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A Fuzzy Knowledge-Based System for Diagnosing Unpredictable Failures in CNC Machine Tools

Antony Colasante[a], Silvia Ceccacci[a]*, Abudukaiyoumu Talipu[a], Maura Mengoni[a]

[a]*Department of Industrial Engineering and Mathematical Science, Polytecnic University of Marche, via Brecce Bianche, Ancona, 60131, Italy*

Abstract

This article proposes the use of an expert knowledge-based system capable of identifying possible machine tool failures caused by accidental events (e.g., cable disconnection, incorrect parameterization of machining, impact event, etc.). The proposed approach aims to identify the unpredictable causes of failures, starting from the analysis of the process data provided by the PLC Data Logger, without requiring to sensorize the machine in order to collect ad hoc condition monitoring data. To this end, it uses the experts rules and Fuzzy Logic algorithms to activate data analysis based on known machine fault conditions. The proposed approach has been validated on real case studies. A prototype system was developed in Python to identify electrospindle failures that occur when the spindle of a CNC machining center for woodworking is subjected to a strong axial impact. The results show that the proposed system is capable of effectively detecting failures caused by impact events and reduces the time needed for the diagnosis by 80%.

Keywords: Machine diagnostics; Expert systems; Fuzzy logic

1. Introduction

One of the main factors that influence the productivity of industrial plant is the unscheduled downtime of the equipment. The environment of machining operations changes unpredictably and often lead to unexpected equipment degradation and failures. Implementing a proper damage identification strategy can bring undisputed benefits in order to heighten structural safety, reduce maintenance costs and avoiding human and economic losses.

* Corresponding author. Tel.: +39 071 2204797; fax: +39 071 2204801.
E-mail address: s.ceccacci@univpm.it

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The increase in awareness regarding the need to optimize manufacturing process efficiency has led to a great deal of research aimed at machine tool diagnostics. As evidenced by many research surveys, such as [1-4], during the past twenty years, enormous efforts have been made to improve Condition-Based Maintenance (CBM) systems with even more effective diagnostic and prognostic capabilities to prevent machine failure and improve the reliability and productivity of production facilities. Today, thanks to the recent introduction of new ICT and IoT technologies, as well as the introduction of AI systems, the research objective is increasingly oriented towards the development of proactive systems, to the point of making the machines capable of "self maintenance" [5].

Research is unanimous in claiming that the implementation of such systems can bring enormous benefits to businesses in terms of reducing the life cycle costs and increasing product reliability. However, despite the undisputed benefits that would make them very attractive, advanced maintenance technologies have not yet been well implemented in the industry. This, as has been claimed by [2], depends on several reasons, including the lack of data due to incorrect data collecting approach, or even no data collection and/or data storage at all: almost all the researches propose diagnostic systems based on the acquisition of condition monitoring data (e.g., vibrations, currents, temperatures, etc.). The acquisition of such data requires the implementation of ad hoc sensors and data storage systems, which often may require the re-design of machine subsystems.

However, CNC machine tools are already able to provide in real time massive state data about machining process (e.g., starting of working session, starting of machine program, changing of a tool, state of the electrospindle, etc.), as they usually implement PLC Data Logger systems. Moreover, a large amount of event data is provided related to errors and faults generated by the diagnostic systems, based on condition monitoring, implemented by driver motion controls (e.g., a driver can determine a machine error/fault when it receives a torque above a certain threshold). All this data together represents a huge wealth of information that machine tool manufacturers can now easily access thanks to the new IoT and ICT technologies introduced with the advent of the Industry 4.0.

However, based on our knowledge, current research does not consider such data useful for diagnostics. Maybe, the overlooking of event data may result from the erroneous belief that event data are not valuable as long as the condition indicators (or features) seem to be working well in reducing equipment failures [2]. However, according to [6], fault prevention using CBM systems is not the only approach that must be adopted to improving the availability of machine systems. In fact, to ensure the minimum machine downtime, it is equally important to adopt tools to facilitate recovery from unforeseeable events and failures.

In this context, the research aims to assess the feasibility of developing an expert system to automate the diagnosis of failures caused by accidental events, based on process data collected through the PLC Data Log system. The proposed system does not require the implementation of ad hoc sensors, but it is able to identify precisely the causes of the failure, analyzing only the process information already provided by the PLC data log. The main contribution of this research is to present a possible application to exploit the potentiality of big data information already available in the machine tool manufacturing industrial sector.

2. Research Background

Determining the causes of unforeseeable failures is of great importance for machine tool manufacturers. In fact, most of the failures that normally occur during the warranty period of the machines are attributable to accidental causes. For example, during the warranty period, many catastrophic spindle failures occur as a result of strong axial impacts on the spindle itself: for example, when the tool is immersed in the material rather than ramping up or hitting the work table. Usually these stresses, which in most cases are due to human error (e.g., process parameterization errors, incorrect actions on the spindle during manual handling, etc.), cause the second pair of front bearings to fail. Based on our knowledge, process data provided by the PLC Data Log in general represents the main source of information the experts use to determine a posteriori the causes of machine failures during the warranty period, in order to avoid disputes with the customer regarding liability for the failure. However, PLC Data Log analysis are very time consuming and may only be carried out by highly specialized and qualified personnel.

Expert systems have been extensively applied in diagnostics because of their ability to simulate human reasoning about a problem domain. In general, an expert system is composed of a database, a knowledge base, and a reasoning engine [7, 8, 9]. Most knowledge-based systems are constructed by using two different approaches: data mining and machine learning techniques, and domain expert knowledge [10]. Data mining and machine learning techniques enable to acquire knowledge directly from existing data, without the help of an expert in the field. The use of these techniques allows to reduce costs and development times because they allow to identify in a short time the model of knowledge. However, they have some drawbacks, such as over-generalization and over-fitting, especially when the training is not performed on a sufficient amount of data [11]. Consequently, as in the industrial environment it is very difficult to collect sufficient machine failure data to ensure appropriate training, machine-learning frameworks have not yet been implemented for machine failure diagnostics, in the industrial practice [12]. On the other hand, to gain knowledge from domain experts is difficult and slow. Moreover, the acquired knowledge is never complete and it is not always easy to mimic the process of human thought in an effective way [13]. Expert knowledge bases can be categorized as logical rule-based (LRS) and fuzzy rule-based (FRS) [14]. Among these, the fuzzy approach is more powerful, because it allows to model knowledge even when it is uncertain or incomplete.

In this context, the present research propose the definition of a fuzzy knowledge-based system to support the diagnosis of unpredictable failure in CNC machine tools.

3. The proposed Knowledge-Based System

The proposed Fuzzy Knowledge-Based System is an expert system consists of sub-components such as the Knowledge base, the Diagnostics module and the Database. We also have some additional modules such as the Parsing module and the Service module (Figure 1).

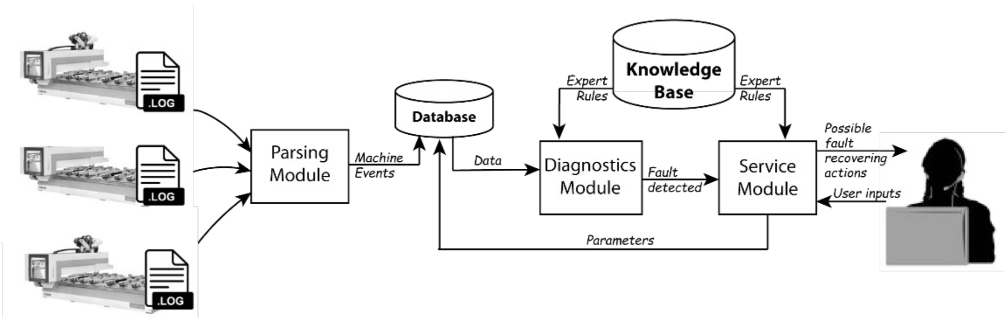


Fig. 1. The schematic layout of the proposed system architecture.

The Database module is a central data storage system specifically designed and constructed for better organizing the event data. The event data in our case, usually stored in the CNC machine generated log files and reported in the format of Structured Text. Directly accessing those log files while running the diagnostics is not efficient and practical. The Parser module is built for resolving this issue. It parses the log files filters and converts the values needed for diagnostics and stores them inside the database.

The Service module is the front end of the system, users interact with the system through the service module. It has an user interface and also capable of providing possible troubleshooting measures to the users to quickly resolve the occurred CNC machine failures. In real life scenarios, service module queries the database based on the variables inserted in the user interface, returns the query result to the Diagnostics module for further analysis.

The Diagnostics module mimics the expert's decision making process. It reasons over various rules predefined by the domain experts and produces diagnostic results. Necessary conversions and calculations are carried out on the query results acquired from the database, then the analysis are conducted accordingly. In analyzing phase, it compares the results passed from the previous step to the pre-set thresholds and executes the corresponding rules defined inside the Knowledge base. It plays a crucial role in finding and identifying the possible causes of the machine faults.

The Knowledge base is the most essential part of the whole system. All the expert knowledge representations necessary for the Diagnostics are stored as a set of logical rules inside the Knowledge base. It provides an interface for the Diagnostics module for accessing the rules. Considering the non-deterministic nature of the machine failures, a set of fuzzy logic rules are also implemented to support the diagnostics. It is a flexible module that new rules can be added incrementally in the future for supporting new types of diagnostics.

The proposed knowledge based system is a network-based system that can scale. It has various deployment potentials. Manufacturers can use it internally to support testing phase of the CNC machines or can be deployed on the cloud to assist customer service.

4. Application to an industrial case study

The proposed system has been applied in the context of CNC machine tool for high precision woodworking, in order to diagnose the spindle failures due to strong axial impact. The spindle represent the most expensive sub-system of the machine and spindle failures due to accidental impact represent the main cause of spindle substitution request during the warranty period.

As it has been said in the introduction section, accidental axial impact can in general occur for several reasons attributable to human errors, including:

- Error occurrence within machine program parameterization: in general, in order to define a machining program, it is necessary to set a series of parameters (e.g., tool length, height of the semi-finished product, thickness of machined piece, thickness of eventual jigs, etc.). Incorrect settings of these parameters can lead to unexpected collision events during the working phase (e.g., spindle may collider with the workpiece, or with the jigs or with the worktable) or during the tool changing phases (e.g., the spindle may collide with the tool itself);
- Improper actions performed by the operator during the manual handling of the spindle: in general, machine tool allow the operator to manually adjust the position of the spindle. An incorrect action performed by the operator may result in catastrophic collision between the spindle and the workpiece or other parts of the machine (e.g., the tool magazine).

The proper identification of these causes of failure are of paramount of interest for machine tool manufacturer, in order to proper manage the disputes with the customer regarding liability for the machine failure during the warranty period.

As can be infer from the examples given above, accidental impacts obviously occur during the handling of the spindle along their axis. Consequently, a way to identify strong accidental axial impact and determine the causes is to analyze the events reported in the log file that are generated by the controller's driver and inverters during the phases of spindle handling. The servo drivers installed on the CNC machines of our case study are Yaskawa, while the inverters can be of different types.

4.1. Development of parser and database

The parser is developed with .Net framework regular expression engine that allows matching patterns against input text. Preprocessed log files are fed into the regular expression engine to extract the predefined patterns which is the information we need to build our database. Then we use Language-Integrated Query (LINQ) to insert the extracted information to SQL Server database.

The event data obtained through the parser we considered can be categorized in:

- Process events: they are related to specific machine states occurred during the machine functioning from the start to the end of a work session. They include process events related to the whole machine (e.g., work session or work program starts and stops) and process events related to specific machine subsystems (e.g., the spindle, the boring head, the edgebanding, etc.) In particular, we considered process events related to the spindle status (e.g., events indicate that the spindle is starting machining, or it is switched on and ready to start machining) and events related to the spindle handling along the various axes. For each process event related data is provided, such as the Timestamp, the code or the description of the event and, in some cases (e.g., events related to spindle handling), the output data generated by the condition monitoring systems embedded by the servo driver controllers. For example at the end of a spindle handling the MaxTorque and the MeanTorque values are provided, which respectively represents the maximum torque and the mean torque delivered by the Yaskawa servo driver during the spindle movement, measured as a percentage of the nominal torque;
- Error events: warning events generated by the CN, based on condition monitoring. In particular we considered the error "YAS 758", a warning about the torque delivered from the drive to the axis;

- Event data related to the manual handling of the spindle (e.g., time stamp related to start/stop of manual handling, handling axis, initial and final movement altitude).

Log files store the event data from different CNC machine components. These components generate Timestamps in various formats. To be able to trace a possible cause of a failure, it is necessary to standardize the different formats and correlate them together. To this purpose, the following solutions have been adopted:

- Conversion of the reported Timestamps in the logfile in the format of date and time;
- Definition of a primary keys to associate each event to the respective work session and work program and the specific machining.

4.2. Definition of diagnostics algorithms

The core of the expert system is the diagnostics module. As you can see from Figure 1, this module takes event data as input from the database, processes them based on the expert-knowledge, and then provide diagnostic indication as an output. The main purpose is to determine whether the failure of the spindle is due to a strong axial impact and, if any, to determine the possible cause that led to the impact event. The implemented algorithms can be divided into two parts: the algorithm based on expert rules and the algorithm based on fuzzy logic.
The algorithm based on expert rules does some basic analysis on the event data then determines the cause of the impact that led to spindle failure. The sequence of actions defined based on the rules are executed following the flowchart below Figure 2. As you can see from the flow chart above, the first control is related to the occurrence of the machine error "YAS 758". When an error occurs, a backward search is conducted to find some notable events that may have caused the error.

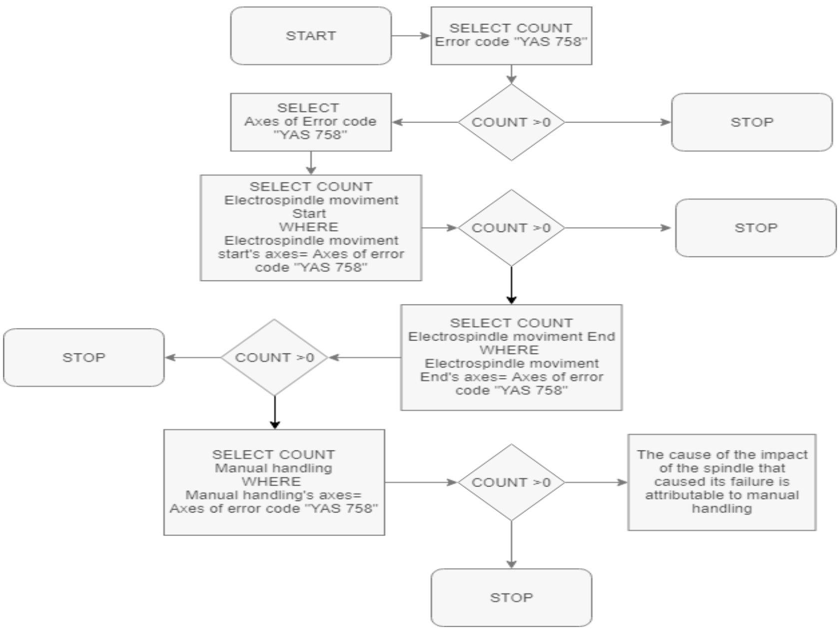


Fig. 2. Flow chart of a diagnostic algorithm.

The YAS 758 event reflects a warning about the torque delivered by the servo drive to the axis. According to the diagram reported in Figure 3, the occurrence of this error is not only related to the amount of the transmitted overload, but also on the detection time of the overload itself.

Although experts consider the YAS 758 as the main diagnostic indicator to determine the occurrence of an axial impact, this error may occur when an overload slightly higher than the nominal one are delivered for a long time and when an overload much higher than the nominal one is delivered for short time.

In addition, very high overloads, delivered for very short period of time (for less than 0.2T), may not generate the error but may still be detrimental to a possible impact event of the spindle.

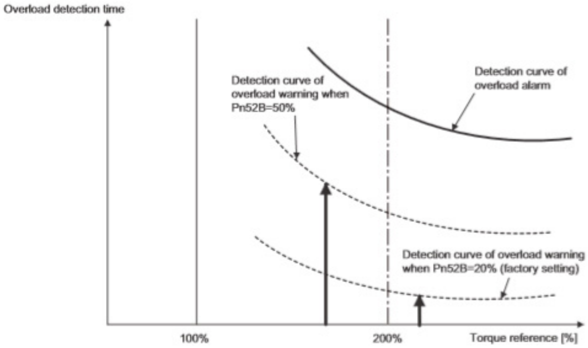


Fig. 3. The logic generating overload warning.

Fuzzy algorithm has been introduced for the following reasons:

- Evaluating the importance and weight of the variables not only considering their presence or not;
- Reducing the rigid structure that characterizes the expert knowledge in such a way as to consider the most disparate cases;
- Providing a diagnostic indication also based on qualitative considerations.

The structure of fuzzy logic approach is reported in Figure 4. The algorithm is mainly based on Sugeno fuzzy model. It checks all the spindle movements to highlight whether the spindle might have been subjected to axial impact, even when no overload alarms have been detected. Considering the output data generated by the condition monitoring systems embedded by the servo driver controllers provided at the end of spindle handling along an axis, (i.e., MaxTorque and MeanTorque values), two fuzzy variables have been defined:

- MaxTorque (MT): maximum load delivered by the servo driver during a spindle handling. This variable is expressed as a percentage of the nominal torque delivered by the axis servo driver.
- Duration (D): it is computed as the difference between MaxTorque and MeanTorque. It estimates the deviation between the average and maximum load registered during a spindle handling. It is an indirect measure of the frequency with which a load comparable to the maximum load is delivered during the handling. A high value of D means that the delivering of a load near to the MaxTorque value occur for very few times. This variable is expressed as a percentage of the nominal torque of the axis servo driver.

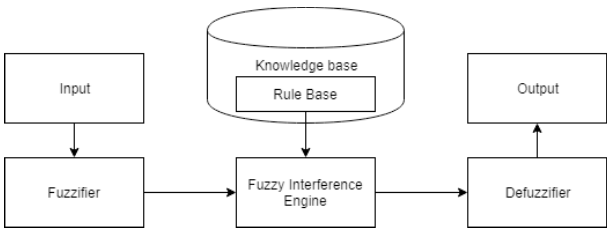
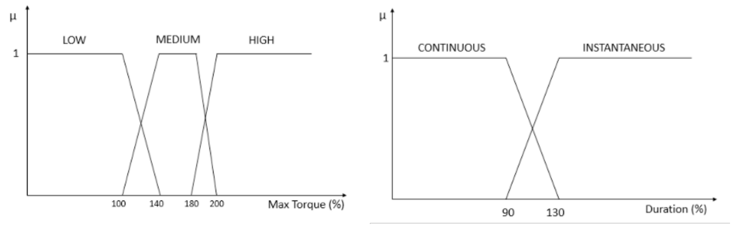


Fig. 4. The structure of fuzzy logic approach.

Three trapezoidal belonging functions corresponding to the expressions "low", "medium" and "high" have been used for the fuzzification of the MaxTorque variable. Two trapezoidal belonging functions corresponding to the expressions “Continuous” and “instantaneous” have been used for the fuzzification of the "Duration" variable as shown in the figure 5. As you can see, on the vertical axis the membership degree (μ) is reported, which can assume a value between zero and one, based on the input value of the fuzzified variable (abscissae). The inferential engine implements a set of six IF-THEN rules (see the table reported in Figure 5), defined on the basis of expert knowledge.

In particular, these rules are based on the logic generating the overload warning (see Figure 3), which is based on the evaluation of the magnitude of the stress and its duration over time. In addition, they are based on the experts' knowledge, gained over the years through the execution of manual analyses.

The rules are characterized by antecedents (IF parts) that involve linguistic variables and the consequents (THEN parts) that involve numeric variables. All the rules use "AND" as fuzzy logic operators. According to the Sugeno model, the system output is represented by six linear membership functions, which determine the probability the spindle has to be subjected to axial impact during the considered handling.



FLS
if MT is "low" and D is "continuous" then the output is 10
if MT is "medium" and D is "continuous" then the output is 30
if MT is "low" and D is "instantaneous" then the output is 30
if MT is "medium" and D is "instantaneous" then the output is 50
if MT is "high" and D is "continuous" then the output is 70
if MT is "high" and D is "instantaneous" then the output is 90

Fig. 5. Membership function of Max Torque and Duration and Rule base of fuzzy logic algorithm.

4.3. Prototype construction

Considering the scalability and cross-platform advantages of web applications, the prototype software is developed in client/server architecture.

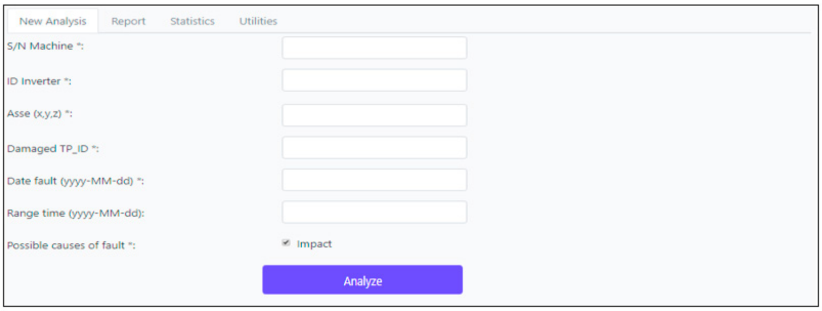


Fig. 6. The User Interface.

The client side of the system has a simple user interface for users to interact with the system and to visualize the diagnostic results. Regarding the better accessibility of the system, responsive design approach has been taken during the user interface development. The database server stores the parsed log file contents in a structured format and make them easily accessible for the diagnostics module. On the server side, we have the server that queries the database according to the user input and make diagnostics based on the knowledge base.

4.4. Validation

The proposed system has been tested on 33 industrial cases of spindle failure due to impact. To this end, the performances of the proposed solution have been determined by comparing in terms of efficiency and effectiveness the diagnostic results determined by users with the support of the system to the diagnostic indications provided by expert technicians who manually examined the logfile.

The effectiveness was measured as the percentage of matches between the diagnostic indication provided by the system and that provided by the experts.

Results demonstrated the effectiveness of the system in determine the cause of the impact: where experts identified the causes of the failure, the system provided diagnostic indications in line with them.

However, as far as the fuzzy algorithm is concerned, a false positive percentage of 13% has been found. The cause of this was mainly found in the inertia of the servo drive in fact in some machine states (for example, at the beginning of the machining or when the machining stops immediately for an emergency) the inertia of the servo drive generates very high values and may causes distortions on the output of the fuzzy algorithm.

5. Conclusion

The evaluation results evidenced that the proposed knowledge-based system is capable of identifying machine tool failures caused by accidental events and determine whenever the failure was caused by human error. The causes of the failure are determined only by analyzing the process data provided by the PLC data log, so that the system does not require the collection of ad hoc sensors data.

Results suggest that the proposed application, if implemented in an industrial context, can bring great benefits in terms of increasing customer service efficiency. The proposed solution represents a possible application to exploit the potentiality of big data information already available in the machine tool manufacturing industrial sector.

Future studies should be conducted to improve the system effectiveness by reducing the occurrence of false-positive results. In particular, proper rules have to be introduced in order to disregard the occurrence of events that may result in strong inertial stresses during the handling. Moreover, the system diagnostic capability should be extended in order to diagnose other typologies of failure. To this end, other studies should be conducted to assess the possibility of deriving the knowledge necessary to identify the causes of accidental failure, directly from the process data, by using data mining tools and machine learning techniques (e.g., Artificial Neural Network, Neuro-fuzzy systems, Bayesian Networks, etc.).

Acknowledgements

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