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Global Optimization of Thermal Fatigue Resistance of Brake Disc Materials Based on Genetic Algorithm and Neural Network

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Abstract. Brake disc is an important component of braking system, its thermal fatigue resistance directly affects the braking effect. In order to avoid the thermal fatigue phenomenon of brake disc, an orthogonal experimental method is presented to optimize thermal fatigue performance, which optimizes the horizontal combination of the four elements, and determines the order of the four elements that affect the thermal fatigue resistance of the material by means of range analysis and variance analysis. A global optimization model based on genetic algorithm and neural network is proposed to solve the local optimal problem in orthogonal experiments. Finally, an comparative experiment is taken, and the results show the efficiency of the orthogonal experimental method combined with the global optimization model on improving the thermal fatigue resistance of the brake disc material.

1. Introduction

Brake system principle is that the brake disc and the hub are assembled together [1-2]. Through dry friction between the brake disc and the brake linings, the kinetic energy of high speed vehicle is turned into heat energy, so the vehicle can be stopped gradually. When braking, the vehicle from high speed to being still only lasts a very short time. The braking system bears huge load. In the braking process, the brake disc has been bearing the effect of friction and wear. If the pressure is too large, the brake disc will deform or crack. The braking is a continuous cycle process. The brake disc has been in alternating hot and cold, so the disc brake in the braking process produces large thermal stress. Under the effect of the thermal stress, the brake disc surface will crack and deformation, namely, thermal fatigue phenomenon. It will make the brake disc invalid [3-5]. Therefore, the brake disc is required to have a good anti fatigue performance.

Zhang Junqing, Zhou Suxia, et al [6] obtained the thermal fatigue experimental of SiCp/A356 particle reinforced composite notched specimens at 20° C~300° C cycle, and obtained the relation between the thermal fatigue crack formation life and geometric dimensions such as notch radius and thickness of specimens. Shi Xiaoling [7] analyzed the variation law of the stress intensity factor of cracks on the friction surfaces of the brake discs. Through a combination of 1:1 gantry experimental and finite element calculation, the mechanism of action between multiple cracks on the friction surface was further studied and further based on fatigue. The damage mechanism theory and fracture mechanics method evaluated the service life of forged steel brake discs. Feng Chenhui [8] studied the effect of carbon-silicon content on the thermal fatigue properties of grey cast iron. The experimental results show that within a certain range of components, the higher the ratio of carbon to silicon, the higher the carbon equivalent of gray cast iron, the greater the thermal fatigue resistance of gray cast iron.

In this paper, the brake disc of ductile iron is studied, the factors of Si, Mn, Mo and Cu are added in ductile iron, and the thermal fatigue performance of ductile iron is optimized by orthogonal experimental design, and the Si, Mn, Mo and the order of influence of Cu factor on the thermal fatigue performance of brake disc; In order to make up for the insufficiency of the orthogonal experimental, the genetic algorithm and neural network algorithm are added, and the global optimization model is set up to optimize it, and finally the level combination of Si, Mn, Mo and Cu factors is obtained. In order to improve the thermal fatigue performance of the brake disc, prolong the service life of the brake disc and increase the braking safety factor of the vehicle, the overall frame of this article is shown in Figure 1.

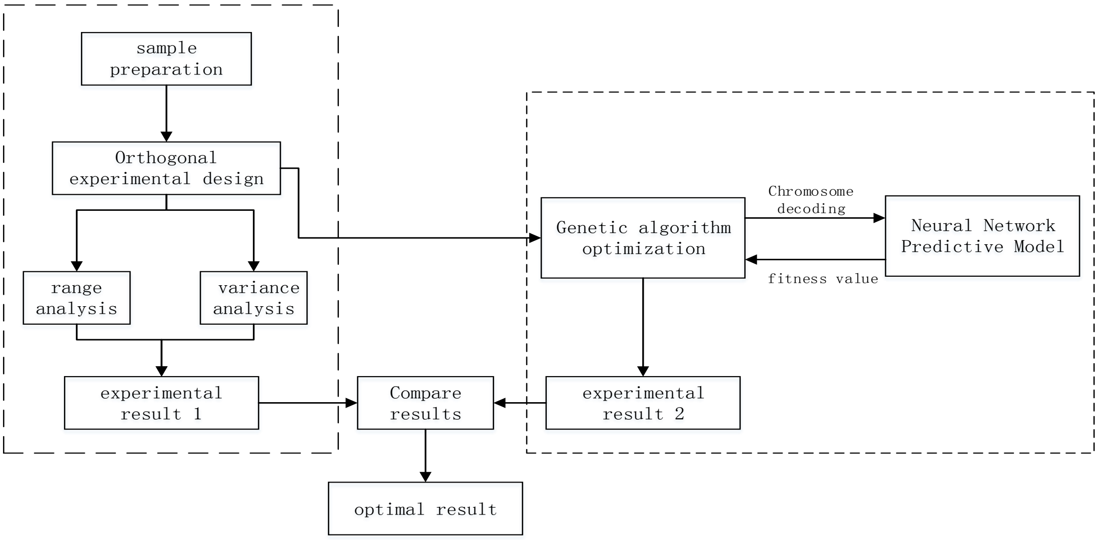

Figure 1. Overall framework

2. Experimental materials and methods

2.1. Preparation of raw materials and samples

The ductile iron is used as raw material in the experimental. Its chemical composition of mass proportion is that of 3.74%C, 1.00%Si, 0.20%Mn, S≤0.02%, P≤0.05%. The spheroidizing agent is rare earth magnesium alloy. The nucleating agent is ferrosilicon 75. After the pig iron in the cupola is melted and desulfurized, the temperature is kept at 1600℃. Then 1.5% of the spheroidizing agent and 1% of the nucleating agent are Added. The treated molten iron is casted into a brake disc. The size of the brake disc for experimental is shown in Figure 2.

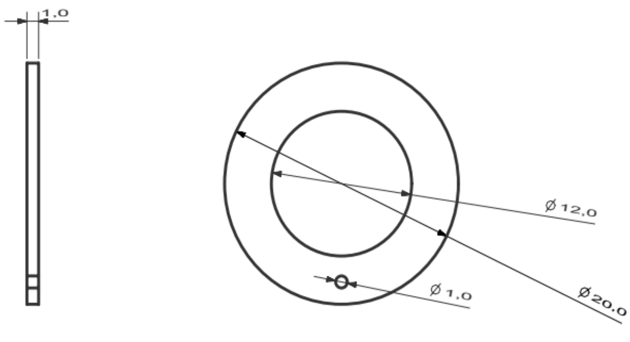

Figure 2. The size of the brake disc for experimental

2.2. Program and method of thermal fatigue experimental

The thermal fatigue experimental is done by metal thermal fatigue experimentaling machine. The specimen is suspended on the transmission device through the hole of φ1. The specimen is made to move vertically to complete the cycle process of heating and cooling. The cycle time is 15s. The electromagnetic relay is used to heat the specimen to 800℃ at 5s. And the cooling water is used to cool it to 20℃ at 10s. From 20℃ to 800℃ by heating and cooled to 20℃ is a cycle. The counter records the time of cycles. The crack occurrence is observed by laser confocal scanning microscope each 50 time cycles. The cycle time is recorded when the crack in the specimen occurs for the first time.

The orthogonal table L9 (3^4) is used to analyze the levels and factors of the experimental. It is shown in Table 1.

Table 1. Levels and factors of the experimental

Levels	Factors			
	Si	Mn	Mo	Cu
1	4.0	0.6	0.1	0.6
2	4.5	0.8	0.3	0.8
3	5.0	1.0	0.5	1.0

2.3. Orthogonal experimental results

Nine groups of specimens are experimentaled. The cycle times of all the groups are recorded when the crack in the specimen occurs. All the cycle times are shown in Table 2. In the experiment, the more the time of cycles in the metal thermal fatigue experimentaling machine is, the stronger the thermal fatigue resistance of the specimen is.

Table 2. Specimen composition and cycle times

Number	Composition（%）				cycles
	Si	Mn	Mo	Cu	
1	4.0	0.6	0.1	0.6	500
2	4.0	0.8	0.3	0.8	750
3	4.0	1.0	0.5	1.0	900
4	4.5	0.6	0.3	1.0	1100
5	4.5	0.8	0.5	0.6	1350
6	4.5	1.0	0.1	0.8	850
7	5.0	0.6	0.5	0.8	1600
8	5.0	0.8	0.1	1.0	1050
9	5.0	1.0	0.3	0.6	1200

2.3.1. Range analysis of orthogonal experiment. Range analysis is used mainly to distinguish the primary and secondary order of each factor in the fight against thermal fatigue, so as to determine what factors can be used to make the thermal fatigue resistance of nodular cast iron better.

①Determine the optimal level combination of experimental factors

Taking Si as an example, the sum of experimental indexes corresponding to the 1 level of Si is:

$$K_1 = y_1 + y_2 + y_3 \tag{1}$$

$$\mathrm{k}_1 = K_1 / 3 \tag{2}$$

The sum of the experimental indexes corresponding to the 2 level of Si is:

$$K_2 = y_1 + y_2 + y_3 \tag{3}$$

$$\mathrm{k}_2 = K_2 / 3 \tag{4}$$

The sum of the experimental indexes corresponding to the 3 level of Si is:

$$K_3 = y_1 + y_2 + y_3 \tag{5}$$

$$\mathrm{k}_3 = K_3 / 3 \tag{6}$$

Range:

$$R = \mathrm{k}_{\max} - k_{\min} \tag{7}$$

The experimental index and the range of the Si, Mn, Mo, Cu can be calculated, as shown in Table 3. According to the data in Table 3, it can be concluded that the optimum level of Si factor is K_3,Mn factor is K_1, Mo factor is K_3, Cu factor is K_2. Therefore, the level combination of the factors with better thermal fatigue resistance is as follows: $Si_3Mn_1Mo_3Cu_2$.

Table 3. experimental index and the extreme difference

	Si	**Mn**	**Mo**	**Cu**
K_1	2150	3200	2400	3050
K_2	3300	3150	3050	3200
K_3	3850	2950	3850	3050
K_1	7166.667	1066.667	800.000	1016.667
K_2	1100.000	1050.000	1016.667	1066.667
K_3	1283.333	983.333	1283.333	1016.667
R	566.666	83.334	483.333	50.000

②Determine the order of the factors

The exponential change trend of factors are shown in Figure 3. The influence of various factors on the thermal fatigue resistance of nodular cast iron is in the order of Si > Mo > Mn > Cu.

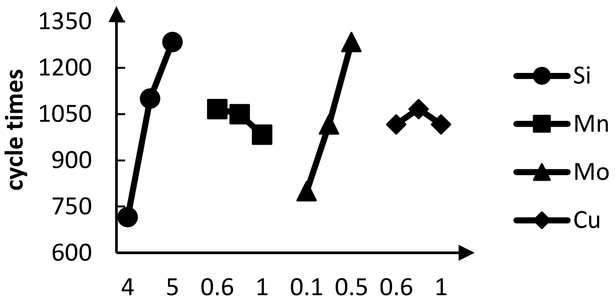

Figure 3. The exponential change trend of factors

2.3.2. Variance analysis of orthogonal experiment. By means of variance analysis, the influence degree of each factor on the thermal fatigue resistance of nodular graphite cast iron is further judged, which makes up the deficiency of extreme difference analysis. The variance analysis table can be go.

①Calculate the sum of squared deviations and degrees of freedom for each factor

Total deviation square sum:

$$SS_T = \sum_{i=1}^{n} X^2{}_{\mathrm{i}} - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n} \tag{8}$$

Column deviation square sum:

$$SS_{\mathrm{j}} = \frac{1}{r}\sum_{i=1}^{m} K^2{}_{ij} - \frac{\left(\sum_{i=1}^{n} X_i\right)^2}{n} \tag{9}$$

Total degree of freedom:

$$\mathrm{df}_T = \mathrm{n} - 1 \tag{10}$$

Factor degree of freedom:

$$\mathrm{df}_{\mathrm{j}} = m - 1 \tag{11}$$

There:j=1,2,3,4.m=3.n=9.r=n/m.

Because Mn, Cu has little effect on the thermal fatigue resistance of ductile iron, it can be seen that Mn,Cu can be taken as the error term.

Error deviation square sum:

$$SS_{\mathrm{e}} = SS_2 + SS_4 \tag{12}$$

Error degree of freedom:

$$\mathrm{df}_{\mathrm{e}} = 2df_j \tag{13}$$

② significance experimental

The analysis of variance table of orthogonal experimental can be obtained by consulting F distribution table, as shown in Table 4. According to the analysis in Table 4, Si and Mo are the significant factors, Mn and Cu are not significant factors.

Table 4. Variance analysis

Factors	Sum of Squared deviation	Degree of freedom	Ratio	Critical value	Significance
Si	490555.556	2	55.187	F0.01＝18.00	*
Mn	7222.222	2	0.812		
Mo	357222.222	2	40.187		*
Cu	10555.556	2	1.188		
SS_e	17777.778	4			
SS_T	865555.56	8			

③Determination of optimal process

The more cycles of the specimen in the thermal fatigue experimentaling machine, the better the thermal fatigue resistance of the specimen, and the factors Si and Mo have great influence on the experimental and are significant factors. The influence of Mn and Cu on the experimental is relatively small and not significant. The smaller the mass fraction of Mn and Cu is, the better the mass fraction is. However, as a brake disc material, the strength and hardness are also involved. The factors Cu can promote the formation of pearlite, reduce or completely inhibit the formation of ferrite, so the mass fraction of Cu can be increased.

3. Global optimization model for thermal fatigue resistance of brake discs using neural networks and genetic algorithms

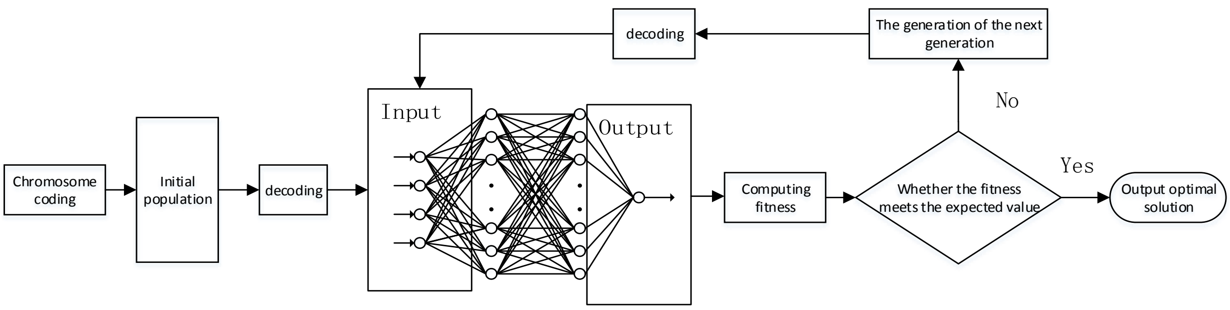

Figure 4. Flow chart of global optimization model

The results of 9 experimentals were obtained by orthogonal experimental in the above section, however, in order to solve the problem, genetic algorithm and neural network algorithm are introduced in this paper. The global optimization model is established by using the global optimizing ability of genetic algorithm and the nonlinear fitting ability of neural network, and its flowchart is shown in Figure 4. As can be seen from Figure 4, the structure framework of global optimization model is built by genetic algorithm in the process, and a neural network predictive model based on neural network is nested.

3.1. Structural framework based on genetic algorithm

In order to obtain the optimum ratio of Si, Mn, Mo and Cu for the thermal fatigue performance of the brake disc, the cycle times are used as the optimization objective, and the optimization model of the parameters in the range of parameters selected by the genetic algorithm is as follows:

$$\begin{cases} Maximum\ numberof\ cycles \\ 4.0\% \le Si \le 5.0\% \\ 0.6\% \le Mn \le 1.0\% \\ 0.1\% \le Mo \le 0.5\% \\ 0.6\% \le Cu \le 1.0\% \end{cases} \tag{14}$$

The initial population number is set to 100, The crossover rate is 0.6, the mutation rate is 0.05, the maximum iteration number is 400, and the genetic iterative counter is gen=0. The initial population was selected by the roulette method. The greater the degree of adaptability, the greater the probability of the individual being selected, the smaller the probability of being selected. After each chromosome is decoded and entered into the neural network predictive model, the output result is used as the input value of the fitness function, so the fitness function is defined as:

$$\mathrm{y} = \max\ (S - \mathrm{cycles}) \tag{15}$$

S is a large enough input parameter. The crossover rate randomly decides to participate in the cross chromosome, and to pair it with a single point crossover operation, with the new chromosome to replace the original chromosome, to get new groups. The individuals in the new population were randomly selected to mutate with mutation rate, and the new chromosomes were substituted for the new ones [9]. When the fitness value reaches the expectation, it terminates the algorithm, outputs the individual with maximum fitness, then decodes it and obtains the optimal parameter combination.

3.2. Prediction Model of fatigue cycle number based on Neural Network

In order to obtain the thermal fatigue cycle times of arbitrary Si, Mn, Mo and Cu factors, the prediction model of the relationship between the thermal fatigue performance of the brake disc and the ratio of Si, Mn, Mo and Cu factors can be established by neural network. The key factors that influence the accuracy of neural network prediction model are the kinds of neural networks, the number of training samples, the number of neurons in the hidden layer, the transfer function and the kinds of training functions.

The method used in this paper is the reverse propagation algorithm (BP algorithm), using MATLAB to train the neural network. The 9 sets of data obtained from the orthogonal experimental were used as training samples, and 4 elements of the orthogonal experimental table, Si, Mn, Mo and Cu as input layer nodes, were normalized to the data before training to improve the precision of the neural network model. The more cycle times of the specimen in the metal thermal fatigue experimentaler, the stronger the thermal fatigue resistance of the specimen, the more the cyclic frequency is used as the output node of the neural network. There is no definite method to determine the number of hidden layer nodes, and the theoretical calculation is complicated:

$$J = (n + m)/2 + a \tag{16}$$

There: J is the number of hidden layer nodes, n is the number of nodes in the input layer, m is the number of nodes in the output layer, a is the range of values for1-10.The number of neurons in the hidden layer can be estimated by formula (15) in the range of 4-13.The extensible range is 4-26.

The input and output relationships between each neuron in the hidden layer are as follows:

$$a_k = f(\sum_{i=1}^{r} w_{ki} p_i + b_k)/n \tag{17}$$

There: p_i Is the output value of the i neuron on the output layer， w_{ki} is the weight of the i th input to the k output， f is an activation function.

Activation function using ReLU function:

$$f(z) = \max(0, z) \tag{18}$$

The advantage of the Relu function compared to the sigmoid function and the Tanh function is that the convergence of SGD has a great acceleration effect [10].

It takes only one threshold to get the activation value, instead of counting the more complex exponential operations.

To solve the problem that the structure of neural network can not be clearly determined, this paper uses the method of trial and error to determine 11 kinds of neural network models of different structures: 4-4-1, 4-6-1, 4-8-1, 4-10-1, 4-4-4-1, 4-5-5-1, 4-6-6-1, 4-7-7-1, 4-8-8-1, 4-9-9, 4-10-10-1. In the training of neural network, the experimental data in Table 2 are used as training samples, but the data samples are too few, and it is easy to fit the phenomenon, so this paper uses the method of cross-validation to take any 8 groups as training sets, and the remaining group as the experimental set, and repeats the cycle. Set the maximum training Times 2000 times, the target error is 0.1.

Aiming at the problem of low training efficiency of traditional BP algorithm, this paper uses additional momentum method and adaptive learning rate algorithm to improve the convergence efficiency of model training.

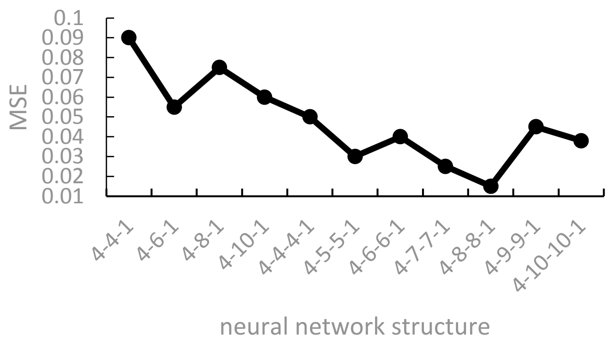

Figure 5. Mean square error of neural network models with different structures

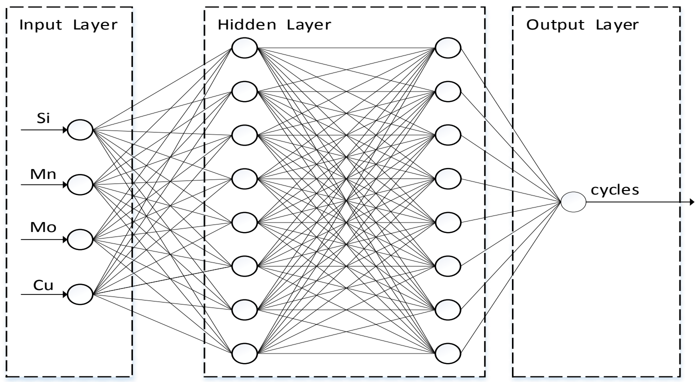

Figure 6. Neural network prediction model

In order to determine the number of neurons in the hidden layer of neural networks, to analyze the errors generated in the training of neural network models with different structures, and the method of mean square error (MSE) is used to evaluate the results, as shown in Figure 5. From Figure 5, we can see that the neural network structure of the double hidden layer is generally good, and the network model of 4-8-8-1 is the best, and the network model is shown in Figure 6.

4. Result contrast analysis

The global optimization model is implemented by MATLAB. After 60 iterations, the number of cycles reaches the maximum, and no change occurs. The genetic algorithm converges, as shown in figure 7.Finally, the optimum alloy factors for improving the thermal fatigue resistance of brake disc materials are obtained as follows: ω (Si) 5.2%, ω (Mn) 0.65%, ω (Mo) 0.5 %, ω (Cu) 0.84%.The number of cycles is 1780.

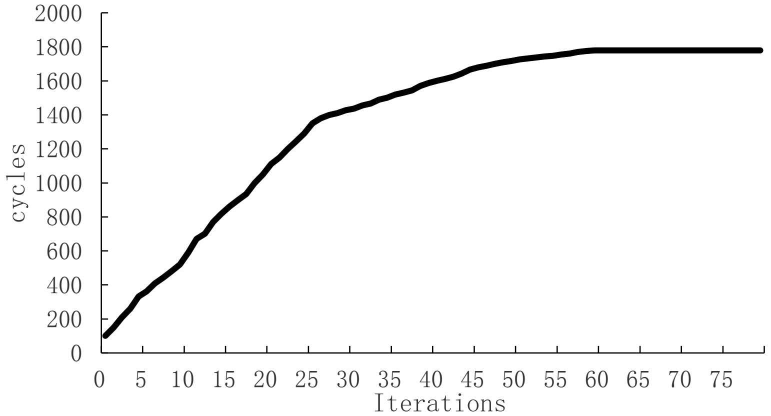

Figure 7. Global optimization process

Finally, the optimal combination obtained by the global optimization model is compared with the optimal combination obtained by the orthogonal experimental. It can be seen from Table 5 that the optimal horizontal combination obtained by the global optimization model is combined with the optimal level obtained by the orthogonal experimental method, and the number of cycles is increased by 11.25 %. Therefore, the effect obtained by the orthogonal experimental method combining the global optimal model is obviously better than that of the single orthogonal experimental method.

Table 5. Comparison of optimal results of optimization methods

Optimization Method	**Si/%**	**Mn/%**	**Mo/%**	**Cu/%**	**cycles**	**relative difference/%**
Orthogonal Experiment	5.0	0.6	0.5	0.8	1600	11.25
GA+BP	5.2	0.65	0.5	0.84	1780	

5. Conclusions

(1) In this paper, the influence of Si, Mn, Mo and Cu on the thermal fatigue resistance of ductile iron is studied by orthogonal experimental by adding a certain proportion of Si, Mn, Mo and Cu factors to the brake disc material. The influence order is obtained by the analysis of the extreme difference and variance of the experimental results: Si>Mo>Mn>Cu.

(2) In view of the problem that the orthogonal experimental can not achieve global optimization, a genetic algorithm and a BP neural network algorithm are proposed for global optimization. The global optimization process is constructed by using the nonlinear fitting ability of neural network and the global optimization ability of genetic algorithm. Finally, the optimal level combination of Si, Mn, Mo and Cu factors for improving the thermal fatigue resistance of the brake disc is obtained, and the optimal combination ratio is ω (Si) 5.2%, ω (Mn) 0.65%, ω (Mo) 0.5 %, ω (Cu) 0.84%.

Acknowledgments
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