Probabilistic modeling of navigation bridge officer's behavior

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***Abstract* — The performance of a navigating officer in critical situations is uncertain and has to be considered in a probabilistic framework, since this may provide an in depth insight in the human – machine interaction. Such a systematic approach will have the objective to understand, to predict and to minimize the role of the human as a causal factor for a casualty in terms of the time sequence needed to perform particular tasks during collision or grounding avoidance activities. By employing the exponential law, it is possible to quantify the cognitive processes of information acquisition, analysis, categorization, decision making and action implementation. Consequently, the minimum required time where an automated system may intervene is determined. In this way, it is expected that it is plausible to prevent the occurrence of a close encounter that could escalate in an accident. Albeit to the lack of an available and appropriate data set, the proposed concept is examined through the small sample results of a published simulation study.**

Keywords — marine accidents; human factors; probabilistic model; automation; cognition

I. Introduction

A combination of standardized training, regulations and advancements in technology has undoubtedly enhanced safety in the maritime industry over the past 100 years. Despite this, residual risks do exist for the sector, as well as emergent risks which result, sometimes unpredictably, from changes in the industry itself and also from changes in the social, economic and political context of shipping. In fact, many of the current risks in shipping are generally associated with human element issues or human factors. In common with other industries, those risks can be associated with problems or failures in organizational management, mistakes on the part of individuals and failures in the supply or recruitment of sufficiently competent workers. Investigations indicate that about 75-95% of maritime accidents can be attributed to human error, whilst a significant proportion of these are caused by fatigue and attention deficit [1]. Although it is widely accepted that the introduction of the International Maritime Organization's (IMO) International Safety Management (ISM) Code has definitely contributed to the promotion of a safety culture and has been dealing with human element aspects, accidents still happen. Recent research indicated that the proactive nature of ISM Code (i.e. the recognition that accidents can be prevented as long as correct procedures and established best practice are followed) has not been realized, whereas possible solutions to safety problems are unfortunately determined in the aftermath of major casualties (reactive approach) [2].

Through the conduct of questionnaires, this considerable gap between the expected outcome of ISM Code and its practice could be attributed to the different cultures aboard and ashore, as well as the fact that the Code is viewed as an administrative tool, mere a regulatory exercise leading to increased paperwork [3]. However, the difficulty with organizational assessments is that they usually depend on observations and interviews with the results relying on the assessor. Therefore, it is suggested to integrate more systematically the human and organizational factors in safety studies and accept that they are as important as the technical aspects [4]. Indeed, published work provides evidence that the incorporation of human factors in marine risk assessments has gained increased popularity. The adopted approaches can vary from integrating human reliability methods with artificial intelligence techniques [5], analyzing the role of human error with Bayesian network [6, 7, 8, 9] and extending it with fuzzy techniques [10], or utilizing classical probability theory [11].

Despite the aforementioned developments, it is necessary to follow an empirical method that does not necessarily look into gaining an understanding of erroneous behavior or the cognitive processes involved, but instead it provides a realistic and simple model to enhance the human operator's reaction time. Thus, it is the purpose of the current paper to quantify the performance of a navigating officer in critical situations within a probabilistic framework. The paper's structure is as follows: in section II the proposed model is outlined, whilst section III deals with its evaluation. Section IV discusses possible implications and section V concludes.

II. Probabilistic Model of Navigator

The navigator's behavior (common to all humans) is usually dependent on the desire to acquire, to understand, to organize and to analyze knowledge of the external environment in a hierarchical order [12]. This need can be described by three separate (mutually exclusive and independent) cognitive processes. The lowest level need is related to handling the observed information and includes filtering, comprehension and retrieval, relating and grouping and prioritization (information pre-processing). Once this need has been met, the

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satisfaction desire moves on to the next level. Hence, the navigator's complex diagnosis and decision making activities are translated into problem statements involving a series of solutions to be selected upon the available situation assessment and response planning (decision making). Finally, the execution of the previously made decision takes place, which is characterized by skill based activities with minimum mental effort [13].

In particular, information pre-processing has the objective to identify potential hazards seen on the horizon or radar screen, to obtain weather data, to understand the current marine traffic situation and to narrow the field of monitored observations. Visual look out is kept and a number of standard navigational equipment is utilized (binoculars, radar, compass, ECDIS – Electronic Chart Display Integrated System, GPS – Global Positioning System, ARPA – Automatic Radar Plotting Aid, charts, air whistle, VHF – Very High Frequency radio) for performing this task. Consequently, taking into account the rules for collision avoidance and the visible information about target path and intention, alternatives for course change or track keeping are examined, leading to a set of internal commands that have to be formulated (decision). Then, an action sequence will be performed to maneuver own vessel [14, 15]. In such circumstances, the challenge is to quantify on a probabilistic basis the role of the aforementioned cognitive demands in terms of reaction time.

A. Formulation of the model

In accordance with the previous discussion, let's assume that the time course of conducting navigation activities is a random variable T consisting of other three random variables: the time x_1 for information pre-processing, the time x_2 for decision making and x_3 the time for task execution (see fig. 1). Published work on human cognition has shown that these variables could be modelled through the exponential law [16], which is only defined for positive values [17]. As long as each process is realized by evaluating the received input, the satisfaction desire decays over time, which can be modeled by a simple negative exponential function (see inset of fig. 1).

During the information pre-processing activities, the assertion exists that as soon as raw data are filtered, are rearranged and are correlated in order to generate facts, the navigation officer becomes aware of the situation and possesses the knowledge as well as the experience on how to proceed. In turn, the acquired observations are sent to the next activity level, articulating decay in the cognitive load. Hence, the probability density for x_1 is:

$$f_1 = \lambda_1 \exp(-\lambda_1 x_1) \tag{1}$$

With $\lambda_1 = 1 / \beta_1$, where β_1 is the critical time threshold for information pre-processing.

The officer then, having the capability to identify a certain number of patterns of interest albeit to relevant constraints (discussed earlier in section II), extrapolates as early as possible the appropriate course. Once again, the decision is fed to the final level and the cognitive load is reduced. Thus, the probability density for x_2 is:

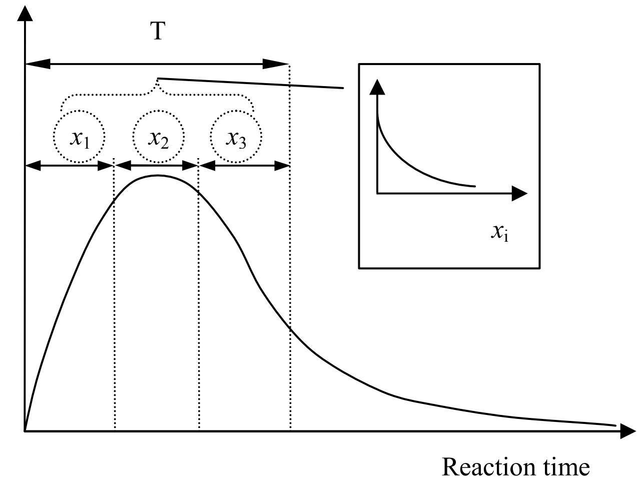

Fig. 1. Schematic representation of the model. The inset shows the progression for each cognitive process.

$$f_2 = \lambda_2 \exp(-\lambda_2 x_2) \tag{2}$$

With $\lambda_2 = 1 / \beta_2$, where β_2 is the critical time threshold for decision making.

Finally, the full potential of accomplishment is conceived by the officer, which it decays as a function of time upon the action sequence is completed. Therefore, the probability density for x_3 is:

$$f_3 = \lambda_3 \exp(-\lambda_3 x_3) \tag{3}$$

With $\lambda_3 = 1 / \beta_3$, where β_3 is the critical time threshold for information pre-processing.

Since the three processes are assumed to be independent, the sum of independent random variables is given by the convolution of their density functions, which under the associative property [18], first the sum of $u = x_1 + x_2$ is calculated and then the sum $T = u + x_3$. Hence:

$$f_u = \int_{-\infty}^{+\infty} f_1(u - x_2)\, f_2(x_2)\, d x_2$$

$$= \int_{0}^{+\infty} f_1(u - x_2)\, f_2(x_2)\, d x_2$$

$$= \int_{0}^{u} f_1(u - x_2)\, f_2(x_2)\, d x_2 + \underbrace{\int_{u}^{+\infty} f_1(u - x_2)\, f_2(x_2)\, d x_2}_{u - x_2 < 0 \rightarrow f = 0 \text{ for } x_2 \in (u, +\infty)}$$

$$= \int_{0}^{u} f_1(u - x_2)\, f_2(x_2)\, d x_2 \tag{4}$$

The density function for the sum u is:

$$f_u = \lambda_1 \lambda_2 (\exp(-\lambda_1 u) - \exp(-\lambda_2 u)) / (\lambda_2 - \lambda_1) \qquad (5)$$

Similarly to the logic of (4), the probability density function of the total time T yields:

$$f_T = \int_0^T f_u(T - x_3)\, f_3(x_3)\, d x_3$$

$$= \left\{ \begin{array}{l} \dfrac{\lambda_1 \lambda_2 \lambda_3 (\exp(-\lambda_1 T) - \exp(-\lambda_3 T))}{(\lambda_1 - \lambda_2)(\lambda_1 - \lambda_3)} \\ -\dfrac{\lambda_1 \lambda_2 \lambda_3 (\exp(-\lambda_2 T) - \exp(-\lambda_3 T))}{(\lambda_1 - \lambda_2)(\lambda_2 - \lambda_3)} \end{array} \right\} \qquad (6)$$

The cumulative distribution function is obtained as:

$$F_T = \int_0^T f_T \, dT$$

$$= \frac{\left\{ \begin{array}{l} \lambda_1^2 (\lambda_2 (\exp(-\lambda_3 T) - 1) - \lambda_3 (\exp(-\lambda_2 T) - 1)) \\ -\lambda_1 (\lambda_2^2 (\exp(-\lambda_3 T) - 1) - \lambda_3^2 (\exp(-\lambda_2 T) - 1)) \\ -\lambda_2 \lambda_3^2 (\exp(-\lambda_1 T) - 1) + \lambda_2^2 \lambda_3 (\exp(-\lambda_1 T) - 1) \end{array} \right\}}{\lambda_2 \lambda_3^2 - \lambda_2^2 \lambda_3 - \lambda_1^2 (\lambda_2 - \lambda_3) + \lambda_1 (\lambda_2^2 - \lambda_3^2)} \qquad (7)$$

III. Evaluation of the Model

The model parameters are evaluated by the bridge simulator results reported in [19] where the collision avoidance behavior of subjects was measured, i.e. the response time to identify close encounter target and take action in accordance with the rules. The sample included 15 values with average 351 seconds and standard deviation 145 seconds. Although the data values are few, they are considered adequate to justify the rationality of the proposed concept. It is noted that the assembly of a complete data set is thought to be out of the scope of the current paper. The parameters in (7) are estimated with the optimization technique proposed in [20], where the absolute value difference between the observed and fitted (parametric) distributions has to be minimized. The calculated chi-square test statistic $\chi^2 = 0.1296$ is significantly lower than the chi-square value ($\chi^2_{95}(11) = 19.6751$). This means that chances are greater than 1 in 20 that the observed data match the hypothesized distribution model. In this case, the model should not be rejected. The threshold times are:

Critical time for information pre-processing $\beta_1 = 157.406$ seconds.

Critical time for decision making $\beta_2 = 92.902$ seconds.

Critical time for action implementation $\beta_3 = 136.351$ seconds.

The prevalence of information pre-processing indicates the strong influence of experience and training in the navigator's situational awareness.

The total time is thus $T = \beta_1 + \beta_2 + \beta_3 = 386.659$ seconds.

This entails that when the navigator exceeds the above time threshold the possibility for collision is increased. The value can be easily calculated by applying Bayes' rule. Let's assume that B is the event of an accident with A_1 and A_2 its partitions for $t < T$ and $t > T$ respectively. It becomes straightforward that:

$$P(A_2|B) = (P(A_2)\, P(B|A_2))/(P(A_2)\, P(B|A_2) + P(A_1)\, P(B|A_1)) \quad (8)$$

The probability that when $t > T$ an accident is likely to occur, yields from (8) by substituting:

$$P(A_2|B) = (9/15\ 3/15)/(9/15\ 3/15 + 6/15\ 12/15) = 27.3\%$$

This value is attributed to the safety margin prior to the collision risk time boundary (see fig. 2) and can potentially reach up to 60%. To this end, it could be argued that, the navigator's reaction time need not be exceeded, if the system intervened with the ultimate goal to avoid any critical encounter that could lead to an accident.

Bringing in mind the automation levels proposed in [21], it is asserted that the collision avoidance system is currently set at level 4 in which a maneuver alternative is suggested, but the navigator retains the authority for executing it or choosing another one. In connection with the aforementioned, it may be possible to justify higher level (i.e. 6 or above) of decision making and action implementation during critical situations in which there is insufficient time for the navigator to respond reliably. At such level, the system may give only a limited time

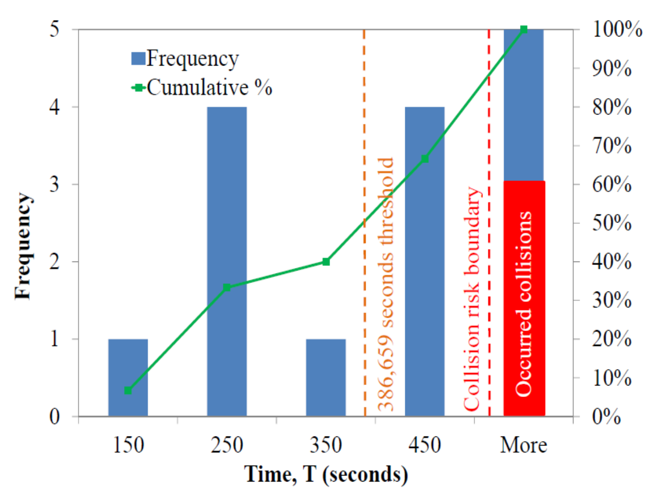

Fig. 2. Histogram of bridge simulator measurements showing the critical threshold time and the collision risk boundary. Note that 60% of the experiments occurred in the time bin more than 450 seconds resulted to collisions

T for example, awaiting the navigator's reply before carrying out the selected decision (diversion – keep course or change track). It is noted that such system shall be designed with the capability to acquire, to analyze and to interpret information from multiple sources simultaneously and to issue the selected decision without the navigator's involvement. Of course, the navigator may exercise acknowledgement and may have the opportunity for review (if required), prior to its execution. It should be stressed that, based on a particular traffic situation, weather, location, vessel characteristics or incomplete input, the system may accept its automation functionality to be degraded. In that sense, it is necessary to determine the specified limits for the system's purely advisory role, i.e. operation at a lower automation level. This mechanism can act as a safeguard when the system generated alternative is not contextually appropriate.

A. Model Validation

To increase the confidence of the model, a comparison is made with the total time needed to perform the navigational activities when following the two parameter Weibull distribution, as suggested by [22]. The maximum likelihood estimates for the scale η and shape parameters ξ are respectively [17]:

η = 466.473 seconds

ξ = 8.732

It is evident that the time threshold T is overestimated almost by 21%. When the cumulative distribution functions are plotted, the comparison can be interpreted directly (see fig. 3). It is realized that the Weibull distribution provides almost 72% higher value, which may be critical in circumstances (i.e. high maritime traffic, canals or enclosed waters) where decisions have to be made fast and reliably as well.

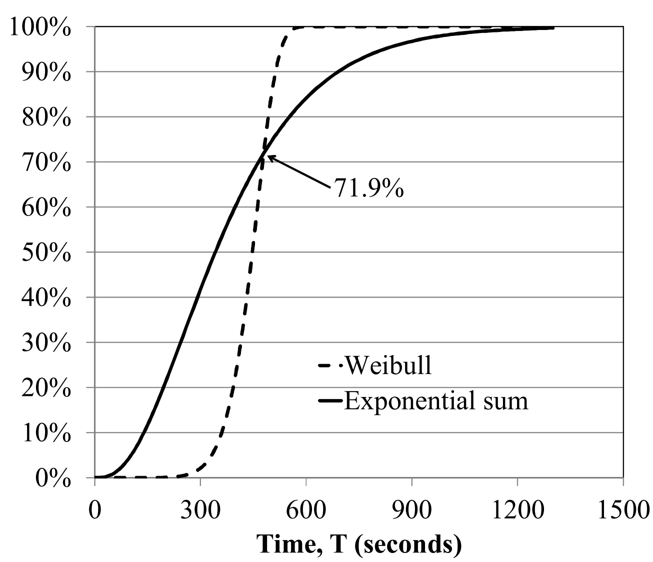

Fig. 3. Comparison of cumulative distribution functions. Note that the exponential sum provides a more realistic description

IV. Discussion

It is realized that the navigators are confronted with data overload due to the increasingly sophisticated navigational technologies. This is translated into the need to divide attention between ECDIS and secondary tasks, such as engine and cargo functions. The efficient time management of these activities is essential and may be critical under stressful, uncertain, or emergency conditions. Thus, it is of paramount importance to reduce the potential for marine casualties, since often navigational accidents such as collisions and groundings are attributed to poor judgment and situational awareness failure. Given the above, navigators shall consider a greater range of potential interpretations of the encounter and occasionally cannot complete necessary information processing activities at appropriate times. Furthermore, they are uncertain about the actions of others and are frustrated due to the reduction of the available time for information gathering and decision making, with the imminent consequence of increased accident risk [23]. To this end, the proposed methodology may assist the design of an automated system that intervenes when the navigator's reaction time either to make the planned track changes according to agreed rules, or to hold the original course longer exceeds the threshold. Certainly, care must be given to keep the navigator "in the loop", i.e. ensure that the human performance costs of skill degradation, unbalanced mental workload, reduced situational awareness and dynamic features of the work environment as well as failure to detect when occasionally automation fails are adequately managed [21].

It is unambiguously accepted that marine navigation is a demanding activity consisting of various tasks related to voyage planning, target evaluation, course planning, adjustment and execution, which can become quite stressful in critical situations. As technology changes, the role of the seafarer in each of these tasks may also change, with the possibility of reducing the number of crew usually required for bridge operations from as many as four (master, watch officer/navigator, helmsman, look out) to just only one. It is anticipated that such setting could play a part into moving forward with the autonomous ship concept, though a human presence aboard shall be expected [24]. The concept of critical threshold time could be incorporated into the bridge simulator training for enhancing the collision and grounding avoidance attributes of the navigators. In addition, the proposed method may be well used when it is appropriate to decide on rigorous commands under harbor maneuvers, as well as within detailed analyses for determining the minimum allowable values of the closest distance. This is important since the allowed time for maneuvering is manifested by the navigator's behavior [25].

V. Conclusion

It should be stressed that the goal of this paper is not to debate the human cognitive system, but to propose a practical and simple approach for evaluating the navigator's behavior. In this respect, it is attempted to model probabilistically the cognitive processes of information pre-processing, decision making and action implementation in order to determine the minimum required time for reliably performing each task. Thus, the needed time to firstly acquire and to register multiple sources of sensors, to organize and to categorize the retrieved information can be expressed through the exponential law. The second stage involves the manipulation of retrieved data, construction of problem statements (i.e. keep course, reduce speed or change track) and selection of the optimum solution albeit to conformance with navigation regulations, also with the exponential distribution. The third and final stage is related to the implementation of a response or action in line with the decision made, which is also exponentially represented. It is asserted that by employing quantifiable and measurable ways to assess the uncertainties associated with the navigator's reaction and the available technical means, the sequence of events that may lead to an accident could be prevented. In addition, the automation capabilities of the navigational equipment could be enhanced as long as the navigator is kept "in the loop". In the absence of a complete data set, the rationality of the proposed method is validated from the limited, though available sample results of a published simulation study.

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