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Optimum Design of Worm Gears with Multiple Computer Aided Techniques

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Summary

Finite element analysis (FEA) has proved to be a useful method to analyse the strength of worm gears; however, it is usually time consuming and difficult for parametric design, and, hence, it is difficult to apply FEA for design optimisation. To overcome this problem, artificial neural network and genetic algorithm are utilised in this research to optimise worm gear design based on FEA results. A new type of worm drive, an involute cylindrical worm matting with an involute helical gear, is taken as an vehicale to illustrate the approach developed.

Introduction

An involute cylindrical worm matting with an involute helical gear is investigated in this research. In comparison to traditional cylindrical worm and wheel drives, this type of worm gear drive has several advantages such as easier to manufacture, hardened tooth surface to achieve hgih acuracy and loading capacity, and mis-matched surfaces for a better lubrication condition.

Due to its complicated tooth geometry and lack of in-depth theoretical analysis, the involute cylindrical worm with helical gear drive has not been investigated enough. This research applies finite element analysis (FEA), artificial neural network (ANN) and genetic algorithm (GA) to conduct the design and optimisation to enable its further engineering application.

FEA has been applied to tackle the problem of tooth contact and distortion in gear research, and became an useful tool in the area, because it exhibits good adaptive and analytical abilities to simulate complicated models and various material properties [1].

However, the FEA may require a large amount of computer time to achieve high calculation accuracy, and, hence, FEA for worm gear design and analysis is of time consuming. It is almost impossible to utilise tridational methods to optimise worm gear design based on FEA results. To overcome the problem, the authors developed a method, which combines ANN and GA to optimize worm gear design based on FEA results. The ANN and GA are capable for acquiring experience from training data [2, 3]. This will enable them to overcome some limitations of finite element method. The training data set must be extensive and consistent in order to ensure proper training for evolutionary algorithms.

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In this paper, a multi-objective optimization and analysis model is presented which combines an error back propagation ANN and GA. The ANN is trained using the FEA results, and then is used to predict the analysis outcame. The GA is applied to optimise design parameters with multiple objectives.

Finite Element Analysis of Worm Gear Strength

To conduct the FEA, 3D models of the worm and the helical gears are established first. Then the worm and helical gear are assembled together to form the drive model [4]. With the 3D models established, the 3D simulation and finite element analysis are carried out. During the simulation and analysis, the finite element model is loaded at all positions in tooth engagement cycle from the beginning till the end of tooth contact. The contact region is analyzed at different positions, and their contact patterns at different tooth engagement stages are investigated. The 3D simulation and finite element analysis are conducted using I-DEAS software package..

Examples of the simulation and FEA results are shown in Figures 1 and 2. The former shows the results at different positions according to the finite element analyses, and the later shows an example of the contact pattern on the gear tooth surfaces.

The cylindrical worm and helical gear drive can be categorized as a type of skew gear drive. For a normal skew gear drive, there is only one pair of teeth in contact during the tooth engagement. However, as indicated in Figure 1, the loaded 3D FEA simulation reveals that when the cylindrical worm engages the helical gear under workload, there are two or three pairs of teeth in contact, which is similar to normal cylindrical worm and wheel drives.

For a standard involute helical gear matting with its worm, the highest contact stress occurs at tooth tip, as indicated in Figure 3, where the contact area is very small. Tip release, i.e., reducing the tooth thickness at the tip of the gear tooth, can avoid the contact impact at tooth tip and hence reduces the contact stress. Comparison of contact stress variation between standard teeth and modified teeth is shown in Figures 3 and 4. It can be seen that before the tooth modification, the maximum contact stress is 650 MPa with the input power 350W (external load); while with tooth modification, the input power increases to 1200W, but the maximum contact stress reduces to 435 MPa.

An experimental investigation [5] was carried out to compare the mesh efficiency between a traditional involute cylindrical worm/wheel drive and an involute cylindrical worm/ helical gear drive with tooth tip release. The results indicate that the latter is better than the former.

In this research, a great number of FEA calculations using the method of tooth

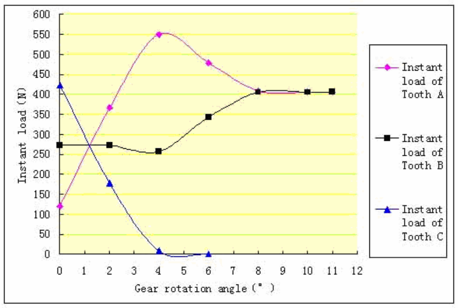

Figure 1: Load shared by gear tooth in contact

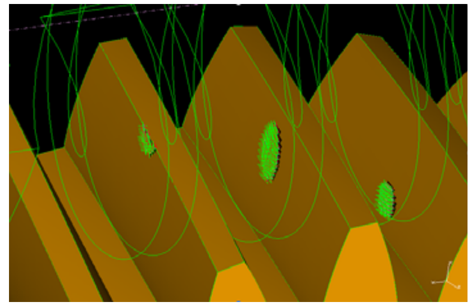

Figure 2: Tooth contact pattern

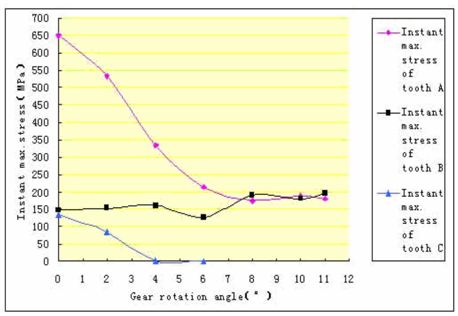

Figure 3: Tooth contact stress (input power 350 W, standard tooth)

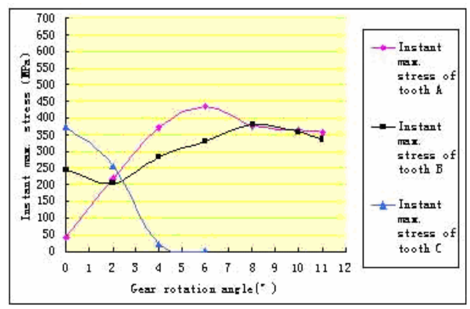

Figure 4: Tooth contact stress (input power 1200 W, with tooth tip release)

modification to eliminate the impact at the gear tooth tip are carried out. Then the FEA results are used as the sources of training and test parameters of the ANN.

Artificial Neural Network (ANN)

Due to the complicated tooth geometry of worm-gear drives, a mathematic formula is hard to be established to represent the relationship between the input parameters and the desired FEA results. To overcome this problem, the ANN is utilised. The function of ANN can be regarded as a multi-dimensional formula of the FEA results.

The network structure adopted in this research is a multilayer perceptron (MLP), and it is designed with the following features:

(1) The neuron network has three layers: input layer, hidden layer and output layer. The input layer includes four neurons, which represent the input load, design and tool parameters, while output layer has three output neurons representing tooth surface contact stresses, tooth bending stresses and tooth deformation.

(2) The network contains one layer of hidden neurons.

(3) The sigmoid function is employed as the nonlinear transfer function of each neuron in the network, as shown below, where c is a constant.

$$\phi(x) = \frac{1}{1 + \exp(-u_i/c)^2}$$

(4) The network exhibits high degrees of connectivity, determined by the synapses of the network.

Back propagation combined with Bayesian algorithm [3] is utilised for the ANN. The utilization of the BP, design of the ANN and its operation procedure are further detailed in [4, 6].

Genetic Algorithm (GA)

Genetic algorithm (GA) are computer-based search techniques patterned after the genetic mechanisms of biological organisms. These robust genetic algorithms have been successfully applied to problems in a variety of fields of study, and their popularity continues to increase due to their efectiveness, their applicablity, and their ease of use [3].

In this research, the GA is used to optimise design parameters with multiple objectives. The design parameters to be optimised include module, central distance, tooth modification factor, pressure angle, and number of teeth; the objective functions include stresses and deformation. The genes are the parameters to be optimised. During the optimisation process, the ANN mentioned above is used to calculate the values of the objective functions.

The operation procedure of the GA in this research is summarized as follows:

(1) Generate a random initial population of candidate solutions in the form of chromosomes.

(2) Evaluate each chromosome in the population according to a pre-defined fitness function.

(3) Employ a selection operator to create new chromosomes. The selection operator biases the new generation of chromosomes toward higher quality solutions. As the chromosomes mate, genetic operators such as crossover and mutation are applied to from new candidate solutions.

(4) Delete members of the existing population to make room for the new candidates.

(5) Evaluate the new chromosomes and insert them into the population.

(6) If a satisfactory solution has been achieved (or if some other stopping criteria has been met), stop; otherwise, go back to step (3).

For further information of the development of the GA, please refer to [4, 6].

An Example

This example is to illustrate the approach developed, where FEA, ANN and GA are combined together to conduct the optimum design of an involute cylindrical worm with helical gear drive.

Simulation of ANN with FEA results. A back propagation ANN is developed. 117 sets of FEA calculation results have been conducted, amongst which 84 sets of results are used to train the ANN, and the rest are used to test the ANN. In this neural network, there are four input vectors that represent central distance, module, number of worm threads, and worm helical angle repectively, while two output vectors stand for the stess and quality of tooth deformation. The outputs are convergent with the desired outputs after the training, as shown in Figure 5. The everage training error is 2.525% and the everage test error is 2.916%.

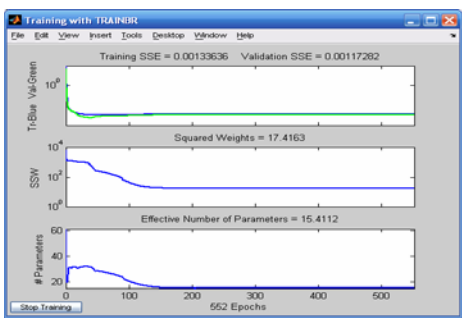

Figure 5: Training process

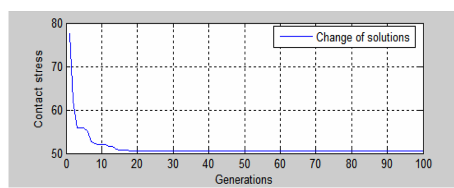

Figure 6: The optimised solutions of the 1^{st} objective function

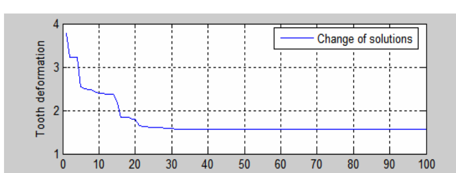

Figure 7: The optimised solutions of the 2^{nd} objective function

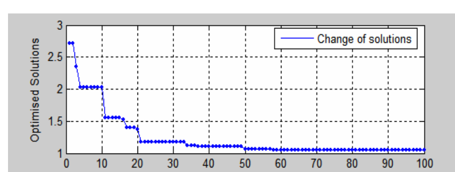

Figure 8: The optimised solutions of the integrated objective functions

GA Optimisation. The GA is used to optimise design parameters with multiple objectives. The design parameters to be optimised include module, ratio of transmission, central distance, number of worm threads and gear teeth, pressure angle, and tooth modification factor; the objective functions include contact stresses, bending stresses and deformation. The goal of the GA is to search for the minimum value of tooth surface stress and the opitimal solution of tooth deformation. During the optimisation process, the ANN mentioned above is used to calculate the values of the objective functions. The optimised solutions of the two objective functions are shown in Figures 7 and 8.

After 100 cycles of iterations, the optimisation results shown in Figure 1.19 are achieved as A=51.1298 mm, Mn=5.0, Z=4 and Beta=8.001°. According to test results, these are ideal outcome.

Conclusion

An approach is developed, which combines FEA, back propagation ANN and multi-objective GA, for optimum design of involute cylindrical worm with involute helical gear drives. The FEA results obtained reveals that this type of worm gear drive has better loading capacities than traditional cylindrical worm wheel drives; the trained ANN can be applied to predict the analysis results when the basic parameters such as central distance, module, number of worm threads, and worm helical angle are inputed into the network; the GA is utilized to optimise design parameters with multiple objectives. The results obtained from the example prove that the approch developed is a usefule tool for the optimum design.

Acknowledgement

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