# On application of some artificial intelligence methods in ship design

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ABSTRACT

*In the paper were presented examples of use of some intelligence tools such as a neural network, expert system and relational database to ship design. The neural network of back-propagation of errors was applied to select required power of ship main propulsion system on the basis of ship main parameters. Results obtained by using the network were compared with resulting values for similar ships found in Access database application. To aid design of the main propulsion system and ship power plant automation fuzzy logic was applied as an element of Case Based Reasoning (CBR) method in Exsys expert system as well as a few methods for selection of similar ships, elaborated by the authors.*

**Keywords** : artificial intelligence, expert systems, neural networks, relational database, Case-Based Reasoning method, aided ship design

## INTRODUCTION

In the subject-matter literature examples of application of artificial intelligence to ship design can be found, especially to its preliminary phase when ship's main parameters are selected on the basis of shipowner's design assumptions. In oder to ensure optimum main dimensions for a ship during its designing the approach which consists in finding ships of similar characteristics and modyfing the selected design solutions, is often applied.

To use information dealing with earlier elaborated similar designs is possible both by means of expert systems on the basis of the Case Based Reasoning method which makes designing a ship of high effectiveness faster and easier, or by means of neural networks which can be teached on the basis of representative examples and results achieved from other sources (e.g. from ship service). Thus the information processing characteristic for traditional expert systems can be deemed complementary to the dispersed parallel processing typical for neural networks.

In this work both the classical artificial intelligence tools together with a relational database were used to exemplify their application to aiding ship design in the following range :

- ★ Selection of power output of ship's main engine (ME) on the basis of overall ship's parameters (mainly its dimensions) by using similarity calculation methods applied in database, based on the Case Based Reasoning (CBR) approach, and then possible verification of results with the use of a neural network.
- ★ Aiding design of ship main propulsion system (MPS) by means of selection of similar ships with the use of fuzzy logic method on the basis of such main propulsion system parameters as ME power output and speed, as well as similarity of the remaining parameters achieved from database application.
- ★ Aiding selection of some parameters of ship power plant automation system on the basis of a domain model or existing designs of similar ships, with the use of fuzzy logic method embedded in an expert system, in cooperation with database application.

In order to select ME power output on the basis of general ship parameters by using similarity calculation methods in database application it was made it possible to verify obtained results by means of a neural network which uses the error back-propagation method. And, for similarity calculations and selection of similar ships within the scope of design of ship main propulsion and power plant automation systems the fuzzy logic method [9] embedded in Exsys system was used, apart from the methods provided in database application [6].

## SELECTION OF MAIN ENGINE POWER OUTPUT BY USING CBR METHOD AND NEURAL NETWORK

To select main engine power output a neural network was used apart from the ship similarity calculation methods provided in database application. The below presented research results are based on the set of 222 ships built by Polish shipyards. The set is composed of very different ships. Each of them is characterized by the following parameters :

Dwt – deadweight, L – overall length, B – breadth,
D – draught, V – speed, as well as ME rated output.

In the performed investigations a relationship between ME power output and the remaining parameters was searched for. A fragment of the ship database containing values of the parameters in question is examplified in Tab.1.

The ME power output values searched out of the ship database, most similar to the power chosen according to particular similarity calculation methods, were compared with the values obtained from the neural network.

In neural network applications the one-directional networks and the teaching method with teacher's assistance are used most often. They were also applied to the investigations on aiding ship design. A classical method of teaching the multi-layer, one-directional network is the back-propagation algorithm, the

*Tab. 1. An example fragment of the ship database*

| Ship No. | Dwt [t] | L [m] | B [m] | D [m] | V [kn] | ME rated output [kW] |
|---|---|---|---|---|---|---|
| 2. | 15 300 | 148.9 | 23 | 8.5 | 14 | 6 800 |
| 4. | 15 300 | 148.9 | 23 | 8.5 | 14 | 6 800 |
| 6. | 7 200 | 169.9 | 28 | 12.3 | 20.5 | 8 600 |
| 8. | 41 600 | 206.5 | 30 | 11.5 | 14.3 | 11 330 |
| 9. | 41 450 | 205 | 30 | 11.48 | 14.6 | 8 338 |
| 10. | 16 500 | 149 | 23 | 8.5 | 18 | 7 230 |
| 11. | 550 | 60.21 | 10.5 | 3.15 | 11 | 1 200 |
| 12. | 210 | 30.25 | 10.2 | 4.72 | 5 | 600 |
| 13. | 1 480 | 90.63 | 15.02 | 5.4 | 15 | 3 600 |
| 15. | 1 564 | 88.88 | 15.22 | 5.4 | 16 | 3 600 |
| 17. | 18 500 | 141.35 | 22.5 | 9.47 | 13 | 6 650 |
| 18. | 2 209 | 102.6 | 17.07 | 5.7 | 16.5 | 5 200 |

most often used in technical applications aimed at modelling unknown processes. It is the most widely known and used algorithm for the neural networks of nonlinear output function. The algorithm's essence consists in the reverse direction of correcting the weights (teaching the network) : beginning from the initial layer to the first hidden layer preceding it, and further up to the first layer. Error measure is a function of network's weights. Teaching the network consists in an adaptive correction of all weights in such a way as to obtain a minimum of the measure.

The error back-propagation method has contributed to broadening the application range of neural networks a.o. to ship design.

In the calculations in question a two-layer network of a continuous unipolar activation function and the classical algorithm of back-propagation of errors of weight changes was used. The set of ships was split in two subsets : teaching and testing. To the testing set 25% of ships were chosen in random. A fragment of the teaching set is shown in Tab.1. The ships of numbers not shown in col.1 of the table were assigned to the testing set.

All values of the ship parameters were normalized in advance to obtain the values within the interval [0,1]. In this case one calculation cycle comprised putting-in parameters of all ships of the teaching set to the network, successively. The network teaching was completed when the cycle rms error $E_m$ achieved a value smaller than the assumed one. The error concerned the difference between the real ship ME power output and that calculated by the network for the same ship.

Convergence of the teaching process with the use of the teaching set of ships, expressed by the relationship between $E_m$ and the number of calculation cycles $L_{cc}$, is presented in Fig.1. The results were obtained for the network of the following features : six inputs, 25 neurons in the hidden layer, one output neuron, the teaching factor $\eta = 0.5$, the activation function parameter $\beta = 1.5$.

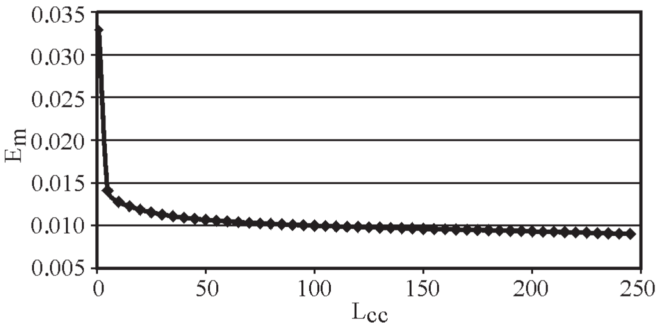


*Fig. 1. Teaching process convergence of the applied neural network*

On completion of teaching the network by means of the teaching set of ships the calulations based on the obtained network's weights were performed with the use of parameters of ships from the testing set. The calculated ME power outputs are compared with the real ones in Fig.2. In the figure are also presented the results obtained by means of the multi-dimensional regression method with the use of 3rd order polynomial model [4].

In the testing calculations the relative rms error *e* expressed by the formula (1) was also calculated :

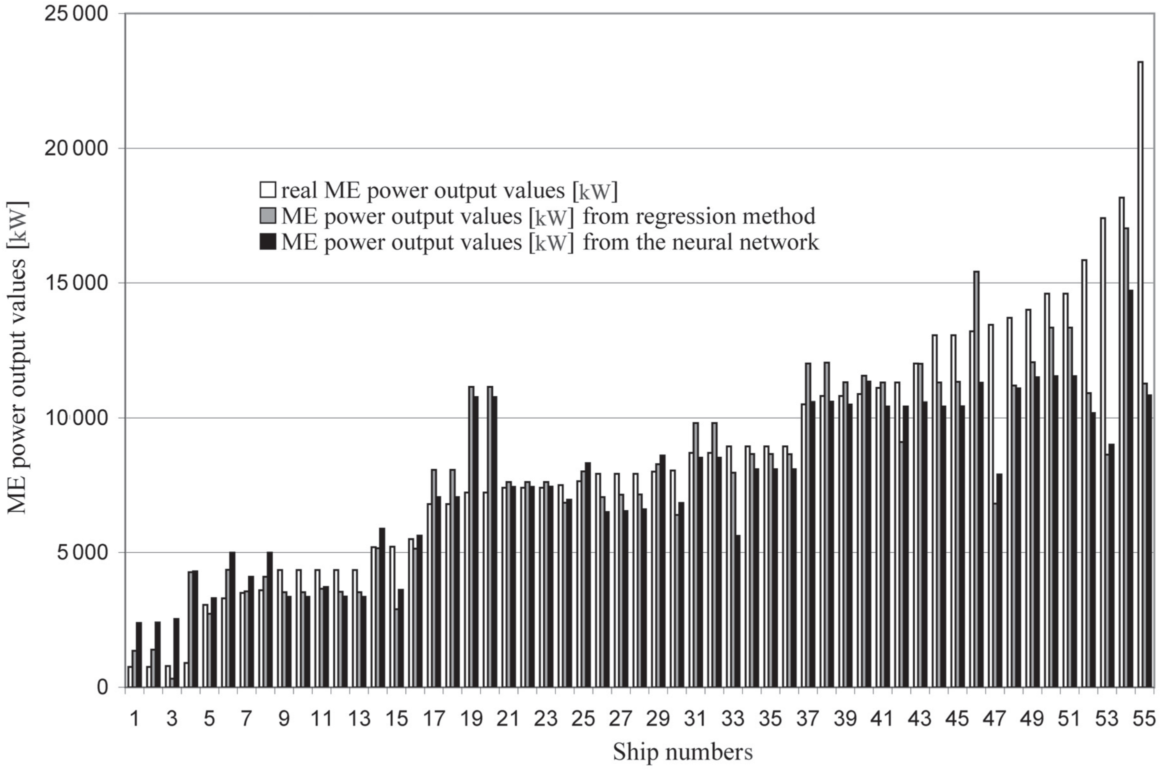


*Fig. 2. Comparison of the results obtained for the testing set of ships*

$$e = \sum_{i=1}^{n} \frac{\left|M_{ri} - M_{oi}\right|}{M_{ri}\, n} 100 \qquad (1)$$

where :

$M_r$ , $M_o$ – real ME power output
and that calculated by the network, respectively.

The following values of the error were obtained :

$e_1$ = 25.61% for the regression method
and $e_2$ = 23.13% for the network.

On the basis of the results of the presented research on the neural network use the following conclusions can be offerred :

- the results obtained from the neural network and those from the regression method are similar, respectively
- the large discrepancy of the results for the testing set (large values of the error *e*) results from the large variety of the considered ships
- for the gradient teaching algorithm of the constant teaching factor η a fast convergence in the initial phase and a very slow one in the further phase of calculations, is characteristic (Fig.1).

For practical applications more effective teaching algorithms and methods of changing the factor η in the course of calculations, should be used.

In the literature sources various modifications of the error back-propagation algorithm, aimed at acceleration of the algorithm's convergence, have been proposed [10].

On the basis of the following ship design parameters : displacement, overall length, breadth, draught, and speed the similar ships were selected and their ME power output values were compared with those designed as well as with relevant values obtained from the neural network [4]. Calculation results dealing with the ships built by Polish shipyards, both obtained by applying the similarity calculation methods embedded in the database and those achieved from the neural network are presented in Tab. 2.

***Tab. 2.*** *ME power output values of similar ships, obtained by using different similarity calculation methods, and by applying the neural network*

| ME power output of designed ship [kW] | ME power output of similar ship | | | | |
|---|---|---|---|---|---|
| | calculated by using the following similarity methods | | | | from the neural network |
| | based on function with lower limit | based on Gaussian function | based on trapezoidal function | based on triangular function | |
| 3 057 | 7 000 | 7 000 | 7 000 | 7 000 | 1 991 |
| 4 350 | 4 350 | 4 350 | 4 350 | 4 350 | 2 503 |
| 5 500 | 5 500 | 5 500 | 5 500 | 5 500 | 5 043 |
| 7 400 | 7 400 | 7 400 | 7 400 | 7 400 | 7 250 |
| 8 043 | 4 800 | 8 048 | 8 048 | 8 048 | 6 537 |
| 11 100 | 13 050 | 13 050 | 12 960 | 13 050 | 11 191 |
| 12 000 | 10 800 | 10 800 | 10 800 | 10 800 | 11 153 |
| 13 050 | 13 050 | 13 050 | 12 960 | 13 050 | 12 900 |
| 13 700 | 13 700 | 13 700 | 13 700 | 12 960 | 13 500 |

In many cases the designer can assume values of certain parameters with a lower or higher tolerance; it specially concerns the upper limit for a required parameter value as another criteria may be decisive, e.g. preference for a given supplier, or more favourable terms of delivery. For other parameters to lower a limiting value of a designed parameter may be recommended e.g. with a view of price criterion. From this point of view choice of a form of similarity function is important. In the subject-matter literature mainly symmetrical similarity functions are presented, e.g. the symmetrical similarity based on the theory of sets, or the above mentioned symmetrical similarity with a lower limit [9].

These authors have enlarged the set of similarity functions by the following ones : triangular, trapezoidal and Gaussian [6]. On the one hand it offers, for designer, a greater flexibility in determining similarity, on the other hand it forces him to select a function complying with requirements and type of an analyzed design parameter of automation system.

**The similarity function with lower limit** makes it possible to limit the range of calculations of similarity of an investigated parameter by establishing its lower limit. In this case the similarity value linearly increases from zero, at the lower limit, up to one.

**The trapezoidal and triangular similarity functions** make it possible to limit the range of similarity calculations by establishing two limits : lower and upper, and in the case of trapezoidal function – also the deviations : lower and upper, allowing to apply some tolerance margin for a given parameter.

**The Gaussian similarity function** treats the similar cases with the highest tolerance, not rejecting even the least similar ones.

From the presented example it results that the ME power output values for the most similar ships, obtained by using particular similarity calculation methods, are not always close to those of the designed ships. It results from that the similar ships were selected on the basis of total similarities of all input parameters. Therefore it is very important to appropriately establish values of weights of the parameters as well as limiting values for investigated ranges and their deviations.

Summing up the performed investigations one can state that the best results are obtained by using the calculation method based on the Gaussian function, and in some cases – the method based on the trapezoidal function.

The differences of the similarities obtained by means of particular methods may result from the following causes :

- a too low number of input parameters of crucial importance for choice of ME power output, has been taken for the comparisons
- a very diverse structure of the investigated set of ships in the database (different types, tasks, gabarites)
- a too low number of the analyzed ships
- a too small set of ships in the database, which is especially important for teaching the neural network.

## FUZZY LOGIC AIDED DESIGN OF SHIP MAIN PROPULSION SYSTEM

The aiding of design of ship main propulsion system (MPS) is carried out by using the probability calculation methods contained in database application, as well as fuzzy logic method embedded in expert system.

Fuzzy logic can be applied simultaneously to any number of parameters. It makes it possible to pass from numerical quantities to linguistic ones by which logical reasoning can be easily performed [8]. The process this way becomes independent of a scale of numerical values of considered parameters. A general schematic diagram of the discussed method of probability determination is presented in Fig.3.

Resulting value of numerical measure of the similarity $M_p$ depends on :

- assumed attribution functions by which input values are fuzzified

✦ definition of rules by which reasoning is carried out
✦ mode of sharpening realization.

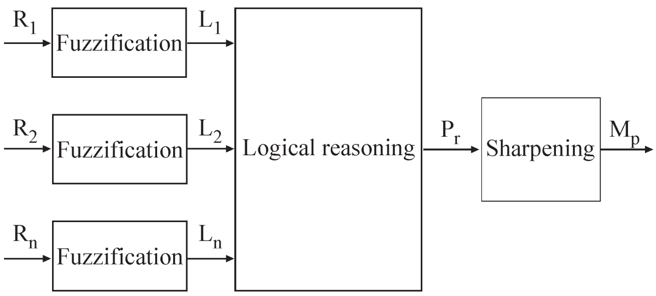


***Fig. 3.*** *Schematic diagram of the fuzzy set method*

where :

$R_1, R_2,..R_n$ – differences of numerical values of considered input parameters
$L_1, L_2,.. L_n$ – sets of linguistic definitions associated with assumed fuzzy sets defined on the basis of the values $R_1, R_2,.. R_n$, respectively
$P_r$ – fuzzified probability
$M_p$ – resulting numerical similarity measure.

The MPS design aiding is carried out in the following way :

➲ in the database application similarity of MPS is calculated on the basis of such non-numerical parameters as : type of ME and its producer, as well as the following numerical parameters : number of MEs and number of propellers.
➲ the weighted sum of similarities of the parameters is introduced, together with the data on ME power output and speed, into the expert system *Exsys* in which the parameters are fuzzified.

Assessment of the calculation methods of MPS similarity of ships in the expert system was carried out on the basis of the data on the selected MPS parameters given in Tab.3, as well as the values of the MPS design parameters contained in Tab.4.

In Tab.4 values of all MPS parameters of a designed ship are recorded.

As far as the MPS is concerned, determination of similarity of ships by using fuzzy logic is based on the following numerical parameters :

♦ the absolute value of difference of ME power output of a designed ship and built one, $R_m$
♦ the absolute value of difference of ME speed of a designed ship and built one, $R_n$
♦ the non-numerical similarity of MPS (calculated in the database) attributed to built ship, $P_o$ , taking values from the interval [0,1].

Calculation of fuzzified similarities is realized in two phases :

➢ the fuzzified similarity of MPS, $P_l$, is calculated on the basis of the fuzzified parameters $R_m$ and $R_n$
➢ the resulting fuzzified similarity of MPS, $P_w$ , is calculated on the basis of the numerical similarity of MPS and fuzzified similarity $P_o$ .

Ships similar to a designed ship are selected on the basis of the maximum resulting fuzzy similarity. To realize the fuzzification process of values of the parameters the attribution functions shown in Fig.4, were applied.

The example logical relationships assumed in rules of the expert system, dealing with the numerical fuzzified similarity of MPS are given in Tab.5, and the resulting fuzzified similarity of MPS – in Tab.6.

***Tab. 3.*** *Data of MPS parameters selected out of the database*

| Ship's No. | Main engine (ME) | | | | | Number of propellers |
|---|---|---|---|---|---|---|
| | Type | Producer | Output | Speed | Number of units | |
| 1. | 6ZB40/48 | SULZER | 3 600 | 500 | 1 | 1 |
| 2. | 12V40/54A | M.A.N. | 7 500 | 450 | 1 | 1 |
| 3. | 16V32D | WÄRTSILÄ | 8 043 | 800 | 1 | 1 |
| 4. | 7S35MC | B & W | 6 650 | 154 | 1 | 1 |
| 5. | 5S60MC | B & W | 10 869 | 102 | 1 | 1 |
| 6. | 6RTA58 | SULZER | 12 960 | 127 | 1 | 1 |
| 7. | 5L35MC | B & W | 3 800 | 200 | 1 | 1 |
| 8. | 6RLB66 | SULZER | 11 100 | 124 | 1 | 1 |
| 9. | 6RTA58 | SULZER | 12 960 | 127 | 1 | 1 |
| 10. | 7RND76 | SULZER | 14 000 | 122 | 1 | 1 |
| 11. | 5RD68 | SULZER | 5 500 | 140 | 1 | 1 |
| 12. | 6ZL40/48 | SULZER | 4 350 | 480 | 1 | 1 |
| 13. | 5K62EF | B & W | 7 400 | 155 | 1 | 1 |
| 14. | 6ZL40/48 | SULZER | 4 350 | 480 | 1 | 1 |
| 15. | 5RD68 | SULZER | 5 500 | 140 | 1 | 1 |
| 16. | 6ZL40/48 | SULZER | 4 350 | 480 | 1 | 1 |
| 17. | K6Z70/120E | M.A.N. | 8 400 | 140 | 1 | 1 |
| 18. | 6RND90 | SULZER | 17 400 | 122 | 1 | 1 |
| 19. | SBA8M528 | DEUTZ | 600 | 620 | 1 | 1 |
| 20. | SBA8M528 | DEUTZ | 600 | 620 | 1 | 1 |
| 21. | SBA8M528 | DEUTZ | 600 | 620 | 1 | 1 |
| 22. | K9Z60/105E | M.A.N. | 9 000 | 165 | 1 | 1 |
| 23. | 6K62EF | B & W | 8 940 | 155 | 1 | 1 |

***Tab. 4.*** *Values of MPS design parameters*

| Ship's symbol | Main engine (ME) | | | | | Number of propellers |
|---|---|---|---|---|---|---|
| | Number of units | Type | Producer | Output [kW] | Speed [rpm] | |
| Designed ship | 1 | 6RTA 76 | HCP SULZER | 17 220 | 104 | 1 |

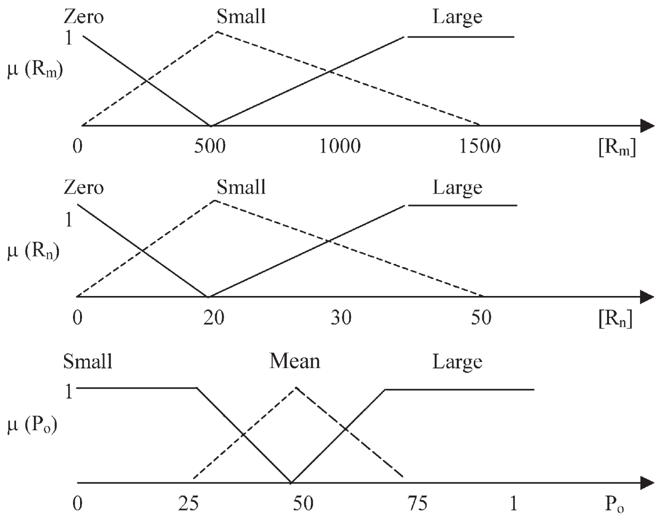


***Fig. 4.*** *Attribution functions for MPS parameters*
*μ – value of membership function determining fuzzy set*

The example rules resulting from Tab.5 and 6 can be written as follows :

If ($R_m$ = zero) and ($R_n$ = zero) then ($P_1$ = large)
If ($P_1$ = large) and ($P_o$ = small) then ($P_w$ = mean).

In the Exsys system the degrees of attribution to fuzzy sets are taken as the so called confidence values. Reasoning by using

***Tab. 5.** Logical relationships in 1st phase of reasoning*

| $R_m$ | Zero | | | Small | | | Large | | |
|---|---|---|---|---|---|---|---|---|---|
| $R_n$ | zero | small | large | zero | small | large | zero | small | large |
| $P_1$ | large | large | mean | large | mean | small | mean | small | small |

***Tab. 6.*** Logical relationships in 2nd phase of reasoning

| $P_1$ | Large | | | Mean | | | Small | | |
|---|---|---|---|---|---|---|---|---|---|
| $P_0$ | small | mean | large | small | mean | large | small | mean | large |
| $P_w$ | mean | large | large | small | mean | large | small | small | mean |

appropriate rules triggers calculating confidence values concerning conclusions from the rules, on the basis of confidence values for premises. On their basis the sharpening is realized in result of which a single numerical value is achieved :

$$Z = W_1C_1 + W_2C_2 + W_3C_3$$

where :

Z – numerical value of MPS similarity (contained within the interval [0, 1]

$C_1$, $C_2$, $C_3$ – confidence values for the values : „large”, „mean”, „small”, respectively, achieved from the reasoning process

$W_1$, $W_2$, $W_3$ – weights having non-negative values, $W_1 + W_2 + W_3 = 1$.

The application of fuzzy logic was tested on several examples (the design data P1÷ P5), and their results dealing with similarity calculations and selection of similar ships are shown in Tab.7.

***Tab. 7.** Calulation results of MPS similarity obtained by using Exsys system*

| Example symbol | MPS power as designed | MPS speed as designed | Number of similar ships | Similarity value | MPS power of similar ship | MPS speed of similar ship | Nos. of similar ships |
|---|---|---|---|---|---|---|---|
| | [kW] | [rpm] | - | - | [kW] | [rpm] | |
| P1 | 16 200 | 107 | 3 | 0.6286 | 18 160 | 110 | 41,60, 124 |
| P2 | 11 400 | 110 | 20 | 0.6286 | 10 800 | 118 | 71 |
| P3 | 6 600 | 150 | 1 | 0.8 | 6 650 | 154 | 4 |
| P4 | 11 000 | 120 | 38 | 0.6286 | 13 050 | 124 | 63 |
| P5 | 17 000 | 500 | 3 | 0.45 | 17 400 | 530 | 84 |

In Tab.8 the calculated similarities and selected similar ships (examples P1÷ P3) selected with the use of fuzzy logic are compared with those obtained by using the database application.

***Tab. 8.** Results of selection of similar ships from database and by using Exsys software*

| Example symbol | MPS power as designed | MPS speed as designed | Similar ship number | MPS power of similar ship | MPS speed of similar ship | Applied method |
|---|---|---|---|---|---|---|
| | [kW] | [rpm] | - | [kW] | [rpm] | - |
| P1 | 6 600 | 150 | 4 | 6 650 | 154 | All applied methods |
| P2 | 11 000 | 120 | 93,117, 114 | 10 800 | 119 | Database methods |
| | | | 63 | 13 050 | 124 | Exsys |
| P3 | 17 000 | 500 | 38,104, 84 | 17 200 | 530 | Database methods |
| | | | 84 | 17 400 | 530 | Exsys |

## AIDING SELECTION PROCESS OF SOME PARAMETERS OF SHIP POWER PLANT AUTOMATION SYSTEM

Apart from aiding MPS design, fuzzy logic was also applied to aiding selection process of some parameters of ship power plant automation system.In the case in question the similarity was related to the features characterizing power plants of built ships as it was assumed that solutions dealing with automation system depended on some features of ship power plant. Because of the large number of accounted-for features, similarity of ships was determined by using some groups of the features. Full set of the considered features was split into subsets related to :

- the whole ship (general similarity determined by a type and size of ship) - Tab.9
- the main propulsion system (MPS) (similarity determined by a type of propulsion system and its main parameters) Tab.10
- selected ship systems (similarity determined by system's function and its design features) - Tab.10
- the electric power plant (similarity determined by a type of generating sets and their main parameters) - Tab.11

***Tab. 9.** Values of general ship parameters*

| Ship symbol | Ship type | Ship deadweight | Number of refrigerated containers | Number of cars | Classification society | Automation class |
|---|---|---|---|---|---|---|
| | | [t] | [pieces] | [pieces] | | |
| B191 | container ship | 1 504 | 200 | 100 | DNV | AUT |
| B222 | bulk carrier | 14 800 | 0 | 0 | LRS | UMS |
| B369 | refrigerated ship | 9 860 | 60 | 0 | DNV | UMS |
| B500 | container ship | 29 600 | 150 | 120 | BV | AUT |
| B501 | roll on–roll off ship | 9 760 | 0 | 80 | DNV | E0 |
| B683 | bulk carrier | 49 000 | 0 | 0 | DNV | E0 |
| B684 | bulk carrier | 48 000 | 0 | 0 | DNV | E0 |
| Designed ship | container ship | 25 000 | 200 | 100 | BV | AUT |

Results of similarity calculations within the range of the subsets are considered as partial similarities whose sum represents the total weighted similarity.

The similarities calculated in the database application were transferred to the Exsys expert system to be fuzzified together with the parameters whose similarities were determined by using fuzzy logic directly.

In Exsys system the B191 ship was selected as the most similar. The partial similarities of this ship calculated with taking into account the weights, are given in Tab.12.

The maximum partial similarities together with symbols of relevant ships as well as maximum total similarity of ship, i.e. sum of partial similarities were transferred from Exsys system to the database.

Partial similarities of the similar ship (B 191), calculated with accounting for appropriate weights, are presented in Tab.13. The maximum partial similarities dealing with different ships are presented in Tab.14.

It should be added that when the entire automation design project of the selected ship does not satisfy assumed requirements its particular elements may be taken from other built ships, selected on the basis of maximum similarities of the systems.

The results concerning investigation of similar ships, carried out by using Exsys system, were obtained on the basis of Tab.14 which contains weighted partial similarities of all ships stored in the database.

Aiding the design of ship main propulsion and automation systems, based on CBR methods consists in automatic searching out of ship database the ships most similar to a designed one [5]. In this scope, the designer selects, out of database fields, the parameters on the basis of which at first the partial similarity of MPS, electric power plant and particular ship's systems, then the similarity of the whole ship, together with their relevant weights, will be calculated. The designer may pass over

*Tab. 10. Values of parameters of MPS and selected ship's systems*

| Ship symbol | Number of MEs | ME type | ME output | ME speed | Number of transmission gears | Number of propellers | Type of propeller(s) | Number of valves in fuel system | Number of valves in bilge system |
|---|---|---|---|---|---|---|---|---|---|
| | [pieces] | - | [kW] | [rpm] | [pieces] | [pieces] | - | [pieces] | [pieces] |
| B191 | 1 | 6L70 MC | 16 200 | 107 | 1 | 1 | of fixed pitch | 22 | 25 |
| B222 | 2 | 6L46 | 6 300 | 500 | | 1 | of controllable pitch | 24 | 30 |
| B369 | 1 | 6RTA 62-R1 | 11 400 | 102 | 2 | 1 | of fixed pitch | 35 | 27 |
| B500 | 1 | 6RTA 76 | 1 7220 | 104 | 0 | 1 | of fixed pitch | 40 | 23 |
| B501 | 4 | 8ZAL 40 S | 23 040 | 510 | 2 | 2 | of controllable pitch | 28 | 33 |
| B683 | 1 | 5RTA 62 U | 8 670 | 102 | 0 | 1 | of fixed pitch | 25 | 28 |
| B684 | 1 | 5S 60 MC | 10 200 | 105 | 2 | 1 | of fixed pitch | 25 | 30 |
| Designed ship | 1 | 6RTA 76 | 16 500 | 110 | 1 | 1 | of fixed pitch | 28 | 30 |

*Tab. 11. Values of electric power plant parameters*

| Ship symbol | GS1 generating set | | | | GS2 generating set | | | | shaft generator |
|---|---|---|---|---|---|---|---|---|---|
| | number | type | output | speed | number | type | output | speed | type |
| | [pieces] | - | [kW] | [rpm] | [pieces] | - | [kW] | [rpm] | - |
| B191 | 3 | 8S20 H | 1 160 | 1 440 | 1 | 6S20 H | 950 | 1 000 | none |
| B222 | 3 | 6L20C | 1 080 | 1 000 | 2 | | 1200 | 920 | |
| B369 | 3 | 6ATL 25H | 1 000 | 920 | 1 | | 850 | 1 440 | |
| B500 | 4 | HCP | 1 200 | 920 | 1 | 6S20 H | 1700 | 800 | |
| B501 | 2 | GR 22 HF | 1 170 | 1 000 | 2 | 8R 22 HF | 1750 | 920 | |
| B683 | 3 | GR 20 | 920 | 920 | 2 | | 1300 | 1 000 | |
| B684 | 3 | KRG-6 | 1 010 | 2 880 | 1 | | 1260 | 800 | |
| Designed ship | 3 | 6ATL25H | 1 500 | 1 000 | 2 | | 1850 | 800 | |

*Tab. 12. Results of investigation of similarities of ships*

| Ship symbol | Similarity | | | | |
|---|---|---|---|---|---|
| | Total | General | of MPS system | of electric power plant | of ship's systems |
| B191 | 0.3051 | 0.3432 | 0.4208 | 0.1680 | 0.2601 |
| B369 | 0.2713 | 0.3164 | 0.3338 | 0.1512 | 0.3040 |
| B501 | 0.1790 | 0.2634 | 0.1479 | 0.1414 | 0.2552 |
| B683 | 0.2047 | 0.2424 | 0.2044 | 0.1550 | 0.2609 |
| B684 | 0.2644 | 0.2448 | 0.2971 | 0.1680 | 0.3534 |
| B500 | 0.2783 | 0.4124 | 0.3165 | 0.1680 | 0.3002 |
| B222 | 0.1992 | 0.2755 | 0.910 | 0.2400 | 0.3160 |

*Tab. 13. Partial similarities of similar ship (B 191)*

| Kind of similarity | Weight of parameter | Value of similarity |
|---|---|---|
| General similarity | 0,1 | 0.343 |
| Similarity of MPS system | 0,4 | 0.420 |
| Similarity of electric power plant | 0,3 | 0.168 |
| Similarity of ship's systems | 0,2 | 0.260 |

*Tab. 14. Maximum partial similarities dealing with different ships*

| Kind of similarity | Ship | Value of similarity |
|---|---|---|
| General similarity | B500 | 0.41 |
| Similarity of MPS system | B191 | 0.42 |
| Similarity of electric power plant | B222 | 0.24 |
| Similarity of ship systems | B684 | 0.35 |
| Total similarity | B191 | 0.30 |

the phase of calculation of weights, in this case they will be assumed equal.

The weighted similarity both partial and total one of the whole ship can be calculated by means of a database application program with the use of any of the proposed method basing on one of the applied similarity functions ( that with lower limit, trapezoidal, triangular or Gaussian one). In the expert system using fuzzy logic, for the searched-out ships most similar to the designed one, are specified values of its partial similarities and of the maximum partial similarities found for a given parameter.

If ambiguous results are obtained from the above mentioned methods the designer is able to verify them by using an error back-propagating neural network, assuming selected database fields as input and output parameters.

## RECAPITULATION

- In recent years intensive research aimed at making use of developments of artificial intelligence, a.o. expert systems and neural networks, in solving different tasks of ship design, have been carried out [2], [3], [4].
- These authors attempted to apply an error back-propagating neural network for selection of power of ship main propulsion system (MPS) on the basis of general ship parameters, a.o. ship main dimensions, in order to find a new solution in the case when already found one is not satisfactory for ship designer.
- The results obtained from the neural network were compared with the values resulting for the similar ships found in the database. It may be concluded that the neural network teached in advance on the basis of solutions of existing ships, with the use of general ship design data, can be applied to verify results achieved by means of the similarity determination methods embedded in the database or expert system.
- Moreover, a fuzzy logic method was used in Exsys expert system to aid design of MPS and ship power plant automation, as a tool supplementary for CBR method ; this approach is an original and novel solution in the area of ship designing.
- The elaborated system together with the database application can serve as an intelligent designer-friendly tool to aid design process of ship automation systems.

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FOREIGN *conference*

# PRADS 2004

The Technical University of Hamburg - Harburg and Schiffbautechnische Gesellschaft organized the successive, 9th International Symposium on:

***Practical Design of Ships and other Floating Structures***

This widely recognized scientific conference was held on 12÷17 September 2004 in Lűbeck - Traveműnde (Germany). It gave an opportunity for international contacts and cooperation of experts to stimulate development of design and production technology with a view of effectiveness and economy as well as safety improvment of ships and other floating objects.

To realize the idea 142 qualified papers were presented during 36 topical sessions on :

- Design methods
- Resistance
- Design loads
- Ultimate load
- Manoeuvring
- Methodology
- Trimarans
- Operation
- Dynamic response
- Design for safety
- Fatigue
- Seakeeping
- Cavitation
- Stability
- Catamarans and pentamarans
- Floating production systems
- Experimental techniques
- Production management
- Slamming and sloshing
- Extreme wave loads
- Hull girder strength
- Springing and torsion
- Novel ship concepts
- Lightweight structures
- Grounding and collision
- Production technology
- High speed monohulls
- Reliability analysis
- Padded drives
- Propellers
- Steel sandwich
- Propulsion
- Design for operation
- Vibration and noise
- Marine engineering
- Computer Integrated Design and manufacturing

In the broad spectrum of topics the greatest number of papers dealt with the following : Fatigue (9 papers), Ultimate load, and Methodology (7 papers each), Design methods, Resistance, Operation, Design for safety, Stability, and Padded drives (6 papers each), Propellers, and Novel ship concepts (5 and 4 papers, respectively).

The presented papers were prepared by experts from 16 European countries as well as Australia, Brazil, People Republic of China, Egypt, India, Japan, Korea, Taiwan and USA.

Among them were also four Polish authors who presented the following problems :

★ *Strength test of steel sandwich panel* – by J. Kozak (Gdańsk University of Technology)

★ *Numerical simulation of crash and grounding of inland waterway transportation barges* – by T. Jastrzębski, M. Taczała (Technical University of Szczecin), and K. Grabowiecki (CIM-MES Project Co., Warsaw)

★ *Efficient freight transport on shallow inland waterways – – Results of the INBAT R&D project* – by T. Jastrzębski (Technical University of Szczecin), as a co-author.

T. Borzęcki from Gdańsk University of Technology, representing Polish scientific circles, took part in the work of the International Standing Committee of the conference.