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APPLICATION OF ADVANCED COMPUTING TECHNOLOGIES IN MARINE SYSTEMS MODELLING AND CONTROL

PRIMJENA NAPREDNIH RAČUNALNIH TEHNOLOGIJA U MODELIRANJU I UPRAVLJANJU POMORSKIH SUSTAVA

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Abstract

The paper deals with some application possibilities of advanced computing technologies in marine systems modelling and control. New computing technologies and techniques like fuzzy logic (FL), expert systems (ES), artificial neural networks (ANN), genetic algorithms (GA), object oriented programming (OOP) offer new, extended possibilities to identification, modelling and control of dynamic systems. This paper presents some possibilities of practical use of advanced computing technologies applied to the modelling and control of marine diesel engines. The emphasis is put on two well recognised techniques, fuzzy logic and expert systems. Some application examples are illustrated in the paper to show effectivness of using such methods and techniques in marine diesel engine modelling and control.

Sažetak

U radu se daju neke mogućnosti primjena novih računalnih tehnologija u modeliranju i upravljanju sustava u pomorstvu. Nove računalne tehnologije i tehnike kao: neizrazita logika (FL), ekspertni sustavi (ES), umjetne neuronske mreže (ANN), genetički algoritmi (GA), objektno orjentirano programiranje (OOP) pružaju nove proširene mogućnosti za identifikaciju, modeliranje i upravljanje dinamičkih sustava. U ovom radu prezentiraju se neke od mogućnosti praktičnog iskorištenja naprednih računalnih tehnologija s primjenom u svrhe modeliranja i upravljanja drodskih dizelskih strojeva. Naglasak se u radu daje na dvije priznate i dobro prihvaćene tehnike, neizrazite logike i ekspertnih sustava. U radu se daje nekoliko primjera primjene ovih tehnika i metoda, te pokazuje njihova učinkovitost.

1. Introduction

The designing of modern control and diagnosis systems of marine complex dynamic processes should be based, not only on real measured data from sensors i.e from monitoring system, but also on comprehensive knowledge and experience of domain experts /**1**/, /**2**/, /**3**/ (see fig. 1.).

If the knowledge about system to be controlled is exact and certain, the efficient way for

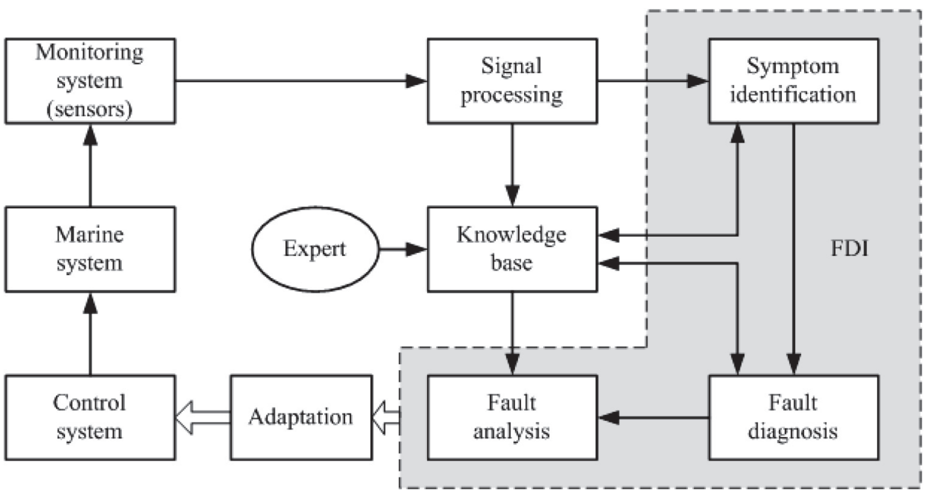

Fig. 1. Control and diagnosis system based on real data and expert knowledge

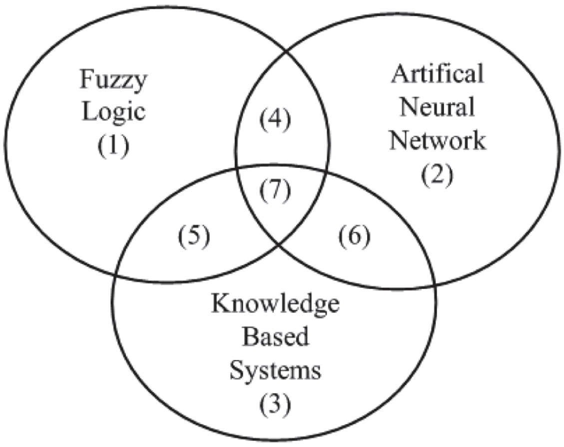

Fig. 2.: Three well recognized soft computing technologies popular in control system design

modelling 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 soft computing technologies like: fuzzy logic (FL), artificial neural networks (ANN) and knowledge based systems (KBS), popularly considered as artificial intelligence techniques. Today's industrial controls designers are employing varying degrees of these three leading computing techniques. As illustrated in Fig. 2. some applications can be solved using just one technology (regions 1, 2, 3), but others might use two (regions 4, 5, 6) or even combination of three technologies at the same time (region 7). All these three technologies have a property in common: they are all model free estimators, meaning that no perfect model, algorithm, or solution, but their combination can be very effective in complex systems identification, modelling, diagnosis and control.

2. Fuzzy modelling in kbs

Consistent and complete knowledge base plays very important role in knowledge based systems i.e expert systems. Fuzzy logic offers mechanisms for explicit knowledge modelling as well as for handling imprecise, uncertain, fuzzy and vague knowledge.

The possible sources of uncertainty and fuzziness in KBS are most often the following:

– inherent human expert fuzzy concepts and reasoning,
– different expert opinions and reasoning ways regarding the same object – problem,
– incomplete and unreliable information,
– heuristic knowledge and expert experience is difficult to test and evaluate and so on.

There are many factors that have to be considered when choosing knowledge representation schemes /**4**/, /**5**/ like: efficiency in terms of computer storage, speed execution, updating, learning capabilities, maintainability etc.

The fuzzy logic approach in knowledge base construction usually consists of the following:

– linguistic variables describing the input and output quantities of the system,
– linguistic terms with the membership functions,
– fuzzification method,
– rule base containing the relevant knowledge (obtained as a result of knowledge elicitation session from domain experts or in another way),
– fuzzy operators (And, Or, ...)
– fuzzy inference method (reasoning and making decisions),
– defuzzification method.

The possible values of a linguistic variables are the linguistic terms which are linguistic interpretations of technical quantities i.e. process parameters like temperature, pressure, level, speed, torque and so on.

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 operation range.

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 -MF). The normalised standard membership functions: linear decreasing, linear increasing, trapezoidal and sigmoidal can be applied to the most technical processes like in the diagnosis and control of marine systems.

Fundamental idea behind fuzzy modelling is to describe system dynamics by establishing the fuzzy input-output relation that can 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 knowledge representation schemes /**6**/ is based on fuzzy rules in the form:

$$\begin{aligned} &If\ OA_1\ is\ x_1\ And\ OA_2\ is\ x_2\ And....Then \\ &CA_1\ is\ y_1\ And\ CA_2\ is\ y_2\ And..., \end{aligned} \tag{1}$$

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

Case example: The model illustration is given here for marine diesel engine fault diagnosis.

Input variables (symptoms): $\Delta T_{CGR}, \Delta T_{CCM}, \Delta p_{SAR}, \Delta n_E$.

Output variable (fault): f_{TCE}.

Rule (engine expert conclusion based on experience):

$$R: \begin{array}{l} If\ \Delta T_{CGR}\ is\ PL\ And\ \Delta T_{CCM}\ is\ PM\ And\ \Delta p_{SAR}\ is\ NM \\ And\ \Delta n_E\ is\ NS\quad Then\quad f_{TCE}\ is\ S \end{array}$$

where: ΔT_{CGR} – combustion gases temperature deviation in turbocharger collector,

ΔT_{CCM} – mean combustion gases temperature deviation in engine cylinders,

Δp_{SAR} – scavenge air pressure deviation,

Δn_E – engine speed deviation from nominal value,

f_{TCE} – turbocharger efficiency.

linguistic terms: PL – Positive Large; PM –Positive Middle; NM – Negative Middle;

NS – Negative Small; S – Small

3. Neuro-fuzzy approach to process modelling and control

Building fuzzy models from data involves methods based on fuzzy logic and approximate reasoning /**7**/, /**8**/ but also ANN techniques with their adaptive and learning possibilities. Integration of expert knowledge and numerical data can be done in two main approaches:

- The expert knowledge can be transformed into a set of *I f- Then* rules creating a certain model structure. Parameters in that structure (membership functions, rule weights,.) can be fine tuned using measured input-output data. At the computational level , a fuzzy model can be seen as a layered structure to which standard learning algorithms can be applied. This approach is usually termed as neuro-fuzzy modelling.
- fuzzy model can be constructed from data giving the extracted rules and MF which can provide a posteriori information of the system's behaviour. An expert, with his knowledge and experience, can modify the rules or add new ones, design additional experiments etc. This approach can be termed as rule extraction. In this paper the attention will be paid to the neuro-fuzzy approach.

Combining knowledge based fuzzy model with a data-driven tuning of the model parameters using ANN techniques is very effective way of non-linear process modelling. Fuzzy models can be seen as logical models which use "*If - Then*" rules and fuzzy logical operators to establish qualitative relationships among the variables in the model. Two *important* steps must be taken with regard to the design of fuzzy model (fig. 3):

- *structure selection*
  - determine input and output model variables,
  - structure of the rules (choice of the fuzzy model type),
  - number and type of membership functions and terms for each variable,

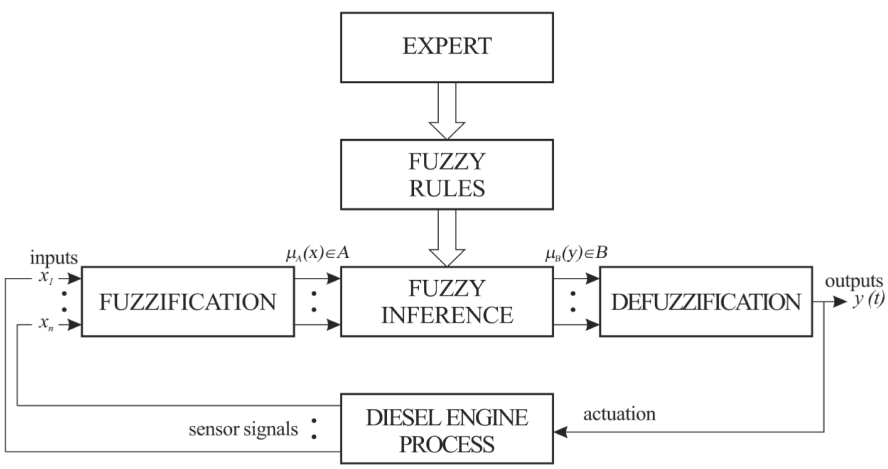

Fig. 3: Fuzzy model structure of diesel engine process using sensor data and expert knowledge

- choice of the inference mechanism, connective fuzzy operators, defuzzification method.

- *parameter adjusting*

After the structure is determined, the performance of a fuzzy model can be fine tuned by adjusting its parameters i.e. membership functions (shape and position) and rule's strength (weights). This can be done very effectively using ANN (fig. 4.).

The most common types of fuzzy models used are of Mamdani and Takagi-Sugeno's type:

Fuzzy model of Mamdani type: fuzzy linguistic rules in such ordinary models are of the following form:

$R^{(j)}$: *If* x_1 *is* A_1^j... *And* x_n *is* A_n^j... *Then* y *is* B^j (2)

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

Takagi and Sugeno's (T-S) fuzzy model extends the linguistic rules to rules with consequent in the form of linear functions of antecedent or premise variables:

$R^{(j)}$: *If* x_1 *is* A_1^j..... *And* x_n *is* A_n^j..... *Then*

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

c_i^j is a consequent parameter, y^j is the system output due to rule $R^{(j)}$, and *i = 1,2,....,J*.

Each rule represents a locally linear model. The final output of the fuzzy model is inferred by taking the weighted average of the y^j :

$$y = \sum_{j=1}^{J} w^j y^j / \sum_{j=1}^{J} w^j \quad (4)$$

where weight w_j implies overall truth value of the j-th rule premise part and is calculated as:

$$w_j = \prod_{k=1}^{n} A_k^i(x_k) \quad (5)$$

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 ANN with adequate learning methods).

Singleton fuzzy model is a special case of T-S model with consequent part in the form of fuzzy singleton.

$R^{(j)}$: *If* x_1 *is* A_1^j... *And* x_n *is* A_n^j... *Then* $y^j = c_0^j$ (6)

Taking rule strength i.e. certainty grade CF ($0 \le CF_j \le 1$) of each rule, the model takes the form:

$R^{(j)}$: *If* x_1 *is* A_1^j... *And* x_n *is* A_n^j... *Then* $y^j = c_0^j$

with CF_j (7)

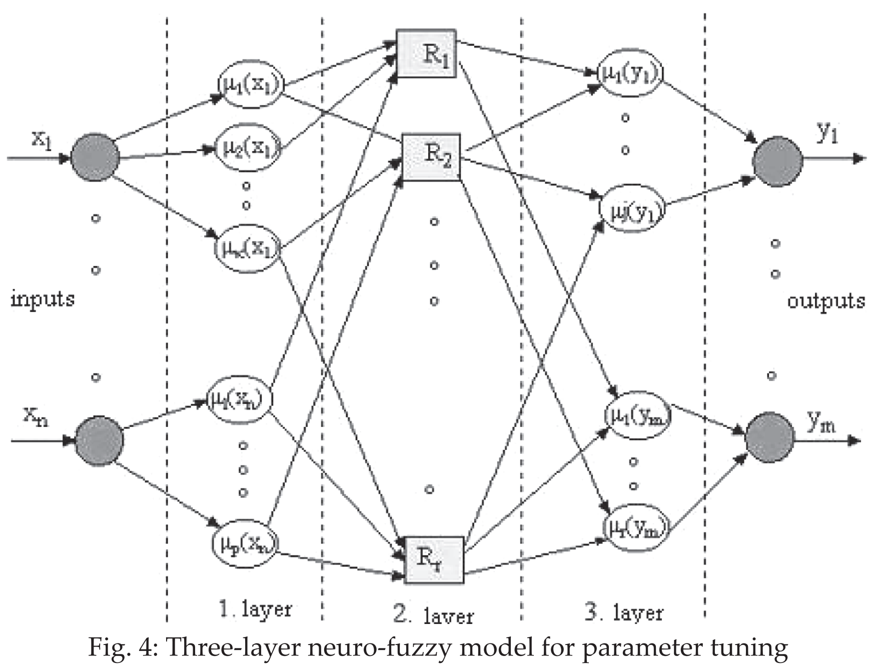

Fig. 4: Three-layer neuro-fuzzy model for parameter tuning

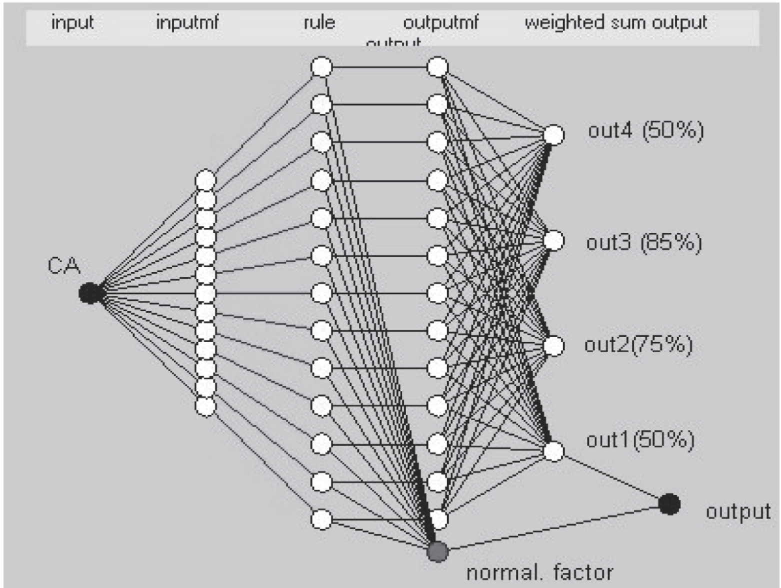

Fig. 5: Neuro-fuzzy model of engine cylinder dynamics

This model, to a certain degree, inherit good identification properties from T-S model and the advantages of better interpretation of the Mamdani model. It is well suited for non-linear function approximation and was chosen to be used in our simulation case.

4. Simulation case

Some simulation, for illustration purpose, was done to show effectiveness of neuro-fuzzy approach. For the modelling of marine diesel engine cylinder dynamics real-time data obtained during engine testing on test bed has been used. The 2-stroke marine diesel propulsion engine was MAN-B&W of type 6S70MC /**9**/, with large hydraulic brake as engine load. The measurement system was based on PC with data acquisition multifunction card and software developed using C language /**10**/.

Cylinder pressure is the most informational engine working condition parameter. Its measurement is the most demanding task because of its dynamic nature and high temperatures influence, so special care was taken for its measurement and pre-processing.

Measuring and acquisition of cylinder pressure data during engine working cycles were strictly in

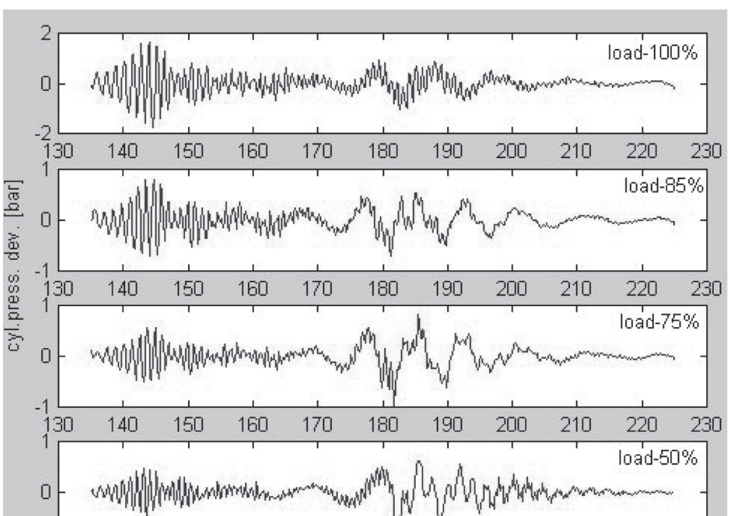

Fig. 6: Engine cylinder pressure deviation during training

correspondence with crankshaft angle (CA) relative to the top dead centre (TDC). Incremental encoder with 2048 discrete angle positions (0.18˚ resolution) was used to detect current crankshaft angle. Two piezoelectric water cooled pressure sensors were used for cylinder engine monitoring during testing cycles. 50 successive working cycles was measured for each cylinder. Testing was done with engine load of 50%, 75%, 85% and full load of 100%. Some pre-processing steps were used to measured data. In the modelling of engine cylinder we used mean values during 50 working cycles of first engine cylinder. Simulation was used in Matlab environment with Fuzzy Logic Toolbox.

Fuzzy subtractive clustering method was used to the set of data for each of four operating points i.e. with engine load of: 50%, 75%, 85%, 100%. After data clustering, adaptive neuro-fuzzy inference method (ANFIS) was used to improve model performance (fig. 5.). Combined learning algorithm was used during model training: least-squares method and back-propagation gradient descent method.

Model performance measure was choosen to be RMSE (root-mean square error). The results obtained with training of 200 epochs were quite good. Fig. 6. shows cylinder pressure deviations between model and nominal process in four operating points. Table 1. gives RMSE without CF for each rule (first row) and with expert's given CF (second row).

The largest deviations are in the range near the TDC because of the very fast dynamic signal changes and high temperatures influence.

Table 1: RMSE with training data after 200 epochs

RMSE [bar]	load 50%	load 75%	load 85%	load 100%
without CF	0.231	0.252	0.261	0.471
with CF	0.219	0.223	0.254	0.452

5. Conclusion

New technologies and computing techniques offer new possibilities in all human activities.

Their power and usefulness are unlimited, but mainly depend on human experts imagination and skill to implement and use them in solving problems, making decisions.

In the paper the possibilities and effectiveness of some recognised fuzzy methods and neural networks techniques to modelling and control of marine systems using real-time data and expert knowledge has been considered . The simulation was done in Matlab with real data originated from testing marine diesel propulsion engine of type MAN-B&W 6S70MC on test bed. We used T-S fuzzy model designed from data and modified by engine expert within ANFIS. The obtained model could be very effectivelly used in optimising engine working regime during testing on test bed, predicting cylinder pressure values in case of faulty sensor or in determining adaptive treshold values for better diagnosis and control.

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