© February 2024| IJIRT | Volume 10 Issue 9 | ISSN: 2349-6002

Optimization of Turning Parameters Using Genetic Algorithm

Vijay Tiwari[1], Dr. Ashutosh Dwivedi[2]
[1,2] Department of Mechanical Engineering,
Vindhya Institute of Technology & Science Satna (M.P.)

Abstract-Steel rolling mills may be distinguished in a variety of ways. The mill's flexibility to roll steel in either hot or cold conditions enables it to create a variety of cross-sections, diameters, and grades. Roll supports are utilized in every rolling mill to secure the rollers that are used to roll the materials. These rollers may break because of excessive cyclic loads or fractures in the rolling parts of the rollers. After all necessary machining procedures have been accomplished, a damaged roller is either replaced with new rollers or using the existing rollers. CNC machines are used to manufacture completed rolls from a cylindrical shape, as well as to repair damaged rolls. Straight turning, taper turning, and circular machining processes are used to create these rolls. Among the machining parameters for turning rolls discussed in this thesis are spindle speed, feed rate, and cut depth. The required functions are the machining time (Mt) and the tool life (L) (Tl). The purpose of this research was to optimise turning parameters using regression and GA in order to obtain the shortest possible machining time and the longest possible tool life (GA). It was feasible to spin cast iron rollers with tungsten-coated carbide inserts using a regression design of experiment approach and regression analysis (in EXCEL). Three process factors were studied for their influence on machine time and tool life using a L9 orthogonal array design. Spindle speed, feed rate, and depth of cut were all studied. Regression analysis was used to build mathematical models of how each individual responds to a scenario.

Keywords: Rolling, Genetic Algorithm, CNC, Tool life

INTRODUCTION

Optimizing the manufacturing process through regulating machining parameters is critical to the success of the process, since machining plays an important part in the whole manufacturing process. Cutting speed, depth of cut, feed rate, and other machining parameters have a significant impact on production operations. An in-depth investigation on metal cutting, namely the relationship between tool life and numerous parameters, was published in 1907 by [1]. To optimise material removal rate, Taylor [1] discovered an optimal/economic cutting speed. Despite Taylor's [1] early work on determining the optimal cutting speed in single pass turning, progress has been modest due to the requirement to optimise all process parameters. A slew of new tool-work material combinations is now available to perform a variety of machining operations. For each novel combination of tool-work material, extensive testing is necessary to demonstrate the empirical performance of any correlation that is presented. Manufacturing companies have relied on highly competent workers for many years, which may have resulted in some optimization of a few factors or objects without the use of any scientific methods. In addition, it is quite difficult to get the most value out of qualified people every time. NC/CNC machines, on the other hand, need precise control of all machining parameters. Modern high-performance computers have made optimization algorithms more attractive for use in engineering design and decision-making processes. A thorough understanding of machining, including equations related tool life, power, and force, as well as variables influencing surface roughness, is required to optimise cutting parameters. A solid grasp of optimization techniques, both mathematical and numerical, is also required. Different analytical and experimental techniques to machining parameter optimization have been studied after the pioneering work of [1]. In the 1950s, [3] investigated the optimization of turning machining settings to maximise output while minimising production costs. Armarego and Brown [4] examined unconstraint machine parameter optimization using differential calculus. For nonferrous materials, Brewer and Rueda [5] performed a simplified optimal analysis. [6] presents a comprehensive survey of the literature on the optimization of machining parameters (by means of different optimization algorithms) in turning operations.

LITERATURE REVIEW

The literature review encompasses a broad spectrum of optimization techniques applied to diverse fields, showcasing the versatility of genetic algorithms. Thirumalai et al. (2021) bring attention to the limitations of Taguchi techniques in dealing with multiple responses in optimization problems. Their study on machining conditions for carbide cutting tools on Inconel 718 employs Multi-Criteria Decision Making (MCDM), specifically the Analytical Hierarchy Process (AHP) and TOPSIS, in conjunction with the Non-dominated Sorting Genetic Algorithm (NSGA-II) to attain a singular optimal solution.

Conversely, Garmejani and Hossainpour (2021) delve into the realm of thermoelectric power production from car exhaust using a Thermoelectric Generator (TEG) system. Employing MATLAB's genetic algorithm for multi-objective optimization, they achieve an efficiency of 6.56%. The study not only presents optimal design points but also highlights Pareto sets, providing insights into trade-offs between investment, power, and second law efficiency. Nili-Ahmadabadi et al. (2021) take a distinctive approach, utilizing the ball-spine inverse design method and a genetic algorithm to optimize pressure distribution for aerodynamic diffusers. The synergy between the genetic algorithm and inverse design resiliently enhances the aerodynamic design of ducts, showcasing the adaptability of genetic algorithms in diverse optimization scenarios. Vijayanand et al. (2021) shift the focus to electroless NiB coating using 3-DMAPS amphoteric surfactant. Mathematical models, including a backpropagation neural network (BPNN), establish a correlation between surfactant concentration and surface roughness. Through genetic algorithm optimization, the study achieves minimal roughness at a critical micelle concentration of 0.0135 mg/L.

Addressing challenges in online retail, Park et al. (2021) employ a genetic algorithm for vehicle routing, considering dynamic orders and rerouting indications to optimize real-world truck routing.

Ciğeroğlu et al. (2021) contribute to the medical field by addressing antibiotic resistance. They utilize a magnetic nanoparticles-rGO-chitosan composite bead for optimizing cefixime (CFX) elimination. The study employs a response surface technique and a genetic algorithm-based artificial neural network (ANN) for efficient optimization across multiple objectives.

Usha and Rao (2020) take on the optimization of cutting force, surface roughness, and temperature in AISI 1040 steel machining with Al_2O_3 nanoparticles and minimal quantity lubrication. The study employs a genetic algorithm for multi-objective optimization, showcasing its effectiveness in enhancing machining parameters. Alexandrino et al. (2020) contribute to structural health monitoring for damage detection, employing a multi-objective genetic algorithm and an artificial neural network. This study highlights the role of genetic algorithms in enhancing the correlation between functional variance and damage parameters in structural health monitoring. Zolpakar et al. (2020) provide a comprehensive review of the Genetic Algorithm (MOGA) for multi-objective optimization, emphasizing its effectiveness in exploring diverse solution areas and comparing it with other optimization methods in manufacturing processes.

Sin and Do Chung (2020) tackle energy-conscious scheduling under Time-of-Use (TOU) pricing, incorporating machine unavailability due to preventative maintenance. They introduce the Hybrid Multi-Objective Genetic Algorithm (HMOGA) for scheduling, outperforming non-dominated sorting genetic algorithm (NSGA-2) and Baron solver in numerical trials. The study's significant contribution lies in establishing a trade-off connection between overall power costs and machine unavailability in a TOU pricing context.

Jiang et al. (2020) optimize the dynamics of an articulated monorail vehicle using a genetic algorithm, enhancing suspension parameters to reduce wheel unload, overturning coefficients, and tire wear. Mosayebi and Sodhi (2020) focus on optimizing evolutionary algorithms for the Traveling Salesman Problem using Design of Experiments theory, improving algorithm efficiency by adjusting parameters for both small and large-scale challenges. Sahali et al. (2016) contribute to cutting parameter estimation, introducing a probabilistic nondominated sorting genetic algorithm (P-NSGA-II) for multi-objective optimization with stochastic production restrictions. The algorithm enhances reliability and robustness, addressing failure probability and economic objectives under uncertainties in machining operations.

Jin et al. (2016) utilize a genetic algorithm to optimize constitutive models for granular soils, guiding the selection of sand models and parameter identification based on triaxial testing. The study provides valuable insights into the optimization of constitutive models for reliable parameter identification in geotechnical engineering. Pashazadeh et al. (2016) optimize resistance spot welding parameters through a hybrid of artificial neural networks and multi-objective genetic algorithm, addressing electrode wear and nugget dimensions. Sathish et al. (2016) focus on surface roughness optimization in turning operations, using Particle Swarm Optimization to determine optimal cutting conditions. Shankar and Eswaran (2016) employ a genetic algorithm-based optimization for elliptic curve cryptography in image encryption, achieving high Peak Signal-to-Noise Ratio (PSNR) compared to other methods. Dhabale and Jatti (2015) optimize turning process parameters for maximal material removal using a genetic algorithm. Empirical modeling based on multiple regression incorporates spindle speed, feed rate, and cut depth, achieving an optimal material removal rate and enhancing flexibility for industrial applications.

Santos et al. (2015) explore the interplay of machining force, chip thickness ratio, and chip disposal in ductile and high-strength aluminum alloys. Central composite design and genetic algorithm identify conditions reducing both machining force and chip thickness ratio, contributing to the optimization of machining processes. Altug et al. (2015) investigate the machinability of Ti6Al4V alloy through various heat treatments and wire electrical discharge machining, optimizing with a genetic algorithm for efficient results. Su et al. (2015) address the complex scheduling challenges of turning machine tools using a mixed 0-1 integer programming model and a hybrid evolutionary algorithm, enhancing process design considering multiple goals.

A combined Genetic Algorithm (GA) and Artificial Neural Network (ANN) model quantitatively evaluates technology choices for building retrofit projects, focusing on energy consumption, retrofit cost, and thermal discomfort. The multi-objective optimization approach identifies trade-offs and interactions between these goals, demonstrated using a school building case study. Alrashdan et al. (2014) employ multi-criteria optimization for end milling of AISI D2 steel. The goal is to reduce machining energy consumption and associated costs while achieving improved surface finish. A cost function considering additional machining and electricity costs is optimized using a genetic algorithm, providing efficient feed and speed options for milling machine operators.

METHODOLOGY

Optimization of Turning Parameters in Machining of the Cast Iron Rolls

Steel rolling mills may vary greatly from one another in a variety of ways. The mill can roll steel in either hot or cold conditions, with varying cross-sections, diameters, and grades. Roll supports, which are installed in every rolling mill, hold the rolls used to roll the materials. Heavy cyclic loads or cracks in the rolling parts might cause these rollers to break. After the necessary machining procedures, the broken rollers are either replaced with new rollers or the old rollers that already existed. To generate completed rolls from a cylindrical shape or to rework existing rolls, CNC machines are employed. Straight turning, taper turning, and circular machining are all used to create these rolls. The machining parameters for turning rolls include spindle speed, feed rate, and cut depth in this project. The goal functions are the machining time (Mt) and tool life (Tl). Using a Genetic Algorithm, this research intended to optimise turning parameters for the shortest possible machining time and the longest possible tool life (GA). When it comes to spinning cast iron rolls utilizing tungsten-coated carbide inserts, Taguchi's design of experiment approach and regression analysis (in EXCEL) are used. Three process factors, namely spindle speed, feed rate, and depth of cut, were tested for machine time and tool life using a L9 orthogonal array design. Regression analysis has been used to create mathematical models for everyone ‘s reaction.

Process

Manufacturing encompasses a wide variety of human activities, from handcraft to high-tech, but is most usually used to describe industrial production, when raw materials are turned into completed things on a massive scale.For example, these completed items may be utilized to manufacture more complicated products, such as household appliances or vehicles, or sold to wholesalers, who in turn sell them to retailers, who in turn sell them to the end users-the end customers. Metal cutting is unusual among industrial techniques in that it may be used to both manufacture and finish goods. It is the most frequent manufacturing process in the world, accounting for 10 to 15 percent of the total cost of all commodities. For the purpose of producing a final product with the required size, shape, and surface roughness, metal cutting is described as the removal of metal chips from a workpiece. Among the several metal cutting procedures, turning is one of the simplest. External cylindrical and conical surfaces are machined by turning, which is typically done on a lathe.

Cutting parameters (speed, feed, and depth of cut) selection is critical in turning operations in order to achieve excellent cutting performance. Optimal cutting settings are needed for the most effective usage of machine equipment. Therefore, an appropriate optimization strategy must be found in order to identify the best possible cutting settings. Complex constraints and nonlinearity make parameter tuning in the turning process very challenging Typically, cutting parameters are set by experience or by consulting a guidebook. Nonetheless, the ranges provided by these sources are only starting points, and they are not the best numbers. A machine and environment- specific cut quality cannot be guaranteed with this method, even if all other factors are equal. Machining parameters may be optimized to improve both the economics of the process as well as the product quality to a considerable degree. It has been determined that Genetic Algorithm is the best method for estimating the cutting parameters that would save machining time while also increasing tool life to a reasonable level.

Researchers have been interested in the optimization of process parameters in machining processes since Gilbert developed an analytical approach in 1950 for calculating the best spindle speed for a single pass turning operation. In machining, selecting the best cutting parameters necessitates the creation of machining models and optimization algorithms that can deal with such models. Many studies have looked at the issue of selecting the best machining conditions for a certain job. In order to meet the fundamental production criteria, several of the writers looked into the optimal process parameters. With the most part, this optimization technique is based on partial differentiation for the purpose of reducing machining time and increasing the life of the cutting tools. Spindle and feed rate are transmitted to chip and work piece friction during the machining process, which results in a significant amount of work piece surface being cut.

RESULT AND DISCUSSION

Experimental Details

On a powerful, stiff lathe (90 KW) of outstanding operating condition, external longitudinal turning was conducted at various Spindle speeds (S), Feed rates (f), and depths of cuts (d). Fig.3 depicts the experimental set-up in a photo-realistic manner. Cast iron roll (Outer Diameter 850mm, and Length 1250mm) hardened to 50–55 SHC was used for the work piece. A coated tungsten carbide cutting tool was employed (RCMX25). To keep the insert in place, a tool holder was used. The following table lists the material's chemical composition and mechanical qualities.

Table 4. 1 Chemical Composition

C	Si	Mn	P	S	Ni	Cr	Mo
3.30	1.59	.61	.051	0.013	1.73	.40	0.29

Table 4. 2 Mechanical Properties

Roll Size	Material Grade	Required Hardness	Actual Hardness
850*1200	GCI	50-55 SH C	52/53 C

The machine tests were conducted under the following circumstances, which are briefly described. As a result, a variety of spindle speeds, feed rates, and depths of cut have been taken across a larger range in order to better understand how these factors affect the efficacy of the dry machining process.

The following are the circumstances under which the experiment was conducted:

Type of Lathe Machine : ‗WaldrichSeizen' CNC Lathe Machine (Germany), 90Kw

Work materials : Cast iron roll (50-55SH C)

Size : Outer Dia 850mm, and length 1200mm

Cutting tool insert : Tungsten Coated Carbide, RCMX-25 Process parameters:

Spindle speed, (S) : 10, 14, and 18 rpm

Feed rate, (f) : 1.2, 1.4, and 1.6mm/rev

Depth of cut, (d) : 8, 9, and 10mm

Figure 4.1 CNC Turning Machine

Figure 4.2Cutting Tool Insert

Methodology

There are two sections to this project. When turning cast iron roll (55 SH C) material using tungsten carbide inserts, an experiment was conducted to determine the effects of minimal machining time and maximum tool life on the machined item. Work on optimizing cutting parameters when turning cast iron rollers by tungsten carbide insert is a second element of this research.

There would be a technique to this:

i. As part of the design of tests, a stopwatch has been used to track the machining time in turns of minutes.
ii. A mathematical algorithm has been used to monitor the tool life, which is measured in minutes, as shown in table 4.
iii. Genetic Algorithm was used to optimise cutting settings (GA). Experimentation with cast iron rollers yielded the data needed for this study. Cutting parameters were analyzed in order for the process of optimization to find the most efficient and effective method of machining. There are statistical models that may be used to determine the problem's objective function and its restrictions.
iv. It has been shown that tungsten carbide (TNMG) inserts may be used to turn cast iron rollers.

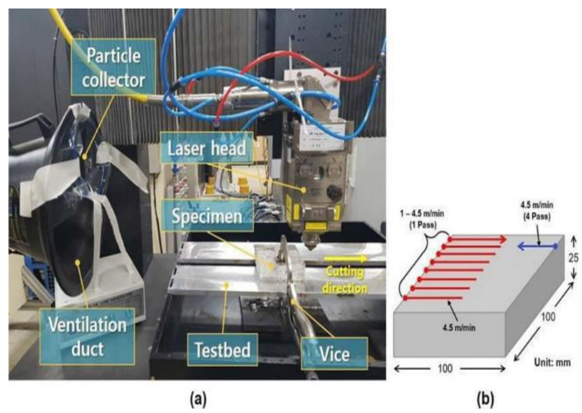

Figure 4.3 Experimental Setup

Design of Experiments

Table 3 shows the three criteria at three levels that were selected in this procedure. A conventional orthogonal L9 fractional factorial array is employed. This orthogonal array has been selected because it may be used to examine the interactions between variables. A trail is shown in each row of the matrix. When conducting a design of experiments (DOE) experiment, the first step is to identify the process factors that have the greatest impact on the final product. Some studies only employ one or two parts of this usual approach, such as screening and characterization; others use all three. The estimation of the influence of a component is unaffected by the other variables that are considered in orthogonal designs, which makes them especially valuable. In factorial designs, all potential levels of all elements may be studied concurrently. A huge number of variables may be examined concurrently, which saves time and money.

Table 3. Cutting Parameters and Levels

Levels	Spindle speed S in rpm	Feed rate fin nun/rev	Depth of cut d in mm
1.00	13.00	1.20	8.00
2.00	15.00	1.40	9.00
3.00	17.00	1.60	10.00

Experiments Conducted

Table 4. Experiments Conducted

S. No	Spindle speed S in rpm X1	Feed Rate fin =free X2	Depth of cut d in mm X3	Machining Time Mt (minutes)	Tool Life T1=1/(S*f) (Minutes)
1	11	1.21	8.1	85.50	100.00
2	11	1.43	9.2	65.00	85.71
3	11	1.61	10.2	41.00	75.00
4	15	1.27	9.3	77.60	71.42
5	15	1.46	10.1	55.70	61.22
6	15	1.64	8.8	70.30	53.57
7	19	1.23	10.1	60.80	55.55
8	19	1.42	8.2	80.40	47.61
9	19	l.62	9.4	53.20	41.66

Genetic Algorithm: Steps Involved

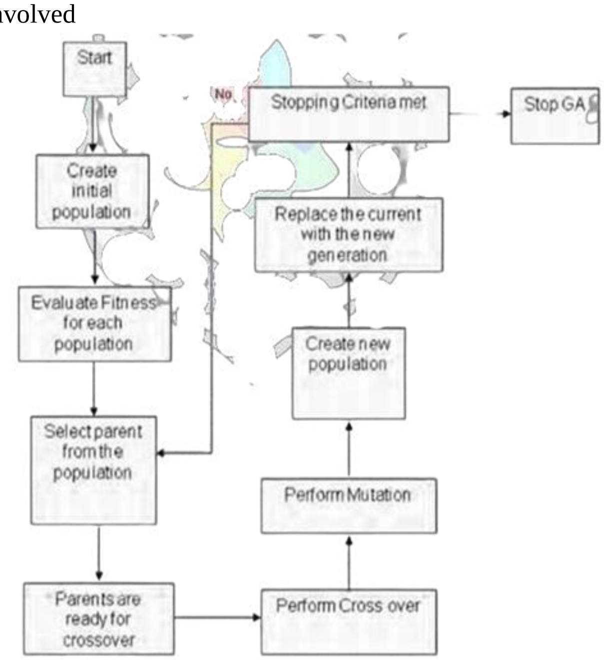

Figure 4 Outline of Genetic Algorithm.

Step 1: Regression analysis in Excel Adv. software is used to generate the objective function equations. Mt vs x1, x2, and x3 in a regression analysis.
Analysis of Variance for Machining Time

Regression Statistics	
Multiple R	0.957331608
R Square	0.916483808
Adjusted R Square	0.866374093
Standard Error	5.259959099
Observations	9

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	1518.059707	506.019902	18.28954344	0.003981817
Residual	5	138.3358486	27.6671697		
Total	8	1656.395556			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	244.6290378	25.77693924	9.49022828	0.000219581
Spindle speed S in rpm X1	0.259934098	0.53722715	0.48384394	0.648943198
Feed Rate f in =free X2	-37.69933781	11.2596166	-3.34819019	0.020369106
Depth of cut d in mm X3	-13.92215802	2.403302389	-5.79292813	0.002159096

As shown in the following equation, Machining Time may be calculated. Minimize Mt = 244.62 +0.259*x_1-37.69*x_2-19.92*x_3.
Where,
Mt = Machining Time x_1 = Spindle Speed x_2 = Feed Rate
x_3 = Depth of Cut
Regression Analysis: Tl versus x_1, x_2, x_3.
Analysis of Variance for Tool Life

Regression Statistics	
Multiple R	0.992378
R Square	0.984815
Adjusted R Square	0.975704
Standard Error	2.954035
Observations	9

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2829.704	943.2347	108.0908	5.76E-05
Residual	5	43.6316	8.72632		
Total	8	2873.336			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	222.8339	14.47653	15.39276	2.1E-05
Spindle speed S in rpm X1	-4.77821	0.301711	-15.837	1.83E-05
Feed Rate f in =free X2	-48.5987	6.323489	-7.68542	0.000595
Depth of cut d in mm X3	-1.70466	1.349714	-1.26298	0.26229

As shown in the following equation, Tools Life may be calculated. Minimize Ts= 222.83 -4.477*x_1-48.59*x_2-1.70*x_3. Where,

Mt = Machining Time x1 = Spindle Speed x2 = Feed Rate

x3 = Depth of Cut

Regression Analysis: Tl versus x1, x2, x3.

Step 2: then MATLAB-R2013a is used to carry out the optimization.

Step 3: The optimization process can only be carried out by a computer program that adheres to objective functions and restrictions. The program's structure is outlined below.

```
%UNTITLED summery of this function goes here
% It is a multi objective function i.e. more than 1 functio
% y(1)....objective 1....@equation for Mt minimize
% y(2)....objective 2....@equation for T1 maximize

% x(1)....spindle speed
% x(2)....feed rate
% x(3)....doc
```

Y1: Minimize Mt = 244.62 +0.259*x1-37.69*x2-19.92*x3. Y2: Minimize Ts= 222.83 -4.477*x1-48.59*x2-1.70*x3.

CONCLUSION

There are many ways in which steel rolling mills might differ from one another. With the ability to roll steel in either hot or cold conditions, the mill can produce steel with a wide range of cross- sections, diameters, and grades. Roll supports, which are found in every rolling mill, are responsible for holding the rollers that are used to roll the materials. These rollers may shatter because of heavy cyclic loads or fractures in the rollers' rolling sections. A damaged roller is either replaced with new rollers or with the old rollers that were already in place after all the appropriate machining operations have been completed. CNC machines are used to create finished rolls from a cylindrical form, as well as to repair existing rolls. These rolls are made by a combination of straight turning, taper turning, and circular machining techniques. In this thesis, the machining parameters for turning rolls include the spindle speed, feed rate, and cut depth, among others. The machining time (Mt) and the tool life (L) are the desired functions (Tl). The goal of this study was to use a regression along with GA to optimize turning parameters in order to achieve the lowest feasible machining time and the longest possible tool life (GA). Using regression design of experiment technique and regression analysis (in EXCEL), it was possible to spin cast iron rollers with tungsten-coated carbide inserts. With the use of an L9 orthogonal array design, three process parameters were investigated for their effects on machine time and tool life. The factors investigated were spindle speed, feed rate, and depth of cut. Regression analysis has been used to develop mathematical models for everyone ‘s behavior to the situation.

REFERENCE

[1] Thirumalai, R., Seenivasan, M., &Panneerselvam, K. (2021). Experimental investigation and multi response optimization of turning process parameters for Inconel 718 using TOPSIS approach. *Materials Today: Proceedings*, *45*, 467-472.

[2] Garmejani, H. A., &Hossainpour, S. (2021). Single and multi-objective optimization of a TEG system for optimum power, cost and second law efficiency using genetic algorithm. *Energy Conversion and Management*, *228*, 113658.

[3] Nili-Ahmadabadi, M., Aghabozorgi, F., Cho, D. S., & Kim, K. C. (2021). Development and validation of a hybrid aerodynamic design method for curved diffusers using genetic algorithm and ball-spine inverse design method. *Alexandria Engineering Journal*, *60*(3), 3021-3036.

[4] Vijayanand, M., Varahamoorthi, R., Kumaradhas, P., Sivamani, S., & Kulkarni, M. V. (2021). Regression-BPNN modelling of surfactant concentration effects in electroless NiB coating and optimization using genetic algorithm. *Surface and Coatings Technology*, *409*, 126878.

[5] Park, H., Son, D., Koo, B., &Jeong, B. (2021). Waiting strategy for the vehicle routing problem with simultaneous pickup and delivery using genetic algorithm. *Expert Systems with Applications*, *165*, 113959.

[6] Ciğeroğlu, Z., Küçükyıldız, G., Erim, B., & Alp, E. (2021). Easy preparation of magnetic nanoparticles-rGO-chitosan composite beads: Optimization study on cefixime removal based on RSM and ANN by using Genetic Algorithm Approach. *Journal of Molecular Structure*, *1224*, 129182.

[7] Usha, M., & Rao, G. S. (2020). Optimization of Multiple Objectives by Genetic Algorithm for Turning of AISI 1040 Steel Using Al2O3 Nano Fluid with MQL. *Tribology in industry*, *42*(1).

[8] Alexandrino, P. D. S. L., Gomes, G. F., & Cunha Jr, S. S. (2020). A robust optimization for damage detection using multiobjective genetic algorithm, neural network and fuzzy decision making. *Inverse Problems in Science and Engineering*, *28*(1), 21-46.

[9] Zolpakar, N. A., Lodhi, S. S., Pathak, S., & Sharma, M. A. (2020). Application of multi-objective genetic algorithm (MOGA) optimization in machining processes. In *Optimization of Manufacturing Processes* (pp. 185-199). Springer, Cham.

[10] Sin, I. H., & Do Chung, B. (2020). Bi-objective optimization approach for energy aware scheduling considering electricity cost and preventive maintenance using genetic algorithm. Journal of Cleaner Production, 244, 118869.

[11] Jiang, Y., Wu, P., Zeng, J., Zhang, Y., Zhang, Y., & Wang, S. (2020). Multi-parameter and multi-objective optimisation of articulated monorail vehicle system dynamics using genetic algorithm. Vehicle System Dynamics, 58(1), 74-91.

[12] Mosayebi, M., & Sodhi, M. (2020, July). Tuning genetic algorithm parameters using design of experiments. In Proceedings of the 2020 Genetic and Evolutionary Computation Conference Companion (pp. 1937-1944).

[13] Solarte-Pardo, B., Hidalgo, D., & Yeh, S. S. (2019). Cutting insert and parameter optimization for turning based on artificial neural networks and a genetic algorithm. Applied Sciences, 9(3), 479.

[14] Lambora, A., Gupta, K., & Chopra, K. (2019, February). Genetic algorithm-A literature review. In 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon) (pp. 380-384). IEEE.

[15] Rana, P. B., Patel, J. L., &Lalwani, D. I. (2019). Parametric optimization of turning process using evolutionary optimization techniques—a review (2000–2016). Soft Computing for Problem Solving, 165-180.

[16] Rekha, P. M., &Dakshayini, M. (2019). Efficient task allocation approach using genetic algorithm for cloud environment. Cluster Computing, 22(4), 1241-1251.

[17] Damanik, I. S., Windarto, A. P., Wanto, A., Andani, S. R., &Saputra, W. (2019, August). Decision tree optimization in C4. 5 algorithm using genetic algorithm. In Journal of Physics:

Conference Series (Vol. 1255, No. 1, p. 012012). IOP Publishing.

[18] Hazir, E., &Ozcan, T. (2019). Response surface methodology integrated with desirability function and genetic algorithm approach for the optimization of CNC machining parameters. Arabian Journal for Science and Engineering, 44(3), 2795-2809.

[19] Narayanan, N. S., Baskar, N., & Ganesan, M. (2018). Multi objective optimization of machining parameters for hard turning OHNS/AISI H13 material, using genetic algorithm. Materials Today: Proceedings, 5(2), 6897-6905.

[20] Starke, A. R., Cardemil, J. M., Escobar, R., & Colle, S. (2018). Multi-objective optimization of hybrid CSP+ PV system using genetic algorithm. Energy, 147, 490-503.

[21] Li, Z., Pourmehrab, M., Elefteriadou, L., &Ranka, S. (2018). Intersection control optimization for automated vehicles using genetic algorithm. Journal of Transportation Engineering, Part A: Systems, 144(12), 04018074.

[22] Pirmohammad, S., &Marzdashti, S. E. (2018). Crashworthiness optimization of combined straight-tapered tubes using genetic algorithm and neural networks. Thin-Walled Structures, 127, 318-332.

[23] Millo, F., Arya, P., &Mallamo, F. (2018). Optimization of automotive diesel engine calibration using genetic algorithm techniques. Energy, 158, 807-819.

[24] Abdelsalam, A. M., & El-Shorbagy, M. A. (2018). Optimization of wind turbines siting in a wind farm using genetic algorithm based local search. Renewable energy, 123, 748-755.

[25] Kalita, K., Shivakoti, I., &Ghadai, R. K. (2017). Optimizing process parameters for laser beam micro-marking using genetic algorithm and particle swarm optimization. Materials and Manufacturing Processes, 32(10), 1101-1108.

[26] Bozorg-Haddad, O., Soleimani, S., &Loáiciga, H. A. (2017). Modeling water-quality parameters using genetic algorithm– least squares support vector regression and genetic programming. Journal of Environmental Engineering, 143(7), 04017021.

[27] Wang, S., Jian, G., Xiao, J., Wen, J., & Zhang, Z. (2017). Optimization investigation on configuration parameters of spiral-wound heat exchanger using Genetic Aggregation response surface and Multi-Objective Genetic Algorithm. Applied Thermal Engineering, 119, 603-609.

[28] Hassoon, M., Kouhi, M. S., Zomorodi-Moghadam, M., &Abdar, M. (2017, September). Rule optimization of boosted c5. 0 classification using genetic algorithm for liver disease prediction. In 2017 international conference on computer and applications (icca) (pp. 299- 305). IEEE.

[29] Sangwan, K. S., & Kant, G. (2017). Optimization of machining parameters for improving energy efficiency using integrated response surface methodology and genetic algorithm approach. Procedia CIRP, 61, 517-522.

[30] Bai, J., Li, Y., &Zuo, W. (2017). Cross-sectional shape optimisation for thin-walled beam crashworthiness with stamping constraints using genetic algorithm. International Journal of Vehicle Design, 73(1-3), 76-95.

[31] Sahali, M. A., Belaidi, I., & Serra, R. (2016). New approach for robust multi-objective optimization of turning parameters using probabilistic genetic algorithm. The International Journal of Advanced Manufacturing Technology, 83(5-8), 1265-1279.

[32] Jin, Y. F., Yin, Z. Y., Shen, S. L., &Hicher, P. Y. (2016). Selection of sand models and identification of parameters using an enhanced genetic algorithm. International Journal for Numerical and Analytical Methods in Geomechanics, 40(8), 1219-1240.

[33] Pashazadeh, H., Gheisari, Y., &Hamedi, M. (2016). Statistical modeling and optimization of resistance spot welding process parameters using neural networks and multi-objective genetic algorithm. Journal of Intelligent Manufacturing, 27(3), 549-559.

[34] Sathish, K., Ramakrishnan, T., &Sathishkumar, S. (2016). Optimization of turning parameters to improve surface finish of 16 Mn Cr 5 material. Advances in Natural and

Applied Sciences, 10(6 SE), 151-157.

[35] Shankar, K., & Eswaran, P. (2016). An efficient image encryption technique based on optimized key generation in ECC using genetic algorithm. In Artificial intelligence and evolutionary computations in engineering systems (pp. 705-714). Springer, New Delhi.

[36] Tan, M. K., Chuo, H. S. E., Chin, R. K. Y., Yeo, K. B., & Teo, K. T. K. (2016, October).

[37] Optimization of urban traffic network signalization using genetic algorithm. In 2016 IEEE Conference on Open Systems (ICOS) (pp. 87-92). IEEE.

[38] Gupta, A. K., Guntuku, S. C., Desu, R. K., &Balu, A. (2015). Optimisation of turning parameters by integrating genetic algorithm with support vector regression and artificial neural networks. The International Journal of Advanced Manufacturing Technology , 77(1-4), 331-339.

[39] Dhabale, R., &Jatti, V. S. (2015). Optimization of material removal rate of AlMg1SiCu in turning operation using genetic algorithm. WSEAS Transactions on Applied and theoretical mechanics, 10, 95-101.

[40] Santos, M. C., Machado, A. R., Barrozo, M. A. S., Jackson, M. J., &Ezugwu, E. O. (2015). Multi-objective optimization of cutting conditions when turning aluminum alloys (1350-O and 7075-T6 grades) using genetic algorithm. The International Journal of Advanced Manufacturing Technology, 76(5), 1123-1138.

[41] Altug, M., Erdem, M., &Ozay, C. (2015). Exper imental investigation of kerf of Ti6Al4V exposed to different heat treatment processes in WEDM and optimization of parameters using genetic algorithm. The International Journal of Advanced Manufacturing Technology, 78(9-12), 1573-1583.

[42] Su, Y., Chu, X., Zhang, Z., & Chen, D. (2015). Process planning optimization on turning machine tool using a hybrid genetic algorithm with local search approach. Advances in Mechanical Engineering, 7(4), 1687814015581241.

[43] Kant, G., & Sangwan, K. S. (2015). Predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm. Procedia Cirp, 31, 453-458.

[44] Afiatdoust, F., &Esmaeilbeigi, M. (2015). Optimal variable shape parameters using genetic algorithm for radial basis function approximation. Ain Shams Engineering Journal, 6(2), 639-647.

[45] Dhabale, R., Jatti, V. S., & Singh, T. P. (2014). Multi-objective optimization of turning process during machining of AlMg1SiCu using non-dominated sorted genetic algorithm. Procedia materials science, 6, 961-966.

[46] Zhang, L., Wang, L., Hinds, G., Lyu, C., Zheng, J., & Li, J. (2014). Multi-objective optimization of lithium-ion battery model using genetic algorithm approach. Journal of Power Sources, 270, 367-378.

[47] Batish, A., Bhattacharya, A., Kaur, M., & Cheema, M. S. (2014). Hard turning: Parametric optimization using genetic algorithm for rough/finish machining and study of surface morphology. Journal of Mechanical Science and Technology, 28(5), 1629-1640.

[48] Hussain, S. A., Pandurangadu, V., & Kumar, K. P. (2014). Optimization of surface roughness in turning of GFRP composites using genetic algorithm. International Journal of Engineering, Science and Technology, 6(1), 49-57.

[49] Cheung, B. C., Carriveau, R., & Ting, D. S. (2014). Multi-objective optimization of an underwater compressed air energy storage system using genetic algorithm. Energy, 74, 396- 404.

[50] Asadi, E., da Silva, M. G., Antunes, C. H., Dias, L., & Glicksman, L. (2014). Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application. Energy and Buildings, 81, 444-456.

[51] Alrashdan, A., Bataineh, O., &Shbool, M. (2014). Multi-criteria end milling parameters optimization of AISI D2 steel using genetic algorithm. The International Journal of Advanced Manufacturing Technology, 73(5-8), 1201-1212.