Journal of KONBiN 1 (13) 2010
ISSN 1895-8281

A FUZZY - NEURON MODEL OF THE SHIP PROPULSION RISK PREDICTION

ROZMYTO - NEURONOWY MODEL PREDYKCJI RYZYKA NAPĘDOWEGO STATKU

Alfred Brandowski, Andrzej Mielewczyk, Hoang Nguyen, Wojciech Frąckowiak

Gdynia Maritime University, ul. Morska 81-87, 81-225 Gdynia, Poland
abrand@am.gdynia.pl

***Abstract**: A prediction model is presented of the ship propulsion risk, i.e. a risk of the consequences of loss of the ship propulsion capability. This is an expert model based on opinions elicited by the ship power plant operators. The risk level depends, among other things, on the reliability state of the ship propulsion system components. This state is defined by operators in a linguistic form. The formal risk model parameters are determined by means of a neural network.*

***Keywords**: risk, ship, fuzzy, neuron.*

***Abstrakt:** Przedstawiony został model predykcji ryzyka napędowego statku, czyli ryzyka konsekwencji utraty zdolności do realizacji przezeń funkcji napędu. Jest to model ekspertowy, oparty na opiniach uzyskanych od operatorów siłowni okrętowych. Poziom ryzyka zależy między innymi od stanów niezawodnościowych urządzeń systemu napędowego statku. Stany te wyznaczają operatorzy w formie lingwistycznej. Parametry formalnego modelu ryzyka wyznacza się siecią neuronową.*

***Słowa kluczowe**: ryzyko, statek, rozmyty, neuronowy.*

1.Introduction

The risk prediction model consists of a dangerous event (DE) module and the event consequence module. The DE connects the two modules - it initiates consequences of particular causes. In the case of propulsion risk (PR), the event DE is immediate loss of the propulsion capability by the ship, i.e. an immediate catastrophic failure (ICF) of its propulsion system (PS). The event may be caused by the PS element failures or operator errors. It is assumed that the model parameter identification will be based on opinions of the ship power plant operators, hereinafter referred to as experts. The opinions will be formulated mainly in a linguistic form, supported to a minimum extent by numerical data.
The ship PS is well developed. In the example of a simple PS presented below, it consists of 11 subsystems (SS) and these of 92 sets of devices (SD) including several hundred devices (D) altogether. The PS sizes, the expert ability to express the opinions necessary to construct a propulsion risk model and the limited number of experts that the authors managed to involve in the study influenced the model form.
The expert investigation methods used in the PR modeling were presented in publications (Brandowski et al. 2008, 2009; Brandowski 2009; Nguyen 2009).

2. The propulsion risk prediction model

The PR model form is determined by data that can be obtained from experts. It is assumed that they elicit annual numbers N of the system ICF type failures, system operating time share in the calendar time of the system observation by the expert $t^{(a)}$ %, linguistic estimation of the share of number of PS fault tree (FT) cuts in the failure number N during a year and linguistic estimation of chance preferences of the occurrence of system ICF specific consequences, on the condition that the event itself occurs. Those opinions are a basis for the construction of a system risk prediction model.
The following assumptions are made as regards the system risk model:

- The system may be only in the active use or stand-by use state. The system ICF type events may occur only in the active use state.
- The formal model of a PS ICF event stream is the Homogeneous Poisson Process (HPP).

It is a renewal process model with negligible renewal duration time. This assumption is justified by the expert opinions, which indicate that ICF failures of PS systems may occur quite frequently, even several times a year, but in general they cause only a relatively short break in normal system operation. Also the exponential time between failures distribution, as in the case of HPP, is characteristic of the operation of many system classes, including the ship devices.

- The HPP parameter is determined in a neural network from data elicited by experts. The network can be calibrated with real data obtained from the system (or a similar systems) operation.
- The failure consequences are determined from data on the chances of occurrence elicited in the expert opinions.
- The operators perform predictions of the system reliability condition and PR, i.e. of the system ICF specific consequences, based on subjective estimations of the analysed system component condition.

For given ICF event a fault tree (FT) is constructed, where the top event is an ICF type PS failure and the basic events are the system minimum cut or cut failures. The notion of minimum cut is generally known. Cut is defined as a set of elements (devices) fulfilling a specific function and loss of that function results in a system ICF. In the case of minimum cut, failures of the same system elements may appear in more than one minimum cuts. Therefore, they are not disjoint events in the probabilistic sense. Besides, obtaining reliable expert opinions on the minimum cut failures is almost unrealistic.

Cuts have defined reliability structures (RS). If those structures and the number of cut failures within a given time interval are known, then the number of failures of particular devices in the cuts can be determined.

The diagram of a model in Figure 1 illustrates the PR prediction within a period of time $t^{(p)}$. The system operator inputs estimated reliability states of the cut elements (block (1) of the model). The elements are devices (D) of the all system cuts. The estimates are made by choosing the value of the linguistic variable *LV = average annual number of ICF events from the set* {*excellent, very small, small, medium, large, very large, critical*} for the individual Ds. The operator may be supported in that process by a database.

Having the reliability states of the FT cuts and their RS structures, average numbers N_{ik} of these cut ICF failures are determined by "operator algorithm" (block (2)). The appropriate methods are presented in section 3 of this paper. They are input data to the neural network.

The neural network, performing generalized regression, determines the system ICF type failure annual number N in the numerical and linguistic values (block (3)). In the first case, the network determines the respective value of an *LV* variable singleton membership function, and in the second case - a corresponding linguistic value of that function. In both cases 7 values of the *LV* were adopted. The network may be more or less complex depending on the number of cuts and the FT structure.

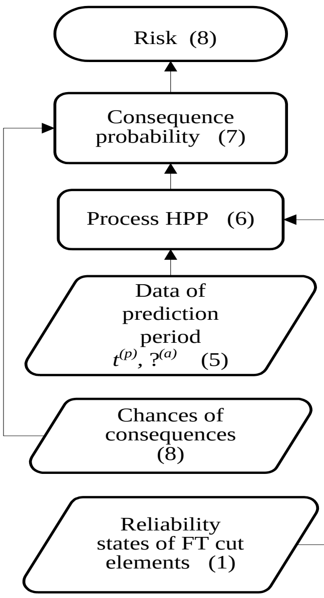

Fig. 1 Diagram of the fuzzy-neuron model of risk prediction

If there is disproportion between the number of entries and the teaching data lot size, then the system FT may be divided at the lower composition levels and then the component networks "assembled" again. In the ship propulsion risk prediction example here below, the ship PS was decomposed into subsystems (SS) and those into sets of devices (SD).
The system reliability condition, according to its operator, i.e. annual number *N* of its ICFs, is presented in a linguistic form by giving the *LV* value determined in block (3) (block (4)).
Input to the model is risk prediction calendar time $t^{(p)}$ [year] and the modeled PS active use time coefficient $\tau^{(a)}$. The prediction time is chosen as needed, in connection with the planned sea voyages.
The probability of the system ICF event occurrence within the prediction time $t^{(p)}$ is determined by a size *K* vector (block (6)):

$$\mathbf{P}\{ICF_k\} = \left[\frac{(\lambda^{(a)} \tau^{(a)} t^{(p)})^k}{k!} e^{-\lambda^{(a)} \tau^{(a)} t^{(p)}} : k = 1,2,\ldots,K \right], \tag{1}$$

where $\lambda^{(a)} = N/\tau\, t$ [1/year] = intensity function (rate of occurrence of failures, ROCOF) related to the active use time, where N = number of the

system ICFs within t = 1 year of observation, with the active use time coefficient τ determined by neural network; k = number of ICFs.
Vector (2) expresses the probability of occurrence of $k = 1,2,\ldots,K$ system ICFs within the prediction time $t^{(p)}$ interval.
Probability of occurrence of specific consequences on the condition of the analysed system ICF occurrence:

$$P\{C/ICF\}, \tag{2}$$

where C = C1 U C2 = very serious casualty C1 or serious casualty C2 (IMO 2005).
This probability value is input by the operator from earlier data obtained from expert investigations for a specific ship type, shipping line, ICF type and ship sailing region. The values may be introduced to the prediction program database.
The consequences C are so serious, that they may occur only once within the prediction time $t^{(p)}$, after any of the K analysed system ICFs. The risk of consequence occurrence after each ICF event is determined by vector whose elements for successive k-th ICFs are sums of probabilities of the products of preceding ICF events, non-occurrence of consequences C of those events and occurrence of the consequences of k-th failure (block (7)):

$$\Re\{C,t^{(p)}\} = \left[P\{C/ICF\}\textstyle\sum_{k=1}^{x} P\{ICF_x\}(1-P\{C/ICF\})^{x-1} : x = 1,2,\ldots,K\right] \tag{3}$$

Risk (3) is presented in block (8).

3. Operator's algorithm

3.1. Cat models

The algorithm allows processing of the subjective estimates of numbers of device D failures, creating FT cuts, into numerical values of the numbers of failures of those cuts, which are the neural network input data. The algorithm is located in block (2) of the prediction model. The data are input to the model during the system operation, when devices change their reliability state. Additionally, the algorithm is meant to aid the operator in estimating the system condition.
The numerical values of the numbers of failures in cuts are determined by computer program from the subjective linguistic estimates of the numbers of failures of component devices D. The estimates are made by the system operators and based on their current knowledge of the device conditions. This is simple when cut is a single-element system, but may be difficult with complex RS cuts. The algorithm aids the operator in the estimates.

Specifically, it allows converting the linguistic values of the numbers of device D ICF events into corresponding numerical values of the cuts. The data that may be used in this case are connected with cuts - the universe of discourse (*UD*) of linguistic variables *LV* of the cut numbers of failures and RS. These numbers are determined from the expert investigations.
Cuts are sets of devices with specific RS - systems in the reliability sense. They may be single- or multi-element systems. They are distinguished in the model because they can cause subsystem ICFs and in consequence a PS failure. Annual numbers of the cut element (device) ICFs change during the operation process due to time, external factors and the operational use.
The conversion problem is consider for the case when in the system FT cuts of subsystems (CSS) are distinguished and in them cuts of sets of devices (CSD). The following CSD notation is adopted:

$$CSD_{ik} = \{e_{ikl} : l = 1,2,\ldots,L\},, \tag{4}$$

where CSD_{ik} = *k-th* cut of i-th subsystem; e_{ikl} = *l-th* element of *k-th* CSD.

The CSD cut renewal process parameters, i.e. intensity functions λ (ROCOF), are determined from the expert investigations of the system PS. In this case, they are applied only to the ICFs causing the loss of CSD function. Annual numbers of failures *N*, whose functions are intensity functions λ, are determined. It may be assumed that the numbers elicited by experts are average values in their space of professional experience gained during multi-year seamanship. Then the asymptotic intensity function takes the form (Misra 1992):

$$\lambda^{(a)} = \frac{N}{\tau t}, \tag{5}$$

where *N* = average number of the analysed system failures during the observation time *t*; *τ* = active use time coefficient; *t* = 1 year = calendar time that the estimate of the number of failures is related to.

We are interested in the ratio of the number of CSD cut ICFs to the number of such failures of the cut elements. It is determined from the formulas of the relation of systems, of specific reliability structures, hazard rate to the hazard rates of their components. It should be remembered that in the case of a HPP the times between failures have exponential distributions, whose parameter is the modeled object hazard rate, in the analysed case equal to the process renewal intensity function λ.

3.2. Fuzzy approach to the cut failure number estimate problem

Our linguistic variables *LV* are estimates of the average annual numbers of ICFs failures N_{ik} of cuts CSD_{ik} and N_{ikl} devices D_{ikl}. We define those variables and their linguistic term-sets *LT-S*. We assume seven-element sets of those values*: excellent, very small, small, medium, high, very high, critical*. We assume that these values represent the reliability state of appropriate objects.
From the expert investigations we obtain the universe of discourse values UD_{ik} of individual cuts. Each of those universes is divided into six equal intervals. We assume that the boundary values

$$N_{ik}^{1}, N_{ik}^{2}, ..., N_{ik}^{7}$$

of those intervals are singleton member functions of the corresponding linguistic variable values LV_{ik}.
The universe of discourse values UD_{ik} are the variability intervals of the N_{ik} numbers of failures of cuts CSD_{ik} and can be expressed as the function of the N_{ikl} numbers of failures of devices D_{ikl}. In the case of a single element RS, parallel RS and with stand-by reserve RS composed of identical elements in terms of reliability, we can easily determine the minimum and maximum numbers of element failures

$$N_{ikl}^{1}, N_{ikl}^{7}$$

of their universes of discourse UD_{ikl} and then the singleton seven-element member functions:

$$N_{ikl}^{1}, N_{ikl}^{2}, ..., N_{ikl}^{7}.$$

If all the cut elements remain in the *excellent state* then the cut is also in the *excellent* state. If all the cut elements remain in the *critical state* then the cut is also in the *critical* state. The situation is more difficult when the cut are not identical in terms of reliability. Then expert opinion-based heuristic solutions must be applied.

4. Case study

The example pertains to the prediction of a seagoing ship propulsion risk. Determination of the probability of loss of propulsion capability is difficult because of the lack of data on the reliability of PS elements and of operators. This applies in particular to the risk estimates connected with decisions made in the ship operation phase.
The object of investigation was a PS consisting of a low-speed piston combustion engine and a constant pitch propeller, installed in a container

carrier operating on the Europe - North America line. The object was decomposed into subsystems (SS) (propulsion assembly and auxiliary installations necessary for the PS functioning - 11 system CS cuts altogether) and the subsystems into sets of devices (SD), which makes 89 subsystem CSS cuts. The system FT consists of alternatives of those cuts.
Using the code (IMO, 2005), five categories of ICF consequences were distinguished, including *very serious casualty C1, serious casualty C2 and three incident categories*. Consequences of the alternative of first two events were investigated (C = C1 U C2).

The consequences are connected with losses. They may involve people, artifacts and natural environment. They are expressed in physical and/or financial values. Detailed data on losses are difficult to obtain, particularly as regards rare events like the C1 and C2 type consequences. They cannot be obtained from experts either, as most of them have never experienced that type of events. In such situation, the risk was related only to the type C consequences of an ICF event.

4.1. Acquisition and processing of expert opinions

The experts in the ICF event investigation were ship mechanical engineers with multi-year experience (50 persons). Special questionnaires were prepared for them, containing definition of the investigated object, SS and SD diagrams, precisely formulated questions and tables for answers. The questions asked pertained to the number of ICF type events caused by equipment failures or human errors within one year and the share of time at sea in the ship operation time (PS observation time by expert). These were the only questions requiring numerical answers.
Other questions were of a linguistic character and pertained to the share of ICF type failures of individual SSs in the annual number of the PS ICF type events and the share of ICF failures of individual SD sets in the annual numbers of SS failures. In both presented cases the experts chose one of five values of the linguistic variables: *very great, great, medium, small, very small*. The elicited linguistic opinions were compared in pairs and then processed by the AHP method (Saaty 1980; Nguyen 2009). The obtained distribution of subsystem shares complies with the engineering knowledge. The greatest shares are due to the main engine and the electric power and fuel supply systems and the smallest - due to the propeller with shaft line.
The experts in the ICF event consequence field were ship mechanical engineers and navigation officers (37 persons). A similar questionnaire was prepared with questions about preferences of possible consequences.

The experts could choose from the following preferences: *equivalence, weak preference, significant preference, strong preference, absolute preference, and inverse of these preferences* (Saaty, 2005; Nguyen 2009). After processing of the so obtained data by the AHP method, a normalized vector of shares of the ICF type event consequences was obtained.

4.2. Some results

Figure 2 presents probability distribution of the occurrence of specific numbers of PS ICF type events depending on its reliability state. Three states were distinguished: excellent, medium and critical. The number of ICF events from 1 to 3 was adopted for each of those states. The probability prediction was performed for the time $t^{(p)}$ = 1 month. The diagram indicates that one ICF type event during 1 month long sea voyage can be realistically expected.

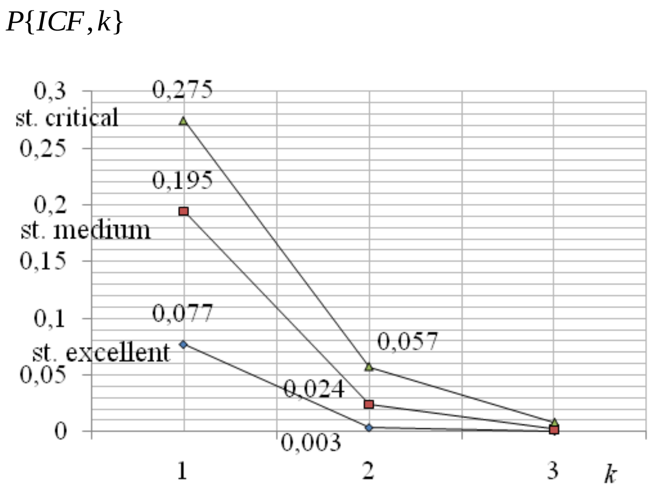

Fig. 2 Probability distribution of the annual numbers of ICF type events for the selected PS reliability states. Prediction time $t^{(p)}$ = 1 month.

Figure 3 presents distribution of PR, i.e. the risk of type C consequences after occurrence of an ICF event, for selected PS reliability states. The diagram shows increased risk with deteriorating PS condition. The change of PS reliability condition from excellent to critical causes more than 3.5-fold increase of the ICF event probability.

The risk in Figure 3 was calculated under the assumption that the type C consequences may occur only once in the prediction time interval.

Therefore, the risk maximum value may be considered its boundary value. The value is 0.025 and occurs after second ICF event, when PS is in a critical state and the prediction time is one month.

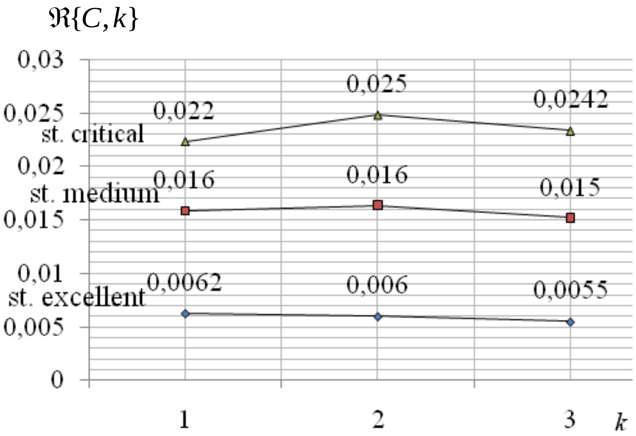

Fig. 3 Risk of type C consequences depending on the number of ICF events and PS reliability state. Prediction time $t^{(p)}$ = 1 month

5. Conclusions

In the expert investigations we have to rely on data obtained from experts and models are constructed from that data. The adequacy and type of obtained information depends on the form and adequacy of the data. The expert competence level must not be exceeded. In the case reported here, it might have happened in the estimates of occurrence of the ICF event consequences. In the authors' opinion, the competence level was not exceeded as the remaining data are concerned, as the choice of experts was careful.

The expert elicited data have an impact on the level of adequacy of models used in the investigations. A number of simplifying assumptions had to be made. Some of them are the following: two states of the use of modeled objects, failures possible only in the active use state, homogeneity of the Poisson renewal process, the cut notion, definition of the ICF event consequences etc.

Results of the propulsion risk estimates quoted in this section are not questionable as regards the order of magnitude of the numbers. Events from the subset of C consequences occur at present in about 2% of the ship population (20 ships out of 1000 in a year). This applies to ships above 500 GT. There are at present about 50 thousand such ships (Graham, 2009). The results are also adequate in terms of trends of changes in the investigated values, which are in compliance with the character of the respective processes.

It has to be taken into account that results of a subjective character may be (but not necessarily) subject to greater errors than those obtained in a real operating process. The adequacy of such investigations depends on the method applied, and particularly on the proper choice of experts, their motivation, as well as the type of questions asked. In the expert investigations the fuzzy methods are especially useful, as they allow the experts to express their opinions in a broader perspective. In the authors' opinion, the main difficulty in the neural network application for modeling is the necessity of having a considerable amount of input and output data for tuning the models. In the prospective investigations the data are generally in short supply. They may be gathered after some time in the operating process of the respective objects, but that may appear to be too late.

1.References

1. IMO, MSC-MEPC.3/Circ.1. Casualty-related matters. Reports on marine casualties and incidents. Revised harmonized reporting procedures. London 2005.
2. Brandowski et al.: *Subjective propulsion risk of a seagoing ship*. Proceedings of ESREL 2008 Conference. Valencia 2008.
3. Brandowski et al.: Risk estimation of a seagoing ship casualty as the consequence of propulsion loss. Proceedings of ESREL 2009 Confernce. Prague 2009.
4. Brandowski A.: *Estimation of the probability of propulsion loss by a seagoing ship based on expert opinions.* Polish Maritime Research 1/2009. Gdansk University of Technology. Gdansk 2009.
5. Saaty T.L.: *The Analytic Hierarchy Process.* New York. McGraw-Hill. New York et al. 1980.
6. Nguyen H.: Application of AHP method in the risk etimation of ship systems. Polish Maritime Research 1/2009. Gdansk University of Technology. Gdańsk 2009.
7. Misra K. B.: Reliability Analysis and Prediction. A Methodology Oriented Treatment. ELSEVIER. Amsterdam, Oxford, New York, Tokyo 1992.
8. Graham P. Casualty and World Fleet Statistics as at 31.12.2008. IUMI Facts & Figures Committee. 2009.

Alfred Brandowski Prof. DSc is working at Gdynia Maritime University in the Department of Engineering Sciences. He studied at Gdansk University of Technology in the Faculty of Shipbuilding and received doctor degree at the same faculty. He received the title of professor of Engineering Sciences in 1990. His specialization is safety science and engineering specially their application to shipping.

Andrew Mielewczyk DSc is working at Gdynia Maritime University in the Department of Engineering Sciences. He studied at the same university. Doctor degree received at the Gdańsk University of Technology in 1999. He received diploma of Chief Engineer Officer for marine practice at general cargo ships in 2006.

Hoang Nguyen DSc received the MSc degree in Power Plants and Propulsion Systems from the Gdańsk University of Technology in 1989, PhD degree in Marine Engineering from the Gdańsk University of Technology in 2001. He is working at Gdynia Marine University in the Department of Engineering Sciences from 1989. His research interests include system reliability modeling, system simulation and risk assessment. He is a fellow of the PRSA.

Wojciech Frackowiak MSc is PhD student and employee of Marine Engineering Department at Gdynia Maritime University since 2002. Received MSc diploma in Marine Propulsion Plants in 2002. From 2002 -2010 participant of marine propulsion system reliability research projects. He holds the Marine 2nd Engineer Certificate.