On risk assessment and decision-making while controlling the ship in adverse weather conditions

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Abstract

As worldwide statistics show [Gale, Patraiko 2007], the increase of ships' size and their technical equipment haven't significantly changed the environmental influences upon them. . .

Ships continue to be lost at sea and suffer heavy damages, such as shifting and loss of cargo, damage or full destruction of deck arrangements and mechanisms, and experiencing cracks and bends in their construction. Additionally, heavy seas decrease ship speed, worsen the comfort of the crew and passengers, and make it difficult to maintain the terms of cargo delivery.
Handling of the ship in the seaway either from practical or from theoretical point of view is one of the most complicated and hard-to-research navigational problems. Mostly, it is connected with the incompleteness and uncertainty of the initial information and environmental conditions, and the multivariate nature of the decision-making problem.

Keywords: *ship, adverse weather conditions, decision-making, intelligence system, neural fuzzy network.*

1 Introduction

A ship passing through storm areas is subject to a series of negative influences and phenomena that may be met in different combinations such as:

- Heavy pitching and heaving accompanied with green water & slamming effects.
- Pitch induced rolling, parametric resonance.
- Synchronous rolling (resonance).
- Reduction of transverse stability.
- Loss of steering, broaching.

All these phenomena can lead to:

- Risk of hull damage due to stresses and vibrations (especially in head waves).
- Risk of losing the deck cargo due to significant accelerations on deck, and green water effect.
- Risk of capsizing (in case of significant reduction of transverse stability, or broaching).
- Crew and passengers fatigue.
- Speed reduction as a result of added resistance & propeller emersion.

Generally the problem of the optimal control of the ship in adverse weather conditions can be solved in two stages:

- Preliminary planning based on the weather forecasts; choosing the optimal safe route;
- Real-time decision-making, adjusting the control mode of the ship (velocity and heading) based on the ship's actual conditions and weather conditions in the stormy area.

The approximate prediction of the ship's behavior on route planning can be roughly estimated using general simplified formulas as presented in Kozyr and Aksutin [2006]. A more accurate prognosis can be achieved using strip theory [Jornee, Massie 2001] or other specific calculations. Usually the main uncertainties in such calculations are in the stochastic nature of the environmental disturbance and highly non-linearity of the ship's behavior.

The onboard assessment of the ship's actual condition on the basis of conventional measuring devices present on most ships (clinometer, gyro compass, log) is not always sufficient. Also, any predictions using conventional diagrams [IMO MSC 1228, 2007] may be inaccurate due to their initial generality and probability of having two or more irregular wave systems in the area.

Thus more accurate calculations using specific software -- together with the support of specific sensors to access the real condition of the ship and the weather -- are needed to assist the navigator in solving this complicated problem.

The increase in computer efficiency, together with the use of probability theory, mathematical statistics and soft computing conceptions nowadays, makes possible the development of an intelligent system for monitoring and providing decision-making support of the navigator handling the ship in the seaway (ISS – Intelligent Seakeeping System).
Generally such a system should have following properties [Nechayev, 2001]:

- The capability to work with incomplete, inaccurate and out-dated information;
- Self-organization and learning capability (self-tuning);
- Robustness;
- The possibility of adaptive reaction due to unplanned events;
- A focus on information from technical devises;

- The capability of analysis and prognosis of plant dynamics;
- A guaranteed time of response;
- Integration of on-board software;
- Separation of operator and ISS functions.

ISS can be divided by following subsystems (fig. 1):

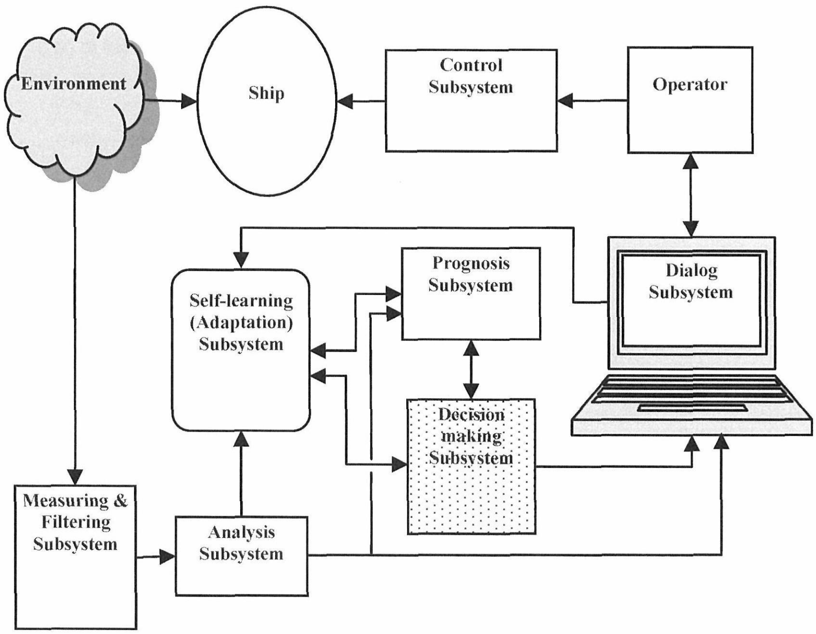

Fig. 1.Intelligence seakeeping system structure.

ISS can be divided by the following subsystems (Fig. 1):
- Measuring and data processing subsystem;
- Analyzing subsystem;
- Prognosis subsystem;
- Decision making subsystem;
- Dialog (output) subsystem;
- Self-organization subsystem;
- Operator.

Obviously, the target section of such ISS is the *decision-making subsystem*, which, depending on the properties of controlled plant and prevalent conditions, generates recommendations for the operator, for instance on the display screen, or sends the signals directly to the control loop.

As mentioned above, in conditions of incomplete initial information and uncertainty of environmental disturbances it is quite difficult to calculate accurately the control mode needed for the ship (course, speed, ballast displacement, autopilot parameters). However, a sufficiently close solution to the problem can be obtained using self-tuning fuzzy-neural networks, which are widely described in the literature, for instance *Borisov et al* [2007].

2 Linguistic approach

The use of fuzzy logic allows us to divide each input and output parameter on fuzzy sets, that can initially be defined in terms of linguistic variables ("*significant rolling amplitude*", "*frequent slamming*" etc.), consisting of intersecting membership functions. That means that each value of the set belongs to one or other linguistic term with defined probability. For instance, rolling amplitude $\theta_{max} = 1°$, belongs to the term "*significant rolling amplitude*" with the probability $P \rightarrow 0$, and to the term "*minimal rolling amplitude*" with the probability $P \rightarrow 1$. In such a way the data coming to the network is input and then processed by a series of mathematical transformations well known from the fuzzy logic theory. On the output, depending on the properties of the net, we obtain fuzzy or discrete values, describing one or other recommendation. In linguistic terms the logical chain of recommendation processing can be given as follows:

INPUT

sea condition:	7 force wave
wave relative direction:	port bow
wave length:	medium
slamming occurrence:	frequent slamming
pitching occurrence:	significant pitch amplitudes
ship's speed:	full ahead
risk:	bending forces applied to the hull exceed safe limits

OUTPUT

fuzzy solution:
reduce the speed significantly;

fuzzy limited solution:
reduce the speed by 4-5 knots;

deterministic solution:
reduce the speed by 4.5 knots.

It should be noted that such a format can be used for the implementation of the interface as a method of dialog of ISS with the operator, however the calculation by itself is based on a strict and complicated mathematical origin, working with discrete, fuzzy and stochastic values.

3 Neural-fuzzy network operation principles and adaptation method.

Generally the operation principle of neural-fuzzy network for decision-making can be described as shown below.
Measuring, analysis and prognosis subsystems send to the network input *m* of antecedents. Let's denote X (M x N) $\in \Re$ as set of all possible antecedents, Y (I x J) $\in \Re$ - set of all possible conclusions (recommendations). M – quantity of input parameters, N – size of the vector of all possible values of an input parameter, I – quantity of output parameters, J - size of the vector of all possible values of an output parameter. Initially in prescribed subsystem any m antecedents can cause I x J conclusions. That means that the calculated probability of efficiency of each solution with current antecedent P(X) = 1.
It's obvious that the network training process consists of finding the values of weight coefficients that determines the relevance of the connections between antecedents and conclusions.

It should be noted that such neural networks contain the competitive type neurons; i.e. on the output of the net not the weighted sum of all neurons is obtained, but the defined quantity of neurons having the highest weights (initially this principle was used in the problems of classification) [Haykin, 2006].

As the main goal of the system is to advise the operator on the optimal control mode for the ship, satisfying the objective function for optimization in this case means the minimization of the general influence of the negative factors impacting the ship in bad weather, for instance: significant ship's oscillations in all directions, additional wave resistance, slamming and green water effects, propeller immersion, reduction of transverse stability, significant probability of broaching, capsizing etc.

The decision making subsystem tuning (training) process can be divided into the next four stages.

Stage 1. By means of an expert appraisal on the operator's level, obviously wrong connections between inputs and outputs (P(X) = 0) are discarded.

Stage 2. The mathematical model of interaction between plant and environment is used. Calculating these data by use of the mathematical model we obtain the set of optimal solutions as a first approximation.

Stage 3. Further adjustment can be performed by the trial tests in the towing tanks that allows significant reduction of wrong solutions made by the systems installed on the real ship.
After preliminary fine-tuning, the ISS unit can be installed on the ship. Generally this unit can appear as a software application integrated into the integrated bridge system, having access to all needed sensors or a fully independent computational block directly connected to the measuring system.
During the operation of the ship, dependending on the measuring system installed on board, part of data necessary for the assessment of ship seakeeping conditions is obtained from sensors (e.g. list, trim and yaw angles), part to be input by the navigator (e.g. if tensor sensors are absent on the ship, the quantity of slamming occurrence during the prescribed period to be input manually).

Step 4. During the ship operation described above, depending on the sea and ship conditions, the system generates the variety of possible ship handling modes in descending order (solutions with the highest probability of effectiveness on top), and the results of ship motion prognosis after performing the maneuver, calculated using the mathematical model. The operator in turn chooses one of the solutions or makes his own, inputting new prescribed motion parameters into the system. After carrying out the maneuver, the system analyses the ship's condition during the prescribed period and "makes conclusion" about efficiency of the decision made. After the weight of this solution with preceding antecedents to be increased or decreased by prescribed rule, that provides the self-learning and adaptive properties of the ISS.

4 Conclusion

Thus, such a conception allows the minimization, on the one hand, of errors in decision-making arising from the inadequacy of basic mathematical models and, on the other hand the incorrectness of expert or operator solutions. However generated solutions should be based not only on strict mathematical calculations, but also on statistical analyses of information, coming from the ship's sensors and on "good seamanship".

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