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Using automation and machine learning to maximize tool use in turning centers for better surface finish

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In modern manufacturing industries, automated machining systems have become a necessity. However, optimizing resource utilization and achieving a good surface finish remain challenging tasks. Excessive tool usage and poor surface finish are common problems encountered in turning centers, which affect productivity and product quality. In this research, we propose an approach that leverages automation and machine learning techniques to maximize tool use and improve surface finish. Our objective is to investigate the relationship between tool life and surface roughness and to develop a method that can optimize cutting parameters for turning centers. We have conducted an experimental study to evaluate the proposed approach, which involves the automatic determination of cutting parameters based on machine learning algorithms, and concluded a cutting speed of 43.10 m/min, the surface finish achieved for aluminum material was 1.98 μm. In the case of mild steel material, the surface finish was 12 μm at a cutting speed of 25.13 m/min. Similarly, for cast iron material, the surface finish was 8.45 μm at a cutting speed of 30.16 m/min. Our results show that the proposed method outperforms the traditional manual method in terms of surface finish, tool usage, and machining time. Our approach can be applied to other machining systems, providing a practical and effective solution to improve the efficiency and quality of machining processes. This paper presents an experiment that explores the relationship between tool life and surface roughness. Furthermore, an automated approach is proposed for eliminating G code in machining, which can improve the efficiency of machine tools and result in a better surface finish. Objective: To maximize tool use and improve surface finish in turning centers by incorporating automation and machine learning. Idea: This research aims to explore the use of automation and machine learning in turning centers to optimize the cutting parameters and achieve a better surface finish. Description of the idea: The study was conducted by performing experiments on three different materials, i.e., aluminum, mild steel, and cast iron. The cutting parameters, including spindle speed, feed, and depth of cut, were controlled by a programmable logic controller (PLC) integrated with a tachometer and Vernier scale. The surface finish was measured using a surface roughness tester, and the data was analyzed using a supervised machine learning algorithm.

***Keywords*: Lathe; CNC Machining; Optimum Point; Machine Learning in Manufacturing; PLC.**

INTRODUCTION

Achieving complete automation in manufacturing is essential for enhancing productivity and quality, minimizing errors and waste, improving safety, and introducing greater flexibility to manufacturing procedures. The fundamental factors that directly and immensely affect the surface finish and tool life in machining are feed, depth of cut, and spindle speed[1]. These machining factors are responsible for defects like Crater wear, Notch wear, Hairy surface finish, Flank wear, Burr formation, etc. For tool life effectiveness, MRR is the most considerable aspect. And MRR is influenced by spindle speed and depth of cut. If the objective is to get a better tool, then the focus has to be on the depth of cut and spindle speed[2]. The friction force between tool and workpiece is also a prime factor for surface finish and tool life, which is also immensely dependent on cutting parameters and cutting fluid[3].

To convert our conventional lathe machine into a semi-automatic lathe machine RETROFITTING term is used. Automating the lathe

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requires the automation of all three cutting parameters, namely the speed, feed, and depth of cut. In which feed and depth of cut are controlled manually, and a motor operates spindle speed. To automate the lathe feed and depth of cut should operate automatically with the help of a motor.

The retrofitting process for conventional lathe machines into semiautomatic control machines demands two key elements, namely, mechanical and electronic parts. In the mechanical part, a design is made to feed the stepper motor to the lead screw. On the other hand, in the electronics part, an electronic circuit containing the motor driver circuit is designed to control the motor movement with the help of programmable logic controller (PLC)[4]. So from this research proposal, the conventional machine can be converted into a CNC machine. In CNC machines, for machining workpieces, G-code/M-code program have to be created. Which is developed by a skilled person, and verify that code is in working status with the concerning our final desired shape. So it takes a particular time. CNC converter and the retrofitted CNC lathe realized G-code free machining. In this, C language is used as programming language and the automatic translation of a STEP-NC program into 6K language codes, which is a native language for CNC machine, and according to this CNC machine navigated[5]. To control motor RPM according to PLC programmed memory servo drives or VFD can be used according to motor type[6]. By using a PLC and servomotor for converting to an automatic machine, minimize cost and reduce machine downtime is achieved[7]. Selecting the optimum cutting parameters immensely affects the surface finish and tool life. The friction force also assists in selecting the optimum cutting point, which can be used as an input parameter[8]. An intelligent system must examine and decide on the process due to the difficulty of accurately describing it in any mathematical model[9–11]. Antony et al.[12] developed an expert knowledge-based system capable of detecting potential machine tool failures brought on by unexpected occurrences. The goal of this study is to use the Six Sigma technique to increase the material productivity of the printing process[13]. Modern production systems are extremely complicated and require thorough analysis before being put into practice. Different models have been put forth to evaluate these systems[14]. The spindle speed and feed rate directly influence the surface roughness. It is observed that the surface roughness increases with increased feed rate and is higher at lower speeds, and vice versa for all feed rates[15]. The use of online monitoring technology in CNC machining operations eliminates the need for post-process quality control and is essential for increasing automation, productivity, and dependability while lowering costs and production times[16–18]. For finding optimum parameters, machining experiments with various input parameters is using Taguchi Design of Experiments (DOE)[22–24]. A machine learning strategy ANN was used to predict cutting speed from the standard machining handbook. This cutting speed is predicted with respect to the hardness of the material[9]. Moreover, geometric algorithms of machine learning strategy are used for optimizing geometry design on the base objective function[25]. Proper selection of cutting parameters and tools can create longer tool life and lower surface roughness[26]. For controlling and maintaining surface finish according to our desired output, close-loop control system logic observes and gives an order to the controller according to the output. In order to improve productivity during the part production processes, optimized machining parameters for CNC machining operations can be obtained by applying cutting-edge machine learning methods[27–38].

All the study research is done to predict new values from existing data. There is not any method or approach presented to use this data in any conventional or automatic machine. So, in this study, an attempt has been made to eliminate G code and follow the optimum point of cutting parameters for turning operation machining from which surface finish and tool life can be better. And also, another approach has been made to convert conventional lathe machines to automatic lathe machines. Optimum point of the cutting parameter was obtained by experimental machining.

Figure 1 Lathe machine KIRLOSKAR TURNMASTER 40.

Figure 2 Mild steel workpiece with HSS tool.

Methodology

To develop a coding-free CNC machining system, it is essential to identify the ideal cutting parameters for each material. This reference data set of machining parameters can be used to achieve a better-quality surface finish and prolong the lifespan of tools without the need for manual coding. In order to fully automate the machining process, conventional lathe machines can be converted into automatic lathes using PLCs. These controllers can operate the automatic lathes based on preset cutting parameters for each material. As a result, the machining process can become more efficient and accurate with less human intervention. To determine the optimum cutting parameters, an experiment was conducted on a conventional lathe machine using three primary machining parameters: feed (f), speed (n), and depth of cut (a). Turning operations were carried out on three different materials, including mild steel, aluminum, and cast iron.

HSS TOOL and CARBIDE TOOL are two different types of tools used in machining processes. Mild steel and aluminum workpieces are 50 mm in diameter and 175 mm in length, whereas cast iron workpieces are 60 mm in diameter and 205 mm in length. The workpiece is separated into six 23-mm sections for ease of machining with various cutting parameters. With a traditional lathe machine, all the workpieces and tools are machined using different cutting parameters while dry. The KIRLOSKAR TURNMASTER 40 lathe is used for the machining process.

Figure 3 Aluminum workpiece with a carbide tool.

Figure 4 Cast iron workpiece with a carbide tool.

Figure 5 Portable surface roughness tester Surftest SJ-210 series.

Workpiece material with respect to machining tool: **Fig. 2** shows mild steel workpiece with an HSS tool and **Figs. 3 and 4** show aluminum and cast-iron workpiece with a carbide tool.

After machining experiments with different cutting parameters, the surface finish is measured using the surface roughness tester. As shown in **Fig. 5**, the portable surface roughness tester Surftest SJ-210 series is used. And to estimate tool life for all the cutting parameters, Taylor's equation is used. Mathematically, the life of a cutting tool is derived from the equation

$$T = cv^{\alpha}f^{\beta}d^{\gamma}$$

T = cutting time, c = Taylor constants, v = cutting speed, f = feed, d = depth of cut, α, β, γ = exponent.

Methods: The experiments were conducted using a retrofitted lathe, which was controlled by the PLC. The cutting parameters were varied for each material, and the surface finish was measured after each experiment. The obtained data was analyzed using a supervised machine learning algorithm to identify the optimal cutting parameters for achieving a better surface finish.

Design of the experiment

For all machining, a cutting parameter is taken with respect to a given factor. The Taguchi Method is utilized to obtain the results of the experiment. The objective of the design of an experiment is to determine the variables in a process that are more effective in-process. The selection of these DOE parameters is based on achieving an improved surface finish, as shown in **Table 1**.

Optimum point finding technique

The machine learning technique is used to find one effective point for machining. In the machine learning technique, a supervised machine algorithm is used because in this research, predicted values are not taken as an optimum point. Linear regression is used to find an optimum point between the dependent value and the independent value. A linear regression algorithm is used because it takes an input of existing data and gives a constant output with respect to an input. From the regression method, identify which independent variable has the most impact on a dependent variable.

An ANOVA table is made for the analysis of regression result. From the acquired deviation between the predicted most impactful and experimented values from this elementary equation. And also, a significant level of result can be determined for the predicted value.

Retrofitting/automation of conventional lathe

To automate a conventional lathe machine, all three cutting parameters—speed, feed, and depth of cut—must be operated automatically. While spindle speed is controlled by the motor, feed and depth of cut are typically controlled manually in conventional machines. To automate these operations, a 1 hp DC motor with a DC supply is connected to the lathe machine as shown in **Fig. 6**. Initial tests were conducted to select the appropriate motor, and a 1 hp motor was found to be sufficient for automating the machining process.

Table 1 Design of experiment.

Spindle speed (RPM)	Feed	Depth of cut
Lowest (50)	Lowest/low/medium	Constant
Low (160)	Lowest/low/medium	Constant
Medium (280–710)	Lowest/low/medium	Constant
High (1,600)	Lowest/low/medium	Constant
Highest (2,240)	Lowest/low/medium	Constant

Figure 6 DC motors are directly mounted to the carriage box of the lathe machine.

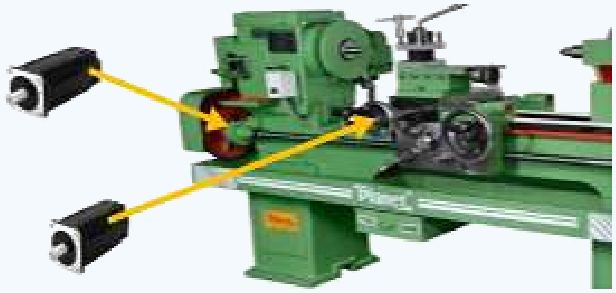

Figure 7 The first motor to the carriage and the second motor to the lead screw of the lathe machine.

Two techniques were identified for mounting the motor to the lathe machine. The first approach involved mounting a 1 hp DC motor to the carriage box with the help of a clamp and bush. The second approach involved mounting one motor to the carriage box for cross-sliding movement and the other motor to the lead screw with a bush and proper stage arrangement as shown in **Fig. 7**. The surface finish results of the second approach were found to be better than the first, so this approach was chosen for automatic machining.

Spindle speed is set using the existing mechanism of the machine. After the two motors are mounted, they are connected to a DC supply for functioning according to a voltage supply. Motor RPM is controlled according to requirements. A PLC is used as the controller, which directs the motor driver based on programmed instructions for movement in both the forward and reverse directions. A ladder diagram is used to create programming logic in the PLC. The Siemens S7200 model PLC is used for controlling eight inputs and six outputs. Ladder logic is created with reference to a timer.

The PLC is attached to the headstock of the lathe machine close to all the motors using a distinctive box. The relation between time and distance (workpiece length) is developed as an equation from reference machined length and time. The effective length of the turning operation must be entered for the machining operation. Programming logic calculates timing for both motor on-off and executes machining from the equation. For every material, timing varies because of its structural property and hardness. A reference equation is formed for every material, which is a one-time process for the automatic approach. The PLC is programmed with the help of MicroWIN software.

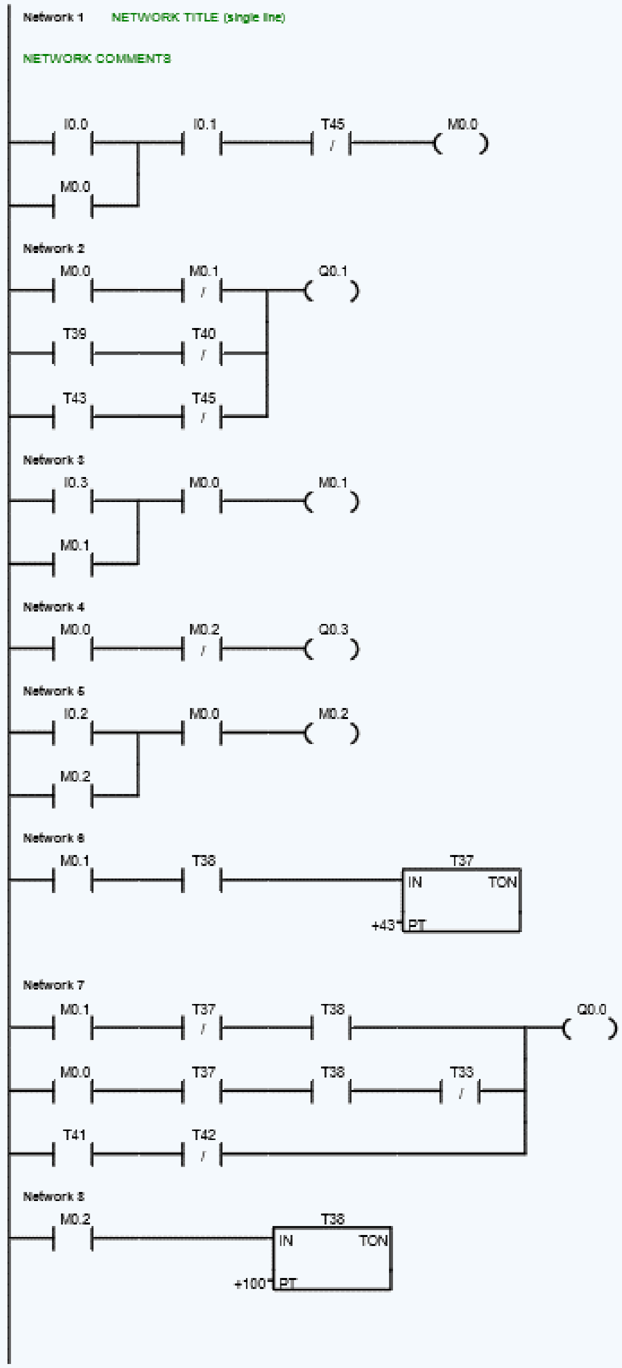

Figure 8 PLC ladder diagram (1).

Spindle speed is settled directly with the existing mechanism of the machine for machining operation. After two motors are mounted with the machine, the motors are connected to a DC supply for functioning according to a voltage supply and from this, controlling of the motor RPM according to our requirements is achieved.

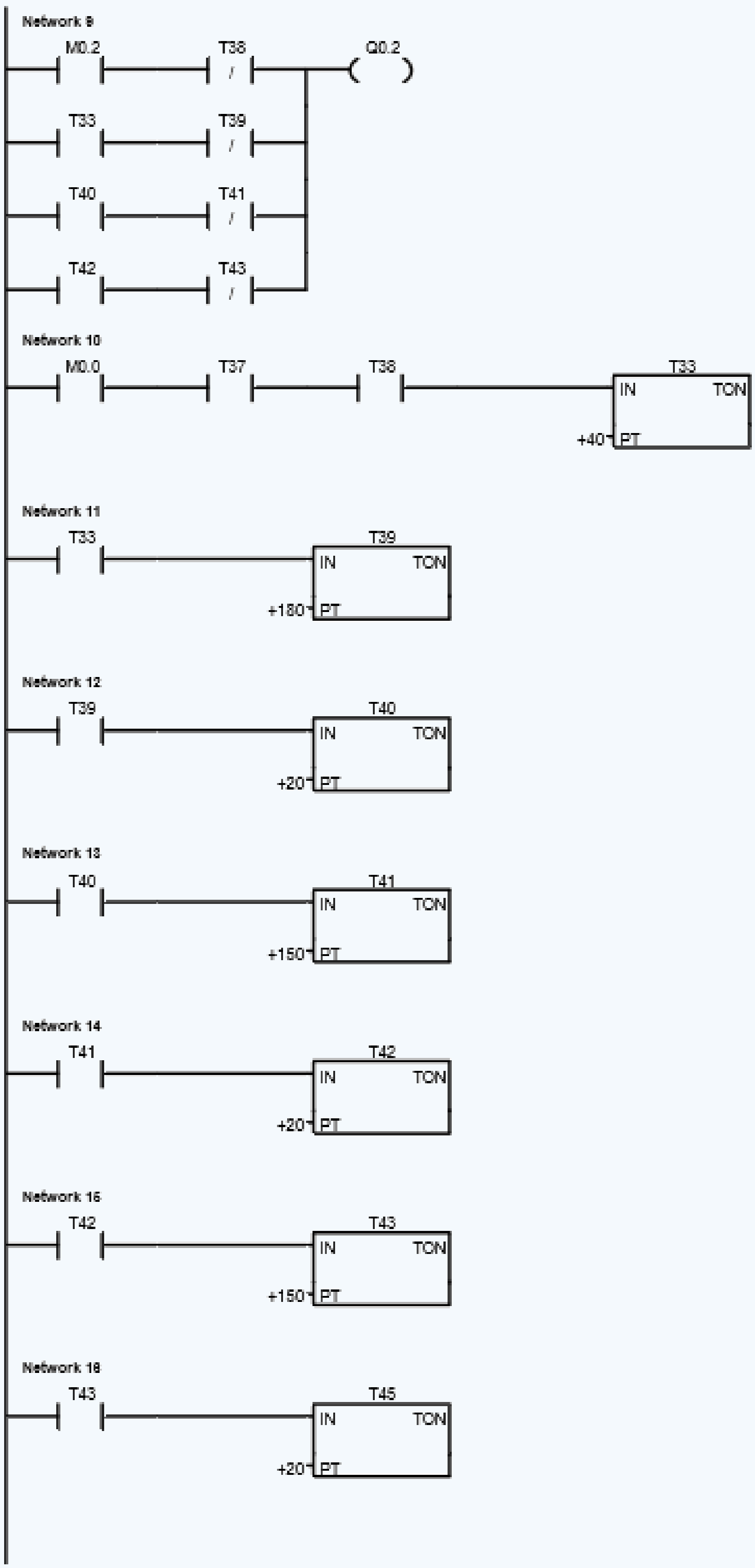

Figure 9 PLC ladder diagram (2).

Ladder diagram programming is done for cross sliding motor and lead screw motor on the timing base and RPM base. Machining starts from the home position, which starts from the limit switch attached. When the limit switch is pressed, it gives input to the PLC by M0.1 and M0.2. For depth of cut motor Q0.0 AND Q0.1 and for feed motor Q0.2 AND Q0.3 are taken as output port. And from that, reverse forward motion is also actuated from relay. At the end of the ladder diagram, all the timer is set with respect to the dimension of the machining for diameter and for length. In the timer, all the timing is set in milliseconds for motor on/off timing.

For automation, a material-recognizing sensor is mounted near the chuck. INDUCTIVE FACTOR 1TYPE sensor is used for sensing purposes. From sensor gives a different signal in the form of a factor number to the PLC, and according to the factor, material is discovered and its timing distance equation is getting into running mode. **Figures 8 and 9** show the ladder diagram of PLC programming. **Table 2** shows the sensor output data for different materials.

The system automatically determines the optimal feed and depth of cut by selecting the appropriate motor RPM using a PLC to control the AC/DC motor drive. The optimal point varies for each material, and the sensor signal is used to control the motor without human intervention. A GUI with sensor input can also be used for direct control without the need for a PLC.

For reference position of the tool concerning the workpiece two limit switches (contact sensor) are used from which at the beginning time of machining the tool is set to a home position. From which it starts calculating timing for machining. The distance has to be between the workpiece and the home position accurately to start machining accurately. In the latest PLC systems like the S71500 SIEMENS and G364 MITSUBISHI, this type of arrangement is not required. In this controller, home position is directly taken with logic by creating the ladder diagram.

Application of the findings of this research can be used to improve the performance and accuracy of turning centers. The use of automated systems and machine learning algorithms can help optimize the cutting parameters and tool life, resulting in better surface finishes and reduced downtime.

Second, the results of this research can be applied to a wide range of materials used in manufacturing processes, such as aluminum, mild steel, and cast iron. This can help in selecting the most suitable cutting parameters for specific materials, leading to improved efficiency and cost-effectiveness.

Third, the application of this research can result in reduced human error and variability, leading to better consistency in the

Table 2 Sensor output in the form of a factor.

Material	Correction factor
Steel	1.00
Cast iron	0.93 . . . 1.05
Stainless steel	0.60 . . . 1.00
Nickel	0.65 . . . 0.75
Brass	0.35 . . . 0.50
Aluminum	0.30 . . . 0.45
Copper	0.25 . . . 0.45

manufacturing process. This can also lead to increased productivity and cost savings in the long run.

Overall, the application of this research can benefit various industries that rely on turning centers for their manufacturing processes, including automotive, aerospace, and general engineering.

RESULT AND DISCUSSION

The authors conducted experiments on different materials using different types of cutting tools. In the case of a mild steel workpiece with an HSS tool, the best surface finish and tool life were obtained at a spindle speed of 2240 RPM, a feed of 0.32 mm/rev, and a depth of cut of 0.5 mm. The surface roughness was 3.92 µm and discontinuous small chips were produced during machining. For an aluminum workpiece with a carbide tool, the optimal cutting parameters were a spindle speed of 710 RPM, a feed of 0.18 mm/rev, and a depth of cut of 0.5 mm, resulting in a surface roughness of 1.14 µm with continuous long chips produced during machining. For the cast iron workpiece with a carbide tool, the best surface finish and tool life were achieved at a spindle speed of 1400 RPM, a feed of 0.18 mm/rev, and a depth of cut of 0.5 mm, resulting in a surface roughness of 6 µm with segmented chips produced during machining. These findings demonstrate that the optimal cutting parameters are dependent on the material and the type of cutting tool used.

- ➢ Blended graphical representation for all the machining:

Figure 11 shows the overall value of surface finish decreases when cutting speed and feed increases. And for tool life, it increases with cutting speed and feed increases.

Machine learning observation for the optimum point of the machining experiment

The algorithm brings the most effective point as predicted values, and from the ANOVA table's residual output observation table plot deviation between predicted values and experimented values can be found. A table

Table 3 Experimental machining data for mild steel.

Spindle speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Cutting speed (m/min)	Ra (µm)
50.00	0.18	0.50	7.85	13.25
	0.25	0.50	7.85	12.93
	0.32	0.50	7.85	14.11
160.00	0.18	0.50	25.13	11.57
	0.25	0.50	25.13	13.27
	0.32	0.50	25.13	11.47
280.00	0.18	0.50	43.10	7.10
	0.25	0.50	43.10	8.55
	0.32	0.50	43.10	10.75
450.00	0.18	0.50	69.27	4.36
	0.25	0.50	69.27	6.63
	0.32	0.50	69.27	11.16
560.00	0.18	0.50	84.45	6.22
	0.25	0.50	84.45	9.80
	0.32	0.50	84.45	11.00
710.00	0.18	0.50	107.07	7.56
	0.25	0.50	107.07	8.00
	0.32	0.50	107.07	9.23
2240.00	0.18	0.50	330.75	6.77
	0.25	0.50	330.75	8.28
	0.32	0.50	330.75	11.30
2240(c.t)	0.18	0.50	330.75	3.97
	0.25	0.50	330.75	4.67
	0.32	0.50	330.75	3.92

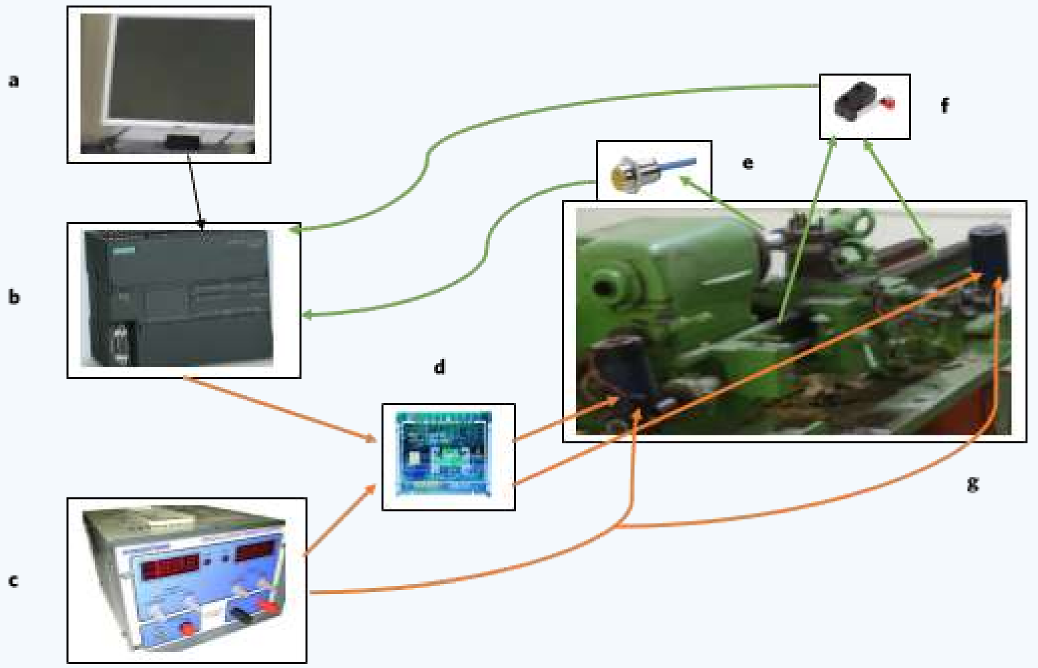

Figure 10 Setup for an automatic/retrofitted lathe. (**a**) computer, (**b**) plcs7200, (**c**) DC supply, (**d**) motor controller (PWM), (**e**) inductive sensor, (**f**) limit switch, (**g**) lathe-motor setup.

Table 4 Experimental machining data for Aluminum.

Spindle speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Cutting speed (m/min)	Ra (μm)	Tool life (min)
50.00	0.18	0.50	7.85	1.36	62.41
	0.25	0.50	7.85	1.74	80.37
	0.32	0.50	7.85	2.44	96.02
160.00	0.18	0.50	25.13	1.20	78.75
	0.25	0.50	25.13	1.75	101.42
	0.32	0.50	25.13	2.49	121.17
280.00	0.18	0.50	43.10	1.57	87.72
	0.25	0.50	43.10	1.95	112.97
	0.32	0.50	43.10	2.89	134.97
450.00	0.18	0.50	69.27	1.23	96.45
	0.25	0.50	69.27	1.73	124.22
	0.32	0.50	69.27	2.37	148.41
560.00	0.18	0.50	84.45	1.65	100.35
	0.25	0.50	84.45	1.71	129.23
	0.32	0.50	84.45	2.29	154.41
710.00	0.18	0.50	107.07	1.14	105.23
	0.25	0.50	107.07	1.62	135.52
	0.32	0.50	107.07	2.27	161.91

Table 4 (*Continued*).

Spindle speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Cutting speed (m/min)	Ra (μm)	Tool life (min)
2240.00	0.18	0.50	330.75	1.36	131.86
	0.25	0.50	330.75	5.15	169.81
	0.32	0.50	330.75	3.71	202.88
2240 HSS	0.18	0.50	330.75	5.72	46.55
	0.25	0.50	330.75	7.39	59.95
	0.32	0.50	330.75	9.36	71.62

Table 5 Experimental machining data for cast iron.

Spindle speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Cutting speed (m/min)	Ra (μm)	Tool life (min)
50.00	0.18	0.50	9.42	8.83	100.87
	0.25	0.50	9.42	7.90	131.19
	0.32	0.50	9.42	8.75	157.83
160.00	0.18	0.50	30.16	8.66	139.70
	0.25	0.50	30.16	9.79	181.69
	0.32	0.50	30.16	9.81	218.59
280.00	0.18	0.50	51.90	6.12	162.63
	0.25	0.50	51.90	8.39	211.52
	0.32	0.50	51.90	10.62	254.47
450.00	0.18	0.50	83.41	7.76	185.74
	0.25	0.50	83.41	7.56	241.57
	0.32	0.50	83.41	8.19	290.63
560.00	0.18	0.50	102.04	6.68	196.53
	0.25	0.50	102.04	6.45	255.60
	0.32	0.50	102.04	9.52	307.50
710.00	0.18	0.50	129.37	6.99	210.03
	0.25	0.50	129.37	8.00	273.16
	0.32	0.50	129.37	10.66	328.63
1400.00	0.18	0.50	250.70	6.05	252.77
	0.25	0.50	250.70	8.51	328.75
	0.32	0.50	250.70	6.00	395.51
1400 HSS	0.18	0.50	250.70	4.94	41.66
	0.25	0.50	250.70	8.69	54.18
	0.32	0.50	250.70	11.14	65.18

plot in which deviation has a minimum value is the most effective value for dependent values. To find an effective value, only one output factor can be considered. In my observation, the surface finish factor is considered.

Figure 12a, b shows that the graph has the lowest deviation (0.023) with respect to the predicted value and it has the positive lowest residuals. So, it should be the most influential parameter for surface finish for a cast iron material workpiece. **Figure 13a, b** shows that the graph has the lowest deviation (0.024) with respect to the predicted value and it has the positive lowest residuals. So it should be the most influential parameter for surface finish for a mild steel material workpiece. **Figure 14a, b** shows that the graph has the lowest deviation (0.073) with respect to the predicted value and it has positive lowest residuals. So it should be the most influential parameter for surface finish for an aluminum material workpiece.

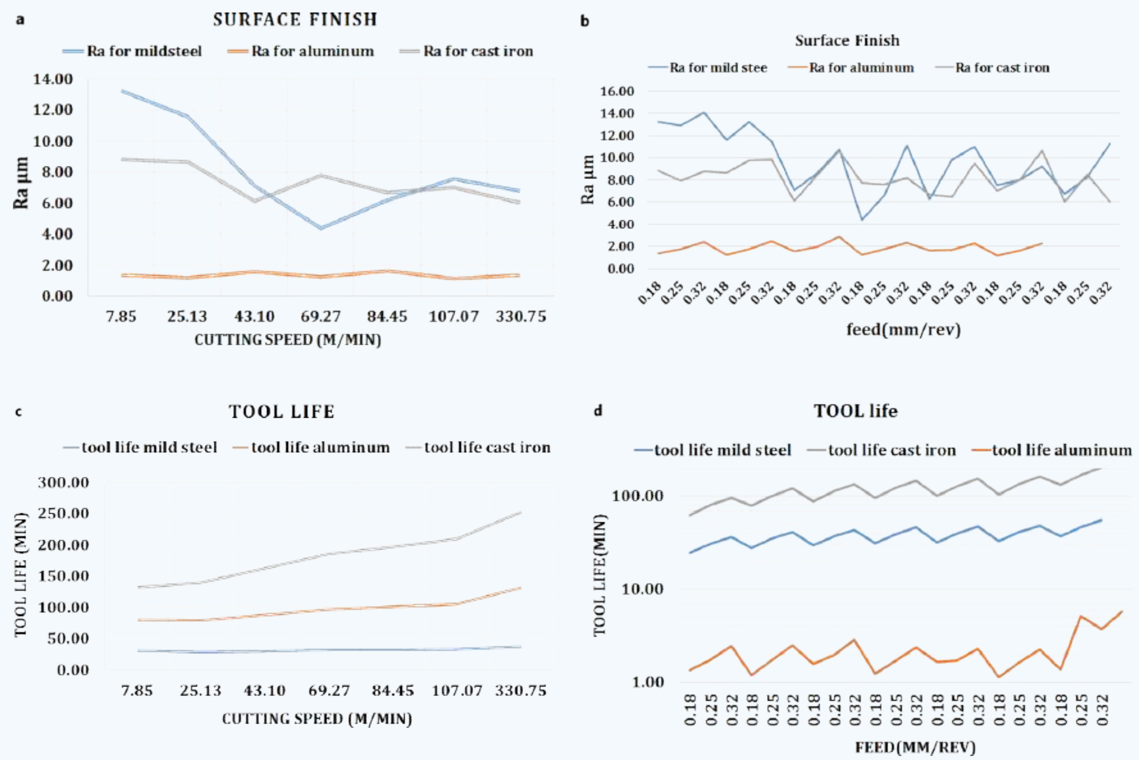

Figure 11 For all the three material blended plots of (**a**) surface finish plot for cutting speed v/s surface roughness, (**b**) surface finish plot for feed v/s surface roughness, (**c**) tool life plot for cutting speed v/s tool life, and (**d**) tool life plot for feed v/s tool life.

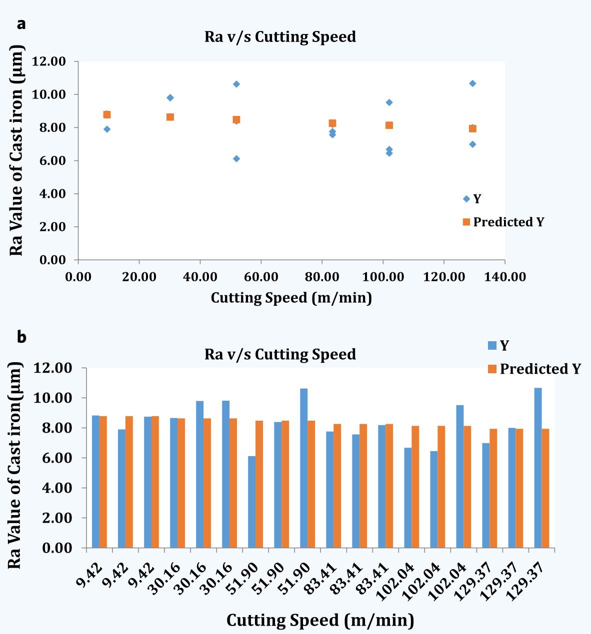

Figure 12 (**a**) and (**b**) Linear regression algorithm plot for cast iron material Ra v/s cutting speed.

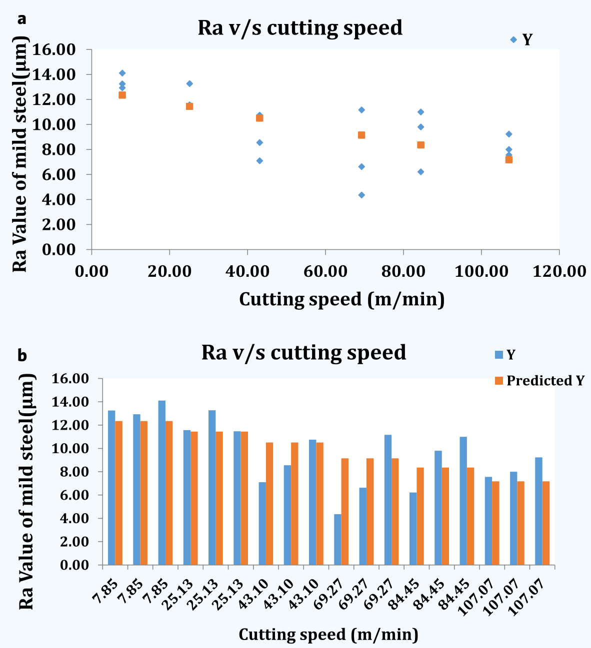

Figure 13 (**a**) and (**b**) Linear regression algorithm plot for mild steel material Ra v/s cutting speed.

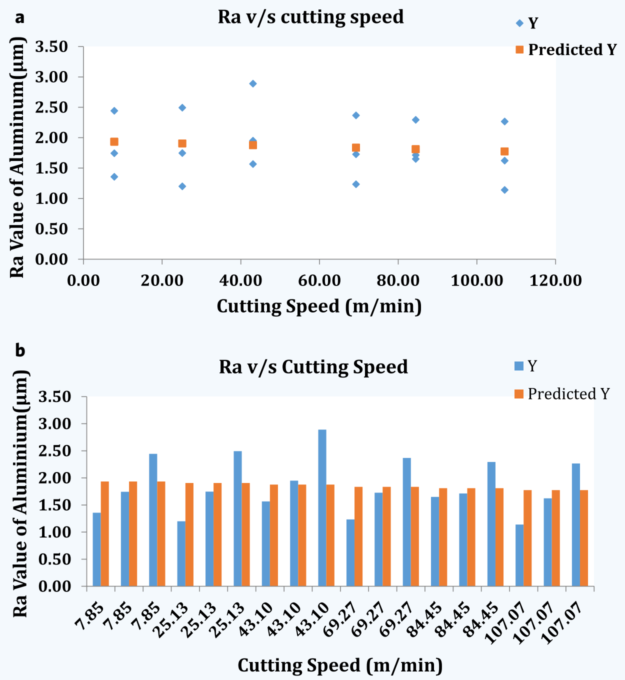

Figure 14 (**a**) and (**b**) Linear regression algorithm plot for aluminum material Ra v/s cutting speed.

Quantitative comparison of results with significant findings: The surface finish achieved for aluminum material was 1.98 µm at a cutting speed of 43.10 m/min, for mild steel material it was 12 µm at a cutting speed of 25.13 m/min, and for cast iron material it was 8.45 µm at a cutting speed of 30.16 m/min. The surface finish obtained using the proposed approach was significantly better than the conventional manual turning operations.

VALIDATION OF RESULTS

Automatic machining

A tachometer is used to check the motor speed and for distance and diameter control according to the program is also accurate, which is measured by the Vernier scale. On automation setup, machining for these three optimum parameters with respect to three materials is done. From that surface finish reading was observed. Reading's data is given in the table. By incorporating tool life data into a machine learning algorithm, the optimal point is identified. Analyzing the table data reveals that the outcomes display fewer discrepancies. So, the automatic turning operation system is worked to a better extent. And it's also accurate in machining.

Generally, the surface finish depends on many aspects. But in a conventional machine, three cutting parameters are highly effective. And these lesser differences in reading occurred because of gear's backlash, the tearing and wearing of many working entities due to a lack of maintenance, etc. In all machining experiments, tool sharpening is done after every experiment.

At a cutting speed of 43.10 m/min, the surface finish achieved for aluminum material was 1.98 µm. In the case of mild steel material, the surface finish was 12 µm at a cutting speed of 25.13 m/min. Similarly, for cast iron material, the surface finish was 8.45 µm at a cutting speed of 30.16 m/min.

Table 6 Observation table for cast iron, mild steel, and aluminum by using a machine learning approach.

	Observation for cast iron		Observation for mild steel		Observation for aluminum	
Sr. No	Predicted Y	Residuals	Predicted Y	Residuals	Predicted Y	Residuals
1	8.778702993	0.047963674	12.34538503	0.904614972	1.93327865	−0.576612
2	8.778702993	−0.882036326	12.34538503	0.584614972	1.93327865	−0.1899453
3	8.778702993	−0.032036326	12.34538503	1.762114972	1.93327865	0.51005468
4	8.633311168	0.023355498	11.44559272	0.124407282	1.905535497	−0.7055355
5	8.633311168	1.156688832	11.44559272	1.824407282	1.905535497	−0.1588688
6	8.633311168	1.180022165	11.44559272	0.024407282	1.905535497	0.58779784
7	8.480870043	−2.364203376	10.50980871	−3.409808714	1.876682618	−0.310016
8	8.480870043	−0.090870043	10.50980871	−1.956475381	1.876682618	0.07331738
9	8.480870043	2.142463291	10.50980871	0.236857952	1.876682618	1.01331738
10	8.259918527	−0.503251861	9.14703236	−4.790365693	1.834664351	−0.601331
11	8.259918527	−0.696585194	9.14703236	−2.520365693	1.834664351	−0.1079977
12	8.259918527	−0.069918527	9.14703236	2.016300973	1.834664351	0.53283565
13	8.129286176	−1.452619509	8.356851112	−2.140184446	1.810300819	−0.1603008
14	8.129286176	−1.679286176	8.356851112	1.443148888	1.810300819	−0.0969675
15	8.129286176	1.387380491	8.356851112	2.639815554	1.810300819	0.48303251
16	7.937633316	−0.950966649	7.178941178	0.381058822	1.773982509	−0.6339825
17	7.937633316	0.059033351	7.178941178	0.821058822	1.773982509	−0.1514825
18	7.937633316	2.724866684	7.178941178	2.054392155	1.773982509	0.49268416

Table 7 Optimum cutting parameters for machining operation.

			Cast iron		Mild steel		Aluminum	
Spindle speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Cutting speed (m/min)	Ra (μm)	Cutting speed (m/min)	Ra (μm)	Cutting speed (m/min)	Ra (μm)
50.00	0.18	0.50	9.42	8.83	7.85	13.25	7.85	1.36
	0.25	0.50	9.42	7.90	7.85	12.93	7.85	1.74
	0.32	0.50	9.42	8.75	7.85	14.11	7.85	2.44
160.00	0.18	0.50	30.16	8.66	25.13	11.57	25.13	1.20
	0.25	0.50	30.16	9.79	25.13	13.27	25.13	1.75
	0.32	0.50	30.16	9.81	25.13	11.47	25.13	2.49
280.00	0.18	0.50	51.90	6.12	43.10	7.10	43.10	1.57
	0.25	0.50	51.90	8.39	43.10	8.55	43.10	1.95
	0.32	0.50	51.90	10.62	43.10	10.75	43.10	2.89

Table 8 Validation of turning center results with an automatic lathe (with PLC).

Spindle speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Cutting speed (m/min)	Surface finish (Ra μm)	Surface finish (Ra μm)
Aluminum					Experiment
280	0.25	0.50	43.10	1.98	1.95
Mild steel					
160	0.32	0.50	25.13	12.00	11.47
Cast iron					
160	0.18	0.50	30.16	8.45	8.66

The novelty of using automation and machine learning to maximize tool use in turning centers for better surface finish lies in the integration of two advanced technologies in the manufacturing process. Automation allows for the reduction of human error and increases the efficiency of machining operations, while machine learning enables the identification of optimal parameters for machining. By combining these technologies, the research aims to achieve a better surface finish and extend the tool life, which could lead to cost savings and improved product quality. Additionally, the study focuses on using machine learning in conjunction with actual experimental data rather than relying on predictive models or handbook information, which is a unique approach to the problem.

Benefits of the research

1. Improved surface finish: The use of automation and machine learning in turning centers leads to better surface finishes, which can increase the quality of products and reduce the need for post-processing.
2. Tool life maximization: The research work helps in maximizing the tool life, which reduces the cost of tool replacement and also saves time in tool changeovers.
3. Reduced downtime: The integration of the PLC with the machine and the use of a supervised machine learning algorithm help to reduce downtime, leading to increased productivity and reduced costs.
4. Potential for automation: The research work paves the way for turning centers to be changed into fully automated systems, which can eliminate the need for G-code and other manual programming methods.

Shortcomings

1. Limited materials: The research work focuses on only three materials, namely aluminum, mild steel, and cast iron. The results may not be applicable to other materials, and further research may be needed to generalize the findings.
2. Limited tool types: The research work uses only one type of tool, which may not be representative of all tools. Further research is required to determine the applicability of the findings to other tool types.

Future research

1. The research work can be expanded to include a more extensive range of materials and tool types to generalize the findings.
2. Further research can be conducted to investigate the impact of other cutting parameters, such as cutting fluid, on the surface finish.
3. The integration of artificial intelligence techniques, such as deep learning, can be explored to further improve the accuracy of the machine learning algorithm.

4. The applicability of the findings to other types of machines, such as milling machines and grinders, can be investigated.

CONCLUSION

The incorporation of machine learning algorithms and automation of the selection of optimum parameters for different materials can improve the accuracy and efficiency of the turning operation system. The results of the validation of the turning center results with the automatic lathe (with PLC) show that the automatic turning operation system is more accurate and consistent in achieving the desired surface finish. The following points are concluded:

- The difference between the surface finish (Ra) values for manual and automatic turning operations is relatively small.
- The retrofitted lathe worked without G-code or any other commanding coding system for turning operations. The PLC directly controls the motor with the help of an integrating circuit and downtime of the machine is reduced.
- Automation and machine learning can be used to maximize tool use in turning centers and improve surface finish.
- Automatic turning operations with a PLC-controlled motor showed relatively small differences in surface finish compared to manual turning operations.
- Retrofitted lathes with integrated circuits and PLC control can reduce downtime and improve efficiency.
- Supervised machine learning algorithms can be used with experiment data to identify optimal turning parameters for different materials.
- This approach has the potential to transform all CNC machines and lathes into fully automated systems without the need for G-code.

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