Development of emission orientated production control strategies using Fuzzy Expert Systems, Neural Networks and Neuro-Fuzzy approaches

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Abstract

In industrial production processes, materials and different forms of energy are provided, converted, stored and transported. 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 so that available resources are utilised most efficiently and reduce emissions and by-products caused by the production process.

Methodical production control strategies can be based on optimal algorithms, production rules or methods of machine learning. Due to the complexity of real production systems, it is advisable to use heuristic approaches.

In order to analyse the behaviour of different control strategies, the developed systems are verified by an exemplary production system from the textile industry, consisting of a dye house, a hydro-power, a boiler house, and a flue gas neutralisation facility.

A verification of the developed systems shows that Fuzzy Expert Systems, Neural Networks, and Neuro-Fuzzy approaches can be applied for the controlling of energy and material flows, taking into account economic and emission orientated goals. The selection of a certain approach mainly depends on the structure of the available production knowledge.

Keywords: Expert systems; Multicriteria analysis; Production and process control; Economics; Neural networks; Hybrid systems

1. Conception of emission orientated production control strategies

Concerning the development of emission orientated production control strategies for the harmonising of energy and material streams, the following criteria have to be considered:

- simultaneous consideration of emission orientated and economic goals (e.g. increase of the efficiency of a disposal unit, reduction of waiting times),
- process and production engineering restrictions,
- a sufficient modelling of the dynamic behaviour of the production system,

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- structure of available production knowledge (e.g. fuzzy knowledge, implicit knowledge).

This requires the development and application of related heuristic approaches or methods of machine learning such as:

- Fuzzy Expert Systems,
- Neural Networks or
- Neuro-Fuzzy approaches.

Hitherto applied methods in the field of production planning and controlling (e.g. linear programming, dynamic programming) are insufficient with respect to an adequate controlling of energy and material streams of interconnected production systems. This is especially true with respect to an adequate modelling of the complexity of real production processes, available process and production knowledge and system dynamics.

2. 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 hydro-power 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 production 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 capacity of all preceding and succeeding production units is variable. Variations can be caused by external factors (e.g. smog, variations of the water level of the inlet of the hydro-power 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). 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 [3]. 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

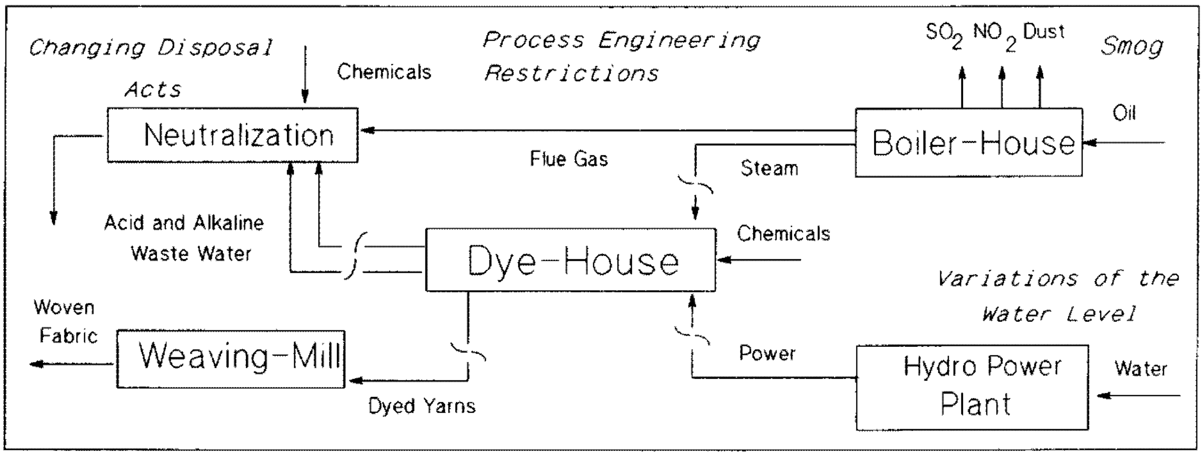

Fig. 1. Structure of an interconnected production system.

- emission orientated goals, such as an increase in 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
- economical goals, such as an increase of the utilisation 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.

Principally the scheduling and technology selection problem can be implemented

- in a successive way by an iterative algorithm (job by job) or
- by an over-all optimisation process (generating a complete schedule).

In view of our mentioned goals, owing to the complexity of real production systems [5] and the structure of the available production knowledge (single priority rules, experience on the influence of the scheduling of single jobs in special production situations), it seems to be more promising to apply successive algorithms in comparison to an over-all optimisation procedure. This is comparable to the way human operators perform this task, takes care of the structure of the available production knowledge and gives a more interpretable result which increases the acceptance of the operators. Furthermore this procedure gives a better basis to react on an unforeseen or short-time variation of relevant production parameters, like disturbances of single aggregates or e.g. a smog event.

3. Emission orientated production control strategies based on Fuzzy Expert Systems

Owing to the structure of the decision problem (number of serial and parallel production processes, multicriteria 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 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 blocks for the harmonisation of the demand and supply of energy,

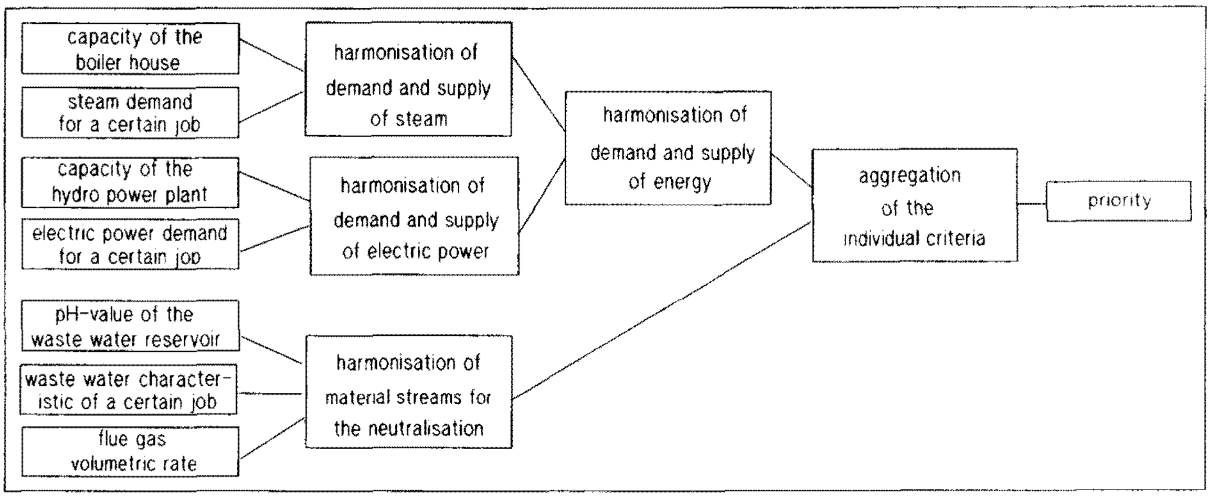

Fig. 2. Structure of a Fuzzy Expert System for controlling energy and material flows.

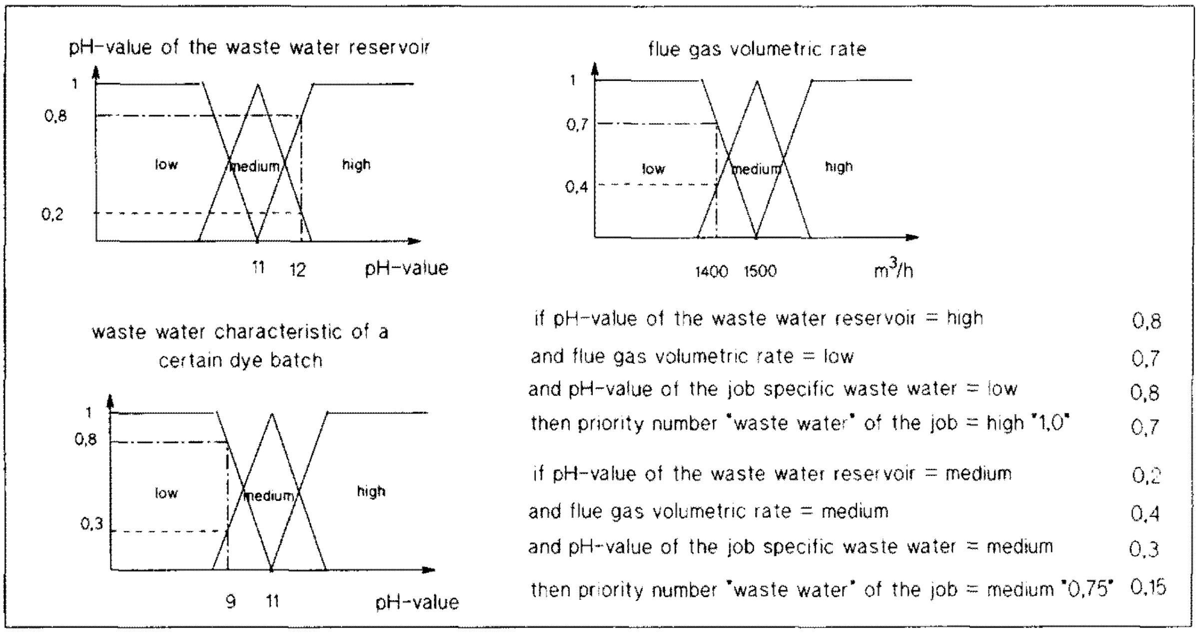

Fig. 3. Exemplary membership functions and rules.

and material streams (e.g. NaOH, CH_3OOH, CO_2, SO_2) for the neutralisation process. The rule blocks consist of 27–81 individual rules [5, 6].

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 [7]. Fig. 3 shows exemplary membership functions and rules of a Fuzzy Expert Controller. An investigation of different membership functions, aggregation operators, controller architectures 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 degrees of sensibleness, it is important to have a consistent theory regarding a proper model of the controlling task. The system represented by bar 10 in Fig. 4 is, for example, 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 bar 9 is more orientated to the flue gas volumetric rate.

In contrast to the efficiency of the neutralisation facility, it has up to now not been possible to set up a Fuzzy Expert System which fulfils the economic goals. Therefore, it is important to notice 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 orientated goals.

4. Emission orientated 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 e.g. included in representative production examples. One way to operationalise implicit knowledge is to use Neural Networks. The construction of production control strategies based on Neural Networks requires the formulation of the

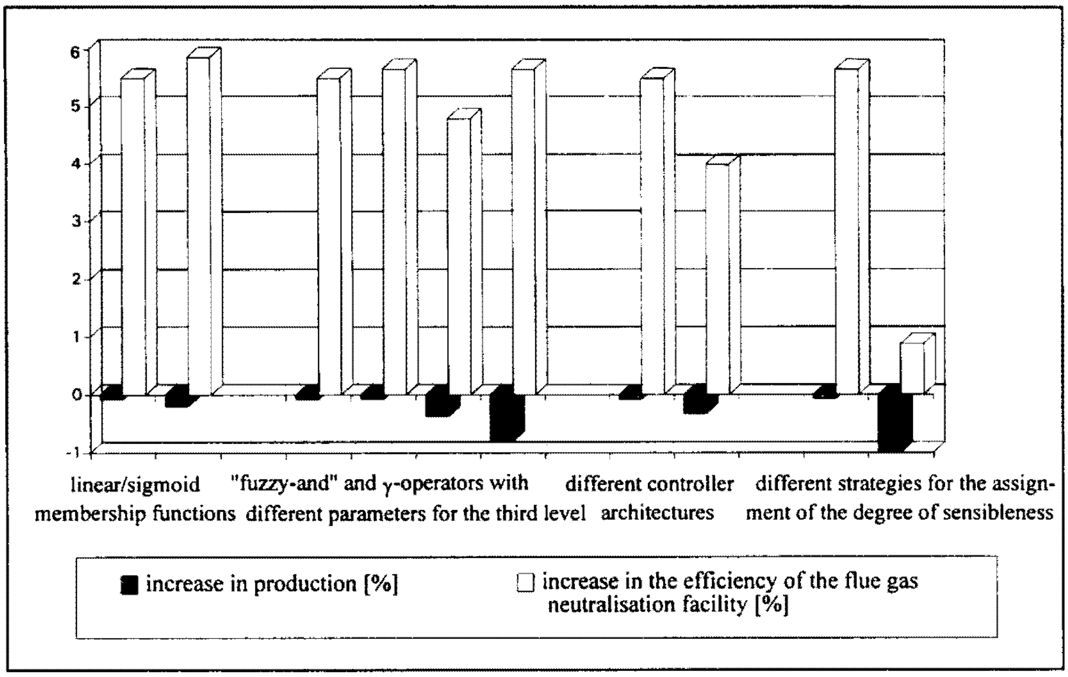

Fig. 4. A comparison of different Fuzzy Expert Systems for the controlling of material and energy flows.

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.

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 [5, 6].

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 8–12 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 back-propagation 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 [4]. Fig. 6 shows the effect of different transfer functions in the hidden layer.

As a χ^2-test shows, it is possible to control the mentioned economic goals using Neural Networks. On the other hand, it was up to now not possible to control the efficiency of the flue gas neutralisation facility as successfully as with Fuzzy Expert systems. This implies that in these cases, 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

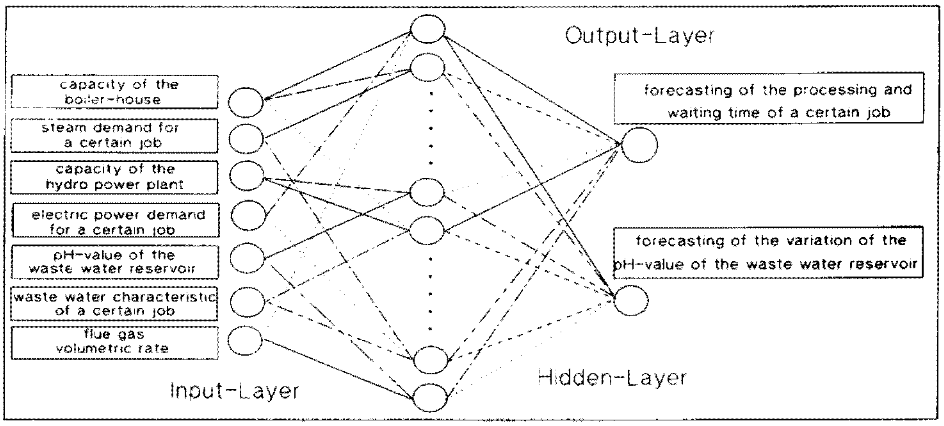

Fig. 5. Structure of a Neural Network for controlling energy and material flows.

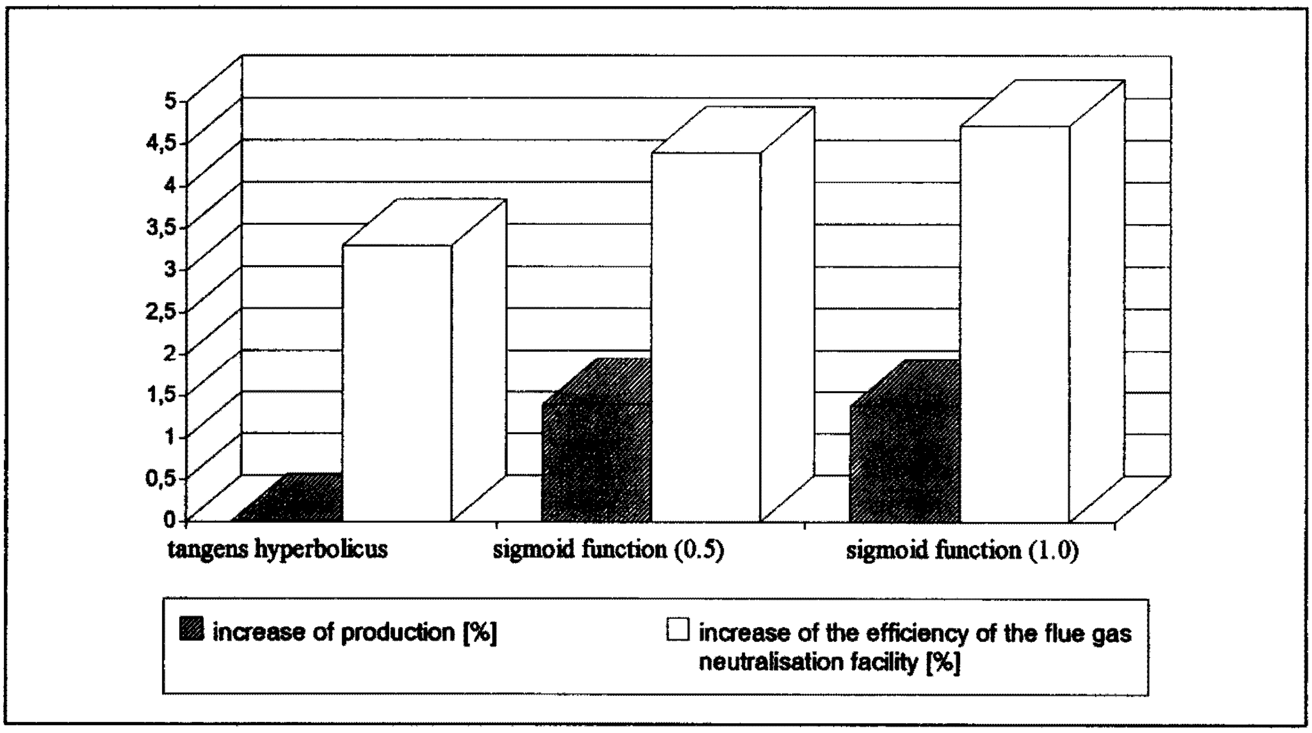

Fig. 6. A comparison of different transfer function in the hidden layer of networks for the controlling of energy and material streams.

complexity of the controlling task, Neural Networks should be applied.

5. Emission orientated 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. In principle, the rule structure of the Fuzzy Expert Controller (FEC) is applied (Fig. 7). The assignment of the degrees of sensibleness for certain rule blocks is achieved by machine learning algorithms. Under certain conditions (e.g. application of "boolean-like" functions as aggregation operators in FEC

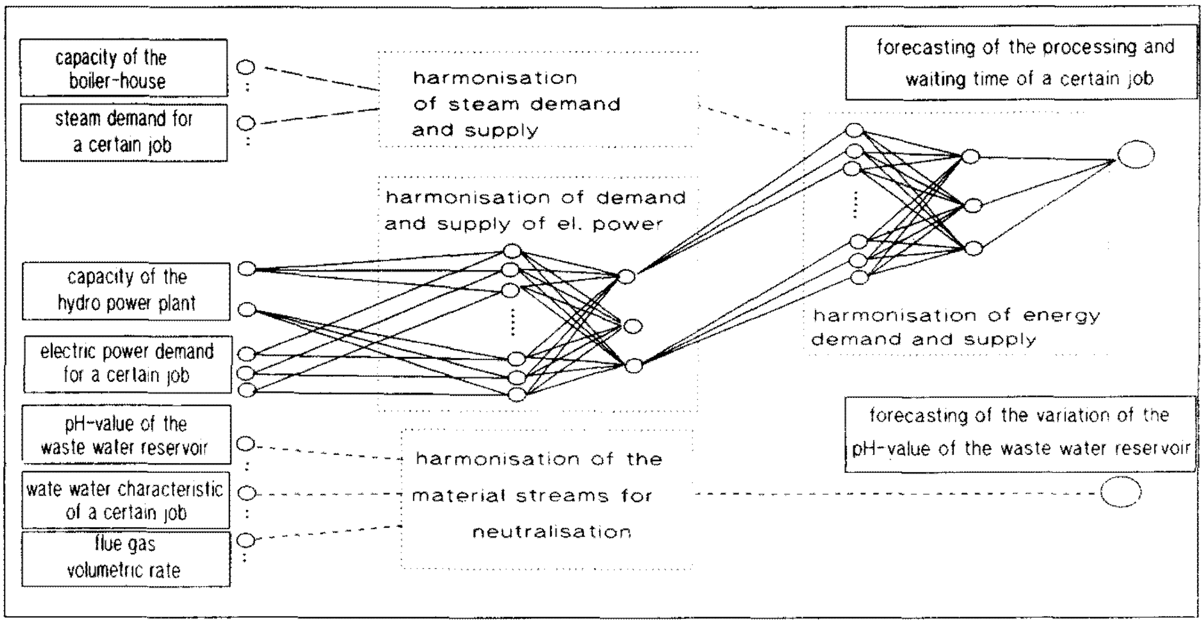

Fig. 7. Structure of a Neuro-Fuzzy System to control energy and material flows.

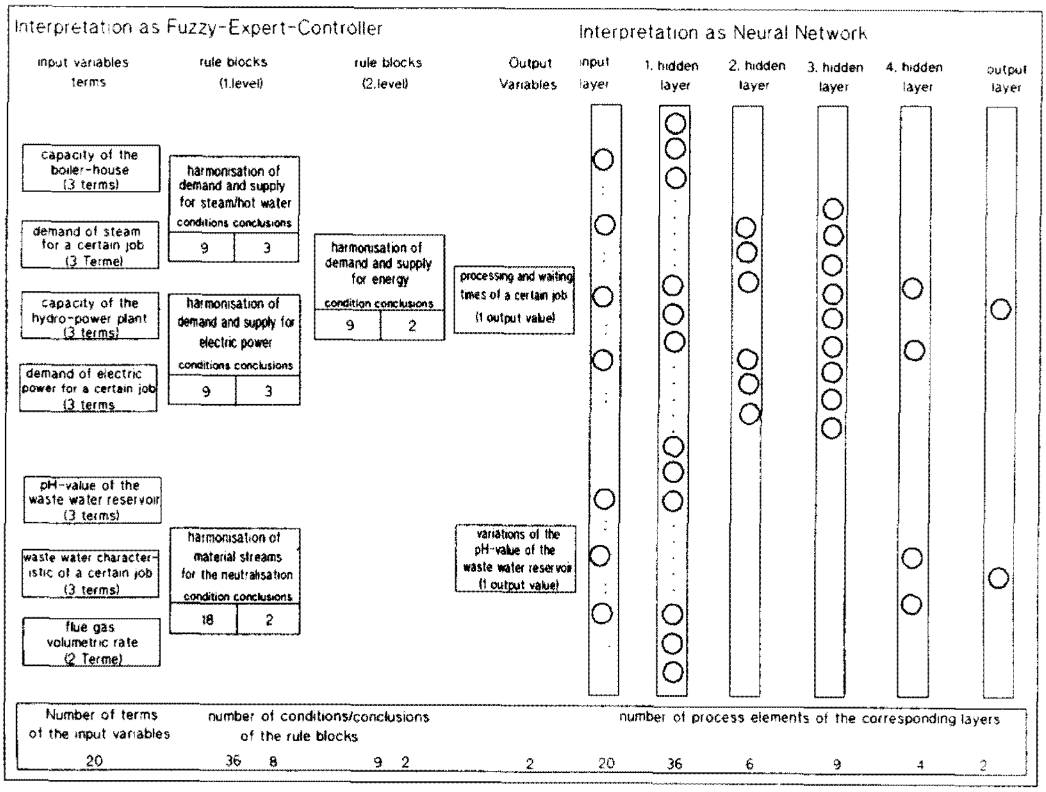

Fig. 8. Interpretation of the Neuro-Fuzzy System as Fuzzy Expert Controller and Neural Network.

and "Sigma-Pi-Units" in Neural Networks), Fuzzy Expert Systems can be interpreted as back-propagation networks and vice versa [5, 6, 2]. Fig. 8 and Tables 1 and 2 show the interpretation of the Neuro-Fuzzy System as a Fuzzy Expert Controller, respectively, as a Neural Network. The architecture

Table 1
Interpretation of the Neuro Fuzzy Systems as Fuzzy Expert Controller and as Neural Network

Interpretation as Neural Network		Interpretation as fuzzy Expert Controller	
Input layer		*Input interface*	
Input parameter	Values of the input variables	Input parameter	Values of the input variables
Transfer function	Sigmoid function	Membership functions of the terms of the input variables	Sigmoid functions
1. Hidden layer		*Rule blocks (1. level) conditions*	
Input function	Minimum function	Aggregation operator	Minimum operator
Transfer function	Identical mapping		
2. Hidden layer		*Rule blocks (1. level) conclusions*	
Input function	Maximum function	Composition operator	Max./prod.-inference
Transfer function	Identical mapping		
3. Hidden layer		*Rule blocks (2. level) conditions*	
Input function	Minimum function	Aggregation operator	Minimum operator
Transfer function	Identical mapping		
4. Hidden layer		*Rule blocks (2. level) conclusions*	
Input function	Maximum function	Composition operator	Max./prod.-inference
Transfer function	Identical mapping		
Output layer		*Output Interfaces*	
Input function	Average operator	Defuzzyfication method	Centre of moment
Transfer function	Identical mapping		

Table 2
Interpretation of the weights of Neuro-Fuzzy System

Input level	Output level	Weight characterisation	Interpretation as Fuzzy Expert Controller
Input layer	1. Hidden layer	Fix	Minimum operator (aggregation operator)
1. Hidden layer	2. Hidden layer	Variable	Degrees of sensibleness (1. level of the composition operators)
2. Hidden layer	3. Hidden layer	Fix	Minimum operator (aggregation operator)
3. Hidden layer	4. Hidden layer	Variable	Degrees of sensibleness (1. level of the compostion operators)
4. Hidden layer	Output layer	Fix	Maxima of the membership functions of the output variables (COM-method)

of the Neuro-Fuzzy System has to be harmonised with the structure of the available production knowledge. If it is sufficient to adapt the degrees of sensibleness of certain rules, and it is admissible to operationalise the corresponding composition operators by the concept of a semantic "or", it is recommendable to use a combination of back-propagation networks and methods of "competitive learning". This approach avoids a calculation of derivations and is efficient with respect to the

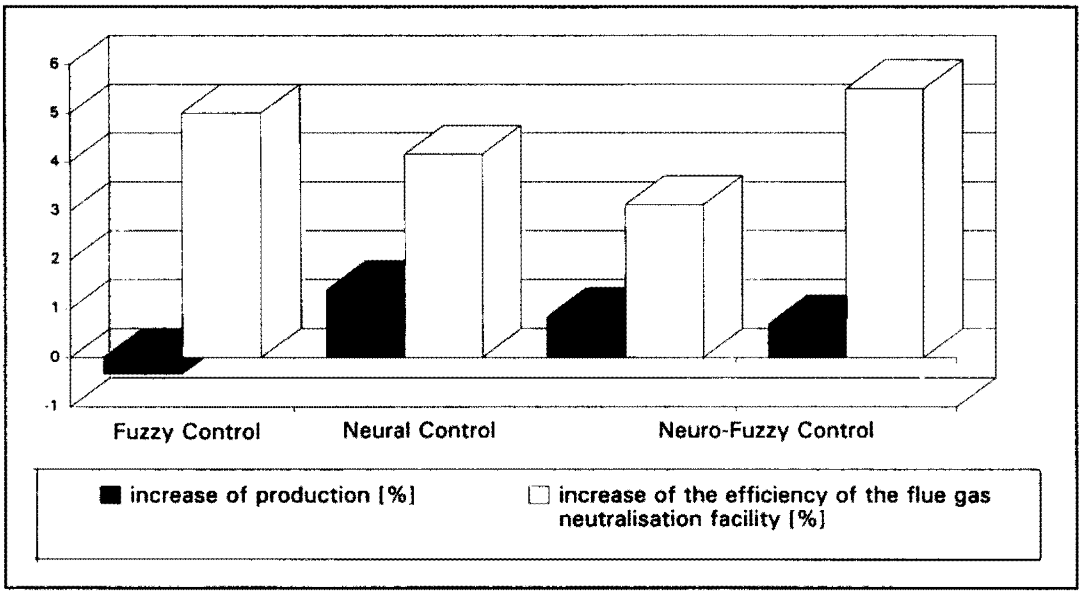

Fig. 9. Comparison of different controlling methods.

mentioned conditions. If these conditions are not fulfilled, back-propagation networks with "Sigma-Pi" activation functions should be used.

The adjustment of the system covers two steps. In a first step the degrees of sensibleness are set from the production examples (Fig. 9, bar 3). 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. 9, bar 4). 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 orientated and economic goals.

6. Conclusions

Analysing the developed production control strategies the following conclusions can be drawn:

- In principle, Fuzzy Expert Systems, Neural Networks and Neuro-Fuzzy Systems can be applied for the controlling of energy and material flows, taking into account economic and emission orientated goals.
- The selection of a certain approach mainly depends on the structure of the available production knowledge.
- In principle, the investigated methods can be applied in manufacturing, chemical engineering and biological process engineering.
- Due to the lack of analytical models, the inhomogeneity of input and output streams and the structure of the controlling tasks, applications in the fields of chemical engineering and especially biological process engineering (e.g. controlling of waste incineration, controlling of waste water treatment) seem to be most promising.

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