# FUZZY MODELLING AND CONTROL OF MARINE DIESEL ENGINE PROCESS

Radovan Antonic[1], member, IEEE , Zoran Vukic[2], member, IEEE and Ljubomir Kuljaca[2], member IEEE

***Abstract*-- Marine diesel engine in ship propulsion is very complex and nonlinear plant. In its modelling for diagnosis and control purpose, not only measuring system, but experts knowledge should play important role.**

**The paper gives an introduction of knowledge modelling techniques i.e. fuzzy models suitable for diesel engine diagnosis and control. Two examples are illustrated for engine faulty condition diagnosis and two simulated examples are given for fuzzy control of diesel engine process: 1. diesel oil viscosity control (Mamdani model used) and 2. shaft speed control (T-S model used).**

*Index Terms*-- **marine diesel engine, knowledge base, fuzzy modelling, fuzzy control**

## I. INTRODUCTION

Modern control and diagnosis system of marine diesel engine process is based, not only on real measured data from monitoring system, but also on comprehensive knowledge i.e. on knowledge base constructed from heuristic knowledge and experience of experts and operators [1, 2, 5] (see fig. 1.).

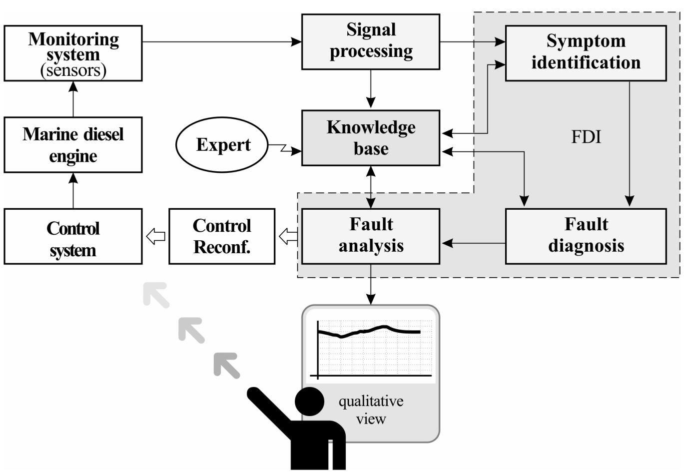


Fig. 1. Control and diagnosis system structure of marine diesel engine process

Expert - human knowledge is fuzzy by its nature and usually vague and imprecise.

[1] Split College of Maritime Studies, Univ. Split
Zrinsko-Frankopanska 38, 21000 Split, Croatia
e-mail: antonic@pfst.hr
[2] Faculty of Electrical Engineering and Computing, Univ. Zagreb
Unska 3, 10000 Zagreb, Croatia

The possible sources of uncertainty and fuzziness in knowledge based systems - KBS are most often the following:

- inherent human expert fuzzy concepts and reasoning,
- differing expert opinions and reasoning ways regarding the same concept - object,
- incomplete and unreliable information,
- matching of similar rather than identical expert experiences,
- heuristic knowledge is difficult to test and evaluate.

If the knowledge about system to be controlled is exact and certain, the efficient way for representing dynamical behaviours of the system is its mathematical model based on differential and algebraic equations or graphical approach like structure system graph. This is a topic of conventional control theory.

In the case the knowledge about system behaviours is mainly inexact and fuzzy, like in faulty working conditions, emergency situations, the more appropriate models could be those based on fuzzy and neuro-fuzzy approach. In the paper, only fuzzy approach will be treated with examples within marine diesel engine control and diagnosis.

## II. FUZZY MODELLING IN KNOWLEDGE BASED SYSTEMS

Complete and consistent knowledge base plays very important role in KB control and diagnosis.

Fuzzy logic offers mechanisms for explicit knowledge modelling as well as for handling uncertainties [6]. There are many factors that have to be considered when choosing knowledge representation schemes, like: efficiency in terms of computer storage, speed execution, innovation - updating, learning capabilities, maintainability etc.

Fundamental idea behind fuzzy modelling is to describe a system dynamics by establishing the fuzzy input-output relation that may be usually expressed in terms of fuzzy *If - Then* rules. Each fuzzy rule maps a fuzzy partition of the input space into another fuzzy partition of the output space.

Consequences from different rules are numerically combined to provide appropriate outputs to given inputs.

The basic paradigm in fuzzy logic KR schemes [3] is based on fuzzy rules of the form:

$$If\ OA_1\ is\ x_1\ And\ OA_2\ is\ x_2\ And\ ...Then\ CA_1\ is\ y_1\ And\ CA_2\ is\ y_2\ And\ ..., \qquad (1)$$

which maps the observable attributes $OA_1, OA_2, ...$ of the given physical process into its adequate controllable attributes $CA_1, CA_2, \ldots$ with $x_1, x_2, \ldots$ as linguistic terms for input variables (observable attributes) and $y_1, y_2, \ldots$ as linguistic terms for output variables (controllable attributes).

The model illustration examples are given here in diesel engine fault diagnosis:

**<u>Diesel engine faulty condition 1</u>: *Increased blowby***

*Observable attributes*: $\Delta MEP$ - Mean Effective Pressure deviation, $\Delta SFC$ - Specific Fuel Consumption deviation.

*Controllable attributes*: $\Delta RLC$ - piston Rings/Linear Clearance deviation.

<u>*Rule*</u>:

$$If\ \Delta MEP\ is\ NH\ And\ \Delta SFC\ is\ PH\ Then\ \Delta RLC\ is\ ZE$$

<u>*Action*</u>: Replace piston rings.

where: *NH* - Negative High; *PH* - Positive High*; ZE* - Zero.

**<u>Diesel engine faulty condition 2</u>: *Turbocharger efficiency decreased (simulated - 50%)***

*Input variables (symptoms)*: $\Delta T_{KIP}$, $\Delta T_{Csr}$, $\Delta p_{RZ}$, $\Delta n_m$

*Output variable (fault)*: $\xi_{prop}$.

*Rule: (expert conclusion based on experience)*:

***R**:* $If\ \Delta T_{KIP}\ is\ PL\ And\ \Delta T_{Csr}\ is\ PM\ And\ \Delta p_{RZ}\ is\ NM$

$And\ \Delta n_m\ is\ NS\ Then\ \xi_{prop}\ is\ S$ .

where: $\Delta T_{KIP}$ - combustion gases temperature deviation; $\Delta T_{Csr}$ - mean cylinders combustion temperature deviation; $\Delta p_{RZ}$ - scavenge air pressure deviation; $\Delta n_m$ - engine speed deviation from nominal value; $\xi_{prop}$ - turbocharger efficiency.

*PL* - Positive Large; *PM* - Positive Middle; *NM* - Negative Middle; *NS* - Negative Small; S - Small.

Because of diesel engine process complexity with its different behaviour subsystems more different fuzzy model types can be used.

Basically, three distinct classes of fuzzy models are most often in practical use:

*A. Linguistic fuzzy models of Mamdani type*

This model is based on fuzzy linguistic rules with linguistic variables. A typical linguistic rule is of the following form [3]:

$$\boldsymbol{R}^{(j)}:\ If\ x_1\ is\ A_1^j \ldots\ And\ x_n\ is\ A_n^j \ldots\ \text{Then}\ y\ is\ B^j \ldots \quad (2)$$

where $A_i^j, and\ B^j$ are linguistic variables - terms, $\underline{x} = (x_1, x_2, \cdots x_n)^T \in U \subset R^n$ and $y \in V \subset R$ are crisp or fuzzy input and output variables of the *j*-th rule, respectively, and *j = 1,2,...J.* Both, the rule antecedents and rule consequents are defined by means of fuzzy sets that are characterised by membership functions $\mu_{a_i}^j$ and $\mu_b^j$.

There are two ways of obtaining linguistic rules. The first and the most straightforward way is by interviewing domain human experts. Such linguistic rules represent the policies and heuristic strategies of the corresponding expert's decision making process. The second way to obtain linguistic rules is to use neural networks training algorithms based on numerical data and adequate learning methods.

The concept of representing a continuous function $y = f(x)$ (for instance, data from an analog sensor) with a set of fuzzy rules is illustrated graphically in fig. 2. [Zadeh (1999)].

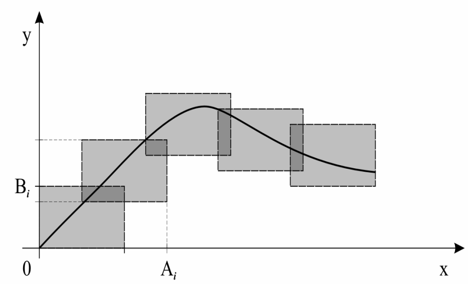


Fig. 2. Fuzzy graph of a function *y = f(x)*

*B. Takagi-Sugeno (T-S) models*

Takagi and Sugeno extended the linguistic rules to rules with consequent in the form of linear functions of antecedent variables. For instance:

$$\boldsymbol{R}^{(j)}:\ If\ x_1\ is\ A_1^j \ldots\ And\ x_n\ is\ A_n^j \ldots\ Then$$

$$y^j = c_0^j + c_1^j x_1 + \ldots + c_n^j x_n \quad (3)$$

where $A_i^j$ are fuzzy sets, $\underline{x} = (x_1, x_2, \cdots x_n)^T \in R^n$ is a crisp input vector, $c_i^j$ are real valued parameters, $y^j$ is the crisp system output due to rule $R^{(j)}$, and *i = 1,2,....,J.*

Each rule represents a locally linear model in the selected working condition. The advantage of this fuzzy linear model is that the parameters $c_i^j$ of the model can be easily identified from numerical data (using artificial neural network learning technique). A weak point of the model is that the interpretation of the fuzzy linear rules is difficult compared to linguistic rules.

*C. Singleton fuzzy models*

One could say that, to a certain degree, singleton fuzzy models inherit the good identification properties from T-S models and the advantages of better interpretation of the linguistic models.

The fuzzy rule consequent part is a fuzzy singleton of the form:

$$\boldsymbol{R}^{(j)}: \quad If\ x_1\ is\ A_1^j .....\ And\ x_n\ is\ A_n^j .....\ Then\ y^j = c_0^j \qquad (4)$$

All three model types can be effectively used in modelling, control and diagnosis of diesel engine process.

## III. FUZZY CONTROL OF DIESEL ENGINE PROCESS

For using fuzzy logic KB systems where inputs and outputs are real-valued variables (from sensors or observers) like in the case of on-line engine diagnosis and control, the most straightforward way is to add fuzzifier to the input and defuzzifier to the output of the fuzzy system as illustrated in fig. 3.

Basically, the most important steps in fuzzy control design are:

- Structure identification i.e. selection of input / output variables,
- Selection of fuzzification strategy,
- Rules identification - fuzzy rules subsets,
- Development of the fuzzy inference mechanism,
- Selection of defuzzification strategy.

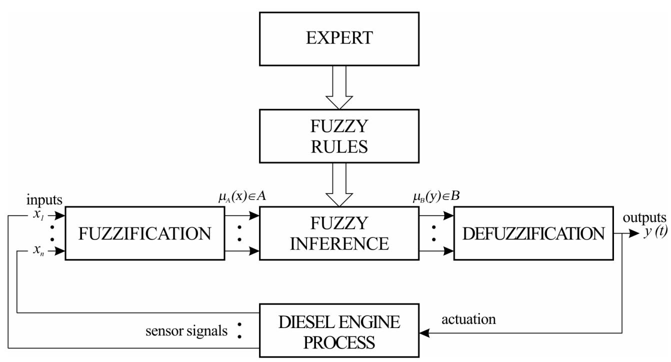


Fig. 3. Fuzzy model of diesel engine control using sensor data and expert knowledge

During structure identification step one have to find which input variables are necessary and most important in the premise part of an implication i.e. those which directly affect the output variables i.e. conclusions. In our example we used knowledge about process dynamics and human-operator's experience as main criteria. The possible values of a linguistic variable (input or output) are the linguistic terms which are linguistic interpretations of technical quantities i.e. process parameters (temperature, viscosity, pressure, speed, torque,..) and have to be determined. When defining a linguistic variable, first what need to be determined is how many terms in domain of definition (universe of discourse) define the linguistic variable. Linguistic variables usually have an odd number of terms because they are defined symmetrically and include a middle term between the extremes.

The degree of truth to which the measurement value of a technical quantity satisfies a certain term of a linguistic variable is called degree of membership (membership function).

The standard normalised membership functions: linear decreasing, linear increasing, trapezoidal and sigmoidal illustrated in fig. 4 can be applied to the most technical processes like diagnosis and control.

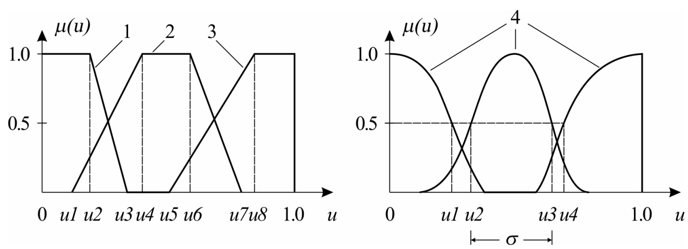


Fig. 4. Standard types of membership functions

Information flow through a fuzzy control system requires that the system inputs go through three major transformations before generating appropriate control outputs i.e. Fuzzification, Fuzzy Rule Inference and Defuzzification processing phases.

In the fuzzification stage vector $\underline{x} = (x_1, x_2, ..., x_n)^T \in X$ of discrete numerical input values from sensors is transformed into set of linguistic variables fuzzy values (membership functions - MF) $\mu_A(x) \in A$. Fig. 5 illustrates an example for control signal error in the range $-\varepsilon_{MAX}\ ; 0\ ; +\varepsilon_{MAX}$ with triangular type of MF and five linguistic terms (NL-Negative Large; NS-Negative Small; NUL; PS-Positive Small ; PL-Positive Large).

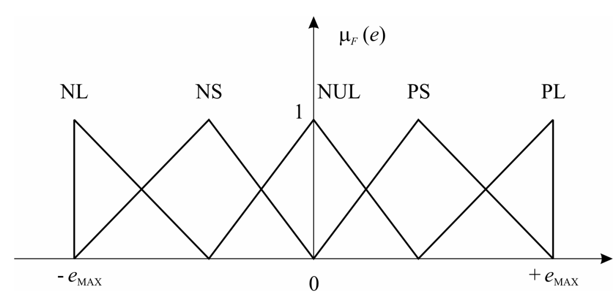


Fig. 5. Fuzzy quantitative space of signal error with five linguistic terms

The choice of type and form of MF (linear, trapezoid, triangular, Gauss, Sigmoid, custom etc.) depends on the designer and problem to be solved.

Fuzzy rules identification step was primarily based on human operator's process control experience and control engineer's knowledge. These rules are used in knowledge base construction and organization.

The Inference Engine together with knowledge base is the key component of fuzzy control system. The most often inference methods used in Mamdani and T-S fuzzy models are the following two:

max-min inference method:

$$\mu_B^i(y) = \max_i \left\{ \min\left[ \mu_{A1}^i(x_1), \mu_{A2}^i(x_2), ..., \right] \mu_{An}^i(x_n), \right\},$$

$$i=1,2,..., l \qquad (5)$$

max-product inference method:

$$\mu_B^i(y) = \max_i \left[ \mu_{A1}^i(x_1) \bullet \mu_{A2}^i(x_2) \bullet \quad \bullet \mu_{An}^i(x_n) \right] \qquad (6)$$

$i=1,2,..., l;$ $\mu_B^i(y)$ - membership function of consequent part of *i*- th rule, *l* - total number of rules.

In the defuzzification phase, fuzzy output values from FLC are transformed into crisp values needed for control action i.e. process actuation. In this processing stage a number of different methods exist, but two of them are quite appropriate for control purpose:

- Center of Area method (CoA):

$$y = y_c = \frac{\sum_{i=1}^{l} \mu_A^i(y_i) y_i}{\sum_{i=1}^{l} \mu_A^i(y_i)} \qquad (7)$$

- Mean of Maximum method (MeOM):

$$y = \frac{1}{l} \sum_{i=1}^{l} y_{i,\max} \qquad (8)$$

### A. *Fuzzy control of diesel engine fuel oil viscosity: simulation example*

Fuzzy model of type Mamdani is used here for fuel oil viscosity control of marine diesel engine (fig. 6). Two input variables to fuzzy controller: fuel oil viscosity deviation $\Delta\vartheta_F$ $(\vartheta_{Fd} - \vartheta_F)$ and fuel oil temperature gradient $\Delta T_F$ and one output i.e. control variable: fuel oil heating steam valve position $\alpha_v$ were used in simulation. Five linguistic terms were used for input variable $\Delta\vartheta_F$: NM-Negative Middle; NS-Negative Small; ZE-ZEro; PS-Positive Small; PM-Positive Middle and three for input variable $\Delta T_F$: NEG-negative; NUL-null; POS-positive. Output i.e. control variable $\alpha_v$ is determined with three fuzzy linguistic terms: OFF (close valve); 1/2 (half open valve); ON (full open valve).

Fuzzy rules were based on the experience of operator/expert process behaviour and some data about fuel oil properties and are expressed like in table 1.

Membership functions for input variables were chosen to be of Gaussian type and for output variable of triangular type (fig. 7). In the fuzzification procedure of input variables fuzzy operators **min** (AND) and **max** (OR) were used and defuzzification procedure was done with **CoA** method. For decision making **max-min** method has been used.

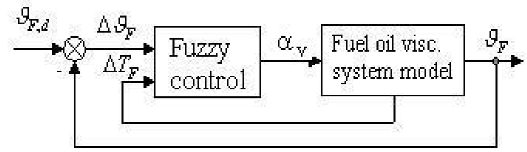


Fig. 6. Fuzzy control loop of diesel fuel oil viscosity

Table 1: Fuzzy rules for diesel oil viscosity control.

| $\Delta\upsilon_F$ / $\Delta T_F$ | NM | NS | ZE | PS | PM |
|---|---|---|---|---|---|
| NEG | ON | 1/2 | 1/2 | 1/2 | OFF |
| NUL | ON | 1/2 | OFF | OFF | OFF |
| POS | 1/2 | 1/2 | OFF | OFF | OFF |

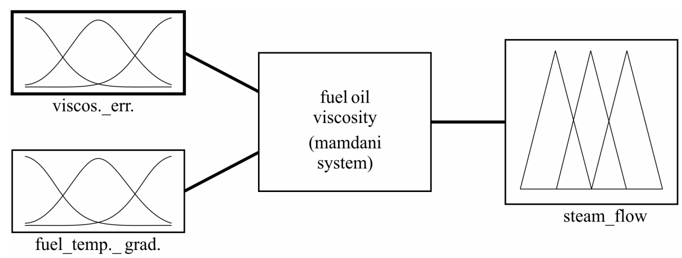


Fig. 7. Simulated fuzzy control of diesel engine fuel oil viscosity

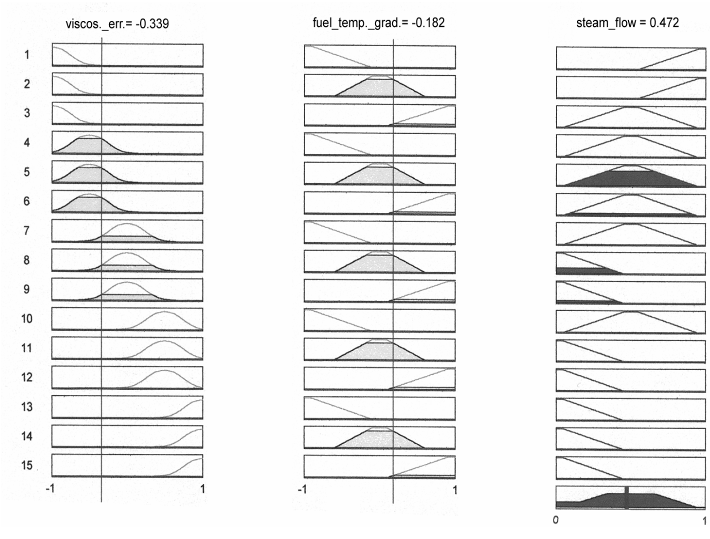


Fig. 8. Output signal to fuel oil viscosity control (implication of type Mamdani)

Fig. 8 shows relative good results obtained in this simulation example. Better results could be obtained with continuously controlled steam valve instead of three position only, what means using T-S model instead of Mamdani type model.

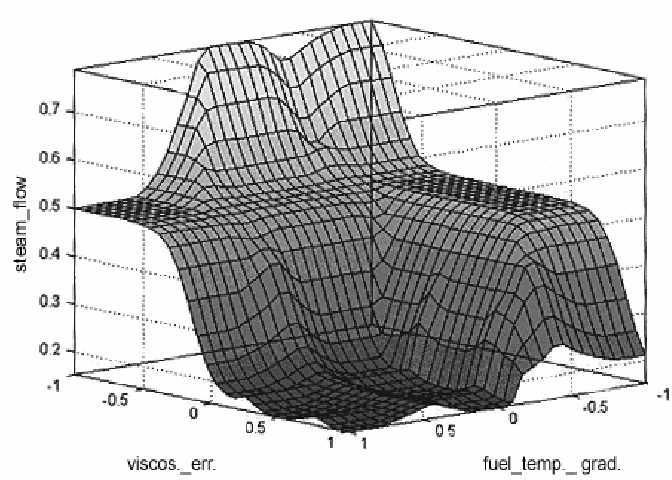


Fig. 9. Control surfaces of fuel oil viscosity control

### B. *Fuzzy control of diesel engine shaft speed dynamics*

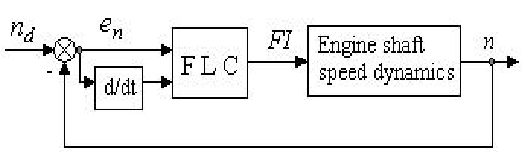


Fig. 10. Fuzzy Logic Controller in engine speed dynamics loop

One effective method for engine speed dynamics control, especially in emergency situation is fuzzy logic control - FLC of diagonal type (see fig. 10. and table 2.) using sliding mode technique.

Table 2: Fuzzy rules of diagonal FLC for engine speed control.

| $e_n$ / $\dot{e}_n$ | PL | PS | ZE | NS | NL |
|---|---|---|---|---|---|
| NL | 0 | NS | NM | NL | NL |
| NS | PS | 0 | NS | NM | NL |
| ZE | PM | PS | 0 | NS | NM |
| PS | PL | PM | PS | 0 | NS |
| PL | PL | PL | PM | PS | 0 |

Transfer characteristic of diagonal type FLC is nonlinear function $FI = f(e_n, \dot{e}_n)$ determined by operating points. Special case is control surface $FI = f(e_n, \dot{e}_n) = 0$ i.e. diagonal surface, where control signal changes its sign. For operating points under diagonal surface, control signal *FI* is positive, but for operating points above diagonal surface, control signal *FI* is negative. It is evident from the condition $e_n \cdot \dot{e}_n < 0$. Control algorithm that provides above condition can be determined by the following rules:

$$IF\ (e_n(t) \cdot \dot{e}_n(t) < 0\ THEN\ hold\ control\ signal\ FI \qquad (9)$$

$$IF\ (e_n(t) \cdot \dot{e}_n(t) > 0\ THEN\ change\ control\ signal\ FI$$
$$\text{(increase / decrease)} \qquad (10)$$

The magnitude of control signal increasing or decreasing is determined by expert's fuzzy rules.

## IV. Conclusion

The application of new technologies on ship systems, especially the software ones like expert systems, fuzzy systems, neural networks, etc. gives new diagnostic and control possibilities. New intelligent systems for diagnosis and control of marine diesel engines use a lot of expert knowledge and experience which is fuzzy in nature. Therefore, in designing such knowledge based systems fuzzy approach is of great importance.

In this paper some recognised fuzzy modelling techniques suitable for diesel engine diagnosis and control are considered. Two modelling examples are illustrated simulating engine faults: 1. increased cylinder blowby and 2. decreased turbocharger efficiency. In fuzzy control of diesel engine process, two simulation examples are given with fuzzy rules elicited from experts using direct interview method: 1. fuzzy control of diesel fuel oil viscosity (Mamdani model used) and 2. engine shaft speed control (T-S model used). Simulation examples were shown the real power of fuzzy approach in modelling and control of marine diesel engine process.

## References


[1] Antonić, R.: Fault Tolerant Control System for Large Diesel Engine in Marine Propulsion, Ph.D. dissertation, Faculty of electrical engineering and computing, Univ. Zagreb, 2002. (in Croatian).

[2] Antonić, R.; Z.Vukić (2002): "Knowledge representation in Diagnosis and Control of marine Diesel Engine", Brodogradnja, **50**, 1, pp. 57-66.

[3] Mamdani, E.H., "Applications of fuzzy logic to approximate reasoning using linguistic synthesis," *IEEE Transactions on Computers*, Vol. 26, No. 12, pp. 1182-1191, 1977.

[4] MathWorks, Inc.(1999): "Fuzzy Logic Toolbox for use with Matlab – User's guide", 1999.

[5] Vukić, Z.; H. Ožbolt; D. Pavleković (1999): "Application of Expert Systems, Fuzzy Algorithms and Neural Networks to Fault Diagnosis in Control Systems", Brodogradnja **47**/1, 41-49.

[6] Zadeh, L.A. (1999): "From Computing with Numbers to Computing with Words – From Manipulation of Measurements to Manipulation of Perceptions", IEEE Trans. On Circuits and Systems, **45**, 1, pp. 105-119.