Fuzzy Cognitive Map Based Machining Process Planning Decision Analysis

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Abstract: Modeling of large systems requires high level of expertise to properly identify and represent complex interrelationships between various elements. In addition to creation of a network of system's elements and their relationships, very important contribution to understanding of its behavior we can get from human experts. Naturally, humans express their experience and beliefs descriptively, emphasizing causal relationship between elements, and also descriptively (linguistically) evaluating their parameters' values instead of precisely doing it. Upon this basis we can use a graphical approach to model a system and capture related knowledge. Such approach picture cause and effect relations creating system's (fuzzy) cognitive map (F)CM. In this paper we present a part of results gathered during research work on fuzzy cognitive maps application in the machining process planning decision analysis. We apply negative-positive-neutral logic based approach to analyze a real industrial problem, namely, what-if problem of low surface quality. Finally we have pointed out the main directions of further research.

Key words: Fuzzy Cognitive Maps, Decision Analysis, Machining Process Planning

1 Introduction

The main idea behind attempts to cope appropriately with complex problems is to describe relationships between various elements (concepts) of a system and thus provide knowledge representation and inference. Such description of a problem should utilize experts' beliefs and cognition about a problem, yielding thorough analysis, reliable forecasting and decision-making. The methodology proposed in the paper aims to contribute the overcoming of shortcomings of traditional knowledge-based systems that lead to expert system failure related to, for instance, incomplete, inconsistent, and ambiguous knowledge bases. Another shortcoming that troubles conventional approaches to complex systems modeling is related to type of relationships between system variables. These appear quite often to be rather causal than explicit IF-THEN rules. Depending on a system we are modeling, its dynamics can additionally bring difficulties in knowledge base development.

Machining process planning is an engineering activity which deals with problems related to (optimal) selection of operations, machinery, tooling, machining parameters, etc., required for production of a given part. Optimality of generated solution depends significantly upon expert-in-the-field experience, beliefs, and knowledge on (machining) system behavior. Such real world (industrial) situation addresses two important issues. On one side, in the machining domain we can find causal dependencies between system variables. For instance, cutting speed should be decreased when machining materials of high hardness, but we can use higher speeds when workpiece material hardness is not so high. Furthermore, it is not recommended to use high feed rates if we use high speeds. Also, we can expect higher wear rate at higher machining speeds. These are only a few causal relationships we can draw between machining system variables. On the other side, different experts provide different views of the same problem and thus different solutions, which in turn may perform different output (overall) effects. In addition, each solution possibly encodes expert's knowledge weakness, as well, expressed through oversight, ignorance and prejudice. But this is just another fact that reflects real situations when making decisions during, for instance, planning of machining operations. In order to obtain an optimal solution refined from mentioned weaknesses we are apt to discuss a problem with other experts trying to reach a consensus. Modeling taxonomy based on graphical representation of causal relations of a problem, namely *fuzzy cognitive maps (FCM)* [6], allows for modeling of each possible view of a problem and then generate global solution by augmenting a set of separate FCMs [6-8], [10-12].

Providing a description of complex system behavior, based on very valuable and important experts' experience and learned knowledge, FCMs enable thorough analysis and come up with an answer to *what-if* question. An *if* input vector of data is composed from lower level decision support system's (DSS) outputs. *What* happens when an input vector affect a system, we can find as an FCM output, suggesting possible actions that bring equilibrium or stable state to a system. That is, FCM is qualitative tool, which cannot present exact mathematical answer but rather to point out the gross behavior of a system, to show the global patterns of how the whole of our (experts) beliefs behaves [1], [6-8], [10-13], [15-16].

The aim of the approach is to promote the methodology for multicriteria decision analysis and reasoning about potential effects of initially generated process plans and related parameters. Traditional computer aided process planning (CAPP) DSS structure lacks at least three important features: (1) uncertainties handling and corresponding approximate reasoning abilities, (2) learning capabilities, and (3) decision analysis [2], [9], [14]. Last decade brought significant progress and improvements related to the first two "missing" features [2], [9], [14], [3-4]. However, no significant results were reported so far upon the third feature. Real industrial practice shows that initially generated process plans and/or process parameters usually require adaptation, adjustment and tuning, which refers to *decision analysis and adaptation reasoning*. Therefore, such a special module should upgrade CAPP DSS structure to support (post-processing) adaptation decision making.

The paper is organized as follows. Next section briefly reviews theoretical background of FCMs. The third section describes process planning decision analysis by FCM. Illustrative example report preliminary research results of FCMs applications in the field of machining process planning and analysis. The research has been conducted in both laboratory and industrial environment.

2 Theoretical Background

FCMs are signed, fuzzy weighted and directed graphs with feedback. The concept nodes C_i are fuzzy sets or even fuzzy systems. That is, nodes of FCM can be viewed as distributed (fuzzy) expert systems. The links, or so-called *edges*, define rules or causal flows between the concept nodes. The modeling framework is based on determination of meaningful concepts, connecting them to form a network, and evaluating the direction of effect of target concept excited by cause concept. The directed link (edge) w_{ij}, from causal concept C_i to target (effect) concept C_j, measures how much C_i causes C_j. Connection n-by-n matrix W contains weights of all edges representing weighted causation rules of system behavior. The edges w_{ij} take values in the fuzzy causal interval [-1, +1]. The edge weights w_{ij} are constant and only the node values change in time.

Weighted causation linkage describes system behavior, but positive or negative logic values interval [0,1], i.e. [-1, 0] constrains a portion of important information about a system. Almost every decision has its consequences, presenting very valuable portion of information upon which we also make our decisions. Since FCM modeling framework involves negative edge weights as well, i.e. edge weights in trivalent {-1, 0, +1} or multivalent [-1,+1] interval, we need adequate logical and relational system to support reasoning with such values. The extensions of classic crisp logic, fuzzy logic, crisp relations and fuzzy relations were proposed by the end of 80's through, so called, *NPN logic* and *NPN relations* [15]; NPN stands for "Negative-Positive-Neutral". We will briefly give the basics of NPN theory in the sequel, and direct interested readers to [15-16].

NPN logic variable (both crisp and fuzzy) may take value in a [-1,+1]. In addition to three individual values from [-1,0), {0}, (0,+1], NPN logic variable may have three compound values as well. Compound values and corresponding mathematical apparatus provide possibility to count, so-called, *side effect* of each decision making path. Side effect measures under what mutual conditions between concepts FCM settles down in equilibrium. These compound values are summarized as follows:

i) (0, 0) – indicates neutral relationship between concepts *i* and *j*, i.e., there is no induced effect between objects *i* and *j* if object *i* is strengthen (excited);

ii) (0, P) – Indicates there is no induced negative relationship; positive relationship has a strength P;

iii) (N, 0) – indicates there is no induced positive relationship; negative relationship has a strength N;

iv) (N, P) – indicates that object *i* has both positive and negative relationships to object *j*; negative relationship has a strength N, and positive relationship has a strength P.

The fourth case of value pair *(a, b)* is the most informational and fully describes the side effect. Namely, if lower bound value $a = N$ is dominant over upper bound value $b = P$, i.e., $|N| > |P|$, when FCM comes to equilibrium, that will cause negative effect from *i*-th object to *j*-th object but also will oppositely produce positive effect to some extend. That means, equilibrium in the system can be reached only if object *i* negatively cause object *j* to some degree, and takes positive effect from object *j* to some lower degree. Object *i* cannot cause object *j* with no harm from object *j*, i.e., without (positive) side effect. Similarly, if upper bound value $b = P$ is dominant over lower bound value $a = N$, i.e., $|N| < |P|$, that will cause positive effect from *i*-th object to *j*-th object but also will oppositely produce negative effect to some extend. In this case object *j* produces negative side effect to object *i*. No dominancy ($|N| = |P|$) resembles Newton's action-reaction law. As much we gain from one side, the same we lose from the other.

Any NPN logic value can be represented as an ordered pair in $[-1, 1] \times [-1, 1]$. The NEG, AND, and OR functions for both NPN crisp and fuzzy logics can be compactly described by the following three logic equations:

$$\mathrm{NEG}(x, y) = (\mathrm{NEG}(y), \mathrm{NEG}(x)) \quad , \tag{1}$$

$$(x, y) * (u, v) = (\min(x * u, x * v, y * u, y * v), \max(x * u, x * v, y * u, y * v)) \quad , \tag{2}$$

$$(x, y) \text{ OR } (u, v) = (\min(x, u), \max(y, v)) \quad . \tag{3}$$

The star operator ($*$) in (2) stands for a general conjunction operator that may be any *T*-norm extended from the interval [0, 1] to [-1, 1]. The extension is made as follows:

$$x * y = \mathrm{sign}(x)\, \mathrm{sign}(y)(|x| * |y|) \quad , \tag{4}$$

where x and y are singleton NPN values (fuzzy or crisp). In this paper we use · (dot or product) operator.

For the sake of briefness we will introduce the following definitions of NPN fuzzy relations, their transitivity and (heuristic) transitive closure, which play important role in reasoning with NPN relations, and skip some other formal definitions, which one can look for in [15].

The following definition is an extension of classical fuzzy (binary) relation [17], which ensures assigning of NPN compound logic values to a NPN fuzzy (binary) relation as an ordered pair of negative, positive or neutral values:

Definition: *An NPN fuzzy (binary) relation* R *in* $X \times Y$, *where* $X = \{x_i\}$ *and* $Y = \{y_j\}$ *are finite sets, is a collection of ordered pairs or a subset of* $X \times Y$ *characterized by a membership function* $\mu_R(x_i, y_j)$ *that associates with each ordered pair* (x_i, y_j) *a strength of relation between* x_i *and* y_j *using an NPN fuzzy logic value.*

One of the very important sources of imprecision in complex systems is related to a transition behavior [5]. The effect of (imprecise) information propagation through a system may have significant influence on final decision-making, depending on weights of connections between concept nodes of a system's network. Next definition provides formal description of *max-*$*$ transitivity property of NPN relations:

Definition: *An NPN relation* R *(crisp or fuzzy) in* $X \times X$, *where* $X = \{x_1, x_2, ..., x_n\}$ *is finite set, is NPN (*max-$*$*) transitive iff, for all* i, j, *and* k, $0 < i, j, k \le n$,

$$\mu_R(x_i, x_k) \ge \max_{x_j} (\mu_R(x_i, x_j) * \mu_R(x_j, x_k)) \quad . \tag{5}$$

Since the connections between system's concepts can be established by different relations we need to compose two or more relations in order to model information propagation, in FCMs usually represented by a fuzzy chain [5]. The (max-$*$) composition of two NPN relations $R \subseteq X \times Y$ and $Q \subseteq Y \times Z$, denoted by $R \circ Q$, is defined by

$$\mu_{R \circ Q} = \max_{y} (\mu_R(x, y) * \mu_Q(y, z)), \quad x \in X, y \in Y, z \in Z \quad , \tag{6}$$

and can be extended to n-fold composition denoted as $R^n = R \circ R \circ \cdots \circ R$.

Definition: *The transitive closure* $\breve{R}$ *of an NPN relation* R *(crisp or fuzzy) in* X, *is the smallest* (max-$*$) *transitive NPN relation containing* R. *Since the NPN logics used for transitive closure computation can be considered as a set of rules (heuristics), such closure is called a* heuristic transitive closure (HTC) *of* R.

Using an heuristic path searching algorithm [15] we can find the possible and the most effective paths from one concept to another. That means, we can find the paths between elements (concept nodes) of FCM with the strongest negative and positive side effects that constrain decision making, according to the above two definitions.

3 Process Planning Decision Analysis

In this section we present a part of both research work and preliminary results of testing in a real industrial environment.

Following NPN logic and NPN relations extensions, we present new methodology for prior solution (decision) analysis in the machining domain, based on networking of meaningful concepts of the system. Prior solutions usually are provided by CAPP ES or an expert and such solutions sometimes turn to be inadequate due to many unexpected reasons. Our approach aims to provide a support to process planner when face a problem, answering *what-if* questions (Fig.1).

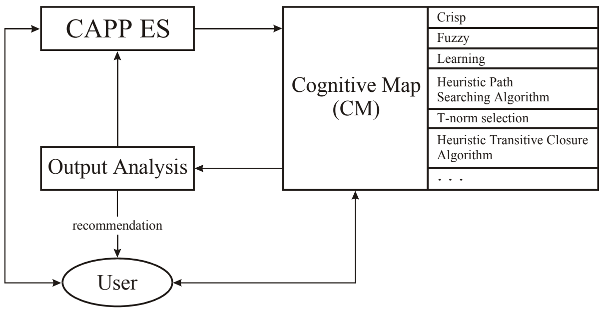

Figure 1: *(F)CM based process planning DSS*

We assume that (initial) process plan provide CAPP ES or an expert autonomously, interactively or by group consensus. Cognitive map (CM) module, shown in Figure 1, and all of its underlying components can be understood as a post-processing unit for conflict resolution. Namely, if the results of initial process plan do not fulfill the requirements of a product we need to make *balanced changes*, since in a connected system every change in any element will cause smaller or larger side-effect in other elements. Therefore balanced changes are of crucial importance for achieving and maintaining equilibrium, i.e. stable state of a complex system. Obviously, we activate CM module only if needed, and after output analysis (F)CM-based process planning DSS provide recommendation to the user on the ways of system balancing in order to produce quality product and achieve overall effectiveness.

In process planning there are a great number of data and information which process planner, i.e., human expert should summarize in order to make decisions. Some of them are objective and related to measurements. The other part is perception-based, i.e., subjective and rely on experience (previously learned knowledge). Anyway, all of it human expert is supposed to interpret and analyze and, finally, make appropriate decisions, leading to selection of optimal process planning elements and parameters' values. These decisions (selections) determine the behavior of a system and influence its overall performance and effectiveness.

It is a practice to select process planning elements and parameters' values upon tools and machines manufacturers' recommendations and personal experience. But very strong influence performs currently presented evidence and recently recorded analogous situations. Thus valuable recommendations cannot be followed precisely but rather approximately. This is caused by the nature (of a part) of information and data, their human interpretation and inability to realize optimal solution without loss of overall effectiveness and unacceptable or necessary increase of costs.

3.1. Process planning NPN FCM

Adjusting any of influential parameters usually effects others. Such effect, namely, side effect, can be acceptable, unacceptable and more or less indifferential, depending on ratio of negative and positive values of an compound NPN relationship. In order to investigate above mentioned problem we have constructed the FCM shown in Figure 2. Edge weights are assessed by experts from industry.

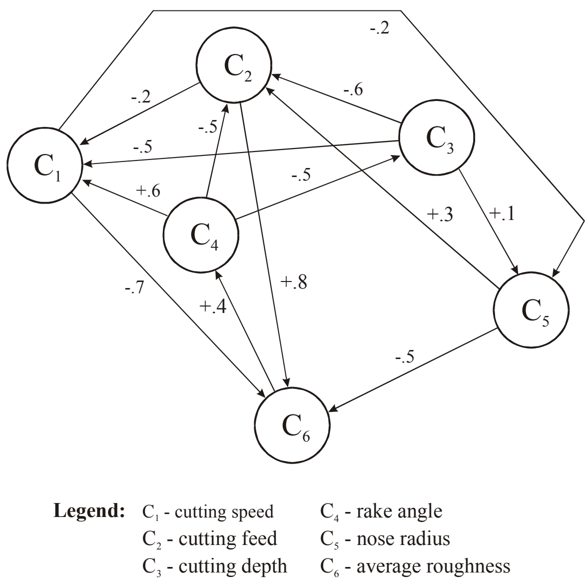

Figure 2: *Machining parameters NPN FCM*

Corresponding connection matrix is:

$$W = \begin{pmatrix} 0 & 0 & 0 & 0 & -0.2 & -0.7 \\ -0.2 & 0 & 0 & 0 & 0 & 0.8 \\ -0.5 & -0.6 & 0 & -0.5 & 0.1 & 0 \\ 0.6 & -0.5 & -0.5 & 0 & 0 & 0.4 \\ 0 & 0.3 & 0 & 0 & 0 & -0.5 \\ -0.7 & 0.8 & 0 & 0 & -0.5 & 0 \end{pmatrix} . \qquad (7)$$

Heuristic path searching algorithm [25] identifies the most effective paths between any two concept nodes of NPN FCM. For critical node in this case (average surface roughness – *Ra*, concept node 6) we have chosen *max-prod* (max- dot) transitivity compositions defined by (2), (4) and (6). Identified heuristic paths are shown in the Table 1.

Obtained results provide an answer to the question *what* should we do *if* prior solution for cutting parameters disable quality machining. Introducing an empirical restriction or constraint factor *RF*

$$RF = \begin{cases} \dfrac{\max(|N|,|P|)}{\min(|N|,|P|)}, & \min(|N|,|P|)\neq 0 \\ \max(|N|,|P|)\cdot 10, & \min(|N|,|P|)=0 \end{cases} \qquad (8)$$

,

compound value distance *d(CV)* = *d(P, N)* (Hamming distance)

$$d(CV) = d(P, N) = |N| + |P| = |P - N| \ , \qquad (9)$$

and restriction strength

$$RS = RF \cdot d(CV) \ , \qquad (10)$$

we can refine obtained results in order to identify the most influential relationships whose negative or positive relationship values are the most restrictive and thus direct us to the most effective problem recovery procedure. These factors are summarized in the Table 2 for *max – prod* heuristic transitive closure.

NPN logic based prior solution analysis provides different, but more informative result, i.e. answer to a given question. Comparing to the answer obtained from process planning FCM we can notice that cutting speed is yet very influential to surface quality ($RS(v)_{max-prod} = 2.64$), which also reflects known physical dependency of cutting process. The same holds for rake angle ($RS(\gamma)_{max-prod} = 1.6$).

The results obtained by max-prod composition are very informative and suggest the following. Inadequate cutting depth ($RS(\delta)_{max-prod} = 1.376$) could cause unacceptable vibrations of the machining system producing (indirectly) rough workpiece surface. Cutting feed has lower restriction strength ($RS(s)_{max-prod} = 0.534$) than it is expected despite high connection weight ($w_{16} = +0.8$). It appears that its strength is balanced and reduced by relatively high influence of rake angle ($w_{42} = -0.5$) and cutting depth ($w_{32} = -0.6$) to the selection of feed. Cutting tool's nose radius has relatively low influence to surface quality ($RS(r)_{max-prod} = 0.509$) only if other elements are properly selected, which is shown through heuristic paths 6-4-1-5 (for dominant lower bound) and 6-4-3-2-1-5 (for upper bound), but implicitly requires attention during initial process planning procedure. Finally, high restriction strength of the surface roughness ($RS(Ra)_{max-prod} = 1.828$) and heuristic path $C_6 – C_6$: 6-4-1-6 (for dominant lower bound) and 6-4-3-2-1-6 (for upper bound) clearly state that adequate cutting geometry (concept node 4) and cutting speed (concept node 1) will provide low surface roughness, despite irritating effects of cutting depth (concept node 3) and cutting feed (concept node 2). However, process planner (decision maker) should keep in mind that cutting tools' parameters depend on a number of other factors thus their changing could increase machining costs and therefore should be changed only if cutting parameters' adjustment and tuning cannot bring required surface quality. In that case the whole process planning procedure should be repeated in order to select appropriate cutting parameters for a new cutting tool (Fig.1).

Table 1: Heuristic paths and compound values of heuristic transitive *max – min* and *max - prod* closure

Concept nodes	$C_6 \to C_1$	$C_6 \to C_2$	$C_6 \to C_3$	$C_6 \to C_4$	$C_6 \to C_5$	$C_6 \to C_6$
Heuristic paths	(6 4 3 2 1) (6 4 1)	(6 4 2) (6 4 3 2)	(6 4 3) (6 4 1 6 4 3)	(-) (6 4)	(6 4 1 5) (6 4 3 2 1 5)	(6 4 1 6) (6 4 3 2 1 6)
Compound values of heuristic transitive *max - prod* closure	(-0.024, 0.24)	(-0.2, 0.12)	(-0.2, 0.034)	(0, 0.4)	(-0.048, 0.005)	(-0.168, 0.017)

Table 2: Restriction factors, compound values' distances, and restriction strengths for *max – prod* heuristic transitive closure

Concept nodes	$C_6 \to C_1$	$C_6 \to C_2$	$C_6 \to C_3$	$C_6 \to C_4$	$C_6 \to C_5$	$C_6 \to C_6$
Restriction factor (RF)	10.00	1.67	5.88	4.00	9.6	9.88
Compound value distance d(CV)	0.264	0.32	0.234	0.4	0.053	0.185
Restriction strength (RS)	2.64	0.534	1.376	1.6	0.509	1.828

4 Conclusion

Complex systems and processes require specific modeling framework to enable causal description of a system behavior. One of the powerful approaches assume cognitive maps as a causal pictures of real world and cognitive mapping as a process of their constructing. This approach prerequisites various expertise conducted by human experts and utilize their experience and beliefs in system behavior. We have presented some of preliminary results of the research work related to the application of the NPN logic-based FCMs in metal cutting process planning decision analysis. The results, so far, proved to be very informative and reliable.

Refinement procedure of NPN FCM output does not necessarily have to be defined as presented (8)-(10). Further development of the methodology will bring additional refinement procedure models, but in this stage it preliminary verifies our approach and demonstrates the strength of FCM representational framework to metal cutting process planning decision analysis. Further research work also includes investigation of different types of FCM augmentation, learning of edge weights and their dynamical behavior.

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