*Journal of Machine Engineering, Vol. 10, No. 3, 2010*

*titanium alloy, nickel alloy, neural network,*
*tool, tool temperature*

Ye Htut SOE [1]
Ikuo TANABE[2]
Tetsuro IYAMA[3]
Yohtaro ABE[2]

# CONTROL OF TOOL TEMPERATURE USING NEURAL NETWORK FOR MACHINING MATERIALS WITH LOW THERMAL CONDUCTIVITY

Recently titanium and nickel alloys have become pre-eminent for aeronautic and astronautic parts. Since these cutting and becomes severely demaged. It is important to control cutting tool temperature. In this paper, the control system of tool tip temperature using inverse analysis of neural network for machining these materials was developed and evaluated. The neural network between cutting conditions and tool temperature was firstly created by a set of teaching data. Then, a mathematical model using algebra was developed. Cutting speed was selected as parameter to be controlled in reducing tool temperature. The relationship between the optimum cutting speed and cutting time was calculated with the inverse analysis of neural network by pre-reading of NC program before cutting. The tool temperature can be maintained at the desired value. The developed system is evaluated by the expaeriments using the turning process and workpiece of Ti6Al4V. From the results, it is concluded that; (1) Tool tip temperature can be controlled by using the proposed inverse analysis of the neural network, (2) CThe cutting tool life can be maintained by this method, for cutting materials with low thermal conductivity.

## 1. INTRODUCTION

Recently, Titanium alloys and Nickel alloys have become pre-eminent for making aeronautic and astronautic parts. The cutting technologies for these materials are also being urgently revealed [4],[10]. Thermal conductivities of these materials are very low and thus, tool temperature becomes very high and the tool strength is reduced. Many investigations to solve this problem have been done by using cutting methods with smaller depth of cut, high speed cutting processing [1] and water evaporation method by supplying water inside the cutting tool for dry grinding process [5]. However, these methods could not successfully achieve efficient cutting of those low thermal conductivity materials. Therefore, in this research, a tool tip temperature control system using a neural network for cutting low thermal conductivity materials is developed and evaluated.

[1] Nagaoka University of Technology, Dept. of Information Science and Control Engineering
[2] Nagaoka University of Technology, Dept. of Mechanical Engineering
[3] Nagaoka University of Technology, Educational affairs section, Mechanics and Machinery Group

The cutting condition is pre-read from the NC program and tool tip temperature is predicted by inverse analysis method using developed neural network. Then, the calculation for optimum cutting speed at which tool tip temperature can be maintained below maximum allowable limit (tool failure temperature) is carried out. After that, NC program is corrected using this new optimum cutting speed for improvement of productivity through improving of tool life.

## 2. THE ALGORITHM OF THE METHOD

The algorithm of the proposed method is shown in Fig. 1. The steps are, (1) Firstly, tool tip temperature values for cutting low thermal conductivity material Ti6Al4V with various cutting conditions are calculated by FEM (Finite Element Method). And then, the neural network is created by using these values as teaching data. (2) Using this neural network, the algebraic relation between tool tip temperature and cutting speed is derived (Inverse Analysis Model). (3) By comparing calculated tool tip temperatures and experimental results, the inverse analysis model will be updated by adjusting a correction coefficient, known as the "Custom-made coefficient". (4) The optimum cutting speed for maintaining maximum allowable tool tip temperature is calculated using the newly developed inverse analysis model.

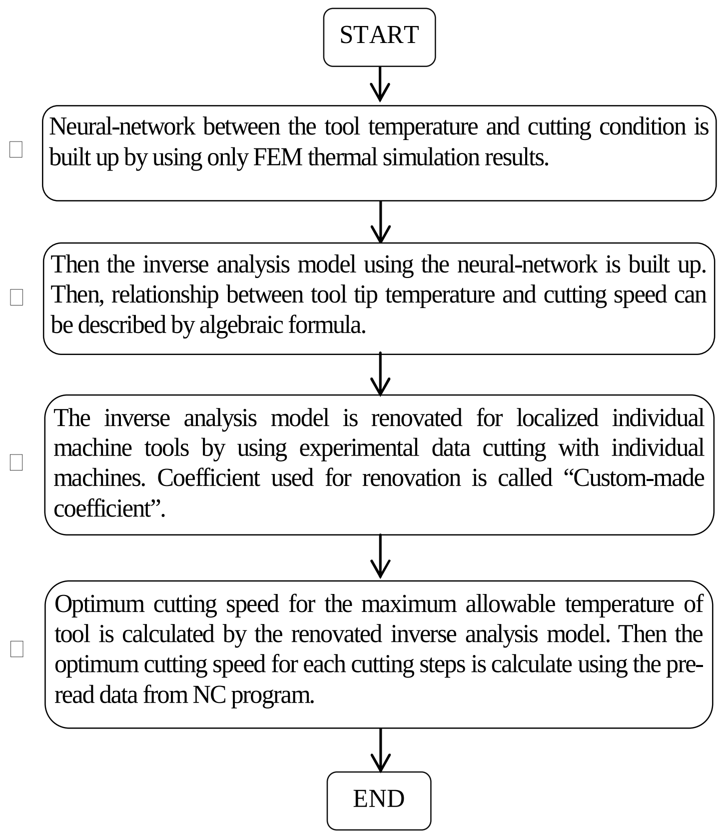



Fig. 1. Flowchart of algorithm regarding the proposed method

# 3. THE STRUCTURE OF INVERSE ANALYSIS MODEL OF NEURAL NETWORK AND THE CALCULATION OF OPTIMUM CUTTING SPEED

## 3.1. THE ILLUSTRATION OF THE OBJECT CUTTING PROCESS

Fig. 2 shows the illustration of work-piece and tool-tip temperature curve along cutting tool path. The work piece is a cylindrical shape with groove at the end of tool path so that to obtain exact cutting length on the cylindrical face. The cutting steps are defined at end face and cylindrical face with rough, medium and finish cutting as shown in tool path of Fig. 2. The cutting processes will be done continuously by changing work-pieces until the tool temperature reaches steady state.

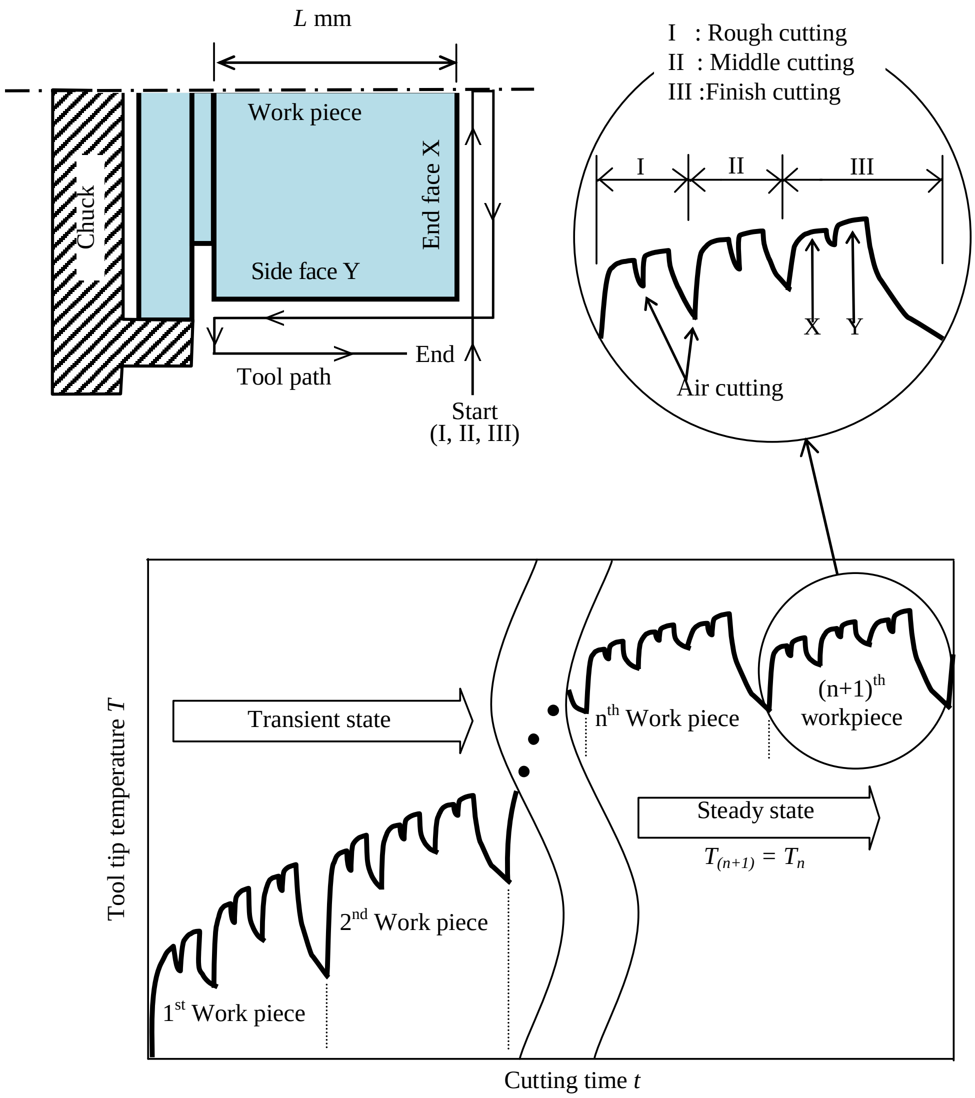



Fig. 2. Schematic view of the relationship between the cutting time and the temperature of the tool

### 3.2. THE STRUCTURE OF NEURAL NETWORK MODEL

The cutting heat conducts into cutting tool from the rake face and the flank face. The amount of heat entering into the tool will be large for those materials with higher cutting resistance, low thermal conductivity, higher frictional coefficient between chip and tool. The heat transfer rate at the place near tool tip will be larger due to large air blowing caused by workpiece and chuck. But, it will be smaller due to less air blowing with barrier of tool post, around tool holder. Heat transfer coefficient is also largely different for the cases of dry cutting and wet cutting. However, this effect is very small for high speed cutting due to extremely fast changing of tool temperature.

Fig. 3 shows the structure of neural network layers. This model is using typical three layers structure [6], input layer, hidden layer and output layer. Sigmoid function in middle layer and linear function in output layer are used respectively. The input factors are (1) tool tip temperature $T_{\mathrm{m-1}}$ at time step $t_{\mathrm{m-1}}$ for time interval $\Delta t$ before the interesting time step $t_{\mathrm{m}}$, (2) cutting condition (cutting depth $d$, feed speed $f$, cutting speed $V$ and cutting time $t_c$ for each step of cutting, (3) time interval $\Delta t$, (4) average heat transfer coefficient $\alpha_{\mathrm{AVE}}$, (5) the theoretical cutting heat energy $Q$ calculated from the thermal properties of workpiece and tool, using cutting theory [7]. The output layer factors are the tool tip temperature gradient $\Delta T_{\mathrm{m}}$ between time step $t_{\mathrm{m-1}}$ and $t_{\mathrm{m}}$. The tool tip temperature $T_{\mathrm{m}}$ at time step $t_{\mathrm{m}}$ can be calculated by using equation (1) with this output result $\Delta T_{\mathrm{m}}$.

$$T_{\mathrm{m}} = \Delta T_{\mathrm{m}} \cdot \Delta t + T_{\mathrm{m-1}} \tag{1}$$

$$\mathrm{m} = 1, 2, 3, \cdot\ \cdot\ \cdot 10$$

| Input data | | |
|---|---|---|
| 1. | Temp. on top of tool at $t_{\mathrm{m-1}}$ | $T_{\mathrm{m-1}}$ |
| 2. | Cutting depth | $d$ |
| | Feed speed | $f$ |
| | Cutting speed | $V$ |
| | Cutting time for each step | $t_{\mathrm{c}}$ |
| 3. | Time interval: $\Delta t = t_{\mathrm{c}} \div 10$ | $\Delta t$ |
| 4. | Average heat transfer coefficient | $\alpha_{\mathrm{AVE}}$ |
| 5. | Heat source | $Q$ |

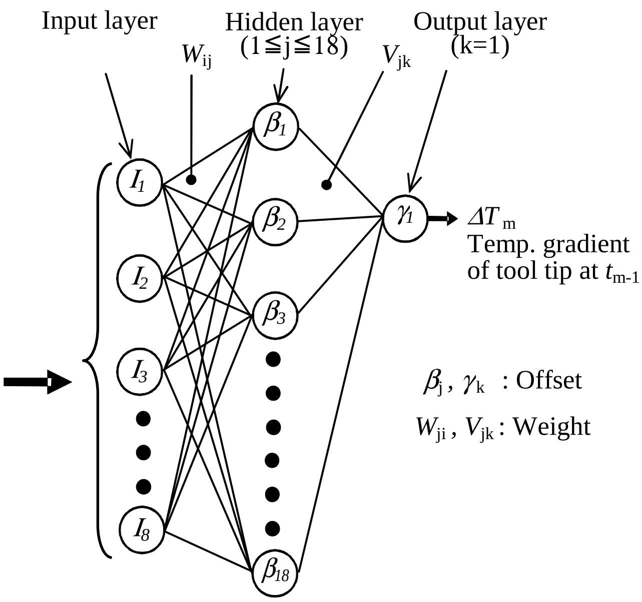



Fig. 3. Neural network model between the cutting condition and the temperature information of tool

In the calculation, the time interval $\Delta t$ is taken 1/10 the time of each cutting step $t_c$. Taking the larger number of time steps could obtain more accurate convergence for neural network. However, this will take long time for calculation and thus, only 10 steps of intervals are used in this method. In the neural network training, it is observed that computing out the temperature gradient $\Delta T_m$ in output layer and substituting it in equation (1), could obtain more accurate convergence with smaller value of error compare with direct calculation of tool tip temperature $T_m$ in output layer.

The neural network training is done in order to satisfy that the sum of the squares of the differences between teaching data and output data to be smallest by using steepest descent method. The weight values $W_{ji}$, $V_{jk}$ and offset values $\beta_j$, $\gamma_k$ are acquired using successive correction method inside the program. Here, $W_{ji}$ is weight between input layer and hidden layer, $V_{jk}$ is weight between hidden layer and output layer, $\beta_j$ is offset for hidden layer and $\gamma_k$ is offset for output layer. Back propagation method is used here. The error function $E_p$ for learning pattern p is shown in equation (2).

$$E_p = \frac{1}{2}\sum_k (Tr_{kp} - D_{kp})^2 \tag{2}$$

Here, $Tr_{kp}$ is the teaching data for unit k which is relating to the learning pattern p, and $D_{kp}$ is output data for unit k which is relating the learning pattern p.

### 3.3. CONSTRUCTION OF TEACHING DATA USING FEM AND TRAINING PROCESS

The teaching data for construction of neural network is simply acquired by calculation using FEM thermal analysis. The FEM model used in analysis is shown in Fig. 4, and Ti6Al4V is selected as workpiece. The heat entering area on the tool is determined using the cutting conditions in Table 1. The amount of heat entering is calculated from the cutting condition and thermal properties of workpiece and tool using cutting theory [7]. The variations of heat transfer coefficient for air and oil at the related places are shown in Fig. 5. In FEM analysis, heat transfer coefficient used for dry cutting is calculated by using the measured values of airflow velocity at the place $P_1$, $P_2$ and $P_3$ around the tool as shown in Fig. 5, and the dynamic viscosity of air at 20°C. For wet cutting, it is calculated using flow velocity of cutting oil on the tool surface $P_4$, for flow rate 1～16ℓ/min of cutting oil and the dynamic viscosity of cutting oil.

The input data to the neural network are spindle speed, diameter of workpiece, distance of tool from chuck, and the output data are heat transfer coefficient at surfaces $P_1$, $P_2$ and $P_3$. Cutting time periods are taken for cutting of (I) rough cutting, (II) medium cutting and (III) finish cutting for end face and cylindrical face as shown in Fig. 2. The calculation is taken till the tool tip temperature reaches the steady state condition. In the simulation, cutting speed $V$, feed speed $f$, cutting depth $d$ and magnification factor $C$ for heat transfer rate are taken as parameters. Then, the basic data set are defined for the conditions where tool tip temperature would become high, middle and low values. By altering only one parameter (Each change element in Table 1,) from the cutting condition *V*, *f*, *d*, *m*, it can be covered for representing the whole range of basic data set. There becomes altogether 54 set of analysis data, included for dry and wet cutting processes. The neural network training is done using these data and tool tip temperature gradient $\Delta T_m$ at each time interval $\Delta t$ for each cutting steps and air cutting intervals along tool path as teaching data.

After training the neural network with 54 set of data, the error value $E_p$ become small enough $6.5\times10^{-32}$ at $55^{th}$ time. Therefore, this developed neural network is possible to use as temperature controlling tool.

Table 1. Data set of FEM analysis for teaching data

| Heat source(Cutting conditions for calculation of cutting heat) and Data sets | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Tool tip temp. | | High | | | | Middle | | | | Low |
| | | Basic condition | Each change element | | Each change element | Basic condition | Each change element | Each change element | | Basic condition |
| Cutting speed *V* mm/min | | 100 | [65] | [30] | [100] | 65 | [30] | [100] | [65] | 30 |
| Feed speed *f* mm/rev | Ⅰ Rough | 0.5 | 0.35 | 0.2 | 0.5 | 0.35 | 0.2 | 0.5 | 0.35 | 0.2 |
| | Ⅱ Middle | 0.4 | 0.3 | 0.2 | 0.4 | 0.3 | 0.2 | 0.4 | 0.3 | 0.2 |
| | Ⅲ Finish | 0.3 | 0.25 | 0.2 | 0.3 | 0.25 | 0.2 | 0.3 | 0.25 | 0.2 |
| Cutting depth *d* mm | Ⅰ Rough | 2.0 | 1.5 | 1.0 | 2.0 | 1.5 | 1.0 | 2.0 | 1.5 | 1.0 |
| | Ⅱ Middle | 1.0 | 0.75 | 0.5 | 1.0 | 0.75 | 0.5 | 1.0 | 0.75 | 0.5 |
| | Ⅲ Finish | 0.5 | 0.3 | 0.1 | 0.5 | 0.3 | 0.1 | 0.5 | 0.3 | 0.1 |
| Magnification *C* $a' = a\times C$ | | 1 | [0] | [4] | [0] | 1 | [4] | [0] | [4] | 1 |
| Total condition sets | | 54 = { Basic condition 1+Each change element [ ] 8 } × { High, Middle, Low ; 3}×{ Dry, Wet ; 2 } | | | | | | | | |
| | | | | | | | P1 | P2 | P3 | P4 |
| | | | | | | Dry | Fig. 4. (a) | Fig. 4. (b) | Fig. 4. (c) | — |
| | | | | | | Wet (10ℓ/min) | — | Fig. 4. (b) | Fig. 4. (c) | Fig. 4. (d) |

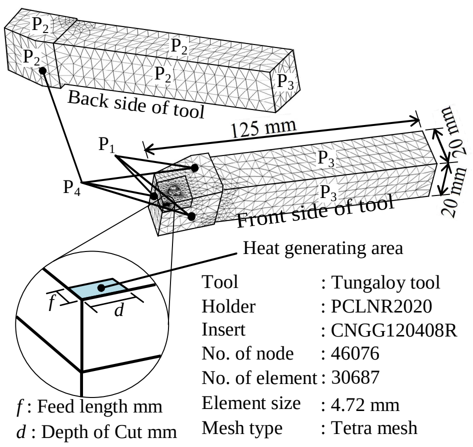
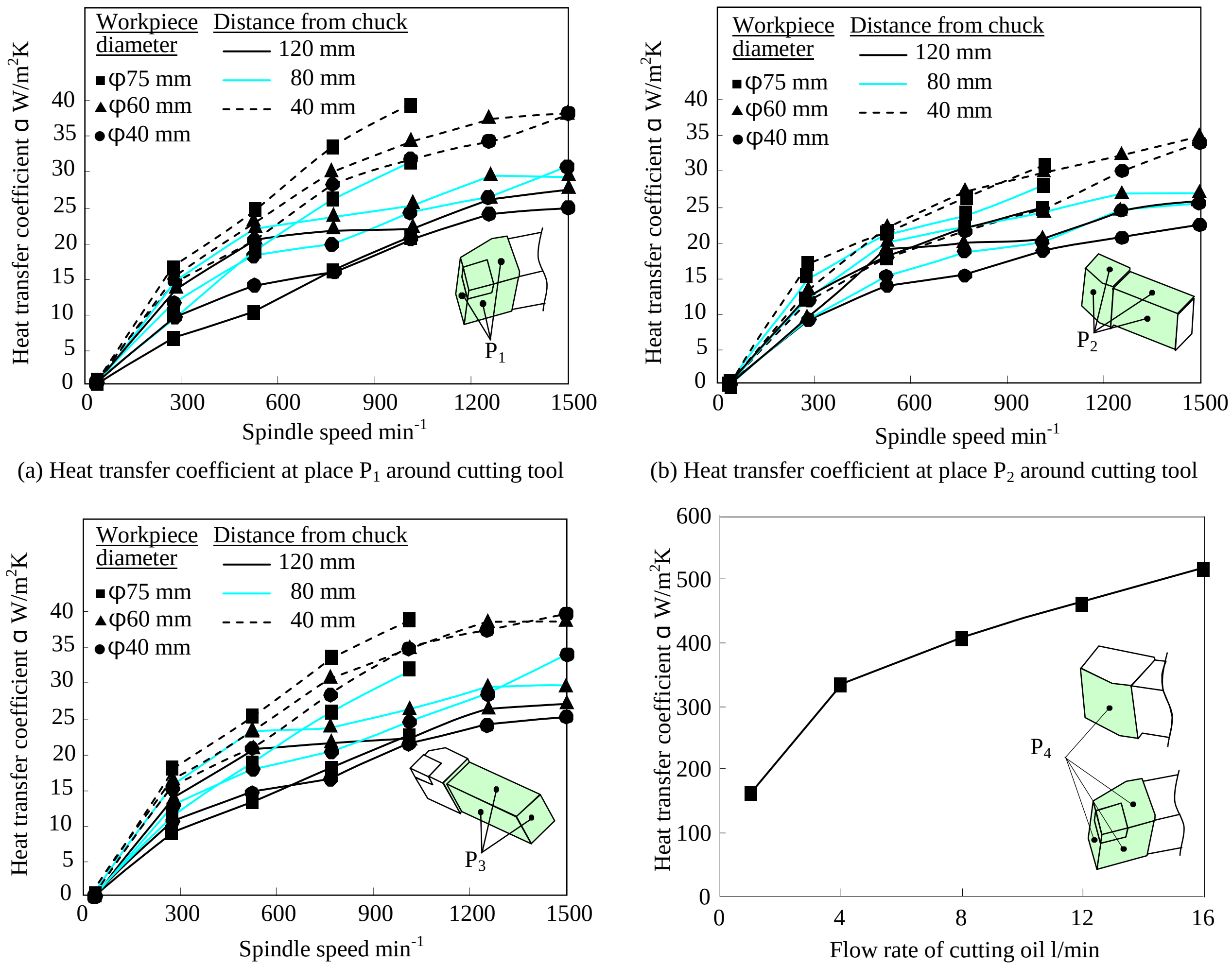



Fig. 4. FEM model for calculation of learning pattern




(a) Heat transfer coefficient at place $P_1$ around cutting tool

(b) Heat transfer coefficient at place $P_2$ around cutting tool

(c) Heat transfer coefficient at place $P_3$ around cutting tool

(d) Relation between heat transfer coeffient and flow rate of cutting oil

Fig. 5. Experimental results for the air flow velocity and the heat transfer coefficeient

3.4. CALCULATION OF CUTTING SPEED USING NEURAL NETWORK

The weight and offset values $W_{ji}$, $V_{jk}$, $\beta_j$, and $\gamma_k$ between each unit are calculated using the neural network developed in previous section. The representative equation (3) is obtained by using these values.

$$\Delta T_m = g\,(W_{ji},\ V_{jk},\ \beta_j,\ \gamma_k,\ T_{m-1},\ V,\ f,\ d,\ t_c,\ \Delta t,\ \lambda \cdot \alpha_{AVE},\ Q)$$

$$= \sum_{j=1}^{18} \frac{V_{jk}}{1+\exp\{-(\sum_{i=1}^{8} W_{ji} \cdot I_i + \beta_j)\}} + \gamma_k \qquad (3)$$

$$I_i = [I_1,\ I_2,\ I_3,\ I_4,\ I_5,\ I_6,\ I_7,\ I_8] = [T_{m-1},\ V,\ f,\ d,\ t_c,\ \Delta t,\ \lambda \cdot \alpha_{AVE},\ Q]$$

Here, $\Delta T_m$ is the temperature gradient of tool tip at output layer for the time $t_{m-1}$. This model will be used in inverse analysis. $\alpha_{AVE}$ is the average value of theoretically calculated heat transfer rate at each pair of $P_1$ (or) $P_4$ and $P_2$, $P_3$ in section 3.3. This $\alpha_{AVE}$ value has been adjusted by multiplying with custom-made coefficient $\lambda$ (will be explained in section. 3.5) for the application on localized individual machines. This is the newly added value to neural network for renovation of calculated tool tip temperature.

The algorithm for calculating optimum cutting speed is shown in Fig. 6. The variation of tool tip temperature in each cutting steps shown in Fig. 2, can be calculated using equation (1) and (3), for time steps $m$ =1, 2, 3, ……. 10 with easy algebraic equation. At that time, the cutting speed at which the tool tip temperature would not exceed the maximum allowable temperature (example 800°C for carbide tool) [8] is iterated using golden section method. And then the new cutting speed obtained from this calculation is used in the actual cutting experiment as optimum cutting condition.

Here, the reason for selecting the cutting speed as main influence parameter to control tool temperature among three factors of, cutting speed, cutting depth and feed speed is, cutting speed governed largest cutting volume [2],[9] and thus the most effective factor for tool temperature. Tool tip temperature at each cutting steps for the work piece is calculated and confirmed whether it is below the maximum allowable temperature and if necessary, the new cutting speed is re-calculated. And then, the final temperature of tool tip at complete cutting of a work piece is calculated. This temperature will be used as the initial temperature for the second workpiece and the related cutting speed for second workpiece will be calculated again. At that time, other cutting parameters are kept constant as in the first

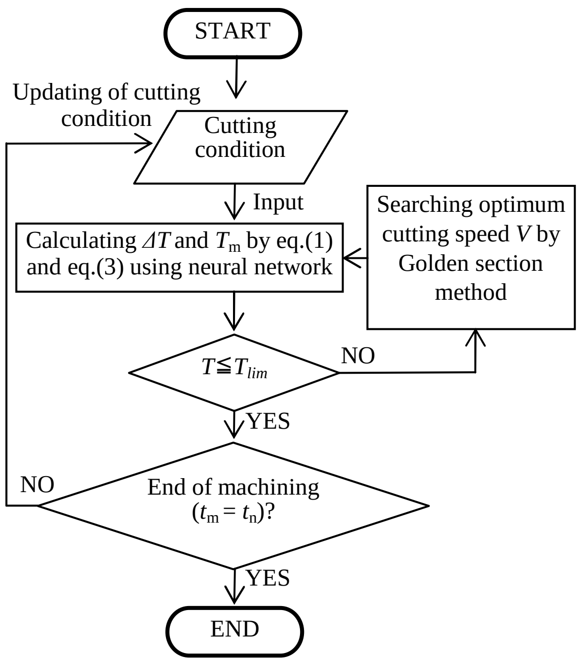



Fig. 6. Algorithm for calculation of optimum cutting speed

workpiece. This process will continue till tool tip temperature reaches steady state condition. Moreover, this operation is applicable before actual cutting by pre-reading NC program and after that, actual cutting process can be done with newly optimized cutting speed in order to maintain the productivity.

### 3.5. MODIFICATION FOR LOCALIZED INDIVIDUAL MACHINES (CUSTOM-MADE COEFFICIENT)

There may have different situations effecting heat transfer coefficient for individual machines in different environments in actual application, even the same cutting condition is used. For the dry cutting, the air flow velocity around the tool largely affects the heat transfer rate. For wet cutting, the oil flow rate has a direct effect. The cutting speed, the distance of tool from the chuck, work-piece diameter, the amount of oil supplying, the structure and location of machine have indirect effects. Therefore, the heat transfer rate is not a constant. For this case, the consideration of localized factor is needed to be put in the proposed method. Therefore, the custom-made coefficient $\lambda$ is applied to theoretical value of average heat transfer coefficient $\alpha_{AVE}$ in equation (3). The custom-made coefficient $\lambda$ represents how many times the actual heat transfer rate for different individual machine differs from that obtained by calculation with FEM analysis in the first time.

In this case, the machine which is subjected to obtain custom-made coefficient $\lambda$ could be operated by following procedure. First, cutting process is taken with cutting condition shown in Table 3., using this machine and the tool temperature will be measured. Then, putting theoretically calculated heat transfer coefficient $\alpha_{AVE}$ in equation (3). Finally the unique unknown value of custom-made coefficient $\lambda$ is obtained. The $\lambda$ value is then inserted in ( $\lambda \cdot \alpha_{AVE}$ ) in the calculations of tool tip temperature. Here, the tool tip temperature is interpolated using FEM simulation method [10], by fitting the measured temperature at two points on cutting tool with thermo-couples.

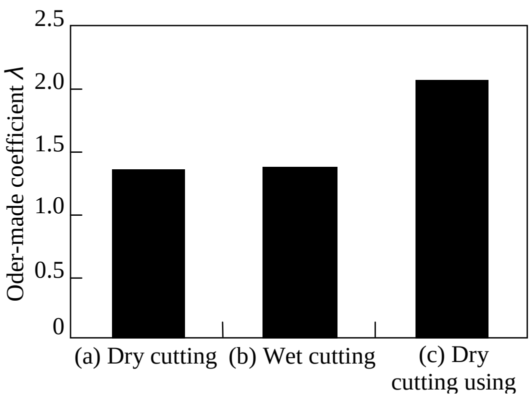



Fig. 7. Relationship between the order-made coefficient $\lambda$ and the machine tool with localized and specific environment

In this study, three cutting experiments to obtain custom-made coefficient $\lambda$ are taken for dry cutting, wet cutting and dry cutting with fan (for creating a different localized machine) are done using the cutting condition in Table 3, and the custom-made coefficient $\lambda$ is calculated based on the tool tip temperature at that time. The results for each cutting process are shown in Fig. 7. The custom-made coefficient $\lambda$ is as shown in (a) dry cutting, (b) wet cutting and (c) dry cutting with fan. The custom-made coefficient $\lambda$ for (a) dry cutting and (b) wet cutting are almost near to 1, for which the process conditions are almost the same as the teaching data when neural network is constructed. The localized value $\lambda$ for (c) dry cutting with fan is different to that of (a) dry cutting. Therefore, it is confirmed that, the proposed method is applicable for different machines in different places, with easy adaption.

## 4. THE EVALUATION FOR CUTTING OF Ti6Al4V

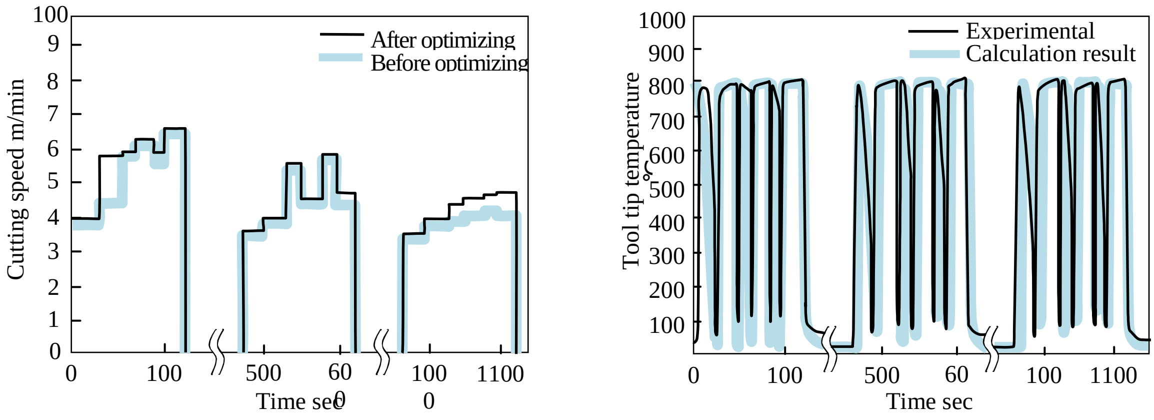
The evaluation for the proposed method was carried out by cutting Ti6Al4V (material with low thermal conductivity) using a lathe with specification mentioned in Table 2. The custom-made coefficient $\lambda$ are, $\lambda = 1.35$ for dry cutting, $\lambda = 1.38$ for wet cutting and $\lambda = 2.08$ for dry cutting with fan respectively. By putting these $\lambda$ values in equation (3), taking maximum allowable tool tip temperature at $800^0$C and using the cutting condition in Table 3, the optimum cutting speed was calculated for each cutting step using proposed method.

Table 2. Specification of the lathe used

| Items of specification | | | Takisawa TAC-460 |
|---|---|---|---|
| Head stock | Power of main motor | kW | 12 |
| | Max. spindle speed | $min^{-1}$ | 1500 |
| | Chuck size | mm | 210 |
| | Chuck type (no. jaws) | | 3 |
| Max. speed (Z direction) | | mm/min | 5000 |
| Max. speed (X direction) | | mm/min | 2500 |
| Coolent type | | | MegaPlus LA20 |
| Coolent flow rate | | ℓ/min | 16 |
| Size of bed | | | 370×340×197 |

Table 3. Cutting conditions used

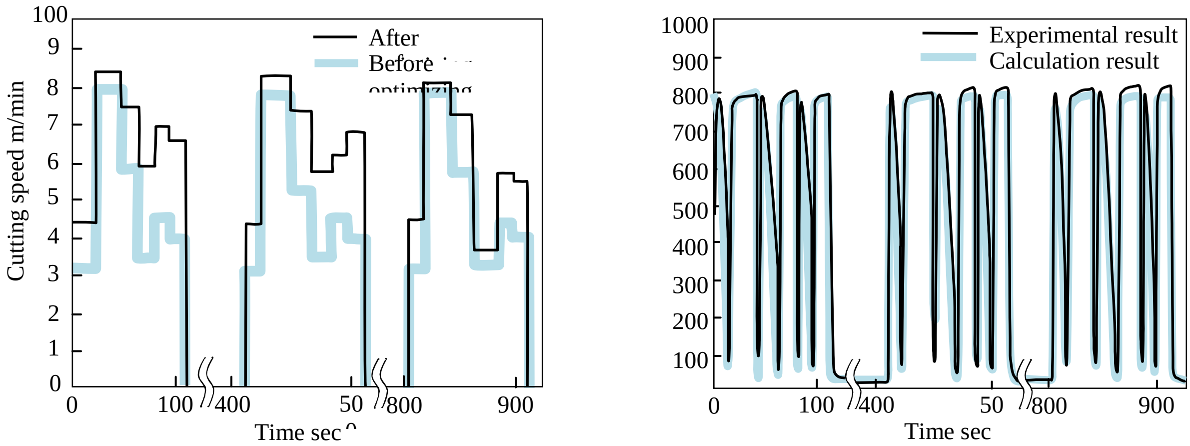
| Cutting condition | | (a) Dry | | | (b) Wet | | | (c) Dry using fan | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | *V* m/min | *f* mm/re | *d* mm | *V* m/min | *f* mm/re | *d* mm | *V* m/min | *f* mm/re | *d* mm |
| End face | Rough | 35.7 | 0.3 | 1.0 | 35.3 | 0.5 | 1.0 | 36.9 | 0.3 | 1.0 |
| | Middle | 36.1 | 0.3 | 1.0 | 61.4 | 0.2 | 0.5 | 58.8 | 0.3 | 0.6 |
| | Finish | 89.5 | 0.35 | 0.2 | 47.3 | 0.35 | 0.5 | 59.5 | 0.35 | 0.5 |
| Side face | Rough | 58.0 | 0.2 | 1.0 | 82.8 | 0.2 | 1.0 | 42.5 | 0.25 | 1.0 |
| | Middle | 45.7 | 0.2 | 0.5 | 63.1 | 0.3 | 0.5 | 60.7 | 0.25 | 0.6 |
| | Finish | 43.8 | 0.2 | 0.4 | 44.5 | 0.35 | 0.3 | 63.4 | 0.25 | 0.5 |
| Cooling method | | Dry | | | Oil (2ℓ/min) | | | Fan air | | |
| Cutting tool | | Carbide TH10 | | | | | | | | |




(a) The optimized cutting speed

(b) Temperature on the tip of the tool

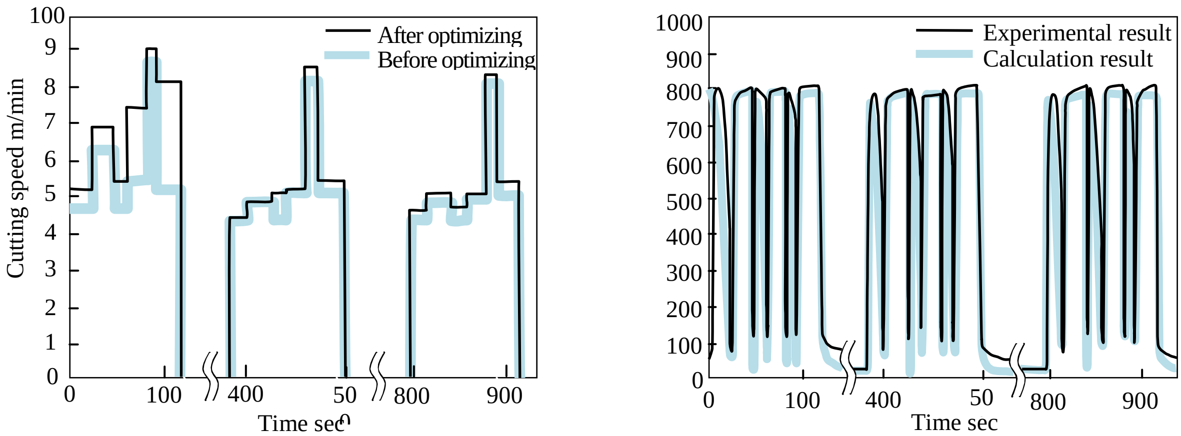
Fig. 8. Optimized cutting speed and temperature on the tip of tool during dry cutting




(a) The optimized cutting speed

(b) Temperature on the tip of the tool

Fig. 9. Optimized cutting speed and temperature on the tip of tool during wet cutting




(a) The optimized cutting speed

(b) Temperature on the tip of the tool

Fig. 10. Optimized cutting speed and temperature on the tip of tool during dry cutting using a fan

The cutting speed before and after optimizing, tool tip temperature for calculated and experimental measurements values for drying cutting, wet cutting and dry cutting with fan are shown in Fig. 8., 9., 10., respectively. The maximum tool tip temperature for dry cutting with fan in Fig. 10, exhibits 1.1% of error comparing with maximum allowable temperature $800^0$C, even though custom-made coefficient $\lambda$ is comparably larger than other two cases. The largest error value is 1.4% among these three cases. Therefore, the proposed method is applicable for any different types of machines at different places by applying custom-made coefficient $\lambda$ for adaption to that environment.

In conventional cutting, it takes long time to determine the optimum cutting conditions with many trial and error estimations. By using proposed method, the optimum cutting condition can be obtained in a short time before cutting.

## 5. CONCLUSION

From this research, it can be concluded that; (1) Tool tip temperature can be controlled by using the developed inverse analysis of neural network. (2) The cutting tool life can be maintained by this method, for cutting materials with low thermal conductivity.

## REFERENCES


[1] HIROSAKI K, SHINTANI K, KATO H., KANEUJI A., 2006, *High Speed Milling of Bio-Titanium Alloys using a Binder-less PcBN Tool*, Journal of the Japan Society for Precision Engineer, 72/11, 1397-1401.

[2] MAHFUDZ AL HUDA, KEIJI YAMADA, TAKASHI UEDA., 1999, *Measurement of tool-chip interface temperature in turning using two-color pyrometer*, Transactions of the Japan Society of Mechanical Engineer, Series C, 65/633, 360-367.

[3] MEKARU SHUNEI, FUKUMOTO ISAO, MAKISHI TAKASHI, HIRAI TOSHIO., 1993, *Tool life processes in orthogonal cutting of difficult to machine materials by coating tools*, Proceeding of the Rhukyu University, 45, 13-20.

[4] NARUTAKI N., YAMANE Y., 1993, *High speed machining of Inconel 718 with ceramic tools*, Annals CIRP, 42/1, 103-106.

[5] TANABE I., BINH H. T., IYAMA T., EIKE KRATZ., 2008, *Development of New Electro Deposited Diamond Tool and Its Compulsory Cooling System for high Speed Grinding of Titanium and Nickel Alloys*, Transactions of the Japan Society of Mechanical Engineer, Series C, 74/747, 2797-2802.

[6] TANABE I., IKEDA S., URANO K., 2003, *Esimation of Optimum Temperature for Cooling Oil on a Spindle Using Inverse Analysis of Neural Network (Effect of Relearning)*, Transactions of the Japan Society of Mechanical Engineer, Series C, 69/679, 819-824.

[7] TAKEYAMA H., 1980, *cutting processing* (in Japanese), Maruzen Co., Ltd., 24-47.

[8] TAKAHIRO S., TOHRU I., KENICHI K., EIJI U., 1987, *Effect of temperature on fracture characteristic of carbide material and on its deterioration process by impact repetition*, Journal of the Japan Society for Precision Engineer, 53/10, 1589-1595.

[9] TAKEYAMA H., *cutting processing* (in Japanese), Maruzen Co., Ltd. 198, 64.

[10] USUKI H.,SATO K., FERUYA S., 2005, *High Speed Dry End Milling of Titanium Alloy with Coated Carbide Tool*, Journal of the Japan Society for Precision Engineer, 71/4, 491-495.