7th IFAC Conference on Manufacturing Modelling, Management,
and Control
International Federation of Automatic Control
June 19-21, 2013. Saint Petersburg, Russia

Modeling Cyclic Interactions within a Production Environment using Transition Adaptive Recurrent Fuzzy Systems

Benjamin Stahl * **Klaus J. Diepold** * **Johannes Pohl** **
Josef Greitemann ** **Christian Plehn** ** **Jonas Koch** **
Boris Lohmann * **Gunther Reinhart** **

* *Institute of Automatic Control, Technische Universität München, D-85748 Garching, Munich, Germany, (e-mail: benjamin.stahld@mytum.de).*
** *Institute for Machine Tools and Industrial Management (iwb),Technische Universität München, D-85748 Garching, Munich, Germany, (e-mail: josef.greitemann@iwb.tum.de).*

Abstract: Numerous dynamic influences affect producing companies and require a continuous adaptation of the production. At present, modeling these influences and their interdependencies is mainly limited to quantitative factors. In this paper, an approach is proposed that allows to model the missing qualitative influences and their interdependencies via recurrent fuzzy systems (RFS), where the transitions between the state variables are additionally weighted (transition adaptation). This allows an easy adaption of a production environment's behavior while maintaining the interpretability of the model and the model-based analysis results. To handle the complexity of the resulting models, a structured way to simplify a large fuzzy rule base, to reduce the number of required weighting coefficients, and to merge the state variable onto a single production effectiveness value is shown. All of this is directly illustrated by exemplarily modeling the influence of some relevant qualitative factors onto a production environment.

Keywords: Recurrent fuzzy systems, Fuzzy expert systems, Production systems, Adaptation, Dynamic behavior

1. INTRODUCTION

Dynamic influences, such as changing customer requirements, ElMaraghy et al. (2009), or increasingly stringent environmental laws, McCarthy et al. (2001), affect the production of producing companies and require a continuous adaptation of the production, Westkämper (2006). These influences can be divided into internal factors, e.g. improvements of manufacturing processes or organizational changes, and external factors, such as changing market demands or emerging technologies, Wiendahl et al. (2007).

Many of these factors are hardly predictable, but well worth to be scrutinized. Especially, cyclically changing factors (cycles), e.g. product life cycles or the evolutionary development (maturity) of manufacturing technologies, follow certain regularities and exert significant influence on the capability and stability of a production environment, Zäh et al. (2009). For example, a significantly increasing production output causes a rearrangement of the production principles and structures, Wiendahl et al. (2007). Although the cycles influencing the production of a company interact with each other, they are barely synchronized, Zäh et al. (2009). Aligned organization of these cycles shows great potential for improvements in production and production planning, Zäh et al. (2010). Therefore, behavior and interaction of different cycles have to be modeled for a comprehensive analysis which supports decision-making in production management.

While some of these cycles can be easily quantified, others - because of a lack of reliable data - cannot. These so-called qualitative cycles are often available via linguistic and probabilistic variables coming from estimates, forecasts and statistics. The knowledge about these cycles and their interactions shows great potential to improve the dynamic production planning process by anticipating the future behavior of a production environment more precisely, Reinhart et al. (2009).

Based on the above mentioned linguistic knowledge it is hardly surprising that fuzzy logic, introduced in Zadeh (1965), is a well established method with a variety of applications in control, production management, qualitative modeling and decision theory, see e.g. Feng (2006), Wong and Lai (2011) and the references therein. However, most of these methods are based on conventional (static) fuzzy set theory which is not able to consider the dynamics within a production environment. Recurrent fuzzy systems (RFS), Gorrini and Bersini (1994), however, are able to tackle this disadvantage as they project the fuzzy theory onto dynamical system's behavior. This article presents an approach for modeling qualitative cycles and their interactions within the production environment in a dynamic way.

The core-dynamics of these cycles are modeled via RFS, while the transitions between the related state variables are additionally weighted (transition adaptation). Accordingly, the obtained Transition Adaptive Recurrent Fuzzy System (TA-RFS) enables a simple modeling process and maintains the interpretability of the model.

The remainder of the paper is as follows: In Section 2 the dynamic production environment is detailed, while in Section 3 the TA-RFS is described. An adapted modeling framework for production environments is shown in Section 4, its application for modeling a production environment is pointed out in Section 5. Finally, a conclusion is drawn in Section 6.

2. DYNAMIC ENVIRONMENT OF PRODUCTION

2.1 Production Planning

The main objective of production planning is to ensure that customer demands and expectations in terms of cost, lead time and quality are satisfied, Bullinger et al. (2003). Therefore, production planning has to control the current state of the production and anticipate possible future developments of the environment in order to trigger adaptations of the production timely. The operational metrics lead time, unit cost and customer demands (number of units produced) are the major indicators for the need of adaptation and the trigger of the planning process, Cisek (2005). One important task within the planning process is to continuously monitor the characteristics of the production due to changes of the environment occurring over time. Therefore, simulations are conducted to predict future behavior. Nowadays, evaluation and simulation models are based on quantitative factors. Often, qualitative factors are not taken into account, Reinhart et al. (2009). Thus, important strategic aspects for production planning, e.g. the adequacy of the production structure for the production task, maturity or development costs of technologies, are not considered. Hence, an approach is needed to integrate qualitatively known dynamical factors into simulation models.

2.2 Cycles and their Interdependencies

Cycles can be described qualitatively and quantitatively. Quantitative cycles, e.g. unit quantities or loss rates, can often be calculated based on reliable data, whereas qualitative cycles, e.g. the competitive potential of a manufacturing technology or estimated market trends, are of a rather complex nature and thus require greater effort to be determined. In addition, cycles show numerous interdependencies which, at present, can also not be characterized quantitatively, though it is possible to specify them in a linguistic way. For instance, increased unit quantities within the product life cycle are accompanied by experience curve effects, Hax and Majluf (1982) and often by elevated maturity of applied technologies over time, Little (1993). Concomitantly, the competitive potential of these technologies decreases, Sommerlatte and Deschamps (2006). Due to a lack of systematic quantification methods, factors like the competitive potential of manufacturing technologies and the impact on unit costs are usually assessed based on estimates or the individual experience of experts, Schöning (2006). Therefore, an approach is needed to deal with the complexity of qualitative cycles, their interdependencies and dynamic effects on production.

3. TRANSITION ADAPTIVE RECURRENT FUZZY SYSTEMS

The theory of discrete-time recurrent fuzzy systems (RFS) and their extension in order to allow a transition-based adaptation is summarized within this Section. A more detailed description of RFS can be found in Gorrini and Bersini (1994); Schwung and Adamy (2010); Diepold and Lohmann (2010).

A RFS is a dynamical fuzzy system whose rule base is compactly given by a linguistic difference equation:

$$\text{If } \mathbf{x}(k) \text{ is } \mathbf{L}^{\mathbf{x}}_{\mathbf{j}} \text{ and } \mathbf{u}(k) \text{ is } \mathbf{L}^{\mathbf{u}}_{\mathbf{q}} \text{ then } \mathbf{x}(k+1) \text{ is } \mathbf{L}^{\mathbf{x}}_{\mathbf{w}(\mathbf{j},\mathbf{q})}. \quad (1)$$

The vectors $\mathbf{L}^{\mathbf{x}}_{\mathbf{j}} = \left[L^{x_1}_j, \ldots, L^{x_n}_j\right]^T$ and $\mathbf{L}^{\mathbf{u}}_{\mathbf{q}} = \left[L^{u_1}_q, \ldots, L^{u_m}_q\right]^T$ characterize the state $\mathbf{x} \in \mathcal{X} \subset \mathbb{R}^d$ and input variables $\mathbf{u} \in \mathcal{U} \subset \mathbb{R}^e$ by linguistic terms. The index vectors $\mathbf{j}$, $\mathbf{q}$ summarize the terms, which are selectable from fuzzy sets $L^{x_i}_j$ and $L^{u_p}_q$ ($j \wedge q \in \{1, 2, \ldots\}$), of a certain rule premise. The corresponding rules conclusion is $\mathbf{L}^{\mathbf{x}}_{\mathbf{w}(\mathbf{j},\mathbf{q})}$. The index vector $\mathbf{w}$ defines the mapping $(\mathbf{j}, \mathbf{q}) \to \mathbf{w}(\mathbf{j}, \mathbf{q})$, yielding to a specific rule.

The rule base (1) can also be interpreted as a deterministic automaton. In such a graph-based discrete event-driven system (DES), the fuzzy sets of the state variables correspond to the discrete automaton states and the fuzzy sets of the input variables form the events firing a state transition. Fig. 1 depicts such an automaton with one state variable with three linguistic characteristics L^x_j, $j \in \{1, 2, 3\}$, and one input variable with two linguistic characteristics L^u_q, $q \in \{1, 2\}$. Accordingly, the rule represented by the red dashed arrow can be read as: If $x(k)$ is L^x_1 and $u(k)$ is L^u_2 then $x(k+1)$ is L^x_3. In addition to that graph-based representation, the transition function of a nonlinear discrete-time dynamical system

$$\mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k)), \quad (2)$$

is derivable via RFS. Each of the description forms (automaton and linguistic as well as nonlinear discrete-time differential equation) offers different design, analysis and optimization possibilities for a dynamical system. This yields to the fact that recurrent fuzzy systems have gained importance. A transition adaptive recurrent fuzzy systems (TA-RFS) is an extension of the graph-based representation of a conventional RFS (Fig. 2). By adding transition weightings $g^{x_i}_{L_j{}', L_j}$ onto each linguistic transition (connected pair) $L'_j|L_j$, meaning the transition $L^{x_i}_j(k)|L^{x_i}_j(k+1)$ of a state variable x_i, the deterministic automaton is transformed into a weighted one. The weightings, which can be understood as firing strengths of the transitions, lead to a slight modification of the de-

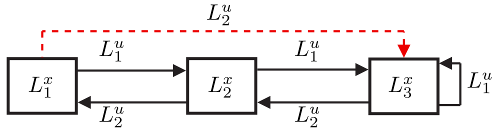


Fig. 1. Automaton schematic of a RFS

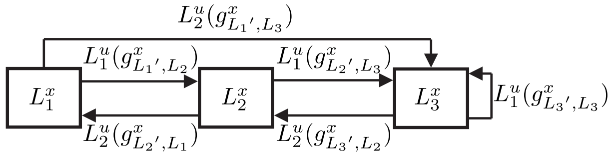


Fig. 2. Automaton schematic of a TA-RFS

fuzzification part of a transition function (2). Considering conventional *sum-product* inference and *Center of Sums* defuzzification with singletons $\mathbf{s}^{\mathbf{x}}_{\mathbf{L_{w(j,q)}}}$, result in

$$\mathbf{x}(k+1) = \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k))$$
$$= \frac{\sum_{\mathbf{j},\mathbf{q}} \mathbf{s}^{\mathbf{x}}_{\mathbf{L_{w(j,q)}}} \mathbf{g}^{\mathbf{x}}_{\mathbf{L_{w(j,q)}}} \prod_i \mu^{x_i}_{L_j}(x_i) \prod_p \mu^{u_p}_{L_q}(u_p)}{\sum_{\mathbf{j},\mathbf{q}} \mathbf{g}^{\mathbf{x}}_{\mathbf{L_{w(j,q)}}} \prod_i \mu^{x_i}_{L_j}(x_i) \prod_p \mu^{u_p}_{L_q}(u_p)}, \tag{3}$$

where $\mu^{x_i}_{L_j}$ and $\mu^{u_p}_{L_q}$ are the membership functions of the crisp valued state $\mathbf{x}$ and input variables $\mathbf{u}$. The TA-RFS is rather known as TP-RFS (*transient probabilistic recurrent fuzzy system*), Diepold and Lohmann (2010); Diepold et al. (2011), where the interpretation and adaptation of the weighings is based on probabilistic analysis. Thus, the weighted automaton turns into a stochastic one. However, the variation of the weighings is not restricted to probability theory. The range of adaption is therefore not longer limited to $[0; 1]$ and can be individually chosen. The expression TA-RFS should clarify this generalization here.

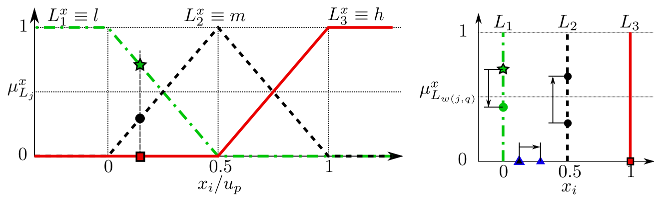
Based on $\mathbf{g}^{\mathbf{x}}_{\mathbf{L_j',L_j}}$, a transparent adaptation of a system's dynamics can be achieved by means of justification and optimization. Also a sensitivity analysis of the state and input variables can be realized. The modeling scheme hereby focuses on interpretability and the easy model creation to improve dynamic production planning. As shown in the following modeling framework, the weightings $\mathbf{g}^{\mathbf{x}}_{\mathbf{L_{w(j,q)}}}$ can be used to adapt the system dynamic in a wide range. Moreover, if the adaption of the TA-RFS using the weightings reaches its limits, it indicates an incomplete rule base or a faulty rule that needs to be reviewed.

4. MODELING FRAMEWORK FOR DYNAMIC PRODUCTION ENVIRONMENTS

As mentioned in Section 2 an approach is needed to handle the complexity of qualitative cycles, their interdependencies and dynamic effects on production. The variety of challenges in production planning and cycle management hinder the creation of a general simulation model. To tackle this disadvantage, an adapted modeling framework with 4 steps is presented, that uses the TA-RFS described in Section 3 to qualitatively model the cyclic interactions within a dynamic production environment: Step 1: Selection of input and state variables, Step 2: Generation of a rule base, Step 3: Adaption of the model's dynamic using the transition-weightings of the TA-RFS, Step 4: Conflation of all states to one production efficiency indicator.

Step 1: Selection of input and state variables

Depending on the application, a set of d key figures of the production environment, whose time-based behavior should be modeled, is selected as state vector $\mathbf{x}(k)$ of



(a) Fuzzification (b) Defuzzification

Fig. 3. *Standardized* membership functions

the system. A set of e parameters, whose time-based behavior is either predetermined or influenceable, is chosen as input vector $\mathbf{u}(k)$. Each input and state variable is then fuzzified by linguistic terms, for example $\mathbf{L_{j/q}} = \{'l' = low, \ 'm' = medium, \ 'h' = high\}$ using triangular membership functions (Fig. 3(a)). A low number of labels initially ensures a high grade of interpretability and facilitates the acquisition of expert knowledge. However, the partition can be refined if additional information is acquired or if the simulation results are insufficient. The linguistic fuzzy sets of the rules' conclusions are represented by equidistant singletons (Fig. 3(b)).

Step 2: Generation of rule base

Using the rule structure described in (1), each rule would have a premise part containing all variables and a conclusion part containing all state variables. Therefore, a complete rule base would require

$$z = \prod_{i=1}^{d} |L_j^{x_i}| \cdot \prod_{p=1}^{e} |L_q^{u_p}| \tag{4}$$

rules, where $|L_j^{x_i}|$ and $|L_q^{u_p}|$ is the cardinality of the fuzzy set of the i^{th} state and p^{th} input variable respectively.

Interpretability and low implementation effort are great issues, since expert knowledge has to be extracted during the modeling phase and the results of the simulation phase should be easily retransferable into the production planning process. The default rule structure (1) is adequate for an automatic rule extraction from data. However, considering expert knowledge, it is neither intuitive to formulate such rules taking multiple state and input variables into account nor is the great number z (4) of resulting rules well interpretable.

To overcome this limitations, a new reduced rule structure is introduced: the future characteristic of each state variable $x_i(k+1)$ depends only on its current characteristic $x_i(k)$ and the current characteristic of one additional variable ($x_r(k)$ or $u_p(k)$). Thereby, state and input variables can be used in several rules. For example:

$$\text{IF}\langle x_2(k){=}\text{h}\rangle \text{ AND } \langle u_2(k){=}\text{h}\rangle\text{,THEN}\langle x_2(k{+}1){=}\text{m}\rangle, \tag{5}$$
$$\text{IF}\langle x_1(k){=}\,\text{l}\rangle \text{ AND } \langle x_3(k){=}\text{m}\rangle\text{,THEN } \langle x_1(k{+}1){=}\,\text{l}\rangle\,. \tag{6}$$

Using this new rule structure, all rules can be summarized in the so-called influence matrix (Fig. 4). The notation is as follows: The state variables written in the cells of the third row of the matrix are influenced by the state and input variables written in the cells of the third column, whereby the resulting linguistic characteristic of the state variable is written into the corresponding cell. The rule described in (5) is marked by an arrow, the belonging premises are marked with dark outlines.

In this way, the maximal number of possible rules can be greatly reduced to

$$z_{r,max} = \sum_{i=1}^{d} |L_j^{x_i}| \cdot (\sum_{i=1}^{d} |L_j^{x_i}| + \sum_{p=1}^{e} |L_q^{u_p}|) - \sum_{i=1}^{d} |L_j^{x_i}|^2, \quad (7)$$

where the influence matrix (Fig. 4) is fully occupied except for the diagonal elements. The minimum number of rules results, if there exists only one set of rules for each state variable to maintain the recurrence.

It has to be noted that each of these rules can be translated into a set of rules conforming the default rule structure (1). Therefore, one rule is generated for every combination $\mathbf{x}(k) = \mathbf{L_j^x}$ and $\mathbf{u}(k) = \mathbf{L_q^u}$ that contains the premise of the simplified rule $x_i(k) = L_j^{x_i}$ and $u_p(k) = L_q^{u_p}$. Thereby, the conclusion of the simplified rule $x_i(k+1) = L_{w(j,q)}^{x_i}$ is assigned to all generated rules. Consequently, the obtained reduced rule base can be seen as core-dynamics of the production environment.

Step 3: Adaption of the TA-RFS dynamics

Each variable and rule might have a different impact onto the dynamics of a production environment. To address this, the weightings of the TA-RFS as presented in Section 3 are considered to balance the interdependencies. However, if each rule is weighted individually, the interpretability of the model will be reduced. To overcome this drawback, the weighting of each rule is calculated from three interpretable balancing parameters which are assigned to the state variable and input variables:

$$\mathbf{g^x_{L_{w(j,q)}}} = \mathbf{h}(gain(x_i), loss(x_i), weight(x_i), weight(u_p)). \quad (8)$$

The first two parameters $(gain(x_i), loss(x_i))$ adjust the firing strength of all rules that have a decreasing or an increasing effect onto the corresponding state variable x_i. These parameters can be used to model whether one state is more likely to be increased or decreased. For example, if the loss parameter is set to $loss(x_1) = 3$ and the gain parameter is set to $gain(x_1) = 1$, every rule that decreases x_1 has a three times higher effect than every rule having an increasing effect. The third parameter $(weight(x_i))$ describes the overall impact of x_i on all depending rules. Since the input variables are not affected by rules they are only addressed the parameters $weight(u_p)$.

Following this scheme, the weight of the rule described in (5) is calculated by $g^{x_2}_{L_{w(j,q)}} = loss(x_2) \cdot weight(u_2)$, as the rule causes a reduction of the linguistic characteristic of the state variable x_2 ($\Rightarrow loss(x_2)$) and u_2 is the influencing variable ($\Rightarrow weight(u_2)$). The influence of the weightings onto the defuzzification is illustrated in Fig. 3(b). The firing strength of the rule's conclusion is scaled and in this way the TA-RFS output is manipulated. According to Section 3, the weightings are not longer interpreted as probabilities. Thus, they are not longer restricted to the interval $\mathbf{g^x_{L_{w(j,q)}}} \in [0; 1]$. Instead, they can be chosen from a free scalable interval.

However, if the weighting of a certain rule reaches its limits the rule base has to be reviewed. This means it has to be checked whether it is necessary to change the corresponding rule in order to achieve the desired dynamic for the simulated model. In this way, it is possible to find incorrectly assessed rules.

Step 4: Calculation of the production efficiency

In order to further increase the interpretability of the simulation results, a production efficiency indicator

$$X = \mathbf{a}^T \cdot (f_1(x_1), ..., f_i(x_i))^T / \sum^{i} a_i \quad (9)$$

is proposed. This indicator takes all state variables into account and conflates them according to their importance for production planning. Thereby, the conflating function is $f_i(x_i) = x_i$ if the influence of the state x_i is desirable (e.g. quality) and $f_i(x_i) = (1 - x_i)$ if it is undesirable (e.g. lead time). The influencing vector $\mathbf{a}$ contains the weights of the state variables $(weight(x_i))$ representing their impact onto production planing. The conflating functions have to be adapted accordingly to the production environment.

The production efficiency indicator can be further used as a cost function in optimization or as a benchmark figure for management.

5. APPLICATION AND SIMULATION

In this section, the modeling procedure is exemplarily applied concerning six relevant state variables

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{pmatrix} = \begin{pmatrix} \text{Number of units} \\ \text{Cost per unit} \\ \text{Quality} \\ \text{Adequacy of the production environment} \\ \text{Lead time} \\ \text{Unit cost of production} \end{pmatrix} \quad (10)$$

and three significant input variables

$$\mathbf{u} = \begin{pmatrix} u_1 \\ u_2 \\ u_3 \end{pmatrix} = \begin{pmatrix} \text{Adequacy of the technology} \\ \text{Maturity} \\ \text{Cost of development} \end{pmatrix} \quad (11)$$

according to Section 2.1. The first three state variables (x_1,x_2,x_3) can be referred to as the product variables, the second three (x_4,x_5,x_6) can be summarized as production environment variables. Number of units (x_1), cost per unit (x_2), unit cost of production (x_6) as well as lead time (x_5) were selected as state variables due to the fact that they are the major indicators for the need of adaptation. Quality (x_3) is essential for the customer satisfaction and causes fluctuations of the number of produced units. Adequacy of the production environment (x_4) combines operational metrics important for the design of a production. The input variables (11) are adequacy of the technology (u_1) as well as maturity (u_2) and cost of development (u_3), as they mirror strategic aspects within technology planning and influence the operation metrics of production. They can be summarized as technology variables, Reinhart and Schindler (2011).

Three linguistic characteristics $\mathbf{L_{j/q/w(j,q)}} = \{'l', 'm', 'h'\}$ are assigned to each variable. Given the six states (10) and three inputs (11) each having these three different characteristics results in a complete rule base with $z = 3^9 = 19683$ rules. Using the simplified rule structure, the maximal number of possible rules $z_{r,max} = 432$ can be calculated using (7) The minimum number of rules to

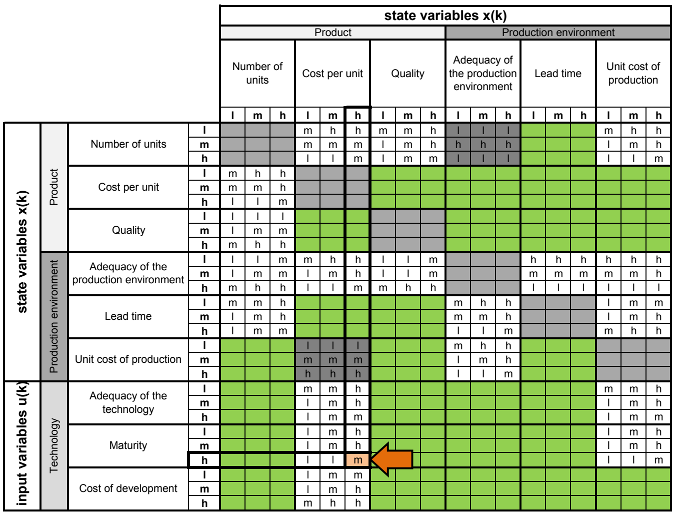


Fig. 4. Influence matrix

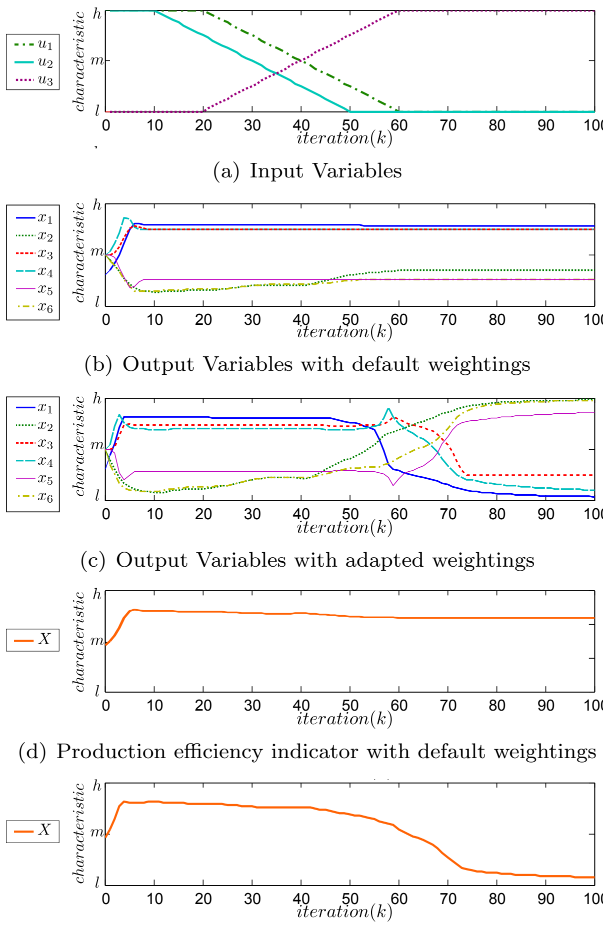
satisfy the recurrence of the model can be calculated by $z_{r,min} = d \cdot |L_j^{x_i}|^2 = 6 \cdot 3^2 = 54$, as there has to be at least one full set of rules ($|L_j^{x_i}|^2$) for all ($d = 6$) state variables.

The matrix given in Fig. 4 describes the used rule base containing $z = 189$ rules whereby $z_{r,min} < z < z_{r,max} << z$ It has to be noted that especially the rules highlighted in dark gray are highly dependable on the production environment.

Setting all rule weightings $g^{x_i}_{L_{w(j,q)}} = 1$, the time-based behavior of the state variables $\mathbf{x}(k)$ (Fig. 5(b)) to a given input $\mathbf{u}(k)$ (Fig. 5(a)) of the production environment is simulated. Thereby, the input prognosticates a negative development of the technology variables $\mathbf{u}(k)$. The technology variables are optimal for the first 10 iterations. As a result the state variables reach an equilibrium where the linguistic characteristics indicate a positive production environment. This is characterized by low costs per unit and lead time with a high quality at the same time. Subsequently, a deterioration of the technology parameters is simulated: the maturity and the adequacy of the technology drop whereby the cost of development increases. The resulting behavior of the state variables (Fig. 5(b)), where the cost per unit increases, is qualitatively plausible. However, the impact of the bad prognosis is relative low as the cost per unit does not even reach $'m'$.

In contrast, Fig. 5(c) shows the simulation of the adapted model considering the weightings in Table 1. Among others, the increased influence of the technology variables $\mathbf{u}(k)$ lead to a new equilibrium of $\mathbf{x}(k)$, which is due to the impact of the negative technology variables significantly worse compared to the one shown in Fig. 5(b). The balancing parameters $(gain(x_i), loss(x_i), weight(x_i), weight(u_p))$ were thereby chosen from an interval $[0; 10]$. Subsequently, the resulting rule-weightings $\mathbf{g}^{\mathbf{x}}_{\mathbf{L_{w(j,q)}}} \in [0; 100]$.

This simulation illustrates that the weightings have the potential to adapt the model to a certain production environment without changing the rule base or the membership functions and thus keeping the interpretability of the model. Furthermore, the understanding of the model is even increased since the evaluations of the balancing parameters $(gain(x_i), loss(x_i), weight(x_i), weight(u_p))$ and weightings $(\mathbf{g}^{\mathbf{x}}_{\mathbf{L_{w(j,q)}}})$ allows the detection of 'strong' rules and variables, meaning rules and variables which have great impact on the dynamic of a production environment. These findings can be retransfered in the production planning process.



(a) Input Variables

(b) Output Variables with default weightings

(c) Output Variables with adapted weightings

(d) Production efficiency indicator with default weightings

(e) Production efficiency indicator with adapted weightings

Fig. 5. *Simulation scenario*

The time-based behavior of the efficiency indicator X (Fig. 5(e)) of the adapted production environment suggests an uneconomic production as it is also shown by the state variables $\mathbf{x}$ in Fig. 5(c). The production efficiency indicator was thereby calculated as follows:

Table 1. Balancing parameters

	gain	loss	weight
Number of units	1	3	1
Cost per unit	1	1	6
Quality	0.9	0.9	1
Adequacy of the production environment	1	1	1
Lead time	1	1	0.5
Unit cost of production	1	1	1
Adequacy of the technology	-	-	3
Maturity	-	-	3
Cost of development	-	-	3

$$X(k) = (1, 6, 1, 1, \frac{1}{2}, 1) \cdot \begin{pmatrix} x_1(k) \\ 1 - x_2(k) \\ x_3(k) \\ x_4(k) \\ 1 - x_5(k) \\ 1 - x_6(k), \end{pmatrix} \cdot \frac{2}{21} \qquad (12)$$

declaring cost per unit, unit cost of production, and lead time as undesired variables where the cost per unit was weighted strongest.

6. CONCLUSION

An adapted modeling framework and simulation results of qualitative cyclic influences onto a production environment has been shown. The proposed model is based on a recurrent fuzzy system where additional transition weightings were applied. A structured way of creating and adapting the model and weightings has been introduced, meaning that the amount of rules and parameters were reduced. Thereby the modeling procedure becomes both, intuitive and highly interpretable. The weightings also enable the adaptation of the model to different production environments, while keeping the same rule base or membership functions. At the same time the weightings allow a structural analysis of the model by detecting high impact relations.

During the exemplary application, the number of rules was greatly reduced from 19683 to 189 and whose weightings were generated from a set of 21 well interpretable balancing parameters. By adjusting the weightings the steady-state behavior of the production environment was changed to a new equilibrium, whereby the linguistic characterization of the introduced production efficiency parameter changed from almost high to low. Consequently, the possibilities of the model concerning production planning and managing have been illustrated.

Future work will involve automated optimization of the model and sensitivity analysis of the input and state variables based on the introduced rule-weightings. Also, the application of Transition Adaptive Recurrent Fuzzy Systems as a combined decision making and control system for production plants will be investigated.

ACKNOWLEDGEMENTS

The authors thank the German Research Foundation (DFG) for funding this work as part of the collaborative research project ‘Managing cycles in innovation processes - Integrated development of product service systems based on technical products’ (SFB 768). This paper is a result of a cooperation of the subprojects A3, A7, B3, and B4.

REFERENCES

Bullinger, H., Warnecke, H., and Westkämper, E. (2003). *Neue Organisationsformen im Unternehmen: Ein Handbuch für das moderne Management.* Utz 2005, Berlin.

Cisek, R. (2005). *Planung und Bewertung von Rekonfigurationsprozessen in Produktionssystemen. Diss. TU München.* Utz 2005, München.

Diepold, K.J. and Lohmann, B. (2010). Transient probabilistic recurrent fuzzy systems. In *Proc. IEEE International Conference on Systems, Man, and Cybernetics*, 3529–3536. Istanbul, Turkey.

Diepold, K.J., Schmidt-Colinet, J., Lohmann, B., and Vogel-Heuser, B. (2011). Intelligent probabilistic recurrent fuzzy control of human-machine systems. In *Proc. IFAC World Congress*, 4857–4862. Milano, Italy.

ElMaraghy, H., Azab, A., Schuh, G., and Pulz, C. (2009). Managing variations in products, processes and manufacturing systems. *Annals of the CIRP - Manufacturing Technology*, 58, 441–446.

Feng, G. (2006). A survey on analysis and design of model-based fuzzy control systems. *IEEE Trans. on Fuzzy Systems*, 14(5), 676–697.

Gorrini, V. and Bersini, H. (1994). Recurrent fuzzy systems. In *Proc. IEEE International Conference on Fuzzy Systems*, 193–198. Orlando, USA.

Hax, A. and Majluf, N. (1982). Competitive cost dynamics: the experience curve. *Interfaces 12*, 5, 50–61.

Little, A. (1993). *Management der F&E-Strategie.* Gabler, Wiesbaden.

McCarthy, J., Canziani, O., Leary, N., and Dokken, D. (2001). *Climate Change 2001: Impacts, Adaptation, and Vulnerability.* Cambridge University Press, Cambridge.

Reinhart, G., Krebs, P., and Zäh, M.F. (2009). Fuzzy logic-based integration of qualitative uncertainties into monetary factory evaluations. In *IEEE International Conference on Control Automation (ICCA)*, 85 – 391. Christchurch.

Reinhart, G. and Schindler, S. (2011). Strategic evaluation of manufacturing technologies. In *18th CIRP International Conference on Life Cycle Engineering (LCE)*, 179–184. Braunschweig.

Schöning, S. (2006). *Potenzialbasierte Bewertung neuer Technologien. Diss. RWTH Aachen.* Shaker, Aachen.

Schwung, A. and Adamy, J. (2010). Nonlinear system modeling via hybrid system representation of recurrent fuzzy systems. In *Proc. IEEE International Conference on Fuzzy Systems*, 1–7. Barcelona, Spain.

Sommerlatte, T. and Deschamps, J.P. (2006). Der strategische Einsatz von Technologien. In A. Little (ed.), *Zeitalter der strategischen Führung*, 39–76. Gabler.

Westkämper, E. (2006). Factory transformability: Adapting the structures of manufacturing. In A. Daschenko (ed.), *Reconfigurable Manufacturing Systems and Transformable Factories*, volume 2, 372–381. Springer, Berlin, Heidelberg.

Wiendahl, H., ElMaraghy, H., Nyhuis, P., Zäh, M., Wiendahl, H., Duffie, N., and Kolakowski, M. (2007). Changeable manufacturing - classification, design and operation. *Annals of the CIRP 56*, 2, 1–25.

Wong, B.K. and Lai, V.S. (2011). A survey of the application of fuzzy set theory in production and operations management:1998–2009. *Int. J. Production Economics*, 129, 157–168.

Zadeh, L. (1965). Fuzzy sets. *Information and Control*, 8(3), 338–353.

Zäh, M., Reinhart, G., Karl, F., Schindler, S., Pohl, J., and Rimpau, C. (2010). Cyclic influences within the production resource planning process. *Production Engineering 4*, 58, 309–317.

Zäh, M., Reinhart, G., Pohl, J., Schindler, S., Karl, F., and Rimpau, C. (2009). Anticipating and managing cyclic behaviour in industry. In *Proceedings of the 3rd International Conference on Changeable, Agile, Reconfigurable and Virtual Production (CARV)*, 16–43. Munich.