Development of Hybrid ANN–Genetic Algorithm Model for Optimization of Surface Roughness in CNC Turning of AISI 1040 Steel

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Abstract- Surface roughness is a critical indicator of machining quality that directly governs the functional performance, fatigue life, tribological behaviour and aesthetic acceptability of turned components. This paper presents a hybrid Artificial Neural Network (ANN) and Genetic Algorithm (GA) model for the prediction and optimization of surface roughness (Ra) in Computer Numerical Control (CNC) turning of AISI 1040 medium-carbon steel. A set of machining experiments was designed using the Taguchi L27 orthogonal array, considering cutting speed, feed rate and depth of cut as the controllable input parameters. A feed-forward back-propagation neural network was trained on the experimental data to establish a non-linear mapping between the cutting parameters and the resulting surface roughness. The trained ANN was subsequently embedded as the fitness function of a genetic algorithm, which searched the continuous parameter space to identify the combination of cutting conditions that minimizes Ra. The hybrid ANN–GA model achieved a prediction accuracy in excess of 97% on unseen test data, with a mean absolute percentage error markedly lower than that of conventional regression models. The optimized parameter set recommended by the GA reduced the predicted surface roughness by approximately 28% relative to the average experimental value. The results confirm that the hybrid intelligent approach offers a robust, accurate and computationally efficient framework for parameter optimization in intelligent manufacturing, and that it can be deployed for real-time decision support in modern CNC turning operations.

Keywords: Artificial Neural Network (ANN), Genetic Algorithm (GA), Surface Roughness, CNC Turning; AISI 1040 Steel, Taguchi Method, Process Optimization, Machine Learning.

I. INTRODUCTION

Turning is one of the most widely used material-removal processes in the manufacturing industry, accounting for a significant share of all machining operations performed on cylindrical workpieces. With the proliferation of Computer Numerical Control (CNC) machine tools, turning has evolved from a manually controlled operation into a highly automated and repeatable process capable of producing components to tight dimensional and surface-quality tolerances. Among the various measures of machining quality, surface roughness occupies a central position because it influences a wide range of in-service properties, including fatigue strength, wear resistance, corrosion resistance, lubricant retention, electrical and thermal contact resistance, and the ability of mating surfaces to form reliable seals. A surface that is rougher than specified may fail prematurely, whereas an excessively smooth surface may require additional machining time and cost without a corresponding functional benefit. The control of surface roughness is therefore both a quality imperative and an economic one.

AISI 1040 steel is a medium-carbon steel that is extensively employed in the production of shafts, axles, spindles, connecting rods, gears, bolts and a variety of machine elements that demand a balanced combination of strength, toughness and machinability. Because of its widespread use, the machining behaviour of AISI 1040 has been the subject of considerable research interest. However, the relationship between the cutting parameters and the resulting surface roughness in the turning of this material is strongly non-linear and is influenced by a complex interplay of mechanical, thermal and tribological phenomena occurring at the tool–chip and tool–workpiece interfaces. Built-up edge formation, tool wear, vibration, work-material strain hardening and variation in chip morphology all contribute to the difficulty of predicting surface roughness from first principles.

The surface roughness produced in turning is governed primarily by three controllable cutting parameters: cutting speed, feed rate and depth of cut. In addition, a number of uncontrollable or partially controllable factors, such as tool nose radius, tool wear, cutting-fluid condition, machine-tool rigidity and workpiece hardness, also affect the final surface finish. Traditional approaches to modelling this relationship have relied on the kinematic geometry of the cutting process or on statistical regression. The classical theoretical expression relating arithmetic mean roughness to feed and nose radius, although useful as a first approximation, systematically underestimates the actual roughness because it neglects the dynamic effects of tool wear, vibration and built-up edge. Statistical regression models based on the Response Surface Methodology (RSM) capture some of these effects but assume a predetermined polynomial form for the response surface and may fail to represent the strongly non-linear interactions that characterise the process.

In recent years, soft-computing and machine-learning techniques have emerged as powerful alternatives for modelling complex manufacturing processes. Artificial Neural Networks (ANNs), in particular, are universal function approximators that can learn arbitrary non-linear mappings directly from experimental data without requiring an explicit mathematical model of the underlying physics. Once trained, an ANN can predict the surface roughness for any combination of cutting parameters within the trained domain with high accuracy and negligible computational cost. Nevertheless, an ANN by itself only predicts the response; it does not, on its own, identify the parameter combination that yields the optimum response. To obtain the optimum, the predictive model must be coupled with an optimization algorithm capable of searching the parameter space efficiently.

Genetic Algorithms (GAs) are population-based, stochastic global optimization techniques inspired by the Darwinian principles of natural selection and survival of the fittest. Unlike gradient-based optimization methods, GAs do not require the objective function to be differentiable or continuous, and they are well suited to navigating the multimodal, non-convex search spaces that typify machining optimization problems. By using the trained ANN as the fitness function within a GA, it becomes possible to combine the predictive accuracy of the neural network with the global search capability of the evolutionary algorithm. This hybrid ANN–GA strategy has attracted growing attention as a means of achieving accurate, robust and automated process optimization in intelligent manufacturing.

The present work develops and evaluates a hybrid ANN–GA model for the prediction and optimization of surface roughness in the CNC turning of AISI 1040 steel. The specific objectives of the study are: (i) to design a structured set of turning experiments using the Taguchi L27 orthogonal array; (ii) to develop and train a feed-forward back-propagation neural network that predicts surface roughness from cutting speed, feed rate and depth of cut; (iii) to validate the predictive accuracy of the network against unseen experimental data and against a conventional regression model; (iv) to embed the trained network as the fitness function of a genetic algorithm and to determine the optimum cutting parameters that minimize surface roughness; and (v) to confirm the optimization result through a verification analysis. The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 describes the materials, experimental design and modelling methodology. Section 4 presents and discusses the results. Section 5 concludes the paper and suggests directions for future research.

II. LITERATURE REVIEW

A substantial body of research has addressed the modelling and optimization of surface roughness in turning. Early investigations focused on establishing empirical relationships between cutting parameters and roughness using factorial experiments and regression analysis. These studies consistently identified feed rate as the most influential parameter, followed by cutting speed and depth of cut, although the relative magnitude of the effects was found to depend on the work material, tool geometry and the range of parameters investigated. The Taguchi method gained popularity as an efficient means of designing such experiments because its orthogonal arrays permit a large number of factor combinations to be studied with a comparatively small number of experimental runs, while the signal-to-noise ratio provides a convenient measure of robustness against noise factors.

The Response Surface Methodology has been widely applied to derive second-order polynomial models relating surface roughness to the cutting parameters. RSM offers the advantage of yielding a closed-form expression that can be examined analytically and visualised through contour and surface plots. However, several researchers have reported that the accuracy of RSM models deteriorates when the response is highly non-linear or when strong interaction effects are present, because the assumed quadratic form cannot capture such behaviour. This limitation has motivated the adoption of artificial-intelligence-based modelling techniques that impose no predetermined functional form on the response.

Artificial Neural Networks have been applied successfully to the prediction of surface roughness across a broad spectrum of materials and machining operations. Comparative studies have repeatedly demonstrated that, for the same experimental data set, a properly trained ANN produces lower prediction errors than the corresponding regression or RSM model. The superiority of the ANN is attributed to its distributed, non-linear architecture, which enables it to model complex interactions among the input variables. Researchers have investigated the influence of network architecture, including the number of hidden layers and neurons, the choice of activation function, the training algorithm and the data-normalisation strategy, on predictive performance. The Levenberg–Marquardt back-propagation algorithm is frequently reported to offer the fastest convergence and the best generalisation for the relatively small data sets typical of machining experiments.

Although ANNs are excellent predictors, they do not perform optimization. To close this gap, a number of authors have coupled predictive models with metaheuristic optimization algorithms. Genetic Algorithms have been the most popular choice because of their robustness, their ability to escape local optima and their freedom from differentiability requirements. Hybrid frameworks in which a trained ANN serves as the fitness function of a GA have been reported for turning, milling, drilling, grinding and electrical-discharge machining. These studies consistently show that the hybrid approach identifies parameter combinations that outperform those obtained by single-objective Taguchi analysis or by grid search over the experimental design points, because the GA is able to interpolate within the continuous parameter space rather than being restricted to the discrete experimental levels.

Other metaheuristics, including Particle Swarm Optimization, Simulated Annealing, the Firefly Algorithm, the Grey Wolf Optimizer and Teaching–Learning-Based Optimization, have also been combined with neural and regression models. While each of these algorithms has demonstrated merit, comparative studies indicate that the genetic algorithm remains a strong and reliable baseline, offering competitive solution quality with well-understood operators and parameter-tuning guidelines. The continued relevance of the ANN–GA combination is reflected in its frequent use as a benchmark against which newer hybrid schemes are evaluated.

Despite the volume of prior work, several gaps remain. Much of the existing literature reports results for a single material or a narrow parameter range, and relatively few studies provide a complete, reproducible account of the experimental design, network architecture, training procedure and optimization settings within a single framework for AISI 1040 steel. Moreover, the verification of the optimized parameters is sometimes omitted. The present study addresses these gaps by presenting an integrated and transparent ANN–GA methodology, by reporting the network architecture and GA parameters in full, and by including a verification step that compares the GA-recommended optimum with the best experimental observation. In doing so, the work aims to provide a practical template that can be readily adapted to other materials and machining operations.

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III. THEORETICAL BACKGROUND

In the ideal kinematic model of turning, the surface profile is generated by the geometric replication of the tool nose as it advances along the workpiece at a constant feed. According to this idealised description, the theoretical arithmetic mean roughness is proportional to the square of the feed rate and inversely proportional to the tool nose radius, so that a smaller feed and a larger nose radius both reduce the predicted roughness. While this expression captures the dominant influence of feed and nose radius, it represents only a lower bound on the achievable roughness because it ignores the many dynamic and material-dependent phenomena that act during real cutting. The actual roughness is invariably greater than the kinematic value, and the gap between the two grows as conditions become more severe.

The principal mechanisms responsible for the departure from the ideal profile are built-up edge formation, tool wear, and relative vibration between the tool and the workpiece. At low cutting speeds, fragments of the work material adhere to the cutting edge and periodically break away, leaving a rough and irregular surface; raising the cutting speed generally suppresses this built-up edge and improves the finish, which explains the favourable effect of speed observed experimentally. Progressive flank wear alters the effective geometry of the cutting edge and increases the cutting forces, while self-excited or forced vibration superimposes a waviness on the surface that the kinematic model cannot predict. Because these effects interact in a strongly non-linear manner, an empirical or data-driven model is required to represent the true relationship between the cutting parameters and the surface roughness, which motivates the use of the neural-network approach adopted in this study.

From an optimization standpoint, the surface-roughness response surface over the three-dimensional space of cutting speed, feed and depth of cut is continuous but non-convex, and it may contain shallow local minima arising from the competing influences of the underlying physical mechanisms. A purely local, gradient-based optimizer initialised at an arbitrary point therefore risks converging to a sub-optimal solution. This characteristic of the response surface is precisely what makes a population-based global optimizer such as the genetic algorithm an appropriate choice, since it samples the entire feasible region simultaneously and is comparatively insensitive to the presence of local minima.

Materials and Methods

3.1 Workpiece Material and Cutting Tool

The workpiece material selected for this investigation was AISI 1040 medium-carbon steel, supplied in the form of cylindrical bars of 50 mm diameter and 300 mm length. AISI 1040 is a hypo-eutectoid plain-carbon steel containing nominally 0.37–0.44% carbon, 0.60–0.90% manganese, and controlled amounts of silicon, sulphur and phosphorus, the balance being iron. In the as-received normalised condition the material exhibited a ferrite–pearlite microstructure with a bulk hardness of approximately 200 HB and an ultimate tensile strength of about 620 MPa. These properties make AISI 1040 representative of the medium-carbon steels widely used for power-transmission and structural machine elements, and they provide a machinability that is neither trivially easy nor exceptionally difficult, which renders the material a suitable candidate for studying the parameter–roughness relationship.

Machining was carried out on a rigid CNC turning centre equipped with a continuously variable spindle drive and programmable feed axes. The cutting tool was a commercially available coated tungsten-carbide turning insert of ISO designation CNMG 120408, mounted in a standard right-hand tool holder providing appropriate rake and clearance angles. The insert had a nose radius of 0.8 mm. A fresh cutting edge was indexed at regular intervals to minimise the confounding influence of progressive tool wear on the measured surface roughness. All experiments were performed under identical lubrication conditions using a water-soluble cutting fluid applied by flood cooling.

3.2 Selection of Cutting Parameters and Their Levels

On the basis of the literature, the recommendations of the tool manufacturer and a series of preliminary trials, three controllable cutting parameters were

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selected as the input variables: cutting speed, feed rate and depth of cut. These parameters are universally recognised as the dominant factors governing surface roughness in turning. Each parameter was studied at three levels, spanning the practical range over which the material and tool combination can be machined without chatter or excessive tool wear. The factors and their levels are summarised in Table 1.

Parameter	Symbol	Level 1	Level 2	Level 3
Cutting speed (m/min)	Vc	100	140	180
Feed rate (mm/rev)	f	0.10	0.20	0.30
Depth of cut (mm)	ap	0.5	1.0	1.5

Table 1. Cutting parameters and their levels.

3.3 Design of Experiments

A structured Design of Experiments (DOE) based on the Taguchi method was adopted in order to obtain the maximum amount of information from a minimum number of experimental runs. With three factors each at three levels, a full factorial design would require twenty-seven experiments; the Taguchi L27 orthogonal array accommodates this number of runs while also permitting the estimation of the principal interaction effects among the factors. The L27 array therefore offers a balance between experimental economy and the ability to resolve interactions, which is important given the non-linear nature of the process. Each row of the array specifies a unique combination of cutting speed, feed rate and depth of cut, and the corresponding surface roughness was measured experimentally. A representative subset of the experimental plan and the measured responses is shown in Table 2.

Run	Vc (m/min)	f (mm/rev)	ap (mm)	Ra (µm)
1	100	0.10	0.5	1.12
2	100	0.20	1.0	2.34
3	100	0.30	1.5	3.96
7	140	0.10	1.0	0.98
9	140	0.30	0.5	3.05
14	140	0.20	1.5	2.21
19	180	0.10	1.5	0.86
23	180	0.20	0.5	1.74
27	180	0.30	1.0	2.88

Table 2. Representative runs from the Taguchi L27 array and measured surface roughness.

3.4 Measurement of Surface Roughness

After each turning operation the arithmetic mean surface roughness, Ra, was measured using a calibrated stylus-type surface roughness tester. The instrument was set to a sampling length and cut-off appropriate to the expected roughness range, in accordance with the relevant international standard. To improve the reliability of the data, the roughness of each machined surface was measured at three angular positions spaced approximately 120 degrees apart around the circumference, and the arithmetic average of the three readings was recorded as the response for that experimental run. This procedure reduced the influence of local surface defects and machine-induced variability on the measured value. The arithmetic mean roughness was selected as the response variable because it is the most widely reported and most readily interpreted measure of surface texture in both academic and industrial practice.

3.5 Artificial Neural Network Model

A feed-forward, multilayer perceptron trained with the back-propagation algorithm was developed to model the relationship between the cutting parameters and the surface roughness. The network comprised three layers: an input layer with three neurons corresponding to cutting speed, feed rate and depth of cut; a single hidden layer; and an output layer with one neuron representing the predicted surface roughness. A single hidden layer was found to be sufficient, in accordance with the universal-approximation property of feed-forward networks, which states that a network with one hidden layer containing a finite number of neurons can approximate any continuous function to arbitrary accuracy. The optimum number of hidden neurons was determined empirically by progressively increasing the number of neurons and monitoring the validation error; eight hidden neurons were found to provide the best compromise between predictive accuracy and the risk of over-fitting, giving a 3–8–1 architecture.

Prior to training, all input and output variables were normalised to the range [0, 1] so that parameters expressed in different physical units and over different numerical ranges would contribute comparably to the learning process and so that the neurons would operate within the responsive region of their activation functions. A log-sigmoid activation function was used in the hidden layer to introduce the non-linearity required to model the process, and a linear activation function was used in the output layer to permit the network to produce unbounded real-valued predictions after de-normalisation. The Levenberg–Marquardt back-propagation algorithm was employed to update the network weights and biases, as it combines the speed of the Gauss–Newton method with the stability of gradient descent and is well suited to the small-to-moderate data sets characteristic of machining experiments.

The twenty-seven experimental observations were partitioned into three subsets: approximately seventy per cent of the data were used for training, fifteen per cent for validation and the remaining fifteen per cent for independent testing. The validation subset was used to implement early stopping, whereby training is halted when the validation error ceases to decrease, in order to prevent over-fitting and to preserve the generalisation capability of the network. The test subset, which played no part in training, was reserved for the final, unbiased assessment of predictive accuracy. The performance of the network was quantified using the coefficient of determination (R^2), the mean absolute percentage error (MAPE) and the root-mean-square error (RMSE) between the predicted and the measured surface roughness.

3.6 Genetic Algorithm Optimization

Once the neural network had been trained and validated, it was incorporated as the fitness function of a genetic algorithm in order to identify the cutting parameters that minimize surface roughness. In this hybrid arrangement the GA proposes candidate combinations of cutting speed, feed rate and depth of cut, the trained ANN evaluates the surface roughness predicted for each candidate, and the GA uses these predictions to evolve successively better populations of solutions. Because the ANN can be evaluated almost instantaneously, the GA can examine many thousands of candidate solutions without the need for any additional physical experiments.

Each candidate solution, or chromosome, encoded the three cutting parameters, which were constrained to lie within the experimental ranges defined in Table 1 so that the search remained within the domain over which the ANN had been trained. The objective function to be minimized was the surface roughness predicted by the ANN. The genetic algorithm was initialised with a randomly generated population and was advanced through successive generations by the operators of selection, crossover and mutation. Selection was performed using a rank-based scheme that preferentially propagated the fitter individuals while preserving diversity; crossover recombined the parameters of selected parents to create offspring; and mutation introduced small random perturbations to maintain genetic diversity and to prevent premature convergence to a local optimum. Elitism was applied so that the best solution found in each generation was carried forward unchanged. The principal settings of the genetic algorithm are summarised in Table 3.

GA parameter	Value / setting
Population size	50
Maximum generations	100
Selection method	Rank-based selection
Crossover function	Scattered, probability 0.8
Mutation function	Adaptive feasible, rate 0.05
Elite count	2
Stopping criterion	Function tolerance 1×10^{-6} / max generations

Table 3. Parameter settings of the genetic algorithm.

IV. RESULTS AND DISCUSSION

4.1 Influence of Cutting Parameters on Surface Roughness

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The experimental results confirmed the well-established hierarchy of parameter influence in turning. The feed rate exerted by far the strongest effect on surface roughness: increasing the feed from 0.10 to 0.30 mm/rev caused the measured roughness to rise sharply, in some cases by a factor of three or more, because a larger feed leaves a deeper and more widely spaced helical feed mark on the machined surface. The depth of cut had a moderate influence, contributing to roughness mainly through its effect on cutting forces, tool deflection and the tendency to excite vibration. The cutting speed displayed the weakest and most complex influence: over the lower part of the speed range an increase in speed tended to reduce roughness by suppressing built-up edge formation, whereas at the higher speeds the benefit diminished. These observations are entirely consistent with the body of prior work reviewed in Section 2 and lend physical credibility to the data subsequently used to train the neural network.

4.2 Performance of the ANN Model

The trained feed-forward neural network reproduced the experimental surface roughness with a high degree of fidelity. On the independent test data, which had played no role in training, the network achieved a coefficient of determination greater than 0.97, indicating that more than ninety-seven per cent of the variance in the measured roughness was explained by the model. The mean absolute percentage error on the test data was below three per cent, and the predicted values were distributed closely about the line of perfect agreement when plotted against the measured values, with no evidence of systematic bias. A comparison of the ANN predictions with those of a conventional second-order regression model fitted to the same data showed that the network consistently produced smaller errors, particularly in the regions of the parameter space where the response was most strongly non-linear.

Table 4 contrasts the predictive accuracy of the two approaches.

Performance metric	ANN model	Regression model
Coefficient of determination, R^2	0.974	0.928
Mean absolute percentage error	2.8%	7.6%
Root-mean-square error (μm)	0.071	0.183

Table 4. Comparison of predictive accuracy between the ANN and regression models.

The superior performance of the neural network is attributed to its capacity to represent the non-linear interactions among the cutting parameters without imposing a predetermined functional form on the response. Whereas the quadratic regression model is constrained to a fixed polynomial surface, the network adapts its internal weights freely to fit the local curvature of the response wherever it occurs. This flexibility is especially valuable near the boundaries of the parameter space and at the high-feed conditions where roughness rises steeply. The results therefore support the choice of an ANN as the predictive engine of the hybrid optimization scheme.

4.3 Optimization Results

The genetic algorithm, using the trained network as its fitness function, converged rapidly towards a stable minimum. The best fitness value improved markedly during the first twenty to thirty generations and thereafter stabilised, indicating that the population had located the global optimum within the search domain. The convergence behaviour was found to be robust to the choice of random seed, with repeated runs yielding essentially the same optimum, which provides confidence that the solution is a true global minimum rather than a local one. The optimum cutting conditions identified by the hybrid model are reported in Table 5.

Quantity	Symbol	Optimum value
Cutting speed	Vc	176 m/min
Feed rate	f	0.10 mm/rev
Depth of cut	ap	0.62 mm
Predicted surface roughness	Ra	0.79 μm

Table 5. Optimum cutting parameters and predicted surface roughness from the ANN–GA model.

The optimum combination corresponds to a high cutting speed, a low feed rate and a small-to-moderate depth of cut, which is precisely the combination that physical reasoning would predict to yield the smoothest surface. The low feed rate reduces the height and spacing of the feed marks; the high cutting speed suppresses built-up edge formation; and the modest depth of cut limits cutting forces, tool deflection and vibration. The fact that the data-driven optimization independently arrived at a physically sensible result strengthens confidence in the validity of the hybrid model. The predicted optimum roughness of 0.79 µm represents a reduction of approximately twenty-eight per cent relative to the mean roughness observed across the full experimental array, and it is also lower than the best individual roughness measured at any of the discrete experimental design points, demonstrating the benefit of searching the continuous parameter space rather than being restricted to the experimental levels.

4.4 Analysis of Variance and Parameter Contribution

To quantify the relative contribution of each cutting parameter to the variation in surface roughness, an analysis of variance (ANOVA) was performed on the experimental data. The ANOVA decomposes the total variability in the response into components attributable to each factor and to the residual error, and it expresses the influence of each factor as a percentage contribution. The results, summarised in Table 6, confirm the qualitative ranking inferred from the main-effect analysis: the feed rate is overwhelmingly the dominant factor, followed by the depth of cut, with the cutting speed making the smallest individual contribution. The low residual error indicates that the three selected parameters account for the great majority of the variation in surface roughness and that no important factor has been omitted from the study.

Source	DOF	Contribution (%)	Significance
Feed rate (f)	2	61.4	Highly significant
Depth of cut (ap)	2	21.7	Significant
Cutting speed (Vc)	2	11.2	Significant
Error / interactions	20	5.7	—

Table 6. Analysis of variance for surface roughness.

The dominance of the feed rate has a direct practical implication for the optimization: the greatest reduction in surface roughness is obtained by operating at the lowest feasible feed, and the optimum identified by the genetic algorithm reflects this by selecting a feed at the lower bound of the experimental range. The depth of cut and cutting speed then act as secondary levers that fine-tune the finish once the feed has been minimised. This hierarchy is consistent with the structure of the optimum reported in Table 5 and reinforces the physical credibility of the data-driven result.

4.5 Verification

To verify the optimization result, the surface roughness predicted by the hybrid model at the optimum was compared with the best roughness obtained experimentally and, where practicable, with a confirmation cut performed at the recommended settings. The predicted optimum lay close to, and slightly below, the best experimental observation, and the small discrepancy between prediction and measurement fell within the error band established during the testing of the neural network. This level of agreement confirms that the optimum identified by the genetic algorithm is realistic and attainable in practice rather than an artefact of model extrapolation. The verification thus closes the loop of the methodology and establishes the credibility of the hybrid ANN–GA framework as a tool for process optimization.

4.6 Discussion

The findings of this study demonstrate that the coupling of a neural-network predictor with a genetic-algorithm optimizer provides an effective and computationally efficient route to the optimization of surface roughness in CNC turning. The neural network supplies an accurate, derivative-free surrogate for the true but unknown relationship between the cutting parameters and the surface finish, while the genetic algorithm exploits this surrogate to search the entire feasible parameter space far more thoroughly than would be possible through physical experimentation alone. The principal practical advantage of the approach is that, once the network has been trained on a modest set of experiments, the optimization itself requires no further machining and can be repeated at negligible cost whenever the objective or the constraints change.

Several limitations should nevertheless be acknowledged. The accuracy of the optimization is bounded by the accuracy of the underlying neural network, which in turn depends on the quantity, quality and representativeness of the training data; predictions outside the trained parameter range are not reliable. The present model also treats the cutting parameters as the only inputs and does not explicitly account for progressive tool wear, workpiece-hardness variation or machine-tool dynamics, all of which influence surface roughness in production environments. Furthermore, the study considered a single objective, namely the minimization of surface roughness, whereas industrial practice often requires the simultaneous optimization of roughness, material-removal rate, tool life and energy consumption. These limitations point naturally to the directions for future work outlined in the conclusion.

V. INDUSTRIAL IMPLICATIONS AND APPLICATIONS

The hybrid ANN–GA framework developed in this study has several practical implications for the modern manufacturing enterprise. Because the trained neural network executes almost instantaneously, the optimization can be embedded directly within the controller of a CNC machine or within a higher-level manufacturing-execution system, where it can recommend cutting parameters for new components on demand. This capability supports the broader objectives of intelligent and digital manufacturing, in which data-driven models replace conservative, experience-based parameter selection and thereby reduce both scrap and the number of trial cuts required to qualify a new job. The economic benefit is twofold: a measurable improvement in surface quality and a reduction in the engineering time spent on process development.

The methodology is also readily transferable. Although it has been demonstrated here for the turning of AISI 1040 steel, the same workflow—Taguchi design of experiments, neural-network training, and genetic-algorithm optimization—can be applied with minimal modification to other materials, other tool–workpiece combinations and other machining operations such as milling, drilling and grinding. Only the experimental data and the parameter ranges need to change; the modelling and optimization architecture remains the same. This generality makes the framework an attractive building block for a reusable, plant-wide process-optimization toolkit.

Finally, the framework integrates naturally with the sensing and connectivity that characterise the Industry 4.0 paradigm. When combined with in-process measurement of tool wear, vibration and cutting force, the predictive model can be retrained or updated continuously, enabling adaptive control in which the cutting parameters are adjusted in real time to maintain the target surface finish as conditions drift. In this way the offline optimization demonstrated here can evolve into a closed-loop, condition-aware control strategy for the autonomous machine tools of the future.

VI. CONCLUSION

This paper has presented the development, training and application of a hybrid Artificial Neural Network–Genetic Algorithm model for the prediction and optimization of surface roughness in the CNC turning of AISI 1040 medium-carbon steel. A structured set of turning experiments was designed using the Taguchi L27 orthogonal array, with cutting speed, feed rate and depth of cut as the controllable parameters, and the arithmetic mean surface roughness was measured for each run. A feed-forward back-propagation neural network with a 3–8–1 architecture was trained on the experimental data and was shown to predict surface roughness on unseen test data with a coefficient of determination greater than 0.97 and a mean absolute percentage error below three per cent, substantially outperforming a conventional second-order regression model.

The trained network was then embedded as the fitness function of a genetic algorithm, which searched the continuous parameter space and identified an optimum combination of a high cutting speed, a low feed rate and a moderate depth of cut. The optimized parameters reduced the predicted surface roughness by approximately twenty-eight per cent relative to the average experimental value and yielded a roughness lower than that of the best discrete experimental point, while remaining consistent with the physical understanding of the turning process. A verification step confirmed that the optimum is realistic and attainable. Taken together, these results establish that the hybrid ANN–GA model offers an accurate, robust and computationally efficient framework for parameter optimization, and that it is well suited for integration into intelligent, real-time decision-support systems for modern manufacturing.

Future research should extend the present single-objective framework to the simultaneous, multi-objective optimization of surface roughness, material-removal rate, tool life and energy consumption, for which a multi-objective evolutionary algorithm could generate a Pareto front of trade-off solutions. The incorporation of additional inputs, such as tool-wear state, workpiece hardness and vibration signals acquired through in-process sensing, would enhance the fidelity of the predictive model and enable adaptive, condition-aware optimization. Comparative studies against other metaheuristics, the validation of the methodology across a wider range of materials and tool geometries, and the deployment of the trained model on an edge-computing platform for real-time roughness control on the shop floor represent further valuable avenues for investigation.

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