

Design and Development of an IoT Kit To Predict Cutting Tool Life and Generate Auto Inventory

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Abstract

For the best tool life, machining precision, and maintenance, a cutting tool life prediction is crucial. As a result, an online smart diagnosis service must be created to establish an auto inventory and anticipate the cutting tool life based on temperature data. Due to the fast-cutting velocity and high work material strength, diffusion wear becomes predominant when the cutting temperature rises significantly. Based on sensorial data gathered at the factory level, knowledge-based algorithms conduct online-based inspections on utilized tool life including tool breakage occurrence. Because heat load influences tool wear rate, a thermistor is fitted to the cutting tool to alert the database server when the temperature rises. based on the data.

Keywords: Machining, IoT, Cutting tool life, Temperature

1.0 Introduction

The method of cutting a piece of raw material into various shapes and sizes to create the end product is referred to as machining. Machining is one of the strategies to reduce expenditure cost, in addition to increasing efficiency. This is owing to its potential to lower the cost of consumption, hence minimizing waste. In other words, it lowers costs, which adds to the advantages of machining. The period during which the tool cuts successfully and efficiently is a critical aspect of machinability evaluation. On the surface, higher production and rapid cost savings appear to be the solution. Reducing the number of tool changes reduction production disturbance, resulting in greater process stabilization, less downtime, and more consistent component delivery. Different cutting parameters and heating temperatures are used during the machining. As cutting speed and temperature are raised, tool life rose by 85 per cent compared to room temperature. The tool life gets reduced as the feed rate increases in conjunction with the heating temperature, and build-up-edge

development is observed at low cutting speeds. The Internet of Things (IoT) enables real-time machine monitoring and precise report generation for enhanced decision-making. The IoT's future possibilities are seemingly endless. One of the advantages of the Internet of Things in the manufacturing business is that it shifts the maintenance paradigm from reactive to proactive. This ensures that machines run at their best and that problems are avoided. By using cloud analysis as a guide, the web host initiates the necessary corrective step. By delivering the states the essential commands to a machine tool control, the local server begins the needed appropriate action. The period between the catastrophic tool failure (CTF) and the actual feed stop should have been as low as 60 milliseconds, but it was 2 seconds [1]. The paper shows that maximum tool-life or minimum temperature for any given metal removal rate of a cutting tool or grinding wheel is governed by the principle of minimum thermal energy resulting in one single relationship between metal removal rate per unit cutting edge length and tool-life [2]. Tool life prediction based on tool-work thermocouple temperature demonstrates the validity of the proposed temperature

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approach for predicting tool life. However, only dry machining was used in the manufacturing process [3]. Make the problems with cloud manufacturing increasingly visible. Several features have been covered, along with the relationships with cloud computing and other kinds of manufacturing, cloud platforms manufacturing, CPS, advanced factory, Industry 4.0, as well as the Industrial IoT. Furthermore, there aren't any examples or recommendations for standardized CMfg implementation [4]. Using a sensor fusion methodology to measure sound pressure and cutting force, the sound signal and consequent force for new, working, and dull tools were forecasted using an AI expert system's assessment procedure [5]. Uses of the Internet of things (IoT in CMfg have been studied for the role of intelligent perception, connectivity, and exposure to resources and raw materials, and capabilities. However, the use of specialized wide applicability, apparatus, and online and in real surveillance is required with a high temperature [6]. A system for keeping track of CNC machine availability and helps with overall manufacturing optimization. After analyzing the sensor data, the machine status including tool availability was identified and then sent to the virtual environment. To improve the distribution of machining tasks over numerous machines, a job allocation system might be developed [7]. In this study, the tool-life equation is derived using temperature data and the association between drill temperature and cutting speed and feed during cast iron drilling is presented. The resulting equation and the results of the standard test are in good agreement [8]. The TMS (tool monitoring system) is a device for automatically monitoring cutting tools in a flexible manufacturing cell (FMC). The results of machining feature recognition using a CSG (constructive solid geometry) model are used to choose tools in the TMS. However, TMS may not be the best option for all scheduling scenarios [9]. By concentrating upon that "manufacturing version" of virtualization, cloud manufacturing will offer practical answers to the manufacturing sector, which is increasingly international and dispersed [10].

2.0 Methodology

Temperature and Tool-Wear: There are two types of tool-wear mechanisms, Mechanical, (a) Tool material abrasion due to mechanical action (b) Microcracks between the tool and the chip caused by cold pressure welds. Physicochemical, (a) Tool-to-chip diffusion (b) Deformation of the plastic begins after tool softening. Cutting parameters, specifically cutting temperature, have such a massive impact on how different phenomena affect tool wear. Tool wear develops gradually as just a result of high temperatures at the tip. Plastic deformation follows by softening of the tool. Cutting parameters,

specifically cutting temperature, have such a massive impact on how diverse phenomena influence tool wear. Tool wear is gradual and caused by the high temperatures at the tip. Because heat load impacts tool wear rate, as shown in Fig.1 flow chart explains a thermocouple is mounted to the cutting tool, which sends a signal to the database server when the temperature rises. Data is stored in the cloud in the form of graphs that can be viewed on a phone from data displaying temperature patterns and diagnosis of the derived formula through programming. HSS is cutting tool steels that can machine and cut materials quickly (due to their high hot hardness). Tools made of high-speed steel function better than those made of older high-carbon steel because they can endure intense heat without losing their temper (hardness). It has been demonstrated that standard high-speed steel delivers an extremely prolonged life of the tool and excellent tool performance at speeds of 30 m/min. Wi-Fi protocol-based object and data interaction are facilitated by the open-source Node MCU platform, which is ESP8266-based. The ESP8266 enables communication with the Internet and Wi-Fi networks. A thermistor is a temperature-dependent resistance thermometer or a resistor. Thermally sensitive resistors are very accurate and cost-effective temperature sensors. The temperature controller sends a little amount of current (bias current) through the sensor. Due to the controller's inability to read resistance, it must be translated into voltage changes by running a biased voltage through the thermistor to supply a control voltage. The nearer the thermistor is to the equipment being monitored, whether it is embedded or surface-mounted, the better will be the outcome. 100K Ohm 1W uin-plated copper leads high-quality carbon film resistor (CFR) with 5% tolerance. A device that stops electricity from flowing through it.

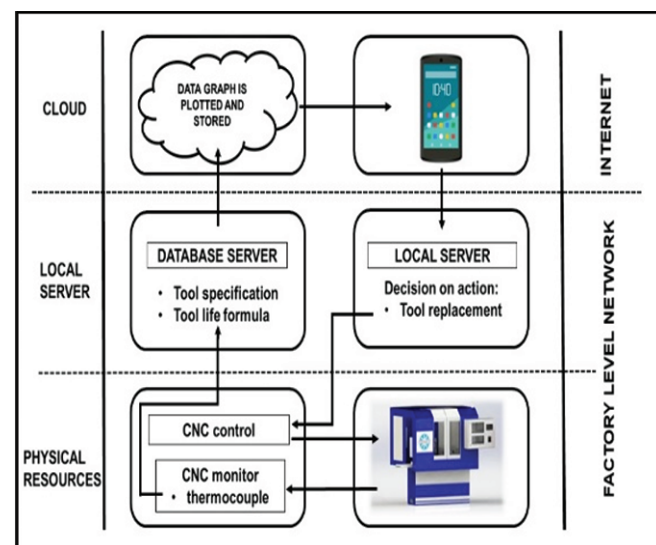


Figure 1: Work flow of an IoT kit to predict cutting tool life

2.1 Experimental Set up

An experiment was carried out in a lathe machine as shown in Fig.2 to determine the temperature gradients at the cutting tool tip with various machining parameters. With an HSS cutting tool and a cylindrical workpiece made of mild steel. Speed, feed, and cutting depth are considered the cutting parameters. The primary information is that the tool's temperature is set to room temperature. The work piece's diameter is 20mm, the cutting tool's width is 12.8mm, then 30mm feed length.



Figure 2: Experimental setup for turning operation

2.2 Implementation of IoT

The embedded IoT circuit is implemented in the cutting tool. It contains a thermistor that senses the temperature of the cutting tool during the turning operation and sends the data to the microcontroller node MCU in the form of binary. The node MCU transfers the recorded data through Gmail.

3.0 Results and Discussion

When the embedded IoT is implemented in the cutting tool during the turning operation, the IoT-containing thermistor senses the temperature of the cutting tool during the operation. The thermistor receives the data and transfers it to the node MCU microcontroller in binary form. The node MCU converts the binary form into the digital form and sends the data to the user through the mail. The node MCU uses the cloud system to transfer the data through the mail. The software used to programme is Arduino IDE the commands are given in C language and the mail to which the information is to be received is mentioned in the programme. The values are assigned based on the data collected during the machining experimentation and 4 groups were made i.e., 30-40, 40-50, 50-60, 60-70. Accordingly, the notifications are sent. Stepped graph and a line graph are plotted for temperature vs time as shown in Figs.4 and 5. Time is taken on the x-axis and temperature is on the y-axis. This graph enables real-time online temperature monitoring during the operation as the time increases, the cutting tool turning the

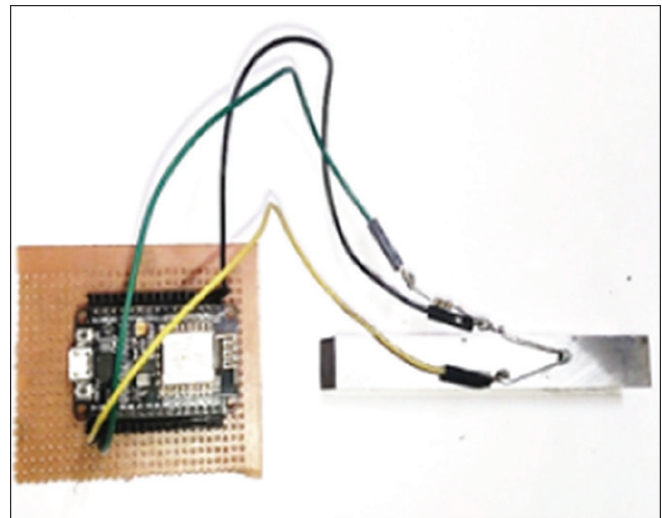


Figure 3: Embedded IoT

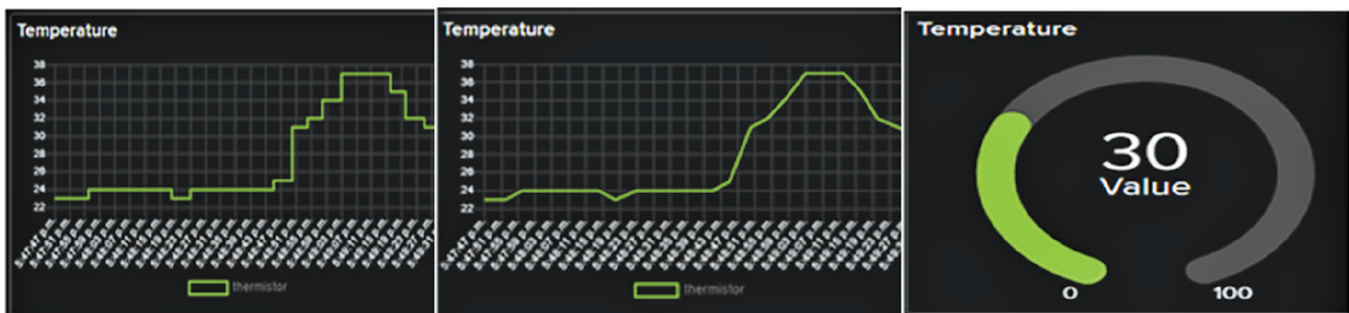


Figure 4: Stepped graph and Line graph of Temp vs time and temperature display at one particular point of time

Table 1: Tabular column of machining data and their corresponding temperature gradients

| Speed (rpm) | Depth of Cut (mm) | Feed (mm/rev) | Temperature in (degrees celsius) | Length of the Tool (mm) | Time duration (minutes) | |
|-------------|-------------------|---------------|----------------------------------|-------------------------|-------------------------|----|
| 250rpm | 0.25 | 0.05 | 32 | 12.8 | 15 | |
| | | 0.11 | 34 | 12.8 | 15 | |
| | | 0.22 | 45 | 12.76 | 15 | |
| | | 0.25 | 56 | 12.76 | 15 | |
| | | 0.35 | 58 | 12.76 | 15 | |
| | | 0.45 | 62 | 12.76 | 15 | |
| | 0.5 | 0.05 | 34 | 12.76 | 15 | |
| | | 0.11 | 35 | 12.76 | 15 | |
| | | 0.22 | 56 | 12.76 | 15 | |
| | | 0.25 | 59 | 12.7 | 15 | |
| | | 0.35 | 63 | 12.7 | 15 | |
| | | 0.45 | 65 | 12.7 | 15 | |
| | | 0.75 | 0.05 | 38 | 12.65 | 15 |
| | | | 0.11 | 43 | 12.65 | 15 |
| | | | 0.22 | 71 | 12.65 | 15 |
| | | | 0.25 | 62 | 12.62 | 15 |
| | | | 0.35 | 72 | 12.62 | 15 |
| | | | 0.45 | 76 | 12.6 | 15 |
| 420rpm | 0.25 | 0.05 | 34 | 12.6 | 15 | |
| | | 0.11 | 33 | 12.6 | 15 | |
| | | 0.22 | 55 | 12.58 | 15 | |
| | | 0.25 | 57 | 12.58 | 15 | |
| | | 0.35 | 63 | 12.58 | 15 | |
| | | 0.45 | 65 | 12.52 | 15 | |
| | 0.5 | 0.05 | 35 | 12.52 | 15 | |
| | | 0.11 | 39 | 12.5 | 15 | |
| | | 0.22 | 39 | 12.45 | 15 | |
| | | 0.25 | 45 | 12.45 | 15 | |
| | | 0.35 | 51 | 12.38 | 15 | |
| | | 0.45 | 55 | 12.36 | 15 | |
| | 0.75 | 0.05 | 42 | 12.36 | 15 | |
| | | 0.11 | 43 | 12.32 | 15 | |
| | | 0.22 | 45 | 12.26 | 15 | |
| | | 0.25 | 52 | 12.24 | 15 | |
| | | 0.35 | 66 | 12.21 | 15 | |
| | | 0.45 | 71 | 12.19 | 15 | |

| Speed (rpm) | Depth of Cut (mm) | Feed (mm/rev) | Temperature in (degrees celsius) | Length of the Tool (mm) | Time duration (minutes) |
|-------------|-------------------|---------------|----------------------------------|-------------------------|-------------------------|
| 720rpm | 0.25 | 0.05 | 31 | 12.11 | 15 |
| | | 0.11 | 33 | 12.11 | 15 |
| | | 0.22 | 36 | 12.09 | 15 |
| | | 0.25 | 40 | 12.05 | 15 |
| | | 0.35 | 42 | 11.92 | 15 |
| | | 0.45 | 47 | 11.88 | 15 |
| | 0.5 | 0.05 | 33 | 11.85 | 15 |
| | | 0.11 | 35 | 11.64 | 15 |
| | | 0.22 | 45 | 11.62 | 15 |
| | | 0.22 | 45 | 11.62 | 15 |
| | | 0.25 | 48 | 11.45 | 15 |
| | | 0.35 | 52 | 11.32 | 15 |
| | 0.75 | 0.45 | 61 | 11.21 | 15 |
| | | 0.05 | 45 | 10.15 | 15 |
| | | 0.11 | 46 | 10.96 | 15 |
| | | 0.22 | 50 | 10.81 | 15 |
| | | 0.25 | 56 | 10.72 | 15 |
| | | 0.35 | 62 | 10.69 | 15 |
| | | 0.45 | 72 | 10.62 | 15 |

material will increase the temperature. In both a stepped and a line graph, it is shown that the temperature of the cutting tool is very low at the initial stage of the operation. Later as the time runs, the temperature of the cutting tool increases gradually and lowers when the operation is done. Here, the process parameters, feed rate with spindle speed are the most effective for the temperature. The temperature of the cutting tool is high for the higher value of feed rate. Depth of cut is less effective to the temperature. The temperature varying for every particular time is displayed in the Adafruit online platform.

Step 1: Cutting tool life equation using temperature
 $\theta = kv^x f^y$... (1)

Where, θ is the temperature of the cutting tool

k is the constant

v is the spindle speed

f is the feed

x and y are coefficients

Step 2: Linear regression method is used to solve the equation (1).

Taking 2 variables,

Y (Dependent variable) = Temperature and

X (Independent variable) = Speed

Iterations (N) = 54

Linear regression equation

$$Y = A + BX$$

$$\begin{bmatrix} n & \sum x \\ \sum n & \sum x^2 \end{bmatrix} \begin{bmatrix} A \\ B \end{bmatrix} = \begin{bmatrix} \sum x \\ \sum xy \end{bmatrix}$$

$$A = 55.6 \quad B = -0.012$$

$$Y = 55.6 + (-0.012) * (250)$$

$$Y = 52.6^\circ\text{C}$$

Step 3: Calculation taking spindle speed, $v = 250$ rpm and feed rate, $f = 0.22$ mm/rev.

$$52.6 = K$$

$$K = 1.626 \times 10^{-66}$$

Step 4: Conclusion by comparing analytical and experimental values

Analytical and experimental temperature values for the speed of 250 rpm and feed of 0.22mm per revolution gives the values around 52°-56°C.

4.0 Conclusions

- Temperature gradients are noticed at various cutting speeds, feeds, and depths. As the tool's speed increased, the tool's wear rate also increased. The information

gathered above will aid in the development of an IoT.

- The IoT kit was created on the results of the experiment. To monitor the current situation using temperature as an input, a complex platform is created.
- Tool life decreased by 85% over room temperature as cutting speed and temperature were increased. Using IoT technology aids in preventing the machine tool from becoming idle.
- The tool's life is indicated in a notification delivered to the smartphone. Additionally, it increases productivity and advances preventive maintenance.

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