International Journal of Modern Manufacturing Technologies
ISSN 2067–3604, Vol. VI, No. 2 / 2014

TOOL MANAGEMENT DECISION-MAKING SYSTEM FOR CNC WORKSHOPS

Adriana Albu [1a], Constantin Cărăuşu [2], Loredana Stanciu[1b]

[1a] Politehnica University Timişoara, Automation and Applied Informatics Department, 2, Vasile Pârvan Blvd., 300223, Timişoara, România
[1,b] Politehnica University Timişoara, Automation and Applied Informatics Department, 2, Vasile Pârvan Blvd., 300223, Timişoara, România
[2] Technical University "Gheorghe Asachi" of Iasi-Romania, Department of Machine Manufacturing Technology, 59A, Dimitrie Mangeron Blvd., 700050, Iaşi, România

Corresponding author: Adriana Albu, adriana.albu@aut.upt.ro

Abstract: Tool management is needed in metalworking so that the information regarding the tools for the job can be uniformly organized and integrated. The information is stored in a database and it is registered and applied by the decisional system tool management. Tool data management consists of specific data fields, graphics and parameters that are essential in production, as opposed to managing general production equipment. The paper shows an approach of tool management using a common CNC controller and decisional elements from artificial intelligence field.
Key words: tool management, decisional system.

1. INTRODUCTION

The Tool life ratio use is an essential factor for the production cost and also for the machine tool efficiency. In practice, there are no cutting tools used hundred percent regarding their catalog tool life. The objective of any manufacturer is to maximize the tool life ratio, in order to reduce the production's costs [5] (Fig. 1).

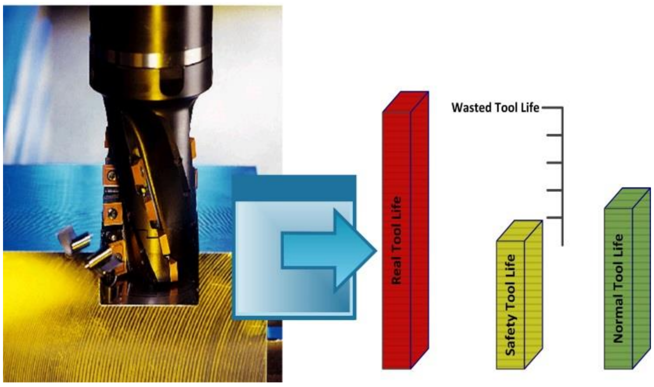

Fig. 1. Various tool life cathegories

The tool life ratio can be maximized without any scientific or technical support (using the cutting tools to the end of their life). But this straight method leads to supplementary costs on other components of the manufacturing system: tool breakage, machine tool breakage, or additional scrap. Therefore, the straight method is in fact more expensive than the rational use of a cutting tool, which doesn't affect the integrity of the tool, of the machine tool or of the part.

The solution is to develop an intelligent method that is able to prevent the tool breakage at an unpredictable moment. The system described by this paper decides regarding the action that should be performed, suggesting one of the following cases:

- the machine continues to work in the most difficult, but also the most profitable operating mode, because there are no risks;
- the operating mode is changed (to an easier one) because the risks of tool breakage are unacceptable;
- the cutting tool is replaced.

This way, the cutting tool has an extended period of use that is close to the catalog tool life and the risks of tool breakage are minimized.

2. THE SYSTEM'S PARAMETERS

The decisional system analyzes several parameters that are given for the job:

- tool type – there are considered twelve possible types of tools (e.g. drill, cutter-miller, reamer, tap);
- manufacturer – six world's largest manufacturers should be enough for any workshop that uses this system;
- material – this is about the materials that are processed and there are considered thirty possible materials (e.g. steel, iron, brass, aluminum);
- working conditions – these are divided into five categories from difficult to easy (or from hard cut to light cut).

Besides these parameters, there are two special parameters:

-operating mode – this is the single feature of the machine that can be set before the job and it specifies the parameters like depth of cut, feed and speed (a_p, F, S); this is also divided into five types from hard to easy;

- tool life – it is a key parameter provided by the CNC controller; this is the first parameter analyzed by the decisional system; if it is greater than or equal to the execution time for that job, then the machine continues to work in hard operating mode; otherwise, the decisional system suggests to change the operating mode or to replace the tool.

All these parameters must satisfy two constraints in order to be used by the decisional system. These are required by the Bayes' theorem that is used in statistical inference (which is part of this decisional system).

First, they must have a binary representation; therefore the parameters will have the values 1 (for true) or 0 (for false). For instance: *Is the tool a drill? Yes* or *No. Are the working conditions difficult? Yes* or *No.* The tool life hasn't such a representation; it is a number between, let say, 0 and 120 minutes and should receive a binary meaning. A solution is to analyze the ratio between the tool life (T_L) and the execution time (E_T). This ratio is a number in the range [0;1) because the tool life is certainly less than the execution time if the decisional system executes this part (if T_L is greater than or equal to E_T, then the machine continues to work in the most difficult operating mode and no other decision is needed). But even this number (the ratio T_L/E_T) doesn't have a binary representation, yet. In order to do this, the range is split into four parts: {[0; 1/4), [1/4; 1/2), [1/2; 3/4), [3/4; 1)}. Now the question *Is the ratio between the tool life and the execution time in the range [1/2; 3/4)* has the answer *Yes* or *No*.

The second constraint is that all these parameters should be independent. It can be considered accomplished for this type of job. For instance, a tool can be used in any operating mode.

These parameters are features of a job. With these features a job can be performed or not. A database with hundreds tests was created. This is in fact a statistical set and it is used by the decisional system that should analyze as many examples as possible in order to generate a viable result. The records in this database have 63 fields, each field having the value 0 or 1. An example of such a record is presented in table 1, where: the tool has the second type (of the twelve possible); the tool is produced by the third manufacturer (of the six considered manufacturers);

- the tool is made of the seventh material (of the thirty possible materials); the working conditions are the most difficult (the first of the five working conditions is true, the rest of them are false); the ratio between the tool life and the execution time belongs to the range [3/4; 1];

- the hardest operating mode was set (the first of the five operating modes is true, the rest of them are false).

In addition to the 62 job's features, each record in the database also stores information that shows if the job could be performed with these settings or not (if the tool was broken or not). This is necessary because the statistical set must contain the output, too.

The features for a new job are stored in a vector that has a structure similar to that of the records from the database (the one presented in table 1). Analyzing the elements of the vector and the records from the database, the statistical part of the decisional system calculates the risks of tool breakage. Then, the system suggests the action that should be performed.

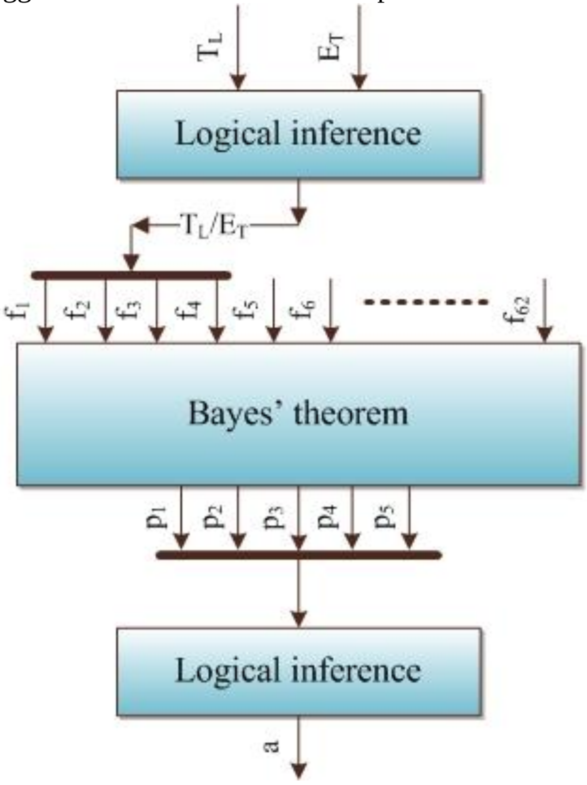

Fig. 2. The decisional system

In the figure 2 the terms involved are: T_L- the tool life from CNC controller; E_T - the execution timefor the job; f1...f4 – T_L /E_T ranges; f5...f62 – other features (e.g. tool type, manufacturer, material); $p_1…p_5$.- the probabilities of tool breaking for each operating mode a – the action (set the operating mode i, i=1…5, or replace the tool).

3. THE DECISIONAL SYSTEM

The decisional system is made of three parts (Fig. 2). First, a simple logical inference is used to decide whether the machine is able to continue the work in hard operating mode or not. Then, if the tool life is less than the execution time, the second part of the decisional system acts. This part is developed based on statistical inference and uses Bayes' theorem.

Table 1. The binary representation of the job's features

Tool types												Manufacturers						Materials 1-13												
0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Materials 14-30																	Working conditions					Tool life ranges				Operating mode				
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0

It makes predictions for each of the five operating modes, calculating the probability that the tool will break. This probability is analyzed by the third part of the decisional system (another logical agent) that decides what is the hardest operating mode that has an acceptable probability or, if none of the five probabilities is acceptable, decides that the tool must be replaced for this job. Therefore, this system uses a couple of mechanisms from artificial intelligence area. The artificial intelligence is a scientific domain that tries to create intelligent computer programs. Even if machines are better than humans regarding their abilities (power, speed) to perform calculations, they are far away from the human judgment. For this reason, humans are still the best standard for the intelligent systems [2]. John McCarthy (who coined the term, being the father of artificial intelligence) defined this field as the one that aims to create tools, which behave in a way that would be considered intelligent if a human would act so [3].

The intelligent computer programs are developed based on a multitude of mechanisms. Two of them (logical and statistical inference) were used to create the decisional system presented by the current paper.

Logical inference determines whether a statement is true or false, while statistical inference associates a probability to each possible case. A logical agent draws a conclusion with respect to the real world [1]; for this reason, it will definitely decide regarding the analyzed statement (for instance, the current system is able to say that the machine may continue to work in the most difficult operating mode, because there are no risks). A probabilistic agent acts with respect to a knowledge state [1]; therefore, its output quantifies uncertainty, being a degree of belief (the statistical part of the decisional system presented here calculates the probability to break the tool in some given conditions, but doesn't decide what action should be performed; this decision is generated by a logical part that analyzes the outputs of the statistical agent). Logical inference is a mechanism used to create decisional systems that draw a conclusion starting from a set of premises. It implements the human reasoning and needs some rules in order to do this. The premises are analyzed according to these rules and a decision is set (just like a human acts). A system developed based on logical inference has a ' graph structure and a chain logical evaluation is applied on this structure.

Logical inference is suitable for cases with simple rules. But sometimes it is very difficult to express the rules, or the transition from the implicit knowledge to explicit rules can lead to loss or distortion of information [4]. For these cases, some other mechanisms from artificial intelligence field should be considered. The current system uses statistical inference for the part that cannot be implemented based on logical inference.

One of the methods used in the most modern artificial intelligence systems for statistical inference is Bayes' theorem. It is a formula with conditioned probabilities and Eq. 1 presents it:

$$p(b \mid f) = \frac{p(f \mid b) \times p(b)}{p(f)} \tag{1}$$

Here *b* and *f* are two events, *b* being a kind of diagnosis from available evidence *f*. Therefore, for this decisional system, Eq. 1 calculates the probability of tool breaks (*b*), knowing that certain events, connected to the input features (*f*), are happening. Bayes' formula could be considered a step backwards because it calculates a probability using other three probabilities, but it is useful in practice when these three probabilities can be easily determined. Usually, the probability in the causal direction ($p(f|b)$) is more evident than the probability in the diagnosis direction ($p(b|f)$) [1].

The probability $p(b)$ is easily calculated, being the frequency of the event *b* (tool breaks) in the entire database *D* (number of records *r* that have the diagnosis *b* equal to 1 – the tool was broken). Eq. 2 shows this:

$$p(b) = \frac{cardinal\{r \in D \mid b(r) = 1\}}{cardinal D} \tag{2}$$

Now, the probability $p(f|b)$ must be calculated. The input features *f* are in fact the parameters that are given or that are set for the job. These are stored as binary values in an input vector $f = \{f_1, f_2, \ldots, f_n\}$, where *n* is the number of parameters. For this case *n* is 62: 12 tool types, 6 manufacturers, 30 materials, 5 working conditions, 4 tool life ranges, and 5 operating modes. Eq. 3 can be used to calculate this probability:

$$p(f \mid b) = \prod_{i=1}^{n} p(f_i \mid b) = \prod_{i=1}^{n} \frac{p(f_i, b)}{p(b)} \tag{3}$$

Each probability $p(f_i,b)$ is in fact the frequency of f_i and *b* in the database *D*. This means that the records *r* that have the parameter f_i and also the output b equal to 1 must be counted (Eq. 4):

$$p(f_i, b) = \frac{cardinal\{r \in D \mid f_i(r) = 1 and b(r) = 1\}}{cardinal D} \quad (4)$$

There is one more probability to calculate, *p(f)*. In order to do this, a short analysis is needed.

Eq. 1 is used further (in Eq. 5) to calculate the probability that the tool doesn't break ($\neg b$) in the same given conditions (f):

$$p(\neg b \mid f) = \frac{p(f \mid \neg b) \cdot p(\neg b)}{p(f)} \quad (5)$$

From Eq. 1 and Eq. 5 can be noticed that the term *1/p(f)* is constant, no matter which probability is calculated. This is considered a normalization constant [1], which ensures that the sum of the calculated probabilities is 1 (as it should be, because this sum represents all possible worlds for this job, anything else being impossible; if these two probabilities are added, the result is the certain event – the event that is surely happening – and its probability is 1). The conclusion is that the probabilities *p(b|f)* and *p(¬b|f)* could be calculated even if *p(f)* is unknown. Though the term *1/p(f)* is ignored in equations Eq. 1 and Eq. 2, the obtained (partial) probabilities are still in a correct relative proportion; the single problem is that their sum is not 1 anymore. This can be solved if each resulted probability is normalized, dividing it by the sum of the partial probabilities and obtaining the true ones [1]. Therefore, *p(f)* can be replaced by this sum, as Eq. 6 shows:

$$p(f) = p(f \mid b) \cdot p(b) + p(f \mid \neg b) \cdot p(\neg b) \quad (6)$$

Now, the probability of tool breaks can be calculated for each of the five operating modes (Eq. 7). The rest of the parameters (besides the operating mode) are unchangeable, because they are given for a specific job.

The system will use these probabilities to decide which operating mode is suitable for the machine (if there is one) or it will suggest to replace the tool. This decision is made based on logical inference.

$$p(b \mid f) = \frac{p(b) \cdot \prod_{i=1}^{n} p(f_i \mid b)}{p(f \mid b) \cdot p(b) + p(f \mid \neg b) \cdot p(\neg b)} \quad (7)$$

The behavior of the entire decisional system is implemented by three functions that are hereby presented:

-The first function – logical agent 1: inputs: tool life (T_L), execution time (E_T); actions: decides whether the machine continues to work in hard operating mode or not (if not, then the rest of the decisional system will be executed); output: the action;

- The second function – probabilistic agent: inputs: the ratio T_L/E_T and the rest of the job's features from the environment; actions: calculates the tool breaks probability for each operating mode; output: the probabilities;

- The third function – logical agent 2: inputs: the probabilities from the probabilistic agent; actions: decides whether another operating mode must be set or the tool must be replaced; output: the final decision.

CONCLUSIONS

The decisional system was trained on 200 cutting tools with various shapes and dimensions. Then it was tested on other 140 cutting tools. The system's accuracy was 98% for tool life expectancy of 100%. A better accuracy can be achieved if the cutting tool is not used to its maximum catalog tool life value. This last condition is applied for expensive parts where the risk of the scrap must be close to zero.

Regarding the artificial intelligence methods selected for the computational engine, the results prove that the decisional system developed is robust, practical, and reliable. These are essential attributes for an industrial process. The same problem can be also solved using other methods from artificial intelligence domain (e.g. neural networks) that might be implemented and tested.

REFERENCES

[1] S. Russell, P. Norvig, *Artificial Intelligence: A Modern Approach*, third ed., Pearson Education, Inc., Publishing as Prentice Hall, United States, 2010, ISBN 978-0-13-604259-4

[2] J. Beal, P. H. Winston, Guest Editors' *Introduction: The New Frontier of Human-Level Artificial Intelligence*, Intelligent Systems, IEEE 24.4: 21-23, 2009

[3] J. McCarthy, *What is Artificial Intelligence?*, Computer Science Department, Stanford University, 2007

[4] J. M. Zurada, *Introduction to Artificial Neural Systems*, Jaico Publishing House, 2012, ISBN 978-8172246501

[5]*** – http://www.walter-tools.com/en-gb/tools/standard_products/Pages/default.aspx, accessed on 2014.11.12

Received: June 11, 2014 / Accepted: December 10, 2014 / Paper available online: December 15, 2014 © International Journal of Modern Manufacturing Technologies.