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Fuzzy–neuron Model of the Ship Propulsion Risk

A. Brandowski, A. Mielewczyk, H. Nguyen & W. Frackowiak
Gdynia Maritime University, Poland

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. The model may be useful in the ship operation decision processes.

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) (Brandowski 2005, Brandowski et al. 2007, 2008, 2009a). 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 modelling were presented in publications (Brandowski 2005; Brandowski et al. 2007, 2008, 2009a; 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.
- Linguistic estimation of chances or 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 catastrophic failures (CF) of some systems may occur quite frequently, even several times a year, but in general they cause only a relatively short break in normal system operation. Serious consequences with longer breaks in the system operation are less frequent. 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 (Modarres et al. 1999, Podsiadlo 2008). It is appropriate when defects of the modeled object and the operator errors are fully random, abrupt and no gradual, without wear and/or ageing-type defects. This corresponds with the situation where inspection and renewals are regularly carried out and prevent that type of defects.

The following assumptions were made with reference to the model:

- 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 which 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. Also in the case of a PS ICF event cause decomposition to the minimum cut level the number of basic events in the FT increases considerably - the top event decomposition is deeper. The more basic events it contains, the more data are needed to tune the neural network in a situation when the number of competent experts available is generally very limited. In the case of cuts (not minimum cuts), they can be arranged to form a complete set of events. The failure numbers are then easier to estimate by experts as the cuts include more devices. Such failures are serious events in the ship operation process, very well remembered by the experts. Besides, there are generally fewer cuts than minimum cuts in the FTs.

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 {minimum, 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.

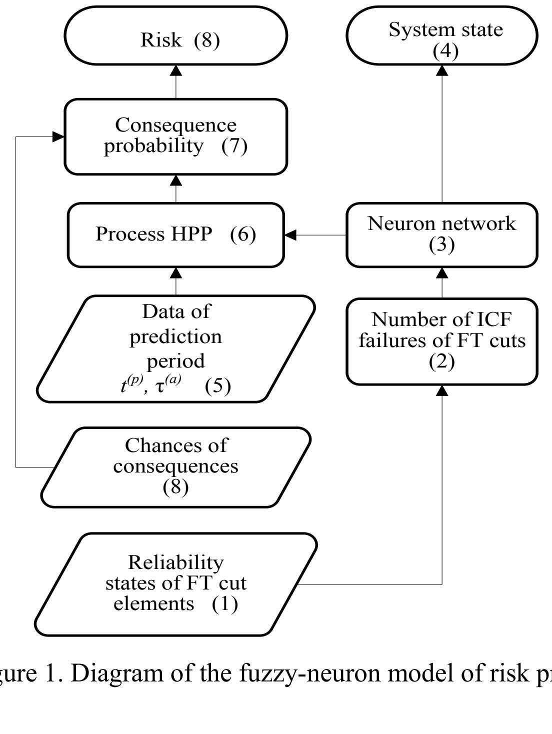

Figure 1. Diagram of the fuzzy-neuron model of risk prediction

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.

The neural network is built for a specific PS, according to its properties and size. Each cut at the FT lowest level implies an entry to the network. The network error decreases with the increasing amount of data. We are interested in teaching data with errors fulfilling some statistical standards and that depends on the number and appropriate choice of experts.

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 PR 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 PS active use time coefficient:

$$\tau^{(a)} = (t^{(a)}/100)\, t^{(p)} \tag{1}$$

where $t^{(a)}$ % = propulsion system active use time as a share of prediction calendar time $t^{(p)}$ (approximately equal to the share of ship at sea time).

The value of $\tau^{(a)}$ coefficient is determined by operator from the earlier or own estimates.

The probability of the system ICF event occurrence within the prediction time $t^{(p)}$ is determined by a size K vector (block (6)):

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

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,…,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:

$$P\{C/ICF\}, \tag{3}$$

where C = C1 $\cap$ 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)):

$$\Re\{C, t^{(p)}\} = [P\left\{C/ICF\right\}\sum_{k=1}^{x} P\{ICF_x\} (1 - P\{C/ICF)^{x-1} : x = 1,2,\dots,K], \tag{4}$$

Risk (4) is presented in block (8).

3 OPERATOR'S ALGORITHM

3.1 *Cut 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. They 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 D device 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 for defined RSs. 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 presented 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:

$$\mathrm{CSD_{ik}} = \{\mathrm{e_{ikl}}, \mathrm{l} = 1,2,\ldots,\mathrm{L_{ikL}}\},, \tag{5}$$

where $\mathrm{CSD_{ik}}$ = *k-th* cut of i-th subsystem, k =1.2,…,K, i = 1,2,…,I; e_{ikl} = *l-th* element of *k-th* CSD, l = 1,2,…, L.

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):

$$\lambda^{(a)} \cong \frac{\bar{N}}{\tau\, t}, \tag{6}$$

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 dependence on 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, failure rate to the failure 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 failure rate, in the analysed case equals to the process renewal intensity function λ. The formulas for the ship system CSD cut reliability structures are given below.

In the case of a single-element structure, the annual numbers of the cut failures and device failures are identical.

$$N_{ik} = N_{ikl},\ \ i \in \{1,2,\ldots,I\},\ \ k \in \{1,2,\ldots,K\}, l = 1, \tag{7}$$

where N_{ik} = annual number of failures of *k-th* cut in *i-th* subsystem; N_{ikl} = annual number of failures of *l-th* device.

In a series RS, the number of system failures is a sum of the numbers of failures of its components.

$$N_{ik} = N_{ik1} + N_{ik2} + \cdots + N_{ikl} + \cdots + N_{ikL} \tag{8}$$

A decisive role in that structure plays a "weak link", i.e. the device with the greatest annual number of failures. The CSD cut number of failures must then be greater than the weak link number of failures.

In a two-element parallel RS, we obtain from the average time between failures formula (Misra, 1992):

$$N_{Ik} = \frac{N_{ik1}^2\, N_{ik2} + N_{ik1}\, N_{ik2}^2}{N_{ik1}\, N_{1k2} + N_{ik1}^2\, N_{1k2}^2} \tag{9}$$

If one element in that structure fails then it becomes a single element structure. Similar expressions can be easily derived for a three-element parallel structure.

In the structures with stand-by reserve, only part of the system elements are actively used, the other part is a reserve used when needed. The reserve is switched on by trigger or by the operator action. The trigger and the system functional part create the series reliability structure. When the trigger failure rate is treated as constant and only one of the two elements is actively used (L = 2), then:

$$N_{ik} = N_{ik}^{p} + \frac{N_{ik1}\, N_{ik2}}{N_{ik2} + N_{ik1}}, \tag{10}$$

where $\boldsymbol{N_{ik}^{p}}$ = annual number of trigger failures.

In the case of a three-element structure (L = 3) with two stand-by elements, we obtain:

$$N_{ik} = N_{ik}^{p} + \frac{N_{ik1} N_{ik2} N_{ik3}}{N_{ik2} N_{ik3} + N_{ik1} N_{1k3} + N_{ik1} N_{ik2}}. \tag{11}$$

In the load-sharing structures, as the expert data on the number of failures in the case when entire cut load is taken over by one device are not available, a parallel RS (equation (9)) is adopted.

In operation, the CSD cut elements may become failure and cannot be operated. If in a two-element RS with stand-by reserve one element is non-operational then it becomes a single element structure. If in a three-element RS with stand-by reserve one element is non-operational then it becomes a two-element structure with one element in reserve. If in that structure two elements are non-operational then it becomes a single-element structure. Identical situation occurs in the case of element failures in the parallel RS systems.

3.2 *Fuzzy approach to the cut failure number estimate problem*

Our variables *LV* are estimates of the average linguistic annual numbers of ICFs failures N_{ik} of cuts $\mathrm{CSD_{ik}}$ and N_{ikl} devices $\mathrm{D_{ikl}}$, i = 1,2, ,I, k = 1,2,…,K, l = 1,2, …,L. We define those variables and their linguistic term-sets *LT-S*. We assume seven-element sets of those values*: minimum, 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

$$N_{ik}^{1}, N_{ik}^{2}, \dots, N_{ik}^{7}$$

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 numbers of failures of cuts CSD_{ik} appearing on the left hand sides of equations (7) – (11). In the case of a single element RS, parallel RS and with stand-by reserve composed of identical elements in terms of reliability, we can easily determine the minimum and maximum numbers of element failures.

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

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

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

If all the cut elements remain in the *minimum* state then the cut is also in the *minimum* 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 elements 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 FT of analysed PS is shown in the Figure 2. For reasons of huge number of SDs the structure of fuel oil subsystem is only described within the lowest FT level. The object was decomposed into subsystems (SS) (propulsion assembly and auxiliary installations necessary for the PS functioning - 11 SSs altogether) and the subsystems into sets of devices ((SD) - 92 sets altogether). Each SS makes the CSS cut and each SD – the SDC cut. In considered case the system FT consists of alternatives of those cuts. In general such FT structure doesn't have to appear in the case of PS.

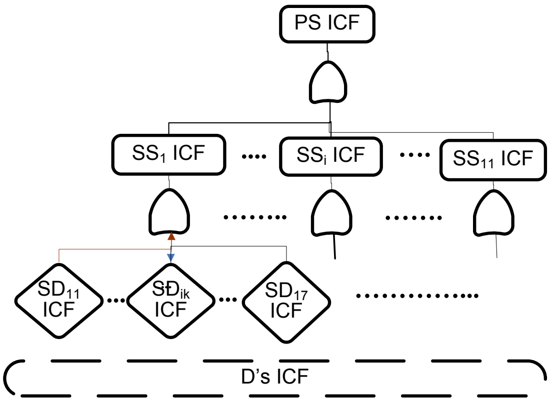

Figure 2. Fault tree of a ship propulsion system ICF
Legend: PS – propulsion system; ICF – immediate catastrophic failure;
SS_i – subsystem, i =1 -fuel oil subsystem, 2 -sea water cooling subs.; 3 – low temperature fresh water cooling subs.; 4 – high temperature fresh water cooling subs.; 5 – startig air subs.; 6 – lubrication oil subs.; 7 – cylider lubrication oil subs.; 8 - electrical subs.; 9 – main engine subs.; 10 – remote control subs.; 11 – propeller + shaft line subs.
SD_{1k} – set of devices; ik = 11 - fuel oil service tanks; 12 – f. o. supply pumps; 13 – f. o. circulating pumps; 14 – f. o. heaters; 15 -filters; 16 – viscosity control arrangement; 17 - piping's heating up steam arrangement.

The FT allowed the building the neural network. The sets of input signals for the network were assigned.

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 ∩ 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 schemes, 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 in number). A similar questionnaire was prepared with questions about preferences of 5 possible consequences (*C1 - very serious casualty, C2 - serious casualty and 3 types of incidents*) of the ICF type event occurrence. The casualty types were defined in accordance with the code (IMO, 2005). 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*

The PR model was subjected to a broad range of tests. Some of the results are presented below. Figures 3 and 4 present the probability of the occurrence of defined numbers ICF type events of PS in dependence on the prediction time, when PS is in excellent and critical reliability states. The number of ICF events from 1 to 5 was adopted for each of those states. The probability was performed for the prediction time $t^{(p)}$ = 1, 3 and 6 months. The diagrams 3 and 4 indicate that the occurrence of ICF events and their numbers are significantly greater when PS is in the critical state than in excellent state.

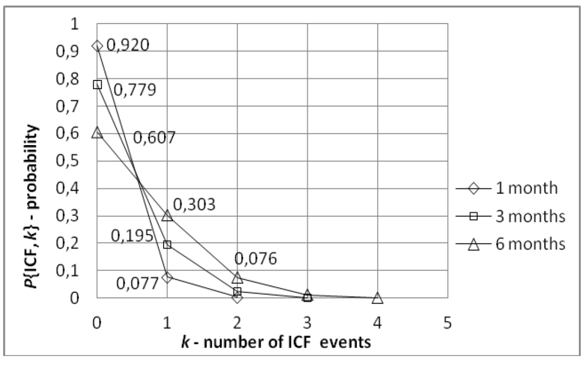

Figure.3. Probability of the ICF type events versus the numbers of those events for the selected times of risk prediction. PS reliability state is excellent.

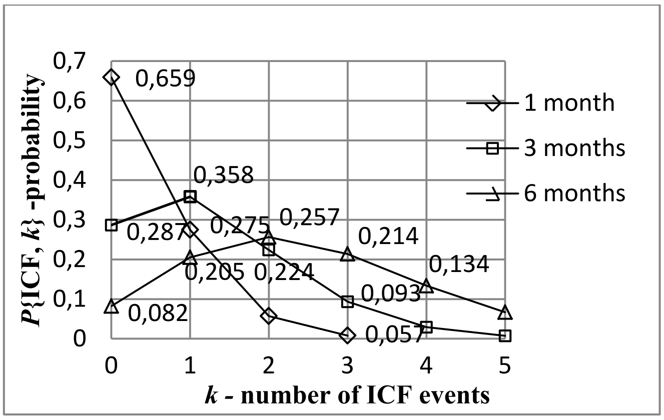

Figure 4. Probability of the ICF type events versus the number of those events for the selected times of risk prediction. PS reliability state is critical.

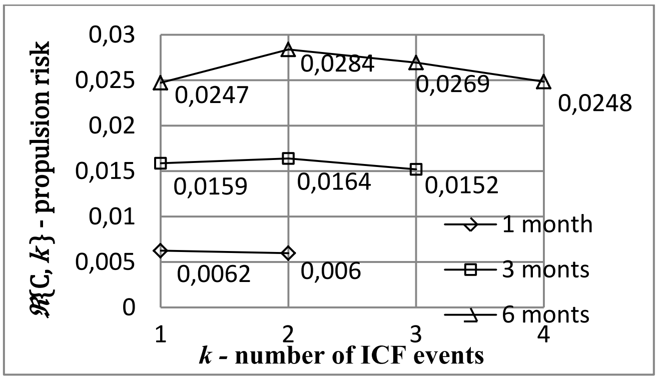

Figure 5. Propulsion risk versus the numbers of ICF events for selected prediction times. PS reliability state excellent.

Figures 5 and 6 presents the PR risk, i.e. the risk of type C consequences after occurrence of an ICF event, for the prediction times $t^{(p)}$ = 1, 3 and 6 months, when PS is in the excellent and critical for states. The diagrams show increased risk with deteriorating PS reliability.

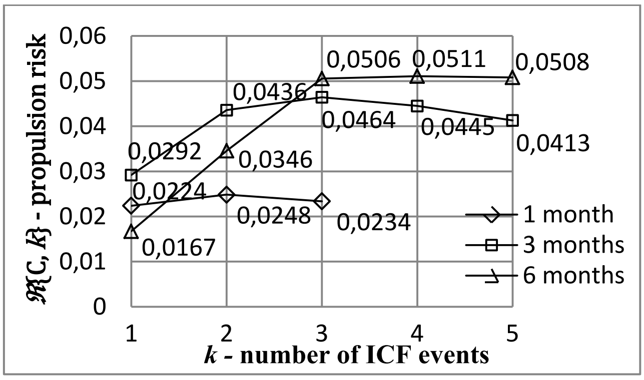

Figure 6. Propulsion risk versus the numbers of the ICF events for selected times of prediction. PS reliability state is critical

5 SUMMARY

A fuzzy-neural model of risk prediction has been developed, based on the knowledge acquired from experts. It is a model of homogeneous Poisson renewal process, where parameters are determined by means of a neural network. The model parameter estimation data were acquired from experts - the modeled system operators. Their opinions were elicited in a numerical form as regards the events observed by them many times and in a linguistic form in the cases where their knowledge might be less precise. The neural network was tuned with the elicited opinions. The network may be calibrated with data collected in the system operation process. In this way the Homogeneous Poisson Process can be adapted to real operating conditions - it becomes non-homogeneous in steps. The model allows prediction of the risk of dangerous events consequences, which may occur due to different systems.

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 - like data like model. 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 section 4 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; Podsiadlo 2008). 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.

There is a chance of further developing and using the risk prediction program, developed under the project, aboard ships and not only for the propulsion systems. It could be coupled with the existing equipment renewal management or operating management programs.

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