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Fuzzy expert system based evaluation framework for management procedure models

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Abstract: Due to the numerous dynamic influences affecting manufacturing companies, a continuous adaptation is required. Tools and methods are developed in order to support management decisions. In most cases however, these tools and methods can hardly be evaluated due to lack of information, especially in strategic environments. A "hardware-in-the-loop"-like evaluation framework for management procedure models is therefore presented in this paper, in order to evaluate and optimize different management procedures. A fuzzy expert system based simulation framework is suggested and a structured procedure for evaluation and optimization is presented. An exemplary application to a production planning process illustrates the new approach.

Keywords: Recurrent fuzzy systems, Fuzzy expert system, Management procedures, Evaluation, Optimization

1. INTRODUCTION

In times of increasing globalization, the long term success of an enterprise is dependent on the ability to continuously adapt to changing internal and external influences on innovation processes, for example the customer demand for innovations, changing laws and regulations, progress in development of product and production technologies (Schenkl et al. (2013)). These factors have strong interdependencies and are subject to partially intransparent dynamics (like the development of market needs). Moreover, companies have to cope with shortened innovation cycles and have to integrate new technologies in their products, services and processes faster.

To handle this increasing dynamic and complexity, methods and tools are being developed across all domains to systematically support the management in anticipation and coordination of these influences. Especially so called procedure models are widely used to help companies improving their business processes. The objective is often to increase process speed or reduce cycle time; to increase quality; or to reduce costs. Some procedures thereby focus the analysis, while others consider the control of the regarded process.

However, since the availability of reliable data especially in strategic environments is limited and enterprises are subject to constant changes, the testing and validations of these procedure models is mostly done by case studies that can naturally only cover a small scope of situations. Furthermore, the impact of alternative procedure models can hardly be compared as the testing conditions cannot be kept constant in reality.

Expert systems are computer programs that model the knowledge of an expert in a specific domain and simulate the judgment behavior of a human in that domain. They are widely used to take an expert view in the absence of a human expertise in various fields from economics to production (Liao (2005)). Fuzzy logic (Zadeh (1965)) can be incorporated into expert system to enhance the performance and reliability of decision making based on imprecise, ambiguous and uncertain data and has wide applications in management (Wong and Lai (2011)). Fuzzy logic principals with expert system form a fuzzy expert system which is able to implement human knowledge and expertise (Baghel and Sharma (2013)). Recurrent fuzzy systems (Gorrini and Bersini (1994)) are able to consider dynamic effects.

Based on these fuzzy expert systems this paper suggests an evaluation framework similar to a hardware-in-a-loop simulation for procedure models in management which allows testing and optimization of management procedures in controlled environment. The management procedures are therefor modeled as recurrent fuzzy expert systems. Subsequent optimization of the expert systems can identify improvements of the management procedure and can be fed back to the management.

The remainder of the paper is structured as follows: Section 2 gives short introduction into recurrent fuzzy systems

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and their extension to transition adaptation. Section 3 describes the evaluation framework as well as a procedure for setting it up, its application for evaluating planning procedures in manufacturing planning is shown in Section 4. Finally, a conclusion is drawn in Section 5.

2. RECURRENT FUZZY SYSTEMS FOR MODELING MANAGEMENT PROCEDURES

This section summarizes the theory of discrete-time recurrent fuzzy systems (RFS)(Gorrini and Bersini (1994); Schwung and Adamy (2010)) and their extension in order to allow a transition-based adaptation (Stahl et al. (2013)).

A RFS dynamical system as described by

$$\mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k)), \tag{1}$$

$$\mathbf{y}(k) = \mathbf{g}(\mathbf{x}(k), \mathbf{u}(k)). \tag{2}$$

Since the output function $\mathbf{g}(\mathbf{x}, \mathbf{u})$ (2) has no effect on the system dynamics and might not even exist, it will not be considered here and $\mathbf{y}(k) = \mathbf{x}(k)$. To specify the transition function $\mathbf{f}(\mathbf{x}, \mathbf{u})$ (1) we first define a set of linguistic values $L^{x_i}_{j_i}$ with $j_i \in \{1, 2, ...\}$ for each component x_i of $\mathbf{x}$. same way, the components u_p of $\mathbf{u}$ are categorized in linguistic values, $L^{u_p}_{q_p}$. Using these linguistic values, rules of the form

$$\begin{aligned}
&\text{If } x_1(k) = L^{x_1}_{j_1} \text{ and ... and } x_n(k) = L^{x_n}_{j_n}\\
&\text{and } u_1(k) = L^{u_1}_{q_1} \text{ and ... and } u_m(k) = L^{u_m}_{q_m}\\
&\text{then } x_1(k+1) = L^{x_1}_{w_1(\mathbf{j},\mathbf{q})} \text{ ... and } x_n(k+1) = L^{x_n}_{w_n(\mathbf{j},\mathbf{q})}
\end{aligned} \tag{3}$$

are defined. Using $\mathbf{L}^{\mathbf{x}}_{\mathbf{j}} = [L^{x_1}_{j_1}, ..., L^{x_n}_{j_n}]$, $\mathbf{L}^{\mathbf{u}}_{\mathbf{q}} = [L^{u_1}_{q_1}, ..., L^{u_m}_{q_n}]$, and $\mathbf{L}^{\mathbf{x}}_{\mathbf{w}(\mathbf{j},\mathbf{q})} = [L^{x_1}_{w_1(\mathbf{j},\mathbf{q})}, ..., L^{x_n}_{w_n(\mathbf{j},\mathbf{q})}]$ the rule base can be compactly given as a linguistic differential equation

$$\text{If } \mathbf{x}(k) = \mathbf{L}^{\mathbf{x}}_{\mathbf{j}} \text{ and } \mathbf{u}(k) = \mathbf{L}^{\mathbf{u}}_{\mathbf{q}} \text{ then } \mathbf{x}(k+1) = \mathbf{L}^{\mathbf{x}}_{\mathbf{w}(\mathbf{j},\mathbf{q})} \tag{4}$$

$\mathbf{w}(\mathbf{j}, \mathbf{q})$ thereby denotes the mapping of rule premises (summarized in $\mathbf{j}, \mathbf{q}$) to their conclusion (summarized in $\mathbf{w}$).

Membership functions $\mu^{x_i}_{L_\mathbf{j}}$ and $\mu^{u_p}_{L_\mathbf{q}}$ are introduced to match the linguistic values $L^{x_i}_{j_i}$ and $L^{u_p}_{q_p}$ with their continuous variables x_i and u_p. Using the algebraic product as aggregation operator and the algebraic sum for accumulation, (4) can be transformed into the mathematic representation

$$\mathbf{x}(k+1) = \frac{\sum_{\mathbf{j},\mathbf{q}} \mathbf{s}^{\mathbf{x}}_{\mathbf{L}_{\mathbf{w}(\mathbf{j},\mathbf{q})}} \prod_i \mu^{x_i}_{L_\mathbf{j}}(x_i) \prod_p \mu^{u_p}_{L_\mathbf{q}}(u_p)}{\sum_{\mathbf{j},\mathbf{q}} \prod_i \mu^{x_i}_{L_\mathbf{j}}(x_i) \prod_p \mu^{u_p}_{L_\mathbf{q}}(u_p)}, \tag{5}$$

where $\mathbf{s}^{\mathbf{x}}_{\mathbf{L}_{\mathbf{w}(\mathbf{j},\mathbf{q})}}$ describes the singleton positions for defuzzifying the linguistic value of each rules outcome $\mathbf{L}^{\mathbf{x}}_{\mathbf{w}(\mathbf{j},\mathbf{q})}$.

Stahl et al. (2013) generalized the transient probabilistic RFS introduced by Diepold and Lohmann (2010) to transition adaptive RFS that allows to balance the impact of the rules outcomes individually to each other by giving rule-weightings $\mathbf{g}^{\mathbf{x}}_{\mathbf{L}_{\mathbf{w}(\mathbf{j},\mathbf{q})}}$ to each rule. The mathematic representation (5) is extended to

$$\mathbf{x}(k+1) = \frac{\sum_{\mathbf{j},\mathbf{q}} \mathbf{s}^{\mathbf{x}}_{\mathbf{L}_{\mathbf{w}(\mathbf{j},\mathbf{q})}} \mathbf{g}^{\mathbf{x}}_{\mathbf{L}_{\mathbf{w}(\mathbf{j},\mathbf{q})}} \prod_i \mu^{x_i}_{L_\mathbf{j}}(x_i) \prod_p \mu^{u_p}_{L_\mathbf{q}}(u_p)}{\sum_{\mathbf{j},\mathbf{q}} \mathbf{g}^{\mathbf{x}}_{\mathbf{L}_{\mathbf{w}(\mathbf{j},\mathbf{q})}} \prod_i \mu^{x_i}_{L_\mathbf{j}}(x_i) \prod_p \mu^{u_p}_{L_\mathbf{q}}(u_p)}. \tag{6}$$

The rule-weightings now allow to include importance and credibility of linguistic rules (4) extracted from experts or procedure models and thus enhance the mathematic modeling of management procedures. Furthermore an optimization of these weightings is suggested to increase the decision quality.

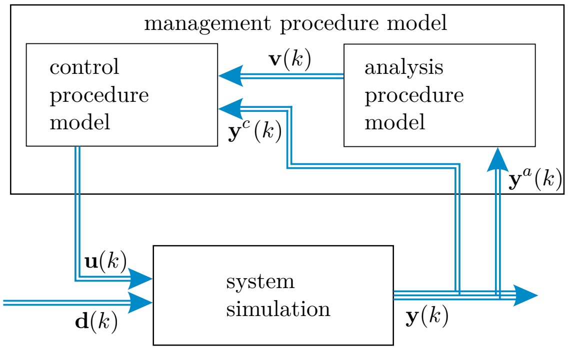

Fig. 1. Evaluation framework

3. EVALUATION AND OPTIMIZATION FRAMEWORK FOR MANAGEMENT PROCEDURES

The objective of the validation framework for management procedure models aims at gaining a better understanding of the impact of different management procedures and decision philosophies on the managed systems outcome through computer based simulation and optimization. Therefore a framework similar to a hardware-in-the-loop system is suggested, where the management procedures are tested in a simulation loop. A procedure is presented to obtain the necessary information and to conduct validation and optimization.

3.1 Evaluation Framework

Fig. 1 illustrates the suggested evaluation framework. A simulation model of the managed system is thereby controlled through a *management input* $\mathbf{u}(k)$ to create a desired *output variables* $\mathbf{y}(k)$ and to handle *external influences* $\mathbf{d}(k)$. The management input $\mathbf{u}(k)$ is automatically generated through an expert system of a management procedure $\mathbf{y}(k)$.

The management procedure is thereby separated in an analysis and a control procedure expert system. This is due to the fact, that the control of certain systems might not be possible based on the measured output variables $\mathbf{y}(k)$, but require additional knowledge of the system, that is qualitative in nature and is not directly measurable, so called *qualitative state variables* $\mathbf{v}(k)$. The analysis procedure expert system therefore estimates the qualitative state variables $\mathbf{v}(k)$ based on the measurable output variables $\mathbf{y}^a(k)$ of the system simulation. The control procedure expert system interferes measured variables $\mathbf{y}^c(k)$ as well as the estimated qualitative ones $\mathbf{v}(k)$ to generate the management input $\mathbf{u}(k)$ for the system simulation.

3.2 Evaluation & Optimization Procedure

For evaluation and optimization of management procedure models, a five step approach is suggested:

Step 1: Modeling of the test system Regarding the structure and functionality of the evaluation framework