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WENJIE HU[1,2,3], OLEKSANDR SHORINOV[1]

[1] National Aerospace University «Kharkiv Aviation Institute», Ukraine
[2] School of aeronautics and astronautics, Nanchang institute of technology, China
[3] China Scholarship Council

OPTIMIZATION OF PARTICLE ACCELERATION PARAMETERS OF SPECIAL COLD SPRAY NOZZLES VIA NEURAL NETWORK AND GENETIC ALGORITHM

*Cold spray technology is a new technology that deposits supersonic solid particles on the surface of materials. There are many factors that affect particle acceleration, such as the geometric structure of the cold spray nozzle (contraction section, throat, expansion section, special nozzle angle, etc.), the parameters of the propellant gas (gas type, gas temperature, gas pressure, etc.), the material properties of particles (metal and non-metal), particle size (generally 10...50 microns), and particle morphology (spherical, irregular shape, etc.). **The objective** of this study was to investigate the influence of particle acceleration parameters on cold spraying. **This work aims to** predict and optimize the particle velocity at the outlet of the special nozzle to meet the critical velocity requirements of various metal particles and thus meet the deposition conditions. **The task** to be solved is to optimize the particle parameters of the special nozzle and obtain the particle velocity at the outlet of the special nozzle. **The methods** used are as follows: Three key parameters that affect particle velocity were selected as research objects: helium gas temperature and pressure when selecting helium gas, and titanium particle diameter as the third parameter. First, 30 sets of particle exit velocity data were sampled using Latin Hypercube Sampling, of which 24 were training data and 6 were prediction data. Then, the neural network was analyzed to obtain the minimum neuronal error value, thereby determining the number of hidden layers. At the same time, the parameters were normalized, and finally, the nozzle exit particle parameters were optimized using genetic algorithm. **The results showed that** after three rounds of optimization and taking the average value, the particle velocity at the outlet of the special nozzle was 591m/s. The optimized parameters were: helium temperature of 694...865 K, a helium pressure of 3.3...3.7 MPa, and a titanium particle diameter of 12...20 microns. When the optimized parameters were input into the numerical simulation software, the result was close to the predicted value. Therefore, the neural network and genetic algorithm optimized the parameters with high accuracy (with an error of 4%) and can be used as a reference for relevant workers.*

Keywords: *cold spray technology; particle acceleration; special nozzle; neural network; genetic algorithm.*

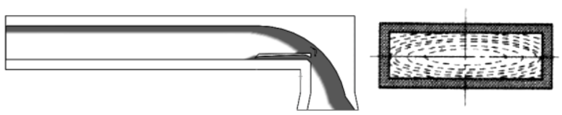
1. Introduction

Supersonic cold gas dynamic spraying technology (cold spraying) is a method of forming coatings by solid-state deposition [1], which is mainly used in the fields of protective coatings, repair coatings, and additive manufacturing [2].

The parameters of cold spraying technology are relatively complex, because there are too many parameters that affect the deposition effect, there are three major categories. The first category is mainly about the structural parameters of parts in the cold spraying system and equipment; the second category is mainly the fluid dynamics and other parameters of the powder flowing through the nozzle path, including temperature, pressure, propulsion inherent gas characteristics; the third category is mainly the process parameters of powder deposition on the surface of the substrate [3], etc.

Although there are many parameters in the field of cold spraying technology, there are many researchers on single factor [4, 5]. Obviously, multi-parameter research is closer to the real value.

Hence, this work on muti-parameter will provide a new idea and theoretical guidance for cold spraying technology. This work chooses special rectangular nozzle [6] as the structural model (Fig. 1), aiming to optimize and explore its influencing parameters with the goal of maximum exit velocity, the particle select pure titanium, the gas select He.



a b

Fig. 1. The initial model of the muti-channel nozzle: a – 3D model; b – rectangular section [6]

2. Latin Hypercube Sampling

Before applying neural networks and genetic algorithms in this article, Latin square sampling was used. Latin Hypercube Sampling (LHS) is a method of approximating random sampling from a multivariate parameter distribution and belongs to stratified sampling techniques. It was first proposed by McKay et al. in 1979, and its main advantages include the characteristic of uniform stratification, which can obtain tail sample values with fewer samples, making it particularly effective in processing large-scale data. In addition, compared to Monte Carlo sampling, Latin hypercube sampling reduces the number of iterations because it uses uniform sampling to sample variables. In practical applications, Latin hypercube sampling is widely used in various fields. In short, by uniformly sampling in each dimension, the correlation between input variables is reduced, thereby improving the accuracy and efficiency of model prediction.

$$y_1 = 400 \times X_1 + 473, \quad (1)$$

$$y_2 = 4 \times X_2 + 1, \quad (2)$$

$$y_3 = 40 \times X_3 + 10. \quad (3)$$

This work study 30 groups of samples needs to be used to obtain numerical results for each group of samples and record the data in Table 1. Among them, 24 groups are used for training the BP neural network, and the remaining 6 groups are used for prediction. The temperature (X_1), pressure (X_2), and particle size (X_3) ranges are 473...873 k, 1...5 MPa, 10...50 μm. Different types of units can be encoded using the following simple formulas (1) – (3), respectively. In order to facilitate the acquisition of particle exit velocity, the input parameters are rounded to one decimal place or rounded to the nearest integer.

Combining Table 1, Figure 2, and Figure 3, although the gas temperature, gas pressure, and particle size selected in this article are key factors affecting the acceleration of cold spray particles, for multi-channel special nozzles, particle size has a significant impact.

Table 1

Latin hypercube sampling test scheme and numerical results

	He T, K	He P, MPa	Powder size, μm		Outlet V, m/s
	617	1.7	26		378
	721	3	18		623
	843	1.3	13		480
	729	2.4	32		384
	593	3.3	29		447
	758	4.6	35		471
	770	3.5	26		492
	701	3.6	39		410
	477	2	28		343
	785	1.5	46		262
	748	2.6	44		351
Input training	678	1.5	23	Output training	356
	508	4.4	36		410
	654	2.8	21		481
	588	4.1	41		405
	560	4	16		595
	826	2.2	49		298
	688	1.9	14		493
	497	3	11		613
	668	5	33		482
	812	3.9	43		404
	547	4.3	45		391
	856	3.2	18		584
	625	2.7	37		363
	635	3.7	24		502
	579	2.2	20		438
Input prediction	800	4.5	40	Output prediction	409
	525	1.1	48		200
	865	4.8	11		806
	532	1.2	31		278

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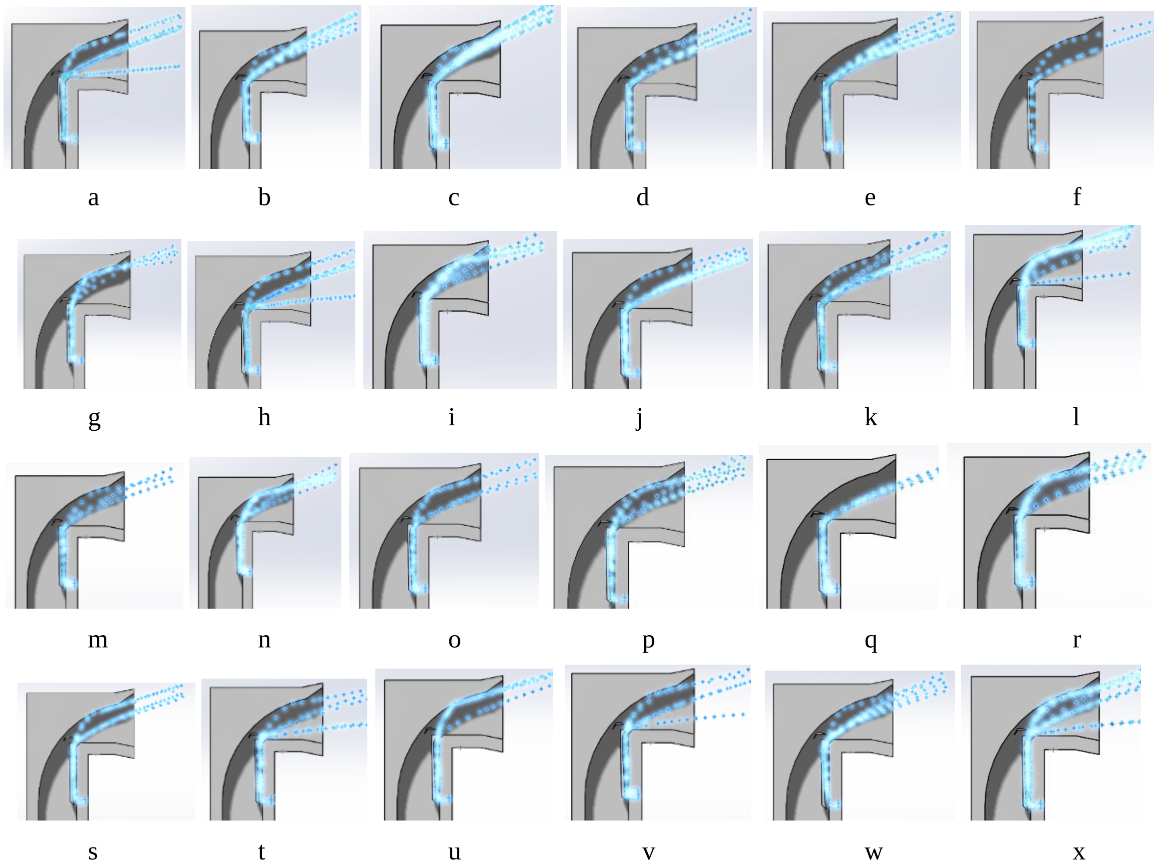

Fig. 2. The movement path of titanium particles (training results): a – 378m/s; b – 623m/s; c – 480m/s; d – 384m/s; e – 447m/s; f – 471m/s; g – 492m/s; h – 410m/s; i – 343m/s; j – 262m/s; k – 351m/s; l – 356m/s; m – 410m/s; n – 481m/s; o – 405m/s; p – 595m/s; q – 298m/s; r – 493m/s; s – 613m/s; t – 482m/s; u – 404m/s; v – 391m/s; w – 584m/s; x – 363m/s

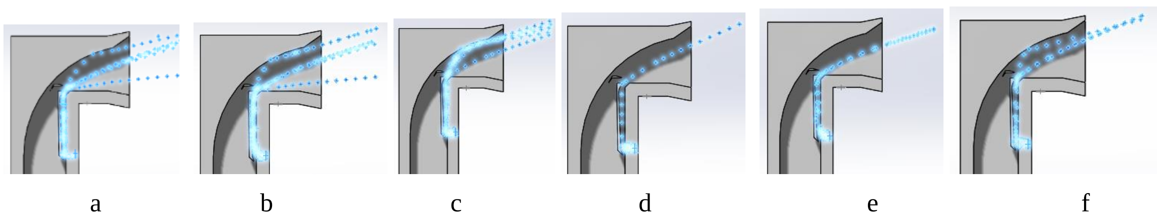

Fig. 3. The movement path of titanium particles (prediction results): a – 502m/s; b – 438m/s; c – 409m/s; d – 200m/s; e – 806m/s; f – 278m/s

For example, when the particle size exceeds 25 microns, even if the gas temperature is high, the particle outlet velocity still cannot reach 500m/s, which makes it impossible for titanium particles to reach the critical deposition velocity. The maximum outlet velocity in Table 1 is 806 m/s, with the following parameters: gas temperature of 865 K, gas pressure of 4.8 MPa, and particle size of 11 microns. These parameters further indicate that for special multi-channel nozzles, it is recommended to consider small-sized particles, then pressure and temperature parameters.

3. BP neural network + genetic algorithm optimization

BP neural network (Back Propagation) was proposed by D. E. Rumelhart and J. L. McClelland in 1986, which is a neural network trained using error backpropagation algorithm. Including input layer, hidden layer, and output layer, information is propagated forward and backward between layers through connection weights [7]. The basic principle of the algorithm is the gradient steepest descent method, and its central idea is to adjust the weights and thresholds of the network so that the mean square error between the actual output value and the expected output value of the network is minimized, the GA+BP neural network prediction method is widely used in materials and manufacturing. Such as Surface hardness prediction model [8] and flow stress prediction model [9].

Research has shown that a three-layer neural network has sufficient accuracy to approximate any continuous function [10]. Therefore, this article adopts a 3-layer neural network, with 3 neurons in the input layer and 1 neuron in the output layer. The transfer functions of the hidden layer and output layer are hyperbolic tangent function (tansig) and linear function (purelin), respectively. The training algorithm is gradient descent method.

When the number of hidden layer neurons is 9, the mean square error of training and prediction is minimized, as the Figure 4 show. Therefore, the final determined network structure is shown in Figure 5.

In order to prevent the impact of singular experimental sample data on neural network training, it is necessary to normalize the data and limit it to the range of [-1 1]. The normalization formula 4 is as follows

$$y_i = 2 \times \frac{x_i - x_{min}}{x_{max} - x_{min}} - 1, \qquad (4)$$

where, x_i (i=1, 2 ... 30) is the training sample, x_{max} and x_{min} are the maximum and minimum values of the training sample respectively, and y_i is the normalized training sample.

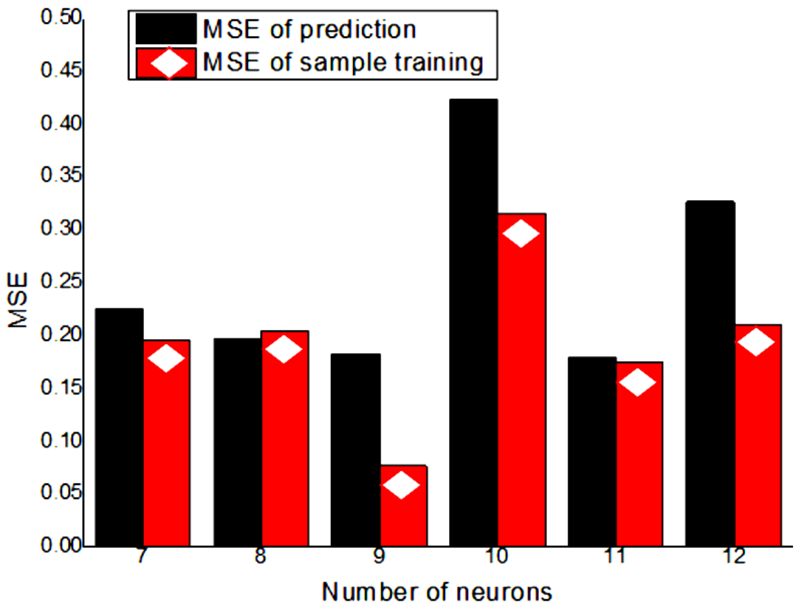

Fig. 4. Mean square error of different number of neurons

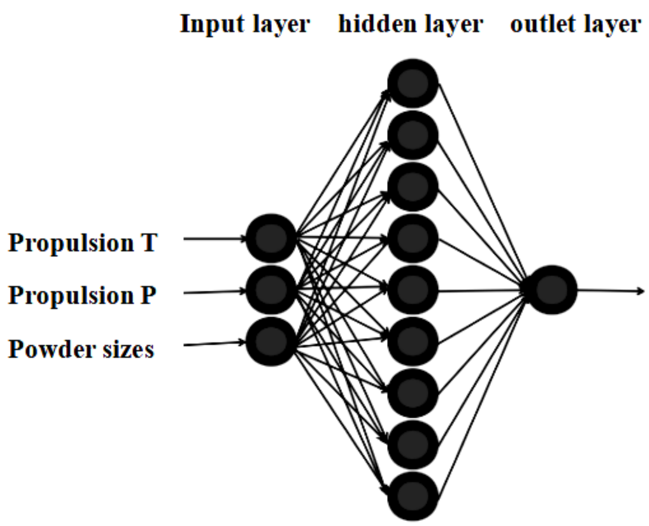

Fig. 5. Three layer neural network model

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The genetic algorithm is used to optimize the initial weight and threshold of the BP neural network to improve the training and prediction accuracy of the BP neural network. In addition, it is necessary to determine the fitness of the individual, which is defined as the formula 5 show.

$$\text{fitness} = \frac{1}{m}\sum_{j=1}^{m}\sum_{i=1}^{q}\left(y_i - t_i\right)^2, \tag{5}$$

where, m is the number of samples, q is the number of neurons in the output layer, y_i is the output, and t_i is the expected output. Using the roulette strategy to select individuals, the smaller the individual fitness value, the greater the probability of being selected. The crossover method is actual recombination, and the mutation method is a real-valued mutation. In this paper, the crossover probability is 0.9, the mutation probability is 0.01, the population size is 30, and the maximum number of iterations is 200.

Taking the exit maximum velocity as the target, the parameters optimized by the genetic algorithm are: The He temperature is 694...865 K, helium pressure is 3.3...3.7 MPa, and titanium particle diameter is 12...20 microns, numerical verification of the parameters are close to predict value of optimization, error is 4 %, and the results values of variable parameters three times are shown in Table 2.

The error using BP+GA method is within the allowable range. The interest points of future research can consider the model establishment of more factors. If the model is adjusted appropriately, it can be further promoted in the cold spray multi-parameter targets field. Therefore, the BP+GA method are feasible for cold spray multi-parameter target optimization and are worth learning from.

4. Conclusions

This paper analyzes the application of BP+GA optimization methods in cold spraying multi-parameters. Furthermore, It gives meaningful conclusions and prospects for reference.

1. BP+GA methods are feasible for multi-parameter target optimization of cold spraying technology and have apparent effects on obtaining the optimal value. The errors of BP+GA is 4 % in this paper.

2. Although the genetic algorithm can optimize multiple parameters, it adopts the roulette betting method, so the results of each parameter are different. Therefore, it is recommended to take the average value of multiple optimization to further reduce the error.

3. There are many optimization methods in the engineering field, and the neural network + genetic algorithm introduced in this paper is not the only method. the method requires a specific programming foundation. Therefore, in the field of cold spraying, multi-disciplinary integration is the research trend in the future.

Contributions of authors: conceptualization, methodology – **Wenjie Hu**; formulation of tasks, analysis – **Wenjie Hu**; analysis of results, visualization – **Wenjie Hu**; original draft preparation, writing – **Wenjie Hu** and **Oleksandr Shorinov**; review and editing – **Oleksandr Shorinov**.

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, author ship or otherwise, that could affect the research and its results presented in this paper.

Financing

This study was conducted with financial support.

Data Availability

The work has associated data in the data repository.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods while creating the presented work.

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Table 2

Results of the BP+GA optimization methods

	T (K)	P (Mpa)	Powder size, μm	$V_{optimal}$, m/s	V_{actual}, m/s	error, %	average error, %
BP+GA	694	3.5	12	604	618	2.3	4
BP+GA	728	3.3	20	604	569	6.2	
BP+GA	865	3.7	15	564	584	3.4	

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ОПТИМІЗАЦІЯ ПАРАМЕТРІВ ПРИСКОРЕННЯ ЧАСТИНОК В СПЕЦІАЛЬНИХ СОПЛАХ ДЛЯ ХОЛОДНОГО ГАЗОДИНАМІЧНОГО НАПИЛЮВАННЯ З ВИКОРИСТАННЯМ НЕЙРОМЕРЕЖЕВОГО ТА ГЕНЕТИЧНИЙ АЛГОРИТМІВ

Веньцзе Ху, О. В. Шорінов

Технологія холодного напилювання – відносно нова технологія надзвукового нанесення твердих частинки на поверхні матеріалів. Існує багато факторів, які впливають на прискорення частинок, наприклад, геометрія сопла для напилювання (його звужувальна та розширена частини, критичний діаметр, кут розкриття тощо), параметри газу-носія (тип газу, температура і тиск газу тощо), властивості матеріалу частинок (металічних і неметалічних), розмір частинок (зазвичай від 10 до 50 мкм), їх морфологія (сферична, неправильна форма тощо). **Метою дослідження** є визначення впливу параметрів напилювання на прискорення частинок в надзвуковому соплі. Ця робота спрямована на прогнозування та оптимізацію швидкості частинок на виході зі спеціального сопла, щоб відповідати вимогам щодо критичної швидкості напилювання для різних металів для заданих умов напилювання. **Завдання**, яке вирішується, полягає в пошуку оптимальних режимів напилювання для забезпечення необхідної швидкості. **Методи дослідження**: три ключові параметри, які найбільш впливають на швидкість частинок – температура та тиск газу (гелію) та діаметр частинок порошку (титану). По-перше, 30 наборів даних швидкості вильоту частинок були відібрані за допомогою латинського гіперкубного відбору, з яких 24 були навчальними даними, а решта шість – данні прогнозування. Потім нейронну мережу аналізували, щоб отримати мінімальне значення помилки нейрона, таким чином визначивши кількість прихованих шарів. У той же час параметри були нормалізовані, і, нарешті, параметри частинок на виході з сопла були оптимізовані за допомогою генетичного алгоритму. Результати показали, що після трьох циклів оптимізації та взяття середнього значення швидкість частинок на виході зі спеціального сопла становила 591 м/с. Отримані наступні оптимізовані параметри: температура газу від 694 до 865 К, тиск від 3,3 до

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3,7 МПа, діаметр частинок титану від 12 до 20 мкм. Коли оптимізовані параметри були використані при чисельному моделюванні, результат був близький до прогнозованого значення. Таким чином, нейронна мережа та генетичний алгоритм оптимізували параметри з високою точністю, з похибкою 4 %.

Ключові слова: технологія холодного газодинамічного напилювання; прискорення частинок; спеціальне сопло; нейронна мережа; генетичний алгоритм.

Веньцзе Ху – асп. каф. технології виробництва авіаційних двигунів, Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут», Харків, Україна;
старш. викл. з подвійною кваліфікацією, Школа аеронавтики та астронавтики, Наньчанський технологічний інститут, Китай.

Шорінов Олександр Володимирович – канд. техн. наук, доц. каф. технології виробництва авіаційних двигунів, Національний аерокосмічний університет ім. М. Є. Жуковського «Харківський авіаційний інститут», Харків, Україна.

Wenjie Hu – PhD Student of the Dept. of Aircraft Engine Manufacturing Technologies, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine; Senior double qualified teacher, School of Aeronautics and Astronautics, Nanchang Institute of Technology, China,
e-mail: 837406613@qq.com, ORCID: 0000-0001-9540-1912.

Oleksandr Shorinov – Cand. of Tech. Sci., Associate Professor at the Dept. of Aircraft Engine Manufacturing Technologies, National Aerospace University "Kharkiv Aviation Institute", Kharkiv, Ukraine,
e-mail: shorinov1@gmail.com, ORCID: 0000-0002-5057-6679,
https://scholar.google.com.hk/citations?hl=zh-CN&user=xLOM1ccAAAAJ