Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 5s (2025)

A Type 2 Fuzzy Logic Model to Predict the Force During the Turning Process

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Article History:

Received: *11-10-2024*

Revised: *27-11-2024*

Accepted: *09-12-2024*

Abstract:

This study introduces a compensatory fuzzy logic system for modelling turning processes by combining the Gaussian mixture model (GMM) with an intervals-based type 2 fuzzy logical system. To simulate the turning process, an IT2FLS is first evoked. The input variables of this model are mapped to the force of cutting and surface quality. The second step is to fix the error residuals by using the GMM within the IT2FLS framework. Most models are built on the premise that the error is normally distributed, which is where the concept for such an inclusion comes from. During its development, the GMM takes stochastic, un-delayed behaviours into account while also refining the derived rules The compensating fuzzy logic system can effectively manage uncertainties, predict the force of cutting and surface quality, and provide users with a comprehensive understanding of the turning processes, according to experimental validation.

Keywords: Fuzzy Logic, GMM, IT2FLS, Error Residuals, Turning Process.

1. Introduction

Multiple revolutions have occurred in the manufacturing business. Predictive analytics has been extensively used in the recent Fourth Industrial Revolution (4IR) to make production processes more predictable, adaptable, and controlled. Among the many sorts of manufacturing processes, the 4IR is most useful for turning operations, which are a kind of machining. It is customary practice to use the turning process, 1 of four famous cutting of metal procedures, to create multi-featured, rotating, and sometimes axisymmetrical components. A cutting tool, either single-pointed or multi-pointed, is fed into a workpiece that is in motion to chip off the necessary materials for the pieces. Much effort has gone into studying and modeling the turning process because of its importance as a fundamental industrial process. Research in this area has included books and articles that try to explain how different cutting variables (such as feed rate and cutting rotational speed) and tool geometries (such as back rake angle) affect the surface roughness, cutting force, and tool wear of a machined specimen.

The turning process as well as its influencing aspects have been thoroughly explained in these books and research articles. Nevertheless, a number of predictive modelling paradigms that may provide consumers with quantitative predictions of how machining parameters will affect output parameters should be developed and put into use to improve this knowledge. Hence, there has been a lot of interest in modelling and forecasting the turning process's cutting force, which is crucial for evaluating the cutting machine's power requirements, as well as the machined part's surface roughness. So far, many methods of predictive modelling have been used, and these methods may be either data-based or physical-driven. To identify the connections between the different cutting input parameters and the process responses, we have tried to comprehend the process behaviour using physical-based models and construct the related mathematical equations. Since the turning process cannot be described by any physical equations, several academic and industrial domains have begun to articulate input/output interactions using data-driven paradigms. This contrasts sharply with the massive advances in computer power over the last few decades. Multiple linear regression techniques may be used to characterize and forecast a machined workpiece's properties as well as several process parameters. To illustrate the point, consider a regression model where the feeding rate, speed of cutting, and the level of cutting are the independent variables and cutting force is the dependent output. These methods overlook the complex interplay between process parameters and fail to take into consideration nonlinear connections between inputs and outcomes. Consequently, a wide range of machining processes have been modelled using artificial neural networks (ANNs). For instance, ANNs were used to manage surface roughness properties and predict the performance of various metal-cutting techniques.

The primary objective of this research article is to provide a predictive modelling framework for the turning process that is both more accurate and easier to understand. For this purpose, a balanced fuzzy logic model that combines the concepts of stochastic and deterministic modelling is introduced. First, model the turning process using an interval type-2 fuzzy logical method (IT2FLS); (ii) use the arithmetic mean value (Ra) for predicting cutting force and surface roughness; (iii) provide a straightforward explanation of the process; and (iv) take into consideration the uncertainties that are frequently linked with the turning process. It is important to note that the cutting force is a major factor in deciding the fate of some turning outputs in terms of both quality and productivity. After that, any unmodeled behaviour, whether stochastic or not, is taken into account by characterizing the resultant error residuals utilizing the Gaussian combination model (GMM), which adjusts for such resultant mistakes. The IT2FLS's modelling performance can be enhanced by adding the GMM to the framework. This is because the GMM can (i) compensate for the error residuals' implicit normality assumption and (ii) extract data that could be hidden in the residuals.

The remaining sections of the study are structured as follows: Section 2 provides a short overview of the experiments that were carried out utilizing a lathe machine. In Section 3, they review the FLS background, namely the IT2FLS, and the findings that were produced. Section 4 presents the GMM along with its results. Section 5 concludes by summarizing the whole study.

2. Experimental Work

Cutting force and machined specimen quality, as shown by surface roughness as measured by the Ra value, are both affected by several turning process factors. Cutting speed, deepness of cut, rate for feed, and lubricant usage were studied in this study as they are important in the turning process. At this point, it should be noted that the four variables studied in this study had their values determined by a series of experimental tests using identical materials and cutting tools. A total of 54 trials were carried out utilizing several input parameters, using a complete factorial design of experiments. Note that every experiment was carried out three times. A cylindrical specimen made of AISI D2 steel with dimensions of 20 mm in diameter and 110 mm in length was machined using a lathe machine, as seen in Figure 1.

Figure 1 Cylindrical Specimen Made of AISI D2

This paper summarizes the chemical composition of cylindrical AISI D2 steel, which is 0.3% silicon, 1.5% carbon, 0.8% molybdenum, 12% chromium and 0.9% vanadium. The feed direction was perpendicular to the cylindrical specimen's longitudinal axis when it was put. In each experiment, a carbide-tipped insert coated with titanium nanoparticles served as the cutting tool. At the end of the cutting operation, we measured the cutting force and Ra, which stands for surface roughness. The suggested model was developed using the observed cutting force and surface roughness as goal outputs. Research in this area focused on cutting force since it is thought to be a useful output for characterizing turning processes in terms of tool wear then, more crucially, superficial texture. Two dial gauges, one measuring cutting force and the other the Ra value, were used in this experiment. The profilometer was a portable stylus-type model with an LCD. Notably, as previously mentioned, the cutting force was directly proportional to the deflection of the tool and tool holder, which was measured using two dial gauges. This study averaged the force of cutting and surface roughness readings from each of the three independent experiments. Cutting force variability ranged from 1.8 to 4.6 and surface roughness variability from 0.7 to 5.7, respectively.

A statistical linear correlation study was carried out between the process variables under examination and the observed cutting force and surface roughness to assess the robustness of the linear correlations between the researched quantitative inputs and outputs. Reasonable values for the correlation coefficients among the majority of the parameters that were examined. Experiments performed with and without lubricant/cutting fluid (dry process) provide varied correlation coefficient values for a few of the evaluated variables. One example is that the correlation between cutting speed and cutting force when cutting fluid is not utilized is much greater than when cutting fluid is used. Lubricant is a typical

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 5s (2025)

input parameter that significantly affects surface roughness (Ra values) and cutting force, as shown by the results of the analysis of the variation test, a statistical tool for examining such relationships.

3. Type-2 Interval Fuzzy Logic

3.1 The Development of Models

Recent developments in computer power have led to the creation of computational intelligence, which in turn has good impacts on several fields, such as healthcare and manufacturing, among others. Computer technologies have also altered the way academic and business researchers think. It follows that data-driven modelling techniques, inspired by the human brain, are built and refined using the seen and gathered data. Paradigm shifts in modelling may supplement or even replace so-called physical-based models, especially for processes for which they are either unavailable or too complicated to construct. As a result, several data-driven paradigms, including ANNs and regression models, have been created and used in fields including healthcare, manufacturing, and maritime technology. Not all of the offered models can capture complicated, highly nonlinear interactions, even when they include strong algorithms (such as regression paradigms). The limited interpretability of some models has led to their label as "black-box ones." This is especially true with ANNs. Consequently, the FLS has been used in many situations so far to create a model that can effectively account for uncertainties and is interpretable.

Fuzzy sets are a good way to express FLSs in most cases. Typically, these fuzzy sets fall into two categories: type-1 and type-2. Type-1 fuzzy logic systems are defined as those in which the rules' antecedents and consequents are defined by the former fuzzy sets (T1FLS). Type-2 fuzzy logic systems (T2FLS) are defined as those in which fuzzy sets with fuzzy membership functions characterize at least one of the antecedents and consequents of the rules. A well-known advantage of the T2FLS over the T1FLS is its ability to efficiently and effectively manage uncertainty. It is well recognized, however, that such a system is thought to be computationally costly. This led to the presentation and subsequent implementation and use of an IT2FLS. Figure 2 depicts the IT2FLS architecture. The first thing to do, as indicated in the image, is to convert the hard data points into type-2 fuzzy collections.

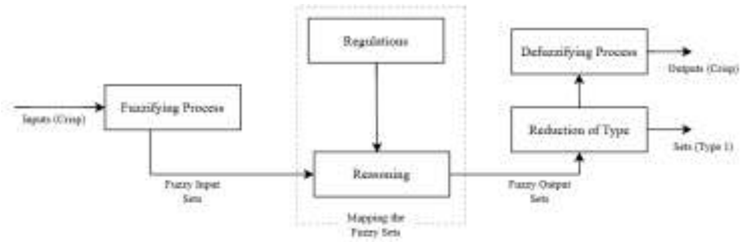


Figure 2 IT2FLS Architecture

Differences between the lower and higher means are indicated by the subscript numbers. "Footprint of uncertainty" is the common term for the darkened region sitting between the two membership functions. The inference procedure involves combining the specified rules to translate the initial fuzzy sets to the resulting fuzzy sets. The rules are usually either discovered and supplied by specialists or abstracted from an existing data collection (the experimental data). A common way to represent these principles is using an IF-THEN statement, like this:

$$\boldsymbol{Rule^{i}}: \boldsymbol{IF}\ x_1\ is\ \widetilde{A_1^{\iota}}\ \dots and\ x_n\ is\ x_n\ is\ \widetilde{A_n^{\iota}}\boldsymbol{THEN}\ y\ is\ \widetilde{B^{\iota}}$$

where $\widetilde{A_j^{\iota}}$ Represents the membership function of the jth rule's antecedent and Bi stands for the rule's consequent. It should be noted that the T1FLS and T2FLS rules are structurally identical; the difference pertains to the nature of the membership functions. The Mamdani fuzzy system is used in the research work that is presented. In this setup, a membership function stands in for $\widetilde{B^{\iota}}$. The fuzzy set is a frequent way to explain functions of membership that are often stated in words, such as low and medium. Fuzzy sets typically provide subjective information about the process being evaluated.

Type-2 fuzzy set outputs are transformed into type-1 ones as a result of the inference process. Typically, the Karnik-Mendel (KM) method is used to establish the upper and lower bounds in this stage. It should be noted that the majority of the computational work is incurred during the type reduction stage. The last step is to use a defuzzification technique to get a clean output by averaging the values.

3.2 Results with Discussion

The roughness of the surface (Ra value) was utilized as a proxy for machining quality in this research, which utilized the IT2FLS to anticipate cutting force. This research made use of the IT2FLS because of its ability to (i)generally) depict very nonlinear input/output connections, (ii)capably handle the uncertainty that may surround the process, and (iii)provide users with a straightforward, language-based comprehension of the process using the If/Then rules. The data was divided into two sets: one for training purposes, which includes 38 trials, and another for testing purposes, which includes 16 experiments. This was done so that the model could be developed using the available data points. The input/output linkages may be learned by the paradigm using the training data set, which is used for rule extraction; the generalization capabilities of FLS can be tested using the testing data set. It should be noted at this point that several division techniques have been explored in the relevant literature up to this point. This study concluded that the simplest and most effective approach was to randomly divide the data into a training set and a testing set. It is important to understand the kind of input parameters being investigated to simulate the turning process effectively. The lubricant parameter was the only one that was treated as a discrete variable; all the others were treated as continuous inputs in this study. The standard deviation and mean of the IT2FLS parameters, including the number of rules, were first set using the interval type-2 fuzzy clustering method with the Gaussian membership function. Then, they were fine-tuned using the backpropagation network's standard steepest descent approach. Finding the optimal number of rules meant minimizing the gap between the desired and expected values. The RMSE gave an approximation of this disparity.

Figure 3 displays the results of the IT2FLS's cutting force performance, with a root-mean-squared error (RMSE) (training, testing) between 1.198 and 1.231. Compared to the training data set, the testing set of data has a somewhat higher RMSE value. This may suggest that there has been an issue with overtraining. In this method, however, the force that cuts values in the test and training sets is linked to this discrepancy, so it is not the case. To provide further context, the value of the RMSE in the set of tests may be severely impacted by three points of data out of sixteen with values larger than 20KGF; hence, the values for error are rather big, albeit they are below ten per cent of the goal value. Calculating the R2 (training, testing) coefficient of determination proves this. Figure 3 further shows that most of the projected values are well-fitting within a 90% confidence range.

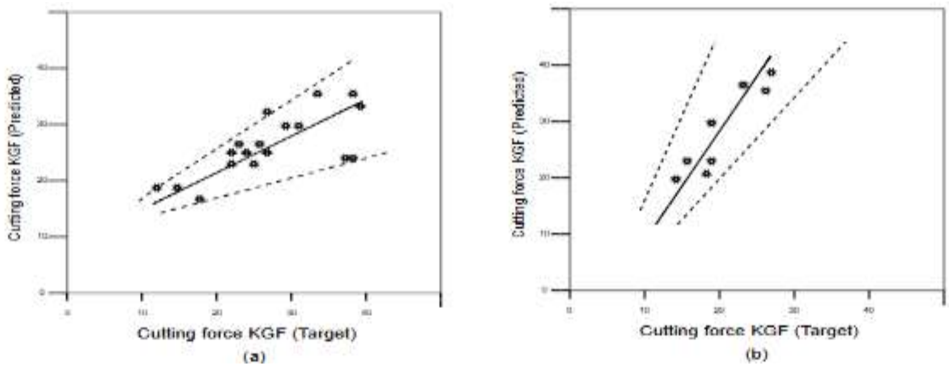
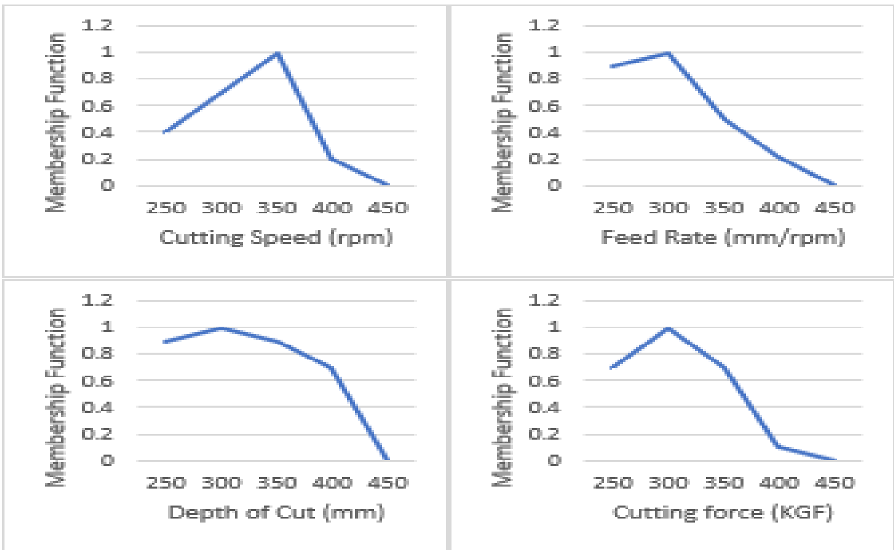


Figure 3 Projected Values are Well-Fitting with Range

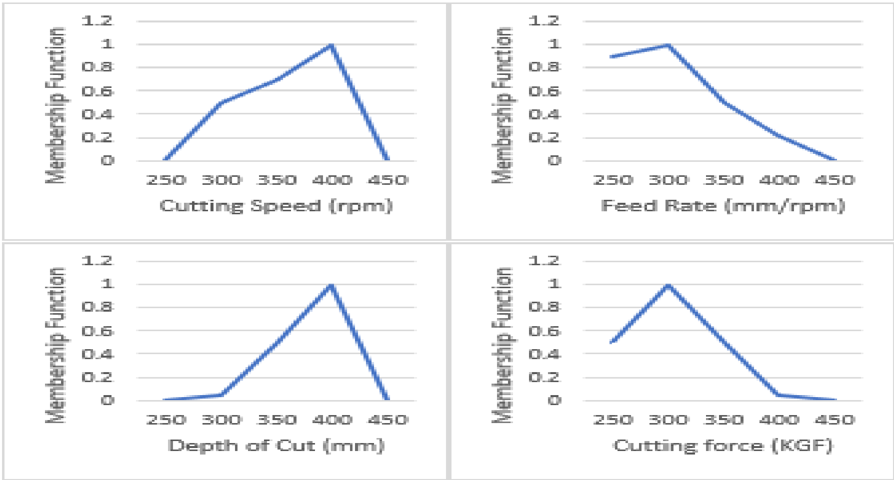
Figure 4 shows two of the six rules illustrated; the shaded region represents the footprint of uncertainty, and the following are some possible language forms of these rules:

- **First Rule:** A medium cutting power is required in the absence of cutting fluid, with a medium cutting speed, a modest feed rate, and a shallow depth of cut.
- **Second Rule:** With cutting fluid, a high feed rate, a medium depth of cut, and a high cutting speed, the cutting force must be high.

Using two parameters simultaneously, Figure 5 shows examples of the cutting force's reaction surfaces. The force that cuts is not a linear relationship between speed of cutting, depth of cut, and feed rate. Additionally, it is observed that the force of cutting is minimal at low depths of cut and fast cutting speeds, but it grows as the length of cut increases. Additionally, the cutting force reaches saturation at a low feed rate when the depth of cut is between 0.16 mm and 0.3 mm. Furthermore, when the rate of feed and the level of cut are both set to high levels, a significant amount of cutting force is seen.



Rule 1



Rule 2

Figure 4 Two of the Six Rules

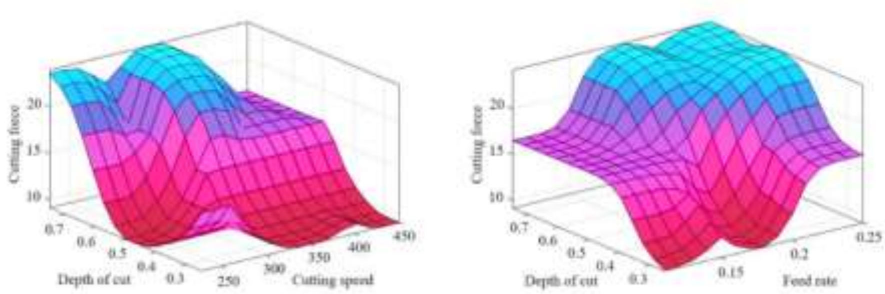


Figure 5 Examples of Cutting Force's Reaction Surfaces

Similarly, the IT2FLS was used to forecast the machinable part's quality, which is reflected in the Ra value for surface roughness. Figure 6 displays the IT2FLS performance for the Ra values using eight rules. The results are shown using RMSE and R2 (training, testing). Because surface roughness measurements are fraught with uncertainty, it is clear that performance metrics for this parameter are inferior to those for cutting force.

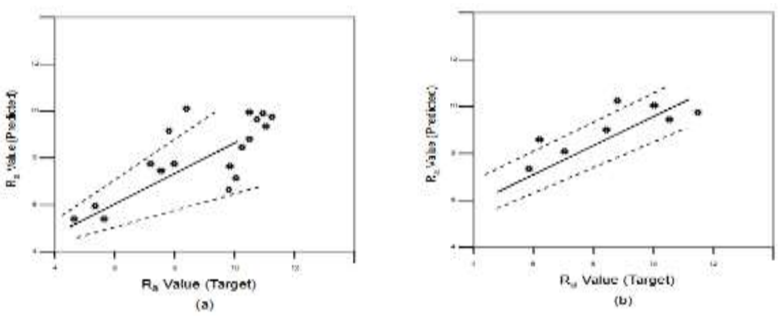


Figure 6 IT2FLS Performance for Ra Values Using Eight Rules

4. A Model for a Gaussian Mixture

4.1 The Development of Models

Assumption of normally distributed collection of error residuals is the basis of most modelling paradigms, including T2FLS and T1FLS. This assumption could not hold water in real-world applications containing noise non-measurable or measurable elements; hence, it might cause a paradigm to have less-than-ideal parameters and lead to the loss of important information. Consequently, several modelling techniques have been developed and used so far to extract this useful information and enhance the accuracy of the models by describing the residuals of the errors. To improve a model's predictive capabilities, for example, by offering a more thorough understanding of the density function, the probabilistic Gaussian mixture model (GMM) has been used. This model is often expressed as a linear amalgamation of many Gaussian components. While the GMM method and all of the other given algorithms in fuzzy logic systems alter the anticipated output values, they do not alter the extracted rules. As a result, the process being studied can no longer be represented by these rules. As a result, the GMM is integrated into the fuzzy logic framework in this study, which improves the derived rules' informativeness. Since the GMM uses the optimal number of Gaussian components to rationally express the probability density function, it was chosen for implementation. Figure 7 shows a schematic representation of the IT2FLS as well as GMM being integrated.

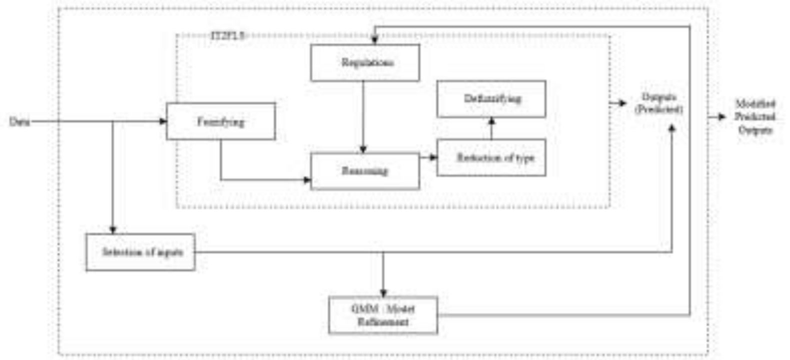


Figure 7 Schematic Representation of the IT2FLS as well as GMM

Figure 7 shows that the first stage in incorporating such a system is to choose the input variables that will be used to describe the mistake. After that, we optimize the famous log-likelihood function to find the best values for the GMM's parameters, which are the covariance, mean, and mixing factor for every Gaussian component. Numerical approaches may be used to estimate the standard deviation and the conditional error mean. The GMM method can account for bias by adding the optimum conditional mean value, which indicates the presence of bias, to the subsequent mean of the linked rule. The defuzzification technique is then used to get a clean output after this stage.

4.2 Results and Discussion

The IT2FLS was developed and optimized with the primary impacts of the process factors under investigation in mind. To account for the potential bias caused by the assumption of error normalcy, the GMM method was applied using just two of the four variables. After experimenting with several combinations of input variables, the one that maximized error compensation was selected. The GMM was built using the cutting force, feed rate, depth of cut, and a vector consisting of the mistakes from the IT2FLS method. To train this model, we used the initial data set and concealed the testing one. The accuracy of predictions for the force of cutting for both the testing and training information sets are displayed in Figure 8, utilizing six Gaussian elements. R2 is between [0.950, and 0.961].

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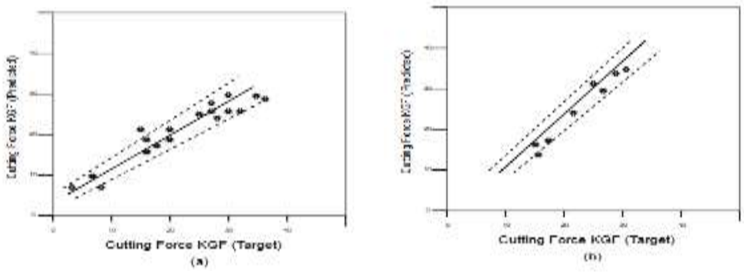
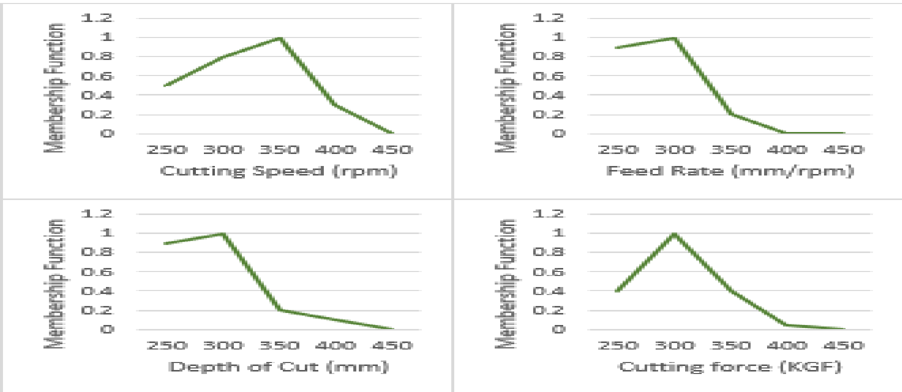
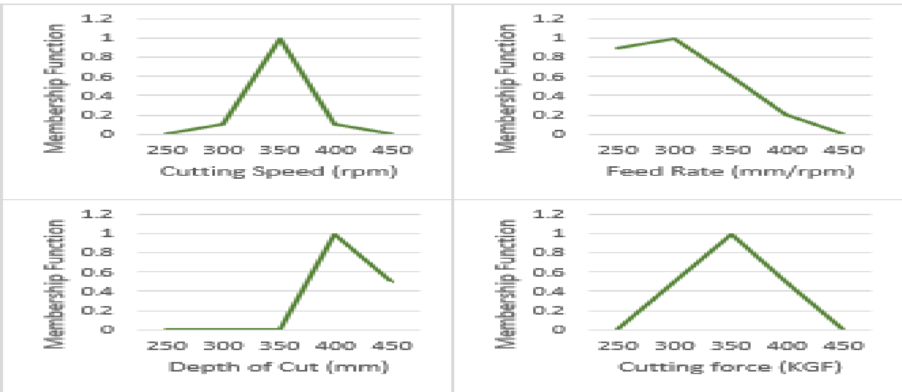


Figure 8 Utilizing Six Gaussian Elements

A general increase of around 8% in the R2 value demonstrates that the GMM may identify potential unmodeled deterministic or stochastic behaviour. Following bias adjustment, Figure 9 displays the two rules given in Section 3 overhead. Figure 9 and Figure 4 both demonstrate rules with identical antecedents; the only variation is in the consequents. The first rule's consequents were shifted to the right by around 0.8 KFG while the second rule's consequentials were shifted to the left by about 0.84 KFG. It should be emphasized that the language forms of these regulations were unaffected by these changes in the resulting mean values.



Rule 1



Rule 2

Figure 9 Rules with Identical Antecedents

The IT2FLS, which was created to reflect the surface roughness, was similarly refined using the GMM technique that was previously described in this work for refining the FLS rules. A noticeable improvement of around 9% in the value of R2 was achieved due to surface roughness. In terms of predictive accuracy, the compensated IT2FLS constructed for cutting force surpasses the one for surface roughness, even if the improved value for the roughness of the surface is somewhat bigger. For the sake of comparison, the GMM approach was used to alter the force of cutting and surface roughness rules obtained by the T1FLSs; this led to significant improvement values.

Overall, when linked to the popular T1FLS and IT2FLS, the given modelling framework, which combines the two, outperforms both in terms of predictive performance. Also, the suggested model, like the famous IT2FLS and T1FLS, is seen as an open model that can handle uncertainties inherently and provide users with a basic comprehension of the process being studied. The suggested modelling framework, on the other hand, is more computationally intensive than IT2FLS and T1FLS. The computational effort has shown improved performance in predicting the force of cutting and surface roughness. Cutting force and roughness of the surface for new materials, among other things, may be predicted using the provided model after training. A data-driven model is what it is. The suggested framework is a step in the right direction for numerous industries, including manufacturing, where a predictive model is needed to do things like (i) make reliable predictions about a product's characteristics in a way that guarantees or, at the very least, enhances the potentially crucial quality aspects (ii) explain the method in plain English while keeping it thorough; (iii) describe the residual errors that account for the normality assumption and represent both random and predictable behaviours.

5. Conclusion

Creating a more accurate and interpretable turning process prediction framework was the primary goal of the reported study. A type-2 interval fuzzy logical system was integrated with GMM in the constructed framework. The turning process was first represented using the IT2FLS, which mapped process parameters to a machined specimen's surface quality and cutting force. The IT2FLS handled uncertainty and effectively predicted cutting force and surface roughness. Further, it included helpful guidelines that are simple to understand and use to manage the turning procedure. To improve the predictive performance, we used the GMM to refine the extracted informative rules and characterize the resulting error residuals. This is because, in most cases, we want the examined attributes to be predicted more accurately. Adding the GMM to the IT2FLS framework resulted in an 8 per cent improvement overall.

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