The Application of Neuron Fuzzy Network for Assessing the Impact of Cutting Mode on Part's Accuracy and Grinding Wheel's Wear in Profile Grinding for Ball Bearing's Inner Ring Groove

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Abstract

The paper presents the results of research and application of adaptive neuro-fuzzy inference system (ANFIT) to predict part's surface roughness value, part's oval level value and grinding stone's wear value in grinding profile for ball bearing's inner ring groove according to parameters such as normal feet rate, the speed of part, the depth of cutting and the number of grinding parts in a grinding cycle. On that basis, the impact of cutting mode on part's surface roughness, part's oval level and grinding wheel's wear is assessed. The comparison of ANFIT predictions, BPNN predictions and experimental data values indicates that results predicted by ANFIT model are more accurate than those predicted by BPNN method. This demonstrates the reliability and applicability in reality of the neurons fuzzy network tool.

Keywords: Profile grinding, surface roughness, cutting mode.

1. Introduction

Grinding is a complex mechanical, physical and chemical interactive process between the elements of technology system through direct interaction between grinding wheel, workpiece and grinding fluid [4,6]. Thus, grinding is a non-linear complicated process which inputs may be affected by some random factors. Previously, processing result can only be assessed after finished grinding. Today, it can predict, forecast or control parameters to achieve the technical and economic efficiency of the machining process. In a system, with fixed cutting regime parameters range, it can easily choose flexible parameters to achieve the required productivity and quality. Therefore, estimation of the output parameters according to cutting mode to setup appropriate one is a basic method and the most effective way to control surface quality, increase productivity. To do this, one of the most important steps is to determine the distribution rule of the effect of cutting mode parameters on the output elements: Cutting force, cutting productivity, surface roughness, grinding wheel wear, etc.

In the profile grinding for ball bearing's inner ring groove, part's surface roughness, part's oval level and grinding wheel's wear are important output parameters. In this profile grinding due to big contact area between grinding wheel and workpiece, the cutting force and the cutting heat arised from this process are much bigger than those generated by other normal grinding processes. Profile grinding wheel is worn continuously and unevenly at various points on its working surface, making its initial shape and accuracy change quickly, causing form errors of processing surface. Thus, grinding wheel's wear, under the profile grinding, influences directly on the precision elements of grinding parts. Especially, in the precision factors, part's surface roughness and part's oval level are the most important factors because they highly affect to working ability of part: abrasion resistance, tired resistance, the stability of joints, etc. Therefore, they need to be forecasted and monitored to improve the economic and technical efficiency of the grinding process [4,6].

According to previous research results show that these output parameters are difficult to be measured directly in machining process, but they could be calculated by the functions of cutting mode. Thus, part's surface roughness, part's oval level and grinding wheel's wear will be estimated through the grinding mode's parameters. Although these parameters have a relationship with each other, but their relationships are very complex and difficult to identify mathematically. In addition, their relationships are non-linear and affected by many unpredictable factors. Besides, the analyzation of multi-variable functions is also difficult. Therefore, traditional approximation methods, such as the least squares

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method, are often not suitable and being replaced by artificial intelligence methods.

There are a lot of public works on the application of artificial intelligence tools in order to predict the different outputs. However, with the issue finding the approximate output values when the set of discrete input values is known, ANFIS model is the most appropriate. Thus, it is widely used to forecast elements in the process. As described in [4, 6], ANFIS network has been applied to forecast surface roughness of part. The various component elements of a typical grinding wheel are analyzed by using neuro – fuzzy technique [7]. Therefore, in this paper ANFIS model is studied to predict part's surface roughness, part's oval level and grinding wheel's wear in grinding profile for ball bearing's inner ring groove.

2. Content of the study

2.1. Theoretical basis of ANFIS

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a tool combining between artificial neural network (ANN) and fuzzy logic (FL). Naturally, ANFIS is a fuzzy inference system but the structure and the value of FIS functions is calculated through the process of learning and optimization of ANN. The integration between ANN and FL allows combining the advantages of both two systems.

The advantage of neural network (ANN) is the ability to learn, but the drawback of it is "black box" type treatment. Its process is rigid and erratic, thus it need to use large data sets to train. Fuzzy logic (FL) has the advantage of flexibility. This method deduces according to the explicit rules, but it depends subjectivity on the user. Thus, it requires user having enough experience in order to be able to choose proper dependency functions and inference rules.

Therefore, the combination of fuzzy logic and neural network makes Neuro-Fuzzy Inference System supplementing each other and combining both advantages of the two systems. Based on its learning ability, neural network provides computing architecture for the fuzzy logic systems. On the other hand, the fuzzy logic systems take into network inference mechanism based on the laws "if ... then". Furthermore, ANFIS also surmounts the caprice of ANN and the subjectivity of FL. Thus, the fuzzy neuron hybrid system which has ANFIS, are common applications in technical issues. That is also the reason that ANFIS is chosen as a tool to solve the problem of forecast of wear of grinding wheel and surface roughness of parts.

Based on fuzzy inference system and artificial neural network model, some researchers have proposed the general model of a ANFIS network as shown in Fig. 1 [4-7].

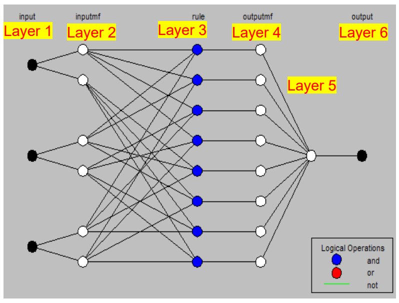

Fig. 1. The ageneral model of a Neuro-Fuzzy network [5-8]

2.2. Applying Neuro-Fuzzy network to estimate part's surface roughness, part's oval level and grinding wheel's wear in grinding profile

Based on the general model of a neurons fuzzy network, the authors have build a neural fuzzy network to predict part's surface roughness, part's oval level and grinding wheel's wear shown in Fig. 2.

In this ANFIS network model, 1^{st} layer is input layer. These inputs include the predestination elements of technology system. For a certain technology system, the inputs are parameters of cutting mode. In case of profile grinding, the parameters of the grinding regime include: The speed of cutting (V_w) for rough grinding and fine grinding, the speed of part (V_s) for rough grinding and fine grinding, the rate of normal feed (F_n) for rough grinding and fine grinding, the depth of cutting (t) for rough grinding and fine grinding, the number of parts in a grinding cycle (N_p). However, for grinding case on CNC grinding machines with a specific grinding stone, the velocity of the grinding wheel is usually chosen according to the specifications of the grinding wheel which has been launched by manufacturer (for example: With the grinding wheel of 500x8x203A/WA100xLV60, the installed speed of the grinding stone V_w is equal to 60 m/sec). Hence, some grinders are designed and manufactured with unmodified spindle speeds. Therefore, in order to simplify the study without loss of generality, this paper only consider four input parameters: The rate of normal feed (F_n), the speed of part (V_s), the depth of cutting (t) and the number of parts in a grinding cycle (N_p). In addition, the authors also found that the regime of cutting for grinding rough have insignificant effect on the quality of grinding parts. Thus, this article only considers cutting regime parameters with fine grinding. Hence, in this ANFIS network model, the author has established layer of input data (Layer 1) including only four neurons, respectively four the parameters of inputs: The rate of normal feed for fine grinding (F_n), the speed of part for fine grinding (V_s), the depth of cutting for fine grinding (t) and the number of parts in a grinding cycle (N_p).

Layer 2 is the fuzzification layer of input data. Each input value will be fuzzied. Each element in this layer is a membership function $\mu_{A_j^i}(x_i)$ having the form of Gauses function. Each variable x_i in this layer is dim into three ranges. Layer 3 is a layer representing fuzzy rules. It consists of 81 neurons. Each neuron in this layer represents a rule Rj. In layer 4, each neuron in this layer calculates the output values for the input values x_i. Layer 5 is the implementation layer of the combination of fuzzy rules. Layer 6 is output layer. Output, which is direct result of the process, is represented by the dynamic parameters of the system and the specific technical parameters of the workpiece and grindstones. In this network model, the output layer only has 1 noron, corresponding to a output quantity that is part's surface roughness (Ra_i), part's oval level (O_i) or grinding wheel's wear (Hz_i). These are three output parameters that should be estimated since they have direct impact to technical and economic efficiency of grinding process. The output layer performs defuzzification and calculate the output values of the neural fuzzy network.

2.3. Experiment and result

The experimental process is performed on the profile grinding machine to grind the 6208 ball bearing's inner ring grove. Experimental conditions are as follows:

- 3MK136B profile grinding machine (Made in China).

- Grinding wheel: 500x8x203A/WA100xLV60.

- Roughness measuring device: SJ400 roughness meter (Made in Japan).

- Devices for measuring grinding wheel's wear are two pneumatic probes. The design of two probes as well as solution for signals acquisition and processing in these pneumatic are presented in [2,3].

- Cutting Mode: The speed of cutting (V_w = 60 m/sec), the rate of normal feed (F_n) changes 3 levels (5, 12, 20) µm/sec, the speed of workpiece (V_s) changes 3 levels (6, 12, 18) m/min, the depth of cutting (t) changes 3 levels (10; 15; 20) µm, the number of parts in a grinding cycle (N_p) changes 30 levels (from the 1st part to the 30th part). Therefore, among 4 input parameters, 3 elements (F_n, V_s, t) have 3 levels and a factor (N_p) has 30 levels. Therefore, the author should choose orthogonal experimental matrix table $L_{810}(3^3.30^1)$ [5,6]. This means that 810 experiments will be conducted.

After conducting the experiments, data are collected and analyzed by ANFIS system. The authors use MALAB software to build the neural network. Although ANFIS GUI, an interactive environment to support the basic functions of ANFIS, is available on matlab software.

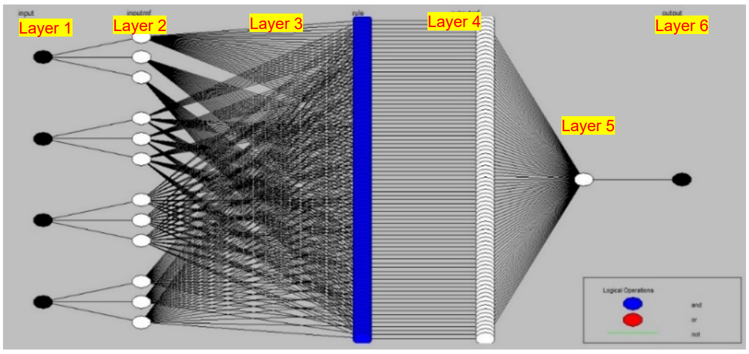

Fig. 2. The ANFIS network structure to predict grinding wheel's wear, part's surface roughness or part's oval level

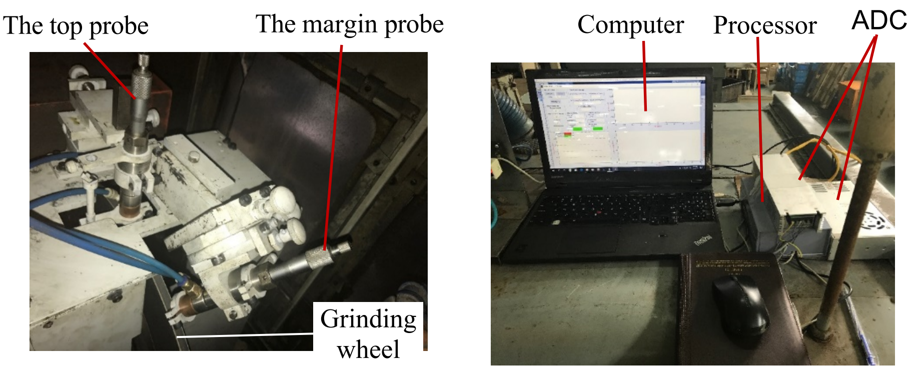

Fig. 3. The model diagram of the experimental system [1-3]

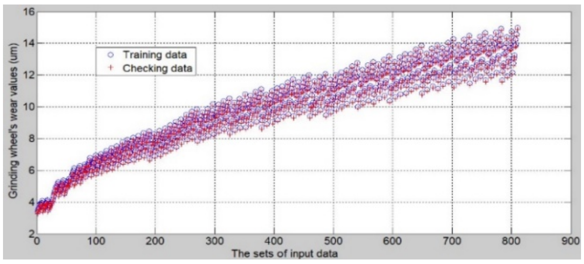

Fig. 4. *The graph shows actual wear values, corresponding to 810 different sets of input data, used as the set of Training data and Checking data to train and check network*

However, for the purpose of increasing automaticity in the process and the flexibility in utilities usage, a program has been established with the basic functions as follows: (1) reading the input data and experimental data from a data table; (2) creating the initial structure of the FIS; (3) trainning the ANN to optimize the parameters of the FIS; (4) Using the FIS has been trained to calculate the full values (Ra_i), (O_i) or (Hz_i) according to 810 sets of input data; (5) Writing the results of (Ra_i), (O_i) or (Hz_i).

It is necessary to use two sets of data to build ANFIS network structure. Fig. 4 indicates two sets of data to train the network to estimate grinding wheel's wear. The first set of data (Training Data) is used to train the ANN, thereby adjusting the membership functions to reduce errors. The second set of data (Checking Data) is used to test the convergence of the process. To ensure objectivity, the Checking Data is different from the Training Data. For increasing the reliability of experimental data, each set of experiments will be performed repeatedly three times. The average results of all three experiments for each set of input will be used to train the network as the Training Data. The results of the third experiment for each set of input will be used to check the network as the Checking Data.

Due to the process of calculating and training the network to predict grinding wheel's wear (Hz_i), part's surface roughness (Ra_i), part's oval level (O_i) are similar, the article only presents and analyzes the process of determining the neuron fuzzy network to estimate grinding wheel's wear (Hz_i). Error graph during training and checking process is plotted in Fig. 5.

Fig. 5 shows that the prediction error of the network decrease continuosly. The output values of the network is more closely to experimental data values. The error decreases after each training cycle (Epoch), but after about 110 epoch the Error does not reduce further. This proves that at this time system begins to overfit. This implies that the parameters of the FIS at that time are unimproved. After training, the structure of the fuzzy inference system (FIS) will be formed. Then, the ANFIS system will determine output values according to input data values.

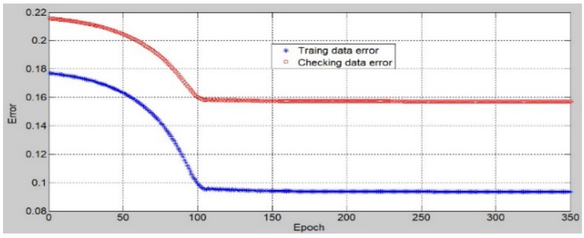

Fig. 5. *Error value graph according to the number of iterations during the ANFIS training process*

From ANFIS prediction values and experimental data values at the above various sets of input data, the program calculates the average value of forecasting error θtb = 0,768% and the dispersion of error σ= 0,631. These values are small. Therefore, the ANFIS system can be used to show relationship between output parameters to input parameters in grinding profile process. Hence, this model is fully qualified to determine the rule of influence between part's surface roughness, part's oval level or grinding wheel's wear and the input parameters of grinding mode.

However, in order to ensure more objective for assessing the predictability of neural fuzzy network, the authors also compare ANFIT predictions with BPNN predictions and experimental data values. Based on the least squares method (BPNN), the authors apply Matlab software to determine experimental regression function for the particular case of grinding wheel's wear. As a result, the relationship function is obtained as follow:

$$Hz_i = C.\mathrm{F}_n^a.\mathrm{V}_s{}^b.t^c.N_p^d = 2.1221\ .\mathrm{F}_n^{0.097}.\mathrm{V}_s{}^{0.0662}.t^{0.0561}.N_p^{0.3818}$$

By the least squares method (BPNN), the average error of 810 prediction sets (θ) is to 1,474%, the error dispersion (σ) is to 1,318. ANFIT predictions, BPNN predictions and experimental data values are shown in Fig. 6.

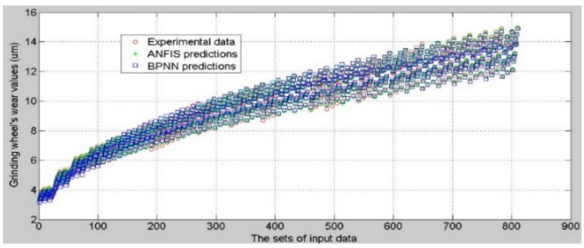

Fig. 6. *The comparison of ANFIT predictions, BPNN predictions and experimental data values at the different sets of input data*

The above graph indicates that ANFIT predictions are always closer to experimental data values than BPNN predictions. Hence, the prediction accuracy of ANFIS model is higher than those of BPNN model both the error of average and the dispersion of error. Therefore, for assessing the impact of cutting regime parameters on part's surface roughness, part's oval level and grinding wheel's wear in grinding profile, the authors apply ANFIT network.

On the basis of the values predicted by the ANFIT network according to the input data sets, this program also has built graphs showing the influence of the input variables on part's surface roughness or part's oval level or grinding wheel's wear as shown in the Fig.s below:

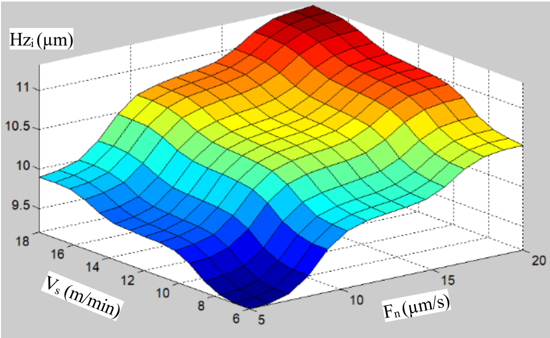

Fig. 7. The relationship between the amount of wear Hz_i and the input variables F_n ,V_s

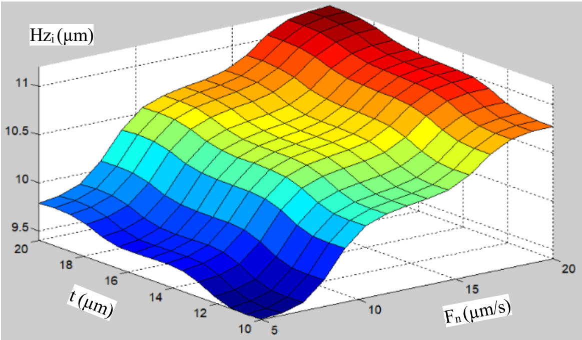

Fig. 8. The relationship between the amount of wear Hz_i and the input variables F_n ,t

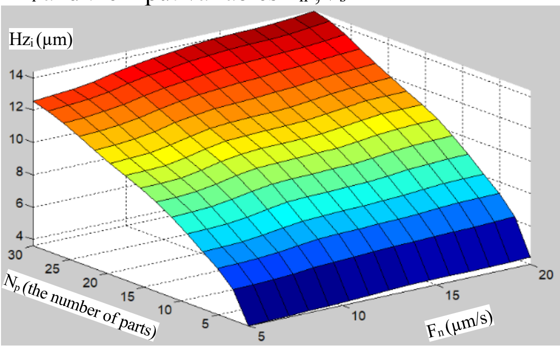

Fig. 9. The relationship between the amount of wear Hz_i and the input variables F_n ,N_p

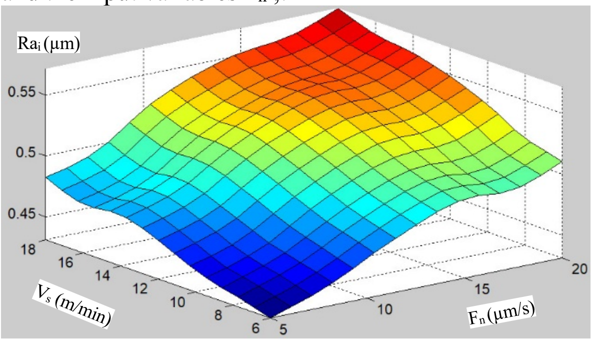

Fig. 10. The relationship between the surface roughness of part Ra_i and the input variables F_n ,V_s

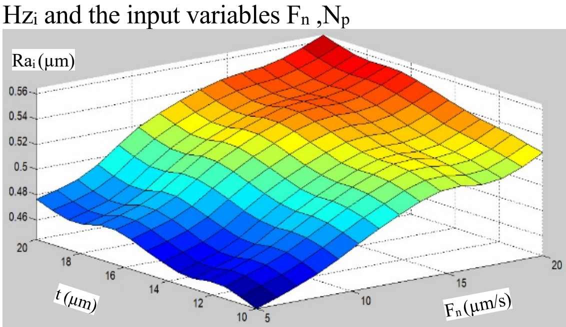

Fig. 11. The relationship between the surface roughness of part Ra_i and the input variables F_n ,t

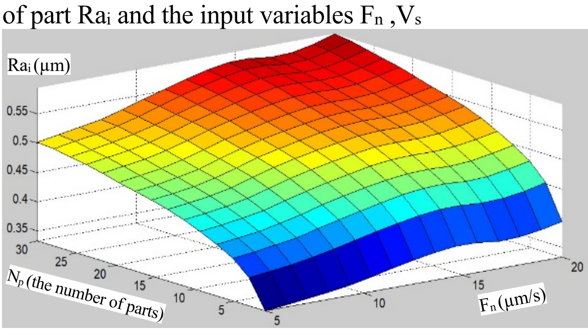

Fig. 12. The relationship between the surface roughness of part Ra_i and the input variables F_n ,N_p

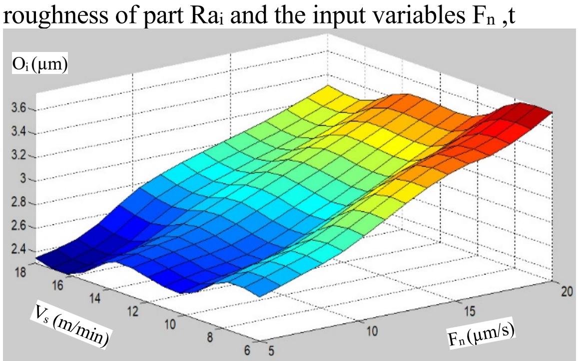

Fig. 13. The relationship between the oval level of part O_i and the input variables F_n ,V_s

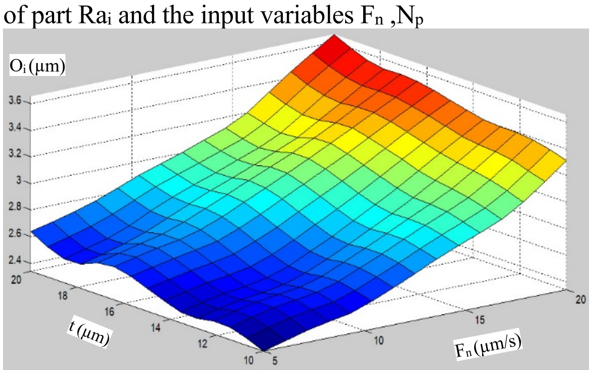

Fig. 14. The relationship between the oval level of part O_i and the input variables F_n ,t

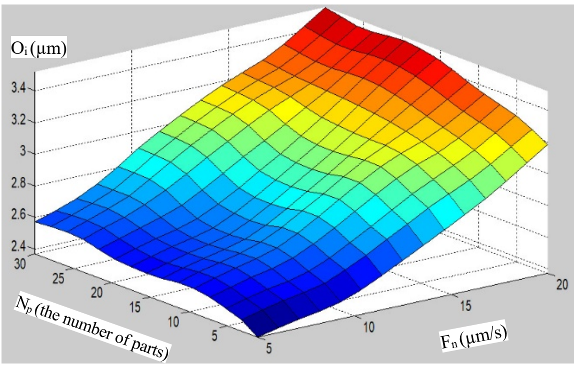

Fig. 15. The relationship between the oval level of part O_i and the input variables F_n ,N_p

From the above graphs, it is possible to draw the significant remarks for researching and applying in the grinding profile process to grind the 6208 ball bearing's inner ring grove as follows:

- When increasing the amount of normal feed rate (F_n), grinding wheel's wear (Hz_i), part's surface roughness (Ra_i) and part's oval level (O_i) will increase. However, the effect of (F_n) on (Hz_i) and (Ra_i) at the low workpiece speed is smaller than at the high workpiece speed. In contrast, in case of part's oval level (O_i), the influence trend is the opposite. At low workpiece rates, the influence degree of normal feed rate (F_n) to part's oval level (O_i) is greater than that of at the high workpiece rates.

- When increasing the rotational speed of workpiece (V_s), grinding wheel's wear (Hz_i) and part's surface roughness (Ra_i) will also increase but the degree of increase is lower than those of when increasing the rate of normal feed (F_n). This shows that the impact of normal feed rate (F_n) on grinding wheel's wear (Hz_i) and part's surface roughness (Ra_i) is greater than that of workpiece speed (V_s). However, in case of the part's oval level (O_i), the effect of workpiece speed on O_i will be reversed. When the rotational speed of workpiece (V_s) increases, the level of oval (O_i) decreases. And vice versa. This is explained as follows: The nature of workpiece rotation is the motion of feed per revolution. When the speed of workpiece (V_s) reduces, the speed of workpiece (V_s) could be smaller than the amount of normal feed rate (F_n). Thus, the distribution of surplus stock over the whole workpiece circumference will be uneven. For example, in the case of the workpiece speed $V_s = 6$ m/min = 100 mm/sec, the number of workpiece revolution per second will be determined as follows:

$$n_p = \frac{100}{\pi.D} = \frac{100}{\pi.48} \approx 0,66(\mathrm{s}^{-1})$$

Therefore, in one second the workpiece rotates 0,66 revolution. If the normal feed rate $F_n = 5$ μm/sec, in one second the workbench will cut into 5 μm. Hence, in the 1st second, grinding wheel cuts into workpiece surface the same amount of metal removal as the amount of normal feed rate (5 μm). However, in the 2nd second, since the rotation of the workpiece has not yet reached its full circle, the grindstone must cut into the workpiece surface the amount of metal removal that is twice as many as the amount of normal feed rate (10 μm). Hence, surplus stock over the entire perimeter of the workpiece will be unevenly distributed throughout the grinding process. As a result, on the whole perimeter of the workpiece, there are some positions where grindstone will cut with a large metal removal. There are some positions where the grindstone will cut with a small metal removal. Therefore, the diameter deviation of grinding part at different cross sections will be increased. This leads to the raise of part's oval level.

In addition, the amount of diameter deviation also depends on the amount of normal feed rate (F_n). If the radial feed rate (F_n) increases, the part's oval level (O_{ct}) will also increase as well. And vice versa. In the case of this, the cause is mainly due to the effects of vibration and grinding wheel's wear.

- When the depth of grinding increase, grinding wheel's wear (Hz_i), part's surface roughness (Ra_i) and part's oval level (O_i) will also increase. However, the amount of increase is negligible. This shows that the impact of cutting depth on grinding wheel's wear and part's accuracy is insignificant.

- When the number of parts in a grinding cycle (N_p) increase, part's surface roughness (Ra_i) and grinding wheel's wear (Hz_i) will also raise. Especially, the impact of (N_p) on part's surface roughness (Ra_i) and grinding wheel's wear (Hz_i) is much greater than the effect of normal feed rate (F_n), workpiece speed (V_s) and cutting depth (t). However, the effect of (N_p) on part's oval level (O_i) is lower than others. This can be explained as follows: The nature of increasing the number of grinding parts in a grinding cycle is to increase the grinding time. In the machining process, grinder dresses grindstone only after the end of a grinding cycle. Thus, parts grinded at the later time will have greater grinding time. Therefore, the more parts are grinded later, the larger the amount of grinding wheel wear. This leads to increase part's surface roughness especially for grinding profile. However, it does not affect significantly the diameter deviation of grinding parts at different cross sections. Thus, part's oval level only increase a small amount.

3. Conclusion

The above experimental results show that the ANFIS application solution for predicting part's surface roughness (Ra_i), part's oval level (O_i), grinding wheel's wear (Hz_i) according to cutting mode parameters in profile grinding process has achieved reliable results. By the ANFIS method, the average value of prediction error θ_{tb} = 0,768% and the dispersion of error σ=0,631. According to BPNN method, the average value of prediction error θ_{tb} = 1,474% and the dispersion of error σ=1,318. Thus, the ANFIS method reliability is higher than that of traditional experimental regression method. This enables accurate assessment of the effect of cutting mode parameters on output parameters (part's surface roughness Ra_i, part's oval level O_i and grinding wheel's wear Hz_i). Therefore, the results of this research will help manufacturers make right decisions facing with many difficult options. This is the basis of the determination and installation of reasonable cutting mode parameters before machining to achieve economic - technical efficiency of the grinding process.

References

[1]. Nguyễn Tiến Thọ, Nguyễn Thị Xuân Bảy, Nguyễn Thị Cẩm Tú, "Kỹ thuật đo lường kiểm tra trong chế tạo cơ khí", Nhà xuất bản Khoa học Kỹ thuật, 2002.

[2]. Nguyễn Anh Tuấn, Nguyễn Viết Tiếp, Vũ Toàn Thắng "Xây dựng hệ đầu đo khí nén để đo lượng mòn đá mài khi mài định hình", Hội nghị khoa học kỹ thuật đo lường toàn quốc lần thứ VI 2015.

[3]. Nguyễn Anh Tuấn, Nguyễn Viết Tiếp, Vũ Toàn Thắng "Nghiên cứu phương pháp đo mòn đá khi mài định hình bằng hệ đầu đo khí nén", Hội nghị KH&CN toàn quốc về cơ khí – động lực 2016.

[4]. Phạm Vũ Dũng, Đào Văn Hiệp "Dự báo độ nhám bề mặt mài hợp kim titan Ti-6Al-4V dùng công cụ nơron mờ thích nghi", Tạp chí khoa học và kỹ thuật – Học viện kỹ thuật quân sự, số 173, 12-2015.

[5]. Nguyễn Ngọc Kiên "Ứng dụng phương pháp trí tuệ nhân tạo và phân tích Taguchi để xác định chế độ cắt tối ưu khi gia công trên máy phay CNC", Luận án tiến sĩ kỹ thuật cơ khí, Hà nội 2014.

[6]. H. Baseri, G. Alinejad, "ANFIS Modeling of the Surface Roughness in Grinding Process", World Academy of Science, Engineering and Technology, Vol.5 2011-01-28.

[7]. A .O. Odior, F.A. Oyawale, A. U. Adoghe "A Neuro-Fuzzy Linguistic Approach to Component Elements of a Grinding Wheel", Industrial Engineering Letters, Vol.3, No.5, 2013.

[8]. Jyh-Shing Roger Jang "ANFIS: Adaptive-Network-Based Fuzzy Inference System", Ieee Transactions on systems, Man, and Cybernetics, Vol. 23, No. 3, 1993.