Applying an Artificial Neural Network to the Control System for Electrochemical Gear-Tooth Profile Modifications

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Gears, crucial components in modern precision machinery for power transmission mechanisms, are required to have low contacting noise with high torque transmission, which makes the use of gear-tooth profile modifications and gear-tooth surface crowning extremely efficient and valuable. Due to the shortcomings of current techniques, such as manual rectification, mechanical modification, and numerically controlled rectification, we propose a novel electrochemical gear-tooth profile modification method based on an artificial neural network control technique. The fundamentals of electrochemical tooth-profile modifications based on real-time control and a mathematical model of the process are discussed in detail. Due to the complex and uncertain relationships among the machining parameters of electrochemical tooth-profile modification processes, we used an artificial neural network to determine the required processing electric current as the tooth-profile modification requirements were supplied. The system was implemented and a practical example was used to demonstrate that this technology is feasible and has potential applications in the production of precision machinery.

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1. Introduction

Gears are critical components in modern precision machinery for power transmission mechanisms. Modern industrial gears found in automobiles, machining tool transmissions, airplanes, *etc.*, are required to have low contacting noise with high torque transmission. To achieve this, a crown gear method in which the tooth surface is modified from the standard (or nominal) tooth surface in the direction of the gear-tooth profile and gear-tooth direction is often used in industry. The crown gear method attempts to move the tooth contact between the gear and pinion around the center of the tooth and change the tooth contact from a line to a point. Gear-tooth profile modifications and gear-tooth crowning do not change the geometric dimensions of the gear smoothness and have many advantages: they can distribute the contact stress throughout the tooth surface and improve the reliability and capacity of the gear transmission by optimizing and meshing; a certain degree of rectification can compensate for manufacturing or assembly errors and stretch distortion, and can improve the smoothness of transmission; they can reduce the effect of heat deformation after machining, resulting in a longer life span; and they can decrease the vibration. All of these advantages improve the smoothness, durability, and reliability of high-speed gear transmissions.

Most manufacturers use manual rectification, mechanical modification, or numerically controlled rectification to apply the crown gear method, but these techniques have the following shortcomings: although we can rectify a gear-tooth profile before hardening by shaving the gear teeth, synchronous crowning will generate errors; the wear-sharpening of the cutting tool will directly influence the machining accuracy; the crowning of a bevel wheel will cause gear-tooth surface distortion; the precision and surface quality of the shaved parts will deteriorate after heat treatment; although we can hone gear teeth after quenching, manufacturing and repairing the processing tools are more difficult than processing the grinding bevel wheel; and grinding a gear can modify the tooth profile of the gear surface and produce a relatively high level of precision but it is also expensive and not very efficient. Moreover, grinding cannot be used to modify inner, multi-joint, or bevel gears, or large-dimension gear wheels. Grinding a gear sometimes introduces errors caused by the high temperatures, and distortion due to the stresses and uneven stress distribution over the gear-tooth surface.

Because mechanical modifications require complex grinding wheels, costly facilities, and restrict of the strength and form of the resulting parts, they cannot satisfy the requirements of modified automotive gears. Numerically controlled modifications and electrical discharge modifications also have deficiencies, such as high cost, lack of machining precision, and problems with the shape and strength of the gears. Some advanced manufacturers are developing more accurate and efficient facilities, and we expect electrochemical gear-tooth profile modification (ECGTPM) to become a valuable new technique.[1]

The fundamental idea behind the ECGTPM process is to apply the theory for the controlled electrical field distribution found in electrochemical machining (ECM) to anticathode gear-profile corrections. By controlling the electrical field based on an erosion law, we can satisfy the requirements for gear-tooth modifications by adjusting the electrical parameters and position of the equipment used to process the gear-tooth surface. At the same time, we can improve the precision of the gear tooth, decrease the roughness of the gear-tooth surface, reduce the meshing noise, and increase the resistance to agglutinate, thereby prolonging the life of the gear. Because ECGTPMs are performed using an electrochemical process, they possess many merits. They are inexpensive and adaptable, and dispense with complex mechanical movements. They are also capable of handling complex-shaped automotive gears with highly rigid surfaces. Since the process is easy to perform and suitable for large-scale manufacturing, it is a useful, efficient, and economical method for modifying gears. The future application of this technique is very promising.[2]

This paper focuses on the implementation of an intelligent control system for the ECGTPM process. A theoretical analysis of the technique has been provided in previous papers.[3-10]

The remainder of this paper is organized as follows. The required facilities for ECGTPMs with real-time control are described in Section 2. An erosion process model for ECGTPMs is discussed in Section 3. An artificial neural network control method is applied to the ECGTPM process with real-time control in Section 4, and an example of using a neural network to obtain the law for processing the electric circuit is given in Section 5. Finally, our conclusions are presented in Section 6.

2. Required Facilities for the ECGTPM Process with Real-Time Control

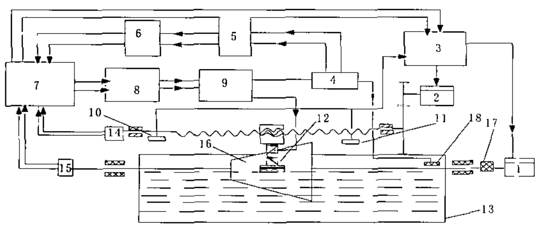

Fig. 1 Diagram showing the electrochemical gear-tooth modification system with real-time control

The architecture of the facilities we designed for the ECGTPM process is shown in Fig. 1. In the figure, 1 and 2 are stepping motors; 3 is a reversing switch controller; 4 is a galvanometer; 5 is an amplifier; 6 is an A/D converter; 7 is a computer; 8 is a D/A converter; 9 is the controlled power; 10 and 11 are left/right direction switches; 12 is a cathode slider; 13 is a processing trough into which DUT#1 electrolyte was poured; 14 and 15 are angular-displacement sensors; 16 is the gear workpiece, which is an anode; 17 is an insulated connector; and 18 is an electric brush. During the gear modifications, we fixed the unmodified pretreated gears on the bearing of a rotor. A stepping motor was used to drive the rotor. An insulated connector (17) connected the stepping motor (1) and gear-revolving shaft. An angular-displacement sensor (15) was located on the other end of the gear-revolving shaft; this was used to check the angle of gears and send a position signal to a computer (7), which served as a reference for controlling the stepping motor (1). A cathode slider (12) was connected to the lead screw by a worm-transmitting mechanism. One end of the lead screw was driven by another stepping motor (2) through a gear transmission mechanism. The other end of the lead screw had another angular-displacement sensor (14) that was used to check the position of the cathode slider (12) relative to the position of the gear-tooth surface and send the relevant signals to the computer (7), which used these signals to control the current and thereby the electrochemical gear-tooth profile modifications. Reversing relay switches were on both sides of the lead slider. When the slider reached the leftmost limit, it was reversed by a right-direction switch (11), which sent a signal to a reversing controller (3). The controller (3) changed the direction of the stepping motor (2) so that the lead screw drove the slider to the right. In the same way, when the slider reached the rightmost limit, a signal was sent from the left-direction switch to the controller (3), which reversed the stepping motor (2) to move the slider to the left.

When modifying a gear, we must make the gear wheel rotate at a certain velocity so that the slider moves in the direction of the gear wheel at a corresponding velocity to ensure that the slider moves continuously in the direction of the gear tip.[4] This ascertains the relationship between the gear-tooth positions and the slider. Since the slider was driven by the lead screw and the rotation of the gear wheel was driven directly by a stepping motor, the computer could easily control the slider so that it moved on the surface of the gear being processed by the reversing switch controlling the rates of the stepping motors (1 and 2).

The ECGTPM method modifies a gear mainly by controlling the metal-eroding capacity at different positions. Based on Faraday's law,

$$V = \eta k I t = \eta k Q \tag{1}$$

where V is the volume of the eroded metal from the processed gear in mm^3, k is the electrochemical equivalent of the metal volume of the processing gear in mm^3/C, I is the current density in A/mm^2, t is the processing time in s, η is the processing efficiency, and Q is the electricity required for the processing in C.

The required electrochemical processing for a gear of a known metal can be ascertained, and the eroded volume of the metal can be determined mainly by the strength of the processing electric current. We developed a device to control these two parameters. During ECGTPMs, our system controlled the intensity of the electric current produced by the electrical source between cathode slider and anode gear wheel based on the relative position of the gear tooth and the slider detected by the angular displacement sensors (14 and 15). The system also adjusted the rates of the stepping motors (1 and 2) to control the rate of the cathode slider movements at different positions of the gear tooth surface. This adjustment controlled the amount of the electrochemical modification that occurred at different positions of the gear tooth. After finishing a tooth modification, the control system adjusted the rotation of the stepping motor (1) to move the gear to the next tooth position. Therefore, these two parameters could be used to modify the gear profile of an entire gear based on different volumes of metal eroded at different positions on the gear surface.

We used a closed-loop control system to increase the precision of the changes in the electric current. A collector ring was used to measure the intensity of the actual electric current signals at different relative positions on the slider and gear. These were changed into digital signals by the A/D converter (6). The computer (7) compared these signals to their target values, which were optimized from experiments. When the current intensity was stronger than the target value, the control system decreased the actual electric current, and vice versa.

3. Modeling the Erosion Process for ECGTPM

For any given voltage and electrolyte parameters such as composition and temperature, we can obtain the required distance from the instantaneous processing point on the gear-tooth surface to the cathode slider. This is the truncation clearance. The metal can only be melted satisfactorily at this distance.

Suppose that the function for the distribution of the through electric current at relative positions on the surface of gear is $I(x)$ and the velocity of the cathode slider processing the surface of the gear relative to gear tooth surface is $v(x)$. Then after a processing time t, the processing depth at x, which is a random point on the gear-tooth surface, is

$$H(x)=\frac{t}{\tau}\int_{-\frac{x_0}{2}}^{\frac{x_0}{2}}\frac{A[I(x+\xi),v(x+\xi)]}{v(x+\xi)}\left[1+\sum_{k=1}^{m}a_k(k\xi)^{2k}\right]d\xi \tag{2}$$

where τ is the scanning time of the cathode to point x, t is the electrochemical machining time of the part, and $A[I,v]$ is the range of the processing volume distribution per unit time,

$$A[I,v]=\begin{cases}0 & [I<I_0]\\ \sum_{j=0}^{n}b_j & [I\geq I_0]\end{cases} \tag{3}$$

Using the above analysis, we can obtain the modification amount $H(x)$ from $I(x)$. However, it is difficult to derive $I(x)$ from $E(x)$, which is the distribution function of the modification amounts at different positions on the gear-tooth profile surface. Furthermore, the actual measured $E(x)$ is always discrete, not an analytical function. During the modifications, the chemical content of the electrolyte, the processing distance, and the intensity of the electric current will change slightly, and the facility installation also has some errors. Therefore, the interaction of the variables and parameters will cause difficulties in obtaining the required electric current and make this calculation very difficult. From the above analysis, we find that the accuracy of the modification amount and the appropriate modification area are directly dependent on the control accuracy of the electric current and kinetic parameters. Thus, the success of the real-time ECGTPMs is mainly dependent on timely accurate current control according to the gear modification requirement. We therefore must find an appropriate method to obtain $I(x)$ from $E(x)$ correctly and easily. We believe that a neural network (NN) can be used to avoid the complex relationships among the parameters in the mathematical model and obtain a mapping from n-dimensional space to m-dimensional space directly. This is helpful when inversely evaluating the rule for controlling the electric current for ECGTPMs.

4. Fundamentals of BP Control

A NN is a powerful data-modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of NN technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. NNs resemble the human brain in the following two ways: they acquire knowledge through learning and their knowledge is stored within interneuron connection strengths known as synaptic weights.

The true power and advantage of NNs lies in their ability to represent both linear and nonlinear relationships and learn these relationships directly from the data being modeled. Traditional linear models are inadequate when it comes to modeling data that contain nonlinear characteristics. The most common NN model is the multilayer perceptron (MLP). This type of NN is a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown.

The NN approach overcomes problem-solving modeling difficulties since it can be used to estimate various functions without the need of focusing on the actual control systems necessary to provide suitable solutions for complex unknown systems, especially those systems that have complex unsolvable mathematical models. Several studies have developed control systems based on NNs.[11-13,19-22]

A predictive control scheme was implemented by an iterative and repetitive optimization process. In recent years, this has become an increasingly accepted tool for controlling nonlinear systems because it can be used to predict future system behaviors. Another viable control strategy involves NNs within a predictive control framework: several studies have used referring feed forward neural networks (FNNs) with external recurrence and off-line training. Donat *et al.*[14] used a multilayer FNN trained with a back-propagation (BP) algorithm together with an optimization problem that was solved with a sequential quadratic programming method. Temeng *et al.*[15] proposed a hybrid multivariable nonlinear predictive control scheme based on a FNN model and the Fletcher variable metric method to solve an optimization problem. Draeger *et al.*[16] used a FNN to perform nonlinear predictions in an extended standard dynamic matrix control algorithm. However, instead of solving a nonlinear optimization problem with a standard nonlinear optimization algorithm, the control action was obtained using a gradient descent algorithm, as in the learning stage. Another approach involves implementing recurrent NNs for modeling purposes in a predictive control structure. Zamarrefio and Vega [17] proposed a neural nonlinear adaptive control technique. Common NN-based control systems use NNs to approximate system functions and apply a feedback control based on the results of the estimated system output. A NN controller is continuously trained in parallel with the work of the entire system to minimize the difference between the predicted and actual system outputs.

Based on the theory of NNs in biology, an artificial NN (ANN) can be used to predigest complex partial differential equations. This requires weights and values for many connected neurons to produce the output. A study on the progress of an ANN can be performed by continuously changing the connection weight and threshold values. After the values from the required relationships have been input and the output has been supplied to a trained ANN, we can forecast the actual output.

A BP network is a forward-propagation network that consists of nonlinear transform cells. Suppose that $x_1, x_2, \ldots, x_n$ are the inputs to the ANN, and $Y_1, Y_2, \ldots, Y_N$ are the outputs from the ANN. For a nonlinear NN, the relationship between the input and output is a nonlinear monotonic ascending function,

$$S_j=\sum_{i=1}^{n}w_{ij}x_i-\theta_j \tag{4}$$

$$u_j=S_j \tag{5}$$

$$Y_j=f(u_j) \tag{6}$$

Equation (4) is the accumulated value of the input of the nerve cell, where w_{ij} is the weight of the nerve cell, θ_j is the threshold value, and S_j is the output of the nerve cell. Equation (5) is the state equation: u_j indicates the state of the nerve cell. In Eq. (6), $f(u_j)$ is a monotonic ascending bounded transform function. For nonlinear changes, Eq. (6) is generally expressed as

$$f(u_j)=\frac{1}{1+e^{-u_j}}=\frac{1}{1+e^{-\left(\sum_{i=1}^{n}w_{ij}x_i-\theta_j\right)}} \tag{7}$$

$$X=(x_1,x_2,\ldots x_n)^T \tag{8}$$

Here, $f(u_j)$ is a continuous differentiable function. It is a first-order differential and the equation for linking weight is quite evident. Its learning algorithm is known as the BP method.

Suppose that the input layer has n neutral cells so that its input is a n-dimensional vector $X\in R^n, X=[x_1,\ldots,x_n]^T$, and the output layer has m neutral cells so that its output is an m-dimensional vector $Y\in R^m, Y=[Y_1,\ldots,Y_m]^T$. Suppose also that the connecting weights between the input and the middle layer are w_{ij} with threshold values θ_j, and the connecting weights between the input and middle layers are w_{ij}' with threshold values θ_j'. The resulting equations are

$$Y_l=f\left(\sum_{j=1}^{n_l}w_{ij}'x_j'-\theta_l'\right) \tag{9}$$

$$X'_j = f\left(\sum_{i=1}^{n} w_{ij} x_i - \theta_i\right) \tag{10}$$

Here, $f(w)$ corresponds to the expression given in Eq. (4). These two equations were used to map the actual n-dimensional space, F, of the BP network, and can be expressed as

$$F : X \in R^n \rightarrow Y \in R^m \tag{11}$$

The learning process for the BP arithmetic used the real mappings (X_1, Y_1), (X_2, Y_2), (X_p, Y_p) as tutors for the ANN. We can obtain the difference between the real mappings and the ANN mappings and by continuously changing the connection weights and thresholds to make them more and more similar.

Since BP arithmetic is used to solve nonlinear optimization problems, difficulties can occur during training, such as low convergence rates or falling into local minimums. We therefore used changeable space training and added a momentum term and an r_1^{p1} factor to improve the performance. In changeable space training, we used $\eta = \eta\varphi$, $\varphi > 1$ when $\Delta E < 0$ and $\eta = \eta\beta$, $\beta < 1$ when $\Delta E > 0$ for the iterative expression for the weights, $w(n_0 + 1) = w(n_0) + \eta(n_0)d(n_0)$, where ϕ and β are constants, and $\Delta E = E_{all}(\eta_0) - E_{all}(\eta_0 - 1)$. We added the momentum factor $0 < \alpha < 1$ to accelerate the rate of convergence and prevent oscillations, giving

$$w(n_0 + 1) = w(n_0) + \eta(n_0)d(n_0) + \alpha\Delta w(n_0) \tag{12}$$

where $\alpha = 0$ if $\Delta E > 0$ and $\alpha > 0$ if $\Delta E < 0$. The r_1^{p1} factor was used to force Y_1^{p1} to leave unwanted areas quickly, where

$$Y_1^{p_1} = \frac{1}{1 + e^{-\alpha}} = \frac{1}{1 + e^{-\sum_k (w'_{1k} x_k'^{p_1} + \theta'_1) r_1^{p_1}}} \tag{13}$$

5. Using an ANN to Obtain the Electric Circuit Processing Law

We explored how to use an ANN to obtain the processing circuit law for ECGTPMs with real-time control based on the example of an automotive gear manufacturing plant in the province of Shangdong, China, which required us to modify a hypoid gear. The gear parameters are shown in Table 1. A large amount of eroding was required at the two ends of the gear in the direction of the gear-tooth tip while less eroding was needed in the middle of the gear. To increase the efficiency of modifications, we set the relative moving rate of the cathode slider and gear $v(x)$ in advance using

$$v(x) = \frac{1}{\sqrt{2\pi}v_m} \exp\left\{-\frac{\left(x - \frac{T}{2}\right)^2}{2v_m^2}\right\} \tag{14}$$

where v_m is the moving rate of the cathode at the midpoint of the gear tooth and T is the time used to modify the tooth. In practical processing, after several tests, we ascertained that $v_m = 5$ mm/s. For this hypoid gear, we selected $T = 30$ s.

The dimensions of the plane cathode were b = 30 mm, approximately equal to the normal pitch, and $l = 10$ mm. The electrolyze processing clearance was δ = 18 mm. Using in-house electrolyte DUT#1, the system could attain a maximum electric current intensity of 100 A.

The functional relationship between the gear-tooth profile modification value $E(x)$ and the gear position x for the proposed BP network is shown in Fig. 2. Once the electrolyte was defined, the following factors determined the processing circuit distribution $I(x)$: the modification value distribution $E(x)$, the relative moving rate of cathode slider to the gear-tooth surface $v(x)$, the processing clearance δ, and the processing time t. If δ, $E(x)$, and $v(x)$ are the input layers of the ANN, the processing circuit distribution $I(x)$ is the output layer, and a concealed layer is located between them; we can then establish an ANN. We adjusted the connecting weights and threshold values for the neurons by selecting 20 groups of values that satisfied the request to train the ANN (not shown here due to length restrictions) and finally obtained a successful mapping.

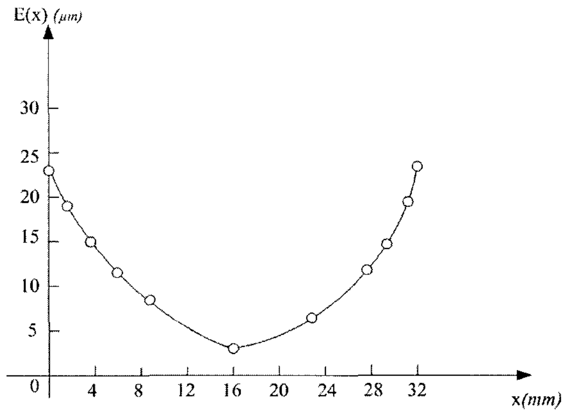

Fig. 2 Required modification distribution

We trained the ANN 35,000 times using a study rate $\lambda = 0.75$ and a momentum factor of 0.5. The network finally attained global convergence. We then obtained $I(x)$ by recording the various connecting weights and threshold values using the output of the ANN, and used this distribution to modify a large hypoid gear. The modifications required 12 min. Afterward, we compared the difference between the actual and required modification distributions, $H(x)$ and $E(x)$. The results, shown in Table 2, indicate that the difference was very small. Therefore, this method for obtaining the processing circuit law based on a known ANN modification is viable.

Our main reason for determining the relative rate of the cathode slider movement using the above principles was to increase the efficiency of the modifications. When modifying a gear, the eroded volume of material at a given point mainly depends on the intensity of the processing electric current and the processing time. The former can be controlled by the controllable electric source while the latter is related to the relative moving rate of the slider: the higher the relative moving rate of the slider, the shorter the processing time and the smaller the eroded volume of material. The principles described above are only suitable for gear modifications in the direction of the gear tooth. Another aim of our method was to preset and simplify the control system. When given the relative moving principles of the slider to the gear tooth surface, if the path of the slider is parallel to the modified hypoid gear tooth surface and the gear parameters are known, we can obtain the moving rate of the slider and rotation rate of the gear at any location. During the modifications, the two angular displacement sensors can measure the angular displacement of the lead screw and the processed gear. Based on the defined arithmetic, we can obtain the positions of the cathode slider and relative point on the gear surface. From these data, the system can control the rotational speed of the stepping motor precisely, allowing the slider to continue sliding on the processed gear surface while accurately modifying the gear-tooth surface. If another gear has different requirements, we simply change the rotational speed at the output layer of the NN model to modify the network model into a multi-input, multi-output BP NN. The control principles remain the same. Thus, our system is very adaptable.

The slider was a rectangular block. When the slider reached a certain position on the gear, an electric field was generated between the gear-tooth profile surface at this position and the slider. The electrical power was higher near the top of the gear and lower near the gear root, which was exactly what was required to modify the gear profile. Thus, when we modified the gear in the direction of the gear tooth, we also modified the edge of gear-tooth profile.

Figures 4 and 5 show the measurement results of the gear teeth before and after modification. (The measurement method is described in detail in Reference.[4]) These figures show that the correct areas were modified by the correct amount. The difference between the requested modifications and our theoretical gear analysis was very small.

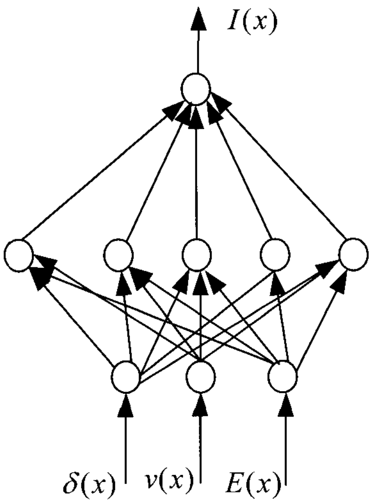

Fig. 3 B-P machining model

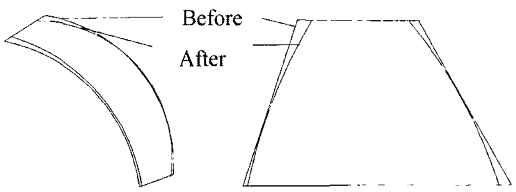

Fig. 4 Profile curve of a gear-tooth before and after modification

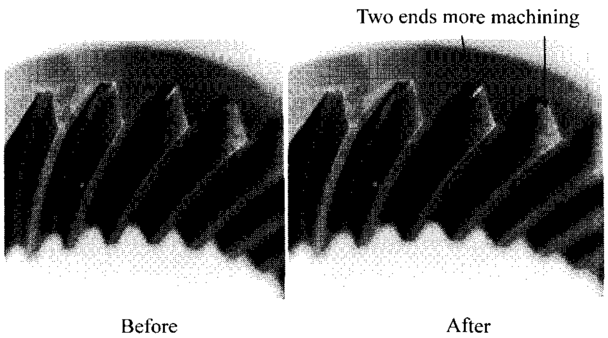

Fig. 5 Meshing area before and after modification

Table 1 Gear parameters

Parameters	Driving gear	Driven gear
Number of teeth	9	39
Module (mm)	4.5	4.5
Face width (mm)	27	27
Average transverse pressure angle (°)	22.5	22.5
Roughness (μm)	3.2	3.2
Midpoint helix angle (°)	32.31	32.31
Side tolerance (mm)	0.2 – 0.3	0.2 – 0.3
Material	20CrMnTi	20CrMnTi
Shaft angle (°)	90	90
Nodus angle (°)	77.43	77.43
Surface angle (°)	78.29	78.29
Root angle (°)	77.36	77.36
Surface rigidity HRC	58 – 64	58 – 64
Core rigidity (HRC)	32 – 45	32 – 45
Rigidified layer (mm)	0.1 – 0.7	0.1 – 0.7
Helix direction	Right	Right

Table 2 Actual and required modification distributions

Position of the tooth surface	Machining circuit (A)	Practical processing (μm)	Theoretical modification (μm)	Error (μm)
1	69.8	25.1	23.9	1.2
2	61.3	19.9	19.2	0.7
3	53.6	15.7	16.0	–0.3
4	45.2	14.1	13.6	0.5
5	36.1	10.2	10.2	0.0
6	28.0	7.2	6.9	0.3
7	20.2	4.3	4.2	0.1
8	12.7	2.5	2.6	–0.1
9	6.5	1.9	1.2	0.7
10	3.3	1.2	0.3	0.9
11	7.2	0.8	0.0	0.8
12	4.1	0.6	0.0	0.6
13	6.9	1.0	0.2	0.8
14	12.0	2.1	1.8	0.3
15	20.2	3.2	2.4	0.8
16	29.8	4.6	3.9	0.7
17	34.5	5.1	5.5	–0.4
18	39.2	7.9	7.9	0.0
19	46.1	10.7	11.3	–0.6
20	49.9	14.1	14.9	–0.8
21	52.3	17.3	17.2	0.1
22	55.7	18.9	19.4	–0.5

The surveyed positions were sampled at points selected every 1.4 mm in the direction of the gear tooth.

6. Conclusions

Electrochemical gear-tooth profile modifications provide a valuable method for gear rectification. The technique has great utility, and is highly efficient and economic. It can be used to modify gears with a rigid gear-tooth surface, large dimensions, and special structures. The technique is extremely valuable in practice and we expect it to be widely adopted by industry. We designed a new facility to control the modifications in real time in order to automate the technique. Based on a known modification value and modification region, we obtained the processing circuit law using an ANN. We validated this type of control method with a practical application. Electrochemical gear-tooth profile modifications were shown to be a useful technique with a large application area that provided the means for solving problems that have troubled gear manufacturers for a long time.

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