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QUALITY-ORIENTED, COMPREHENSIVE MODELLING OF MACHINING PROCESSES

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Abstract: Modelling of machining operations is a key issue in today's manufacturing. Reliable and effective models are needed in order to plan and control machining processes. The paper gives a short overview of modelling approaches frequently used in manufacturing with emphasis on the workpiece quality. Classical, e.g. differential equation-based techniques focus on the special aspects of machining (e.g. cutting forces, temperature, tool wear) and cannot handle the whole complexity of the processes manifested in the great number of variables and their stochastic, non-linear relations.
The paper introduces a concept for quality-oriented, comprehensive modelling of machining processes. It incorporates a large number of variables grouped into input, output and in-process categories. Fundamental features of the concept are the ability to learn from experience, and the flexibility in realising various, task dependent mappings with their inherent model building capability.
Keywords: modelling, cutting processes, artificial neural networks (ANNs)

1 INTRODUCTION

Very intensive research activities are conducted all over the world for the modelling of machining processes. Process models are considered as abstract representations of processes linking causes and effects or transforming process inputs into outputs. They can be classified in two groups: fundamental or micro models and applied or macro models. Our goal is to develop a framework for applied modelling, which is able to manage the cutting processes in their whole complexity.

Paragraph 2 outlines the complicated relations between some physical phenomena of the cutting process. In paragraph 3 classical models are reviewed. A large number of input and output parameters are listed in paragraph 4, which are needed to handle the multivariable character of the cutting process. In paragraphs 5 and 6 three model types and the transformations of knowledge between them are reviewed and the ANN model is proposed as the basic element of the cutting model framework described in paragraph 7.

2 PHYSICAL PHENOMENA AND THEIR INTERRELATIONSHIPS

Because of the complicated relationships between the phenomena incorporated into the cutting model, the machining process is hard to be decomposed [1] (Figure 1).

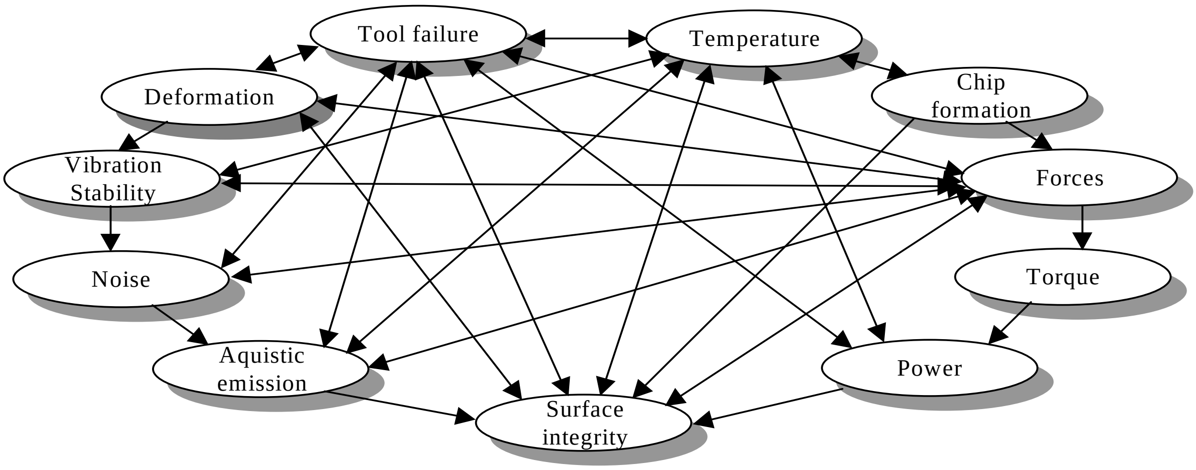

Figure 1. Some physical phenomena and their interrelationships

Mathematical (informative) methods used in the applied model group can be enumerated as follows:

- a set of deterministic equations to describe the steady-state features (conditions) of the process
- a set of stochastic formulae to handle the deviations of the output parameters (process uncertainty)
- complex models based on Artificial Intelligent (AI) methods.

3 CLASSICAL CUTTING MODELS

Fundamental cutting process models are based on the description of the chip removing phenomena by the classical physics, elastic-plastic deformation (fracture theory) or empirical measuring – curve fitting methods [2]. The first description of the machinability function (transformation) was introduced by Taylor and completed later establishing an empirical relationship between the tool life "T" and cutting parameters: cutting speed "v_c", feed "f" and "a" depth of cut (turning operation). For the deterministic tool life model T= f(v_c , f, a) empirically values of the exponents are necessary.

The first shear plane model of the cutting process, ($F_c=A*\tau_c*[ctg\phi+tg(\phi+\omega)]$), which is based on pure theoretical aspects, was developed by Merchant. The generally used cutting force model ($F_c=k_1*h^{1-m}*b$) developed by Kinzle is based on stress theory and empirical work too. ("k_1", "h", "b" denote the cutting force constant, the chip thickness and the width of chip, respectively).

The models in the applied group may be structured as an exponential empirical formula:

The formula:	where the process engagement conditions are:
$I = C \cdot v_c^z \cdot f^x \cdot a_p^y \cdot a_e^m$, or after linearization with logarithm: $I^* = c^* + z \cdot v_c^* + x \cdot f^* + y \cdot a_e^* + m \cdot a_p^*$	$v_{c\,min} < v_c < v_{c\,max}$, $f_{min} < f < f_{max}$, $a_{e\,min} < a_e < a_{e\,max}$, $a_{p\,min} < a_p < a_{p\,max}$ $I_{min} < I < I_{max}$

(Cutting feature "I", depth of cut "a_p", width of cut "a_e") The complex transformation matrix of the linearized model is demonstrated in Figure 3. Is must be emphasized that some cutting features (chip breaking, process stability, tool breaking) could not be characterised by this deterministic empirical model. In general, these types of models have been inaccurate and of limited validity, due to the complexity of the object (for instance: tool wear depends on the independent input parameters and some output parameters such as cutting force variation, process stability etc.) and the limitation of the applied approximation. It must be emphasized, that although the deterministic approach helps to answer and understand the basic principles of metal cutting processes, it is important to develop other methods witch are able to handle the complexity of cutting, process uncertainty and are able to transform the information into knowledge [3].

4 INPUT-OUTPUT AND IN-PROCESS PARAMETERS

To describe the complete machining system [1], one of the most important questions is to determine the input-output features.

To determine all the important input and output parameters, first, the main groups (Figure 2.), the relevant parameters and their notations and units were determined. Among the parameters are continuous variables and logical "OR" decisions. The proposed model refers to the tool path length where the cutting parameters are not changed. If some parameters change the model is used appropriately.

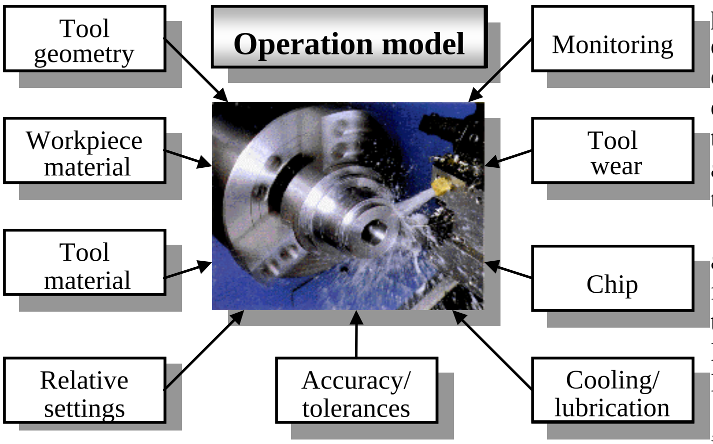

Figure 2. Parameter groups of the operation model

Some parameters can be used as input and as output variables, as well. This is the way to follow the changes of these variables along the process. If, e.g., I is one of these variables: I_{input} means the state of the variable before and I_{output} after the cutting process.

The next list shows the parameters incorporated in the investigations.

The **tool geometry** group consists of:

- Micro parameters:
  - Previous machining:
    - Grindid: Fine machined "OR" Not fine machined
    - "OR" Not grindid.
  - Edge radius (r_β)[μm]
- Macro parameters:
  - Monolith:
    - Tool length to be used (l_f)[mm]
    - Group: N "OR" H "OR" W
  - Throw away insert:
    - Positive "OR" Negative
    - Type of chip breaker: None "OR" "OR" PM "OR" PF "OR" PR "OR" MF "OR" MR "OR" QM "OR" QF "OR" QR
    - Inscribe circle diameter (d)[mm]
    - Edge length (l_f)[mm]

    - Insert thickness (S)[mm]
    - Orthogonal rake angle (γ_o)[°]
    - Orthogonal clearance angle (α)[°]
    - Inclination angle (λ)[°]
    - Cutting edge angle (κ)[°]
    - Include angle (ε)[°]
    - Edge number:
      - Single edge:
        - Corner radius (r_ε)[mm]
      - "OR" Multiple edge:
        - Width of fuzette (r_ε)[mm]
        - Tool diameter (d_s)[mm]
        - Cutter half cone angle (φ_s)[°]
        - Distance of the corner radius center from the rotation axis (C_r)[mm]
        - Distance of the corner radius center from the tool tip (C_a)[mm]
        - Number of cutting edges (Z_s)[.]
        - Run out - radial - average (μ_r)[mm]
        - Run out - radial - deviation (σ_r)[mm]
        - Run out - axial - average (μ_a)[mm]
        - Run out - axial – deviation (σ_a)[mm]

The **workpiece material** group consists of:

- Surface layer:
  - Pre-produced: "OR" Casted "OR" Drawned "OR" Rolled "OR" Forged
  - "OR" Machined: Rough "OR" Fined "OR" Finished
- Heat treatment: Normalised "OR" Tempered "OR" Quenched
- Ingredients:
  - Impurities (S%)[%]
  - Carbonising:
    - Normal hardening (CN%)[%]
    - Precitipation hardening (CK%)[%]
- Material parameters:
  - Maximum tensile strength (R_M)[Pas]
  - 0.2 tensile strength ($R_{M\ 0.2}$)[Pas]
  - Modulus of elasticity (E)[Pas]
  - μ (μ)[Pas]
  - Vickers hardness (HV_{100N})[HV]
  - Impact energy (KC)[KC]
- Cutting speed constant (C_v)[]
- Main cutting constant (k_1)[]
- Main cutting force exponents:
  - (X_F)[]
  - (Y_F)[]
  - (Z_F)[]

The **tool material** group consist of:

- Coating:
  - Not coated
  - "OR" Coated
    - Temperature of the coating: Very law "OR" Low "OR" High
    - Structure of christalographic:
      - Monochristal
      - "OR" Polichristal
        - Porosity (VP)[%]
- Cutting ability:
  - Tool live constant (C_T)[]
  - Tool live exponent (Z_T)[]
- Ingredients:
  - Impurities (S%)[%]
  - Carbonising:
    - Normal hardening (CN%)[%]
    - Precitipation hardening (CK%)[%]
- Material parameters:
  - Maximum tensile strength (R_M)[Pas]
  - 0.2 tensile strength ($R_{M\ 0.2}$)[Pas]
  - Modulus of elasticity (E)[Pas]
  - μ (μ)[Pas]
  - Vickers hardness (HV_{100N})[HV]
  - Impact energy (KC)[KC]

The **relative setting** group consists of:

- tool path length (L)[mm]
- Surface first curvature of the workpiece (ρ_1)[1/mm]
- Surface second curvature of the workpiece (ρ_2)[1/mm]
- Immersion (contact) angle (φ)[°]
- Depth of cut (tool axis direction) (a_p)[mm]
- Depth of cut (perpendicular to the tool axis) (a_e)[mm]
- Velocity (cutting speed along the ρ_1) (v_c)[m/sec]
- Velocity (cutting speed along the ρ_2) (v_f)[m/sec]
- Velocity (cutting speed along d_s) (v_s)[m/sec]
- Single edge:
  - Feed per workpiece revolution (f)[mm]
- Multiple edge:
  - Feed per tool revolution (f)[mm]

The **accuracy/tolerances** group consists of:

- positioning accuracy projected to the first surface curvature (V_{P1})[mm]
- positioning accuracy projected to the second surface curvature (V_{P2})[mm]
- Main spindle run-out (radial) (e_{rad})[μm]
- Main spindle run-out (axial) (e_{ax})[μm]
- Average of the surface curvature ρ_1 along machining length (μ_{GM1})[1/mm]
- Deviation of the surface curvature ρ_1 along machining length (σ_{GM1})[1/mm]
- Average of the surface curvature ρ_2 along machining length (μ_{GM2})[1/mm]
- Deviation of the surface curvature ρ_2 along machining length (σ_{GM2})[1/mm]
- Surface roughness along ρ_1 (R_{a1})[μm]
- Surface roughness along ρ_2 (R_{a2})[μm]

The **cooling/lubrication** group consist of:

- No cooling
- "OR" Cooling
  - Solid

- Graphite: There is “OR” There is no graphite
- “OR” Sulphides: There is “OR” There is no sulphide
- “OR” Plastic material: There is “OR” There is no plastic material

- “OR” Fluid
  - Media – coolant: Water “OR” Oil “OR” Spirit “OR” Others
  - Ingredients - lubrication: “OR” Oils “OR” Petroleum “OR” Graphite “OR” Sulphite
  - Cooling method:
    - Mist
      - Pressure (Pl)[Pas]
      - Volume (V_e)[m^3]
      - Volume rate (Ql)[m^3/sec]
    - “OR” Flooding
      - Pressure (Pl)[Pas]
      - Volume rate (Ql)[m^3/sec]
    - “OR” Inside
      - Pressure (Pl)[Pas]
      - Volume rate (Ql)[m^3/sec]
  - Media volume divided by ingredient – ratio (V%)[%]
- Gas
  - Media – coolant: Air “OR” Nitrogen
  - Ingredients - lubrication: “OR” Oils “OR” Petroleum
  - Media volume divided by ingredient – ratio (V%)[%]

The **chip group** consists of:

- Chip thickness:
  - Theoretical chip thickness (h)[mm]
  - Theoretical maximum of the chip thickness ($h_{c\ max}$)[mm]
  - Measured chip thickness (h)[mm]
  - Measured maximum of the chip thickness ($h_{c\ max}$)[mm]
- Chip form:
  - chip ratio (space for chip/theoretical volume of the chip) (K)[]

The **tool-wearing** group consists of:

- Wearing:
  - Average flank wear (VB)[mm]
  - Maximum flank wear (VB_{max})[mm]
  - Total removed volume by this tool (V_c)[mm^3]
- Tool breakage: Broken “OR” Not broken

The **monitoring group** consist of:

- Force:
  - Along ρ_1:
    - Alteration (max-min) (ΔF_c)[N]
    - Trend (inclination of the line) (m F_c)[]
    - Average (μF_c)[N]
  - Along ρ_2:
    - Alteration (max-min) (ΔF_f)[N]
    - Trend (inclination of the line) (m F_f)[]
    - Average (μF_f)[N]
  - Normal force:
    - Alteration (max-min) (ΔF_p)[N]
    - Trend (inclination of the line) (m F_p)[]
    - Average (μF_p)[N]
- Cutting power:
  - Cutting power on the main spindle:
    - Alteration (max-min) (ΔP_c)[W]
    - Trend (inclination of the line) (m P_c)[]
    - Average (μP_c)[W]
  - Cutting power on the feed engine:
    - Alteration (max-min) (ΔP_f)[W]
    - Trend (inclination of the line) (m P_f)[]
    - Average (μP_f)[W]
- Temperature:
    - Alteration (max-min) (ΔT)[C°]
    - Trend (inclination of the line) (mT)[]
    - Average (μT)[C°]

5 COMPARISON AMONG CUTTING PROCESS MODELLING METHODS

Three methods of cutting process modelling are investigated (Figure 3):

Physical/empirical approach: Theoretical recognition and empirical experience determine this type of basic models. Their coefficients are defined with the help of multiple regression calculations. The model structure used can be regarded as input for the regression calculation as well as the basic experimental data.

Neural network approach: In the field of neural networks various net structures and training methods are used. **N**eural networks possess most of the following characteristics [4]:

- powerful parallel computing and mapping structure,
- strong abilities of learning and self-organisation,
- strong abilities to store and retrieve knowledge by content rather than by address,
- feasibility for hardware implementation and real-time control,
- few prior assumptions or specific requirements for modelling.

Fuzzy set theory: Fuzzy sets allow a continuous flow of matching and unmatching. Model’s input and output parameters are associated with “linguistic variables” and with the help of these variables, the production rules for the actual modelling can be generated. Relaying on the rules an inference mechanism uses and determines the linguistic variables of the output parameters. Fuzzy models have the advantages that their rules can be generated from empirical knowledge [5]. The Fuzzy model as well as neural network models are able to accept a large number of input and output parameters, but learning is easier in the case of the neural network model.

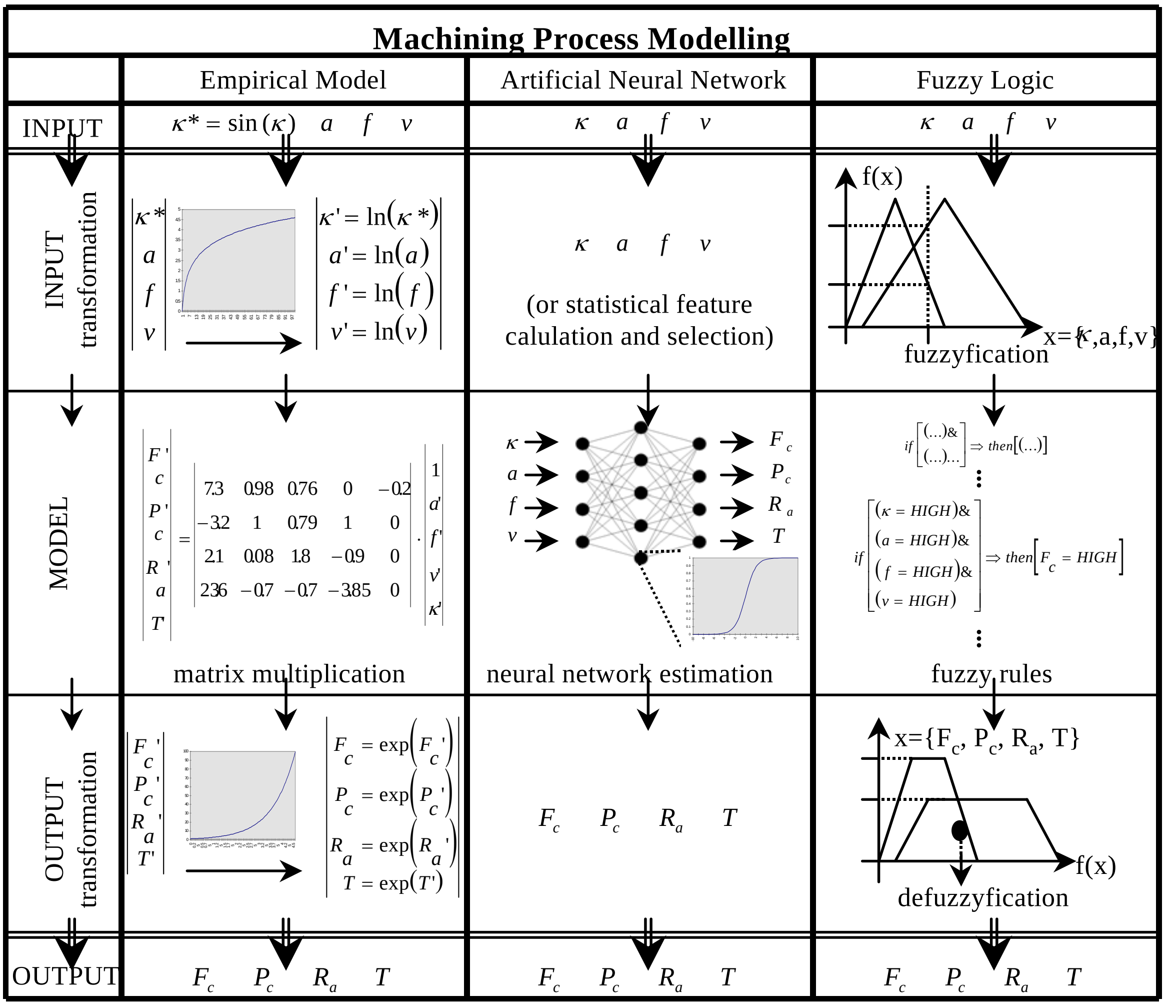

Figure 3. Data handling of three cutting model methods

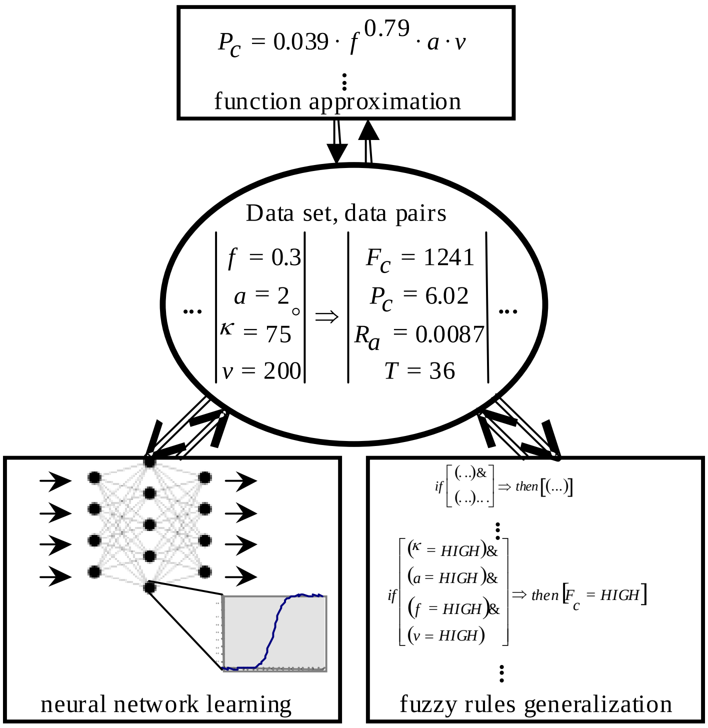

Figure 1. Transformation methods of models

6 TRANSFORMATIONS OF THE CUTTING MODELS

Learning capability is the reason why a neural network based cutting model is proposed in the paper. There are techniques as well to transform the knowledge of one of these models to the other model and vice-versa. One useful knowledge transformation method can be done with the help of input, output data pairs. If one of these models and the boundaries (min and max bounds of the parameters) of its use are given, a set of input-output data pairs can be calculated. Based on these data pairs:

- Structure and weights of the ANNs can be learnt,
- empirical function fitting can be calculated by minimal squares method,
- rules can be determined by the neurofuzzy method [5].

7 FRAMEWORK OF AN ANN BASED CUTTING MODEL

The proposed neural network based cutting model has input and output parameters from the data set presented above. It is to be seen that there are two types of parameters: decision variables (e.g. whether there is or there is no cooling) and continuous variables (e.g. Young modulus).

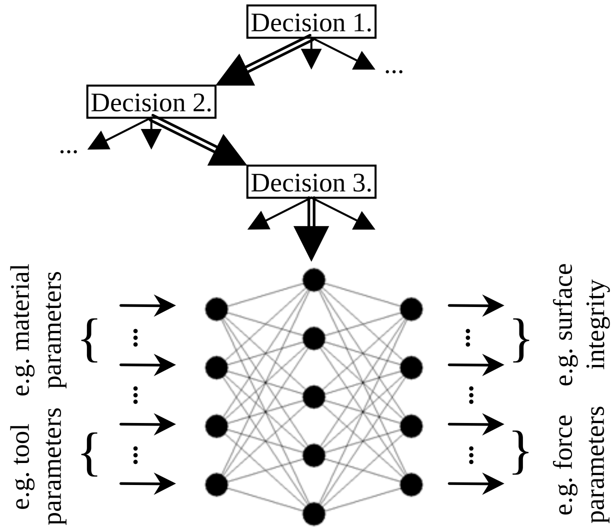

Figure 5. The use of the ANN based cutting model.

ANNs can successfully handle continuous variables. To handle the validity of an ANN model the possible intervals for each parameter have to be given. A set of min. and max. vector pairs can be used to determine the validity of an ANN.

In the case of a single vector pair: one of the vectors consists of minimum and the other of maximum values of parameters. The ANN is useful when each variable of the input vector - given by the user - is above the related minimum and below the related maximum parameters of the given data pair.

But one vector pair determines only one field of validity that's why the storing of a set of min. and max. data pairs is needed to determine several fields of validity.

To build up this model new data sets have to be given to be learnt by the ANN. The building up process consists of three steps:

1 Determination of the related ANN, based on the decision variables of the new data set.
2 ANN learning, based on the new data set, which consists of data from previous learning and the new data set given by the user.
3 Storing of:
   3.1 the enlarged min. and max. limits of the cutting model validity
   3.2 the data pairs used for learning.

The use of the proposed cutting model involves three steps (Figure 5.):

1. Determination of the relevant input, output variables, the related ANN and the limit of the use of this ANN, based on the decision variables. This step is a selection of a leaf on a tree built by the decision variables.
2. Information of the user if the model could be used on the parameter field requested by her/him. The model is valid if there is a single vector pair among the set of min. and max. vectors where the ANN is valid.
3. The ANN estimation of the related output variables based on the given input variables.

This model is large to manage the whole cutting process by a large number of decisions and continuous input and output variables, but at one factory, usually, only a part of this model is needed.

9 CONCLUSION

In the paper a new concept of comprehensive cutting modelling has been presented. To manage the whole cutting process the necessary input and output variables were determined. The most frequently used modelling methods and knowledge transformation techniques among them were reviewed. Because of its learning capability, an ANN based model is proposed. By this model decision variables are used to determine the ANN, the related input and output variables and the limits of the validity of the model. Also the building up and the use of this model were described.

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