Supervision Controller for Real-time Surface Quality Assurance in CNC Machining using Artificial Intelligence

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Abstract

A major challenge for Computer Numerical Control (CNC) machining is how to manufacture high-quality workpieces effectively. Consequences of poor surface quality incur re-processing and higher wastes generating negative impacts on production costs and profitability. The complex relationships between surface quality and machining parameters could overwhelm machinists' capabilities to correctly select machining parameters to produce satisfied quality of machined workpieces. This paper presents a novel approach of designing an intelligent supervision controller for real-time adjustments on feed rate and spindle speed to achieve desired surface quality of machined workpieces. The controller is an innovative model-based closed-loop system, consisting of a surface roughness prediction model and a multi-variable controller, to ensure real-time improvements on surface quality during machining processes. A case study based on milling processes for BS EN24T steel alloy has been used for testing and validating the approach. Simulation results show that the controller significantly reduced the difference between required and predicted surface roughness from 3.6 μm (based on planned parameters) to 0.12 μm (after the supervision controller adjustments). The results demonstrate that the proposed approach can effectively support high-quality machining processes.

Keywords: CNC machining, Surface roughness, Quality control, Smart manufacturing

1. INTRODUCTION

For Computer Numerical Control (CNC) machining, the surface quality of machined workpieces is an important criterion to evaluate the performance of production processes. Poor surface quality generates high waste and mal-functionality of products, as well as customer dissatisfactions (Benardos & Vosniakos, 2003). Surface quality (measured by the surface roughness) is difficult to be predicted solely based on machinists' experiences, as machining input parameters (*e.g.*, feed rate, spindle speed) generate complex effects on such criterion (Lu, 2008). Consequently, it is challenging to select the correct machining parameters that will precisely meet the technical requirements of machined parts. Nevertheless, majority of the companies have been still using machinists' experiences to control the surface quality of machined parts, which leads to low efficiency in decision making and low surface quality in machining control. Hence, new approaches for surface quality control, which can efficiently guide machining processes to meet the technical requirements of surface quality for machined workpieces, are urgently required.

Nowadays, a number of researchers have conducted investigations on new approaches for CNC machining control in achieving better surface quality of machined workpieces. Some prediction models based on empirical approaches have been developed to analyze the relationships between machining parameters and surface roughness. Empirical findings have been identified for further development of optimized control, and the majority of them have been built based on Artificial Intelligence (AI) algorithms (Acayaba & Escalona, 2015; Aouici et al., 2012; Baek et al., 2001; Benardos & Vosniakos, 2002; Ezugwu et al., 2005; Mia et al., 2018; Pimenov et al., 2017; Svalina et al., 2017). For instance, based on empirical approaches and AI, a prediction model for surface roughness has been developed (Aouici *et al*., 2012). In the research, it is aimed to provide optimized machining conditions of minimizing cutting forces to improve surface roughness. Combined neural-fuzzy approaches have been developed in (Jiao *et al*., 2004) and (Abburi & Dixit, 2006), which have been validated through turning case studies. The authors have stated and justified that the methods are ideally suited for surface roughness prediction owing to open model structures, which can incorporate human expertise and process uncertainties. By using neural networks and the harmony search algorithm, an approach has been presented by defining optimum machining parameters in order to achieve minimum surface roughness (Razfar *et al.*, 2011). A neural networks-based research of predicting surface roughness of machine workpieces in face milling at various cutting speeds, feeds, and depths has been presented in (Saric *et al*., 2013). A genetically optimized neural network system has been proposed for the prediction of constrained optimal machining conditions in minimizing surface roughness (Elhami *et al*., 2013). In summary, the aforementioned approaches can assist engineers in selecting machining parameters to minimize the surface roughness during process planning. On the other hand, research of real-time control still needs further investigation.

To support real-time monitoring during machining execution, an investigation based on digital images for predicting surface roughness has been presented in (Simunovic *et al*., 2016). In the approach, an adaptive neuro-fuzzy inference system has been developed by considering spindle speed, feed per tooth, and cutting depth. Furthermore, this work is presented as an investigative study for developing a real-time monitoring system for machining processes. However, in the research, real-time correction of machining parameters to ensure surface roughness has not been considered yet. An evolutionary neuro-fuzzy system has been proposed in (Svalina *et al*., 2017), through which optimal machining parameters to controlling surface roughness during real-time execution have been identified. In addition, the use of image processing to assess the quality of free-form profiles for quality control after machining processes have been proposed in (Younis, 1998; Pacella *et al*., 2017). Although these reviewed approaches have offered good results for monitoring surface quality, real-time control on surface quality is still required.

Approaches to real-time monitoring and control in CNC machining have become more evident in recent years. Online optimization through adaptive control can provide significant advances in improving manufacturing efficiency, surface quality and tool-life saving (Stavropoulos *et al*., 2013). Furthermore, this work highlights that Adaptive Control (AC) has been introduced as an effective method of optimizing machining parameters online. In recent years, the implementation of fuzzy logic models for predicting and controlling surface roughness has raised as this technique gains popularity from its abilities to model process uncertainties (Kabini, 2011; Kirby & Chen, 2007; Lovato *et al*., 2018; Moreira *et al*., 2017). Moreover, Fuzzy Logic Controllers (FLC) have been increasingly applied owing to its successful capabilities in processing linear and highly non-linear systems (Mudi *et al*., 2013). An FLC uses a flexible set of if-then rules, dealing with process complexity by creating heuristics to be aligned with human knowledge and experiences more closely (Lu, 2008). According to (Bai & Wang, 2006) and (Sugeno, 1985), FLC has been proved to be superior to conventional non-fuzzy controllers. Some key contributions of fuzzy systems for modeling and control have been highlighted in (Nguyen & Sugeno, 2012). In summary, these research works have been great incentives of using neuro-fuzzy and FLC methods for assisting in improving the surface quality problem during real-time machine execution.

To further improve real-time control on surface quality, in this paper, a novel and systematic approach using a fuzzy logic based supervision controller has been developed. Based on intelligent real-time control of machining parameters (feed rate and spindle speed), it is aimed to ensure that surface quality requirements during machining processes can be met. In this approach, neuro-fuzzy, FLC and classical control theory are integrated to develop the novel supervision controller. A neuro-fuzzy prediction model is used to estimate the surface roughness based on real-time input of machining parameters monitored via smart sensors mounted on CNC machines. In order to provide a training set for the prediction model, feed rate, spindle speed and their relationships with surface roughness are investigated through Taguchi design of experiments and empirical analysis. During machining processes, real-time feed rates and spindle speeds are used as input to analyze surface roughness, which is further compared with required surface roughness. If there are deviations, control commands will be triggered for real-time adjustments on those machining parameters to ensure surface quality. The control command is innovatively designed using fuzzy logic controllers, cascaded by proportional integral sub-controllers, to enhance the performance of the proposed system. A milling case study based on milling processes for the BS EN24T steel alloy has been used to validate the system performance through a simulation environment. Through the case study, it clearly demonstrates that the approach is effective to support high-quality machining processes. It is evidenced by the significant improvements promoted by the controller, when correcting planned parameters by machinists to achieve technical requirements for the surface quality.

This paper is structured as follows: Section 2 presents the research idea and controller design. The experimental design for data collection is given in Section 3. In Section 4, the case study for testing and validating the system, and relevant analysis is provided in detail. Finally, conclusions are drawn in Section 5.

2. SYSTEM DESIGN

2.1 Research Idea and Background

Conventionally, process planning for CNC machine tools depends on a machinist's knowledge and experience for selecting machining parameters (*e.g.*, feed rate and spindle speed). To prevent poor surface quality, the most common strategy is to select conservative machining parameters. However, this strategy is unable to achieve desired surface quality and high metal removal rate (Lu, 2008). The research idea in this paper is to develop a multi-variable intelligent supervision controller, which will enable surface quality assurance during CNC machining.

The proposed idea is illustrated in Figure 1. Smart sensors are mounted in the CNC machine to acquire real-time data of machining parameters (*e.g.*, feed rate and spindle speed). This will be pre-processed in a data processor and used as inputs to the supervision controller. This controller comprises of a surface roughness predictor based on the acquired inputs so that the quality of the workpiece will be assessed in real time by comparing the predicted and the desired surface roughness (*i.e.*, technical requirements). The results from the surface roughness comparison will be used to trigger the commands of the controller for adjusting the feed rate and spindle speed. Such commands are defined by fuzzy rule based-proportional integral loops for the control adjustment, which will be designed to correct those machining parameters until the technical requirements and tolerances of quality control are met. Thus, the goal of the supervision controller presented in this work is to ensure that the technical requirements for the surface quality of machined workpieces are achieved. That is, it supports machinists in doing-right-first-time, and avoiding all the aforementioned drawbacks of poor surface quality during execution.

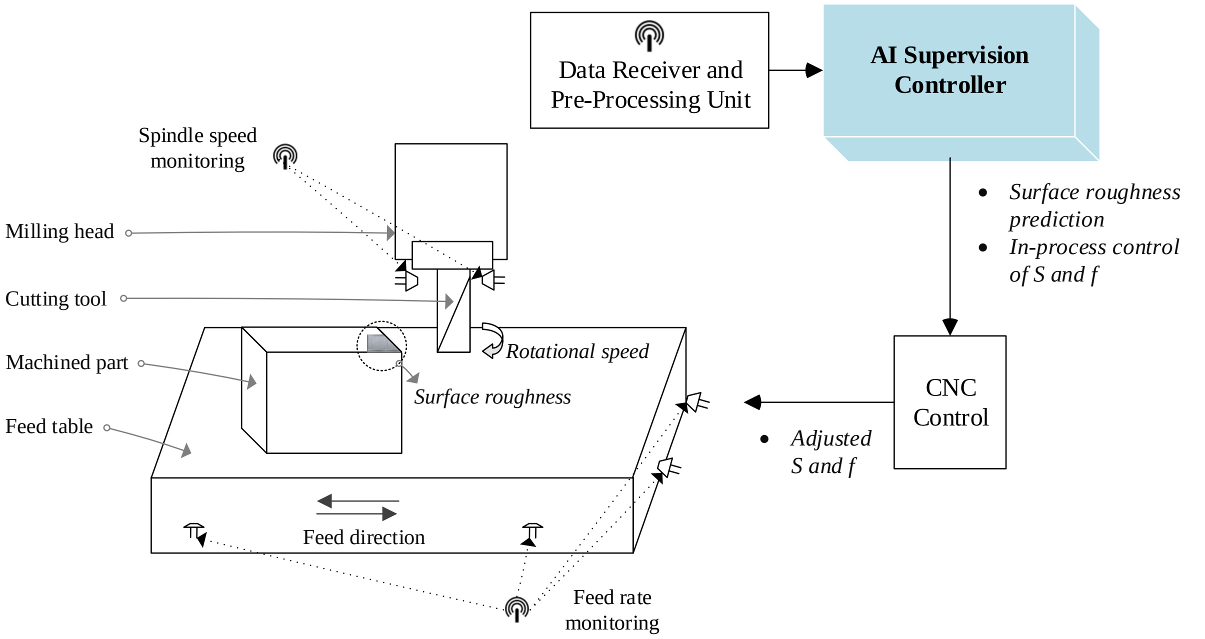


Figure 1: CNC machining enabled by the supervision controller for surface quality assurance

The implementation of fuzzy logic models for predicting and controlling surface quality has raised recently, as this technique gains popularity from its abilities to model uncertainties (Kabini, 2011; Kirby & Chen, 2007; Moreira, et al., 2017; Lovato, et al., 2018). In addition, combined neural networks and fuzzy logic approaches, called neuro-fuzzy approaches, have been developed by (Abburi & Dixit, 2006; Jiao, et al., 2004). Neuro-fuzzy approaches are considered suitable for surface roughness prediction owing to the open model structures, which can incorporate human expertise and decision uncertainties.

Besides, Fuzzy Logic Controllers (FLC) or fuzzy rule based controllers have been increasingly applied due to its successful applications in linear and highly non-linear systems (Mudi, et al., 2013). FLC uses a flexible set of if-then rules to align closely with human knowledge (Lu, 2008). According to (Sugeno & Michio, 1985) and (Bai & Wang, 2006), FLC has been proved to be superior to other conventional non-fuzzy controllers. Some key contributions of fuzzy systems for modeling and control have been highlighted in (Nguyen & Sugeno, 2012). These research works have given great incentives to the use of neuro-fuzzy and FLC for assisting in solving the surface quality problem.

Therefore, in this research, neuro-fuzzy and FLC are the selected methods for designing the supervision controller. The controller will be tested and validated using a case study involving side milling on BS EN24T under the MATLAB/Simulink simulation environment.

2.2 Procedures for the Controller Design

This section presents the development of a systematic methodology to achieve the aim of this research work. The control design procedure is divided into four steps, stated as follows:

I. Surface roughness modeling – qualitative analysis: Surface roughness measurements are implemented by using a surface quality testing equipment. Taguchi design of experiments (DoE) is performed by including different levels of feed rates and spindle speeds, to carry experimental trials of CNC machining of producing machined workpieces. Data are collected to support building a qualitative model to analyze the correlation between the selected machining parameters (*i.e*., feed rate and spindle speed) and the surface quality. More derails are given in Sections 3.1 and 3.2.

II. Surface roughness modeling – training for neuro-fuzzy models: In addition, the aforementioned data would be used to train the neuro-fuzzy and fuzzy logic models. The feed rate and spindle speed represent the model input while the output generates the surface roughness. This stage is to develop a quantitative model to predict the surface roughness in real time (prediction model for surface roughness). More derails are given in Section 3.3.

III. Supervision control design: The above surface roughness prediction models will be employed to build the decision-making system which triggers a closed-loop control algorithm. The output of the surface roughness model is compared to the desired surface roughness (tolerance requirements) so that the error is calculated. This error is used as an input to the supervision controller which is comprised of two fuzzy rule-based sub-controllers and two Proportional Integral (PI) sub-controllers. The two fuzzy rule-based sub-controllers will determine the feed rate and spindle speed scaling factors based on the error, and the cascaded PI sub-controllers will use the scaling factors to correct the feed rate or spindle speed. More derails are given in Sections 3.4 and 3.5.

IV. Supervision control validation: The controller design is developed using MATLAB/Simulink and tested using a milling case study. Testing the system in a simulation environment will evaluate the effectiveness of the prediction and control sub-systems, as well as providing traceability of the surface roughness profile based on the adjustments of feed rate and spindle speed. Such the profile represents a binding outcome for the learning process in research and development, and will help identifying opportunities for improvements on controller design. Moreover, the simulation assessment is one important step prior to constructing and implementing the physical system in future. A comparison between the process planning in the current practices and the supervision controller results will be carried out. In the former, the feed rate and spindle speed were heuristically defined by experienced machinists to achieve several scenarios containing technical requirements of surface roughness. Then, the machinists' decisions (or planned parameters) will be used as initial conditions to the supervision controller design. Each scenario will be run for three times, and each simulation run was set to 2000s, which time limit was selected based on pre-tests (the tests showed that such value would be more than enough for the controller to operate and find the optimal cutting conditions). Consequently, the surface roughness profile will be generated and analyzed, demonstrating the abilities of the controller design in correcting the machining parameters and achieving the technical requirements. More details will be provided in Section 4.

3. EXPERIMENTAL DESIGN AND DATA COLLECTION

The experimental details used to acquire the data for the knowledge construction are presented here. An experimental design (DoE) was performed to analyze the effects of machining parameters, *i.e*., spindle speed (S) and feed rate (f), on the surface roughness. Different levels of S and f were selected and tested in the experiments using a vertical 3-axis milling machine Haas VF-3 (30HP) 415 V. Table 1 shows the experimental set-up details.

Table 1: DoE and initial set-up details for the experiments

Machining Conditions	Level/Description				
Levels	1	2	3	4	5
Spindle speed / rpm	3000	3670	4000	4350	5000
Feed rate / mm min^{-1}	300	870	1115	1430	2000
Workpiece material	BS EN24T Alloy (AISI 4340)				
Material composition	C 0.36-0.44 / Si 0.10-0.35 / Mn 0.45-0.70 / S<0.040 / P<0.035 / Cr 1.00-1.40 / Mo 0.20-0.35 / Ni 1.30-1.70				
Hardness/Thermal coefficient	248-302 HB / 13.1 (10^{-6}/K)				
Tooling geometry	Guhring End Mill				
Material type	Coated solid carbide				
Diameter / N flute	16 mm / 4				
Lubrication condition	OFF (dry cutting)				
Cutting mode	Up milling				

End milling operations were selected for the experiments due to its wide applicability in CNC machining processes in the industry sector. The set-up of the experiment is presented in Figure 2 (a). The machined workpieces from the experimental trials were tested in the surface quality equipment Mitutoyo FormTracer 3100, using a stylus profilometer, as shown in Figure 2 (b). The measured surface roughness (*Ra*) data was saved for analysis (Figure 2 (c)).

The machining parameter feed rate plays a major impact on the productivity, which can be estimated through the material removal rate (*MRR*). For this reason, the *MRR* of each experimental trial will be calculated to analyze the productivity rate. Equation 1 was used to obtain the *MRR*.

$$MRR = f \cdot a_p \cdot a_e \tag{1}$$

where *MRR* is the material removal rate in mm^3/min, a_p and a_e are the depth of cut and width of cut (which were selected as 32 mm and 4 mm), respectively. The selection of these values for the depth of cut and width of cut target a high material removal rate, and match with the final dimensions of the part geometry. Meanwhile, the parameters a_p and a_e are difficult to be adjusted in-process, requiring rewriting a part program (Stavropoulos, Chantzis, Doukas, Papacharalampopoulos, & Chryssolouris, 2013). For this reason, these two values will not be considered for the real time control actions.

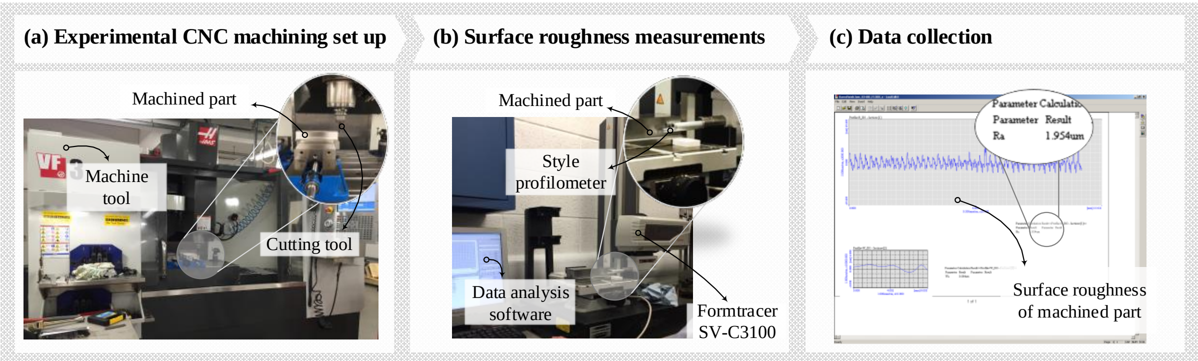


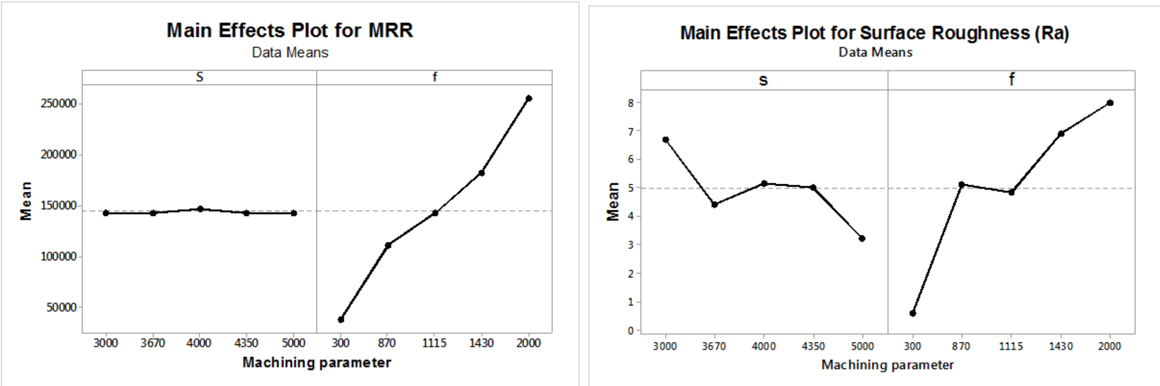
Figure 2: Experimental set-up for the data collection

3.1 Experimental Results – Qualitative Analysis

The experimental results obtained from the CNC machining trials are presented in Table 2. Main effects analysis was carried out to quantify the effects of inputs feed rate (*f*) and spindle speed (*S*), the outputs *MRR* and surface roughness (Ra). This will provide the essential knowledge required to develop a qualitative model for analysis to support the controller architecture. The main effects plots obtained from the experimental results are presented in Figure 3.

Table 2: Experimental results

Trial	*Spindle Speed (S) / rpm*	*Feed Rate (f) / mm min^{-1}*	*Material Removal Rate (MRR) / mm^3 min^{-1}*	*Surface Roughness (Ra) / µm*
1	3000	1115	142720	6.7
2	3670	1115	142720	4.4
3	4350	1115	142720	5
4	5000	1115	142720	3.2
5	4000	300	38400	0.7
6	4000	870	111360	5.1
7	4000	1430	183040	6.9
8	4000	2000	256000	8

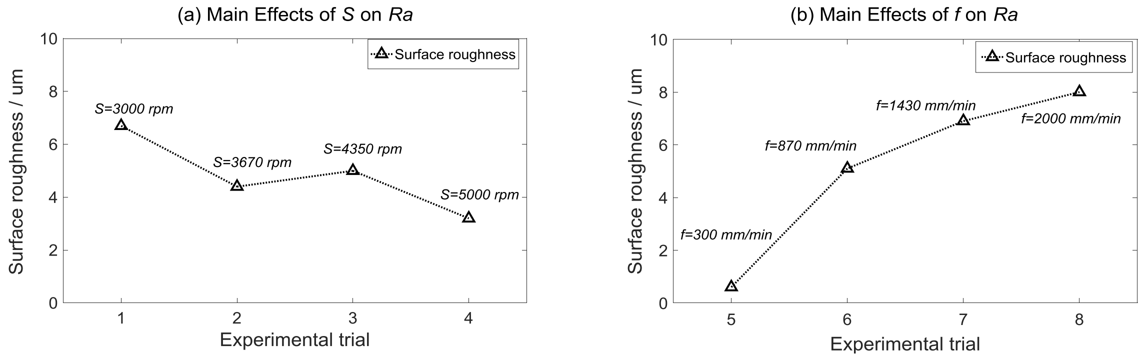


(a) *S* (rpm) and *f* (mm/min) vs *MRR* (cm3/min) (b) *S* and *f* vs surface roughness (*Ra*)

Figure 3: The main effects of *S* and *f* on *MRR* and surface roughness

The results from the experimental results and main effect plots (Figure 3) are summarized as follows:

- By changing the levels of spindle speeds (*S*), variations of up to 3.5 µm were observed on the surface roughness. By changing the levels of feed rates (*f*), variations of up to 7.4 µm were observed on the surface roughness. These values will be used to define the fuzzy logic models and control strategies for multiple-variable control in the controller design.
- Spindle speed and feed rate play significant effects on the surface roughness, and only feed rate plays an effect on machining time. These are evidenced by the plots of spindle speed and feed rate for *MRR* and surface roughness, respectively, shown in Figure 3.
- Feed rate presents greater effects on the surface roughness compared to the spindle speed, as revealed by the steeper curve of *f* plot, shown in Figure 3 (b).
- Higher spindle speeds could improve the surface quality, but these are nonlinearly correlated as shown in Figure 4 (a). Significant changes in *Ra* were observed from 3000 to 3670 rpm, and from 4350 to 5000 rpm, while a lower impact on *Ra* was observed from 3670 to 4350 rpm.
- Lower feed rates will tend to improve the surface quality, but these are nonlinearly correlated, *i.e.*, the response acts differently for the changes in *f*, as shown in Figure 4 (b). Furthermore, significant changes in *Ra* were observed from 300 to 670 mm/min, and from 1430 to 2000 mm/min, while a fewer impact was observed from 670 to 1430 levels.



(a) *S* vs surface roughness, for *f* = 1115 mm/min (b) *f* vs surface roughness, for *S* = 4000 rpm

Figure 4: Surface roughness as a function of Spindle speed (a) and Feed rate (b) for machining BS EN24T (AISI 4340)

The significant impacts of spindle speed and feed rate to the surface roughness validate the selection of these machining parameters to be the controllable variables of the supervision controller, employed to support CNC machining process to meet the technical requirements of surface quality through their correct adjustment.

4. SUPERVISION CONTROLLER: PREDICTION MODEL, CONTROL DESIGN AND SCHEMATIC

In this section, the control strategies of the supervision controller are described in detail. The supervision controller is a closed-loop system, consisting of a surface roughness prediction model (described in Section 3.3), a multi-variable supervision controller, and a unit feedback (in Figure 4).

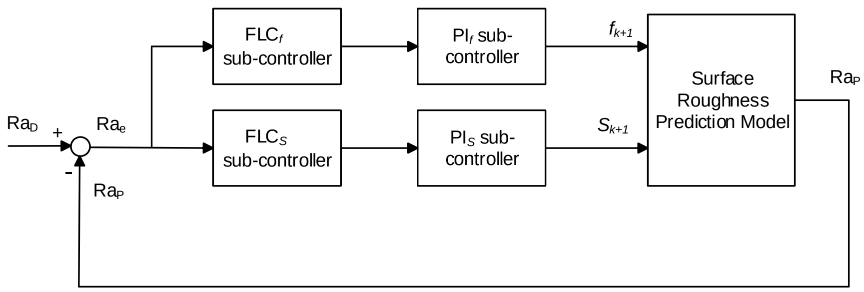


Figure 5: Block diagram of the supervision controller, where the subscripts *f*, *S*, *D*, and *P* refer to feed rate, spindle speed, desired and predicted, respectively

4.1 Surface Roughness Prediction Model – Design and Training of Neuro-fuzzy Model

The supervision controller for surface quality assurance will require a surface roughness prediction model, as shown in Figure 5. Such model will monitor the conditions of CNC machining processes and provide the measurements in real time for the controller system. The prediction model is based on the readings of the feed rate (*f*) spindle speed (*S*). *f* and *S* are then adjusted in-process to achieve the required surface roughness. Coping with multiple machining parameters in real-time control is more challenging due to the trade-offs between manufacturing requirements such as the surface quality and productivity, and the nonlinearity between the inputs and the surface roughness (Lu, 2008). Thus, the prediction model has been developed using the Adaptive Neuro-fuzzy Inference System (ANFIS) (also called neuro-fuzzy) modeling method. The general architecture of a two-input single-output neuro-fuzzy model is shown in Figure 6.

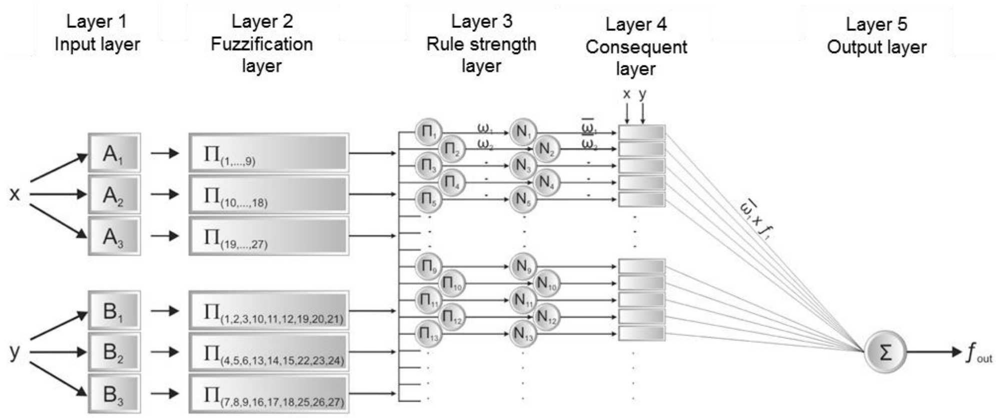


Figure 6: General architecture of the ANFIS model

The neuro-fuzzy model is a Sugeno type of fuzzy logic model. The Sugeno method is computationally effective and works well with optimization and adaptive techniques, which makes it suitable for the application. More information on this type of fuzzy logic model can be find in (Sugeno & Michio, 1985). The model's engine is defined by the fuzzy inference system (FIS), which is comprised of the input membership functions, the fuzzy rules, and the output equations. This method is a programmed procedure for defining all the FIS coefficients (also called parameters) by using experimental data for training the FIS. From Figure 6, it can be seen that the layers of the ANFIS model consist of a number of nodes described by node functions. Layer 1 and 2 include adaptive nodes, and the node functions can be described as below:

$$Q_{1,i} = \mu A_j\left(x\right)\begin{cases} j=1, f_{ori}=1,K\ ,9 \\ j=2, f_{ori}=10,K\ ,18 \\ M \end{cases}$$
$$Q_{1,i} = \mu B_j\left(x\right)\begin{cases} j=1, f_{ori}=1,2,3,10,11,12,19,20,21 \\ j=2, f_{ori}=4,5,6,13,14,15,22,23,24 \\ M \end{cases} \quad (2)$$

Where x and y are nodes inputs, A_j and B_j are linguistic labels, while μA_j and μB_j are membership functions (MF). Membership functions define the degree of membership in which some variable satisfies the defined rule premise. The fuzzy rules can be written as shown in Equation 3 and weights (w_i) are defined by the output equations to be used in the defuzzification process (to obtain the final crisp output).

$$\begin{aligned} &Rule1\text{: } IF\ x\ is\ A_1\ and\ y\ is\ B_1\ then\ z\ is\ f_1(x,y) \\ &Rule2\text{: } IF\ x\ is\ A_1\ and\ y\ is\ B_2\ then\ z\ is\ f_2(x,y) \\ &\ldots \\ &Rule\ n \end{aligned} \quad (3)$$

In the present case, the triangular input MF is applied, which general form is shown in Figure 7.

$$\mu_A(x)=\begin{cases} 0, & x\le a \\ \dfrac{x-a}{b-a}, & a<x\le b \\ \dfrac{c-x}{c-b}, & x=b \\ 0, & x\ge c \end{cases}$$

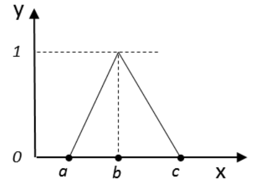


Figure 7: Triangular MF crisp to fuzzy conversion equations

Moreover, the defuzzification method is a weighted average, to obtain the final crisp output. The general formula to obtain it is shown in Equation 4.

$$FinalOutput = \sum_{i=1}^{N} w_i f_i \bigg/ \sum_{i=1}^{N} w_i \tag{4}$$

Thus, the data collected through the experimental trials will be used to train the neuro-fuzzy model using backpropagation and the least squares algorithms to obtain the FIS of the model. This way, the predictive model to estimate the surface roughness as a function of the machining parameters (*i.e.*, feed rate and spindle speed) will be formed. The input ranges of spindle speed and feed rate are defined considering the safe cutting zone of machining. The cutting zones were defined in the DoE, where for the spindle speed the range is between 3000 and 5000 rpm, and for the feed rate the range is between 300 and 2000 mm/min, respectively.

Several attempts of fuzzy sets (*i.e.*, number and shape of the membership functions) were made to achieve the model with the maximum predictive accuracy. As a result, the best model is represented by the inputs modelled by six triangular-shaped MFs and 36 inference rules. The fuzzy sets are illustrated in Figure 8. The final error of our prediction model based on the validation data is 0.1 µm, which provides a minimum predictive accuracy of 83.3%.

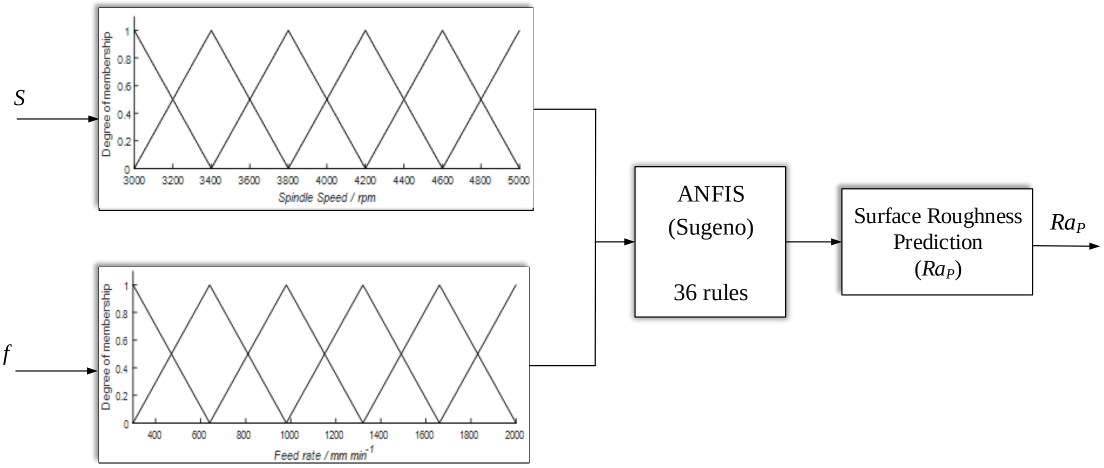


Figure 8: Neuro-fuzzy surface roughness predictive model based on Spindle Speed and Feed rate

Accordingly, the prediction model will provide the predicted surface roughness (Ra_P) based on the machining parameters, i.e., feed rate and spindle speed. The Ra_P values will be used to assess the quality of the current machining conditions based on the technical requirements or desired surface roughness (Ra_D). The next step will be the control strategies using the multi-variable fuzzy logic controllers.

4.2 Controller Design and Strategies

As shown in Figure 8, the supervision controller has two sub-controllers, called Fuzzy Logic Controllers (FLC) and classical proportional integral sub-controllers (PI) for the feed rate and spindle speed adjustments. Therefore, it is necessary to develop the sub-controllers for feed rate (FLC_f) and spindle speed (FLC_S) which are cascaded by the PI loop, to promote the multi-variable control.

FLC_f and FLC_S are rule-based models that output the scaling factors to augment the PI control of feed rate and spindle speed, respectively. An FLC consists of a set of rules of the form:

IF (a set of conditions are satisfied) THEN (a set of consequences can be inferred)

Since the antecedents and the consequents of the IF-THEN rules are associated with fuzzy concepts (linguistic terms), they are also called fuzzy conditional statements. The inputs of fuzzy rule-based systems should be given by fuzzy sets, and therefore, the crisp inputs will have to be fuzzified. In addition, the output of a fuzzy system is always a fuzzy set, and therefore, the fuzzy value will have to be defuzzied. Fuzzy logic control systems usually consist of four major parts: fuzzification interface, fuzzy rule base, fuzzy inference engine and defuzzification interface (as shown in Figure 9).

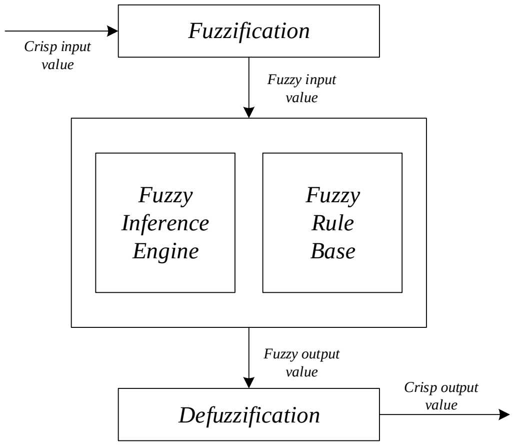


Figure 9: Fuzzy Logic Controller schematic

The FLC_f and FLC_S have been developed using the Mamdani fuzzy logic method (Mamdani & Assilian, 1975). In this method, the fuzzy implication is modelled by Mamdani's minimum operator. The conjunction operator is *min*, the t-norm from compositional rule is *min* and for the aggregation of the rules the *max* operator is used. A more comprehensive explanation on this method can be found in (Dadios Elmer, 2012). The fuzzy sets and inference rules of the FLC_f and FLC_S were defined heuristically based on the findings of the experimental results and CNC machining process knowledge gained through analysis, respectively. The design procedure of the FLC_f and FLC_S dependents on the value of the surface roughness error (Ra_e), *i.e.*, the difference between the desired and the predicted surface roughness, as shown in Equation 5.

$$Ra_e = Ra_D - Ra_P \tag{5}$$

where Ra_e, Ra_D, Ra_P are the error, desired and predicted surface roughness, in µm.

This multi-variable decoupling is needed so the control loop of *f* will only be triggered by surface roughness errors that are above a certain threshold, this way reducing the negative impact of parameters control on the process productivity (measured by the material removal rate, MRR). Such threshold will be defined considering the maximum change that *S* can promote to minimize Ra_e, which will be defined considered the data analysis in Section 3.2. The data analysis revealed that changes up to 3.5 µm can be achieved by correcting only the spindle speed. Thus, a threshold of 2/3 of this value is selected for the activation of *f* corrections, provided the high significance of this parameter on the *Ra* and MRR.

The range of Ra_e was defined considering the minimum and maximum values of surface roughness from the measured results shown in Table 2. This further supports defining the membership functions (MF), responsible to transform the crisp input into the fuzzy input. The output of FLC_S and FLC_f are the scaling factors λ_s and λ_f, respectively, which crisp values are obtained using the centroid defuzzification method (Equation 6). The decision of the number and shape of the output MFs lies on the significance of each machining parameter on the surface roughness.

$$FinalOutput = \int_z \mu(z)zdz \Big/ \int_z \mu(z)dz \tag{6}$$

As a result, the structure of the FLC_S is determined by six triangular input MFs, six triangular output MFs, and six IF-THEN inference rules (as presented in Figure 9). Besides, the structure of the FLC_f is determined by six triangular input MFs, six trapezoidal output MFs, and six IF-THEN inference rules (as presented in Figure 10).

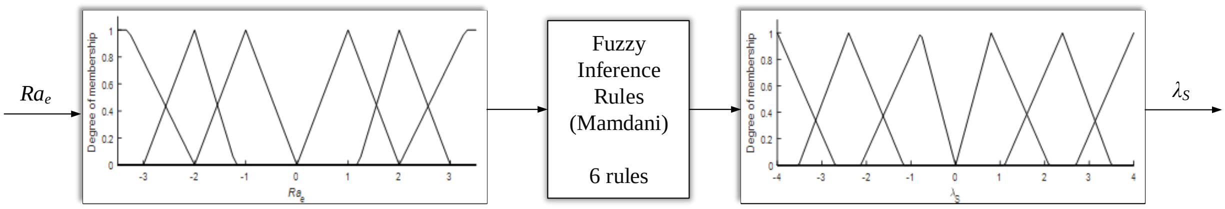


Figure 9: Fuzzy logic model for the spindle speed scaling factor (FLC_S)

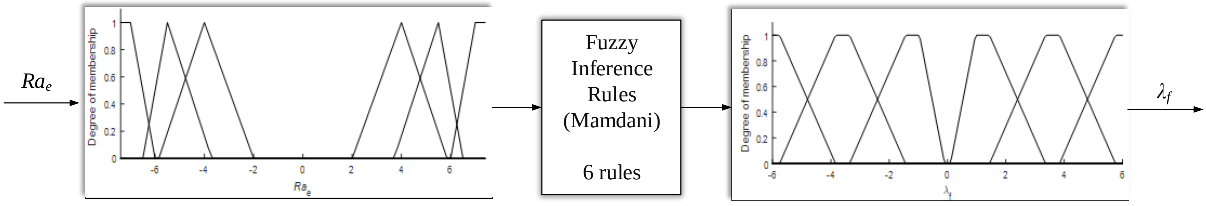


Figure 10: Mamdani fuzzy logic model for the feed rate scaling factor (FLC_f)

Furthermore, the fuzzy inference rules for the FLC_S can be described as: if the surface roughness error (Ra_e) is negative (*e.g.*, between -3.5 and 0), it means that the predicted surface roughness (Ra_P) is greater than the desired (Ra_D) (based on Equation 5). Consequently, in order to minimize Ra_e, *i.e*., to obtain Ra_P equal the Ra_D, the spindle speed should be increased, according to the relationship between *S* and *Ra*, revealed by the empirical analysis.

For the FLC_f, the range of input to activate the control action follows the multi-variable control strategy defined previously, where the feed rate control should be only triggered when Ra_e *is* greater than 2 μm or smaller than -2 μm. This can be seen in the input model of Figure 9 (left side). In addition, if Ra_e is negative (*i.e.*, between -7.4 and -2), the fuzzy rules have been defined to decrease the feed rate, according to the relationship between *f* and *Ra*, revealed by the empirical analysis.

A correction combination of fuzzy sets and fuzzy rules should address the nonlinearities between *S* and *f* with the *Ra*. Moreover, the significances of spindle speed and feed rate on the surface roughness have been considered in the design of both FLC input MF. That is, due to the feed rate effects on the productivity, values of Ra_e between -2 μm and 0, and 0 and 2 μm, will not activate control commands on this parameter and will trigger the correction of spindle speed only. In this case, the fuzzy logic open model structure played a crucial role in addressing the multi-variable control strategy and supported making a balanced trade-off between surface roughness and productivity rate on this challenging problem.

Thus, the controller system covers the entire safe cutting zones of *S* and *f* to promote the supervision and correction of these machining parameters. As a result, the final surface quality of the machined workpiece will be as desired by the process engineers.

4.3 Schematic and Functioning of the Supervision Controller

The schematic of the supervision controller, targeting to ensure the required surface quality of machined workpiece is met, is presented in Figure 11. It is designed to supervise and proposed the most appropriate feed rate and spindle speed to achieve the desired quality technical requirements.

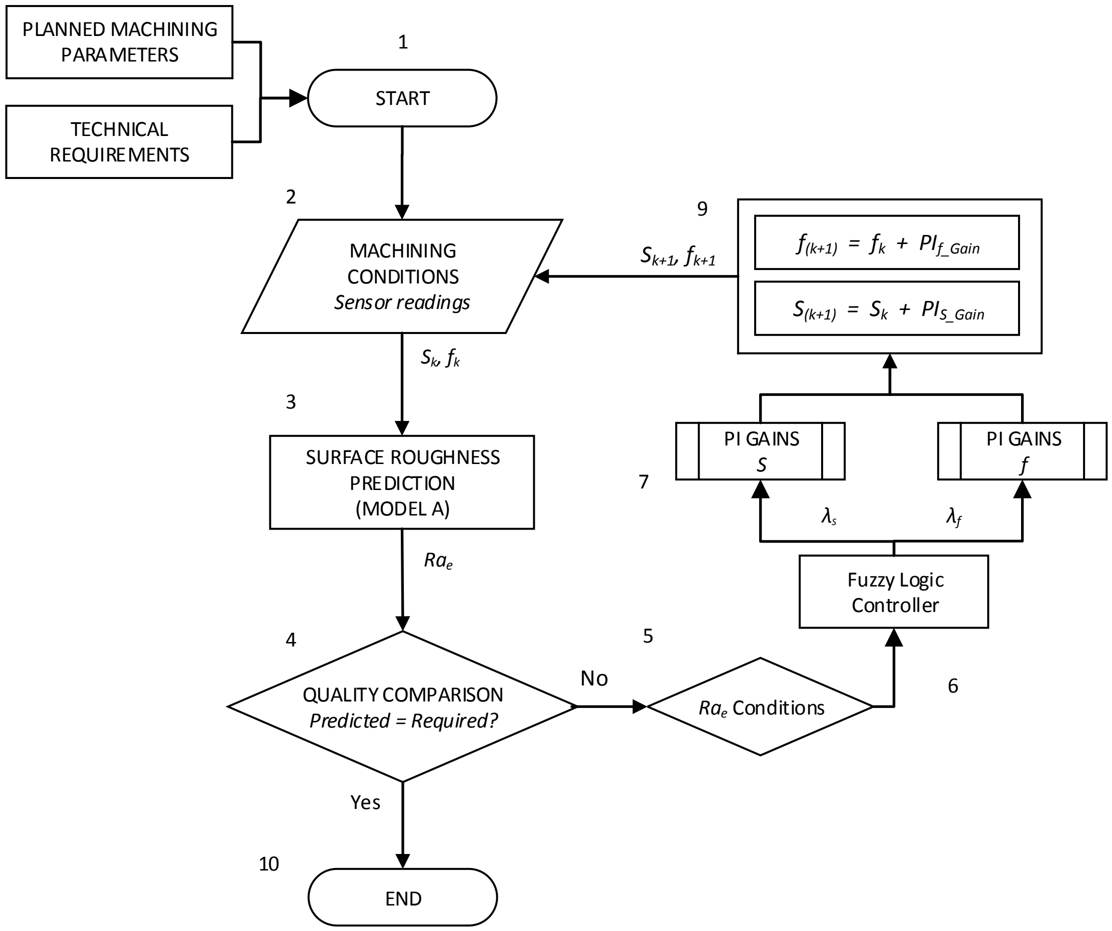


Figure 11: Supervision controller schematic for the surface quality assurance in milling

The supervision controller functioning can be described by the following steps:

- Step 1: the initial set up using the planned machining parameters and the technical requirements for the surface roughness are provided by the engineer for the controller initialization
- Step 2: CNC machining will start and the readings from the smart sensors employed in the CNC machine for monitoring the feed rate and spindle speed at time sample *k* will be used in the decision system in Step 4.
- Step 3: the neuro-fuzzy prediction model will use the sensor signals to estimate the surface roughness in real time.
- Step 4: the predicted surface roughness (Ra_P) at time *k* will be compared to the desired surface roughness (Ra_D), *i.e.*, the technical requirements, and the surface roughness error (Ra_e) will be calculated using Equation 6, this way, assessing if the surface quality meets the requirements.
- Step 5: if Ra_e indicates that the technical requirements will not be achieved, *i.e.*, Ra_e is greater than the tolerance of quality control (± 5% of Ra_D), then Ra_e will be used to trigger the multiple-variable control loop to adjust the *f* and *S*. Otherwise, the values of *f* and *S* are kept the same and no command control is activated.
- Step 6: the value of Ra_e is used to activate the adjustment of *f* and *S*. Accordingly, the fuzzy logic controllers for *f* and *S* receives the value Ra_e and calculates the scaling factors λ_f and λ_S, respectively, to provide the appropriate proportional and integral gains to correct these machining parameters. The experimental results will be used to define the FLC models, employed to augment the *S* and *f* gains.
- Steps 7 and 8: comprises of the proportional and integral gains that will augment the factors λ_f and λ_S to correctly adjust *f* and *S*, respectively. Such design self-tunes the controller performance based on the previous Ra_e, at time *k-1*. Furthermore, in Step 7, the FLC_S will be activated for Ra_e values smaller than 3.5 µm or greater than -3.5 µm. This strategy will force the activation of FLC_f only (Step 8) in order to achieve Ra_e smaller this threshold (since *Ra* is more sensitive to *f* than to

S). In addition, it will avoid the drawbacks of correlation effects caused by the changes in S and f at the same time. Consequently, when the Ra_e is smaller than the set threshold, S only should able to deal with the error minimization. Therefore, the FLC_f is only activated for Ra_e values greater than 2 μm or smaller than -2 μm. This way, the impact on the material removal rate is also minimized, since such Ra_e can be dealt by corrections in the S only – which will not affect the MRR.

- Step 9: the corrected values of f and S, *i.e.*, $f_{(k+1)}$ and $S_{(k+1)}$ will be calculated using Equations 7 and 8, respectively, and will be provided to the CNC machine control.

$$f_{(k+1)} = f_{(k)} + PI_{f_{(k)}} \tag{7}$$

$$S_{(k+1)} = S_{(k)} + PI_{S_{(k)}} \tag{8}$$

where S_k and PI_s are the spindle speed, the proportional, and the integral augmented gains for the spindle speed, at time k, respectively; and f_k and PI_f are the feed rate, the proportional, and the integral augmented gains for the feed rate, at time k, respectively. After that, the next supervised loop starts based on the corrected machining conditions, and the loop restarts in Step 3.

- Step 10: the control commands are terminated when the Ra_e is zero or within the tolerance of quality control.

5. CASE STUDY: SIDE MILLING ON BS EN24T STEEL ALLOY

In this section, a case study of milling operations is presented to validate the approach for surface quality assurance. The experimental data discussed earlier has been used to develop the surface roughness prediction model and the fuzzy logic controllers for the feed rate and spindle speed. In addition, several technical requirements will be used to compare the performance between a traditional machining process (*i.e.*, based on the expertise of machinists for defining the f and S values heuristically) and this supervised machining process (*i.e.*, based on the supervision and multivariable control of the supervision controller).

The prediction model presented in Section 3.3, the controllers shown in Section 3.4 and the scheme provided in Section 3.5, have been implemented to develop the simulation model of the supervision controller for the quality assurance in a MATLAB/Simulink environment. The flow of the supervision controller is presented in Figure 12.

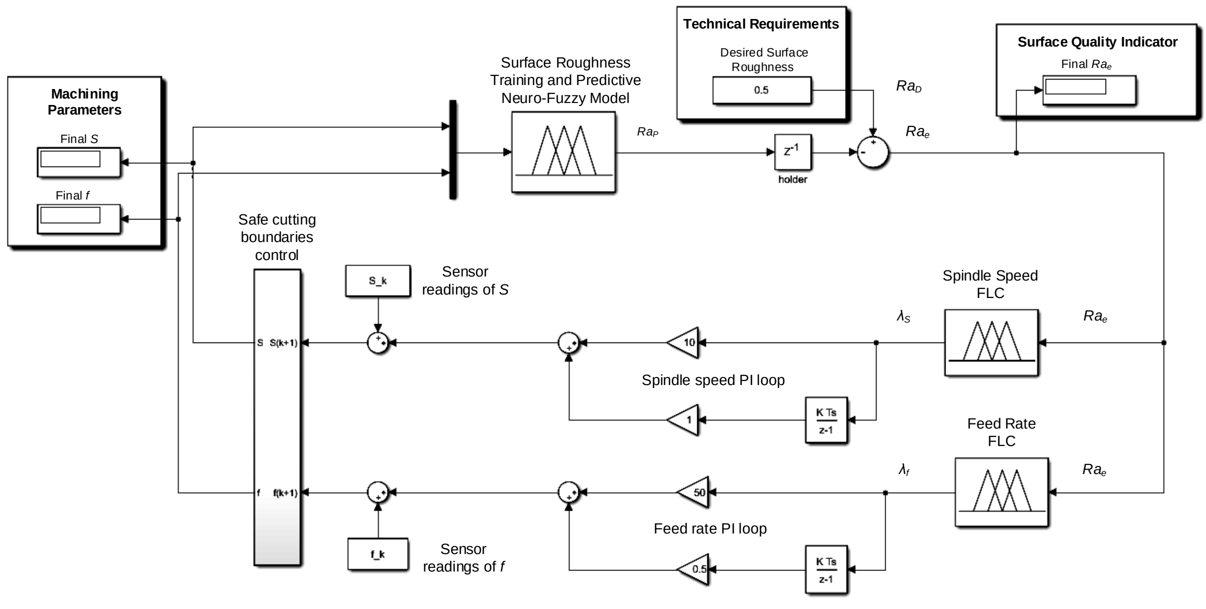


Figure 12: AI supervision controller for quality assurance in milling.

To evaluate the capabilities and robustness of the multiple-variable control design and strategies, several application scenarios have been defined by considering different technical requirements for surface roughness. These scenarios have been presented to two experienced machinists, who have been asked to define the initial conditions of feed rate and spindle speed. Six values of technical requirements for the surface roughness of the machined workpieces have been selected, ranging from 0.5 µm to 7 µm. In addition, two initial conditions for each of the machining parameters have been selected by considering their extreme values, *i.e.*, its minimum and maximum values based on the safe machining boundaries. Since the machining parameters have conflicting effects on the surface roughness, the test should exhaust the abilities of the controller in selecting the appropriate machining parameters to achieve the technical requirements. The results of the tests are presented in Table 3 and Figure 13.

Table 3: Results from performance tests on multivariable AI supervision controller

Technical Requirement (Ra_D) / µm		Planned Parameters (Machinists' decision)				AI Supervision Controller			
		S / rpm	f / mm min^{-1}	Absolute Error (Ra_e) / µm	Ra_e / %	Adjusted S / rpm	Adjusted f / mm min^{-1}	Absolute Error (Ra_e) / µm	Ra_e / %
a)	0.5	5000	300	0.1	20	4128	300	0.002	0.43
b)	1	5000	600	0.99	98.7	5000	600	0.99	98.7
c)	3	4000	1200	3.6	118.8	4969	1053	0.12	4
d)	4.5	3500	1680	0.88	19.6	4818	1579	0.001	0.02
e)	6	3000	1800	2	33.6	4177	1801	0.095	1.6
f)	7	3000	2000	2.9	40.7	4172	1947	0.006	0.1

The results achieved by the AI supervision controller in all tests, except for Test (b), have showed that great improvements could be made by the proposed approach through the adjustment of S and f. For instance, in Test (c), the controller has corrected the machinist's initial f and S so that improvement the Ra_e has been reduced from 3.6 µm to 0.12 µm, which correspond to an 4 % of the technical requirement, *i.e.*, the final quality is within the tolerance of quality control (± 5% of Ra_D). Furthermore, the best machining parameters revealed are f = 1053 mm/min and S = 4969 rpm.

In Test (b), when the technical requirement is 1 µm and the chosen values of feed rate and spindle speed are 5000 rpm and 600 mm/min, respectively, the controller couldn't refine the process conditions and the error is not minimized. The reason is that the condition established in the system design for the feed rate control loop, *i.e.*, control commands, will only be activated for Ra_e > 2 µm. As shown in Figure 13 (b), the value of Ra_e is always smaller than 2 µm. As thus, the feed rate controller has not been activated. Since the spindle speed has been already in its best condition, the desired surface roughness could not be achieved. One way of overcoming this limitation is by reducing the threshold for feed control. Another way is to include an extra loop for the feed rate control which would take action in case the Ra_e is greater than the tolerance and the spindle is at its maximum speed. This will be the future research for improvement.

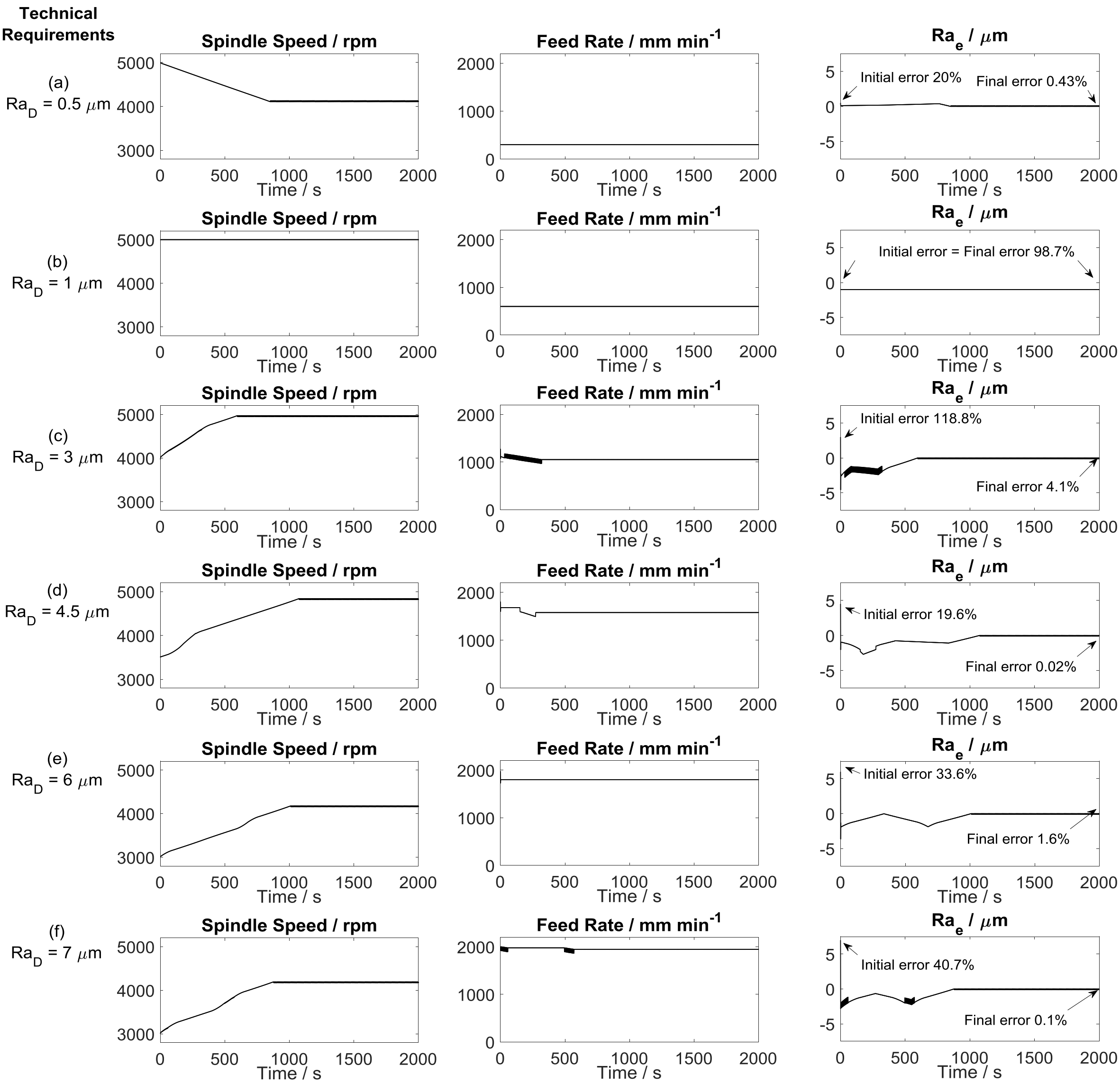


Figure 5: Correction of spindle speed and feed rate to achieve technical requirements

The overall results from the performance test, presented in Table 3, show that the supervision controller is able to improve the quality of the output up to 114.7% through the correction of machining parameters feed rate and spindle speed, based on the chosen values by the CNC machinists, as shown in Test (c). Furthermore, it ensures that the surface roughness of the machined workpiece would meet the technical requirements, by providing surface roughness errors between 0.02% and 4% of the required value. Hence, the results achieved show that the supervision controller is a potential effective tool for supporting high-quality CNC machining processes. The main advantage of the multi-variable AI supervision controller is that it is able to cover a wide range of technical requirements by providing accurate control of *f* and *S*, and it is also able to supervise the cutting quality and correct the machining parameters effectively and efficiently to ensure the quality of machined workpieces.

6. CONCLUSIONS AND FURTHER WORK

This paper presents a novel approach to improve surface quality control in Computer Numerical Controlled (CNC) machining processes. In the research, an innovative supervision controller, consisting of a surface roughness prediction model and a multi-variable controller, is designed to ensure that the technical requirements of surface quality will be achieved through in-process optimal adjustments of key machining parameters, i.e., feed rate and spindle speed. A case study based on milling processes for BS EN24T steel alloy has been used for research validation. The results from the case study show that the system significantly improved the quality of the machining process, in comparison with initial conditions given by experienced machinists. In the scenario of the case study, the system minimized the surface roughness error from 3.6 µm (based on the cutting conditions defined by the machinists) to 0.12 µm (after the optimal adjustments made by the supervision controller). This way guarantees that the surface quality is within the quality control tolerance by a margin between 0.02% - 4%. Thus, the proposed approach overcomes the limitations of the current solutions in the literature and represents a vital step towards smart control for high-precision machining.

Future work will involve taking into account the dynamics of CNC machining such as cutting tool wear into the model and control loop. Meanwhile, the system can be extensible to other applications (such as turning) by adopting predictive models from the applications into the close-loop and supervision controller paradigm.

REFERENCES

Abburi, N. R., & Dixit, U. S. (2006). A knowledge-based system for the prediction of surface roughness in turning process. *Robotics and Computer-Integrated Manufacturing*, *22*(4), 363–372. https://doi.org/10.1016/J.RCIM.2005.08.002

Acayaba, G. M. A., & Escalona, P. M. de. (2015). Prediction of surface roughness in low speed turning of AISI316 austenitic stainless steel. *CIRP Journal of Manufacturing Science and Technology*, *11*, 62–67. https://doi.org/10.1016/j.cirpj.2015.08.004

Aouici, H., Yallese, M. A., Chaoui, K., Mabrouki, T., & Rigal, J.-F. (2012). Analysis of surface roughness and cutting force components in hard turning with CBN tool: Prediction model and cutting conditions optimization. *Measurement*, *45*(3), 344–353. https://doi.org/10.1016/J.MEASUREMENT.2011.11.011

Baek, D. K., Ko, T. J., & Kim, H. S. (2001). Optimization of feedrate in a face milling operation using a surface roughness model. *International Journal of Machine Tools and Manufacture*, *41*(3), 451–462. https://doi.org/10.1016/S0890-6955(00)00039-0

Bai, Y., & Wang, D. (2006). Fundamentals of fuzzy logic control – Fuzzy sets , fuzzy rules and defuzzifications. *Advanced Fuzzy Logic Technologies in Industrial Applications*, 334–351. https://doi.org/10.1007/978-1-84628-469-4_2

Benardos, P. G., & Vosniakos, G. C. (2002). Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments. *Robotics and Computer-Integrated Manufacturing*, *18*(5), 343–354. https://doi.org/https://doi.org/10.1016/S0736-5845(02)00005-4

Benardos, P. G., & Vosniakos, G. C. (2003). Predicting surface roughness in machining: A review. *International Journal of Machine Tools and Manufacture*, *43*(8), 833–844. https://doi.org/10.1016/S0890-6955(03)00059-2

Chen, J. C., & Savage, M. (2001). A fuzzy-net-based multilevel in-process surface roughness recognition system in milling operations. *The International Journal of Advanced Manufacturing Technology*, *17*(9), 670–676.

Dadios Elmer, P. (2012). Fuzzy logic–controls, concepts, theories and applications. *Croatia, InTech, ISBN*, 953–978.

Ezugwu, E. O., Fadare, D. A., Bonney, J., Da Silva, R. B., & Sales, W. F. (2005). Modelling the correlation between cutting and process parameters in high-speed machining of Inconel 718 alloy using an artificial neural network. *International Journal of Machine Tools and Manufacture*, *45*(12–13), 1375–1385. https://doi.org/10.1016/J.IJMACHTOOLS.2005.02.004

Fang, X. D., & Jawahir, I. S. (1994). Predicting total machining performance in finish turning using integrated fuzzy-set models of the machinability parameters. *The International Journal of Production Research*, *32*(4), 833–849.

Grzesik, W. (1996). A revised model for predicting surface roughness in turning. *Wear*, *194*(1–2), 143–148.

Jiao, Y., Lei, S., Pei, Z. J., & Lee, E. S. (2004). Fuzzy adaptive networks in machining process modeling: surface roughness prediction for turning operations. *International Journal of Machine Tools and Manufacture*, *44*(15), 1643–1651. https://doi.org/10.1016/J.IJMACHTOOLS.2004.06.004

Kabini, S. K. (2011). Design of an adaptive fuzzy logic controller for cylindrical plunge grinding process.

(Doctoral dissertation, JKUAT).

Kirby, E. D., & Chen, J. C. (2007). Development of a fuzzy-nets-based surface roughness prediction system in turning operations. *Computers & Industrial Engineering*, *53*(1), 30–42.

Lu, C. (2008). Study on prediction of surface quality in machining process. *Journal of Materials Processing Technology*, *205*(1–3), 439–450. https://doi.org/10.1016/J.JMATPROTEC.2007.11.270

Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, *7*(1), 1–13.

Mia, M., Morshed, M. S., Kharshiduzzaman, M., Razi, M. H., Mostafa, M. R., Rahman, S. M. S., Kamal, A. M. (2018). Prediction and optimization of surface roughness in minimum quantity coolant lubrication applied turning of high hardness steel. *Measurement: Journal of the International Measurement Confederation*, *118*, 43–51. https://doi.org/10.1016/j.measurement.2018.01.012

Moreira, L. C., Lu, X., Fitzpatrick, M. E., Li, W.D., & Booth, G. (2017). Supervision control for quality assurance in milling processes. In *Proceedings of International Conference on Computers and Industrial Engineering, CIE*.

Mudi, R. K., Simhachalam, D., & Mondal, A. (2013). An Augmented Self-tuning Fuzzy Logic Controller with Its Real-Time Implementation (pp. 67–75). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-35314-7_9

Nguyen, H. T., & Sugeno, M. (2012). *Fuzzy systems: modeling and control* (Vol. 2). Springer Science & Business Media.

Pimenov, D. Y., Bustillo, A., & Mikolajczyk, T. (2017). Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth. *Journal of Intelligent Manufacturing*, 1–17. https://doi.org/10.1007/s10845-017-1381-8

Rizvi, S. A. (2018). Optimization of machining parameters affecting surface roughness of EN8 Steel in CNC Turning by Using the Taguchi Technique, (December 2016).

Stavropoulos, P., Chantzis, D., Doukas, C., Papacharalampopoulos, A., & Chryssolouris, G. (2013). Monitoring and control of manufacturing processes: A review. *Procedia CIRP*, *8*, 421–425. https://doi.org/10.1016/j.procir.2013.06.127

Sugeno, M., & Michio. (1985). *Industrial applications of fuzzy control*. North-Holland.

Svalina, I., Šimunović, G., Šarić, T., & Lujić, R. (2017). Evolutionary neuro-fuzzy system for surface roughness evaluation. *Applied Soft Computing*, *52*, 593–604. https://doi.org/10.1016/J.ASOC.2016.10.010

Volpe Lovato, A., Hora Fontes, C., Embiruçu, M., & Kalid, R. (2018). A fuzzy modeling approach to optimize control and decision making in conflict management in air traffic control. *Computers & Industrial Engineering*, *115*, 167–189. https://doi.org/10.1016/j.cie.2017.11.008

Wang, X., & Feng, C. X. (2002). Development of empirical models for surface roughness prediction in finish turning. *The International Journal of Advanced Manufacturing Technology*, *20*(5), 348–356.