Management Applications of Fuzzy Control

Introduction
Fuzziness is a form of uncertainty. It embraces in particular linguistic and informational uncertainty [1]. Linguistic uncertainty is characterized by a lack of precision and the indefinite nature of human language. (“high” interest rates). Informational uncertainty exists when many descriptors are necessary to describe a term clearly (“creditworthy” company). In contrast to stochastic uncertainty, it is not adequate to model these forms of uncertainty based on probability theory.

Since the mid 1960s, fuzzy set theory has been developed by Zadeh, Zimmermann [1] [2] and others as a theoretical basis in order to model fuzziness. Fuzzy Set Theory is well-established in the technical domain. Fuzzy control [3] was the first - and still is the most frequent practical application of fuzzy sets. In 1975, a cement kiln built in Denmark became the first industrial application of fuzzy control. Later, the idea of fuzzy control was particularly successful in Japan. Today, we find fuzzy control applications in many aspects of daily life, such as automatized chemical process control, gear shifts that adapt to the car driver, and driverless train operations. In addition, many applications of other fuzzy techniques, such as fuzzy data analysis and Neuro-Fuzzy Systems, can be identified.

Fuzzy systems are successful, because they allow for a relatively straightforward modelling and transparent model structure even in complex tasks [4]. Moreover, they demonstrate robust behaviour, for instance in dynamic environments.

The adequate treatment of fuzziness also has a great significance in practical management. For instance, qualitative expert judgements, potential information overflow and vague relationships characterize important management domains such as knowledge management, strategic foresight and customer relationship management. In this paper, the concept of a fuzzy controller as a knowledge-based system is transferred to the management domain. Similarities and differences are highlighted and some sample applications in management are given.
Fuzzy Set Theory and Fuzzy Control

Fuzzy systems and fuzzy methods have a solid mathematical basis. In classical set theory, an element \( x \) out of a basic set \( X \) (\( x \in X \)) either definitely belongs to a set \( A \) or it definitely does not belong to \( A \). However, for many real circumstances such a strict distinction does not render an appropriate representation. In fact, gradual membership prevails in reality. Thus a fuzzy set \( \tilde{A} \) is characterized by the fact that the membership of an element \( x \) to \( \tilde{A} \) can be indicated by a real number which is usually standardized on the range of values \([0.1]\), thus describing formally a fuzzy set \( \tilde{A} \) by a real value membership function \( \mu_{\tilde{A}} \) is: \( \mu_{\tilde{A}} : X \rightarrow [0,1] \). Herein, a value \( \mu_{\tilde{A}}(x) = 0 \) means that \( x \) does not belong to the fuzzy set \( \tilde{A} \), while a value \( \mu_{\tilde{A}}(x) = 1 \) indicates full membership. Values within the interval \( 0 \leq \mu_{\tilde{A}}(x) \leq 1 \) indicate a partial membership of \( x \) in the set \( \tilde{A} \). The classical, non-fuzzy set \( A \) can be interpreted as a special fuzzy set, where only two alternatives, no membership or full membership, exist.\(^1\)

The application domain of technical control is characterised by the goal to automatize the supervision and correcting activities for complex (non-linear) technical processes. In classical control theory, the design of a controller is based on a mathematical model of the technical process, frequently in the form of differential equations that define the system response to it’s inputs. Fuzzy controllers differ from that by modeling the know how of a human control expert for the technical process [4]. Usually, this know how is expressed in logic rules (IF-THEN statements) where fuzzy sets are employed to model qualitative terms like “high” and “low” that the expert uses in his rules.

![Fig. 1: Structure of a fuzzy controller](image)

\(^1\) For a more detailed introduction to fuzzy set theory see [2], [4], and [5].
Figure 1 outlines the general structure of a fuzzy controller. The input and output of the controller are generally crisp (not fuzzy) values, while the inference mechanism is based on fuzzy data. Thus, initially the input data is individually mapped from crisp to fuzzy values, a step that uses sets of membership functions. The result is for each fuzzy set a real value in the interval $[0,1]$. This is called “fuzzification”. Because neighbouring fuzzy sets overlap, an input variable’s state does not jump abruptly from one state to the next. Instead, it loses value in one membership function while gaining value in the next. Through fuzzification the compatibility of the facts (measurements) with rule antecedents is determined. In contrast to classical expert systems, rule antecedents of fuzzy controllers may only be fulfilled partly. All rules from the knowledge base with antecedents that have strictly positive membership values are activated in parallel. Even conflicting rules may be simultaneously active.

![Max-Min Inference](image)

**Fig. 2: Principle of max-min inference and center of gravity defuzzification**

Usually, rules have several antecedents that are aggregated using fuzzy operators, such as AND, OR, and NOT. Moreover, rules may be weighted to express the confidence of the process expert in the rule. Then, by applying fuzzy inference the fuzzy values of input variables are mapped on the output variable of the fuzzy controller. Frequently, the fuzzy minimum operator (AND) is used for this purpose. Figure 2 highlights for the example of the AND-operator, how fuzzy sets of the output variable are cut off at the level of the minimum of fuzzified inputs. As several rules can be active simultaneously,
their results must be accumulated. Often this is achieved by using the fuzzy maximum operator (OR). The combination of max and min operators is called max-min-inference and a common form of inference mechanism to determine the fuzzy output of the controller. At last, a “defuzzification” step provides a crisp output value, often by calculating the center of gravity for the combined output fuzzy set of all active rules (figure 2).

**Applying Fuzzy Control in Management**

On an abstract level, fuzzy controllers are used to model human knowledge about complex, non-linear processes in a transparent, formal way that allows for automated execution. In the management domain during the 80ies and 90ies, there was a strong movement to model human expertise in rule-based “expert systems”. These generally suffered from brittleness at the border of their domain of expertise, as well as from often great complexity in the rule base and inference mechanism that prompted design and performance problems. Fuzzy controllers are also rule-based systems, but contrary to classical expert systems, the structure of their knowledge base is much simpler, and they rely on a simple feedforward inference mechanism without backtracking.

Potential applications of fuzzy control-like systems in management can be found where:

− analytical models of the domain are impossible or require a prohibitive effort,
− the results of analytical models are intransparent and have no acceptance,
− qualitative judgements and/or vague relationships are important,
− human expertise about the complex application domain is available in the company.

Based on these criteria, many areas of management qualify for the application of fuzzy rule based systems. In our research group, amongst others, the following successful applications were developed:

− weather-dependent production planning in an industrial bakery [6],
− fuzzy analysis of company balance sheets [7],
− forecasting consulting effort for it-projects [8],
− modelling corporate strategy in a fuzzy balanced scorecard [9],
− modelling qualitative information in management simulation games [10].

The system structure is always basically equivalent to that of a fuzzy controller as given in figure 1. Again, the rule base contains expert knowledge (if-then statements) about important relationships between variables of the application domain. However, some important differences between technical fuzzy controllers and similar fuzzy rule-based systems in management application exist:
Contrary to technical process control, where in short intervals repeated measurements are performed and a control variable is adapted, the cycle of determining inputs, reasoning, and deciding about the output is only performed once in management applications. Thus, the output result is of greater importance than in traditional fuzzy control, as it cannot be corrected by a consecutive inference cycle. (However, the fuzzy system may be used for simulations with different input combinations [9].)

The rule base is generally more complex, because the number of relevant input (and sometimes output) variables is higher in management, so that expert knowledge cannot be summarized in only five to ten rules, as can be done in many technical control applications. To avoid problems with large knowledge bases, fuzzy rule-based systems in management applications frequently take the form of a hierarchical fuzzy controller, where several interrelated rule bases exist that individually solve parts of the overall problem. The total output is then determined by a hierarchical cascade of intermediate results.

Hence, the system design process can be more complex than in technical fuzzy controllers. Moreover, determining the output quality during the design phase of the rule-based system is sometimes difficult and may rely on expert judgements.

A true automation of decision making is often not the goal with fuzzy rule-based systems in management. It is more a device for supporting human decisions.

Input data is frequently quantitative, as in technical control, but it may suffice or render desired extra information to have the output also in qualitative form, giving all positive membership values for output fuzzy sets. Thereby, information about the risk of the decision (output) is available to management.

To increase management acceptance for the fuzzy rule-based output in decision support, it is desirable (and possible) to construct an explanation component. Such a component makes use of intermediate results of the hierarchical fuzzy system to explain how the final output was generated [11].

A brief example [8] will help to make these differences more accessible. Figure 3 outlines the general structure of a fuzzy rule-based system that takes certain characteristics of a planned consulting project as input (left side of fig. 3) and generates an estimation of required consulting effort (mandays), separated for different parts of the project, as output. The result can then be used in the quotation of the consulting company to win the respective customer order. The idea in this case was to support and eventually even automate the otherwise laborious manual process of estimating consulting effort. Know
how of experienced consultants was structured in several rule bases to allow for a hierarchical decomposition of the overall estimation problem. Every triangle in fig. 3 corresponds to one fuzzy controller, roughly analogous in structure to fig. 1. A cascade of intermediate results (only an excerpt of the whole system is given in fig. 3) then leads to the final effort estimation. This tool showed good performance in practical tests when compared to manual results. Of course, effort estimation is always domain-specific, but the general idea can be quickly transferred from one consulting domain to another.

Fig. 3: Structure of a hierarchical fuzzy controller that estimates consulting effort, based on project characteristics that sales staff provided (excerpt) [8]

References:

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