INTEGRATING ANN AND CS TO IMPROVE TOOL WEAR PREDICTION IN HIGH-SPEED DRY TURNING OF SKD11 STEEL

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Abstract

This article presents the results of improving an artificial neural network (ANN) to predict the tool wear in high-speed dry turning of SKD11 steel. The original ANN was a back-propagation (BPN) model with the Gradient Descent algorithm (GD). In the improved model, so-called ANN-CS, some parameters were optimized by the Cuckoo search algorithm (CS). Both models were trained, validated, and tested with the same experimental machining dataset based on performance indices, such as R^2, MSE, RMSE, and MAPE. The results show that the ANN-CS gives higher prediction accuracy in comparison with the BPN. Especially, the improvement is as high as 30% with the MAPE index. This research result has important implications in choosing artificial intelligence network models suitable for the nature and amount of data that is both large and different. Moreover, this result can help researchers have more basis to choose the training model with high accuracy.

Keywords: *Tool wear; neural networks; back propagation network; Cuckoo Search.*

Abbreviations

AI: Artificial Intelligent	MSE: Mean Square Error
ANN: Artificial Neural Network	MAPE: Mean Absolute Percentage Error
OA: Optimal Algorithm	PSO: Particle Swarm Optimization
BPN: Back-Propagation Network	R^2: Determination Coefficient
CS: Cuckoo Search	RMSE: Root Mean Square Error
GA: Genetic Algorithm	TW: Tool wear
GD: Gradient Descent	CF: Cutting Parameters

1. Introduction

Wear and failure of cutting tools are serious problems in cutting in general and high-speed machining of hard materials in particular. It not only increases the production cost but also reduces the product quality. Tool wear (TW) interrupts machining and substantially increases total machining time. TW accounts for about 20% of total machine downtime, leading to dramatic increases in production costs [1]. Besides, tool wear and

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tool breakage can lead to consequences, such as unsatisfactory workpieces, or worse, can lead to machine failure. Tool wear is a complex problem [2] and it depends on many factors in the machining process such as the characteristics of the cutting tool (cutting tool geometry, cutting tool material, heat resistance and wear resistance), cutting parameters (depth of cut, cutting speed and feed rate), characteristics of the workpiece (material composition, mechanical properties), physical phenomena during machining (friction, cutting force, vibration, cutting temperature) [3-5]. There are a number of typical tool wear prediction methods that have been used recently based on types of signals obtained from experiments. Specifically, these signals include cutting force, vibration, sound, cutting heat, and images.

The rapid development of computer science has made AI networks a popular choice for building predictive models. The efficiency of applying ANN compared with other prediction methods presented in [6, 7]. Different types of neural networks such as forward propagation [8, 9], convolutional neural network [10] and back-propagation networks are widely used because of their superiority and effectiveness [11, 12]. There are a number of methods to help ANN models effectively reduce the loss function value such as using back-propagation model with Gradient Descent technique [11, 12], ANN structure with optimization algorithms [13, 14] or a combination of using BPN and OA [15-18]. The study in [14] clearly showed that, CS uses a much smaller set of algorithm control parameters than GA and PSO. Therefore, the computational cost and algorithm running time of CS are less than other methods. Complexity is reduced while efficiency is still guaranteed. The study in [15] presents the comparison results between a BPN model and a forward propagation network (FNN) combined with the GA algorithm. The study in [16] developed CS algorithms for optimization matters, based on the adaptation of howler birds to reproduce and parasitize the other birds' nests. The BPN is combined with the PSO in [17] for fault prediction and transformer operating conditions. The set of values is constantly updated by the PSO algorithm. The results of evaluation by the RMSE index show that the hybrid network gives more accurate results and the ability to converge faster than the conventional network. The power and torque of the heat engine in the study [18] were predicted by the ANN-PSO, ANN-ICA (Imperialist Competitive Algorithm) network. Model quality was assessed using the MSE (Mean Square Error) index. The results show that these hybrid networks have higher efficiency than the simple ANN networks.

This article presents the results of creating ANN models in the form of BPN and ANN-CS to predict the wear value of cutting tools in dry turning hardened steel SKD11 after heat treatment. The type of cutting tool wear of interest in this study is flank wear. The BPN structure used in this study is selected from the results of testing many different

BPN structures. ANN model quality evaluation criteria include R^2, MSE, RMSE and MAPE. The structure of this article is described through Section 1 with the basics of high-speed machining of hard materials, physical characteristics when machining and types of ANN models. Section 2 presents the model of performing experiments, measuring cutting force value and cutting tool wear. Then, the network structure of BPN and ANN-CS is described in detail with quality evaluation criteria. Finally, wear value prediction results corresponding to specific ANNs are described. Several key assessments are given in the Conclusion part.

2. Materials and methods

2.1. Back propagation network

The BPN model uses the GD algorithm to continuously adjust the coefficients b_i and w_i through the inverse loss function derivative from the last layer to the first layer [11, 12]. The final layer is precomputed because its value is close to the predicted output value and loss function value. The derivative calculation of the previous classes is done based on the “Chain rule”. The derivative value is calculated for each specific consecutive point of the loss function. The algorithm will stop when the loss function value reaches the minimum.

The advantage of the BPN model using GD algorithm is that it avoids the phenomenon of high bias (this is the case where the optimal set of parameters b_i and w_i are found too quickly and they satisfy the global optimal value. This whole iteration of the optimization algorithm only takes a unique set of b_i and w_i values, which leads to the final artificial network being unreliable enough to conclude). The limitation of this method is evident when the loss function is complicated and the structure of the ANN is complex. In this case, the loss function depends on the b_i and w_i values and has many local minima. If the control of the global minimum is not good, then most likely, the training of the BPN will stop at local minimums that have not yet reached the global minimum. Therefore, the BPN network will not be fully optimized.

2.2. Cuckoo Search algorithm

Howler birds (parasitic birds - PB) are birds with strange properties with laying eggs in the nests of other birds (host birds). These eggs are hatched by birds of other species and nurture them. It is difficult or impossible for other birds to detect howler eggs in their nests due to the following main reasons:

- PB steals and disposes of host birds' eggs to increase the viability of surrogate eggs.
- PB eggs have a high degree of imitation of the color and pattern of the host's eggshell, so they can lie discreetly among other host eggs. This is their adaptive and

genetic ability.

- After the PB eggs hatch, the young PB tend to instinctively push the host eggs or the host chicks out of the nest to increase their chances of survival.

- Young PB can also imitate the calls of other young birds to compete for food supplies [19, 20].

Of course, the host birds also have a chance to spot unusual eggs that are not laid by them. If this infestation is detected, the host bird can remove the parasitic eggs or abandon the old nest to live in a new nest.

Inspired by the adaptation of PB to reproduce and parasitize the nests of other birds, Yang and Deb [16] developed CS algorithms for optimization problems. The assumptions specified for this algorithm include:

- Each PB only lays 1 egg and puts it in a randomly selected host bird's nest. Each egg or each host bird's nest represents a set of solutions to the problem at hand.

- Based on the acclimatization condition, only part of the host nests (PB eggs are not detected or interpreted as the best solution) are saved for the next iteration.

- The number of host birds' nests is fixed. Each host bird can detect the parasitic egg based on probability $p \in [0, 1]$. If the host bird detects a parasitic egg, the nest is discarded along with the PB's eggs in it in the next loop. The host bird will leave and start a new nest.

The search for a random new nest in the search space is defined as follows:

$$x_i^{t+1} = x_i^t + \alpha \times L(\lambda) \tag{1}$$

in which x_i^{t+1} is the newly created solution (or newly formed nest), t is the current number of iterations, α is the scaling factor, if α is too small then the new nest is located quite close to the old nest that has just been excluded. Therefore, the search algorithm is inefficient. But if the coefficient α is too large, new nests can be formed outside the search range [21].

Therefore, to ensure balance and diversification, the α value is usually chosen as 1 in most cases [16]. The constant λ is an index in the "Levy's flight" algorithm. Usually, the λ value is $\lambda \in [1;3]$. The distribution function $L(\lambda)$ in the "Levy's flight" algorithm is considered as follows:

$$L(\lambda) = \left| \frac{\Gamma(1+\lambda) \times \sin(\frac{\lambda\pi}{2})}{\Gamma(\frac{1+\lambda}{2}) \times \lambda \times 2^{(\frac{\lambda-1}{2})}} \right|^{\frac{1}{\lambda}} \tag{2}$$

in which Γ is the standard function. The proposed probabilistic value for detecting invasive eggs $p = 0.25$ is appropriate according to [16]. Furthermore, the convergence speed is not much affected by the value of p [22]. The CS algorithm can be described in Fig. 1.

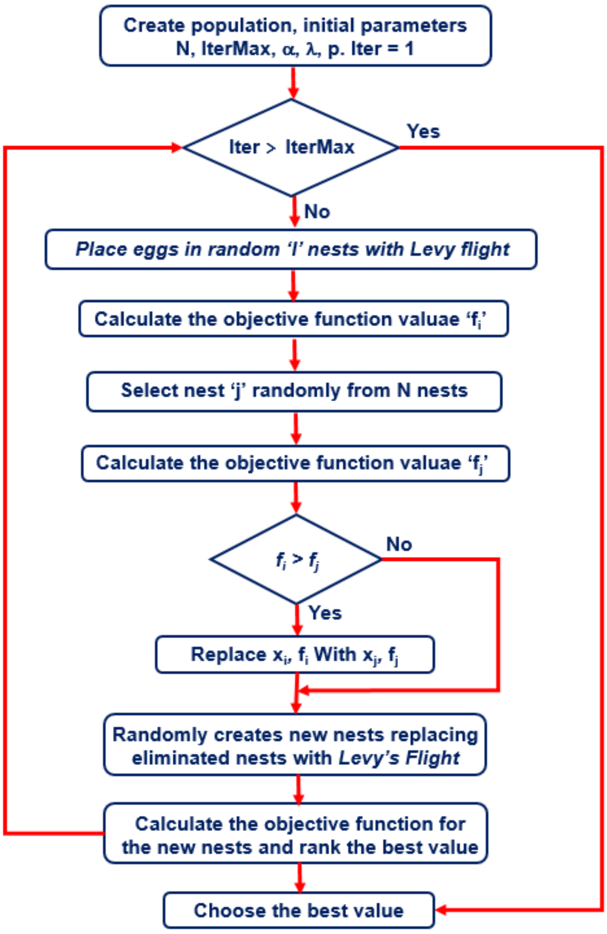

Fig. 1. CS algorithm diagram.

2.3. ANN-CS hybrid network and assessment criteria

Based on the above analysis, this article focuses on building a ANN-CS hybrid network with a combination of CS and ANN algorithm to overcome the limitations and promote the advantages of separate methods. Specifically, the hybrid network allows us to achieve the global minimum and avoid the High Bias phenomenon in the case of a fixed number of hidden layers and the number of neurons in each layer, searching for the best bias and weight parameters. The algorithm diagram for the ANN-CS improved network is shown in Fig. 2.

The indexes R^2 [23], MSE [24], RMSE [25, 26] and MAPE [27] were used to evaluate the training quality of neural networks. The R^2 index is determined as follows:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (y_{pi} - y_{ri})^2}{\sum_{i=1}^{N} y_{pi}^2} \right) \tag{3}$$

in which y_{pi} and y_{ri} are the predicted and actual tool wear values in the i^{th} experiment, respectively. The total number of experiments is N.

The MSE index is calculated as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_{pi} - y_{ri})^2 \tag{4}$$

Similar to MSE, the RMSE index is described as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_{pi} - y_{ri})^2} \tag{5}$$

The MAPE index is used to measure the performance or degree of error between the predicted dataset and the actual data set. This indicator is expressed as follows:

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left(\left| \frac{y_{pi} - y_{ri}}{y_{ri}} \right| \right) \times 100\% \tag{6}$$

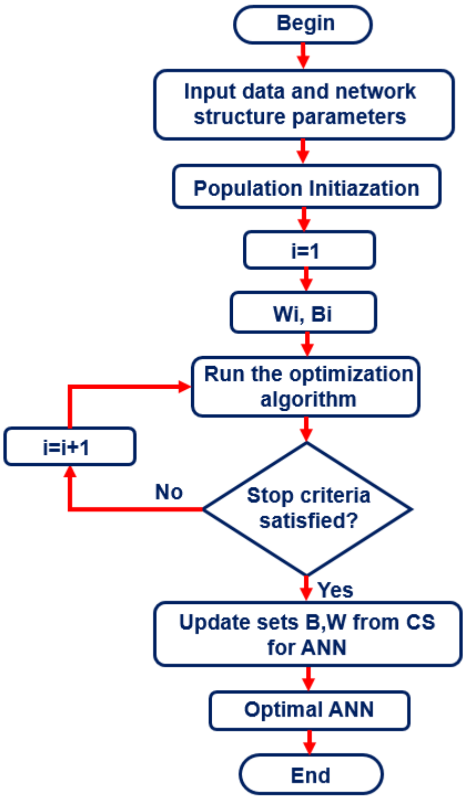

Fig. 2. Implementation diagram of the ANN-CS model.

3. Experiment study and results

3.1. Experiment setup

The whole experiment was carried out on a HASS-ST10 lathe machine. Select SKD11 steel workpiece that has been heat treated to reach hardness 54 - 56 HRC, length is 300 mm and diameter is 30 mm (Fig. 3a). One test piece is cut from each workpiece corresponding to each experiment to perform turning with 5 different diameter values. Hardness is measured at the five diameter locations, respectively (Fig. 3b). Hardness measurement results at different workpiece diameter values give approximately the same results. This shows that the hardness in the outer and inner layers is not different. The chemical composition of the embryos is described in Tab. 1.

Table 1. Chemical composition SKD11 steel

Composition	C	Si	Mn	Cr	Ni	Mo	Va
Value (%)	1.45 - 1.65	≤ 0.4	≤ 0.35	11.0 - 12.5	11.0 - 12.5	0.4 - 0.6	0.15 - 0.3

For cutting tools, choose the CBN insert piece with symbol TNP-VNGA168408G2 (MB8025) of MITSUBISHI with specifications including IC = 9.525 mm (Insert IC Size); LE = 16.606 mm (Insert Cutting Edge Length); S = 4.76 mm (Insert Thickness); RE = 0.8 mm (Corner Radius); D1 = 3.81 mm (Insert Hole Size). The 9257BA-Kistler 3-component dynamometer is used to record the variation value of the CF in the three directions x, y, z respectively Fx, Fy, Fz. The instrument is supplied with the control box 5233A1, A/D converter, NI USB-6009 receiver (DAQ) and DASYLab 10.0 software. The tool wear value was determined after each machining interval with the help of an electron microscope UM012C. The experimental system is depicted in Fig. 4. Perform continuous layer-by-layer finishing machining. For each cut, the tool runs correspond to the actual cutting distance Lc (mm). After each cutting length Lc, the cutting tool moves to the electron microscope position, the maximum height VBmax is measured on the computer with the help of MicroCapture software on the background of digital images taken and record once. The test is stopped when the tool wear height reaches VBmax ≥ 0.6 (mm). At that time, the new turning tool insert will be replaced. Each experiment used one insert piece.

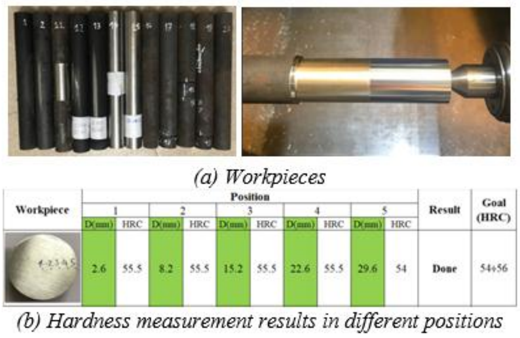

Fig. 3. Workpiece.

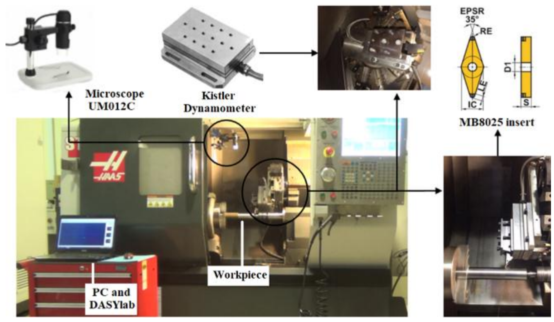

Fig. 4. Machining and measuring systems.

The technical parameters are described in Tab. 2 in which V_c (mm/min) is cutting speed, f (mm/rev) is feedrate and a_p (mm) is depth of cut.

Table 2. Cutting parameters

Parameters	Level 1	Level 2	Level 3
V_c (mm/min)	80	125	170
f (mm/rev)	0.07	0.11	0.15
a_p (mm)	0.1	0.175	0.25

3.2. Establishing the BPN and ANN-CS

BPN network (7-5-10-1 structure) is built with an input layer, hidden layers and an output layer as shown in Fig. 5.

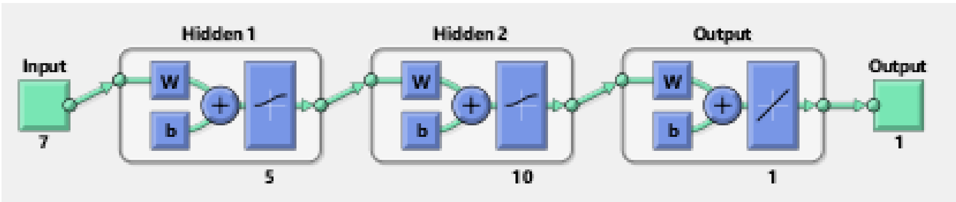

Fig. 5. The 7-5-10-1 network structure.

The input layer has seven variables including cutting speed V_c (m/min), feed rate f (mm/rev), depth of cut a_p (mm), cutting force components *Fx*, *Fy*, *Fz* (N), machining time (*Time* - seconds). The output layer has a variable which is the tool wear value *VB* (mm). The specific BPN and the CS algorithm parameters are presented in Tab. 3.

Table 3. BPN parameters and Initial parameters CS

No	Parameters of BPN	Values	Parameters of CS	Values
1	Number of input and output variables	7; 1	Number of original bird's nest populations	300
2	Number of neurons in hidden layer 1 and layer 2	5; 10	Number of interations in search space	1000
3	Data Split Ratio: Training/ Validation/Testing	80%/10%/10%	Probability of detecting PB eggs	0.25
4	Number of experiments	290	Number of variables in a search solution	111
5	Transfer and training function	Logsig; traingdx	The coefficient λ in the Levy algorithm	1.5
6	Maximum number of epochs	10000	Scale factor α	1

Note that the number of variables to be found for the optimization problem is determined from the number of coefficients *B* (bias) and weights *W* (weight) from the input layer, the hidden layers and the output layer.

3.3. VB prediction results and evaluation

The results of the regression analysis for the network structure during the training process are shown in Fig. 6 and Fig. 7. The analysis results show that the ANN-CS training process gives higher quality (R = 0.958) than the BPN network (R = 0.905). This leads to the prediction results of the hybrid network closer to the real value than the PBN model. The results of prediction during training are depicted in Fig. 8 and Fig. 9. Accordingly, despite the large number of experiments, it is easy to recognize, that the predicted values closely follow the actual values.

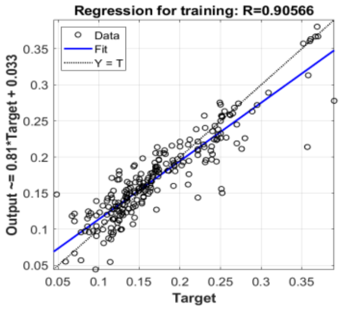

Fig. 6. Regression in BPN.

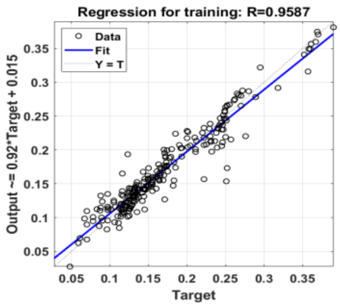

Fig. 7. Regression in ANN-CS.

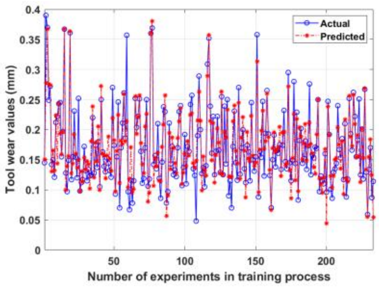

Fig. 8. Prediction tool wear results in training process for BPN.

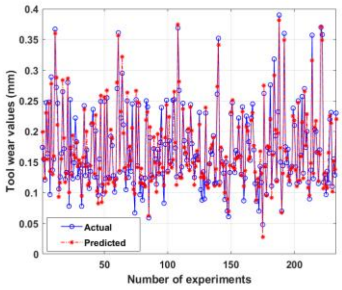

Fig. 9. Prediction tool wear results in training process for ANN-CS.

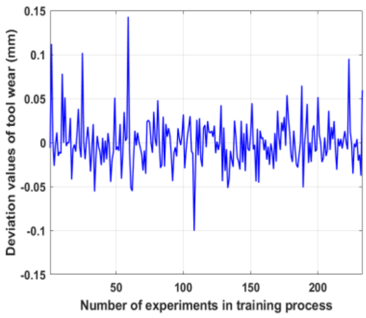

Fig. 10. Deviation values in training for the BPN model.

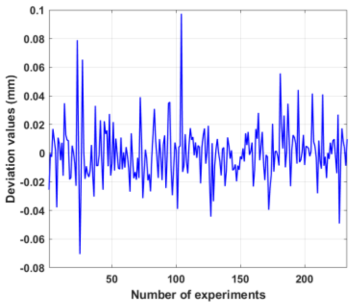

Fig. 11. Deviation values in training for the ANN-CS.

The actual and predicted results during training for the BPN model and the ANN-CS model are shown in Fig. 10 and Fig. 11, respectively. Accordingly, the largest deviation for the BPN is 0.143 (mm), while the one in for ANN-CS is 0.098 (mm). Consider the results of testing two network models from Fig. 12 to Fig. 15. Similar to the training process, the prediction results are quite close to the actual value in both models. The maximum deviation value of the two models BPN and ANN-CS is 0.05 (mm) and 0.021 (mm), respectively.

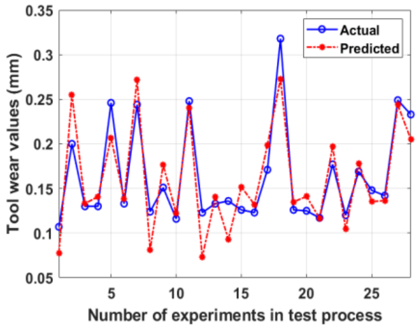

Fig. 12. Prediction results in testing process for BPN.

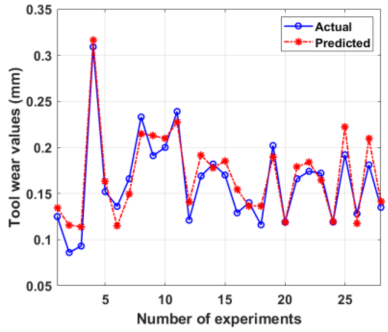

Fig. 13. Prediction results in testing process for ANN-CS.

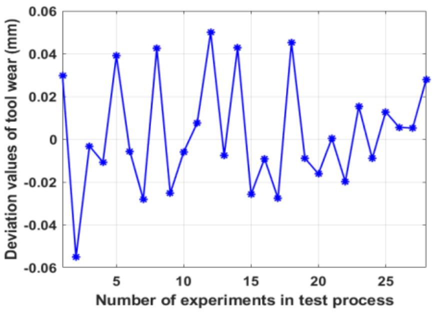

Fig. 14. Deviation values between actual and predicted tool wear for test BPN.

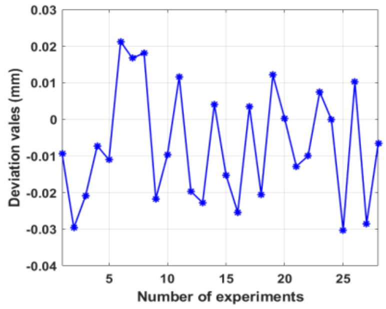

Fig. 15. Deviation values between actual and predicted tool wear for test ANN-CS.

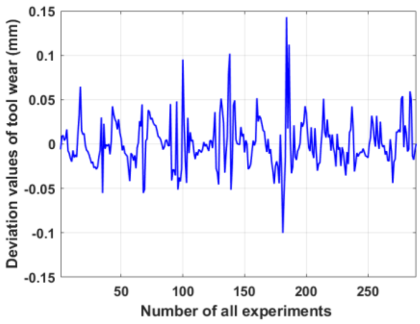

Fig. 16. Deviation values for all data in the BPN model.

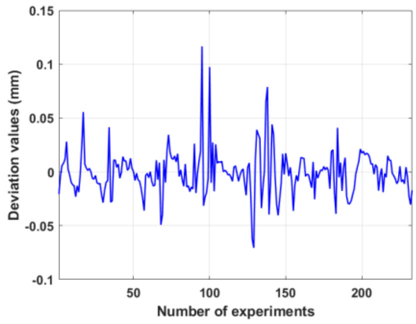

Fig. 17. Deviation values for all data in the ANN-CS model.

Fig. 16 and Fig. 17 show the difference in the tool wear value between the predicted values of the two models compared with the actual data. Basically, the difference value of both models is not too different with the largest error near 0.15 (mm). Fig. 18, Fig. 19, and Fig. 20 show a more intuitive comparison of the deviation between the predicted values of the two network models compared with the actual measured value.

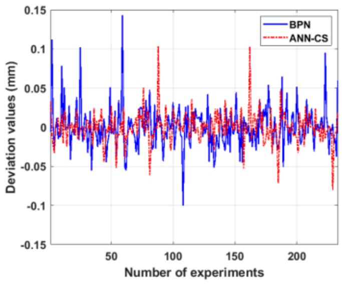

Fig. 18. Prediction deviation values of two models in training process.

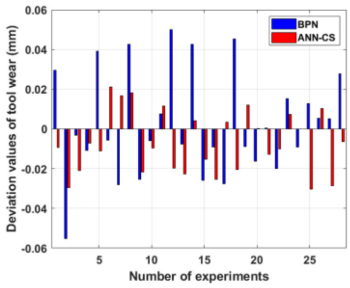

Fig. 19. Deviation values of network models in testing process.

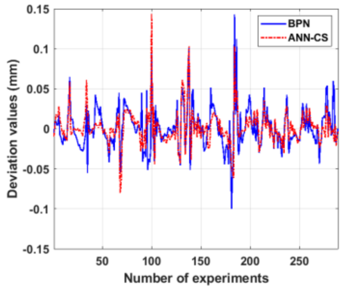

Fig. 20. Deviation values of network models in all experimental data.

Table 4 compares the calculating results of all performance indices for BPN and ANN-CS with the corresponding data sets: training, testing, and all data.

Table 4. Performance comparison of BPN and ANN-CS

Criteria	Models	Training process	Test process	All data
R^2	BPN	0.9876	0.948	0.983
	ANN-CS	0.989	0.991	0.987
	Deviation	Increase 0.014	Increase 0.043	Increase 0.004
MSE	BPN	7.9×10^{-4}	6.76×10^{-4}	7.52×10^{-4}
	ANN-CS	3.67×10^{-4}	2.83×10^{-4}	4.18×10^{-4}
	Deviation	Reduce 4.23×10^{-4}	Reduce 3.84×10^{-4}	Reduce 3.04×10^{-4}
RMSE	BPN	0.0281	0.026	0.0274
	ANN-CS	0.0192	0.017	0.0204
	Deviation	Reduce 0.0089	Reduce 0.0090	Reduce 0.0070
MAPE (%)	BPN	13.169	15.34	13.71
	ANN-CS	8.967	9.03	9.58
	Deviation	Reduce 4.202	Reduce 6.31	Reduce 4.13

Accordingly, both network models show high predictive quality in all processes through the R^2 index. Basically, the accuracy of the ANN-CS model is slightly higher than that of the BPN model when considering the entire experimental data set. The error index of prediction results of MSE and RMSE show that the hybrid network model has a smaller error than the BPN model. Especially, the MAPE index shows the most obvious difference between the two BPN models and the ANN-CS hybrid model. The MAPE value of the improved model decreased significantly in all the processes such as training

(4.202 reductions, corresponding to 31.9%), testing (6.31 reductions corresponding to 41.1%) and compared with the whole experimental data (4.13 reductions corresponding to 30.1%). This shows that with the same initial experimental data set used for two different network configurations and each data evaluated with the same equal weight, the ANN-CS model gives a much higher average absolute accuracy than the BPN model. Accordingly, the prediction performance of the ANN-CS model is higher.

4. Conclusions

Two neural network models including BPN and improved ANN using CS optimization algorithm have been established to predict the tool wear in high-speed dry turning of SKD11 steel. In particular, the MAPE index of the ANN-CS network shows a 30% higher accuracy in all stages of network training than the BPN network. Some important points can be drawn as follows:

- The prediction accuracy between BPN and ANN-CS is almost the same on the R^2, MSE and RMSE indices. The ANN-CS model provides indicators that show higher predictive quality than the BPN model.

- The MAPE index of the ANN-CS model is lower than that of the BPN model, which means that the ANN-CS model has higher performance and accuracy.

- The ANN-CS hybrid network model can significantly overcome the limitations that arise from using a BPN alone or an ANN using an optimal algorithm such as Overfitting or High Bias phenomenon.

Based on the research results, the use of the ANN-CS model has important practical significance in avoiding the appearance of local optimal values and the High Bias phenomenon. Although these problems do not appear often, they can greatly affect the model's prediction results.

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KẾT HỢP ANN VÀ CS NHẰM NÂNG CAO CHẤT LƯỢNG DỰ ĐOÁN ĐỘ MÒN DỤNG CỤ KHI TIỆN KHÔ TỐC ĐỘ CAO THÉP SKD11

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Tóm tắt: Bài báo trình bày kết quả cải tiến mạng nơ ron nhân tạo (ANN) để dự đoán lượng mòn dụng cụ khi tiện khô tốc độ cao thép SKD11. ANN nguyên thủy là mô hình lan truyền ngược (BPN) với thuật toán độ dốc giảm dần (GD). Trong mô hình cải tiến, được gọi là ANN-CS, một số tham số được tối ưu hóa bằng thuật toán tìm kiếm Cuckoo (CS). Cả hai mô hình đều được huấn luyện, kiểm tra và xác nhận với cùng một tập dữ liệu gia công thử nghiệm dựa trên các chỉ số hiệu năng, như R^2, MSE, RMSE và MAPE. Kết quả cho thấy ANN-CS cho độ chính xác dự đoán cao hơn so với BPN. Đặc biệt, mức cải thiện lên tới 30% với chỉ số MAPE. Kết quả nghiên cứu này có ý nghĩa quan trọng trong việc chọn lựa các mô hình mạng trí tuệ nhân tạo phù hợp với tính chất, số lượng dữ liệu lớn và khác biệt.

Từ khóa: *Mòn dụng cụ; mạng nơ ron; mạng lan truyền ngược; Cuckoo Search.*

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