

Optimizing Machining Processes with the Aid of Bayesian Networks

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Abstract: Product quality in machining processes like drilling or milling depends on a variety of parameters like the cutting speed or the feed rate as well as dependencies among these parameters. The type of lubrication, method of chip removal and tool wear also play a decisive role for quality characteristics like roughness, roundness or surface finish. Finding an optimal combination for all these influencing factors to meet the required quality properties is a demanding task. In this paper a Bayesian network will be presented which covers the relations and dependencies between influencing parameters, quality characteristics as well as additional process relevant variables for a spiral drilling process. The network is quantified, i.e. the network is provided with the required conditional and unconditional probability values, by parameter learning with the aid of a dataset from the considered spiral drilling process. Finally, the network model will be tested and validated with the help of selected application scenarios and it turns out, that it yields plausible results.

Keywords: Machining Production, Bayesian Networks, Quality Optimization

1. Introduction

Machining is one of the most important manufacturing operations in industry. In order to improve the manufacturing productivity and the product quality, a Bayesian network model for the machining process will be developed to qualitatively optimize both. The model will support the machine operator to determine an appropriate combination of the influencing parameters to meet the required quality specifications. Furthermore, the model will enable him to realistically predict the quality of the part or product.

2. Background

2.1 Machining processes

Machining processes are various material removal processes in which a cutting tool removes unwanted material from a workpiece to produce the desired shape. The workpiece is typically cut from a larger piece of stock, which is available in different standard shapes, such as flat sheets, solid bars, hollow tubes, and shaped beams. Machining can be used to create a variety of features including holes, slots, pockets, flat surfaces, and even complex surface contours. Also, while machined parts are typically metal, almost all materials can be machined, including metals, plastics, composites, and wood. Particularly in drilling, the rotating tool is fed vertically into the stationary workpiece to create a hole. A drill bit enters the workpiece axially and cuts a blind hole or a through hole with a diameter equal to that of the tool.

2.2 Bayesian Networks

Probabilistic graphical models (Darwiche, 2014) are a framework of statistical models for encoding probability distributions where a graphical structure encodes a set of conditional dependence and independence relations over a set of random variables representing a problem domain. Bayesian networks are directed acyclic graphs (DAG) where the nodes represent events (random variables) with a finite set of states and the arrows stand for dependencies between any pair of nodes in the network. These networks allow bidirectional reasoning, namely from cause to effect as well as from effect to cause.

2.2.1 Definition of Bayesian Networks

More technically, a Bayesian network is a pair (G, P) , where $G=(V, E)$ is a directed acyclic graph over a set of random variables V and E is a set of directed edges that represent probabilistic relationships between variables in V (Pearl, 1988). P is a set of conditional probability distributions (CPDs) that quantify the strength of the relations induced by E . Specifically, P contains for each V in V , the CPD $P(V|pa(V))$, where $pa(V)$ is the set of parent variables of V in G .

Such a Bayesian network supports both diagnostic and prognostic reasoning by computing the posterior probability $P(H|e)$ of an unobservable hypothesis H given observed evidence $e = \{e_1, \dots, e_m\}$, where each e_j is the observed state of the variables $E = \{E_1, \dots, E_m\}$.

2.2.2 Methodology for Creating Bayesian Networks

The construction of a Bayesian network for a complex problem is usually a demanding task, involving different sources of expertise that provide model engineering skills as well as deep understanding of the problem domain. The model building process requires careful problem definition, identification of the relevant variables as well as the underlying dependencies among these variables, and finally the elicitation of the probability distributions. The development of a Bayesian network is an iterative process (Kjærulff & Madsen, 2014) as depicted in figure 1.

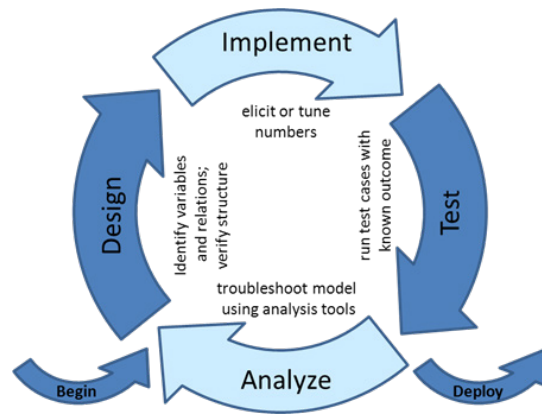


Figure 1. The different phases in model development

During the model development process we run through the different development phases until tests no longer uncover undesired behavior of the model. In the design phase the relevant variables together with their states are defined and the structure of the network is specified. During the next phase in the development cycle the network will be quantified, i.e. the probability values are determined. In the following phase the model will be tested with aid of appropriate data, and finally the behavior of the model will be analyzed.

3. Model for process optimization

Bayesian networks are not an appropriate tool for numerical optimization in the usual sense of the word. Rather, the aim of the developed model is to qualitatively identify tendencies like *if the feed rate is decreasing, the surface finish will improve* or *if the cutting speed is decreasing, the surface finish tends to get worse*.

3.1 Construction of the Bayesian Model for process optimization

As already mentioned in section 2.2.2 the construction of a Bayesian network starts out with the definition of the relevant nodes together with an appropriate set of states. In the next step the topology of the net has to be determined, i.e. it has to be defined between which pairs of nodes a link is necessary and in which direction it points. As soon as the structure of the network is fully specified, it has to be quantified, i.e. the conditional probability tables have to be filled with appropriate values.

3.1.1 Defining the topology of the Bayesian Network

The definition of the topology of the net is straightforward in this application (see figure2). Influencing parameters like *Cutting Speed* or *Feed Rate* are modeled as root nodes (yellow nodes in figure 2). Quality characteristics like *Bore Diameter* or *Surface Finish*, on the other hand, are represented as leaf nodes in the network (blue nodes in figure 2). The degradation of the tool, represented by the node *Mechanical Wear* (orange node in figure 2), has an impact on all quality characteristics. On the other hand, the degradation is directly influenced by the yellow nodes. The influencing parameters have links to quality characteristics or to the tool wear or to both.

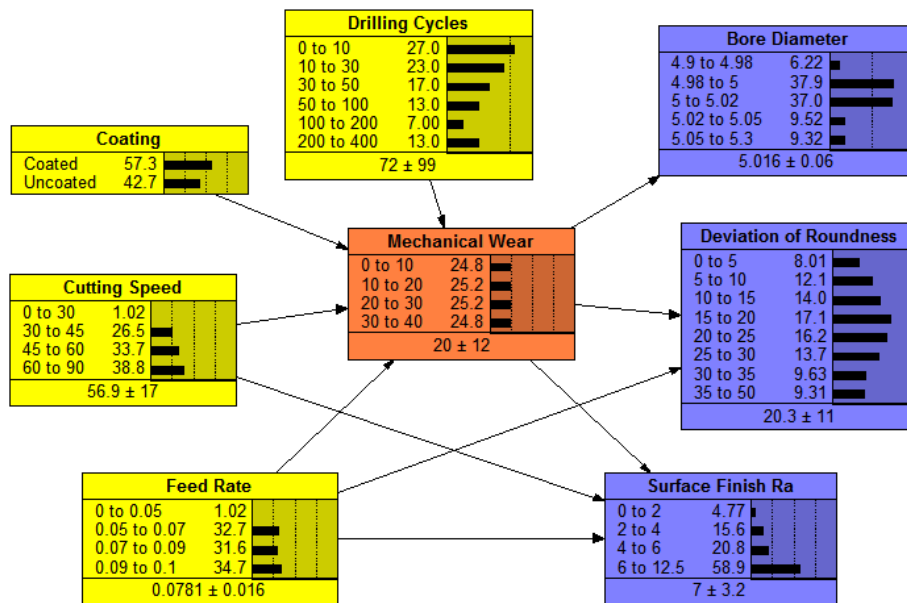


Figure 2. Bayesian Model for a Spiral Drill Process

Since all the nodes represent continuous variables, they have to be discretized appropriately. This means that the range of each variable has to be subdivided into disjoint intervals which cover the whole range of the respective variable. It is important to make sure that you define as many states as necessary and as few as possible, since the more states there are in the network the more probabilities have to be specified.

3.1.2 Eliciting the probability values of the Bayesian Network

Defining the probability distributions in the network can be done by parameter learning (Neapolitan, 2004), by prior knowledge or by a combination of the two. In our application regarding the spiral drilling process we used basically learning from a dataset of cases and only little prior knowledge. Figure 3 shows an example for prior knowledge in the form of an equation for the node *Mechanical Wear*.

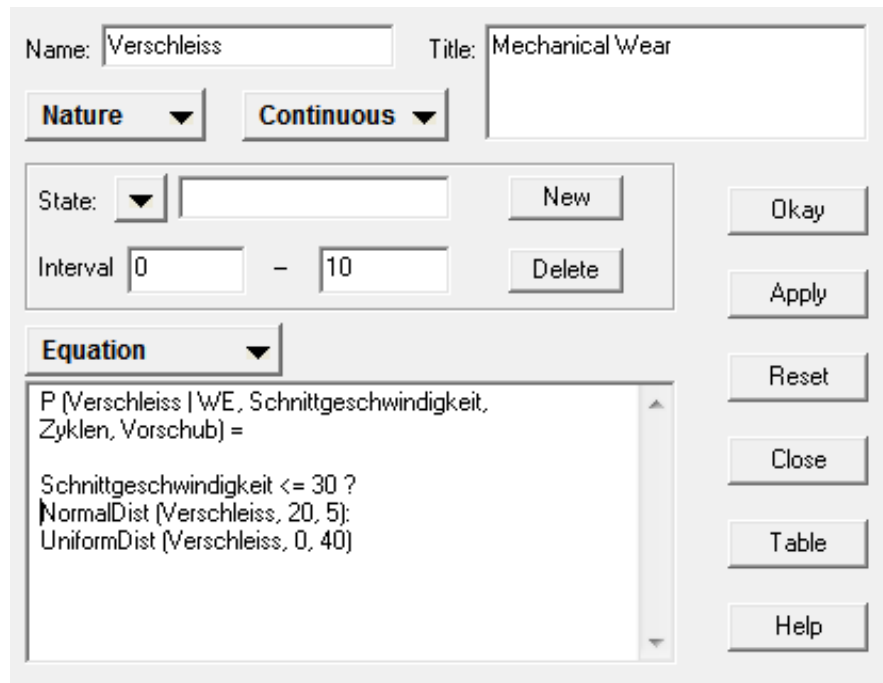


Figure 3. Prior knowledge in the form of an equation for the node *Mechanical Wear*

The rest of the network's probability tables were learned from a dataset with less than one hundred cases which have been observed in the spiral drilling process. This is enough for learning the root and leaf nodes in our model. However, some more cases would have been needed to learn the node *Mechanical Wear* satisfactorily, since its probability table is much bigger than the others as the node *Mechanical Wear* has several predecessors.

3.2 Application of the developed model

With the help of the developed model it is possible to simulate the real drilling process. This can be done in different ways. On one hand it can be investigated how nodes in the network change when the influencing parameters are manipulated (causal reasoning). On the other hand it can be examined what effects occur when the distributions of the leaf nodes are modified (diagnostic reasoning).

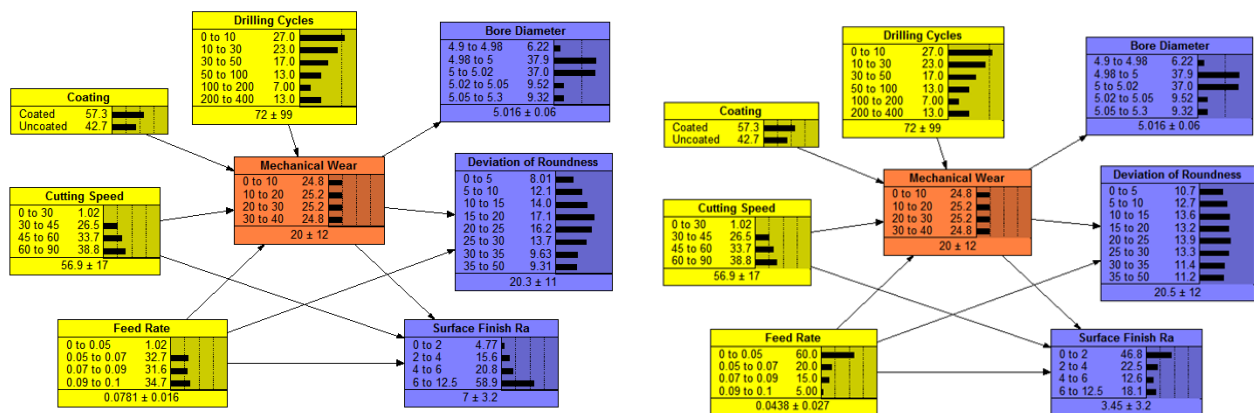


Figure 4. Rather low feed rate results in a better surface finish

Figure 4 shows the original model on the left side and the changed model on the right. It can be observed that the surface finish will improve significantly when the distribution of the feed rate is changed to rather low values. However, in figure 5 is illustrated what happens when modify the net by changing the distribution of the cutting speed to rather low values, namely the surface finish gets even worse.

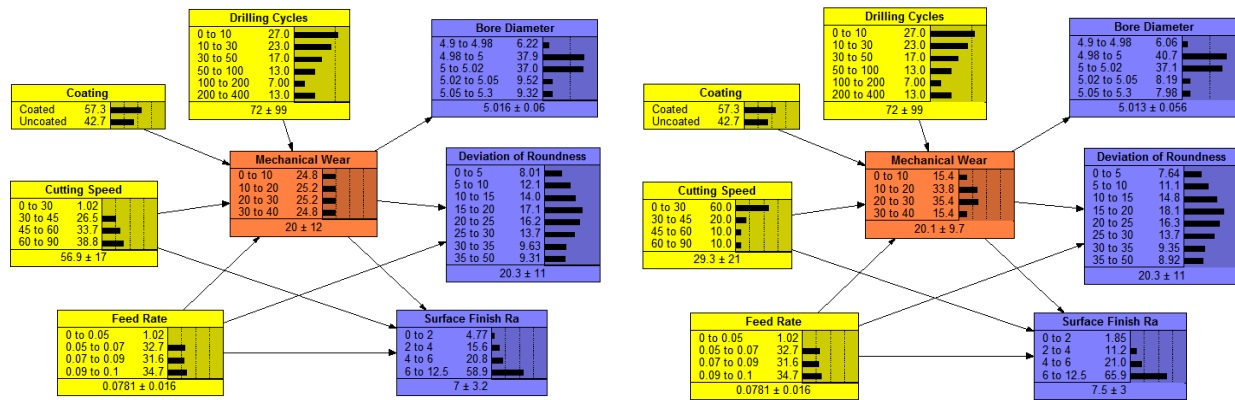


Figure 5. Rather low cutting speed results in less quality of the surface finish

Obviously, for a good surface finish we have to choose rather low values for the feed rate and high values for the cutting speed. Consequently, we set the feed rate to the lowest possible state and the cutting speed to the highest value. As figure 6 shows, this results in a very good surface finish, even much better than in figure 4.

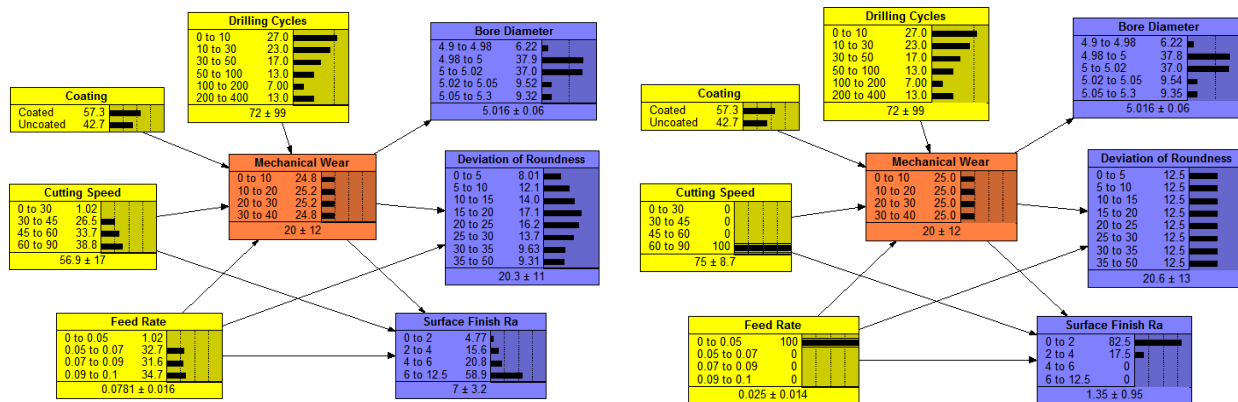


Figure 6. High cutting speed and low feed rate of results in good surface finish

4. Conclusion

In this paper we presented a Bayesian network model to qualitatively optimize a spiral drilling process. The model was tested and validated with the help of selected application scenarios. Experts from the field of drilling considered the results as absolutely plausible. The dataset from our study for learning the parameters of the model was too small to really analyze the role of the tool wear. However, the model is capable to constantly update and adapt its parameters. Furthermore, in future networks there have to be some more factors to be modeled like processing temperature, chip formation as well as type of lubrication, which all play a crucial for the quality of the part or product.

5. References

- Darwiche, A. (2014). *Modeling and reasoning with Bayesian networks*. Cambridge University Press, New York, USA.
- Kjaerulff, U.B., Madsen A.L. (2014): *Bayesian networks and influence diagrams: A guide to construction and analysis*. Springer, New York, USA.
- Neapolitan, R.E. (2004). *Learning Bayesian networks*. Upper Saddle River NJ, Pearson Prentice Hall series in artificial intelligence, USA.
- Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems – Networks of Plausible Inference*. Morgan Kaufmann Publishers, San Mateo, California.