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ANN-BASED CHIP-FORM CLASSIFICATION IN TURNING

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Abstract − Today's complex manufacturing systems operate in a changing environment rife with uncertainty strengthening the requirement for developing production systems with the ability of self adaptation. Market competition forces production firms to work more and more efficiently. As a consequence, continuously increasing material removal rate and flexible automation tools, without active human supervision can be observed as trends also in the metal cutting industry. Monitoring the chip breaking process is one of the important factors for automated supervision. The paper presents artificial neural network (ANN) based models for identifying the cutting chip form based on measured monitoring data.

Keywords: Cutting chip, Monitoring, Neural network

1. INTRODUCTION

In metal cutting there is a tendency to achieve increased metal removal rate through high degree of automation and without active human supervision. This tendency requires reliable and controlled machining process.

Surface finish, workpiece accuracy, tool-life and force components are widely emphasized. In general, less attention is paid to chip control, the occurrence of acceptable chip forms in the working zone, or the chip formation and chip breaking aspects; however, they have strong effects on the above features. Several chip control methods and techniques have been developed and applied in the practice:

- Inserts or cutting edges with chip breakers are widely used, but the selection and the design of the perfect geometry are still a problem.
- Predictive models developed through experimental database help in the selection of cutting tools and cutting conditions.
- Special means to produce broken chips (use of vibrating tools, high pressure coolant, hardened workpiece material, etc.) are successfully applied for some operations.

Fig. 1. shows the ISO standard [1], supporting the importance of the cutting chip form for making coded classification possible.

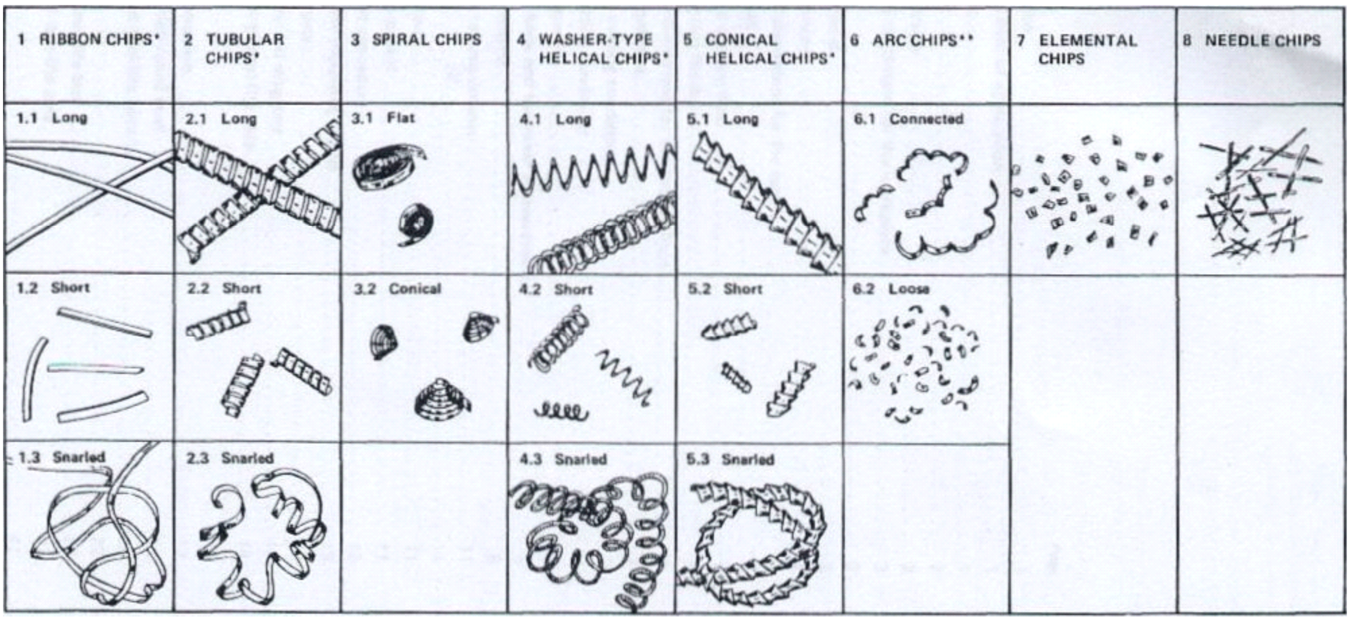

Fig. 1. The ISO 3685-1977 (E) containing the standard chip forms

The type, or often called the form of the cutting chip is an important feature of cutting processes. It influences:

- the stability of the process – e.g. long chips can disturb the machine, the environment and they have negative effect on the cutting process itself,
- the environmental effect of the production – e.g. small, broken chips are far easier to handle, store, transport and recycle.

2. CONCEPT

The importance of the cutting chip form initiated research aiming at building up a system for classifying chip forms. Some attempts have been made till now to predict the breakability and shapes of chips, analytically [1-2]. The chip breakability diagrams (chip charts) supplied by tool vendors do not seem to be reproducible, and can mainly be used for the determination of the chip breaking region. These diagrams provide only a qualitative assessment of chip breakability under a given set of conditions. Some other possible methods for identifying the chip form (e.g. simple human-look or camera-based methods) are known. The time aspect of the chip identification plays an important role, the identification can be on-line and off-line, as well. The research reported on here aimed at preparing off-line chip identification and classification system, however, its further improvement allows extending the method to the field of on-line solutions. The developed tool is expected to support decisions also on higher levels of manufacturing control, e.g. process planning, beyond the envisaged, original monitoring application.

The above research goals suggested exploiting the manufacturing and monitoring data of the cutting process to support the classification.

Reliable process models are extremely important in the different fields of computer integrated manufacturing. They are required e.g. for selecting optimal parameters during process planning, for designing and implementing adaptive control systems or model-based monitoring algorithms. A reliable model is required for the chip form classification, too.

The applied artificial neural networks, neuro-fuzzy (NF) systems are general, multivariable, non-linear estimators, therefore, they offer a very effective process modelling approach. Soft computing techniques like this seem to be a viable solution for intelligent control and monitoring systems where real-time functioning, uncertainty handling, sensor integration, and learning are essential features [4-5].

Based on the above advantages of ANN based modeling and on the possibility for collecting different monitoring data during the cutting processes, ANN was proposed as a model of the experiment.

Several experiments were performed by varying the cutting parameters, using the same machine, material and cutting tool for generating the data set required for training and testing the ANN model.

3. DESCTRIPTION OF THE CUTTING PROCESS

Applying ANNs as models require numerical parameters describing the analyzed system. As introduced in the previous paragraph, monitoring data are partly applied for the description of the cutting process. Data channels were build up delivering information from different acquisition sensors as enumerated bellow:

- The energy aspect of the process is characterized by the power consumption of the turning machine.
- Three components of the cutting force (Fig. 2.) were measured by using a piezzo-electric sensor incorporated in the tool holder.

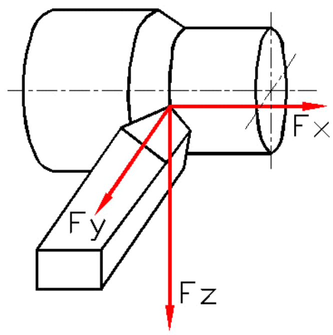

Fig. 2. The appointed directions concerning the calculated signal features

Thirteen statistical parameters were calculated from each of the time-series (three components of force and power signals), consequently, they were transformed into a set of monitoring-oriented description parameters. Typical measured signals are presented in Fig. 3.

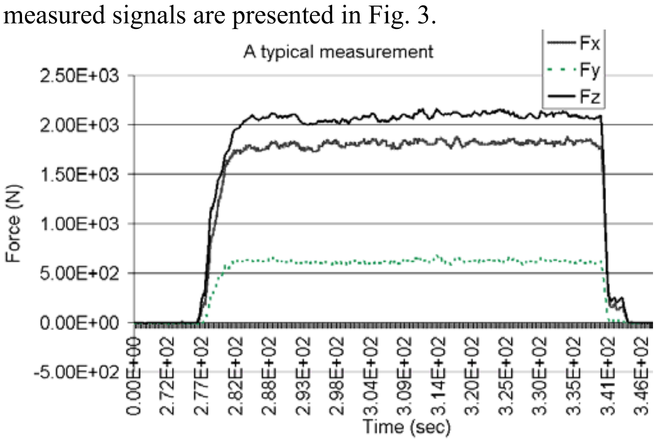

Fig. 3. Typical time signals of the three force components

The following paragraph lists the statistical features calculated form each of the time series [6]:

- Average
- Mean of the signal quadratic values
- Deviation
- Standard deviation
- Power of the signal
- 3. central moment
- 4. central moment
- Skewness

- Excess
- Maximum value of the signal divided by the deviation
- Minimum value of the signal divided by the deviation
- Signal maximum
- Signal minimum

Further parameters were measured for the detailed description of the process, its environment and effect:

- Surface quality of the resulted individual work-pieces was measured and coded by a simple Ra value.
- The tool insert condition was continually controlled by the value of the tool wear (VB) acquired after an experiment. If the tool turns to worn (the VB parameter exceeds a prescribed limit), it was changed immediately.
- One temperature value was measured per experiment by the determination of the resistance change of an electrical cycle, incorporating the contact surface of the chip removal.
- Naturally, the basic setting data (depth of cut, feed per revolution and speed) were also given as process description parameters.

Eleven data called "engineering parameters" were also formulated. These data partly incorporate the description features of the cutting process.

- Average of the force in the feed direction (F_x in Fig. 2.) divided by the product of cutting speed and feed
- Average of the force in the turning speed vector direction (F_z in Fig. 2.) divided by the product of cutting speed and feed
- Average of the force in the third perpendicular direction (F_y in Fig. 2.) divided by the product of cutting speed and feed
- Average of the force in the feed direction (F_x in Fig. 2.) divided by the product of depth of cut and feed
- Average of the force in the turning speed vector direction (F_z in Fig. 2.) divided by the product of depth of cut and feed
- Average of the force in the third perpendicular direction (F_y in Fig. 2.) divided by the product of depth of cut and feed
- Temperature multiplied by cutting speed
- Workpiece roughness multiplied by cutting speed
- Average of the power signal divided by the average of the force component perpendicular to the rotation axle of the turning machine (F_y in Fig. 2.)
- Average of the power signal divided by the product of the average of the force component parallel to the depth of cut (F_y in Fig. 2.) and the cutting speed
- The "specific cutting energy": the average of the power signal divided by the product of feed and depth of cut.

As a summary, ninety-seven parameters were used per experiment to describe the cutting process serving as the parameter basis for the determination of the chip form.

3. CODING THE COLLECTED CUTTING CHIP

Fig. 3. shows some of the generated chips collected during the cutting experiments. They were coded by human evaluation, applying the above ISO standard. As it was experienced, this coding was a quite difficult step, because the ordering of a chip into a class proved sometimes to be ambiguous.

Fig. 3. Some collected chips, showing the variety in their forms

We think that this human evaluation resulted in a certain level of classification error. This uncertainty of the chip coding might have brought a certain level of noise in the learning and classification phases.

4. CLASSIFICATION TASKS

Originating from the different coding of the same chips, the above ISO standard also gives the possibility to formulate five classification tasks. The chip form classes to be identified in these assignments are listed as follows:

1. ribbon, tubular, spiral, washer-type, conical-helical, arc;
2. long, short, snarled
3. ribbon_long, ribbon_snarled, tubular_long, tubular_short, tubular_snarled, spiral_flat, spiral_conical, washer-type_long, washer-type_short, washer-type_snarled, conical_long, conical_short, arc_connected, arc_loose;
4. flat, short, snarled, long, conical, connected, loose;
5. good, acceptable, dangerous – describing the stability of chip removal.

These assignments were subdivided into two subtasks as described in the next paragraph.

5. SELECTION OF THE DESCRIPTION PARAMETERS RELEVANT TO ASSIGNMENTS

The applied feature selection technique, which is based on the data of the measurements, done already is one of the common methods for selecting the most relevant parameters describing the process [6]. This technique is based on the set of collected parameters (input and output parameters together) and gives a sequence of the input parameters based on their incorporated information content, on the one hand, and assigns a measure to sequence elements, on the other. Some of the "best" features completed with the three cutting parameters were selected from the above ones, serving as the basis of the ANN-based chip form classification. Parameters often selected: e.g. average, distribution and power of the force signal components, etc., as enumerated in the next paragraph.

All the analyzed classification tasks were divided into two subtasks:

- The first subtask takes some of the best features resulted from the feature selection technique as model inputs.
- The second subtask has the same input parameters as the first one, extended with the three main cutting parameters (speed, feed, depth of cut).

6. CLASSIFICATION SUCCESS

Selected features extended with the three main cutting parameters in some cases formed the inputs and chip form classes were the output parameters of the applied ANN model.

The difference between the recognition rates resulting from the training and testing phases of the ANN applied in a classification assignment was minimized to ensure modeling generalization. The relative limited amount of cutting experiments and, consequently, of data vectors explains this method, because there were not too many data to form two separated, large data set for training and testing.

Significant differences derived from the classification power of the models in the different assignments, as below:

1. Classes to be identified: ribbon, tubular, spiral, washer-type, conical-helical, arc
   The best features were:
   - signal power of force component F_y,
   - average of force component F_y,
   - minimum value of force component F_y, during the measurement,
   - maximum value of force component F_z, during the measurement,
   - maximum value of force component F_y, during the measurement,
   - signal power of force component F_z,
   - average of force component F_z,
   - minimum value of force component F_z, during the measurement,
   - standard deviation of the whole force vector (containing all three components)
   - signal power of the whole force vector,
   - average of the whole force vector,
   - standard deviation of the vector formed by the y and the z directions of the force components,

   The recognition rate in classification was as follows:
   - using the above features as input parameters: 69%,
   - using the above features as inputs but changing the last three features by the three main cutting parameters (speed, feed, depth of cut): 80%.
2. Classes to be identified: long, short, snarled
   The best features were:
   - cutting speed,
   - average of force component F_x, divided by the product of feed and depth of cut,
   - third central moment of force component F_z,
   - third central moment of the measured power signal,
   - maximum value of force component F_x, divided by its standard deviation,
   - minimum value of force component F_x, divided by its standard deviation,
   - third central moment of the vector formed by the y and the z directions of force components,
   - third central moment of the whole force vector,
   - Skewness of force component F_x,
   - third central moment of force component F_y,
   - mean of force signal F_x quadratic values,
   - deviation of the whole force vector.

   The recognition rate in classification was as follows:
   - using the above features as input parameters: 63%,
   - using the above features as inputs extended with two further cutting parameters (feed, depth of cut): 68%.
3. Classes to be identified: ribbon_long, ribbon_snarled, tubular_long, tubular_short, tubular_snarled, spiral_flat, spiral_conical, washer-type_long, washer-type_short, washer-type_snarled, conical_long, conical_short, arc_connected, arc_loose
   The best features were:
   - cutting speed,
   - temperature,
   - minimum value of force signal F_y,
   - power of force signal F_y,
   - average of force signal F_y,
   - maximum value of force component F_z,
   - power of force signal F_z,
   - average of force component F_z,
   - minimum value of force signal F_z,

   The recognition rate in classification was as follows:
   - using the above features as input parameters: 63%,
   - using the above features as inputs extended with two further cutting parameters (feed, depth of cut): 63%.
4. Classes to be identified: flat, short, snarled, long, conical, connected, loose
   The best features were:
   - maximum of force signal F_z,
   - power of force component F_z,
   - average of force component F_z,
   - minimum of force signal F_z,
   - standard deviation of the whole force vector,
   - power of the whole force vector,
   - average of the whole force vector,
   - power of force vector component F_y,
   - average of force vector component F_y,
   - minimum of force signal F_y,
   - maximum of force signal F_y,

- standard deviation of the vector formed by the y and the z directions of the force components,
- power of the same force vector component as above,
- average of the same force vector component as above.

The recognition rate in classification was as follows:
- using the above features as input parameters: 63%,
- using the above features as inputs extended with the above appointed cutting parameters: 52%.

5. Classes to be identified: good, acceptable, dangers

The best features were:
- cutting speed,
- average of force component F_x, divided by the product of feed and depth of cut,
- third central moment of force component F_z,
- maximum value of force component F_x, divided by its standard deviation,
- minimum value of force component F_x, divided by its standard deviation,
- third central moment of the measured power signal,
- third central moment of the vector formed by the y and the z directions of the force components,
- Skewness of force vector F_x,
- third central moment of the F_y force vector,
- third central moment of the whole force vector,
- Skewness of the measured power signal,
- Mean of force signal F_x quadratic values

The recognition rate in classification was as follows:
- using the above features as input parameters: 63%
- using the above features as inputs extending with the missing, above appointed cutting parameters: 73%

Recognition rates are difficult to compare due to the differences between the numbers of classes in the different assignments. The same amount of data vectors was applied for training and testing in the given assignments, consequently, the reliability of the recognition rate is higher in the case of fewer classes.

7. CONCLUSION

The paper illustrated an ANN-based method for identifying the cutting chip form. Continuously increasing material removal rate and flexible automation tools, without active human supervision can be experienced as a trend also in metal cutting industry. Monitoring the chip breaking process is one of the important factors for automated supervision.

A large number of parameters of machine setting, direct measurement values and the calculated factors of typical monitoring signals were applied as the basis information set for determination of the cutting chip form. Numerous experimental tests were performed to collect real measurement data for building up and testing ANN models for classification. A frequently used feature selection method was applied to pre-select the most important features. The chips of the experiments were collected and coded by using the relevant ISO standard. Five classification assignments were formed and their recognition ratios were reported on above. Beyond these research results, new techniques [5][7] allow that the generated ANN models may ensure the basis for determining machine settings and tolerances for monitoring parameters in order to get a pre-selected chip form for serving cutting efficiency, economic or environmental aspects. This technique is applied in other production-modeling fields, e.g., in lamp manufacturing industry [8]. Another future extension of research is to perform similar experiments, by using monitoring data in a certain time-window of the cutting process to move towards on-line supervising and control.

8. ACKNOWLEDGENENT

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