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A comparison of fuzzy expert systems, neural networks and neuro-fuzzy approaches
Controlling energy and material flows

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Abstract

In industrial production processes, materials and different forms of energy are provided, transformed respectively converted, stored and transported. With this process joint products in different states of aggregation are emitted. Environmental impacts can be identified at any stage of the energy and material flow process. Due to the fact that production units and processes are interconnected with energy and material flows, it is of special interest to develop production control mechanisms which control the energy and material streams in a way that utilizes available resources most efficiently and reduces emissions and by-products caused by the production process. These production control strategies have to consider variations in the input and output flows of succeeding and preceding production units.

The development of production control strategies depends especially on the structure of integrated production systems. If it is possible to influence the energy and material flows by the selection of special production processes and an adequate allocation of jobs and aggregates, the construction of production control strategies can be reduced to a combined scheduling and technology selection problem.

Methodical production control strategies can be based on optimal algorithms (e.g. dynamic programming) heuristics (e.g. rule-based approaches) and methods of machine learning (e.g. neural networks). Due to the complexity of real production systems, it is advisable to use rule-based approaches or neural networks depending on the structure of the available production knowledge.

Keywords: Fuzzy logic; Neural networks; Production control

1. Analysis of the production system under investigation

To analyse the behaviour of different production control mechanisms e.g. based on fuzzy expert systems, neural networks and neuro-fuzzy approaches, the described methods are verified by an exemplary production system from the textile industry (Fig. 1). The production system under investigation consists of a dye-house, a boiler-house, a hydropower plant and a flue gas neutralisation facility. The dye-house covers two stages of production, the dyeing process and the drying of the dyed yarns. The two stages of pro-

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duction require steam/hot water and electric power, which are supplied by the preceding power plants. The flue gas of the boiler-house is used to neutralise the mainly alkaline waste water of the dye-house at the flue gas neutralisation facility. The storage of steam/hot water as well as the capacity of the waste water reservoir are limited. The capacities of all preceding and succeeding production units are variable. Variations can be caused by external factors (e.g. smog, variations of the water level of the inlet of the hydropower plant).

For the investigation of different production scenarios (e.g. different operating modi of the power plants, smog events, machinery disturbances) the production system is modelled with a simulation tool (SLAM). A comprehensive description of SLAM is given in Pritsker (1986). The physical structure of the production system (e.g. aggregates, potential energy and material flows between the aggregates), available resources and system functions (e.g. queues, the allocation of aggregates) are modelled graphically. Process- and job-specific data (e.g. process parameters, recipe formulations, energy-demand functions) are modelled in a C-database. Certain production rules (e.g. for the resetting of the equipment) and interfaces to intelligent systems (e.g. fuzzy expert systems and neural networks) are programmed in FORTRAN and C.

A system analysis of the investigated production system shows that

- emission-oriented goals, such as an increase of the efficiency of the flue gas neutralisation facility, reduction of CO_2 emissions, reduction of supplementary chemicals (HCl, H_2SO_4) for the neutralisation process in cases of a waste water excess and a reduction of waste heat losses as well as
- economic goals, such as an increase of the utilization of the equipment, a shortage of the average waiting time

correlate with the harmonising of energy and material flows, which can be influenced by the selection of certain dyeing processes and an adequate allocation of dye batches and dye vats.

2. Emission-oriented production control strategies based on fuzzy expert systems

Owing to the structure of the decision problem (number of serial and parallel production processes, multi-criteria goal function, dynamic behaviour of the energy and material flows, fuzziness of the production knowledge), fuzzy expert systems are implemented to perform the planning decisions described. In any planning situation the corresponding fuzzy expert system is evoked and calculates a priority number for every potential combination of a dye batch and an applicable dyeing process. This number is relatively high if the energy demand (steam/hot water, electric power) and the characteristics of the waste water implied by a certain job correlate with the current state of the system (pH-value in waste water reservoir, energy supply). Fig. 2 shows a typical structure of a fuzzy expert controller with rule

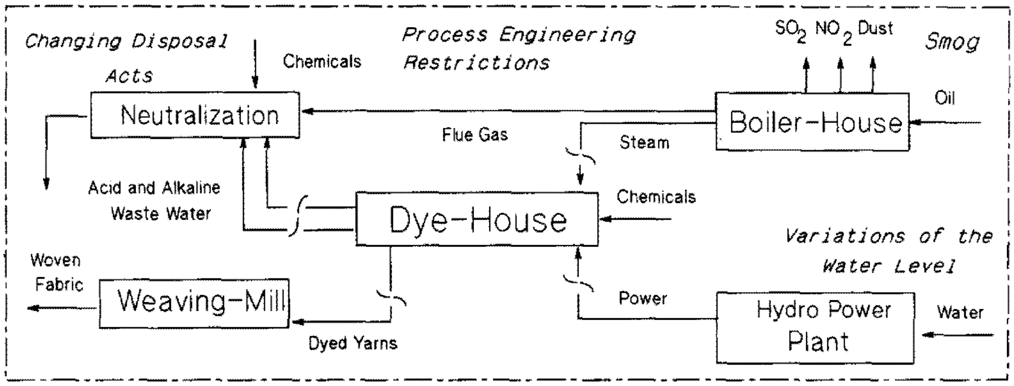

Fig. 1. Structure of an interconnected production system.

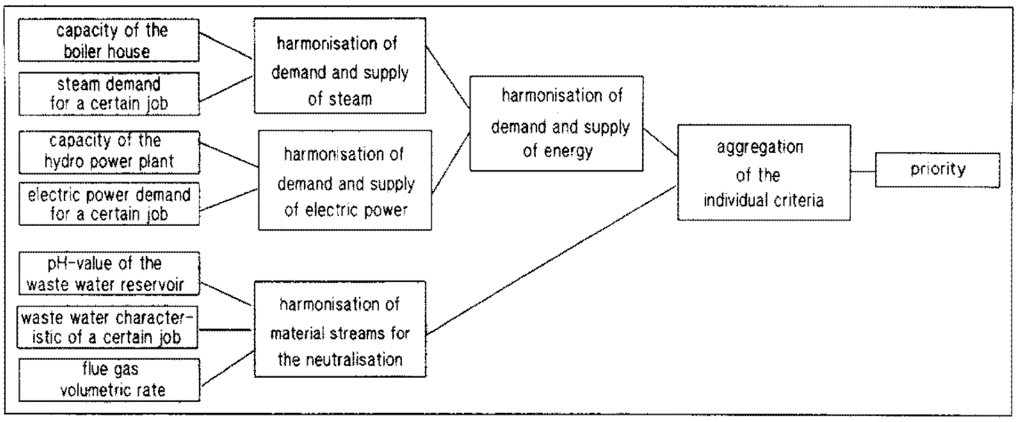

Fig. 2. Structure of a fuzzy expert system for controlling energy and material flows.

blocks for the harmonisation of the demand and supply of energy, and material streams (e.g., NaOH, CH_3OOH, CO_2, SO_2) for the neutralisation process. The rule blocks consist of 27 to 81 individual rules (Tuma, 1994).

The development of fuzzy expert systems requires the definition of membership functions, selection of aggregation operators, assignment of a degree of sensibleness for each rule and the selection of a defuzzification method. A comprehensive description of fuzzy expert systems is given in Zimmermann (1991). Fig. 3 shows exemplary membership functions and rules of a fuzzy expert controller. An investigation of different membership functions, aggregation operators and strategies for the assignment of the degrees of sensibleness shows that the most critical point seems to be the assignment of a degree of sensibleness for each rule (Fig. 4). This determines the influence of individual rules and represents the inference structure of the fuzzy expert controller. To adjust the degree of sensibleness, it is important to have a consistent theory regarding a proper model of the controlling task. The system represented by bars 11 and 12 in Fig. 4, for example, is based on the idea that the pH-value of the waste water reservoir is the key parameter for controlling the material flows for the neutralisation process. The adjustment of the degrees of sensibleness of the system represented by bars 9 and 10 is

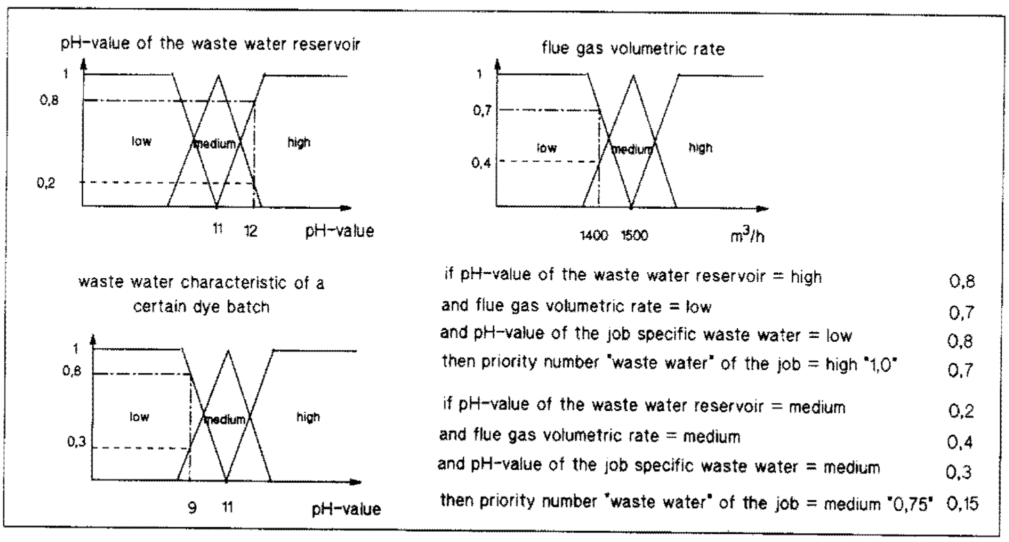

Fig. 3. Exemplary membership functions and rules.

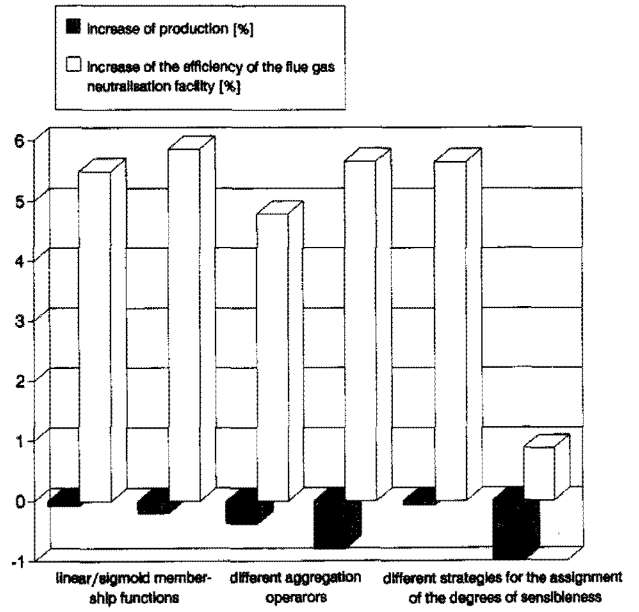

Fig. 4. A comparison of different FECs (Fuzzy Expert Controllers) for the controlling of material and energy flows.

more oriented at the flue gas volumetric rate. The reason for the relative weak influence of the application of different aggregation operators is a restrictive preselection of available operators in order to apply compensatory operators with a quite good empirical fit. The system represented by bars 5 and 6 in Fig. 4 uses γ-operators, the system represented by bars 7 and 8 uses "fuzzy-and" operators to model the aggregation of the energy- and environmental-orientated goals (Fig. 2). An analysis of the real system showed that the economic and environmental-orientated goals are not exclusive (Tuma, 1994). A detailed description of the mentioned aggregation operators is given in Zimmermann (1991).

In contrast to the efficiency of the neutralisation facility, up to now it has not been possible to set up a fuzzy expert system which fulfils the economic goals. Therefore, it is important to note that the dependencies of the parameters and the corresponding inference structure concerning the achievement of the mentioned economic goals, which are correlated in a certain way with the harmonising of energy demand and supply, are much more complicated compared to the emission-oriented goals.

3. Emission-oriented production control strategies based on neural networks

If it is not possible to construct a consistent model, i.e. to formulate explicit rules, implicit knowledge can be used. Implicit planning knowledge is for example included in representative production examples. One way to operationalize implicit knowledge is to use neural networks. The construction of production control strategies based on neural networks requires the formulation of the controlling task in a manner which can be processed by an adequate network architecture, acquisition of representative training examples, selection, teaching and testing of adequate network architectures.

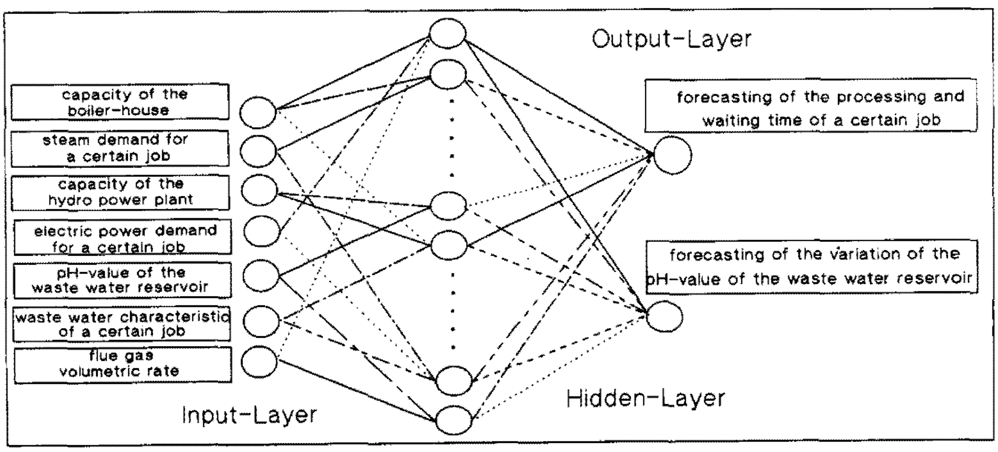

Fig. 5. Structure of a neural network for controlling energy and material flows.

The described scheduling and technology selection problem can be formulated as a forecasting problem. At any time, when a job has to be scheduled, the corresponding neural networks are evoked. For every possible combination of a dye batch and an applicable dyeing process, the expected processing and waiting time and the expected variation of the pH-value of the waste water reservoir are predicted (Tuma, 1994).

The acquisition of representative production examples is based on the analysis of different simulation scenarios. Two-hundred scenarios (different operating modi of the power plants, disturbances of preceding and succeeding production units) are chosen at random from a set of 6912 possible scenarios. For each scenario 8 to 12 break points, representing certain states (pH-value of the waste water reservoir, flue gas volumetric rate, available power of the power plants), are chosen at random. At these break points, different planning alternatives are scheduled. The most critical point in this context is the selection of evaluation parameters and the determination of the time, when the influence of the different alternatives should be evaluated. If for example the chosen evaluation time for the single alternatives is too late, the influence of a certain decision could be covered by succeeding decisions.

Due to the requirements of the forecasting problem, a backpropagation network with three layers is selected (Fig. 5). The input function is the weighted summation, the transfer function is the sigmoid function or the tangens hyperbolicus, the output function is the direct output. A detailed description of the backpropagation algorithm is given in Rumelhart and McClelland (1986).

As a χ^2-test shows, it is possible to control the mentioned economic goals using neural networks. On the other hand, up to now it was not possible to control the efficiency of the flue gas neutralisation facility as successfully as with fuzzy expert systems. This implies that in fields where a consistent theory can be constructed, it is advisable to use rule-based systems such as fuzzy expert systems. If, however, this is not possible due to the complexity of the controlling task, neural networks should be applied.

4. Emission-oriented production control strategies based on neuro-fuzzy approaches

In order to combine the advantages of fuzzy expert systems dealing with explicit knowledge and neural networks dealing with implicit knowledge, a neuro-fuzzy approach is developed to control energy and material flows (see Fig. 6). In principle, the rule structure of a fuzzy expert system is applied. The assignment of the degrees of sensibleness for certain rule blocks is achieved by machine learning algorithms. Under certain

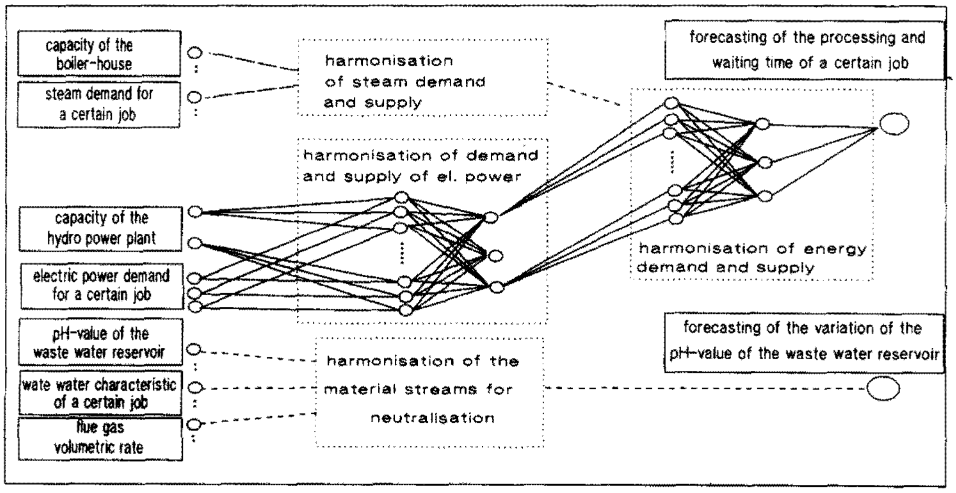

Fig. 6. Structure of a neuro-fuzzy system to control energy and material flows.

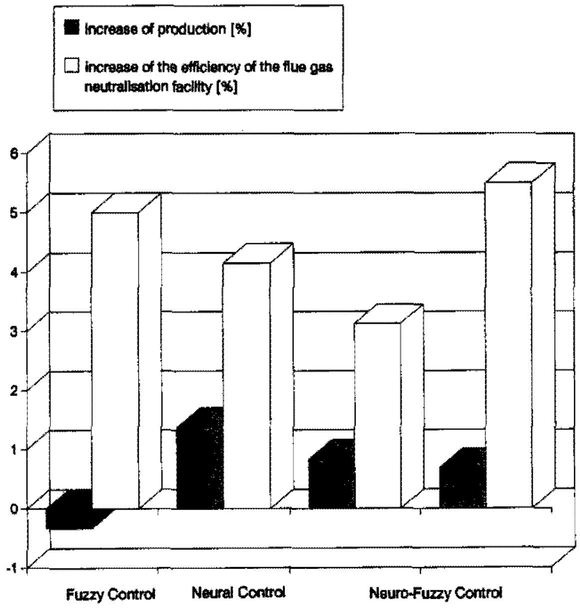

Fig. 7. Comparison of different controlling methods.

conditions (e.g. the weighted summation as input function of the neural network and the average operator as composition operator of the corresponding fuzzy expert system), fuzzy expert systems can be interpreted as backpropagation networks and vice versa (Berenji, 1990; Tuma, 1994).

The adjustment of the system covers two steps. In a first step the degrees of sensibleness are set from the production examples (Fig. 7, bars 5 and 6). In a second step the interpretable weights (degrees of sensibleness) of these rule blocks, for which a consistent theory exists (e.g. the controlling of the flue gas neutralisation facility) are adjusted manually (Fig. 7, bars 7 and 8). This procedure combines the capabilities of machine learning, evaluating implicit knowledge, and the human capabilities for constructing a consistent theory of a closed problem with respect to the advantages of fuzzy expert systems and neural networks. This is of special interest in fields of ambiguous knowledge, such as the controlling of energy and material flows, taking into consideration emission-oriented and economic goals.

References

Berenji, H., 1990. Neural networks and fuzzy logic in intelligent control. In: 5th IEEE International Symposium on Intelligent Control, 2: 916–920.

Pritsker, A., 1986. Introduction to Simulation and SLAM. Ellis Horwood, New York.

Rumelhart, D.E. and McClelland, J.A., 1986. Parallel Distributed Processing. Cambridge, MA.

Tuma, A., 1994. Entwicklung emissionsorientierter Methoden zur Abstimmung von Stoff- und Energieströmen auf der Basis von fuzzyfizierten Expertensystemen, Neuronalen Netzen und Neuro-Fuzzy-Ansätzen. Peter Lang Verlag, Frankfurt a. M.

Zimmermann, H.-J., 1991. Fuzzy Set Theory and its Applications. Kluwer, Boston.