	41.20
20	52.0	80.2	45.0	41.25
21	52.0	85.0	45.0	41.29
22	52.0	75.0	49.3	39.94
23	52.0	80.2	49.3	39.91
24	52.0	85.0	49.3	39.99
25	52.0	75.0	54.0	39.60
26	52.0	80.2	54.0	39.66
27	52.0	85.0	54.0	39.69

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