# A VERSATILE EXPERT SYSTEM SENECA IN CHEMICAL AND SYSTEM ENGINEERING

Mirko DOHNAL

*Department of Mechanical Engineering, Technical University, 602 00 Brno, Kraví hora*

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Mathematical model (statistical, analytical, fuzzy) is a certain integration of primary data into a form ensuring simple use and solving the problem under consideration. Any processing of information is an irreversible process. In order that this loss of information may be minimized, an expert system SENECA has been developed. With the aid of algorithms of artifical intelligence this system utilizes directly the primary data in order to solve the given problem. The system has been based on the fuzzy similarity. The versatility of the proposed expert system rests in the fact that in a very simple manner an expert base can be implemented into this system. This base represents a fuzzy description of the primary data, concerning the problem under consideration. The primary data may be represented by laboratory measurements, by results of passive observation of a real equipment, literature data, experience, analogies, *etc.* The data are therefore very diverse. The approach is demonstrated on a two-dimensional model of a fermentor.

Computer aided design (CAD) methods have already reached a level that permits their routine utilization in industry to solve important problems (simulation, optimization, computer graphics, data banks and their various combinations)[1]. In the course of the last about five years, however, new generation of the CAD methods has been developed, making use of algorithms on the basis of artificial intelligence. This new development offers, so far unheard, possibilities of utilizing the advantages of computer technique and human ability to draw conclusions on the basis of incomplete and partly contradicting information[2].

Considerable part of thus far developed algorithms utilizes recent results of the development of programming languages (*e.g.* PROLOG). The necessity, however, has not been so far eliminated to at least partly modify the algorithms and thus also the programs. Each modification of the complicated programs is very laborious[2].

Artificial intelligence is based on application of heuristics. If the set of heuristics is changed, the algorithm also changes. In case that the heuristics are described as fuzzy relations, more flexible programs can be written. This diminishes the extent of necessary modifications during these arrangements or expansion of the set of applied heuristics.

*Artificial Intelligence*

There exist a number of monographs offering a review of available methods[4]. In the following text we shall present some of the basic ideas which form foundations of the methodics of expert systems.

There is considerable difference between information and knowledge[4]. For this reason the pig's principle (the more, the better) shall not be applied in the near future for acquisition of information of technical and economical character for design purposes.

Artificial intelligence may help in case that the user is unable to express, or even does not know, what he really wants to know[5]. Recent times have seen tremendeous development of expert systems[6,7]. An expert system represents means of concentrating knowledge of human experts in the form of programs and data[7-10].

*Expert Systems*

Problems solved today by expert systems have existed ever since the moment decisions had to be made on complex problems in the engineering practice. Accordingly, it is possible to regard the theory of decision as a certain predecesor of expert systems.

There exist several definitions of expert systems. These definitions differ one from another mainly in the way they look at the role of a human in the process of application of expert systems. In one extreme the expert system is downgraded to an information system[11].

Unlike the classic data bank the expert system is then supplemented with an intelligent interface[12]. This intelligent interface permits the user, who does not know exactly what he needs, to obtain relevant information from the data base. What the user further does with the obtained information is entirely his own bussines.

The other extreme rests in that the expert system solves the problem without human interference. The two approaches have their own known advantages as well as disadvantages, which are identical with the attempts to automate creative work through the use of computers.

The expert system proper is formed by an expert base and service programs. These service programs are to do, on the one hand, the work together with the expert base (up-dating, search, *etc.*) and, on the other hand, utilize the retrieved information. The expert bases are formed by pre-processed information or store typical examples.

Selection of typical examples represents, in a way, also data pre-processing. The advantage, however, is that the data remain in the original form. This facilitates up-dating of the expert base[13].

*Primary Information*

Primary information is an information which is at the disposal at the very beginning of solution of the problem at hand. Thus it is not only the results of our own experiments with all the necessary details. Primary information are also experiments of other authors, data from the literature, *etc.*, all being termed the second-hand information[4].

Location of relevant information in the expert base is often a subjective task. The user need not be aware of what everything in the data base (expert base) exists and, most often, the information may be ill-addressable. The addressability is the property of information. A perfect addressability means that within the given information system the information may be unambiguously stored. This also permits retrieval of the information without difficulties.

In solving engineering problems, however, one has to work with information which is difficult to address[14] (*e.g.* diagnostis[15], reliability[16], cost calculation[17]). In addition, the information changes, becomes obsolete, is being up-dated, *etc.*

Such information problems have been existing for considerable period of time. Only recently, however, did they become important. Large banks of data are being set up and primary information is being stored without having been pre-processed. Current approach is to eliminate difficulties with poor addressability of information by a suitable formal pre-processing which increases the addressability.

*Data Pre-processing*

Every real process of information processing is irreversible. The information content of results of a process of information processing is thus always lower than the input amount of information.

A typical formal approach used to increase the addressability of information of engineering and natural-science character is statistics. The data stored in the bank are thus not the primary information but statistical quantities (*e.g.* averages, variances, *etc.*), which characterize the original primary information. By this process, however, considerable amount of information is lost. The reason for statistical pre-processing is the simplicity of application of the statistical model. It is certainly very easy,for instance, to substitute into a polynomial obtained by the least-squares method.

Statistics is unable to accept information partially subjective. Information of this character plays an important role particularly in evaluation of operational data. However, even laboratory information contains data about the experimental method, accuracy of probes, etc. If we have at our disposal several sets of measurements which are not entirely homogeneous, it is statistically difficult to homogenize them into a single entity.

The above difficulties initiated usage of fuzzy descriptions[18]. The fuzzy descriptions utilize a greater amount of information than statistical models and, thanks to the human interference, are more flexible. They have a greater ability to adapt to the studied dependence[19].

Fuzzy mathematics is, however, also only a formal apparatus which, in a certain manner, pre-processes the primary data. The result is then easier to address. It contains, however, less information than the original primary data. The next logical step in the development of modelling are therefore methods which would work with the primary data.

Any method represents a certain formal mechanism, the application of which causes loss of information. However, it is necessary to avoid to the maximum extent pre-processing of the information and therefore storing certain simplified description of the primary data. Maximum losses of information are associated with this very pre-processing.

Statistical description requires a large number of data. It necessitates drastic minimization of the number of independent variables[17,18]. Fuzzy model, thanks to its partial fuzzines, enables description on the basis of the same amount of primary information a greater connection between a greater number of variables. This is thanks to the fact that human brain inputs into the model information of semi-subjective character, which is of no use for statistics (experience, analogies).

This fact leads to the development of the expert system SENECA which is capable of working directly with primary data.

## EXPERT SYSTEM SENECA

The concept of similarity[11] has been utilized as a basis for determination of the relevance of the information. If, however, the expert system is interpreted on the basis of similarity, it is suitable only for the search of relevant information[12,14]. The expert system SENECA (SENsible Expert CAtalogue) makes use of the relevant information to solve the underlying problem. For this purpose, however, a more flexible definition of similarity is needed than available in the literature, see *e.g.*[20].

For the understanding of the following text knowledge of some basic notions of the fuzzy theory is needed, at least in the extent of ref.[18]. More than sufficient review of the fuzzy mathematics may be found in ref.[21].

A fuzzy model is formed by a set of statements which have the folowing structure[21].

$$\begin{array}{l} \text{if } \boldsymbol{A}_1 \text{ then } \boldsymbol{B}_1 \text{ or} \\ \text{if } \boldsymbol{A}_2 \text{ then } \boldsymbol{B}_2 \text{ or} \\ \vdots \\ \text{if } \boldsymbol{A}_m \text{ then } \boldsymbol{B}_m\,. \end{array} \qquad (1)$$

All fuzzy sets that appear in this structure. $\mathbf{A}_i$, $\mathbf{B}_i$, $i = 1, 2, \ldots$, must be specified by its degree of membership. The sets $\mathbf{A}_i$ may be, and in practice mostly are, multidimensional[18].

$$\mathbf{A}_i = \mathbf{A}_{i,1} \times \mathbf{A}_{i,2} \times \ldots \times \mathbf{A}_{i,n} \tag{2}$$

If a fuzzy "question" $\mathbf{Q}$ is formulated as an $n$-dimensional fuzzy set, then a fuzzy set may be found, representing a response, $\mathbf{R}$ to the question, $\mathbf{Q}$. This is the problem of, so-called, fuzzy simulation[18]. The response is a one-dimensional set on the universe of fuzzy set, $\mathbf{B}$.

Fuzzy model does not admit extrapolation[21]. If a question, $\mathbf{Q}$, is asked, which is too "far" from the model (*1*), the response, $\mathbf{R}$, is a special fuzzy set and namely such that all elements of the universe have a zero degree of membership. In other words, a fuzzy model responds "I do not know".

The expert system SENECA has been developed for a user with a university education. It does not forsee the necessity of programming. Minimum knowledge of fuzzy mathematics is a prerequisite. Experience shows that after a two-hour instruction the system can be independently utilized.

### *Fuzzification*

The inability to extrapolate is mostly a useful property of the fuzzy model. If, however, a fuzzy model is to be used to plan experiments, or to optimize, this property must be eliminated. Fuzzy extrapolation poses a problem analogous to conventional extrapolation. Conventional extrapolation formulas do not indicate when an admissible degree has been exceeded and the result is therefore not very reliable. Also with the conventional extrapolations it is necessary to choose to what extent we want "integrally" or "locally" extrapolate (interpolate). The degree of "integrity" has been determined here by the number of points of primary information, which appear in the interpolation formulas.

To a point in an $n$-dimensional space corresponds an $n$-dimensional fuzzy set, Eq. (*2*). Fuzzy model, Eq. (*1*), in this interpretation is analogous to $m$ points in an $n$-dimensional space which are used for interpolation (extrapolation).

With the aid of the extension principle[21] conventional interpolation formulas could be adapted to fuzzy interpolation. Much simpler, however, is the fuzzification of the question $\mathbf{Q}$. The main purpose of fuzzification is to partly or entirely compensate the property of the maxmin operator, which makes extrapolation impossible. Fuzzification, similarly as the determination of the degree of membership, is to some extent subjective.

Within the scope of this paper the computational side of the fuzzification is not studied. Here it depends on the relationship of the algorithm and the model (*e.g.* the stop criterion).

If the response, **R**, is of the type **N** – do not know – the question may be fuzzificated and a response be sought to this fuzzy question. Fuzzification rests in that some of the elements of the universe of the question **Q**, which originally had a zero degree of membership to this question, are assigned a non-zero degree of membership.

Practice has shown that a piecewise linear function in Fig. 1 is sufficient to describe real problems. Let all fuzzy sets in Eq. (*1*) $\mathbf{B}_i$, $\mathbf{A}_{ij}$, $i = 1, 2 \ldots, m, j = 1, 2 \ldots, n$ have their degrees of membership defined by means of four points $a, b, c$, and $d$ (see Fig. 1). The same description holds for the question **Q**. Fuzziness rests in that the point $a$ is shifted to the left and the point $d$ to the right.

Now it suffices to choose an algorithm of repeated fuzzification of the question, **Q**, and it is possible to use a fuzzy simulation for the determination of relevant information. The structure in Eq. (*1*) may be declared to be an expert base. If no response is received to the question **Q** it means that there is no answer in the expert base relevant to the too narrowly formulated question, **Q**.

We shall now fuzzificate the question. This makes the question more universal. The fuzzy question is again confronted with the expert base, Eq. (*1*). If again no relevant answer is found (*i.e.* no adequate conditional expression) due to the fuzzines of the question, the question is further fuzzificated. The obtained question is even more universal and is again confronted with the expert base. This procedure is repeated so long until relevant information is obtained from the expert base.

If a suitable program is available for fuzzy simulation it sufficies to specify the algorithm of fuzzification (see *block 1* of Fig. 2) and to determine when sufficiently relevant information is obtained (*block 2*), and the expert system is capable of not only searching for the information but also solving the problem at hand.

Fuzzification of a question can be achieved in several ways. Following algorithms of fuzzification have been tested (see Fig. 1):

– additive

$$d_i^{r+1} = d_i^0 + rSW_i$$
$$a_i^{r+1} = a_i^0 - rSW_i \qquad (3)$$

– multiplicative

$$d_i^{r+1} = d_i^r(1 + SW_i)$$
$$a_i^{r+1} = a_i^r(1 - SW_i)\,, \qquad (4)$$

where $W_i$, $i = 1, 2 \ldots n$ are weights of independent variables, $S$ is the coefficient of fuzzification and $d_i^r$, $a_i^r$ designate values of the constants $d$ and $a$ (see Fig. 1) after the $r$-th fuzzification.

Both additive and multiplicative fuzzification is easy as far as the algorithm is concerned. Its basic disadvantage rests in that is not possible to assign different weights to independent variables in different points of the space. Solution of practical problems, however, makes this necessary[13].

Let us consider the case when the data in the expert base on existing equipment for manufacture of a certain product, the weight of investment cost, and the operating costs are not, using human judgment, constant due to the safety weight. In region of high safety, the weight is low. If the choice is made in region with high probability of break down, the weight of the safety is considerably increased. This is the reason why it is important to have the option of the weight being variable with the values of independent variables. These constraints, however, are not deterministic. Neither a stochastic model would be possible in this case. It is therefore necessary to use again fuzzy models to describe the function $W_i(X)$, $i = 1, \ldots, n$.

The stop criterion (*block 2*, Fig. 2) is the key problem. If the SENECA system were to be used only to locate relevant information, an improper choice of the stop criterion would cause merely that the user would be offered more information

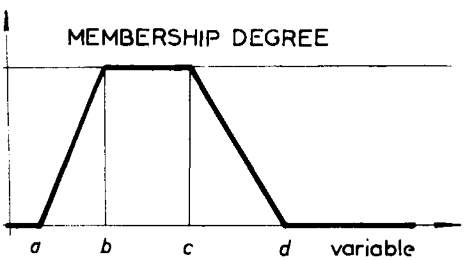


FIG. 1
The piecewise linear function of the grade of membership

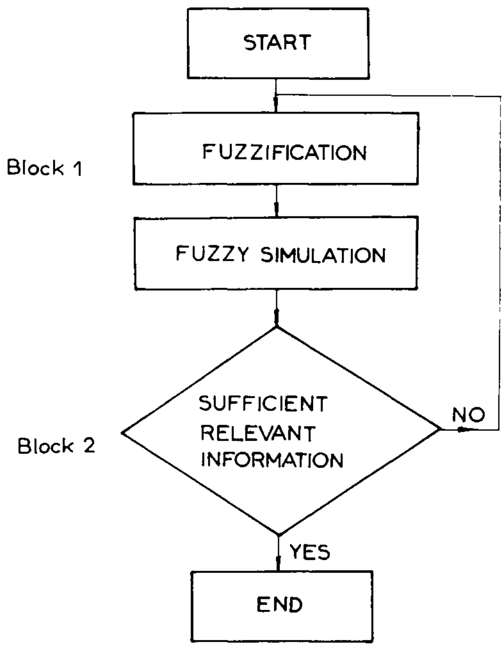


FIG. 2
Fuzzy oriented expert system

than he had asked for. The stop criterion determines the "width" of the set of conditional statements surrounding the question from which the answer shall be constructed.

The simplest stop criterion that can be used in the SENECA system is the location of the first set of active statements. The definition of an active statement may be found in ref.[18]. For illustration serves the following example.

## EXAMPLE

The example describes a fermentor. Its independent variables are the rate of dilution, $D$ ($h^{-1}$) and the growth rate, $\mu$ ($h^{-1}$). The dependent variable is the specific production of biomass $U$ ($kg\, m^{-3}\, h^{-1}$).

Fuzzy quantities, appearing both with independent and dependent variables, are shown in Table I. The meaning of the constants $a$, $b$, $c$ and $d$ follows from Fig. 1.

The meaning of abbreviations used in Table I is following: VS very small, M medium, L large, VL very large, A around, H high. Linguistic values, given in the left hand column of Table I, are used to specify the set of statements, shown in Table II. Each of these statements has a certain weight. This weight is a subjective assessment of the seriousness of information on the basis of which the statement was formed.

At the disposal are two sets of primary data. Within the first set there are 6 results available. On the basis of these experimental results statements number 1, 3, 6, 7, 8 and 9 were determined. The weight of these statements equals unity. The second set of primary data is given by the statements number 2, 4, 5, and 10. All statements from the second set of primary data have the weight 0·9. Statements number 11 through 15 have been worked out on the basis of literature data. Their weight was taken to be 0·7. Since we are using rather strongly fuzzificated linguistic values to describe statements 11 – 15 (M, VS, *etc.*) and relatively low weight of the statements, it is ensured that within the expert base the difference in the accuracy of the primary and literature data is sufficently distinct. The last statement number 16 is based on subjective speculation and its weight is set accordingly to 0·3 only.

Within the expert system SENECA it is possible to assign different weights also to individual variables. Examples given here are solved on the assumption that the weight of the first independent variable, $D$, is 0·8 and the second, $\mu$, unity.

These data fully describe the expert base, available to solve the problems associated with the studied fermentor. Table III summarizes the set of questions, **Q**, to which answer is sought from the SENECA system carrying the expert base described in Tables I and II.

The first six questions are deterministic, *i.e.* (see Fig. 1):

$$a = b = c = d\,.$$

These deterministic questions, however, are evaluated by means of a fuzzy model. This is the reason why the answer is a fuzzy set. In reality, however, the questions cannot be deterministic. For instance, in the case of the above fermentor it is not possible to maintain constant value of both independent variables. It is impossible to assume ideal operation of the fermentor. Its dynamic will show, as well as, the effect of the surroundings and imperfections of the control. It is therefore advantageous to ask also fuzzy questions. The questions 7 and 8 are fuzzy.

TABLE I
List of fuzzy sets

| Variables | Set Identificator | Break Points | | | |
|---|---|---|---|---|---|
| | | *a* | *b* | *c* | *d* |
| Rate of dilution $D$, $h^{-1}$ | VS | 0 | 0 | 0·15 | 0·18 |
| | M | 0·33 | 0·39 | 0·45 | 0·5 |
| | H | 0·45 | 0·5 | 0·55 | 0·58 |
| | A01 | 0·095 | 0·1 | 0·1 | 0·105 |
| | A04 | 0·39 | 0·4 | 0·4 | 0·41 |
| | A05 | 0·49 | 0·5 | 0·5 | 0·52 |
| | A45 | 0·42 | 0·45 | 0·45 | 0·47 |
| | A48 | 0·47 | 0·48 | 0·48 | 0·5 |
| | A52 | 0·5 | 0·52 | 0·52 | 0·53 |
| Growth rate $\mu$, $h^{-1}$ | S | 0 | 0 | 0·6 | 0·7 |
| | M | 0·75 | 0·8 | 1 | 1·2 |
| | H | 1 | 1·2 | 1·4 | 1·6 |
| | A04 | 0·39 | 0·4 | 0·4 | 0·41 |
| | A08 | 0·75 | 0·8 | 0·81 | 0·82 |
| | A12 | 1·15 | 1·2 | 1·2 | 1·25 |
| | A082 | 0·8 | 0·82 | 0·82 | 0·85 |
| Specific production of biomass $U$, $kgm^{-3}$ $h^{-1}$ | VS | 0 | 5 | 20 | 30 |
| | M | 20 | 30 | 70 | 75 |
| | L | 70 | 75 | 90 | 95 |
| | VL | 90 | 100 | 100 | 108 |
| | A15 | 13 | 15 | 15 | 17 |
| | A40 | 37 | 40 | 40 | 43 |
| | A80 | 75 | 80 | 80 | 85 |
| | A100 | 95 | 100 | 100 | 105 |
| | A92 | 91 | 92 | 92 | 94·5 |
| | A93 | 90 | 93 | 93 | 95 |
| | A96 | 94 | 96 | 96 | 98 |
| | A81 | 80 | 81 | 81 | 83 |

TABLE II

Set of conditional statements

| Conditional statement number | Independent variables $D$ | Independent variables $\mu$ | Dependent variable $U$ | Weight |
|---|---|---|---|---|
| 1 | A05 | A08 | A100 | 1 |
| 2 | A04 | A08 | A80 | 0·9 |
| 3 | A04 | A12 | A40 | 1 |
| 4 | A01 | A04 | A40 | 0·9 |
| 5 | A01 | A12 | A15 | 0·9 |
| 6 | A45 | A08 | A92 | 1 |
| 7 | A48 | A08 | A93 | 1 |
| 8 | A52 | A82 | A96 | 1 |
| 9 | A05 | A08 | A96 | 1 |
| 10 | A04 | A08 | A81 | 0·9 |
| 11 | H | M | VL | 0·7 |
| 12 | M | M | L | 0·7 |
| 13 | M | H | M | 0·7 |
| 14 | VS | S | S | 0·7 |
| 15 | VS | H | VS | 0·7 |
| 16 | M | — | M | 0·3 |

TABLE III

List of deterministic and fuzzy questions

| Question | $D$ | | | | $\mu$ | | | |
|---|---|---|---|---|---|---|---|---|
| | $a$ | $b$ | $c$ | $d$ | $a$ | $b$ | $c$ | $d$ |
| 1 | 0·48 | 0·48 | 0·48 | 0·48 | 0·8 | 0·8 | 0·8 | 0·8 |
| 2 | 0·5 | 0·5 | 0·5 | 0·5 | 0·85 | 0·85 | 0·85 | 0·85 |
| 3 | 0·55 | 0·55 | 0·55 | 0·55 | 0·9 | 0·9 | 0·9 | 0·9 |
| 4 | 0·55 | 0·55 | 0·55 | 0·55 | 1 | 1 | 1 | 1 |
| 5 | 0·55 | 0·55 | 0·55 | 0·55 | 1·2 | 1·2 | 1·2 | 1·2 |
| 6 | 0·55 | 0·55 | 0·55 | 0·55 | 1·6 | 1·6 | 1·6 | 1·6 |
| 7 | 0·475 | 0·48 | 0·48 | 0·485 | 0·78 | 0·8 | 0·8 | 0·82 |
| 8 | 0·47 | 0·48 | 0·48 | 0·49 | 0·75 | 0·8 | 0·8 | 0·85 |
| 9 | 0·53 | 0·55 | 0·55 | 0·58 | 1·15 | 1·2 | 1·2 | 1·25 |
| 10 | 0·505 | 0·55 | 0·55 | 0·605 | 1·264 | 1·6 | 1·6 | 1·736 |

Resulting fuzzy sets, *i.e.* 8 responses, are summarized in Table IV. This table shows also following discrete values from the universe of dependent variables $U = 70, 75, 80, 81, 83, 85, 90, 91, 92, 93, 94, 94\cdot5, 95, 96, 100, 105, 108$. For these values the degrees of membership are given. It is seen, for example, that the value $70 \text{ kg m}^{-3}$ belongs to the response to the question number 1 with the degree of membership 0. Consequently, it certainly does not belong to it. The second column of the Table IV gives always numbers of active statements from Table II. The designation all indicates that all statements are active. The value $U = 92$, of the dependent variable, belongs to the question number 1 with the membership degree 0·667 (active statement number 7). The largest membership degree has the value $U = 93$. It is therefore the first numerical representation NR1 (ref.[18]) of this answer. See the last but one line of Table IV. The second numerical representation NR2 of the first response is 91, 95. NR2 is the weighted average[18]. The weight of an element of universe equals its membership degree.

The responses to questions 2, 3, and 4 are the same. Table IV therefore gives only the response number 2. This suggests certain "inflexibility" of the model. This is,

TABLE IV
Responses

| $U$ | 1 | | 2 | | 5 | | 6 | | 7 | | 8 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 70 | 0 | all | 0 | all | 0 | all | 0 | all | 0 | all | 0 | all |
| 75 | 0·224 | 12 | 0 | all | 0 | all | 0 | all | 0·254 | 12 | 0·28 | 12 |
| 80 | 0·224 | 12 | 0 | all | 0 | all | 0 | all | 0·254 | 12 | 0·28 | 12 |
| 81 | 0·224 | 12 | 0 | all | 0 | all | 0 | all | 0·254 | 12 | 0·28 | 12 |
| 83 | 0·224 | 12 | 0 | all | 0 | all | 0 | all | 0·254 | 12 | 0·28 | 12 |
| 85 | 0·224 | 12 | 0 | all | 0 | all | 0 | all | 0·254 | 12 | 0·28 | 12 |
| 90 | 0·224 | 12 | 0 | all | 0 | all | 0 | all | 0·254 | 12 | 0·28 | 12 |
| 91 | 0·333 | 7 | 0·07 | 11 | 0·07 | 11 | 0 | all | 0·333 | 3 | 0·333 | 7 |
| 92 | 0·667 | 7 | 0·14 | 11 | 0·14 | 11 | 0 | all | 0·667 | 7 | 0·667 | 7 |
| 93 | 0·8 | 7 | 0·21 | 11 | 0·175 | 11 | 0 | all | 0·8 | 7 | 0·8 | 7 |
| 94 | 0·5 | 7 | 0·28 | 11 | 0·175 | 11 | 0 | all | 0·5 | 7 | 0·5 | 11 |
| 94·5 | 0·315 | 11 | 0·315 | 11 | 0·175 | 11 | 0 | all | 0·315 | 11 | 0·315 | 11 |
| 95 | 0·336 | 11 | 0·35 | 11 | 0·175 | 11 | 0 | all | 0·35 | 11 | 0·35 | 11 |
| 96 | 0·336 | 11 | 0·42 | 11 | 0·175 | 11 | 0 | all | 0·356 | 11 | 0·373 | 11 |
| 98 | 0·336 | 11 | 0·56 | 11 | 0·175 | 11 | 0 | all | 0·356 | 11 | 0·373 | 11 |
| 100 | 0·336 | 11 | 0·56 | 11 | 0·175 | 11 | 0 | all | 0·356 | 11 | 0·373 | 11 |
| 105 | 0·262 | 11 | 0·262 | 11 | 0·175 | 11 | 0 | all | 0·262 | 11 | 0·262 | 11 |
| 108 | 0 | all | 0 | all | 0 | all | 0 | all | 0 | all | 0 | all |
| NR1 | 93 | | 99 | | 99 | | — | | 93 | | 93 | |
| NR2 | 91·95 | | 96·88 | | 96·25 | | — | | 91·72 | | 91·53 | |

however, a common feature of the fuzzy models. All questions, excepting the fifth and the sixth, were answered without fuzzification. For these questions we thus could have used the programming system CONFUCIUS for fuzzy simulation[22].

Questions number 5 and 6 were fuzzificated multiplicatively. The used fuzzificated form of these questions is given in Table III as questions number 9 and 10. Question number 9 (*i.e.* unfuzzificated question number 5) in Table III could have been answered already after the first fuzzification. Question number 6 (*i.e.* the fuzzificated question number 10 in Table III) was purposely located so as to make its answer impossible even after tenfold fuzzification. In partice it would mean that the user of the expert system came to the conclusion that fuzzification of the question number 6 is such that eventual additional fuzzification would not lead to a "reasonable" result.

Similarly as the conventional interpolation formulas also fuzzification may be theoretically applied to any situation. It suffices only to increase the multiplicative coefficient $S$ (see Eqs (*3*, *4*)) or increase the number of maximum admissible fuzzifications. The choice of these parameters is to some extent subjective. If these values are low the expert system will more frequently answer "do not know". Then there is no other alternative than to supplement the expert base.

## CONCLUSION

Information is a key problem in the design of chemical equipment[23] and apparently also in its operation[24]. Accordingly, it is necessary to devote maximum attention to preservation of all available information in a form useable in practice. This idea, common to all engineering branches, stimulated development of various data bases[25]. These data bases, however, were unable to cope with the inhomogeneity of the input information. For this reason various methods of artifical intelligence were put to use. This gave rise to expert systems.

A number of questions, associated with expert systems, are so far unclear in principle. Nearly everything from the little that has been tested, may be solved by a number of ways. It seems, however, that the philosophy with artificial intelligence tackles the problems is very useful for a number of important chemical engineering and biotechnological problems[26].

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