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Dedicated Type-2 Fuzzy Logic Systems: A Novel Approach to DeNOx Filtration Systems

Adam Niewiadomski, Marcin Kacprowicz

Institute of Information Technology
ul. Wólczańska 215, 90-924 Łódź
Lodz University of Technology, Łódź, Poland

Abstract. *The paper presents some novel research on applications of Type-2 Fuzzy Logic Systems to support the Selective Catalytic Reduction process (SCR). The aim of the research is to design and test higher order fuzzy logic systems and their genuine modifications to manage data in DeNOx systems responsible for controlling emission of nitrogen oxides (NO, NO_2). Since in real applications, it is still performed under the supervision of a human expert, the scope is to replace, at least partially, his/her participation with dedicated type-2 fuzzy logic systems. As the result, it is shown that the proposed systems with new means of learning fuzzy IF-THEN rules allow us to compute parameters much closer to those determined by experts, even in a comparison to some earlier approaches based on traditional fuzzy logic.*
Keywords: *fuzzy logic, Selective Catalytic Reduction (SCR), air pollution, nitrogen oxides, adjustable air filters, ammonia valve, dedictaed Type-2 Fuzzy Logic System, learning fuzzy rules.*

1. Introduction

Attempts to create systems working similarly to (or even replacing) human experts is a very common field of research nowadays. In particular, in cases when expressing knowledge by natural language is simpler (or the only possible manner) to analytical/strict formulae, e.g. when it can not be determined precisely, or

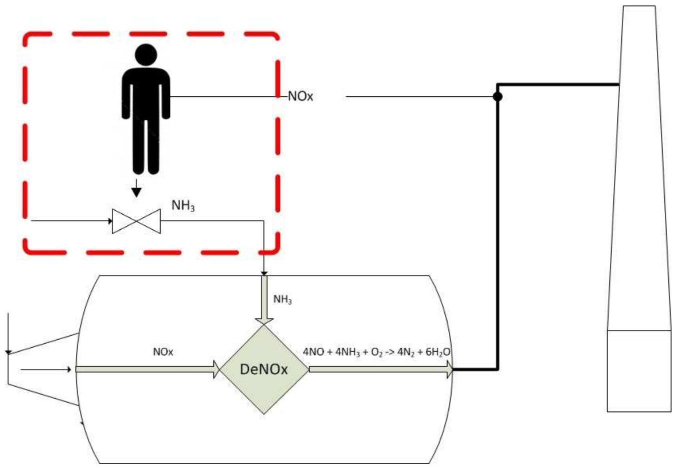

Figure 1: Selective catalytic reduction (SCR) process, human-supported (a scheme).

require linguistic and/or non-linear models, Fuzzy Logic Systems (FLS) and their higher-order extensions are very promising and handy tools. Examples of development of such systems, and their profitable applications are widely presented in the literature, e.g. [1, 2]. Aims of these methods are to cover certain issues as close as possible to actions that human experts take in corresponding situations/problems. Popularity of Fuzzy Logic Systems is primarily due to the fact that they can be used when experts in a given field express their knowledge in a linguistic and not mathematical way. Confirmed efficiency of these systems is being mentioned in plenty of issues, e.g. crane control systems [3], elevator control [4] or water quality control systems [5, 6].

Hence, in this paper an attempt of creating a type-2 fuzzy logic system (T2FLS) that enables managing the DeNOx system parameters. DeNOx is a mechanism that controls the process of the so-called Selective Catalytic Reduction (SCR) to reduce amounts of harmful nitrogen oxides exhausted to the atmosphere. As for now, this process is controlled and managed by a human experts manually, see Fig. 1. The scope is to propose an intelligent tool, based on type-2 fuzzy logic to suggest parameters for the DeNOx system, preferably, as close to human decision as possible, see Fig. 2.

The rest of the paper is organised as follows: Section 2 describes briefly the

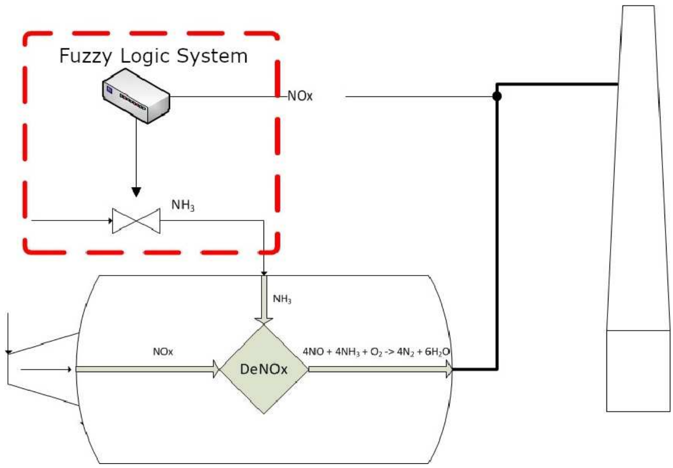

Figure 2: Selective catalytic reduction process assisted by a Type-2 Fuzzy Logic System.

SCR process and possible applications of fuzzy logic, mostly with respect to data uncertainty appearing in expert decisions making. Section 3 presents general structure of a type-2 fuzzy logic system and, more detailed, some genuine elements being authors' contribution to the issue. The results are evaluated and discussed in Section 4, with respect to some earlier evaluations based on traditional and interval-valued fuzzy logic systems. Finally, we conclude in Section 5 with some new possibilities and directions of the research.

2. Knowledge specification and uncertainty of data in managing the Selective Catalytic Reduction process

One of the best-known and efficient methods for reducing nitrogen oxides (NO, NO_2) is the DeNOx system based on the Selective Catalytic Reduction (SCR) [7]. This method uses ammonia (NH_3) as a reducing gas injected to the reduction chamber. It is described by the following formulae:

$$4NO+4NH_3+O_2=4N_2+6H_2O, \quad (1)$$

$$6NO_2+8NH_3=7N_2+12H_2O. \quad (2)$$

The DeNOx system performs the catalytic reduction and its main task to reduce nitrogen oxides in chemical processes in which these oxides are harmful by-products. As for now, managing the parameters of this process must take place under human control due to the non-linearity of the process and many factors that influence the efficiency of the chemical reaction. The solutions known from the literature do not give satisfactory results or are not similar enough to human actions. Therefore, the attempt to develop fuzzy logic systems potentially extended with new implications and new methods of learning fuzzy rules that would allow to increase the efficiency of these systems should be considered justified.Due to the non-linearity of this process and the influence of many factors on it, system parameters are managed under human control (of course, in the case of large industrial installations). According to literature, indispensable elements when developing a system with a knowledge base such as Fuzzy Logic Systems (FLS) and Type-2 Fuzzy Logic Systems are:

1. acquiring knowledge from an expert
2. systematization and assessment of knowledge
3. presenting knowledge in a form consistent with the adopted formalism
   (a) fuzzy sets representing input data,
   (b) fuzzy sets representing output data,
   (c) IF THEN rules database,
   (d) selection of fuzzing operators, aggregations and implications consistent with the nature of the input data.

If traditional decision-making systems can not be used, for example due to the lack of an appropriate process model, fuzzy logic systems handling uncertain information are applied. Problems with process modeling are very characteristic for cases in which high degree of indeterminacy of data appears and/or knowledge is imprecise, data are incomplete, data relationships are undefined or difficult to determine. Despite the advantages of human intuition and rational thinking in action, the machine should not forget about such elements as emotions, psychophysical conditions and knowledge and experience in the field. Fuzzy Logic Systems are able to handle, at least partially, these problems and work on unreliable data. Fuzzy logic systems also works in situations where problems are unstructured, i.e. for it is impossible to arrange the algorithm or experience and intuition are necessary. Applications of Fuzzy Logic Systems in solving problems and issues described are given e.g. in [8]-[12].

3. Type-2 fuzzy logic systems and learning rules for managing SCR

Research on fuzzy logic systems allowed us to obtain better results when using some additional methods of learning fuzzy rules, than results obtained without learning. It is a premise now to use another modifications and improvements of fuzzy logic methods: in this particular case we propose to use type-2 fuzzy logic systems based on type-2 fuzzy sets. The main reason is that these systems handle knowledge of several experts in the form of type-2 fuzzy sets and determining „confidence level" for individual experts, which is definitely a possibility to keep the most crucial entry data in their consistent form without aggregating them (and, in consequence, loosing some parameters influencing final performance). Apart from new look at learning IF-THEN rules, it is profitable to extend traditional fuzzy implications (including the so-called engineering implications) to forms suitable for type-2 fuzzy sets.

3.1. Structure and details of the dedicated type-2 fuzzy logic system

A type-2 fuzzy set in a non-empty universe of discourse $\mathcal{X}$ is a set of ordered pairs

$$\widetilde{A} = \{\langle x, \mu_{\widetilde{A}}(x)\rangle : x \in \mathcal{X}\} \tag{3}$$

where $\mu_{\widetilde{A}}(x) \colon \mathcal{X} \to \mathcal{FS}([0,1])$ is a membership function of a type-2 fuzzy set and $\mathcal{FS}([0,1])$ is a set of all fuzzy sets in $[0,1]$. Type-2 fuzzy sets are also known as „fuzzy-fuzzy sets" or „fuzzy-valued fuzzy sets" and it is their most important feature to express membership degrees with imprecise, here: fuzzy, values, not only with real numbers, as traditional fuzzy sets do [13, 14]. Thanks to it, new potential of developing fuzzy logic systems, in the sense of Mamdani [8] can be visible. A structure of type-2 fuzzy logic system is illustrated in Fig. 3.

Fuzzification: acquiring data from experts In the case of traditional fuzzy logic systems, knowledge is obtained from one expert in a linguistic form. As a result, traditional fuzzy sets are created to determine the NO and NO_2 input values, and output values, i.e. the opening degree of the ammonia valve.

Knowing that the knowledge from one expert can be subjective and contain errors, it seems natural to take into account a larger number of experts. Such an

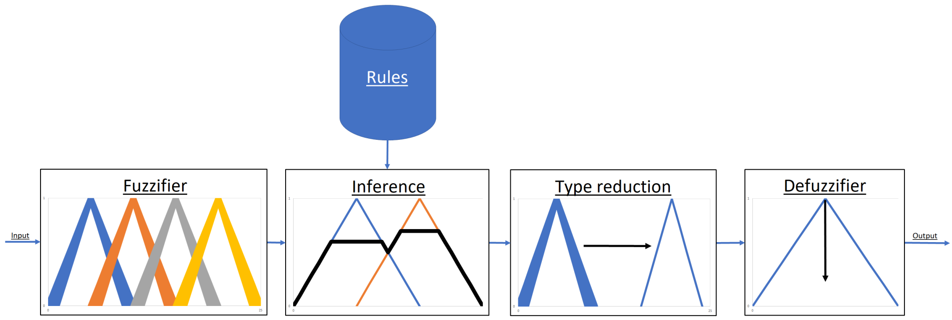

Figure 3: Type-2 Fuzzy Logic System: a general structure

approach eliminates or partially reduces the problems of possible subjective assessments by one expert only. Such possibilities are offered by higher-order fuzzy logic systems, based on two or more membership functions for given linguistic values. As it is expected, this approach approximates the entry data more carefully, without averaging them. In the designed type-2 fuzzy logic system, the entry data are collected from three experts with different experience (related to the period being involved in handling DeNOx), and, instead of their aggregation, e.g. via weighted average, type-2 fuzzy logic systems are able to handle such an uncertainty. A general schema of representing entry data with type-2 fuzzy sets is depicted in Fig. 4.

Thanks to secondary membership functions μ_x, for each $x \in \mathcal{X}$, it is possible to determine the „confidence level" of the knowledge of experts individually. „Confidence level" can also be explained here as „level of experience" (the closer to 1, the higher). In practice, it means taking into account the linguistic values proposed by experts as separate primary membership functions and assigning to each of them secondary membership degrees dependent directly on their experience in handling DeNOx, as mentioned above.

IF-THEN rules and fuzzy implication In fuzzy logic systems, knowledge is obtained from experts using linguistic forms. As results, fuzzy rules in the form of IF-THEN are obtained:

Example:

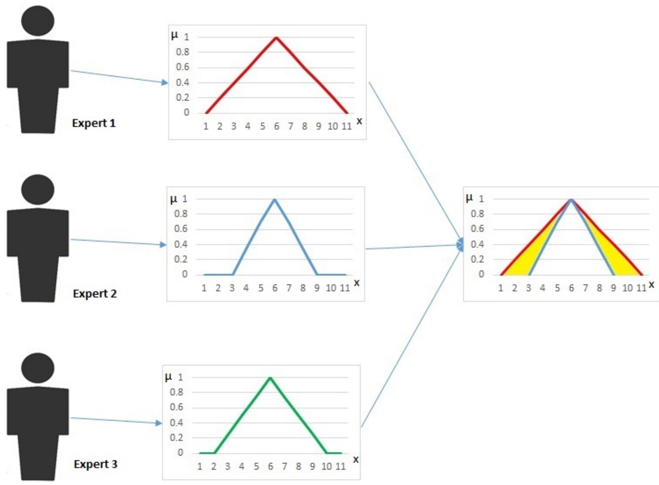

Figure 4: A schematic illustration of acquiring linguistic knowledge from experts and representing it as a type-2 fuzzy set

IF (NO IS Low) AND (NO_2 IS Low) THEN Valve opening angle IS Low
IF (NO IS Low) AND (NO_2 High) THEN Valve opening angle IS Medium
IF (NO IS Medium) AND (NO_2 High) THEN Valve opening angle IS Very High

Type-reduction and defuzzification Using the Extension Principle, the centroid of the Type-2 Fuzzy Set $\widetilde{B}$ in a finite $\mathcal{Y}=\{y_1, y_2, \ldots, y_M\}$, $M \in \mathbb{M}$, in which the membership degrees are in the form of

$$\mu_{\widetilde{B}}(y_i) = \int_{u \in J_{y_i}} f_{y_i}(u)/u, \tag{4}$$

where $J_{y_i} \subseteq [0,1]$, $i = 1, 2, \ldots, M$, is a set of all primary membership of y_i to $\widetilde{B}$, is given as:

$$C_{\widetilde{B}} = \int_{u_1 \in J_{y_1}} \cdots \int_{u_M \in J_{y_N}} (f_{y_1}(u_1) * \ldots * f_{y_N}(u_M)) \Bigg/ \frac{\sum_{i=1}^{M} x_i u_i}{\sum_{i=1}^{M} u_i}, \tag{5}$$

where $u_i \in J_{y_i}$, and $*$ is a T-norm.

The defuzzification for all simulations is done using the Height Method (6) (see Fig.5). The Height Method uses heights of each input fuzzy sets that create

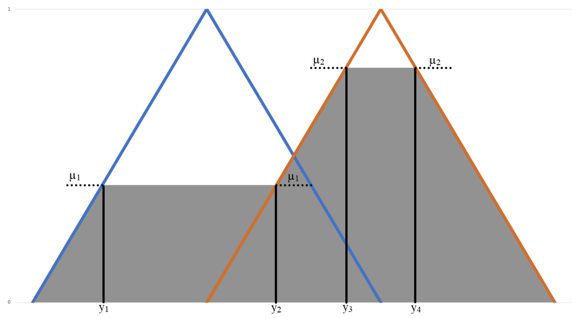

Figure 5: A graphical explanation of the Height Method; μ_i is value of fuzzy rule activation on this fuzzy set, and y_i are representatives values each of fuzzy sets.

output fuzzy sets as antecedents of fuzzy rules (after type-reduction). The heights of fuzzy sets are μ_{Ci*} (taken as weights) and y_i are representative points, see [**?**]. The Height Method is simple and efficient.

$$y^* = \frac{\sum_{i=1}^{M} y_i \mu_{Ci*}}{\sum_{i=1}^{M} \mu_{Ci*}}, \tag{6}$$

where y^* is the value of the fuzzy output, μ_{Ci*} is the value of the activation of i-th fuzzy rule, y_i is the element Y representative for fuzzy set and M is number off all fuzzy sets which taking apart in creation output fuzzy set.

3.2. New algorithms for learning fuzzy rules

The rule base in fuzzy logic systems is usually determined on knowledge and experience provided by experts in informal or even linguistic forms. This approach does not guarantee, however, that the set of rules is optimal, and problems appear when several experts propose different rules with similar, overlapping or contradictory succedents. That is why the rule base needs to be tuned to improve algorithms of selecting rules that are activated in inference. The presented algorithms of learning fuzzy rules in a type-2 fuzzy logic system are extensions of similar proposals for traditional fuzzy logic systems [15].

Algorithm 1 Learning rules in type-2 fuzzy logic systems (SR_I)

```
for all succedents do
    if the first degree of membership == max Activation value then
        Counter of the antecedent ← Counter of the antecedent + 1
```

Algorithm 2 Learning rules in type-2 fuzzy logic systems (SR_{II})

```
for all succedents do
    if the first degree of membership > 0 then
        Counter of the antecedent ← Counter of the antecedent + 1
```

Algorithm 3 Learning rules in type-2 fuzzy logic systems (SR_{III})

```
for all succedents do
    if the first degree of membership > 0 then
        Counter of the antecedent ← Counter of the antecedent + First Degree of membership
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Simulations show that the use of Type-2 Fuzzy Logic allow improving the performance of the dedicated fuzzy logic system, see Table 1.

4. Evaluations and discussion

As reference values of the operation of fuzzy logic systems, systems known from the literature have been implemented. Then, that producing the best results is selected. In order to verify the results obtained in the experiment with the values given by experts, three comparative methods are used.

4.1. Evaluation: test sets, reference sets, and comparison methods

The evaluations is based on 6 data sets, $|X_1| = |X_2| = |X_3| = 10\,000$ and $|X_4| = |X_5| = |X_6| = 100\,000$ samples each, $X_i = \{x_1, x_2, \ldots, x_N\}$, where $x_j = (\overline{x}_1, \overline{x}_2) \in \mathcal{X}_{\mathrm{NO}} \times \mathcal{X}_{\mathrm{NO}_2}$, $i = 1,2,\ldots,6$, $j = 1,2,\ldots,N$, $N = 10\,000$ for $i = 1,2,3$ or $N = 100\,000$ for $i = 4,5,6$. x_j is a value of concentration of NO and NO_2 (read from sensors of the DeNOx system) expressed with integers in $[0,400]$ mg/m^3. Measurements are read every 2 seconds which is determined by the capabilities of the solenoid valves used to dispense ammonia, the inertia of the system and some legal circumstances regarding emission of nitrogen oxides. The permissible concentration of nitrogen oxides, for thermal units with a capacity below 50 MW from the combustion of solid fuels in the form of coal and coke, is 400 mg/m^3. Output data are real numbers from the range $[0.00, 100.00]$ specifying the opening in [%] of the ammonia dispensing valve to the reaction chamber of the filter. To determine expected value of opening valve [%] 3 experts are asked to define (base on data sets X_1,…, X_6) vectors of expected values. That give 18 vectors $E_{WI}(X_1)$,…, $E_{WI}(X_6)$ with are aggregated to 6 vectors $E(X_1)$,…, $E(X_6)$ using the weighted average according to (7):

$$e = \frac{\sum_{i=1}^{n} e_i * W_i}{\sum_{i=1}^{n} W_i} \tag{7}$$

where e is the expected value after aggregation, e_i is the expected value of the i-th expert, and W_i is the weight assigned to the i-th expert related to how long he works on DeNOx. In the considered case, the weights are:

1. expert 1 - $W_1 = 3$
2. expert 2 - $W_2 = 20$
3. expert 3 - $W_3 = 13$

The same vectors (X_1,…, X_6) are use to make calculation by Type-2 Fuzzy Logic System with proposal new learning methods. It is give 6 vectors $|C_1| = |C_2| = |C_3| = 10\,000$ and $|C_4| = |C_5| = |C_6| = 100\,000$ corresponding to vectors $E(X_1)$,…, $E(X_6)$ of the same length.

The results calculated by the system were compared with the data proposed by the expert. For each set of samples two vectors are compare: $|E_i|$ - vector containing the output values proposed by the expert, $|C_i|$ - vector containing the output values calculated by the fuzzy logic system. Their comparison was carried out using three methods. The first method is the minimum-maximum, the second is the Persona Correlation Coefficient (PCC), the third is the Mean Absolute Percent Error (MAPE).

$$\text{min - max}(E, C) = \frac{\sum_{i=1}^{n} \min\{e_i, c_i\}}{\sum_{i=1}^{n} \max\{e_i, c_i\}} \tag{8}$$

where $E = \{e_1, e_2, ..., e_n\}$, $C = \{c_1, c_2, ..., c_n\}$, c_i is the actual value calculated by the fuzzy system, and e_i is the value proposed by a human expert. The values of the min-max(E, C) method show the similarity of the E and C vectors. The maximum value of the min-max(E, C) method is 1 – which means that the vectors are identical, and hence the calculated values by the system are the same as the opening values of the ammonia dispensing valve proposed by the expert.

$$r_{(E,C)} = \frac{\sum_{i=1}^{n}(e_i - \overline{e})(c_i - \overline{c})}{\sqrt{\sum_{i=1}^{n}(e_i - \overline{e})^2}\sqrt{\sum_{i=1}^{n}(c_i - \overline{c})^2}} \tag{9}$$

where $r \in [-1; 1]$, $\overline{e} = \frac{1}{n}\sum_{i=1}^{n} e_i$ i $\overline{c} = \frac{1}{n}\sum_{i=1}^{n} c_i$. PCC value represents the correlation between vectors E and C. Values -1 means total negative correlation, 0 means no correlation, and 1 means total positive correlation. The Mean Absolute Percentage Error (MAPE), is also known as the Average Absolute Percentage Deviation (MAPE).

$$M = \frac{1}{n}\sum_{i=1}^{n} \mid \frac{c_i - e_i}{c_i} \mid \tag{10}$$

The results presented in Table 1 are interpreted: for the comparative method of min-max and PCC, values closer to 1 mean larger agreement between the results calculated by the system and the values proposed by the expert. In the case of MAPEs, however, the larger agreement, the differences calculated are smaller.

All simulations are performed using data obtained from experts separately and as aggregated data. The article presents the results in relation to aggregate values.

4.2. Results and discussion

In Table 1, the best results obtained by Type-2 Fuzzy Logic Systems are presented with reference results of fuzzy logic systems elaborated and described in some earlier published literature. The proposed new methods of fuzzy rules learning allow you to get better results for fuzzy logic systems. Among the 8 new variants of Type-2 Fuzzy Logic Systems, those giving the best results are presented in Table 1, row 4., thanks to using the proposed methods of fuzzy rules learning, are presented as benefits from described and implemented methods as effective system supporting an expert in the process of defining parameters for the selective catalytic reduction system. The results can be explained with numbers illustrating, to a greater extent, the obtained effects. Although differences between traditional

Table 1: Values of Measures of Similarity min-max(E,C), Values Pearson Correlation Coefficient (PCC) And Values Mean Absolute Percentage Error (MAPE) Output Data Calculated by Type-1 and Type-2 Fuzzy Logic Systems and Values Proposed by Experts After Aggregation.

	min-max(E,C)	**PCC**	**MAPE**	**Description**
1.	0.925	0.910	19.35 %	Fuzzy Logic System based on T-norm min [16]
2.	0.945	0.936	17.46 %	Interval-Valued Fuzzy Logic System [17]
3.	0.929	0.924	16.38 %	Type-2 Fuzzy Logic System [18]
4.	**0.957**	**0.960**	**8.49 %**	**Type-2 Fuzzy Logic System with learning fuzzy rules via Algorithm 1**
5.	0.954	0.955	9.16 %	Type-2 Fuzzy Logic System with with learning fuzzy rules via Algorithm 2
6.	0.955	0.958	8.56 %	Type-2 Fuzzy Logic System with with learning fuzzy rules via Algorithm 3

fuzzy logic systems and Type-2 Fuzzy Logic Systems using new methods of learning rules may seem small, their explanation in terms of amount of NO and NO_2 into the atmosphere are huge. The year production of 8 100 Mg is declared in [19], hence the improvement of ammonia dosing accuracy with respect to expert expectations from 0.925 to 0.957 calculated using the min-max method is 0.03, which is an equivalent of 260 Mg less nitrogen oxides emitted to the atmosphere per year. Or in other words, it is $\sim$ 21.5 Mg of nitrogen oxides per month, which is equivalent of$\sim$ 54mln m^3 more air totally free of nitrogen oxides per month.

5. Conclusions

The new solution in the field of fuzzy logic is presented in this paper: algorithms for learning rules in type-2 fuzzy logic system. Results of simulation confirm the efficiency of a type-2 fuzzy logic system dedicated for the particular problem of managing nitrogen oxides emission in the DeNOx system. The promising results, see Table 1., are obtained mostly with the use of type-2 fuzzy logic systems, that handle imperfect knowledge better than traditional FLSs. Besides, as the author contribution, new methods of learning type-2 fuzzy rules are introduced. They allow us to increase the similarity of the dedicated type-2 fuzzy logic system's response to values proposed by experts in the considered issue. Another important conclusion is that the use of type-2 fuzzy sets enables increasing the consistency of results obtained taking into account the knowledge acquired from many experts using secondary membership functions of type-2 fuzzy sets as handy tools to express additional data, e.g. expert experience.

The presented research allows us to conclude that further works on applying higher-order fuzzy logic systems in computer-aided management of industrial gases emission is worth continuing and opens new possibilities of introducing AI methods in the field.

References

[1] Starczewski, J., *Advanced Concepts in Fuzzy Logic and Systems with Membership Uncertainty*, Vol. 284 of *Studies in Fuzziness and Soft Computing*, Springer, 2013.

[2] Kashyap, S. K., *IR and color image fusion using interval type 2 fuzzy logic system*, In: Cognitive Computing and Information Processing (CCIP), 2015 International Conference on, March 2015, pp. 1–4.

[3] Yasunobu, S. and Hasegawa, T., *Evaluation of an automatic container crane operation system based on predictive fuzzy control*, Control Theory Adv. Technol., vol. 2, no. 3, 1986, pp. 419–432.

[4] Fujitec, F., *FLEX-8800 series elevator group control system*, Fujitec Co., Ltd., Osaka, Japan, 1988.

[5] Itoh, O., Gotoh, K., Nakayama, T., and Takamizawa, S., *Application of fuzzy control to activated sludge process*, in Proc. 2nd IFSA Congress, Tokyo, Japan, July, 1987, pp. 282–285.

[6] Yagishita, O., Itoh, O., and Sugeno, M., *Application of fuzzy reasoning to the water purification process*, in Industrial Applications of Fuuy Control, M. Sugeno, Ed. Amsterdam: North-Holland, 1985, pp. 19–40.

[7] Prabhakar, S., Karthikeyan, M., Annamalai, K., and Banugopan, V. N., *Control of emission characteristics by using Selective Catalytic Reduction (SCR) in D.I. diesel engine*, IEEE Conference Publications, 2010.

[8] Mamdani, E., *Applications of fuzzy algorithms for control of a simple dynamic plant*, Proc.IEE 121, 1974.

[9] Tanaka, K., Sano, M., and Watanabe, H., *Identification and analysis of fuzzy model for air pollution-an approach to self-learning control of CO concentration*, IEEE Conference Publications, Vol. 3, 1992, pp. 1431 – 1436.

[10] Wang, B. and Chen, Z., *A GIS-based Fuzzy Aggregation Modeling Approach for Air Pollution Risk Assessment*, IEEE Conference Publications, Vol. 2, 2012, pp. 957–961.

[11] Cai, D. L. and Chen, W. K., *Knowledge-BaseD Air Quality Management Study by FuzzY Logic Principle*, IEEE Conference Publications, Vol. 2, 2009, pp. 3064–3069.

[12] Ramesh, L., Chowdhury, S., Chowdhury, S., Saha, A., and Song, Y., *Efficiency Optimization of Induction Motor Using a Fuzzy Logic Based Optimum Flux Search Controller*, IEEE Conference Publications, 2006, pp. 1–6.

[13] Zadeh, L. A., *The concept of a linguistic variable and its application to approximate reasoning*, Inform, Vol. 8, (1975), pp. 199–249.

[14] Mendel, J. M., *Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions*, Prentice Hall, 2001.

[15] Kacprowicz, M. and Niewiadomski, A., *On Dedicated Fuzzy Logic Systems for Emission Control of Industrial Gases*, Trends in Logic XIII, 2014.

[16] Kacprowicz, M. and Niewiadomski, A., *Managing Data on Air Pollution Using Fuzzy Controller*, Computer Methods in Practice, (2012), pp. 46–57.

[17] Niewiadomski, A. and Kacprowicz, M., *Higher order fuzzy logic in controlling selective catalytic reduction systems*, Bulletin of the Polish Academy of Sciences Technical Sciences, Vol. 62, No. 4, 2014, pp. 743–750.

[18] Kacprowicz, M., Niewiadomski, A., and Renkas, K., *Learning Rules for Type-2 Fuzzy Logic System in the Control of DeNOx Filter*, Lecture Notes in Computer Science - Springer, Vol. 9119, 2015.

[19] ORLEN, P., *Annual Report 2012 PKN ORLEN*, Tech. rep., PKN ORLEN, 2012.