



Utilizing a Magnetic Abrasive Finishing Technique (MAF) Via Adaptive Neuro Fuzzy (ANFIS)

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Abstract

An experimental study was conducted for measuring the quality of surface finishing roughness using magnetic abrasive finishing technique (MAF) on brass plate which is very difficult to be polished by a conventional machining process where the cost is high and much more susceptible to surface damage as compared to other materials. Four operation parameters were studied, the gap between the work piece and the electromagnetic inductor, the current that generates the flux, the rotational spindle speed and amount of abrasive powder size considering constant linear feed movement between machine head and workpiece. Adaptive Neuro fuzzy inference system (ANFIS) was implemented for evaluation of a series of experiments and a verification with respect to specimen roughness change has been optimized and usefully achieved by obtained results were an average of the error between the surface roughness predicted by model simulation and that of direct measure is 2.0222 %.

Keywords: Magnetic abrasive finishing (MAF), adaptive Neuro fuzzy inference system (ANFIS), (AR) average roughness, (RMSE) root mean square error, membership function (MF).

1. Introduction

Magnetic abrasive finishing (MAF) is a super finishing method comparing with the other traditional operation of surface finishing like grinding, lapping etc., due to the attitude of the magnetic flux controlling to its cutting force combining with flexibility of magnetic powder and brush shape which minimize the possibility of micro cracks on the surface of the workpiece. At (MAF) the workpiece is held between the machine table that imposed to directional feed rate and the magnetic poles of the head nose (inductor) where the gap between the workpiece and the nose is filled with abrasive particle powder that shaped by the flux. This configuration act as smooth grinding brush and behaves like multipoint cutting tool operation [1][2]. Wang and Hu [3] described the principle of the process and

finishing characteristics of unbounded magnetic abrasive within internal tubing finishing. They also deal with the design and fabrication of MAF setup for finishing three kinds of materials tubing, such as (Ly12) aluminum alloy, (316L) stainless steel and (H62) brass. Geeng et al. [4] Also described the process principles and its finishing characteristics of unbounded magnetic abrasive within cylindrical magnetic abrasive finishing. They investigated the finishing characteristics on surface roughness and material removal as well as their mechanisms. Mori et al. [5] examined the magnetic field, acting forces and provides a fundamental understanding of the process mechanism. A planar type process for a non-magnetic material, stainless steel, was introduced. Maiboroda and Khomenko [6] investigated how the frictional force between magnetic-abrasive powders and (Ti) alloy surface

varies during magnetic-abrasive machining in relation to the technological parameters. They studied experimentally the effects of five types of powders with different grain sizes.

Dhirendra et al. [7] Reported the experimental findings about the forces acting during MAF and provides correlation between the surface finish and the forces.

Nazar [8] Reported the experimental findings of the forces acting during MAF and provides correlation between the surface finish and this force. It is concluded that forces and the change in surface roughness (ΔRa) increase with the increasing of the current value impose to the electromagnet (or magnetic flux density) and the decreasing in the working gap. The researchers filled the working gap with a homogeneous mixture of silicon carbide abrasives and ferromagnetic iron particles at a ratio of 25:75 in weight, respectively.

In this paper a model based on (ANFIS) for (AMF) process was performed using brass metal workpieces to estimate its surface roughness and an adoption of objective simulation is carried out to optimize the solution obtained by the model.

2. Experiments

An electromagnetic inductor was designed and manufactured to implement (MAF) on workpiece by milling machine as shown in Fig. 1. Consist of (1) inductor of steel road wrapped with a coil of wire (2) work piece (brass) (3) D.C power supply (4) machine spindle (5) inductor body (6) shank (7) milling table. While Fig. 2. Shows (1) magnetic powder particle (2) abrasive brush (3) gap between head nose and work piece.

The inductor material is low carbon steel (C15) with a cross section of (A) =14cm² and long of (L) is (75mm) and copper wire diameter of (ϕ)=1mm and number of turns is (N 2400) while the powder is (40%) iron and (60%) quartz centered in (1200 c°) and then were crushed to (150 μ m) of approximated diameter shows under SEM, JSM-6360 LV scanning microscope shown in Fig. 3.

The process parameters has been changed during the operation as follows: the working gap from (10 to 20)mm, current responsible to change the flux from (1.5 to 3.5) Amp, volume of the powder from (2 to 4) cm³ and the rotation speed from (175 to 5250) RPM with a feed rate of (30) mm/min.

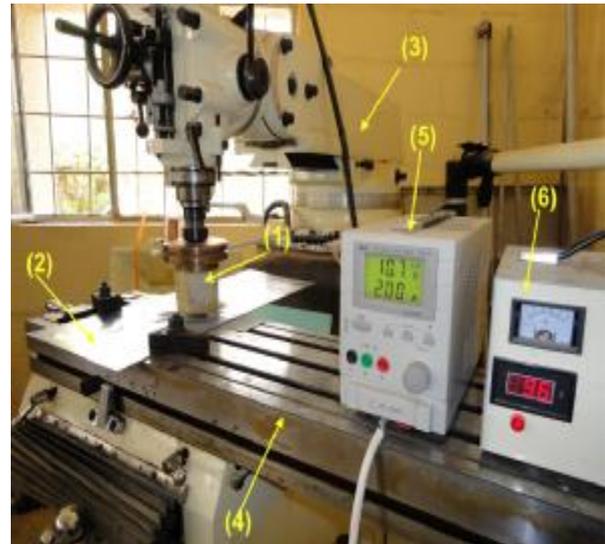


Fig. 1. Magnetic abrasive Devices.

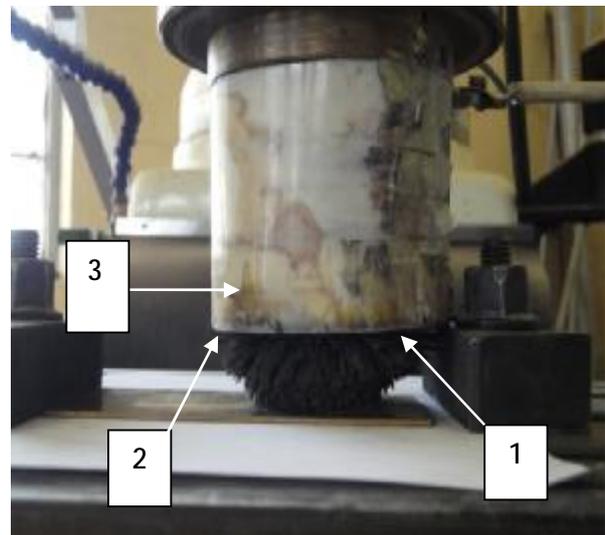


Fig. 2. Magnetic brush of electromagnet poles.



Fig. 3. SEM (X 100) of magnetic abrasive particles.

The work piece is divided into nine parts represent the three level configuration as shown in Tables (1 and 2) respectively. Some of them were operated traditionally and the other has been simulated as an artificial intelligent base of (ANFIS) (Fig. 4.) Each piece is fixed in such a way that the center of the work piece coincides with the center of the head nose. The required gap between them is filled with powder abrasive particles. After each experiment, the change in surface roughness value (ΔRA) is determined by measuring (RA) via tester TR220 (Fig. 5).

**Table 1,
Three Level parameters.**

Parameters	Units	Levels
Rotational speed (P ₁)	Rpm	175 - 350 - 525
Coil current (P ₂)	Amp	1.5 - 2.5 - 3.5
Volume of powder (P ₃)	cm ³	2.0 – 3.0 – 4.0
Working gap (P ₄)	Mm	1.0 - 1.5 - 2.0

**Table 2,
Parameters configuration.**

Exp.	Factors			
	Rotational speed (P ₁) (rpm)	Coil current (P ₂) (Amp)	Volume of powder (P ₃) (Cm ³)	Working gap (P ₄) (mm)
1	175	1.5	2	2
2	350	2.5	3	3
3	525	3.5	4	4
4	350	1.5	4	4
5	525	2.5	2	2
6	175	3.5	3	3
7	525	1.5	3	3
8	175	2.5	4	4
9	350	3.5	2	2



Fig. 4. Photo of some of the work pieces.



Fig. 5. Surface roughness tester, (TR-220).

3. ANFIS Optimization Technique

ANFIS is a hybrid predictive method that combines the neural network tool to the fuzzy approaches to generate mapping scheme between input parameters and output results. The structure of this model consist of five layers, each layer is constructed by several nodes. ANFIS behave just like the neural network where the structure of each layer is obtained by the node of the previous layers as shown in Fig. 6. A Numbers of initiating data among all data set have been selected as training data, and then the trained network was validated by other data set. The root mean square error (RMSE) is applied to this work for inspection purposes of the trained model as follows :

$$RMSE = \sqrt{[1/Tr \sum_{i=1}^{TR} (ti - Yi)^2]} \quad \dots(1)$$

Where (Tr) are the total number of training samples, (ti)is the real output value, and (Yi) is the ANFIS output value in training from matlab

platform using fuzzy tool representing by ANFIS guide user interface with the adoption the attitude of E AND C. A fuzzy inference system of sugeno model is conducted as follows:

A two rule sugeno ANFIS has rules of the form

If x is A1 and y1 is B1 THEN
 $f = p_1 x + q_1 y + r_1 \quad \dots(2)$

If x is A2 and y2 is B2 THEN
 $f = p_2 x + q_2 y + r_2 \quad \dots(3)$

For the training network fig 3E the RMSE was set to (0.02) and the iteration number was (30)epochs where the layers act as follow:

Layer 1 (Fuzzification layer): It transforms the crisp inputs

(Xi) to linguistic labels (A_{ij}, like small, medium, large etc.) with a degree of membership. The output of node (O_{ij}) or could represent by (k_i) is expressed as follows:

$$O_{ij1} = O_{k1} = \mu_{ij}(X_i), \quad i = 1 \dots m, \quad j = 1 \dots n \quad \dots(4)$$

Where (μ_{ij}) is the (jth) membership function for the input (X_i).

Layer 2 (Product layer): For each node (k) in this layer, the

The output represents a weighting factor (e) (firing strength) of the rule

(k). The output (W_k) is the product of all its inputs as follows:

$$O_{k2} = W_k = u_1 e_1(X_1) u_2 e_2(X_2) \dots u_m e_m(X_m) \quad \dots(5)$$

$$K = 1 \dots n, e_1, e_2 \dots e_m, = 1 \dots n$$

Layer 3 (Normalized layer): The output of each node (k) in

This layer represents the normalized weighting factor (W_k) of the (kth) rule as follows:

$$O_{k3} = W_k / (W_1 + W_2 + \dots + W_n) \quad \dots(6)$$

Layer 4 (De-fuzzification layer): Each node of this layer gives a weighted output of the first order TSK-type fuzzy if then rule as follows:

$$O_{k4} = W_k | f_k \quad \dots(7)$$

Where f_k represents the output of (kth) TSK (Takagi-sugeno-Kang)-type fuzzy rules.

Layer 5 (Output layer): This single-node layer represents the overall output (Y) of the network as the sum of all weighted outputs of the rules:

$$O_5 = Y = \sum_{k=1}^n (W_k | f_k) \quad \dots(8)$$

It is inevitable to consider that the fuzzy set is a decision-making process comparison with ANFIS, which raise the ability of the knowledge base decision-making system with its capability to produce the rules for simulation process.

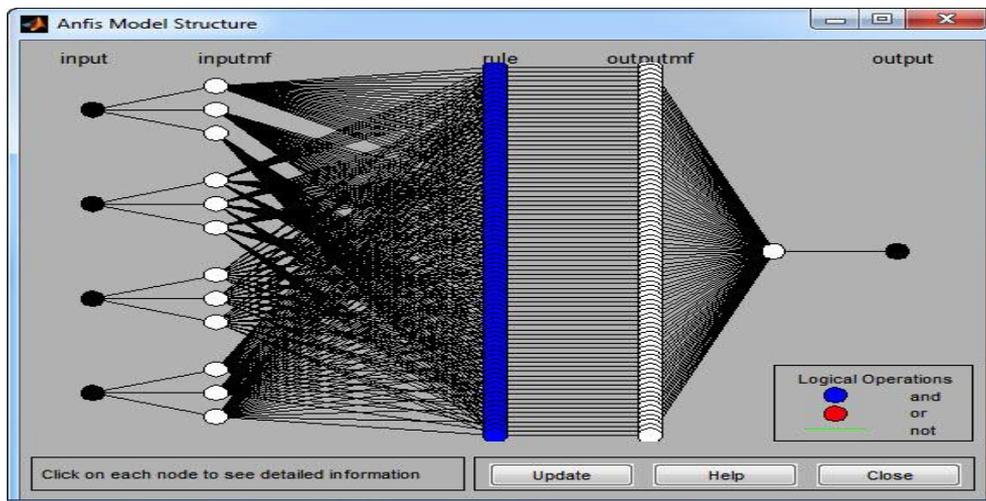


Fig. 6. ANFIS network structure.

4. Results and Discussion

After using several types of membership function, the Gaussian function Fig. 7. Was selected to be more accumulate with modeling behavior as follows:

$$U(x) = \exp[-(x-c)^2 / 2\sigma^2] \quad \dots(9)$$

Where:

U(X) represents the MF input and x,σ,c are parameters for Gaussian function shape that selected from the platform.

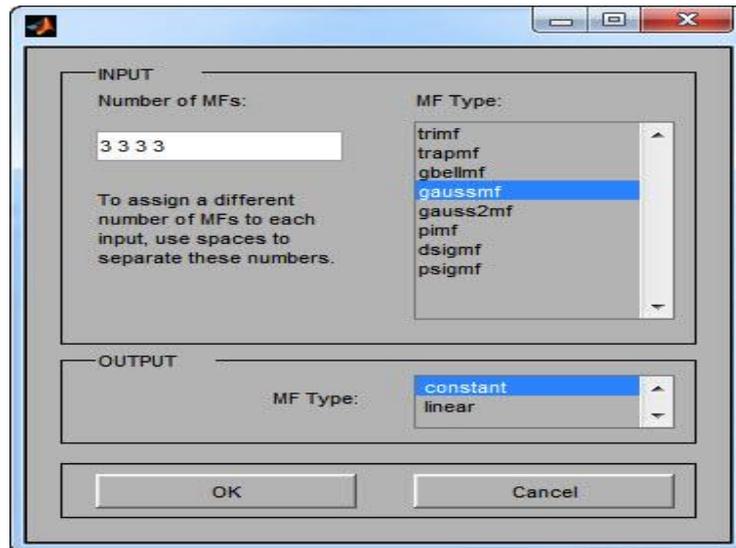


Fig. 7. Gaussian function selection box.

The experimental data are mapped to ANFIS and evaluates as patterns tanning/testing formed vectors where the training and testing performance for ANFIS was checked by the equation number (1).

The topology of the number of sets and epochs dedicates the number of rules used by sugeno ANFIS that reach 81 rules and its relate to the number of data and a comparison of experimental training /testing measured with those estimated by

ANFIS network as shown in Fig. (8 and 9) respectively.

It is obvious to recognize the simulation fitting that shows good agreement for a wide range of acceptability and reliability.

Table 3. Show the RMSE process result of ANFIS model for a different type of MF. Where Fig. 10. Show the training error curve.

After carrying out the process some of work pieces are shown in Fig. 11.

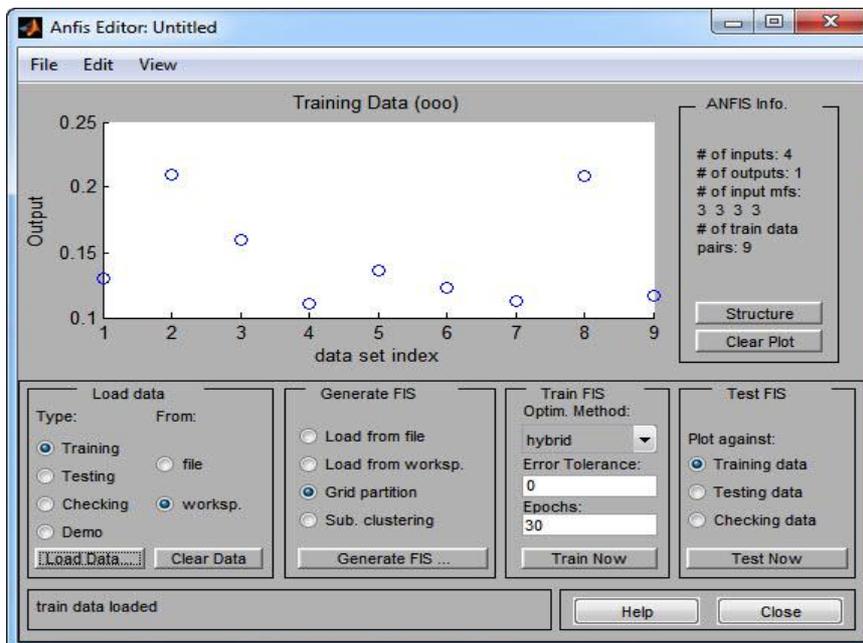


Fig. 8. Training session.

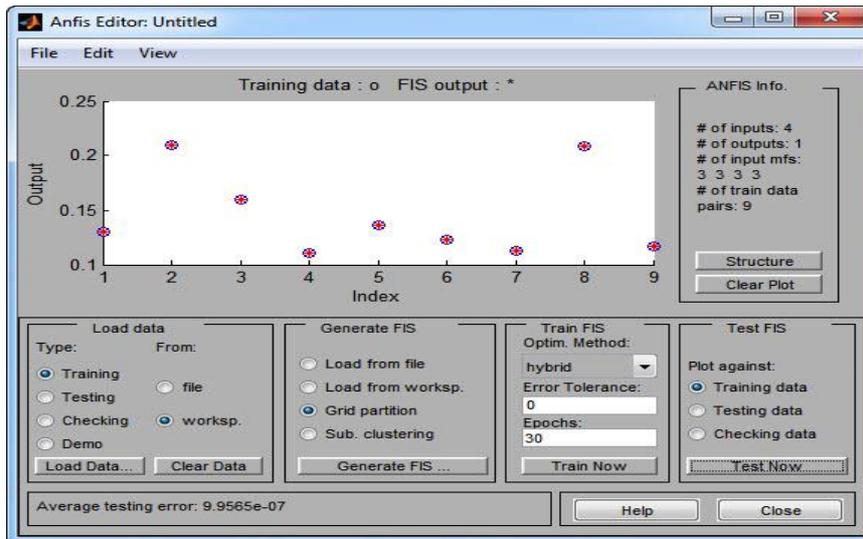


Fig. 9. Verification session.

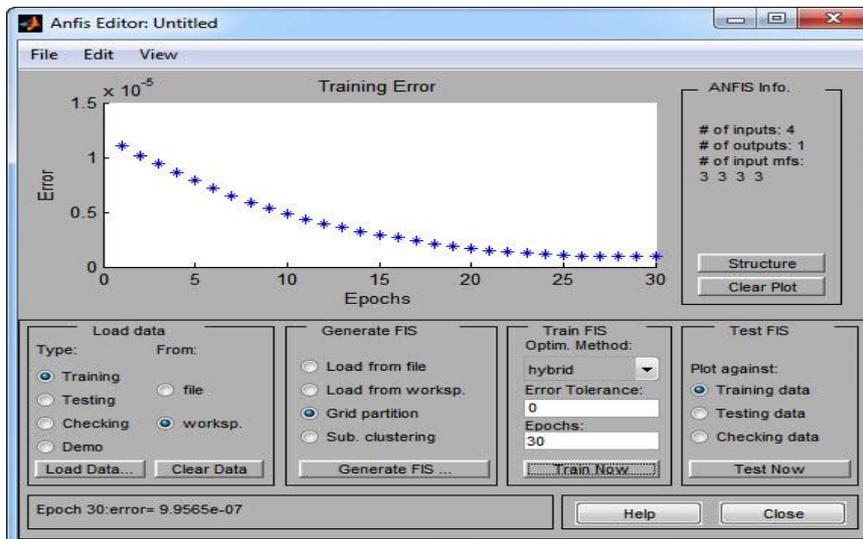


Fig. 10. The error curve during the ANFIS process.

Table 3,
Parameters results of ANFIS model .

Current mAmp	Gap mmm	Powder cc	Speed r/rev	Rf u	error
1.5	1	2	175	0.13	2.1
1.75	1.12	2.25	218.75	0.21	2.4
2	1.24	2.5	262.5	0.16	2.2
2.25	1.36	2.75	306.25	0.111	1.7
2.5	1.48	3	350	0.136	1.2
2.75	1.6	3.25	393.75	0.123	2.6
3	1.72	3.5	437.4	0.113	2.1
3.25	1.84	3.75	481.25	0.209	1.4
3.5	2	4	525	0.117	2.5
					Sum.18.2
					18.2/9=2.02



Fig. 11. Pieces show the location of smooth mirror.

5. Conclusion and Future Work

The most effective factor acting on ANFIS is the accuracy of the simulation model which is depend on the type of MF of Gaussian shape and the value of RMSE which is presume to be low on this operation which is mean more reliability and acceptability. The value number of Gaussian MF is twice the number of inputs, which are four for current research and need to be examining more to find if this happened by chance or there is a case of correlation. To explain this phenomenon, the researcher intends to approve in future work. The number of RMSE is dedicated to make the training epochs continue until it become below the target and that corresponding to the amount of epochs been settled and this arise the question if the epochs cycle change with the respect to time series how could this situation effect the prediction confidence. This neuro fuzzy model enhance the result with respect to other model such as the traditional neural network because of its rapid adaptation too bserve the structure of the process, also it is adapted to the increasing or adding of new inputs parameters regards to the expansion ability of fuzzy sets numbers and learning rules. More expected future result is to evaluating a good (quality and quantity) data sampling to obtain smaller results error (less than the acquired value of 0.022) in addition to how the flux shape could effect the powder figuration.

6. Reference

- [1] S.C. Jayswal, V.K. Jain, and P.M. Dixit, "Modeling and simulation of magnetic abrasive finishing process", *International Journal of Advanced Manufacturing Technology*, Vol.26 (2005), pp. 477–490.
- [2] Ching-Tien Lin, Lieh-Dai Yang, and Han-Ming Chow, "Study of magnetic abrasive finishing in free-form surface operations using the Taguchi method", *International Journal of Advanced Manufacturing Technology*, (2006).
- [3] Yan Wang, and Dejin Hu, "Study on the inner surface finishing of tubing by magnetic abrasive finishing", *International Journal of Machine Tools & Manufacture*, Vol.45 (2005), pp. 43–49.
- [4] Geeng-Wei Chang, Biing-Hwa, and Yan, Rong-Tzong Hsu, "Study on cylindrical magnetic abrasive finishing using unbounded magnetic abrasives", *International Journal of Machine Tools & Manufacture*, Vol.42 (2002), pp. 575–583.
- [5] T. Mori, K. Hirota, and Y. Kawashima, "Clarification of magnetic abrasive finishing mechanism", *Journal of Materials Processing Technology*, Vols.143-144 (2003), pp. 682–686.
- [6] V. S. Maiboroda and E. A. Khomenko, "Tribotechnical characteristics of ferroabrasive powders in magnetic-abrasion machining", *Journal of Powder Metallurgy and Metal Ceramics*, Vol.42 (2003), pp.9-10.
- [7] Dharendra K. Singh, V.K. Jain, and V. Raghuram., "Parametric study of magnetic abrasive finishing process", *Journal of Materials Processing Technology*, Vol.149 (2004), pp. 22–29.
- [8] Nazar kais M.naif "Study on the Parameter Optimization in Magnetic Abrasive Polishing for Brass Plate Using Taguchi Method "journal of college of engineering, vol,3(2011).
- [9] Jae-SeobKwak and Tae-Kyung Kwak, "Parameter Optimization in Magnetic Abrasive Polishing for Magnesium Plate", *IEEE*, Vol.5 (2010), pp.544–547.

التنفيح بأسلوب العصبيات المضربة لتطوير التشغيل بطريقة التنعيم بالاحتكاك المغناطيسي

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الخلاصة

تم اجراء دراسته تطبيقيه لقياس نوعية السطوح المنعمه بطريقة الاحتكاك المغناطيسي على عينات لوجيه من البراص المعروفه بكونها تحتاج الى متطلبات خاصه في عمليات التنعيم لمثل هذا النوع من المعادن من كلف تشغيله ومهاره عاليه وضروف تشغيليه خاصه. تم اختيار مجموعه من المعايير المؤثره على ضروف التشغيل لمثل هذا النوع من التنعيم والذي يتم عن طريق وضع ماده ابريه لتملى الفراغ بين القطب المغناطيسي الدوار للماكنه وبين العينه المراد تشغيلها ، اذ تعتبر هذه الفجوة من المعايير الحساسه في هذا النوع من التشغيل فضلا عن شدة التيار المستخدم لتوليد الحث المغناطيسي وكمية ماده الابريه المستخدمه وسرعة دوران القطب المغناطيسي الحامل لماده التنعيم. تم الانتفاع من اسلوب العصبيات المضربه للحصول على توليفة مثلى من المعايير ضمن تشكيلة المعايير المستخدمه في حاله العمليه ووصل الانتفاع الى توليفة مقاربه للتجارب العمليه بنسبة خطأ ٢.٠٢٢٢ % . وان التوليفه قابله للتغير بمعايير مختلفه دون الرجوع الى التطبيق العملي مما يوفر الوقت والمجهود خاصه للمعادن العاليه الكلفه التي لاتحتمل اجراء التجارب العمليه دون التأكد من صحة المعطيات.