行政院國家科學委員會專題研究計畫 成果報告

BTA 深孔鑽精準制振與減油潤滑之研究及系統開發
研究成果報告(精簡版)

計 畫 類 別 ：個別型
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執 行 單 位 ：國立交通大學機械工程學系（所）

計畫主持人：秦繼華

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計畫參與人員：　　執行機構及單位名稱

1、中文摘要

深孔鑽是高附加價值的加工方式，主要用在航太、汽車與國防工業上。過往的研究顯示，深孔鑽的長刀桿本身具有動態，若能對刀桿精準制振，將進一步提高深孔鑽削的品質，本計畫研發刀桿精準制振器，利用磁流變液可改變阻尼的特性，在刀桿振動模態發生的關鍵位置，針對不同加工參數，做刀桿精準制振，使特定刀桿振動模態受到制約，進一步提升深孔加工的品質。此外，本計畫亦進行深孔鑽的貧油切削研究，設計油氣混合器，將壓縮空氣與冷卻潤滑劑混合打入，以田口氏法規劃實驗，並以神經網路分析加工品質。本計畫使原本高品質的深孔加工，獲得進一步品質提升。

關鍵詞：深孔鑽, 精準制振, 磁流變液減振器, 減油潤滑, 神經網路分析

Abstract

Deep hole drilling is a high quality, high value-added hole making technology essential to the aviation, automobile and defense industries. Past researches revealed that the long shaft of deep hole drilling has its own dynamics which may influence the hole quality in a negative way. This study conducts precision suppression of shaft vibration with an aim to further improve hole making quality. A Magnetorheological fluid damper is designed and installed with the knowledge of position and shape of vibration modes to perform precision suppression of shaft vibration. In addition to that, An air-lubricant mixing adapter is designed to study minimum quantity lubrication (MQL) for deep hole drilling process. Taguchi method is adopted to plan the experiments and neural network analysis is performed on the experimental results. The studies conducted in this project further advance the quality and the value of deep hole drilling technology.

Keywords: deep hole drilling, precision vibration suppression, Magnetorheological fluid damper, minimum quantity lubrication, neural network analysis

2、緣由與目的

在深孔鑽的長期研究中，本實驗室過去已建立 BTA 深孔鑽刀桿公式的統治方程式 [1, 2]，發現，深孔鑽刀頭的側向位移是許多模態效應的總和，因而產生一種想法：若能抑制某個模態，使其不被激發出來，則該模態的$\phi(z)$就不影響刀頭側向位移，若能進一步抑制主要（dominant）的模態，應該可以減少刀頭側向位移，因而增加鑽削精度。於是產生了精準制振的想法，也就是，準確的將某個振動模態鎮壓下去。至於制振手段，係採用可以改變阻尼力之磁流變液流體（Magnetorheological fluid）設計制振器，針對刀桿的特定位置，進行減振。

另一方面，金屬切削加工普遍面臨一項挑戰：減少切削潤滑劑的使用。這一方面是成本考量，例如金屬切削加工中，刀具成本約佔 2 to 4%，潤滑劑成本竟然佔到 7 to 17% [3]，另一方面，是環保要求[4]。本計畫設計油氣混合器，將壓縮空氣與切削潤滑劑混合，觀察 MQL 對切削過程之影響。

在實驗方法中，採用田口氏法做實驗規劃，並用神經網路分析實驗結果。

3、研究方法

3.1 運動方程式

應用Hamilton's principle, 推導出含流體之深孔鑽旋轉刀桿之運動方程式如下：

$$\ddot{u}+\frac{2\rho_f A_f U}{\rho A+\rho_f A_f}\dot{u}'+\frac{\rho_f A_f U^2}{\rho A+\rho_f A_f}u''+\frac{EI}{\rho A+\rho_f A_f}u''''=0$$

若刀桿不轉，及忽略流體，則上式與[5]同。

若加裝 MR-制振器，其阻尼為 c，則可導出刀桿運動方程式如下：

$$\ddot{u}+\frac{2\rho_f A_f U}{\rho A+\rho_f A_f}\dot{u}'+\frac{\rho_f A_f U^2}{\rho A+\rho_f A_f}u''+\frac{EI}{\rho A+\rho_f A_f}u''''+\frac{c}{\rho A+\rho_f A_f}\dot{u}\delta(x-\alpha L)=0$$

運用 Galerkin's method，假設 $\tilde{u}(\bar{x},t)\approx\sum_{r=1}^{n}u_r(\bar{x})\eta_r(t)$ 代入上式，解出 MR-流體制振器作用下之導桿特性，表 1 顯示一例。

表 1 MR-流體制振器對振頻之影響

mode	未制振 Hz	制振 Hz
1	22.37	21.90
2	61.67	61.63
3	120.90	120.90
4	199.86	199.82
5	298.56	298.56
6	416.99	416.98
7	555.16	555.16
8	713.08	713.08
9	890.73	890.72
10	1088.12	1088.12

3.2 設計開發

本計畫中設計出 MR 流體制振器如圖 1，圖 2 為制振器之電腦繪圖，圖 3 顯示為貧油潤滑而設計及安裝之油氣混合器，圖 4 為實驗機台。

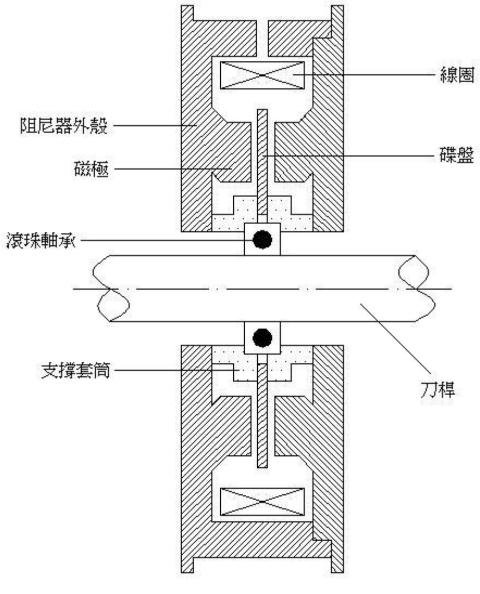

圖 1 MR 流體制振器設計示意圖

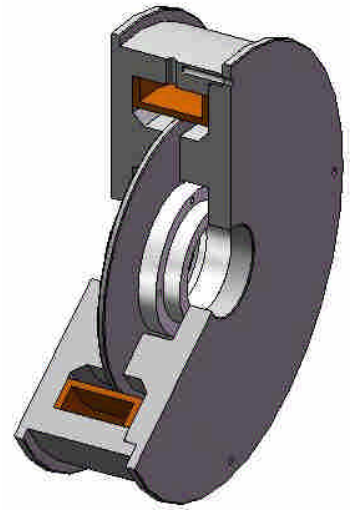

圖 2 MR 流體制振器 CAD 示意圖

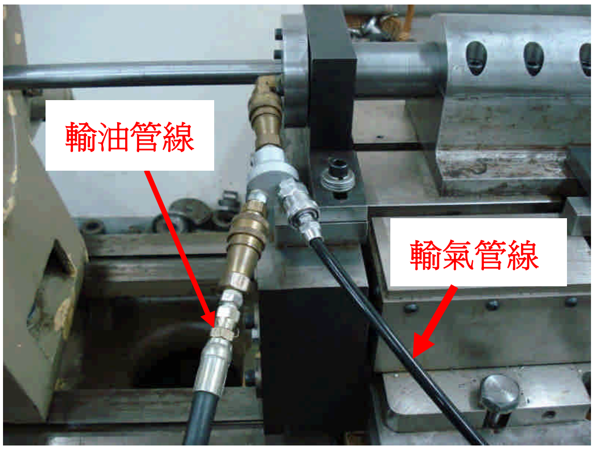

圖 3 貧油潤滑之油氣混合器

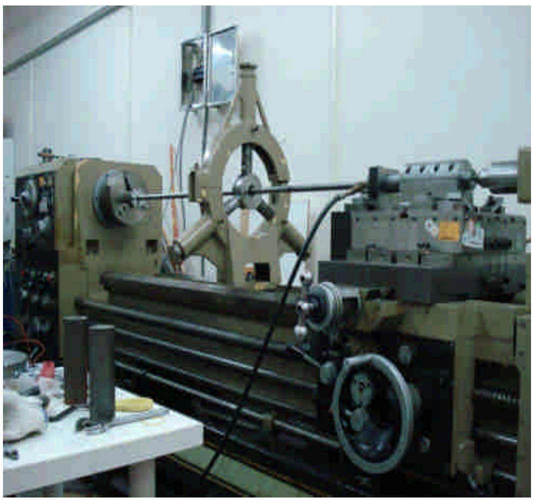

圖 4 深孔鑽之精準制振與貧油潤滑實驗機台

3.3 實驗規劃

表 2 單純供油實驗規劃

代號	控制因子	水準 1	水準 2	水準 3
A	主軸轉速 N rpm	390	585	855
B	刀具進給率 mm/rev	0.05	0.07	0.10
C	支承位置 L mm	400	800	1200

表 3 用田口式直交表$L_9(3^4)$之單純供油實驗規劃

Exp	N rpm	S mm/rev	L mm
1	390	0.05	400
2	390	0.07	800
3	390	0.10	1200
4	585	0.05	800
5	585	0.07	1200
6	585	0.10	400
7	855	0.05	1200
8	855	0.07	400
9	855	0.10	800

表 4 貧油切削實驗規劃

代號	控制因子	水準 1	水準 2	水準 3
A	主軸轉速 N rpm	390	585	855
B	刀具進給率 mm/rev	0.05	0.07	0.10
C	支承位置 L mm	400	800	1200
D	壓縮空氣 P kg/cm^2	7	10	12

表5　採用田口式直交表$L_9(3^4)$之貧油實驗配置圖

Exp.	N rpm	S mm/rev	L mm	P kg/cm^2
1	390	0.05	400	7
2	390	0.07	800	10
3	390	0.10	1200	12
4	585	0.05	800	12
5	585	0.07	1200	7
6	585	0.10	400	10
7	855	0.05	1200	10
8	855	0.07	400	12
9	855	0.10	800	7

表 6 制振實驗規劃

代號	控制因子	水準 1	水準 2	水準 3
A	主軸轉速 N rpm	390	585	855
B	刀具進給率 mm/rev	0.05	0.07	0.10
C	Damper 位置 H mm	400	800	1200
D	電流 I A	0	0.5	1

表 7 採用田口式直交表$L_9(3^4)$之制振實驗配置圖

Exp	N rpm	S mm/rev	H mm	I A
1	390	0.05	400	0
2	390	0.07	800	0.5
3	390	0.10	1200	1
4	585	0.05	400	1
5	585	0.07	800	0
6	585	0.10	1200	0.5
7	855	0.05	400	0.5
8	855	0.07	800	1
9	855	0.10	1200	0

表 8 貧油與制振實驗規劃

代號	控制因子	水準 1	水準 2	水準 3
A	主軸轉速 N rpm	390	585	855
B	刀具進給率 mm/rev	0.05	0.07	0.10
C	Damper 位置 H mm	400	800	1200
D	電流 I A	0	0.5	1
E	壓縮空氣 P kg/cm^2	7	10	12

3.4 實驗結果與分析

表 9 制振前後之振幅比較表
（轉速：855 rpm）

頻率 Hz	制振前 μm	制振後 μm
17.75	24.3092	16.237
35.5	1.7039	0.6099
43.25	1.1061	0.9961

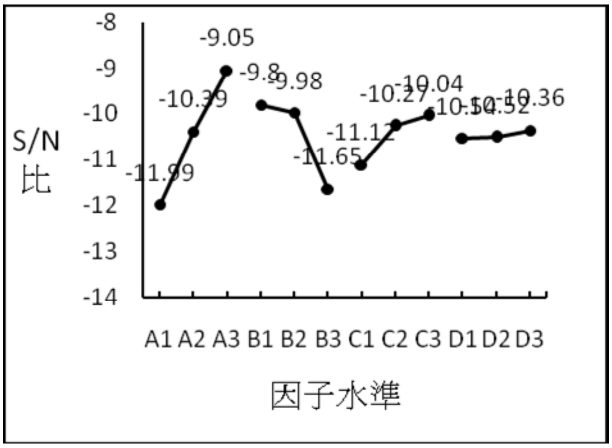

圖 5 單純供油實驗因子效果圖

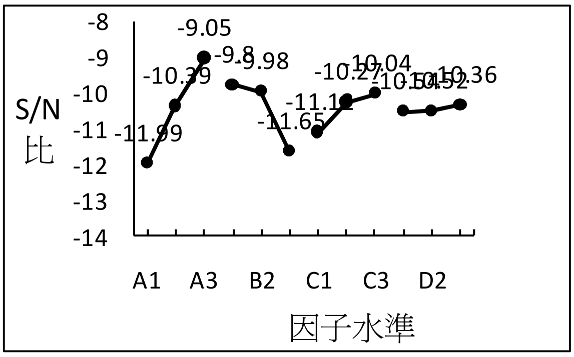

圖 6 貧油實驗因子效果圖

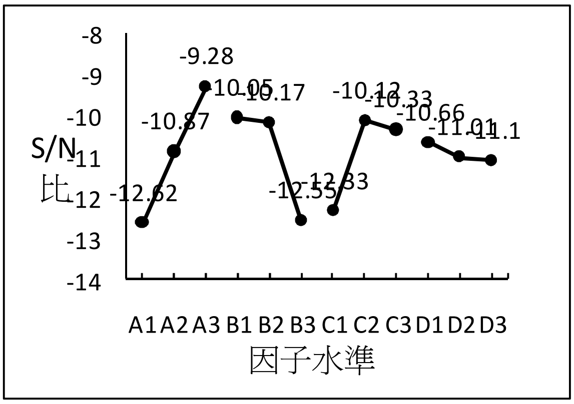

圖 7 制振實驗因子效果圖

制振實驗的最佳參數組合為 $A_3B_1C_2D_1$，也就是主軸轉速 855(rpm)、刀具進給率 0.05(mm/rev)、damper 位置 800(mm)及 damper 電流 0(A)，為最佳的參數組合。

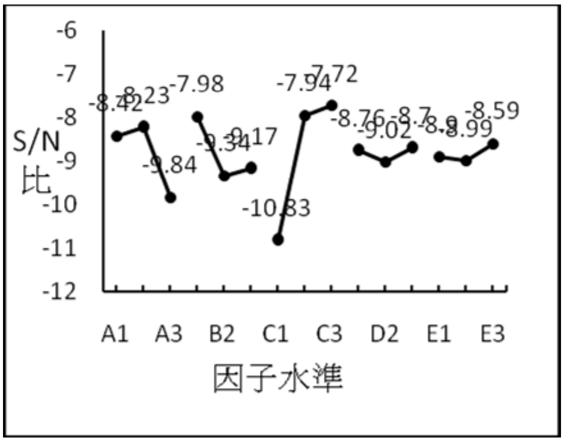

圖 8 貧油與制振混合實驗因子效果圖

由上圖可知，貧油與制振混合實驗的最佳參數組合為 $A_2B_1C_3D_3E_3$，也就是主軸轉速 585(rpm)、刀具進給率 0.05(mm/rev)、damper 位置 1200(mm)、damper 電流 1(A)及壓縮氣壓 12(kg/cm^2)，為最佳的參數組合。

為進一步了解控制因子對實驗的影響性，對各控制因子進行變異數分析(ANOVA)，之後做兩次確認實驗，結果如表 10。

表 10　貧油與制振混合之確認實驗

實驗編號	粗糙度 Ra 值(μm)					
	y1	y2	y3	y4	平均值	S/N 比
19	1.97	2.11	1.97	1.98	2.01	-6.06
20	2.02	1.95	1.90	2.02	1.97	-5.90

由上表顯示，兩組實驗結果之 S/N 比皆落在信賴區間之內，表示此貧油與制振混合實驗的田口式參數設計是成功的。

3.5 類神經網路最佳化實驗結果與分析

使用 matlab 軟體中的類神經網路工具箱進行網路的設計，以主軸轉速、刀具進給率、制振器位置、制振器電流及壓縮氣壓等 5 項加工參數的數值作為所建網路之輸入資料，而網路的輸出目標就是 18 組實驗所量得的粗糙度值。網路的型態設定為前饋式倒傳遞類神經網路，演算法選擇 Levenberg-Marquardt 演算法，性能函數為 MSE，網路的訓練參數 μ_k＝0.001，θ＝10。

表 11 顯示九種所設計之類神經網路之結果。由表 11 中可知，5-7-1 之類神經網路結果最好。以此 5-7-1 之類神經網路對貧油與制振混合實驗的最佳參數組合$A_2B_1C_3D_3E_3$組合進行因子最佳化的設計，可得，主軸轉速 585(rpm)、刀具進給率 0.05(mm/rev)、damper 位置 1000(mm)、damper 電流 0.8(A)及壓縮氣壓 11(kg/cm^2)屬最佳化後的參數因子組合。

表 11 九種類神經網路架構之比較

網路架構	均方誤差 (MSE)	確認實驗結果	與表 8 誤差%
5-2-1	0.1313	2.3857	19.88
5-3-1	0.0987	2.3274	16.95
5-4-1	0.0399	2.0953	5.29
5-5-1	0.1286	2.2771	14.43
5-6-1	0.1286	2.1649	8.79
5-7-1	0.0282	2.0365	2.34
5-8-1	0.0872	2.0784	4.44
5-9-1	0.0872	2.1342	7.25
5-10-1	0.1300	2.2983	15.49

表 12 類神經網路參數最佳化後之實驗結果驗證

實驗編號	粗糙度 Ra 值(μm)					
	y1	y2	y3	y4	平均值	S/N 比
21	1.60	1.66	1.88	2.10	1.81	-5.20

上表顯示，在以類神經網路最佳化後，制振與貧油架構下之深孔鑽削達到更進一步品質提升。

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行政院國家科學委員會補助專題研究計畫成果報告

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計畫類別：■個別型計畫　　□整合型計畫

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計畫主持人：秦繼華

共同主持人：

計畫參與人員：

本成果報告包括以下應繳交之附件：

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□國際合作研究計畫國外研究報告書一份

執行單位：國立交通大學機械工程系所

中　華　民　國　98 年 10 月 27 日

MANUFACTURING QUALITY IMPROVEMENT BY NEURAL NETWORKS UPON TAGUCHI METHOD

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ABSTRACT
In developing new manufacturing and material handling process the influence of process parameters upon the target object need to be evaluated in order to find the adequate operation settings. An efficient method is the Taguchi method which reduces the number of experiments and has the capability of finding the optimal setting of process parameters. This paper proposes the construction of neural network upon Taguchi results to further advance the quality of a new deep hole drilling process. It is shown that neural network produces process parameter setting better than the "optimal setting" obtained by Taguchi method.

KEY WORDS
Neural networks, simulation optimization, Taguchi method, deep hole drilling, manufacturing quality

1. Introduction

In dealing with dynamic systems great efforts are usually devoted to the investigation and modeling of the systems. Purpose of such efforts is to understand the systems more accurately so that better system design and control are possible. However, highly non-linear systems are often highly opaque and accurate modeling is often difficult. The emergence of non-traditional techniques such as soft computing offers a convenient approach in dealing with difficult dynamic systems without getting involved in the deep insight of the system dynamics.

The so-called soft computing is meant, among others, for neural networks, fuzzy logic and genetic algorithms. A natural evolution is to combine components of soft computing to form new intelligent algorithms, for example neural networks combined with fuzzy logic or fuzzy logic combined with genetic algorithms.

While soft computing can unfold power of new performance by mutual integration and interweaving between components, it also has the potential to unfold new ability by combining with conventional problem-solution means [1, 2].

The purpose of this study is to investigate an approach by combining one component of soft computing, the neural networks, with one of the most efficient planning techniques in manufacturing: Taguchi method. Taguchi method not only reduces the necessity of large number of experiments but also discloses the best (so-called optimal) parameter setting that produces the best production quality. Yet this paper shows that by constructing neural network upon the proven Taguchi optimal results the "optimal" quality obtained by Taguchi method can be further improved.

2. Neural Networks Optimization of the New Deep Hole Drilling Process

2.1 A new deep hole drilling process

This study is a part of a bigger project in which a new manufacturing process, a magnetorheological fluid (MR-fluid) damped and minimum-quantity-lubricated (MQL) deep hole drilling, is developed.

Deep-hole drilling is an important process for the production of high-precision workpiece with high-quality holes [3]. Its main areas of application are in the defense, aircraft and automobile industries. Since the ratio of hole depth to hole diameter exceeds ten, a long tool shaft is needed which claims its own dynamics when machining.

In order to influence the shaft dynamics and upgrade the process with the environmental-friendly feature of less lubricant consumption, a magnetorheological fluid damper and a MQL rig were designed to create a MR-fluid damped and minimum-quantity-lubricated deep hole drilling process.

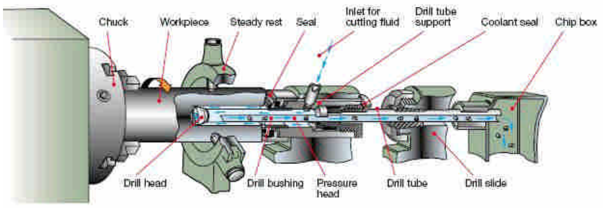

Figure 1 BTA Deep hole drilling process [4]

Figure 1 is the BTA (Boring and Trepanning Association) deep hole drilling process [4]. In a BTA deep hole drilling process the compressed cutting fluid is introduced in the fore part of drilling shaft and, after passing the cutting edge, flushes backwards within the internal of the shaft carrying away the cutting chips.

In order to suppress the shaft vibration in a manipulative way the MR-fluid is chosen in view of its capability of changing damping capacity.

A MR-fluid damper (shown in figure 2) is designed and fabricated. The MR-fluid damper and the minimum-quantity-lubricated deep hole drilling machine is set up as shown in figure 3. Since the design of MR-fluid damper and the MQL rig are not topics of this paper so the corresponding details are omitted.


Figure 2 The designed magnetorheological fluid damper

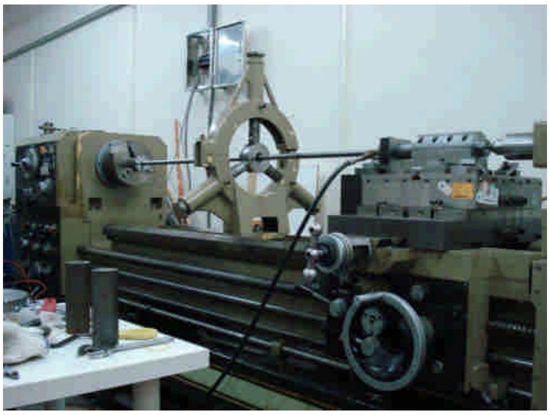
Figure 3 The testing machine for the new deep hole drilling process

2.2 Taguchi method and neural networks

For the sake of completeness the Taguchi method and the neural networks are briefed as follows.

Taguchi methods [5] enable studies of the entire factor space with only a small number of experiments by using a special design of orthogonal arrays.

The signal-to-noise (S/N) ratio instead of the average is used in the Taguchi method to convert the experimental data into a value for the determination of the optimum setting analysis.

There are three different types of S/N ratio [5] among which the STB (smaller-the-best) S/N ratio is chosen because the surface roughness is chosen as the quality criterion in the subsequent experiments:

$$SN_{STB} = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n} y_i^{\,2}\right]$$

Figure 4 is the flow chart of Taguchi method.

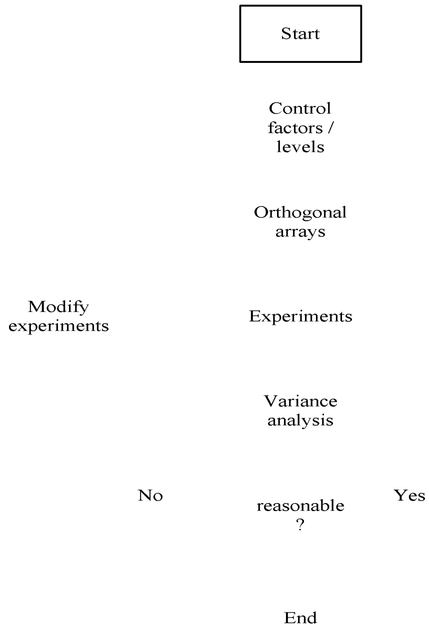

Figure 4 Flow chart of Taguchi method

Neural networks are artificial instruments inspired by biological nervous systems. Figure 5 shows an elementary neuron with R inputs. The neural network shown in figure 5 is seen as one layer, multiple layers each contains many neurons may form neural networks capable of simulating highly non-linear system dynamics

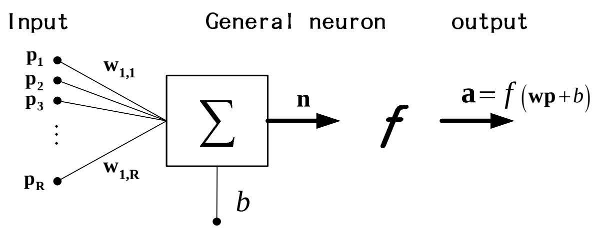

Figure 5 An elementary neuron

2.3 Experiments

Experimental equipment and setup are as follows:

Machine: SAN SHING SK26120 lathe (retrofitted)
Drill head: diameter 24.11mm

Drill shaft: length 1600 mm
Workpiece: AISI 1020
Hydraulic aggregate: pressure 5kg/cm^2
Air compressor: pressure 16kg/cm^2

Table 1 Control factors and experimental levels for the new BTA drilling process

	Control factor	Level 1	Level 2	Level 3
A	Tool speed N (rpm)	390	585	855
B	Tool feed S (mm/rev)	0.05	0.07	0.10
C	MR-Damper location L (mm)	400	800	1200
D	MR-Damper current I (amp)	0	0.5	1
E	Air pressure P (kg/cm^2)	7	10	12

Five control factors each with three levels will require 3^5 =243 experiments, however, by using a modified Taguchi orthogonal array $L_{18}(3^5)$ as shown in table 2 the number of experiments reduces to 18.

Table 2 Taguchi orthogonal array $L_{18}(3^5)$

	A	B	C	D	E
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	2	1	1	2	2
5	2	2	2	3	3
6	2	3	3	1	1
7	3	1	2	1	3
8	3	2	3	2	1
9	3	3	1	3	2
10	1	1	3	3	2
11	1	2	1	1	3
12	1	3	2	2	1
13	2	1	2	3	1
14	2	2	3	1	2
15	2	3	1	2	3
16	3	1	3	2	3
17	3	2	1	3	1
18	3	3	2	1	2

Table 3 is the real layout of experiments according to Taguchi orthogonal array $L_{18}(3^5)$ as shown in table 2.

Table 3 Layout of experimental design

exp	N(rpm)	S(mm/rev)	H(mm)	I(A)	P(kg/cm^2)
1	390	0.05	400	0	7
2	390	0.07	800	0.5	10
3	390	0.10	1200	1	12
4	585	0.05	400	0.5	10
5	585	0.07	800	1	12
6	585	0.10	1200	0	7
7	855	0.05	800	0	12
8	855	0.07	1200	0.5	7
9	855	0.10	400	1	10
10	390	0.05	1200	1	10
11	390	0.07	400	0	12
12	390	0.10	800	0.5	7
13	585	0.05	800	1	7
14	585	0.07	1200	0	10
15	585	0.10	400	0.5	12
16	855	0.05	1200	0.5	12
17	855	0.07	400	1	7
18	855	0.10	800	0	10

Table 4 Experimental results performed according to the layout of table 3

no exp	Roughness Ra (µm)					
	y_1	y_2	y_3	y_4	average	S/N
1	2.51	2.67	2.43	2.64	2.56	-8.18
2	2.37	2.45	2.26	2.60	2.42	-7.69
3	2.25	2.30	2.29	2.28	2.28	-7.16
4	3.08	3.26	3.17	3.29	3.20	-10.11
5	2.09	2.06	2.15	2.24	2.14	-6.59
6	2.37	2.41	2.22	2.23	2.31	-7.27
7	2.18	2.14	2.21	2.22	2.19	-6.80
8	2.83	2.95	2.99	2.78	2.89	-9.21
9	3.88	3.79	4.02	3.94	3.91	-11.84
10	2.14	2.07	2.13	2.05	2.10	-6.44
11	4.09	4.27	4.15	4.25	4.19	-12.45
12	2.83	2.62	2.54	2.73	2.68	-8.57
13	2.51	2.49	2.37	2.42	2.45	-7.78
14	2.63	2.42	2.19	2.40	2.41	-7.66
15	3.27	2.95	3.14	3.23	3.15	-9.97
16	2.63	2.56	2.83	2.72	2.69	-8.59
17	3.96	4.44	3.98	4.29	4.17	-12.41
18	3.05	3.27	3.16	3.42	3.23	-10.18

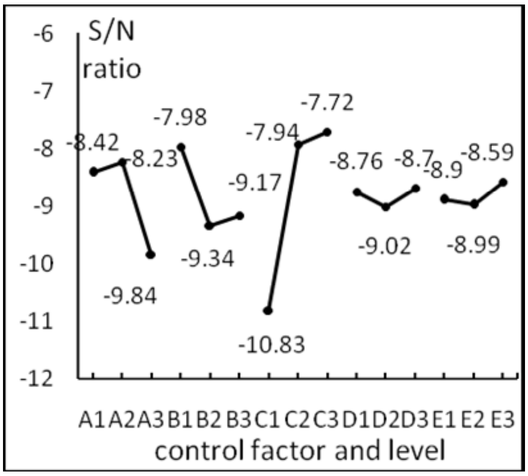

Figure 6 Overview of S/N ratios of control factors

Figure 6 shows the average S/N ratios of each individual control factor. Since bigger S/N ratio means better quality, the best combination can be read from figure 6 as $A_2B_1C_3D_3E_3$. That means the parameter combination listed in table 5 will produce the optimal hole quality with the least roughness.

Table 5 optimal setting predicted by Taguchi method

	Control factor	settings
A_2	Tool speed N	585 (rpm)
B_1	Tool feed S	0.05 (mm/rev)
C_3	MR-Damper location L	1200 (mm)
D_3	MR-Damper current I	1 (amp)
E_3	Air pressure P	12 (kg/cm^2)

Table 6 Results of confirmatory tests for Taguchi method

no exp	Roughness Ra (μm)					
	y_1	y_2	y_3	y_4	average	S/N
19	1.97	2.11	1.97	1.98	2.01	−6.06
20	2.02	1.95	1.90	2.02	1.97	−5.90

The S/N ratios in table 6 are better than that in table 4 which confirms that the optimum setting has indeed produced the best possible quality of manufacturing.

The results in table 6 are the best that traditional experiment design can possibly reach.

2.4 Neural Networks Optimization

Starting from the results brought about by Taguchi method, a backpropagation neural network will be designed to further the quality improvement.

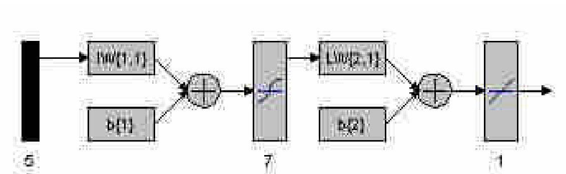

Figure 7 A backpropagation neural network constructed by using Matlab [6]

A 5-7-1 backpropagation neural network is designed and trained by using Matlab [6] (figure 7). Taking over the optimal setting $A_2B_1C_3D_3E_3$ produced by Taguchi method, the neural network optimizes the control factors one by one, starting from the least significant factor gradually proceeds to the most significant factor.

The neural network simulation proceeds from damper current, air pressure, tool feed, tool speed to damper location. Figure 8 shows the results of simulation optimization by the neural network with respect to tool speed from which 585 rpm is optimal.

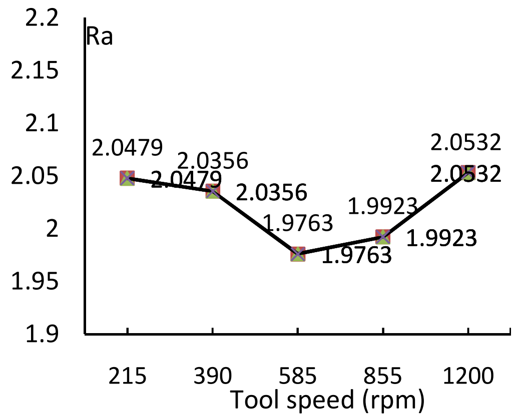

Figure 8 Simulation done by neural network w.r.t. tool speed (Ra in μm)

Starting from the best parameter setting $A_2B_1C_3D_3E_3$ the neural network reaches the following (Table 7) setting which is better than the "optimal" from Taguchi method.

Table 7 Setting optimized by neural network

	Control factor	settings
A	Tool speed N	585 (rpm)
B	Tool feed S	0.05 (mm/rev)
C	MR-Damper location L	1000 (mm)
D	MR-Damper current I	0.8 (amp)
E	Air pressure P	11 (kg/cm^2)

A confirmatory experiment using the setting in table 7 is conducted and the results are listed in table 8.

Table 8 Confirmatory tests for the setting optimized by neural network

no exp	Roughness Ra (μm)					
	y_1	y_2	y_3	y_4	average	S/N
21	1.60	1.66	1.88	2.10	1.81	−5.20

The S/N ratio -5.20 in table 8 by neural network is obviously better than that (-6.06 and -5.90) in table 6 by Taguchi method.

It is thus proven that the neural network further advanced the quality that is supposed to be the optimal given by the already efficient Taguchi method.

3. Conclusion

In the development of a new manufacturing process, the BTA deep hole drilling, new techniques of magnetorheological fluid damping and minimum-quantity-lubrication are added to the conventional process. New process features and new process parameters require thorough investigation to establish knowledge about the new manufacturing process.

This paper takes advantage of one component of soft computing, neural networks, to further advance the optimal results produced by the proven Taguchi method. An optimal parameter setting is first obtained by experiments using Taguchi orthogonal array, and upon that parameter setting a backpropagation neural network is constructed, trained and eventually experimentally examined.

The final experimental examination confirms that the neural network has further advanced the manufacturing quality found and seen by Taguchi method as the optimal.

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