A MODEL FOR FORECASTING MENTAL FATIGUE IN MARITIME OPERATIONS

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ABSTRACT

Assessing seafarers' mental fatigue levels helps identifying potential operational risks and the ability to simulate future scenarios can be used during planning and management, to ensure safer operational conditions. In this work, we propose a framework for modelling seafarers' future mental fatigue levels using a combination of both physiological and environmental sensors and model- and data-based techniques. We established building blocks of this framework and presented examples of how it can be applied in different scenarios as soon as enough data is collected to feed the data-based section of the model. Once properly trained, this framework can be used not only to assess human-related operational risks but also to provide the necessary information to ensure that these issues are addressed before potential danger escalates to real accidents.

MENTAL FATIGUE IN MARITIME OPERATION

Safety-critical operations is an increasing concern across all industries dealing with human-machine interaction and systems. Human-related issues are the main cause of accidents in fields such as driving (Williamson et al., 2011), commercial air transport (Suraweera et al., 2013), and maritime operations (Chauvin et al., 2013). Among the most common issues, we can highlight situational awareness and human errors. The main contributing factors leading to these challenges are excessive workload, stress and fatigue, specially mental fatigue (MF).

The maritime industry presents especial fatigue-related challenges connected to the intrinsic nature of maritime operations. This includes long and irregular working hours, long periods away from home, unpredictable environmental factors, and no clear separation between work and leisure. The International Maritime Organization (IMO) defines in its Guidelines on Fatigue (IMO, 2019) several factors influencing fatigue in seafarers. These factors can be categorized as seafarer-specific factors, management factors, ship-specific factors, environmental factors, and operational factors.

Among the seafarer-specific factors we can highlight psychological and physiological characteristics and personal habits. Ship-specific factors cover all aspects related to the design and condition of the ship, such as ship motion and responses, level of automation and reliability, and physical comfort in accommodation and work spaces. Environmental factors include aspects such as noise, vibration, ship motion, ventilation and temperature.

With so many contributing factors, monitoring and controlling MF levels in maritime operations is a complex task. Among the available option to assess MF, several subjective approaches are presented in the literature. Self assessment is the most common subjective approach and can rely on the use of questionnaires, such as Chalder Fatigue Scale (Chalder et al., 1993) and Epworth Sleepiness Scale (Johns, 1991), and sleeping diaries (Wadsworth et al., 2006). Although useful for tracking the user's MF profile, these methods are generally not suitable for real-time applications.

For more a realiable MF assessment, deterministic approaches are recommended. In this case, the use of physiological sensors, such as eye trackers, electrocardiogram (ECG), and electroencephalogram (EEG), is recognized as the best way to reliably assess MF in real-time (Sahayadhas et al., 2012). This is due to the intrinsic relation between changes in physiological signals and variations in MF levels.

After establishing the required understanding about the causes and how to measure MF, a natural follow up question is how can we model the MF development. Answering this question is important since a good MF development model can be used for an early intervention or operational planning. Addressing this task is a challenging issue, due to the effect of external factors in the development of MF and how difficult it is to objectively relate these factors to their effects. In the work, we describe a framework for modelling MF de-

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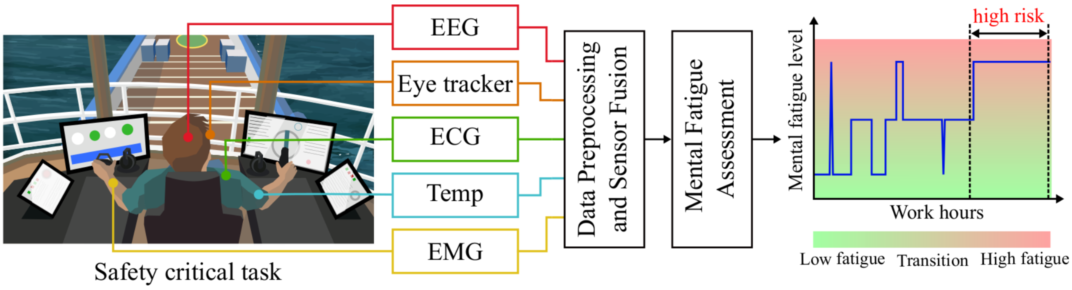

Fig. 1. Framework for Mental Fatigue Assessment

velopment, taking into account not only the seafarer's physiological condition but also the effects of external factors.

MEASURING AND MODELLING MENTAL FATIGUE SCENARIOS

Being able to monitor the development of seafarers' MF state in real-time can be beneficial for the safety of demanding maritime operations. A proper MF profile of all operators taking part in a complex operation enables a more precise risk assessment, which in turn can help preventing causalities.

Let's consider an operational scenario where a pilot is maneuvering a platform supply vessel (PSV) close to an oil rig for cargo unloading. Using a set of physiological sensors, one can monitor this pilot and perform an MF level assessment. This MF profile can be used to perform the operational risk assessment based on how long the operator stayed in a critical MF level. What a critical MF level is and how long the operator needs to be in this state to indicate operational risks need to be defined via experiments. This MF assessment framework is presented in Fig. 1 (Based on (Monteiro et al., 2020)).

Although MF assessment can be a useful tool for reducing the risk of causalities, it presents a limitation regarding how early we can intervene in the operation. This limitation is due to the fact that the assessment system measures only the current state of the operator. Once a dangerous condition is assessed, measures need to be taken in order to mitigate the operational risk. This delay between assessment and action can be sufficient a time window for the assessed risk to turn into a real accident. Thus being able to anticipate the risky period is important to prepare the necessary mitigation measures on time.

Supposing we can assess the operator's MF state in the current operational scenario (S_0), how can this scenario develop in the next, for example, two hours? If, after the assessment of scenario S_0, the weather conditions develop to a much rougher sea state, how will the operator's MF level be affected? If a collision between the PSV and the oil rig happens, how will this stressful situation come into play in the operator's performance? These different external factors can make the prediction of future scenarios very hard, since the original scenario can lead to several possible future scenarios. This branching is presented in Fig. 2.

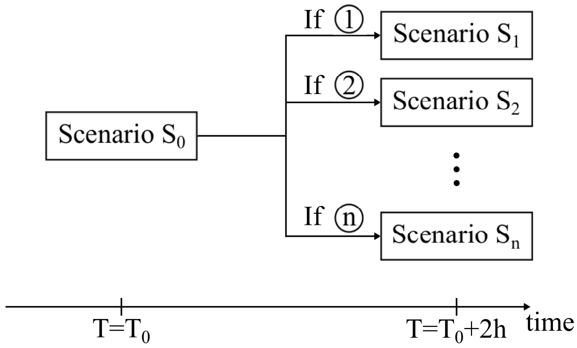

Fig. 2. Branching of Scenarios

The current work aims to extend our previous studies (Monteiro et al., 2019, 2020) by adding a prediction capability to our MF assessment framework. So, the question we want to answer in this paper is: How can we model and simulate other MF scenarios from the current assessed scenario? Can this theoretical model be calibrated and validated with real data gathered from day-to-day operations? In order to be able to answer these questions, we need to address four important points. First, which factors affect the progression of the MF state? Then, how to measure and quantify these factors? Later, how to integrate these measurements and the current MF assessment into an MF prediction algorithm? Finally, how can real data can be used to calibrate these models?

Contributing Factors

As presented in the previous section, there are several factors that affect the development of MF in seafarers. For our analysis we will group these contributing factors in time and distress. Time refers to the natural progression of MF due to physiological and psychological factors, and the prolonged exposition to environmental factors. Distress is related to unexpected and emergency situations. These events can be punctual or have long duration. They elevate MF levels by increasing workload, tension, and stress levels.

Sensors

In this work we propose the use of two different classes of sensors: physiological and environmental sensors. Physiological sensors are the most reliable way to assess MF levels, since the physiological symptoms of MF can be captured as they start to develop. The most usual physiological sensors used to monitor MF include eye tracker, electrocardiogram (ECG), electroencephalogram (EEG), and body temperature sensors. Ideally, we would like to have as much sensor information available as possible to help in the decision making process. Practically, the use of several sensors attached to a seafarer's body can hinder the proper execution of complex tasks. So, this trade-off between the amount of data and sensors needs to be taken into consideration when selecting which physiological sensors to use for real-life applications.

Environmental sensors are used to quantify factors that are external to the seafarers. They include gyroscopes, accelerometers, weather sensors, cameras, sound level meters, etc. In opposition to physiological sensors, there is no limit for the number of environmental sensors to apply when monitoring maritime operations. Additionally, most vessels already record data for several of the sensors cited above, so there is little extra setup to be done regarding the environmental sensor. The challenge is how to correlate this kind of sensor data and variations in a seafarer's MF level.

Mental Fatigue Prediction

There are two main steps when trying to forecast MF scenarios. First, we need to assess the seafarer's current MF level. Then, we need to predict the expected MF level based on the seafarer's current MF level and time and distress effects. Fig. 3 presents our proposed framework for forecasting MF scenarios, including the assessment and prediction steps.

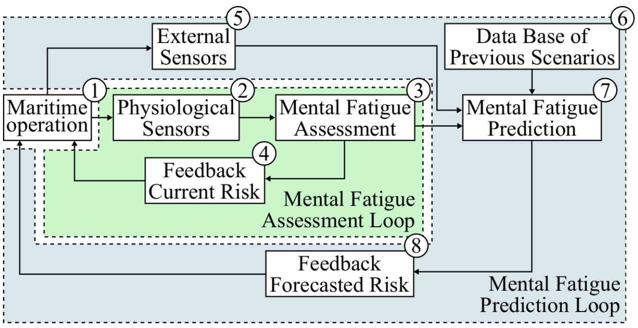

Fig. 3. Framework for Mental Fatigue Prediction

The MF assessment loop is responsible for determining the seafarers' current MF state at a certain operation (1). The assessment is performed using only data from physiological sensors (2). This data is acquired in real time as time-series. After any required preprocessing, the data can be used as the input to an MF assessment algorithm (3) responsible to determine the current MF level. Here, two different approaches are viable. One possible approach is to use neural networks to classify the input data in different levels in an MF scale. Another alternative is to apply a model-based approach, which defines MF levels in a deterministic way by modeling the MF representation using the sensors data and expert knowledge. With the profiled MF progression, a risk assessment algorithm can be used to inform the seafarer about the current operational risk level (4).

The assessed MF state in a time-stamp t_0 is correlated to all the environmental sensors (5) data collected at that time stamp. The time-series of the MF profile and the time-series of the environmental sensors are stored in a database of previous scenarios (6), which can be used for training the MF prediction algorithm (7). In this case, it is considered a data-driven algorithm. Besides being stored in the database, the MF profile and the environmental sensors data are the inputs for the MF prediction algorithm. Using the combination of recent environmental sensors data and the current MF level of an operator, the trained algorithm can produce a prediction about the expected MF level of said operator in the near future, and a risk assessment algorithm can be used to inform the seafarer about the projected operational risk level (8). The main difference between the algorithms implemented in (3) and (7) is that in (3) we only rely on instantaneous physiological sensor data, while in (7) we consider the instantaneous physiological and external sensors data, while relying on a database of previous scenarios.

Database of Previous Scenarios

For this application, we are handling complex data. The complexity of the data is defined by two main factors: several disparate data sources and data size. Firstly, the environmental sensors can provide data in different domains, which can be hard to fuse in a meaningful way. For example, a camera provides a video feed, while an accelerometer provides accelerations in different directions. In order to efficiently store and handle all external sensor data, having all data in the same domain can be very helpful. Most sensors data are generated as time-series data, which is basically a stream of time-stamp/value pairs. In this case, having time as a common domain is the simplest solution to facilitate the data fusion process. So, in order to ensure that all sensors speak the same language, some preprocessing may be needed for some sensors to extract time-domain features that can be stored in the data base and fused with other sensors data.

With the huge amount of time-series data produced by the environmental sensors, the computational complexity to handle this information is high. In this case, a specialized time-series database can go a long way improving the system's overall efficiency. In a time-series database, new incoming data is stored in a sequential manner, usually ordered by time-stamp. In this case, new data is inserted in the database instead of old values being updated. This allows for tracking how the data changes with time, making it possible to understand tendencies in the past and predict trends in the future. Traditional databases can be employed to handle time-series data, but usually they lack the tools to handle two important aspects of time-series data: scale and usability.

Regarding the scale factor, the amount of data that needs to be stored when handling time-series can grow very fast. This is specially true when handling several sensors operating at high frequencies. In order to effi-

ciently handle this huge amount of data, the database needs to be optimized to provide bigger ingest rate, faster querying and optimized operations for data compression. This optimization is only possible when the time variable is considered a first priority during the database framework design.
Usually, only storing the time-series data is not enough. Regarding the usability factor, it is important that we are able to perform operations that are characteristic of this kind of data. Some examples of these operations include data retention policies, continuous queries, and flexible time aggregations.

Data-driven Mental Fatigue Prediction

Once enough data is stored in the database for both the MF assessment and external sensors, fully data-driven methods can be effectively applied to perform the MF prediction. The minimum amount of data necessary to perform a good prediction is a relative matter, since it depends on both the complexity of the prediction and its expected accuracy. One natural candidate for this task would be a long-short term memory (LSTM) neural network (Hochreiter & Schmidhuber, 1997). This neural network is capable of learning long-term dependencies in time-series data by using a memory cell to regulate the information flow (Fig. 4). The information flow is controlled by non-linear gating units that include input gates (i_t), output gates (o_t) and forget gates (f_t). A complete formulation of the LSTM algorithm and examples of applications in time-series prediction can be easily found in the literature, for example (Ellefsen et al., 2019). By training the LSTM algorithm in a data stream composed by all the physiological and environmental sensors, it can learn to predict the MF state by applying the penalty functions automatically, without the need to manually tune the penalty functions parameters. The appropriate network structure, including number of layers and neurons, needs to be determined during the training process, according to the desired precision criteria for the prediction task.

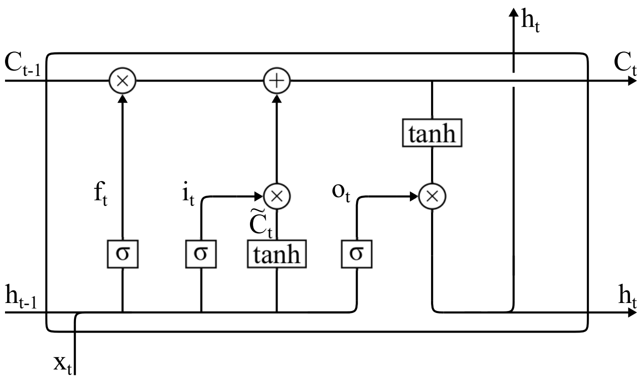

Fig. 4. LSTM Memory Cell

MODELING MENTAL FATIGUE PROGRESSION

As presented in Fig. 3, the prediction of future MF states depends on a database of physiological and environmental sensors data. In order to establish a foundation for the handling of this data, we can discuss how the integration between physiological and environmental factors can be applied for forecasting MF levels in seafarers. Since we do not have an established database, we need to first model the effects of time and distress over the MF level. This theoretical modeling can be then used to exemplify our proposed approach.

Time Dependant Mental Fatigue Progression

The simplest effect to model is the effect of time. Due to physiological and environmental factors, MF accumulates as time goes by. There is an initial rested state that progresses to a maximum level of MF where staying awake would be almost impossible. Although this situation can sound a little extreme, it is not unlikely to happen, specially during night shifts. Eq. 1 can be used to model this time dependent MF progression

$$MF(t) = \frac{\alpha}{2} + \alpha \frac{\arctan\left(\beta\left(t - \frac{T}{\gamma}\right)\right)}{\pi} \qquad (1)$$

where T is the total duration of the prediction, γ indicates the position of the inflection point of the curve, β dictates the inflection angle, π is the non-dimensionalization constant for the arctan function and α scales the function to our desired MF scale.
Fig. 5 presents the proposed model for the time aspect of the MF progression, with the theoretical limits for restedness and tiredness.

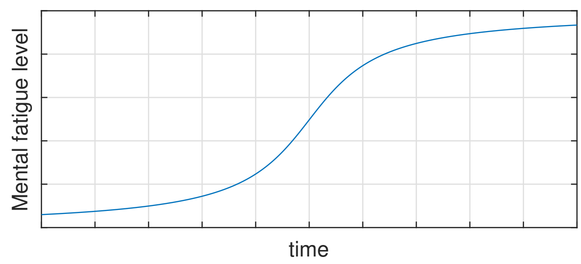

Fig. 5. Time-dependant Mental Fatigue Progression Model

Fig. 5 shows the time-dependant MF progression for $\alpha = 1$, $\beta = 0.2$, and $\gamma = 2$.

Distress Dependant Mental Fatigue Progression

The effects of distress over the time dependent MF progression will be modeled as penalties to the natural MF development. There are several possible causes of distress (IMO, 2019), and for simplicity we will group them into continuous and punctual effects.
Continuous effects represent disturbances that take place continuously, for an extended period of time. Such effects include higher then normal noise levels, excessive vessel motion due to weather conditions, long watch shifts at night, etc. The effects of distress do not push the MF level over the theoretical MF limit. Instead, they accelerate the MF development. For modeling continuous effects, we propose the use of the fol-

lowing Gaussian-like function:

$$P_{const}(t) = a_1 \exp\left(\frac{-(t - \frac{T}{b_1})^2}{2{c_1}^2}\right) \tag{2}$$

where a_1 is the scale factor for the penalty, T/b_1 dictates the position of center of the normal distribution, and c_1 represents its spread. The penalty is applied in the time dependant MF progression as follows:

$$MF'(t) = MF(t) \cdot (1 + P_{const}(t)) \tag{3}$$

Fig. 6 shows the continuous effect penalty function for $a_1 = 0.15$, $b_1 = 2.5$, and $c_1 = 0.1$.

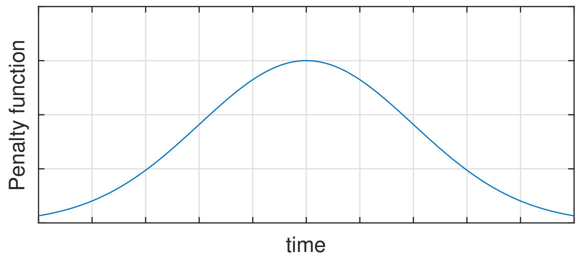

Fig. 6. Penalty Function Model for Continuous Distress

Punctual effects represent disturbances that have short duration but can effect the MF development in the long term. This kind of effect includes, for example, a vessel collision with other vessel or marine structure, accidents with cargo handling, and man overboard scenarios. Punctual effects are more relevant when they have an acute impact on the seafarer's situational awareness and sense of danger, triggering a burst of adrenaline. This phenomenon can, in the short term, increase attention and, in the long term, increase MF progression due to the increase in tension and workload levels.
In order to model punctual effects, we propose the use of a combination of Gaussian-like functions. The negative portion of the equation models the increase in attention after a serious, unexpected event occurs, while the positive portion models the long term increase in the MF progression levels.

$$P_{short}(t) = -a_2 \exp\left(\frac{-(t - \frac{T}{b_2})^2}{2{c_2}^2}\right) + a_3 \exp\left(\frac{-(t - \frac{T}{b_3})^2}{2{c_3}^2}\right) \tag{4}$$

where the variables a, b and c are analogous to the ones presented for Eq. 2. The way the punctual penalty is applied to the time dependant MF progression is the same described in Eq 3. Fig. 7 shows the punctual effect penalty function for $a_2 = 0.75$, $b_2 = 2.8$, $c_2 = 0.35$, $a_3 = 0.25$, $b_3 = 2.3$, and $c_3 = 0.15$.

Tunning Models

Previously we described the modeling of the MF development process based on the time-dependant MF progression and penalty functions. So one may ask: how could I tune the parameters that compose the penalty functions for different scenarios? The answer for this question lays on the time-series complex data stored in the previous scenarios database.

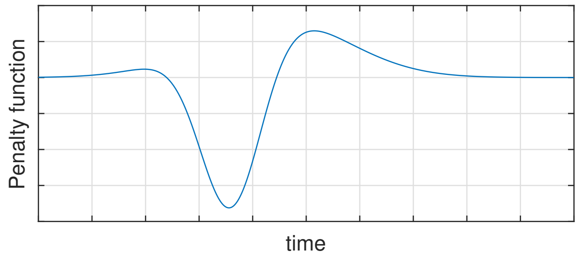

Fig. 7. Penalty Function Model for Punctual Distress

Initially, when no previous scenarios data are available, the prediction capabilities of the proposed framework are poor. Normal operation data is the easiest kind of data to come around. It is produced by the assessment framework when no distress factor is in play. It is essential for implementing a time-dependant MF state forecasting strategy. Using this prediction model as a baseline, the penalty functions for a specific operational conditions (including one or more distress factors) can be approximated using the inverse of the mapping function presented in Eq. 3. This new equation can be written as:

$$P_{const}(t) = \frac{MF'(t)}{MF(t)} - 1 \tag{5}$$

The obtained penalty function can then be approximated to the formulation of either continuous or punctual penalties by defining the appropriate parameters. Defined this way, the parameters can be stored and recovered when a similar distress factor takes place during the MF monitoring of an operator. Once calibrated with real data, the proposed framework can be used as management and planning tools. These applications are exemplified in the next section.

SIMULATING MENTAL FATIGUE SCENARIOS

Management Tool

As a management tool, this framework can be used for assessing, in real-time, the operational risk related to seafarers' MF condition. At any given time during an operation, the MF level assessed from an operator until that time and the data from the environmental sensors can be used to forecast how the MF level is expected to change in the near future. The MF level can fall under good (green), attention (yellow) or dangerous (red) ranges. Fig. 8 shows the composition of the predicted MF state for a seafarer. The assessed MF levels (1) is used to extrapolate the time dependant progression of the MF state (2). Environmental sensor data is used to calculate punctual (3) and continuous (4) penalty functions. Applying all this data in Eq. 3, the system outputs the predicted MF state (5).
With this information, a manager can keep track of the operational risks related to the seafarer's MF state. In a scenario where this risk surpasses some predefined criteria, the manager can act by alerting the seafarer

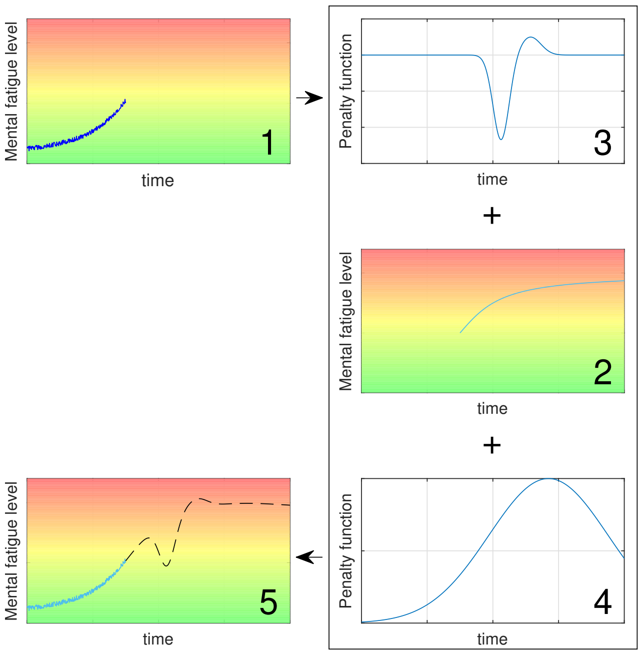

Fig. 8. Mental Fatigue Prediction Composition

about the dangerous condition or even plan a break or a change of operator.

Planning Tool

As a planning tool, this framework can be used for evaluating different possible scenarios during a demanding operation. Based on these possible scenarios, worst case conditions for the seafarers can be identified and the risks involved in the operation can be assessed. Consider for example a crane operation taking place offshore by a construction vessel. The crane operator presents his own time dependant MF progression (S_0), disregarding any external complicating factors. But what if during the operation the weather conditions worsen (S_1), or there is an accident damaging one important component that should be installed (S_2), or an unforeseen delay takes place (S_3) or there is a malfunction in one equipment (S_4). How can these different scenarios effect workload and stress and impact the MF development of the said operator? The utilization of the proposed framework to investigate all these possible scenarios is presented in Fig. 9.

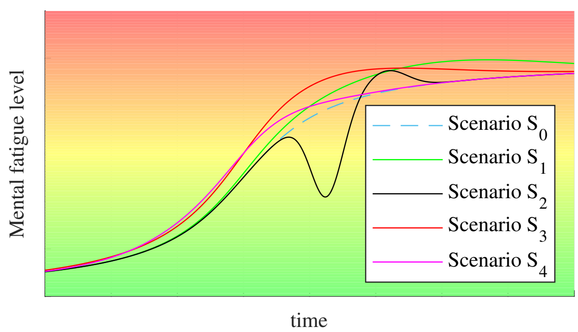

Fig. 9. Comparing Different Possible Scenarios

With the prediction model for the different scenarios at hand, the operation can be planned to account for the risks related to high MF levels. The operation can be planned for the worst case scenario in order to ensure a higher safety factor. But it also can be planned for less risky scenarios if the probability for the worst case condition is low. Another viable option involves planning for a scenario represented by a weighted average of the possible modeled scenarios, where the weighting factor is the probability of occurrence of each scenario.

TOWARDS AN INTELLIGENT MODEL FOR MENTAL FATIGUE AND HUMAN ERROR PREDICTION

The work here presented was developed as a simple and fundamental approach to put in practice the framework from Fig. 3. Originally, the framework was developed as a way to transform real data from operations into an assessment for MF. The reality is that this real-operations data is not available, and much has been done only from experiments in simulators. The equations here presented can be used as a comparison and benchmark, elegantly in terms of coefficients of well know equations.

We are aware that the presented model is an *educated guess* on how MF seems to behave based on the literature and current research at NTNU. We attempted here to navigate between the two worlds of the literature found in this topic. One extreme, very human and social based, which describes MF qualitatively and is intrinsically connected to the psychological aspects of a human-being performing a safety-critical task in demanding operations at the sea. No wonder IMO uses this side of the spectrum to describe the types and limits of MF, given that no number is able to properly and safely estimate MF in maritime operations. In this way, we understand the problem, but no data is given for decision-making.

On the other extreme, data-driven methods are wide spreading in all fields, promising that a well trained AI will be able to estimate everything with more precision than just a narrow sample of human experience, providing accurate decision-making. The database previously described requires a large amount of complex-data. This intensive data-driven approach demands hundreds of hours of real-data operation that need to be collected, filtered, stored and fed to an advanced AI algorithm. We also observed in recent experiments in simulators (Monteiro et al., 2019; Kari et al., 2019) that physiological factors can add extra complexity to the operations, and demand time and patience to be set up and used. Remote sensor technology, such as Open CV, may be the solution, but they have yet a long path before being commercially applicable in such a narrow niche as maritime operations.

We do believe that having a functional model, able to theoretically predict MF based on time and distress, is a fundamental piece to achieve the framework proposed. In this context, we call for an open and collaborative approach to calibrate, improve and validate our model. The source code is available at an online repository (https://github.com/thiagogabrielm/MFM).

We plan to continue the experiments at NTNU, and currently we are gathering data from our research vessel. This is, however, a small sample yet for properly training AI. In this sense, having a sound mathematical model as the one here described seems a good initial step for other actors to use and adapt our model. If we are right, we will be able to present a library of tangible coefficients, calibrated for each operation. In the future, connecting these coefficients to each MF aspect from IMO, can be the basis for a sound regulation on MF and, therefore, safer operations.

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