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Modelling Ship Officer Performance Variability Using Functional Resonance Analysis Method and Dynamic Bayesian Network

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ABSTRACT: Ship maneuvering is a complex operation with inherent uncertainties. To express this complexity in system performance during the navigation process, an analysis model has been developed using Functional Resonance Analysis Method (FRAM) and Dynamic Bayesian Network (DBN). The functional level of dynamic work onboard is assessed and modeled using FRAM qualitatively, in which a key function and the function's potential coupling for specific instantiation are identified. Further analysis is done by integrating the FRAM analysis with DBN for quantification. The evolution of system performance over time is determined through changes in the probability of function's mode, namely strategic, tactical opportunistic, and scrambled. The model presented in this study concerns the fluctuation of ship officer performance to overcome the obstacles during the encounter event. As a result, the integration of FRAM-DBN shows promising usability to evaluate human performance. The essence of human adaptive capacity is also highlighted through system resilience potency, that is, the potency to learn, respond, monitor, and anticipate. We also discuss how this finding contributes to enhance safety analysis, in specific, to provide explicit representation of the dynamic in human performance in ship navigation based on Safety-II idea.

1 INTRODUCTION

The shipping industry has an essential role in global trade and commerce, as the majority of goods are transported by ship. Given the complexity of shipping operations, ensuring the safety and efficiency of ships and their crew is of paramount importance. Shipping operation is understood as a complex socio-technical system. It requires a complex interaction between social and technical components to achieve the intended goals. A complex socio-technical system has unique properties called emergence phenomena. This idea explained the situation where the system has ability beyond its individual component ability when it is working as a whole. Based on this perspective, safety in ship operation is acknowledged as an emergence phenomena arising from the complex socio-technical system rather than a property of the system [1].

Resilience engineering [2] is a core representative of this new safety idea. Along with this initiative, the Functional Resonance Analysis Method (FRAM) is a well-established framework that has been introduced to provide resilience engineering ideas in its application. This method analyses the interaction between different elements of a system and understands how their dependency contributes to system performance. The FRAM has been successfully applied in a variety of domains, including safety-critical industries such as aviation[3], offshore oil and gas [4], and the maritime industry [5], [6].

The process of ship maneuvering is dynamic with continuous command and feedback between the officer on watch (OOW) and the helmsman. It escalates in different traffic and environmental situation. Indeed, the system hardly relays on the OOW's capacity to decide on appropriate action. This implies the necessity of proper performance adjustment to maintain the system works normally under dynamic working condition. In this case, human adaptability and flexibility are essential to achieve this kind of purpose. The definition of safety in this manner is introduced by a term called Safety-II [7]. Hence, under this consideration, it is important to understand deeper this adaptable performance more, in specific of how the fluctuation affects system output.

The application of FRAM in this study is to identify the functional basis of ship maneuvering activity and provide a systematic expression of it through functions and potential couplings. Analysis in FRAM is qualitative in nature. It provides an explicit understanding of the system's functionality in the form of FRAM model but lacks in function's performance representation. One solution that can be applied is cooperating with the method of quantitative analysis. Some available studies have existed regarding this matter, such as the application of Monte Carlo evolution [3] and modified Fuzzy FRAM-CREAM with cellular automata simulation [8].

Therefore, in addition to the FRAM, this study employs a Dynamic Bayesian Network (DBN) for mathematical modeling. DBN is an extended version of the Bayesian Network (BN). It is a type of probabilistic graphical model that can be used to model complex, dynamic systems over time. BN has been widely applied in the maritime industry, especially to predict the probability of ship accidents [9]–[11]. One of the advantages of DBN is this method can handle temporal dependencies and allow for the modeling of time-varying influences on system behavior. The basic idea of this quantitative expression is to model the discrete probabilistic dependencies between functions at each point in time, and then to propagate these dependencies over time to express a dynamic change in the system.

A case study from ship handling simulation has been chosen to perform the analysis. The FRAM-DBN integration in this study aimed to develop a comprehensive model of ship officer variability performance, providing insights into how changes in officer performance over time influence system output. The meaning of using this specific case is to provide actual-time segregation for every decision initiative and actual evidence of performance for DBN analysis. Furthermore, the FRAM model can also be built for a specific instantiation. This is a simple analysis that design to present what to expect from performance adjustment, and how can normal performance be disrupted and then produce undesired outcomes. In conclusion, the essence of human performance for establishing an adapted system can be addressed, and what strategy must be built to enhance it to possess a higher level of resilience.

2 METHOD

This section explains a set of methods applied in this study. First is the qualitative analysis using FRAM and build the FRAM model. Second is integrating the FRAM analysis with quantitative analysis based on DBN. In addition to that method integration, the control model from Cognitive Reliability and Error Analysis Method (CREAM) has been brought to provide characteristic for FRAM function. This characteristic includes strategic, tactical, opportunistic, and scrambled.

2.1 *FRAM as a retrospective analysis*

The FRAM [12], [13] has been widely implemented to assess system safety in various fields. System resilience [2] terminology, as a core of FRAM, promotes new ideas for safety research by acknowledging safety as an emergent phenomenon instead of a property of the system. This implies the need on looking for what was done in the everyday operation of the system (Work-As-Done) and how safety is present in the system. The term function is used to express the need for something to be done by the system. The function is classified into three categories including human, technological, and organization. FRAM has four basic principles, including the equivalent of success and failure, approximate adjustment, the principle of emergence, and functional resonance.

Function in FRAM is presented as a hexagon with six aspects to characterize the type of information in function's dependency. Input represents the information or material to trigger the process in function. Precondition refers to the conditions that exist prior to the function starting its operation. In this sense, precondition is complementary information that explains the pre-event or preparation that has been done before a function is carried out. Time is the temporal dimension of the function, including the timing and sequencing of events. Control represents the mechanisms used to control the function, including procedures, rules, and policies. Resource is something that is used or consumed by the function, including energy, competence, people, tools, materials, etc. The output represents the results of the function's work. Outputs can be seen as a signal that starts a downstream function.

The relationship of function is described in two forms. First is temporal relationships, namely upstream and downstream functions. This expresses a function's dependency on specific time observation. The downstream function is affecting the process that happened in the downstream function, and this role can change over time based on the potential coupling and time of function activation. Second, the general role of background and foreground functions. Background function presents a function that only has output or input as its aspect. It means the function is only affecting the other functions in the system. On the other hand, the foreground function is a function that has more than 1 aspect. This function receives information from background or foreground functions, and also produces an output for other foreground or background functions. In other words, these roles refer to the relative importance of the function in the model. The foreground function denotes the matter being studied in the model, i.e., the focus of the investigation.

The essence of ship maneuvering events is derived by conducting an experiment in ship handling simulators. Furthermore, one specific result of the simulation has been chosen as factual information to build the FRAM model. The selected case is a case where the participants experience a collision during the simulation. In this case, FRAM is used as a retrospective analysis. The identification is focused on how the system should have functioned for achieving its goal, which is to avoid the target ship safely. As a result, the change of situation from normal performance to disrupted performance can be recognized.

2.2 *Officer performance quantitative representation using DBN*

DBN is an extension of the Bayesian Network (BN) with the ability to handle temporal dependency among nodes that change over time. This advantage makes DBN suitable to be applied for establishing an explicit representation of the dynamic in performance of ship officers during encounter events. DBN presents a pair of time slices of BN (Xt-1 → Xt), where Xt-1 is the initial BN that defines the initial probability of P(X), and Xt is the BN in the next time slice that contains the conditional probability of two-time slice. This state transition probability can be expressed as:

$$P(X_t \mid X_{t-1}) = \prod_{x=1}^{n_t} P\left(X_t^i \mid Pa\left(X_t^i\right)\right) \tag{1}$$

where *P(X)* is the set of variables; X_t^i is the *i*-th node of time slice *t*; $Pa\left(X_t^i\right)$ is the parent node of X_t^i; n_t is the number of nodes in the *t*-th time slice. In order to solve this mathematical equation, the SMILE modeler provided by BAYESFUSION has been applied in this work. In addition, the DBN modeling has also been done using the GeNIe software.

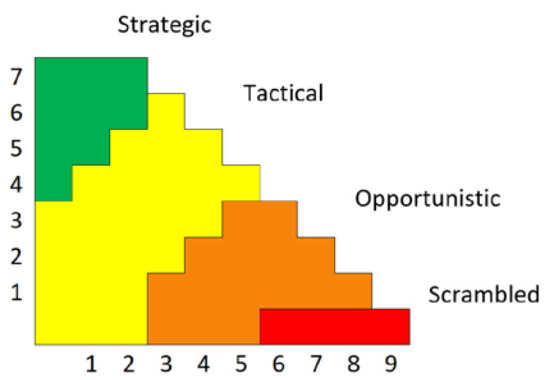


Figure 1. Relationship between control mode and common performance condition

In this study, DBN is used to provide a quantitative expression of the qualitative analysis that has been provided by FRAM. To integrate the FRAM with DBN, it is necessary to define a characteristic for each function to generate a conditional probability table (CPT). In this study, we decided to use the control mode expressed in CREAM [14] to generally characterize the FRAM function. It consists of strategic, tactical, opportunistic, and scrambled. Strategic control mode involves considering the global context, using a wider time horizon and higher-level goals, leading to more efficient and robust performance, and planning based on the functional dependencies between task steps. Tactical control mode involves performance based on limited planning, ad hoc needs, and frequently used procedures that may seem rule-based due to context or performance conditions. Opportunistic control mode entails determining the next action based on salient features of the current context, frequently resulting in functional fixation, driven by perceptually dominant features of the interface or frequently used, familiar heuristics. Scrambled control mode involves unpredictable decision-making without much thought, often occurring during high task demands or in unfamiliar, rapidly changing situations that lead to a loss of situational awareness, potentially culminating in momentary panic. Hence, the temporal relationship of the function's mode in which the explicit representation of changes in performance over time is presented through Bayesian thinking.

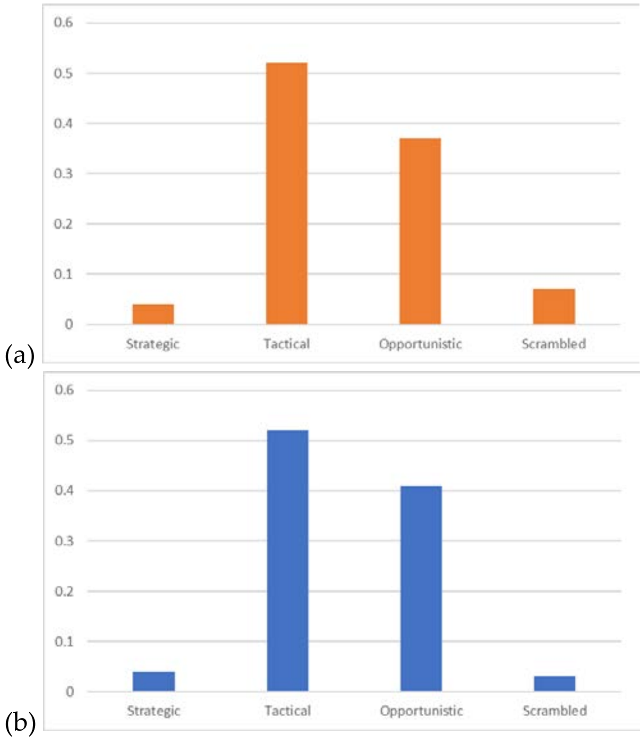


Figure 2. Discrete probability distribution of control mode based on (a) CPC's output variability [15] and (b) probabilistic approach [16].

The determination of control mode in CREAM can be derived by evaluating a defined criterion of a task. However, in this study, we approach the determination of the control mode in the form of a discrete probability distribution. Figure 2 shows one example of the discrete probability of the control model in a given context of a common performance condition. Based on this basis, it is possible to use this idea to determine the CPT for the initial condition of DBN. Therefore, the estimation of CPT for FRAM function in maneuvering event is generated by coopering discrete probability of CREAM control mode with an adjustment based on the common knowledge of officer performance in ship navigation.

3 CASE STUDY

A result from a ship handling simulation experiment has been chosen to provide a factual story of ship maneuvering events. The chosen simulation contains an accident event in which the action taken by the participant in each time slice is recognized. A deeper understanding of participant's decisions has also been elaborated through structured interviews. The participant is a licensed Officer with one experience on board a ship as a Cadet. This is partial information provided for the purpose of providing contextual evidence for FRAM-DBN analysis. This simulation is designed with a high level of maneuvering ability such that the full potency of the participant to cope with the situation can be observed.

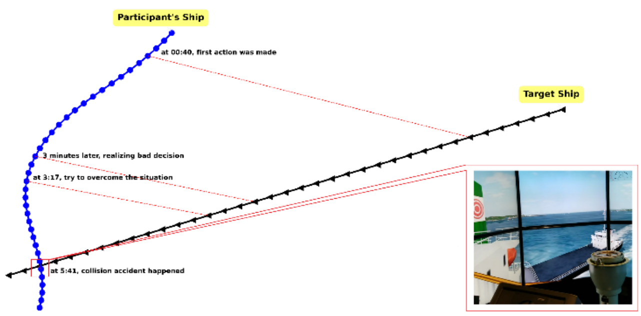


Figure 3. Ship trajectory of the simulation result.

The event is last about six minutes. In this situation, the target ship is moving from the northeast and heading southwest. On the other hand, the participant's ship is initially heading southwest and the final destination is in the southwest. The difficulty is rising because the target's speed is faster than the participant's speed. Therefore, he needs to maneuver his ship to the destination and avoid the target ship safely. The clarification of the participant's decision to overcome the situation is presented in Table 2. Five questions were asked of the participant for further understanding of his decision, including:

- When actually do you start to think to make this decision?
- What information do you need before making this decision?
- What makes you decide to take this action? Why did you do it at that time?
- What was your strategy to avoid this target ship at this moment? Do you have thought about that? Please explain.
- What factors do you consider the most to decide this action?

Table 1. Time step and participant's explanation for each decision.

Step	Recorded time	Description
0	±00:00	Start to perform an action. Monitoring the target ship's situation and building a strategy to reach the destination.
1	±00:40	An initial decision has been made by ordering "Port 20." After seeing the radar and understanding the target situation, he made a sharp turn to the portside to avoid the target. The participant says, "I did not think much because the target ship was an overtaking ship and my ship was a maintenance ship. I admit that I have had a feeling of colliding at this moment."
2	Up to ±03:00	Continue to monitor the situation.
3	±03:17	Realize that the first decision was bad. He tried to overcome the situation by ordering "starboard 10" but did not work well. The participant says, "At about 3:00, I was very embarrassed as the target ship approached. I could not think of anything at that moment. In fact, before making this decision, I should have asked the target about her intention."
4	±05:41	The collision accident happened

4 RESULTS

4.1 *FRAM model and analysis*

The implementation of FRAM in ship navigation to assess the potency of system resilience has been done by Adhita et al. [5]. For simplification, the dynamic FRAM model for ship maneuvering during the simulation experiment has been introduced as shown in Figure 4. The model consists of five background functions, which present the focus function for being studied, including <To monitor (by OOW>, <To do direct lookout>, <To watch electronic devices>, <To decide action (make judgment)>, and <To control the rudder/engine>. The temporal changes in the function's dependency and function's updated role over time have also been presented in the model.

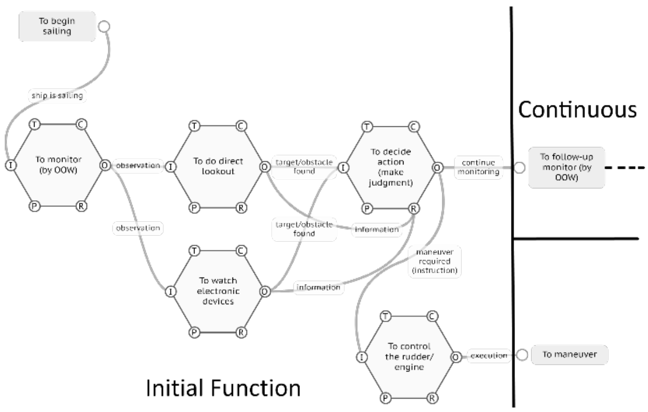


Figure 4. Simplified dynamic FRAM model for ship maneuvering in a simulation experiment.

This simple FRAM model of ship maneuvering activity (to avoid the target ship) in Figure 4 shows the intended functional process of system performance. <To monitor (By OOW)>, <To do direct

lookout>, and <To watch electronic devices> plays an important role for monitoring and learning processes. <To monitor (By OOW)> produces initial information such as strategy and expectation about the current vicinity situation to activate <To do direct lookout> and <To watch electronic devices>. Once the information is collected, the system starts to decide what kind of response should be done to cope with the situation through <To decide action (make judgment)>. Soon after that, the anticipation strategy is start to produce through the connection of <To decide action (make judgment)> and <To follow-up monitor (by OOW>. Finally, the process of function activation is repeated over time until the target ship can be avoided.

This model shows the potency of functional resonance can be triggered in any connection that exists between functions. Furthermore, the continuous process of function activation can increase the emergence of functional resonance. The longest the repetition, the higher the tendency for emerging resonance. The case of collision accident explained in Section 3 shows an example of how this resonance phenomenon affects function performance. An early signal of high variability performance from monitoring and lookout functions was felt at around 00:40. This is probably the primary cause of the amplifying effect that emerges in function <To decide action (make a judgment)> then produces an unwanted outcome, in this case, the order of "starboard 20." The last adjustment has also performed "too late" in terms of timing, which resulting the effort to maintain the system to work normally cannot be achieved.

4.2 *DBN for modeling dynamic performance in ship maneuvering*

To perform the DBN calculation, first, we convert the FRAM model to be Dynamic Bayesian Network model as presented in Figure 5. The continuous expression is marked by the edge with a number [1] on it. This edge expresses that the information in <To monitor (by OOW> at t=1 is updated by itself at t=0 and <To decide action (make judgment)> at t=0. Then, the process is looped exactly as how it expresses in the FRAM model. The specific time step (t=0 to t=4) to iterate the calculation is stated based on the case study in Chapter 3.

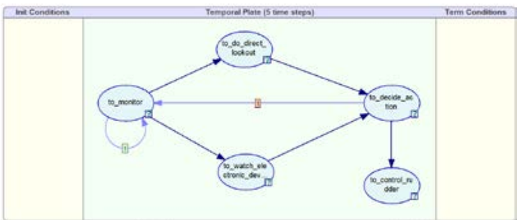


Figure 5. DBN model using GeNIe Software.

The number of CPTs in the initial node set depends on the number of nodes' characteristics and the number of edges pointing to the node. In total, 176 combinations of conditional probability of function have been created. As explained in Chapter 2, the generated CPTs are determined using the adjusted description of control mode with common knowledge of ship navigation. For example, <To do direct lookout> and <To watch electronic devices> are treated equally, in which the function is complementing each other. In the case of one function performing "strategic", and the other performing "scrambled", it will affect <To decide action (make judgement)> output more likely to be "tactical" or "opportunistic" as presented in Table 2. The logical way of thinking is the same as using "if-then rules" in an intuitive way.

Table 2. Example of discrete CPT for <To decide action>.

	To do direct lookout	Strategic			
	To watch electronic devices	St	Ta	Op	Sc
To decide action	Strategic	0.9558	0.45	0.0511	0.003
	Tactical	0.0442	0.545	0.6333	0.4226
	Opportunistic	0	0.005	0.3138	0.4854
	Scrambled	0	0	0.0018	0.089

St – Strategic
Ta – Tactical
Op – Opportunistic
Sc – Scrambled

The adjusted value of CPT is also considering the situation being assessed. It includes the familiarity with the situation in the simulation, the difficulty level of the encounter event given the participant's personal experience, etc. This considers important to produce reasonable results. The proposed DBN is intentionally exclusive for the case study.

Table 3. Example of discrete CPT for <To do direct lookout>.

	To monitor (by OOW)			
To do direct lookout	Strategic	Tactical	Opportunistic	Scrambled
Strategic	0.75	0.05	0	0
Tactical	0.25	0.8	0.1	0
Opportunistic	0	0.15	0.85	0.2
Scrambled	0	0	0.05	0.8

As a result, Figure 6 shows the expected performance of the officer to maneuver the ship in the encounter event. The probability of the performance to be strategic is around 10% to 16%, tactical is around 32% to 48%, opportunistic is around 30% to 39%, and scrambled is around 8% to 13%. The up and down in each time slice shows the updated belief of performance due to the function's dependency, which is quite stable and reasonable. This implies the suitability of the given CPT and the model proposed for the analysis has been achieved.

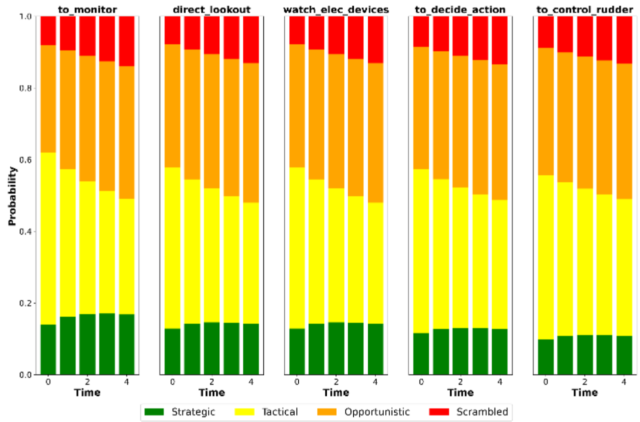


Figure 6. The evolution of expected normal performance of ship officer in each time step.

FRAM analysis has provided qualitative analysis for the case study. The fact that the emergence of a scrambled mode of <To decide action (make judgment)> at t=3 (±03:17) and speculation of the potency of functional resonance as well as the possibility of impact from the initial decision possesses important information for the DBN evaluation. Therefore, we proposed three assumptions to present the situation in a more explicit way.

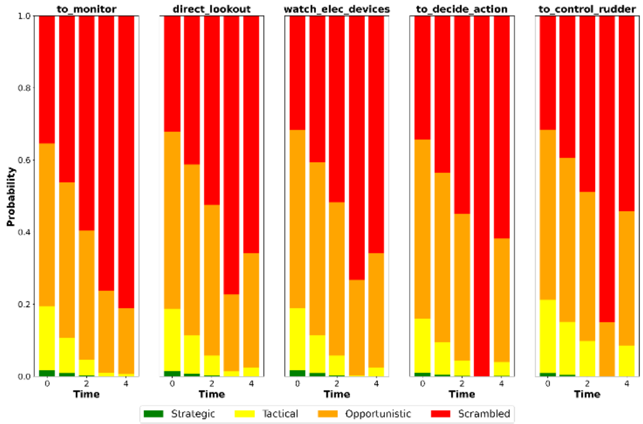
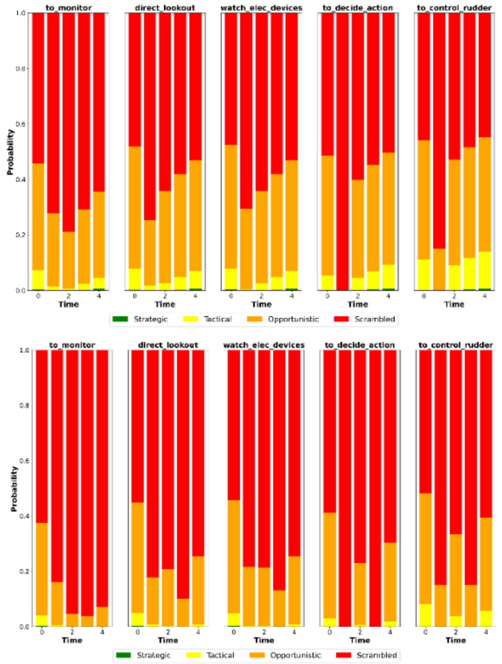


Figure 7. The evolution of performance in each function given the evidence of scrambled mode of <To decide action (make judgment)> at t=3.

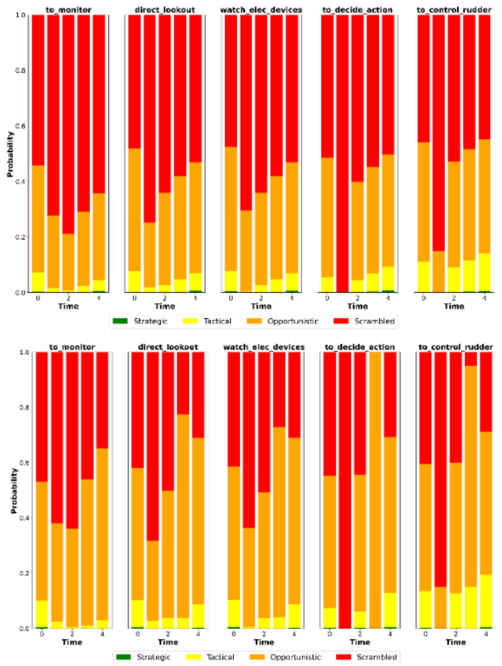
The first assumption: the fact that the scrambled mode of <To decide action (make judgment)> has emerged at t=3 (±03:17). Figure 7 present what is the possible situation that happened before t=3 and how the accident happened at t=4. In this case, the evidence of <To decide action (make judgment)> is set to be 100% scrambled. It can be seen, the probability of scrambled and opportunistic modes before t=3 is increasing in all functions. Specifically, <To monitor (by OOW)> shows the worst situation among others. In addition, the probability of <To control rudder> to be in a scrambled mode is increasing up to more than 50% presents how bad the decision at t=3 was so that the accident happened at t=4.



(a)

(b)

Figure 8. The evolution of performance in each function given the evidence of scrambled mode of <To decide action (make judgment)> at (a) t=1 and (B) t=3.



(a)

(b)

Figure 9. The evolution of performance in each function given the evidence of scrambled and opportunistic modes of <To decide action (make judgment)> at (a) t=1 and (B) t=3.

The second assumption: the first assumption shows that the extreme changes in <To decide action (make judgment)> at t=4 has a strong tendency to indicate huge changes happened in the previous time step. It is strengthened by the participant's argument about his first action which is not carefully considering the target situation. Therefore, Figure 8 shows the situation if at t=1 <To decide action (make judgment)> is in the scrambled mode and at t=3 the same mode appeared for the second time. This situation shows that all functions are turned into an extremely bad situation.

The third assumption: the best scenario that was expected to occur. Given the second assumption, if the scrambled mode occurred at t=3, there is about 20% to 30% chance for the opportunistic mode to happen in the next sequence of function activation. Let set <To decide action (make judgment)> to be opportunistic at t=3. The result in Figure 9 shows the system drastically change to the opportunistic mode as expected. This expresses how the situation could be if the participant tries to communicate with the target ship as he mentioned. In addition, this could also express the possible adjustment if the action to overcome the bad decision at t=1 was taken before 3:00.

5 DISCUSSION

This study presents the solution for assessing safety based on the Safety-II perspective using FRAM-DBN analysis. A case study of a ship collision accident has been chosen to provide system degraded performance from normal to disrupted. This collaboration has been found excellent, especially to assess the dynamic changes in function performance over time. The proposed method is able to provide a further understanding of the function's temporal dependency. The DBN analysis complements the FRAM analysis and provides a more in-depth understanding of the function's performance in the encounter event. Moreover, the proposed DBN can be used as a decision support tool for officers in similar situations, providing insights into the expected performance and potential consequences of different actions.

The analysis shows the essence of performance adjustment for establishing safety in ship maneuvering. The accident was found to happen due to the inability of the system to produce a proper adjustment. This is strengthened by the fact that the target ship hits the stern side of the participant's ship. It indicates that a slightly better adjustment in the decision at t=3 to overcome the unwanted performance at t=1 could prevent the collision accident to happen. Furthermore, the assumptions in the DBN analysis proposed helped to illustrate these potential consequences of different decisions made by the officer, highlighting the importance of decision-making skills in ship navigation.

The concept of Safety-II strongly encourages approaching safety from how it is present in everyday operations. Although the case being studied is the accident event, the mean is to provide the point of view of normal and disrupted performance, such that both situations can be explicitly presented. The importance of local adjustment in the ship maneuvering process has been highlighted. From different instance in different time slice, the officer performs different strategy to continuously follows the working dynamic. In this current example, the unwanted adjustment is presented. However, the understanding of what is expected could be can also be provided. It indicates the need for enhancing human performance flexibility for a better level of ship resilience. Obviously, there is a boundary for system flexibility to cope with a certain level of dynamic situations. Finding a balance of it can be another problem to solve. Given today's phenomena of AI and autonomy, a higher level of ship resilience can also be achieved by incorporating humans and technology through human-autonomous interaction.

For a more comprehensive analysis, future studies must consider a modification in the input data to determine CPT. Expanding the network can also be considered for more understanding of specific factors that influence the change in performance. The FRAM also facilitates expandability, especially for the "loose" couplings in function.

6 CONCLUSION

The use of FRAM-DBN analysis in this study provides a valuable tool for analysing the performance of ship officers during the maneuvering process. Continuous expression of changes in officer performance over time can be greatly presented using the dynamic FRAM model and discrete probability distribution of the function's performance mode in DBN. This elaborated FRAM analysis shows what is to be expected in the normal performance of ship navigation and how the performance degradation happened based on the case study being assessed. The application of this proposed method is limited to the case being analysed in this research. However, the usability for a more complex implementation has been recognized. In order to enhance the resilience of ship navigation, a thorough understanding of human flexibility and adaptability in response to unexpected situations is essential.

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