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Cutting Machine Power Supply of SEAM Optimization Design Based on BP Neural Network and Genetic Algorithm

Xu Yan[1], Jianping Zhou[1, 2*], Cao Jiong[1] and Yiliang Yin[1]

[1]*School of Mechanical Engineering, Xinjiang University, China*
[2]*School of Mechanical Engineering, Xi'an Jiaotong University, China*
{lilixiu_z, linkzhou, caojiong_mail, yinyiliang007}@163.com
**Corresponding author: Jianping Zhou, e-mail: linkzhou@163.com*
Tel.: +86 13579208817

Abstract

The successful application of short electric arc machining (SEAM) technology can solve the long-standing technical problem of hard-facing materials processing which machinery manufacturing industry generally faces. In the article, we trained high power supply neural network model by using the simulation data. And on this basis, we optimize parameters of power supply combined with genetic algorithm based on objective weighting method to guide parameters changes to meet the requirements. The results, by analyzing startup test and load-mutation test, show that the power supply have the advantages of stable output voltage and fast response speed, which meet the expectant targets and machining requirements. At last, through cutting experiment of SEAM on nickel-based superalloy, the power supply of SEAM designed by this new method is verified that its electric properties meet processing requirements of SEAM.

Keywords: *Short electric arc machining (SEAM), Matlab simulation, neural network, genetic algorithm, optimal design*

1. Introduction

The technology of SEAM can effectively cut high hardness, high strength and difficult processing conductive materials [1, 2], and it has huge potential in the field of high hardness, high strength and difficult processing conductive materials.

Each of component parameters of main circuit has a direct impact on the performance of power supply in SEAM [3, 4], such as electromagnetic compatibility, electrical properties, which make the design cycle of power supply longer and material consumption huger.

The neural network model of high power supply is discussed and established by using experimental data and simulation data, which form a new fitness function of genetic algorithm. And on the basis of that, the parameters of power supply are optimized through genetic algorithm based on objective weighting.

Through the new method based on BP neural network and genetic algorithm (BP-GA), the conflicting problems of between multi-objective parameters in traditional design can effectively be solved, and the uncertainty in design and manufacturing process is reduced. In addition, this new optimal method also lessens frequencies of debugging of test running and changing the parameters compared with the traditional feasibility design method. The causes of these unfavorable factors mainly lie in that there is no suitable theory used to establish accurate model of power supply in traditional feasibility design method, so this new method is a very effective way for high power supply to optimize its parameters to meet processing requirements of SEAM.

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And we use this new optimal method to guide the 36V/2000A high-power optimization design and production to verify that its electric properties meet processing requirements of SEAM.

2. Simulation Model of Power Supply Based on Matlab Software

Main circuit topology of power supply is shown in Figure 1. It is made up of input rectifier and filter circuit, DC/DC conversion circuit and pulse generating circuit. Magnetic compatibility and electric performance of power supply are mainly determined by the DC/DC conversion circuit. Therefore, DC/DC conversion circuit is a key factor in establishing the simulation model of power supply in SEAM [5].

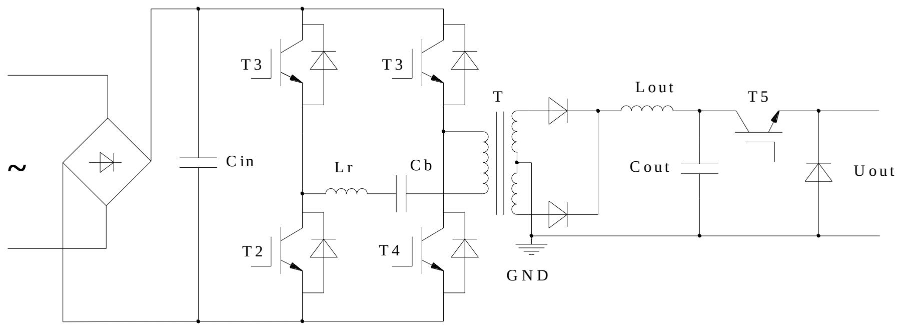


Figure 1. The Main Circuit Topology of Power Supply

It is very difficult to establish a precise mathematical model or transfer function for power supply, because power supply is a discrete, nonlinear system. Matlab software has a powerful scientific computing function, and it has become a basic analysis tool in dynamic system simulation [6, 7]. So, it has becoming an important step for analysis and design of power supply system to use the Simulink of Matlab software [8].

The main circuit of power supply in SEAM has following components: IGBT, high frequency transformer, diodes, switch tubes, resistances, capacitances and inductances, etc. These components can be simulated by using ready-made or combination components in Simulink, SimulinkExtra and SimPowerSystems module library, thus the working state of power supply can be intuitively and efficiently simulated. The simulation model of power supply is shown in Figure 2, four IGBT are encapsulated into SubInverter module; the phase shifting pulse generator is encapsulated into SubPWM module; the load mutation devices are encapsulated into SubOnToOff and SubOffToOn module.

The solver's parameters of Simulink should be identified before simulation. And calculation process of simulation is established by Power System Blockset (PSB) on the basic circuit principle and the numerical solution of differential equation. The system of ordinary differential equations of main circuit established by PSB as follow:

$$x' = \mathbf{A}x + f(x) \tag{1}$$

Where **A** is matrix.

Because PSB could accurately simulate the dynamic performance of the IGBT and diode, ordinary differential equation of switching power supply established by PSB is a rigid system of equations, namely, the eigenvalues of matrix A is different, In this case, the simulation algorithm adopts variable order numerical differentiation formulates (NDFS), namely the ode15s algorithm which is suitable for solving the problem of rigidity which Runge-Kutta method cannot do. Simulation uses mode variable step length, which can automatically adjust according to need by the PSB to ensure the stability of solution and calculation speed.

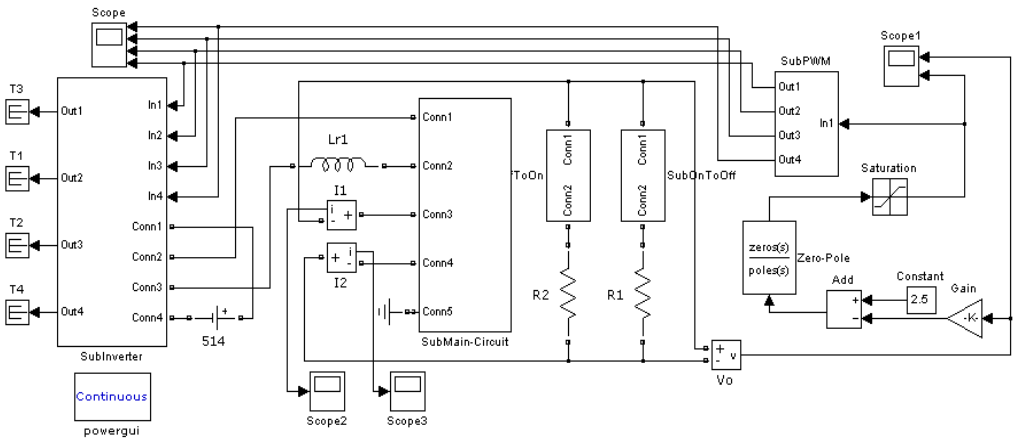


Figure 2. Phase-Shift Full Bridge Converter Model Simulation Experiment Platform

3. Power Supply's Mapping Relationship Building of BP Neural Network

Optimization design of high power supply is to seek an optimal solution in a set of parameters which can ensure SEAM's performance or economic indicators to achieve the optimal. So, in the process of optimization design, the mathematical model of power supply is very important. The optimization mathematical model can be described as:

$$\min F(X) = \left(f_1(X), f_2(X), f_3(X), f_4(X)\right) \quad \text{s.t} \quad x_{i\min} \le x_i \le x_{i\max} \quad i=0, 1,\ldots, 7 \tag{1}$$

Where $X = (x_1, x_2, \ldots, x_7)^T$ is input variables of power supply model, $x_{i\min} \le x_i \le x_{i\max}$ is X's decision space, and $\left(f_1(x), f_2(x), f_3(x), f_4(x)\right)$ is child of the objective functions which are conflict between them.

The biggest characteristic and advantage of neural network are that it can realize system's highly nonlinear mapping just by using sample data without a mathematic system model. So, in the process of power supply's optimization, between its parameters which will be designed and the objective functions a nonlinear contact could be established by using learning ability of neural network to replace the traditional design method. By this way, we can get the mathematical model of optimization design of power supply based on neural network, because this kind of nonlinear contact could be stored in the neural network's structure and weights through neural network learning [9, 10].

3.1. Learning Samples Design of BP Neural Network

The scientificity and rationality of the training data selection have extremely important impact on network design of power supply. The BP neural network input includes: main circuit input filter capacitor C_{in}, output filter capacitor C_{out}, output filter inductance L_{out}, current limiting resistor R_c, IGBT protection circuit R_{IGBT} and C_{IGBT}, and resonant inductor L_R. The output of the BP neural network is performances of power supply, namely output voltage fluctuation Vo, IGBT peak voltage U, the output voltage overshoot sigma σ% and regulate time Ts, a total of four parameters. The BP neural network inputs and outputs can be represented as:

$$\mathbf{y}_i = f^3\left(\mathbf{LW}^{3,2} f^2\left(\mathbf{LW}^{2,1} f\left(\mathbf{IW}^{1,1}\mathbf{P}_i + \mathbf{b}^1\right) + \mathbf{b}^2\right) + \mathbf{b}^3\right) \tag{3}$$

Where:

$\mathbf{P}_i = [C_{in}, C_{out}, L_{out}, R_c, R_{IGBT}, C_{IGBT}, L_R]_i$ inputs;

$\mathbf{y}_i = [\Delta V_o, U, \sigma\%, T_s]_i$ outputs;

i training group;

$\mathbf{IW}^{1,1}$, $\mathbf{LW}^{2,1}$, $\mathbf{LW}^{3,2}$; input layer, first layer to second layer, and second layer to the third layer weight vector;

$\mathbf{b}^1$, $\mathbf{b}^2$, $\mathbf{b}^3$; network threshold vector of each layer;

Transfer function of input layer and output layer nerve cell is tansig which benefits functional approximation.

Input data is produced by using random functions of Matlab near the feasible design parameters, inputs range as shown in Table 1.The outputs of the training data are obtained by the Simulink simulation. Inner linkage contained in inputs and outputs data can be learned by neural network.

Table 1. Input Variable Scope of Power Supply

Input Variable	Minimum Value	Maximum Value	Unit
C_{in}	0.0016	0.002	F
C_{out}	0. 38	1. 5	F
L_{out}	0.075	0.1	H
R_c	380	420	Ω
R_{IGBT}	100	130	Ω
C_{IGBT}	0.003	0.006	F
L_R	0.0001	0.00036	H

3.2. Structure and Algorithm of BP Neural Network

Neural network toolbox based on Matlab software provides a variety of neural network structure, three layer BP neural network model is the most widely used. The neurons of BP neural network use Sigmoid transfer function which is differentiable function, so it can realize any nonlinear mapping of the input and output, making it have more extensive application in the field of function approximation [11].

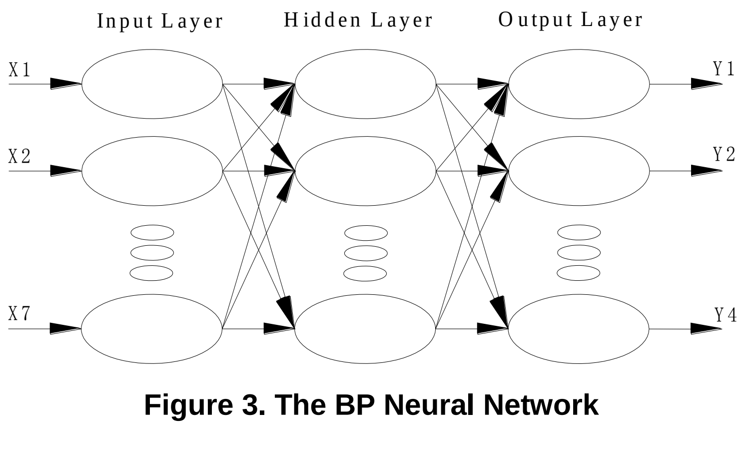


Figure 3. The BP Neural Network

In order to improve the BP neural network learning speed and increase the reliability of the algorithm, we have to improve the BP algorithm, namely introducing momentum item.

When the weights are corrected by BP neural network through using additional momentum method, this method not only consider the effect of error on the gradient, but take into account the influence of change trend in error curved surface. It likes a low pass filter, and it has an excellent property which allows the network to ignore small changes. The method is based on each of weight changes plus a value which is proportional to the variable quantity of previous sub-weight. And generate new weight changes based on back propagation method. Weight adjustment formula with additional momentum term is:

$$\omega(k+1)=\omega(k)+\eta\left[(1-\alpha)D(k)+\alpha D(k-1)\right] \tag{4}$$

Where $w(k)$ is weight vector, k is training number, α is momentum factor and $0<\alpha<1$, η is learning rate and its value is 0.95; $\omega(k)$ can represent a single connection weights, and also said the connection weight vector. $D(k)=\frac{\partial E}{\partial \omega(k)}$ is negative gradient at k time, where E is training error.

3.3. BP Neural Network Training

When multi-layer network structure is determined and the training data get ready, we can apply BP algorithm to train the network. The BP neural network adopts three layer structures, the number of hidden layer nodes is 20, and the total error e is 0.01. In Matlab7.8 neural network toolbox, BP training steps are as follows:

(1) Initialize weights and thresholds. Put all weighting coefficients and thresholds for minimum random number to ensure that the network is not saturated by large weighted value;

(2) Provide the training set, input vector:

$$P=\left[C_{in}, C_{out}, L_{out}, R_{c}, R_{IGBT}, C_{IGBT}, L_{R}\right]_{500} \tag{5}$$

Output vector:

$$y=\left[\Delta V_{o}, U, \sigma\%, T_{s}\right]_{500} \tag{6}$$

(3) Set training parameter value, expected minimum error value, maximum cycles, and fixed weights learning rate lr;

(4) Start cycle training: for epoch=1: biggest cycles;

(5) Calculate error of the network;

(6) Calculate error changes of D1 and D2 of each layer back propagation, and count the weights of each layer and the new weight;

(7) Check whether the SSE is less than the expected minimum error value, If so, the training ended; If not, continues.

4. Genetic Algorithm Based on Objective Weighting Method

The basic idea of genetic algorithm based on the objective weighting method is to give each target vector its own weight, and then sum them after each target vector multiplied by its own weight, which form a new objective function, namely, turn multi-objective function into single objective function to solve [12-14]. And it is widely used in nonlinear and multi-objective optimization problems.

Common multi-objective weighting method as follow:

$$F(X)=\sum_{i=1}^{m}\omega_i\cdot f_i(X) \qquad (7)$$

Where ω_i (i=1, 2, 3,…, m) is non-negative weight coefficient of objective function $f_i(X)$,and satisfy $\sum_{i=1}^{m}\omega_i=1$.

We combine BP neural network model with common multi-objective weighting method to form a new evaluation function, namely, a new fitness function of genetic algorithm. Therefore, multi-objective optimization problem could be turned into single object optimization.

In view of the high power supply's optimization, it belongs to multi-objective problems. The main parameters of genetic algorithm based on the objective weighting method are shown in Table 2 below:

Table 2. Parameter Settings of Genetic Algorithm Based on Objective Weighting Method

Major Parameter	Settings
crossing-over rate	0.4
aberration rate	0.2
population size	20
genetic algebra	100
macrovar	7

Genetic algorithm based on the objective weighting method parameter optimization steps are as follows:

(1) Inputs variable scope. For multi-parameter optimization problem of power supply, floating-point encoding is used, because the binary encoding scalability is not strong and straightforward, and the string is so short that express precision of weights is not enough accurate. For floating-point coding, each of gene value in individual are expressed by a floating point number in a range, and coding length of individual is equal to the number of decision variables. The scope of each variable corresponding is shown in Table 1.

(2) Randomly generate initial parent groups. Group size is 20; respectively get random value in the X vector component within their scope, and get the initial solution vector X_0 .

(3) Parent individual fitness evaluation. By BP neural network learning and training, we establish the fitness function of genetic algorithm by using input-output mapping relation model of power supply based on BP neural network. Definition of the i^{th} parent individual fitness function value is:

$$F(X)=\sum_{i=1}^{4}\omega_i\cdot f_i(X) \qquad (8)$$

Where ω_i (i=1,2,3,4) is nonnegative weight coefficient in objective functions, and meet $\sum_{i=1}^{4}\omega_i=1$ .Considering processing condition of power supply in SEAM, namely, the output voltage waveform has a great influence on the processing, so take $\omega=[0.5,0.2,0.2,0.1]^T$.

(4) The probability choice of parent individual. Use proportion choice way, and individual i choice probability is:

$$P_i=F_i\Big/\sum_{i=1}^{20}F_i \qquad (9)$$

(5) Parent individuals' crossover. Select randomly two individuals from the population, then do crossover operation according to crossover probability 0.4 given beforehand.

(6) The variation of offspring. The allele obtained by each of gene mutations distributes near the original value of the gene in larger probability density, and also has a certain probability density in far away from the original value of the gene [15].

(7) Evolutionary iteration. N offspring individuals who are obtained by step (6) turn into new parent; judge whether new parent meet algebra or satisfaction solution designed in advance, If not satisfied, the algorithm shift to the step (3), enter into the evolutionary process, reciprocating cycle until close to the optimal value. Figure 4 is parameter optimization flow chart of genetic algorithm based on the objective weighting method.

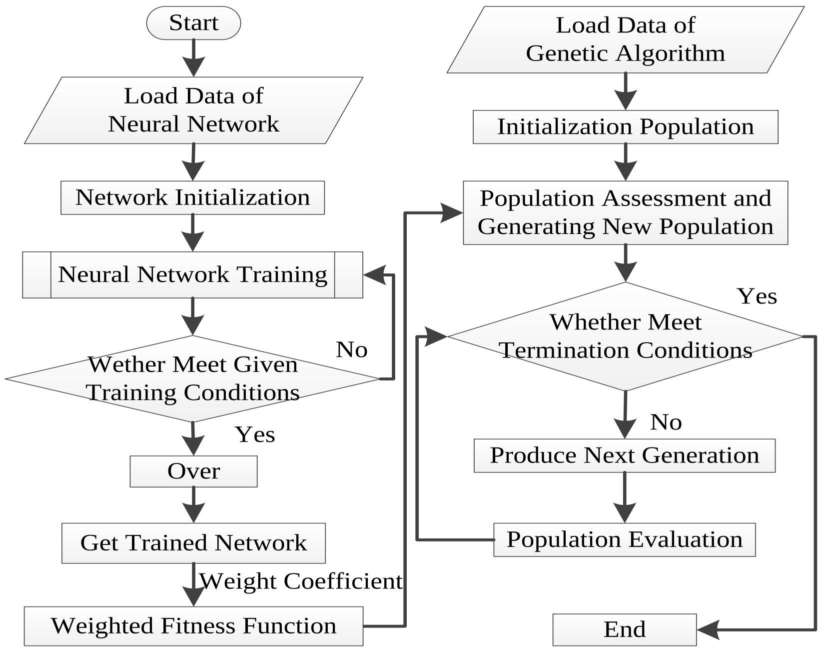


Figure 4. Parameter Optimization Flow Chart of Genetic Algorithm Based on Objective Weighting Method

5. Simulation and Test

By experimental data, Neural Network Toolbox, and Genetic Algorithm Toolbox in Matlab Simulink software, we establish the optimal simulation model of high power supply of SEAM. And use the model to simulate and study to make the performance index of power supply meet the demand in SEAM.

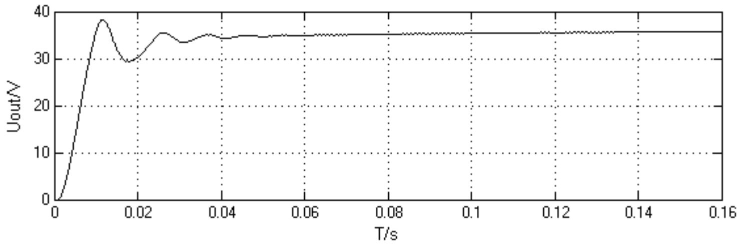
The optimization simulation model of 36V/2000A is tested on the simulation platform. And its circuit optimization and simulation model parameters as shown in Table 3.

Table 3. Simulation Model Parameters of Power Supply

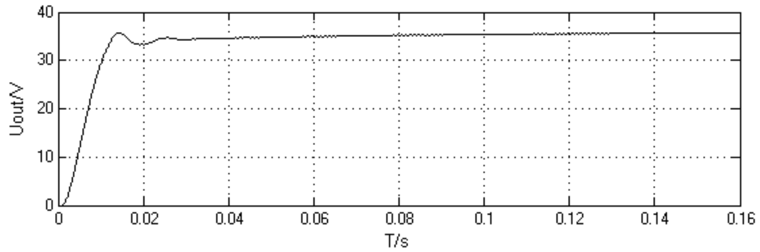
Variable Name	Parameter Values	Variable Name	Parameter Values
C_{in} / F	0.0016	R_1 / Ω	0.036
C_{out} / F	1	R_2 / Ω	0.033
L_{out} / H	0.8	sampling coefficient	0.0694
R_c / Ω	400	SatuRation	15
R_{IGBT} / Ω	100	zero-frequency gain	5.2×10^{6}
C_{IGBT} / F	0.0034	Zero Point /KHz	400
L_R / H	0.000108	Pole Point /KHz	4×10^{-4}

4.1. Startup Test

Figure 5 is startup waveform of output voltage based on feasibility design and optimal design.



(A) Simulation Output Voltage of Feasibility Design



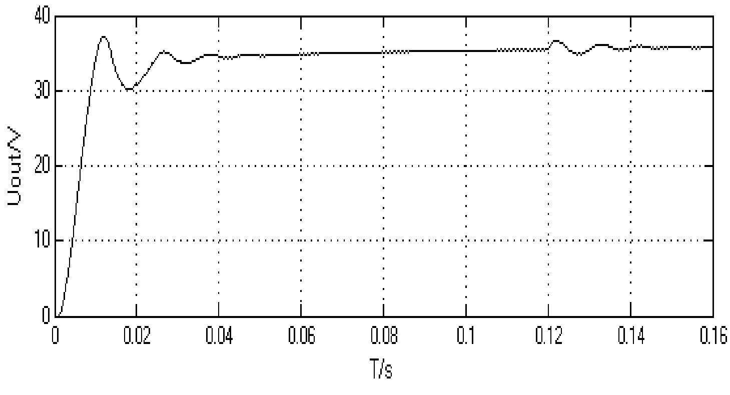
(B) Simulation Output Voltage of BP-GA Optimization Design

Figure 5. The Startup Waveform of Output Voltage Based On Feasibility Design and Optimal Design

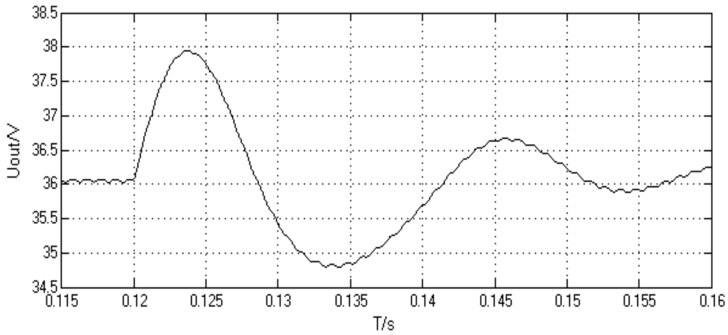
As shown in Figure 9, overshoot of BP-GA optimization design is 8.3%, and overshoot time is 50ms; overshoot of feasibility design is 3.3%, and overshoot time is 30ms. Therefore, we can draw a conclusion that BP-GA optimization design has better properties than feasibility design.

4.2. Load Mutation Test

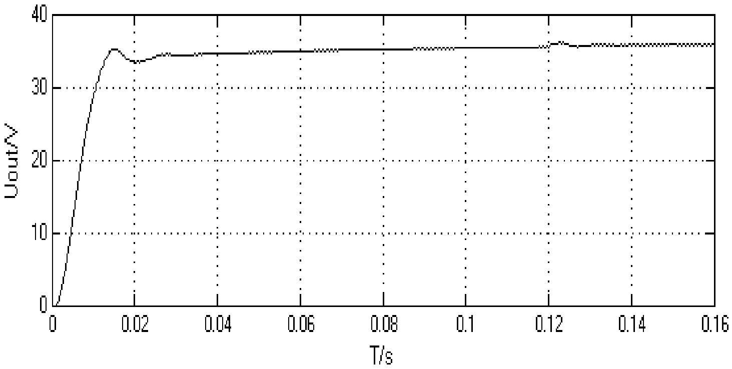
According to the national standard output voltage waveform overshoot amount of power supply in load mutation is less than or equal to 10%, and overshoot time is less than or equal to 0.1s. Figure 6 are load-mutation output voltage waveform based on feasibility design, optimal design and experimental prototype.



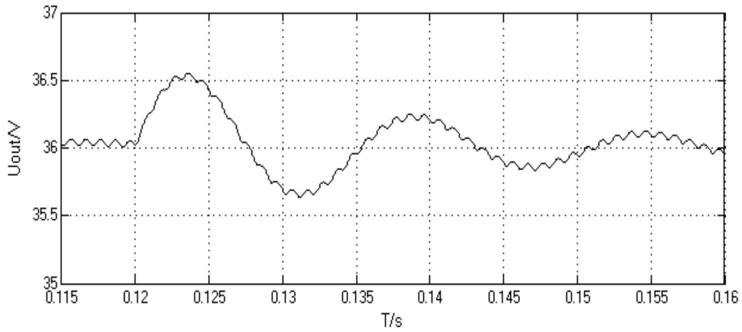
(a) Simulation Output Voltage of Feasibility Design in Load Mutation Test



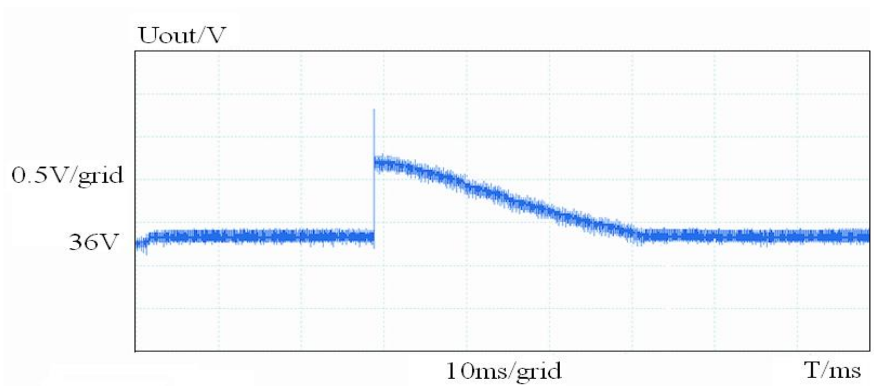
(b) Detail View of Simulation Output Voltage of Feasibility Design in Load Mutation Test



(c) Simulation Output Voltage of BP-GA Optimization Design in Load Mutation Test



(d) Detail View of Simulation Output Voltage of BP-GA Optimization Design in Load Mutation Test



(e) Output Voltage in Load Mutation Test of Experimental Prototype

Figure 6. Load-Mutation Output Voltage Waveform Based on Feasibility Design, Optimal Design and Experimental Prototype

As shown in Figure 6, output voltage waveform of load mutation test is sampled by precise oscilloscope PicoScope 6402. Overshoot amount of simulation output voltage is 5.5% in feasibility design, and overshoot time is 40 ms; Overshoot of simulation output voltage is 1.67% in optimization design, and overshoot time is 30 ms; Overshoot amount of output voltage is 2.3% in load mutation test of experimental prototype, and overshoot time is 30 ms.

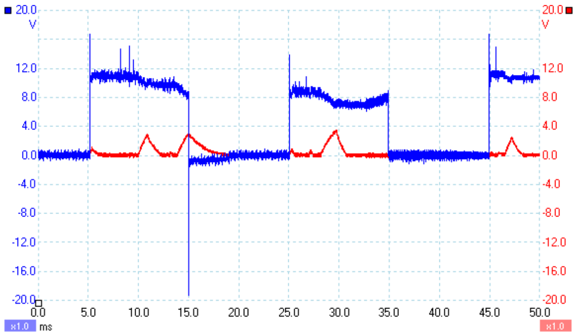
Overshoot and overshoot time of mutation load voltage designed by BP-GA optimization design conform to the requirements of national standard.

It can be seen from the startup test and load mutation test that power supply designed by BP-GA optimization design has excellent electrical properties, and provides accurate output voltage for pulse generating circuit.

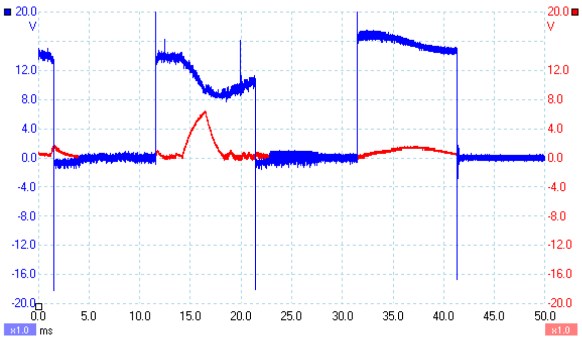
6. Processing Experiment of SEAM Based on Nickel-Base Superalloy

In order to verify whether the electric properties of power supply designed by this new method can meet processing requirements of SEAM, cutting experiments were done based on nickel-base superalloy in 10V, 15V and 20V voltage.

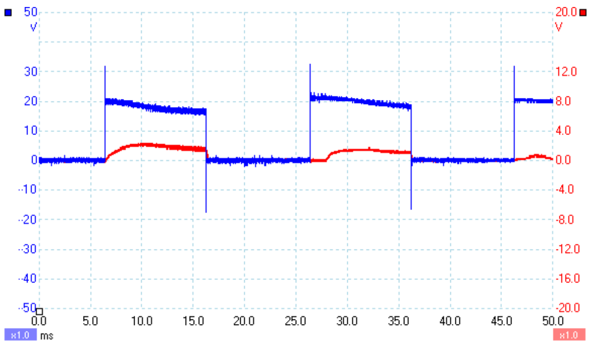
Tool's material is brass, and its shape is siphonate. Figure 7 illustrates that voltage and current waveform of experiment prototype power in 10V, 15V and 20V short electric arc milling machine processing. The output voltage frequency is 50Hz and the duty ratio is 50%; Cooling adopts water vapor mixing: the water pressure is 0.8-1.2Mpa and pressure is 0.1-0.4 Mpa; processed specimen material is nickel-base superalloy GH4169.



(a) Machining Voltage and Current Waveform of NC Milling Machine in 10V



(b) Machining Voltage and Current Waveform of NC Milling Machine in 15V



(c) Machining Voltage and Current Waveform of NC Milling Machine in 20V

Figure 7. Machining Voltage and Current Waveform of NC Milling Machine in 10V, 15V and 20V

Use PicoScope 6402 oscilloscope to sampling: probe 1 (blue) collect output voltage signal; probe 2 (red) collect output current signal. Output current is measured by CE-IZ04-86C3 current sensor to sampling current signal, and sampling ratio is 200 A/V.

As can be seen from the Figure 7, in three pictures, the time of establishing discharge channels is the shortest in 10V; the time of 15V take second place; 20V is the slowest. On the other hand, discharge current can reach more than 1600A in 20V; 15V take second place; 10V's is least, about 700A.

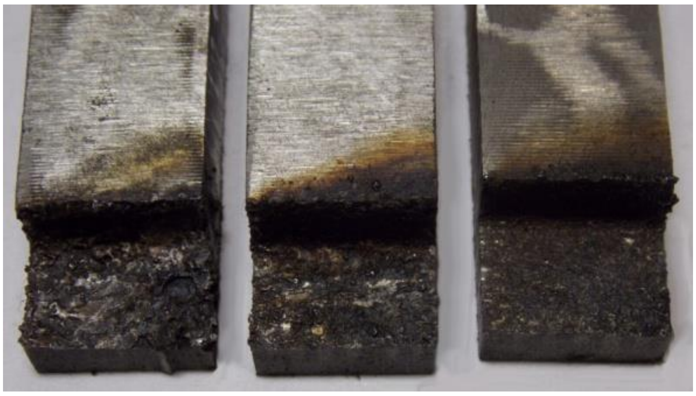


Figure 8. Test Specimen Machined by NC Milling Machine in 10V, 15V and 20V

Specimen processing can be seen from Figure 8, processing voltage is 10V, 20V and 15V in turn from left to right.

It can be seen from Figure 7 and Figure 8 that arc discharge channel can be effectively established which is essential for SEAM to removal metal or non-metallic material and also play a critical role to machining quality of SEAM. So, the power supply designed by this new method is verified that its electric properties meet processing requirements of SEAM.

7. Conclusion

In the article, on the basis of estimating SEAM power project, the neural network model of power supply is trained and the mapping relation model is set up by establishing and using the power supply Matlab simulation data. And on this basis we optimize power supply parameters combined with genetic algorithm based on objective weighting method to guide the power parameter changes to meet the requirements. This new method not only save debugging time and reduce repeatedly design process, but also economize the debug and test cost, and achieve the effect of get half work times, although adding the process of BP neural network model and optimization model. At last, by analyzing startup test, load-mutation test, results of simulation and tests, results show that the power supply designed by this new method have the superiority of stable output voltage and fast response speed, which provides important technical support for SEAM's research.

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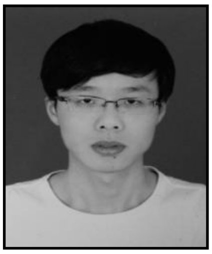
Authors

Xu Yan the master's degrees in Mechanical Engineering from Xin Jiang University, China, in 2013. She is a Professor in School of Mechanical Engineering, Xinjiang University. His recent interests focus on Special Processing Technology.

Jianping Zhou received the Ph.D. degrees in Mechanical Engineering from Xi'an Jiaotong University, Xi'an, China, in 2013. He is a Professor in School of Mechanical Engineering, Xinjiang University. His recent interests focus on Special Processing Technology.

Cao Jiong is enrolled in a fourth-year student in Mechanical Manufacture and Automation major in Xin Jiang University, Xi Jiang, China. He currently studies for a master's degree in Mechatronic Engineering at Xin Jiang University. His recent interests focus on Special Processing Technology.



YiLiang Yin is enrolled in a fourth-year student in Mechanical Manufacture and Automation major in Xin Jiang University. He currently studies for a master's degree in Mechatronic Engineering at Xin Jiang University. His recent interests focus on Special Processing Technology.