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ANALYSIS OF HUMAN AND ORGANIZATIONAL FACTORS IN MARINE TRAFFIC RISK MODELING

Literature review

Maria Hänninen

TEKNILLINEN KORKEAKOULU
TEKNISKA HÖGSKOLAN
HELSINKI UNIVERSITY OF TECHNOLOGY
TECHNISCHE UNIVERSITÄT HELSINKI
UNIVERSITE DE TECHNOLOGIE D'HELSINKI

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Abstract

This report is a literature review that describes the existing techniques for modeling human factors as a cause in marine traffic accidents. The report serves as a background for marine traffic accident risk assessment in the Gulf of Finland. The focus is on modeling techniques, especially on the use of Bayesian networks.

A common approach for estimating the probability of a collision or grounding involves the use of so-called causation probability. The causation probability denotes the conditional probability of a ship failing to avoid the accident, i.e., not making an evasive maneuver, while being on a collision or grounding course. Since the majority of marine accidents have been cited to be caused by human errors, the causation probability estimation is heavily influenced by estimation of human failure probability.

In many studies of marine accident probabilities, a model for estimating the causation probability or human failure has not been constructed but a probability value derived from previous studies has been applied. Although there exists literature on human error theories in general, the number of publications of models describing the parameters, their dependencies, and occurrence probabilities of the factors contributing to the probability of not making the evasive maneuver or human failure in marine traffic is low.

The extent in modeling the probability of human failure in probabilistic marine traffic risk assessments found in the literature varies. The approach used in models does also vary from rather practical, domain-specific point of view to models based on theoretical frameworks of human error in general. No human failure model found in the literature considers the specific risks of winter navigation which are necessary to be included in the model when the failure probabilities of marine traffic in the Gulf of Finland shall be estimated.

Keywords (and classification)
human error, human failure, human and organizational factors, ship traffic safety, accident probability, probabilistic risk assessment, Bayesian networks

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PREFACE

This report has been written within SAFGOF-project, which is a multidisciplinary project conducted in Kotka Research Maritime Centre by Universities of Helsinki and Turku, Helsinki University of Technology and Kymenlaakso University of Applied Sciences. In the SAFGOF- project, the accident risks of marine traffic in the Gulf of Finland are estimated in current traffic situation and in year 2015. Also, the direct environmental effects and the risk of environmental accidents can be evaluated. Finally, the effects of national and international legislation and other management actions are modeled, to produce advice and support to governmental decision makers. The aim of this study, conducted in Kotka Maritime Research Centre and Helsinki University of Technology's Department of Applied Mechanics, is to report the state-of-the-art in modeling human factor in marine traffic risk assessment. The application of Bayesian network techniques in modeling is studied in more closely.

For funding the project, the author wishes to thank European Union, European regional development fund, Regional Council of Kymenlaakso, City of Kotka, Kotka-Hamina regional development company Cursor Ltd., Kotka Maritime Research Association Merikotka, and Kotka Maritime Research Center Corporate Group.

In Kotka, 8.12.2008

Maria Hänninen

1 INTRODUCTION

1.1 Probabilistic risk assessment of collisions and groundings

In probabilistic risk assessment (PRA) the risk is defined as a product of the probability of an occurrence of an unwanted event and the magnitude of the event's consequences:

$$\text{risk} = \text{probability x consequences}$$

Marine traffic in the Gulf of Finland has been increasing rapidly during the last 20 years. As traffic volumes grow, the probability of a collision or grounding accident with severe consequences increases. In a previously conducted literature review /1/, the existing models for marine traffic accident frequency estimation were overviewed. Most of the existing collision and grounding models, for example /2, 3, 4/, were based on the concepts of geometrical probability and causation probability. Geometrical probability denoted the probability of a ship being on a collision or grounding course. It was based on ship traffic distribution transverse the waterway or lane and the assumption that the ships were sailing blindly in the waterway. Causation probability denoted the conditional probability of failing to avoid the accident while being on a collision or grounding course. Actual collision or grounding probability was then derived as a product of these two probabilities. Traditionally the causation probability has been estimated based on the difference in calculated geometrical probability, which solely predicts too many accidents, and statistics-based accident frequency. In more modern models the value for causation probability has been estimated based on some kind of model for not making an evasive movement.

Not making an evasive movement while being on a collision or grounding course can be a result of a technical failure such as failure of steering system or propulsion machinery, human failure, or environmental factors. Technical failure was reported as the primary reason of the accident in 9.4 % of collision and grounding accidents in the Gulf of Finland, and in 25 % of the cases the primary reason had been conditions outside the vessel /5/. According to Hetherington et al. /6/, the improved technology such as navigational aids has reduced accident frequencies and severity, but in the other hand revealed human failure's underlying role as an accident cause. Human failure has been commonly stated as the most typical cause group of marine traffic accidents: different studies have shown that 43 % - 96 % of the accidents had been caused by humans /5, 6, 7, 8/. Since technological devices are designed, constructed and taken care by humans, technical failures could also be thought as human failures /9/. Gluver and Olsen /10/ stated that while environmental factors have sometimes been given as the cause of marine traffic accidents, the actual cause has been insufficient compensation or reaction by the mariner to the conditions, i.e. human failure. Thus, it could be stated that nearly all marine traffic accidents are caused by human erroneous actions.

1.2 Definitions of human factors and human errors

Terms ”human factor” and ”human error” are often used interchangeably as referring to the cause of an accident happened because of people, an individual or organization, as opposed to because of a technical fault. Originally human factors were defined to be the scientific study of the man-machine interaction /11/. More recently human factors also included the effects of individual, group and organizational factors on safety /11/. According to Ren et al. /12/, human factors deal with manpower, organization management, allocation of responsibility, automation, communication, skills, training, health, safety, prevention of errors or accidents, and design and layout of equipment and workplaces. Human errors mean acts which can either directly or indirectly cause an accident /11/. Rasmussen defined human error as "human acts which are judged by somebody to deviate from some kind of reference act … they are subjective and vary with time" /13/, cited in /11/. In short, human factors trigger human errors /14/. Hollnagel /15/ used the term "human erroneous action" as the cause to an observed outcome rather than "human error" because of the ambiguity of common usage of the term "error".

Gordon /11/ proposed a framework of the relationships between human factors, which are the underlying causes of accidents, and human errors, which are the immediate causes. The framework is presented in figure 1. The types of human factors and human errors are described in more detail in the following chapters.

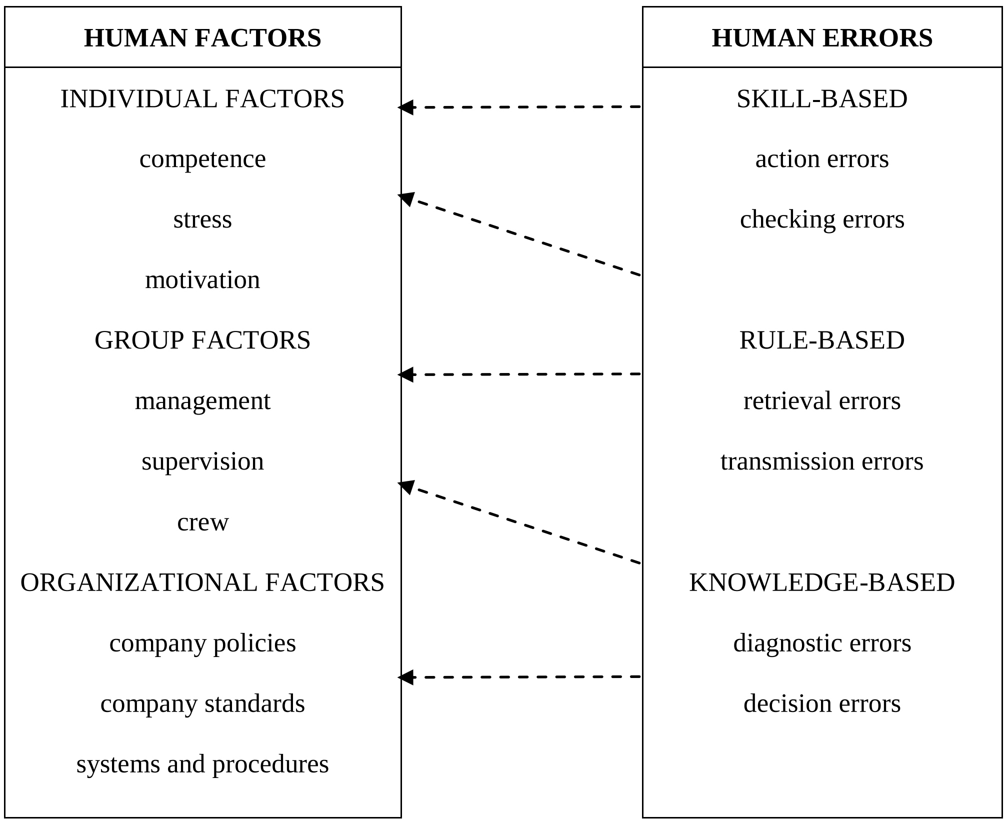

Figure 1. *Relationships between human factors and human errors according to Gordon /11/*

1.3 Report focus, limitations and structure

Human error and human factor as an accident cause are very broad and ambiguous subjects. Because the aim in this literature review was to study the existing techniques and models of human factor estimation as a background for marine traffic accident risk assessment in the Gulf of Finland, topics such as mitigating the human factors causing marine traffic accidents are not covered in this report. The focus is on modeling techniques, especially on the use of Bayesian networks, and theories of human error will be covered very briefly.

This report is organized as follows. Chapter two describes human factors in marine domain. Human error classifications are described in chapter three. Chapter four introduces a well-known “Swiss cheese” theoretical model for human elements in accident causation. Two very commonly used methods for human reliability analysis are presented in chapter five. In chapter six the actual modeling of human failure probability is discussed and some examples of models applied in marine domain risk assessments are described. Finally, summary and discussion based on the reviewed literature can be found in chapter seven.

2 HUMAN FACTORS IN MARINE DOMAIN

2.1 Introduction

Human factors affecting safety can be divided into organizational, group and individual factors. Some examples of organizational factors are management commitment to safety, safety training, open communication, environmental control and management, stable workforce, and positive safety promotion policy. Examples of group factors are line-management style, good supervision and clear understanding of own and other team members' roles and responsibilities. Individual factors are related to factors which affect a person's performance such as human-machine interface and competence, stress, motivation and workload of an individual. /11/

In IMO's FSA guidelines /16/, some examples of personal factors and unfavorable conditions which could lead to human errors were given. These factors are presented in table 1. Hetherington et al. /6/ reviewed the literature on individual and organizational factors related to shipping accidents and addressed the failures in three levels: design level, personnel level, and organizational and management level. The factors at each of these levels are presented in table 2. Some of the factors listed in tables 1 and/or 2 are discussed in the following.

Table 1. *Examples of human-related hazards listed in FSA guidelines /16/*

Personal factors	**Organizational and leadership factors**	**Task features**	**Onboard working conditions**
Reduced ability e.g. vision or hearing	Inadequate vessel management	Task complexity and task load	Physical stress e.g. from noise or sea motion
Lack of motivation	Inadequate ship owner management	Unfamiliarity of the task	Ergonomic conditions
Lack of ability	Inadequate manning	Ambiguity of the task goal	Social climate
Fatigue	Inadequate routines	Different tasks competing for attention	Environmental conditions
Stress			

Table 2. *Human factors affecting marine accidents at design, personnel, and organizational and management levels /6/*

Design level	**Personnel level**	**Organizational level**
Automation	Fatigue Stress Health Situation awareness Decision making and cognitive demands Communication Language and cultural diversity	Safety training (BRM/BTM, ERM) Safety climate Safety culture

2.2 Automation

Based on literature, Hetherington et al. /6/ proposed questions of whether the growing amount of automation on bridge has had negative effects such as increased cognitive demands and cognitive reluctance. Hollnagel /15/ stated that "the danger exists that automation is introduced for that which **can** be automated, rather than for that which **should** be automated". According to Schager /9/, humans tend to rely on technological aids over own observation, especially if human observation is vague or contradictory. Rothblum /7/ stated that almost all automation onboard is poorly designed and human factors engineering methods are not yet as commonly used in marine industry than in other industries. In a study of co-operation on bridge /17/, operational personnel, authorities, shipping companies and training organizations were interviewed and almost all interviewees found safety threats in using navigation and maneuvering aids, especially in the form of overreliance and possible equipment malfunctions.

2.3 Fatigue

Falling asleep on watch or a decrease in alertness because of fatigue is well-known and not a new cause of marine traffic accidents /18/. Current trends of increasing marine traffic, shorter sea passages, reduced manning and extended hours of duty are increasingly demanding for seamen /6/. Decreased alertness and slowed reaction speed caused by fatigue affects situation awareness /18/. Fatigue may also have an effect on communication atmosphere on bridge /18/.

When factors contributing to fatigue in bridge work were studied by presenting questionnaires to watch officers /18/, it was found that 17 % of respondents had fallen asleep and over 40 % had been near nodding off at least once on watch. The most important factors affecting alertness had been the time of day, the length of the previous sleep period and the time since the person had last woken up. 6/6 watch system increased the likeliness of symptoms of tiredness compared to other watch systems. Age and weight did not explain fatigue symptoms alone but they increased the risk of getting sleep apnea. /18/

2.4 Situation awareness

Situation awareness means the person's ability to construct a mental model on what is happening at the moment and how the situation will develop /6/. Based on marine accident reports, Grech et al. /19/ found that 71 % of human errors were related to situation awareness problems. Situation awareness errors were categorized further into three groups: failure to correctly perceive information, failure to correctly integrate or comprehend information, and failure to project future actions or state of the system /19/. Almost 60 % of SA-errors were failures to correctly perceive information, and the distribution of SA-errors was in line with previous results from aviation domain /19/.

2.5 Decision making and cognitive demands

Hockey et al. /20/, cited in /6/, studied the effect of secondary task on collision risk. The study was done using ship simulator and students as test subjects /20/, cited in /6/. It was found that as mental workload increased, collision threat increased and there was a detriment in performance on the secondary task /20/, cited in /6/. In a study where attention and workload were studied /21/, evidence was found to support the hypothesis that workload and attention were correlated: higher level of mental workload induced higher attention, while very low level of workload resulted in very low attention.

In two separate studies of officers' collision avoidance behavior /22/, cited in /23/, /24/, it was found that subjects allowed oncoming ships to approach within close range before taking actions, which behavior was not in line with the teaching to use the available sea-room and stay several miles away from other ships. Subjects showed a tendency to wait until approaching vessel's lights were showing no matter if they had detected it earlier or not /22/, cited in /23/, and the decision-making in collision avoidance was related to officers' personal characteristic: some officers took avoiding action resulting a closest point of approach (CPA) of less than one mile in all simulation exercises even though there had been sufficient sea room for a much larger CPA /24/. The violation of collision regulations was mainly due to ship officers' spontaneous action, not because of lack of knowledge /24/. In poor visibility the officers were statistically significantly more cautious in collision avoidance than in good visibility /24/. Despite of this behavior, only 3.5 % of these close encounters led to a collision caused by subject's action /24/.

2.6 Teamwork and communication

Based on a review of five case studies and a literature review on recent accident studies, Gatfield et al. /25/ stated that poor team performance leading to loss of situation awareness was a very common cause of marine accidents. The root causes of poor team performance lied in national, organizational and professional cultures: procedure violations, lack of communication and system understanding between team members /25/.

Marine traffic accident report analysis /17/ showed that in many cases communication on bridge had been scarce. On bridge there had been lack of communication concerning changed circumstances, between pilot and crew, or between bridge and engine room personnel. Based on interviews of mariners, speechlessness in bridge was a known problem. It was believed to be a result of authority relationships influencing communication climate. Further, bridge personnel had different conceptions of things that needed to be discussed of. /17/

2.7 Safety training, safety culture and safety climate

The effects of factors at organizational level such as of improving safety culture or safety climate are not easy to measure /6/. Knapp and Franses /26/ studied the dependencies of frequency of port State control inspections on ships, the probability of detention and the probability of casualties. It was found that the probability of serious and less serious casualties increased when the frequency of detention increased but on the other hand, the probability of very serious casualty decreased /26/. In the risk assessment of Washington State Ferry traffic /27/, it was concluded that the single most effective risk management intervention would be the implementation of fleet-wide ISM (International Safety Management) not existing at the time of study, whose effect was estimated to be 15 % of decrease in potential accident rate.

3 HUMAN ERROR CLASSIFICATIONS

Reason /23/ categorized human errors into three basic error types based on skill-rule-knowledge classification of human performance by Rasmussen /28/. The error types were skill-based slips and lapses, rule-based mistakes, and knowledge-based mistakes. These three error types were differentiated along several factors. This differentiation is shown in table 3. /23/

Table 3. *Reason's /23/ error types and distinctions between the types along several factors*

Factor	**Slips and lapses**	**Rule-based mistakes**	**Knowledge-based mistakes**
Individual's type of activity	Routine actions	Problem solving activity	Problem solving activity
Focus of attention	On something other than the primary task	On problem-related issues	On problem-related issues
Control mode	Automatic processors (schemata)	Automatic processors (stored rules)	Limited, conscious processed
Predictability of error types	Largely predictable	Largely predictable	Variable
The ratio of error to opportunity for error	Absolute numbers may be high, but opportunity ratio low	Absolute numbers small, but opportunity ratio high	Absolute numbers small, but opportunity ratio high
The influence of situational factors	Low to moderate; intrinsic factors likely to dominate	Low to moderate; intrinsic factors likely to dominate	Extrinsic factors likely to dominate
Ease of detection	Detection usually fairly rapid and effective	Difficult, often only achieved through external intervention	Difficult, often only achieved through external intervention
Relationship to change	Knowledge of change not accessed at proper time	When and how anticipated change will occur unknown	Changes not prepared for or anticipated

Generic error-modeling system (GEMS) is a conceptual framework for human error that attempts to present the possible origins of the three basic error types and describes how switching between the error levels occurs. Slips and lapses, the errors at skill-based level, occur prior to problem detection and are typically associated to monitoring failures. These can be caused by inattention, a necessary check is omitted, or by overattention, an attentional check is made at an inappropriate moment. Rule-based and knowledge-based errors follow the detection of a problem. Rule-based mistakes arise from the misapplication of "good rules", which means using a rule that is beneficial in certain situation in dissimilar circumstances, or from application of "bad rules". One of GEMS's vital features is the assumption that humans try to find a solution to a problem at rule-based performance level before resorting to the knowledge-based level. Only after realizing that a satisfactory result cannot be attained by applying stored problem-handling rules, they will move into knowledge-based level and even then, at first, search for cues that remind them of previously successful rules for adaptation to current situation. The dynamics of GEMS are presented in figure 2. /23/

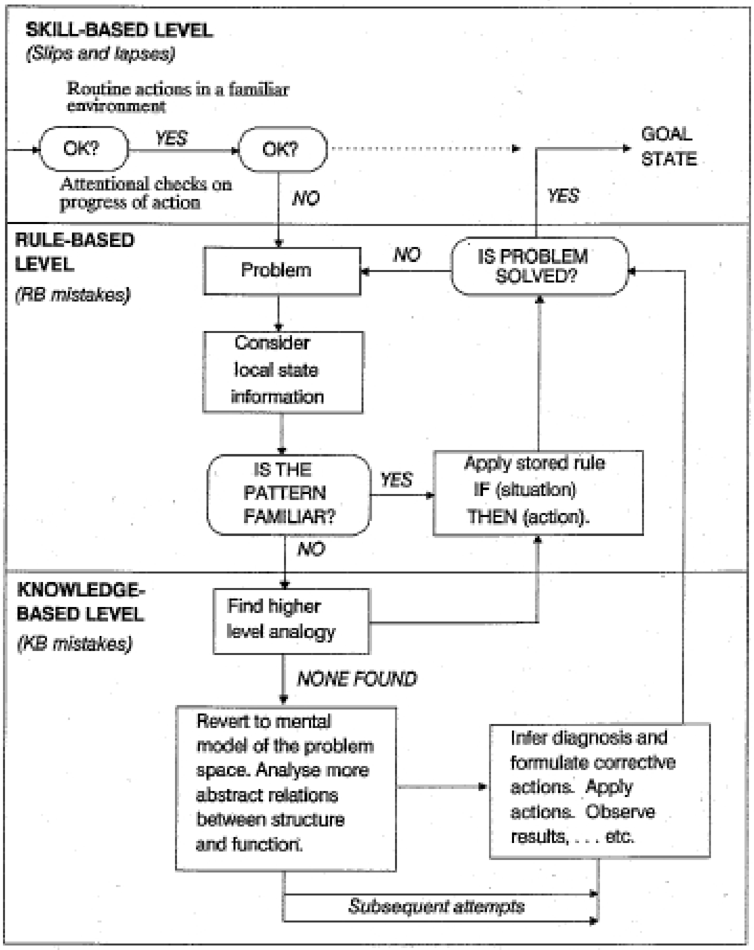

Figure 2. *Dynamics and error levels of GEMS /23/*

Kontogiannis and Embrey /29/, cited in /11/, presented another error type classification. The error categories were /29/, cited in /11/,

1. Action errors
   - No action taken
   - Wrong action taken
   - Correct action on wrong object
2. Checking errors
   - Checks omitted

- Wrong checks made
- Correct check on wrong object

3. Retrieval errors
    - Required information not available
    - Wrong information received
4. Transmission errors
    - No information sent
    - Wrong information sent
    - Information sent to wrong place
5. Diagnostic errors
    - Actual situation misinterpreted
6. Decision errors
    - Circumstances considered but wrong decision made

The relationships of these categories to Reason's categories presented by Gordon /11/ can be seen in figure 1: action and checking errors are related to slips and lapses, retrieval and transmission errors to rule-based mistakes, and diagnostic and decision errors to knowledge-based errors.

Gluver and Olsen /10/ divided human failures in marine accidents into the following groups:

- No action
    - Absence
    - Present but not attentive
    - Attentive but problem not realized
- Unintended wrong action
    - Situation misunderstood
    - Situation understood, wrong action chosen
    - Communication problems (e.g., pilot/master)
- Intended wrong action
    - Navigational basis (charts) is not updated
    - Confusion of buoys and/or landmarks

- Maneuvering capabilities overestimated
- Clearance requirements underestimated

In International Maritime Organization’s Formal Safety Assessment guidelines /16/ some typical examples of human errors were listed. These are shown in table 4.

Table 4. *Examples of human errors listed in FSA guidelines by International Maritime Organization /16/*

Physical Errors	**Mental Errors**
Action omitted	Lack of knowledge of system/situation
Action too much/little	Lack of attention
Action in wrong direction	Failure to remember procedures
Action mistimed	Communication breakdowns
Action on wrong object	Miscalculation

4 HUMAN ELEMENTS IN ACCIDENT CAUSATION IN COMPLEX SYSTEMS

4.1 Active and latent errors

Two kinds of error occurring in a complex system such as marine transportation can be distinguished: active and latent errors. The effects of active errors are felt almost immediately after the accident while the consequences of latent errors may not be visible until a certain combination with other factors occurs. Active errors are the ones made by pilot, control room crew, ship officers and other “front-line” operators. Designers, high-level decision makers, managers, maintenance personnel etc. are most likely causing latent errors. /23/

According to Reason /23/, previous accidents have shown that the biggest threat to a complex system’s safety comes from latent errors. A disaster may have been lurking in the system a long before the accident due to poor design, incorrect installation, faulty maintenance, poor management decisions, etc., and the operator has just added the finishing touch. Because of this, improvements in the immediate human-machine interface might not have a great impact on improving safety. /23/

4.2 Reason’s “Swiss cheese” accident causation model

Reason /23/ proposed a framework for accident causation in a complex system constructed of hierarchical components or levels. These levels represent organization’s or system’s defenses against failure.

Reason stated that primary origins of latent failures are fallible decisions made at the manager and designer level, which is the top failure level in “Swiss cheese” model. Fallible high-level decision-making can be a result of the difference in two goals that are in short-term conflict: maximizing both production and safety. These failures are a part of designing and managing process and cannot be totally prevented, but their consequences should be recognized and prevented in time. /23/

The next failure level in the model, line management deficiencies, includes persons who implement the strategies of the higher-level decision-makers. At this level the unsafe effect of fallible decisions can be mitigated or good decisions can be transformed into even better ones. On the other hand, incompetency in line management may boost the negative effects of fallible decisions or cause good decisions to have negative effects on safety. Budgets or resources decided at higher-level have effect on the magnitude of line management influence on fallible decisions. /23/

Deficiencies at line management level can manifest at the next level, psychological preconditions for unsafe acts. These preconditions are latent states that create potential for unsafe acts. Examples of the preconditions of unsafe acts are stress, inattention and lack of motivation. Interactions between line management deficiencies and the preconditions for unsafe acts are described very complex: One deficiency can produce a variety of preconditions, or a single precondition can be a result of multiple deficiencies at line management level. /23/

The next level, unsafe acts, means the actual performances of humans and machines. Unsafe acts can be either unintended or intended. Unintended actions can be classified into three basic error types described in chapter 3. Intended actions can be divided into mistakes or violations. Besides being an error or violation, unsafe act is committed in the presence of a potential hazard that could cause injury or damage. The occurrences of unsafe acts depend on psychological precursors and complicated interactions within the system and with environment. Very few unsafe acts will result in an accident. /23/

The last level in the model is defense level which constitutes from safeguards such as personal safety equipment and defense in depth of nuclear power plants. Inadequate defenses can be made up many elements and consist of both latent and active failures. /23/

Figure 3 presents the dynamics of accident causation in "Swiss cheese" model, where a trajectory of accident opportunity passes through each level from "windows of opportunity". These windows' locations and sizes vary over time and if they line up, an accident occurs. A set of causal factors finding an appropriate trajectory through the system is very unlikely. /23/

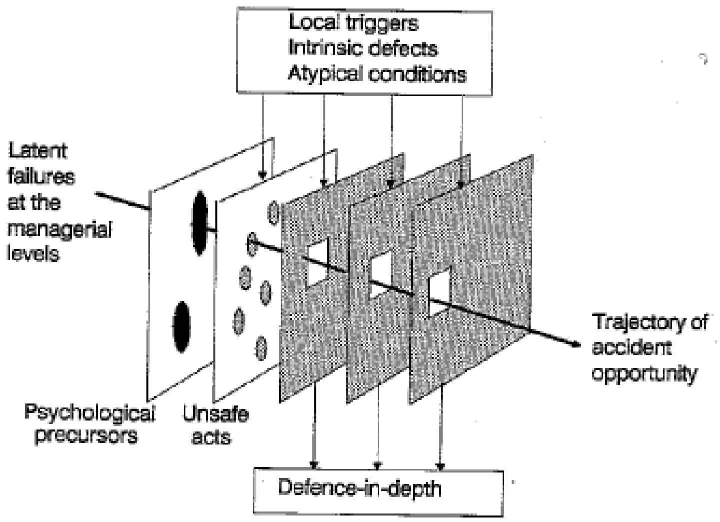

Figure 3. *Dynamics of accident causation in a system of multiple productive levels. The trajectory of accident opportunity passes through weaknesses in the levels /23/*

In the "Swiss cheese" model, each of the contributing components is necessary for accident occurrence but none of them is sufficient on its own /23/. When 100 accidents were studied /30/, it was found that human failure contributed to 94 of these cases. Each of the errors was a necessary condition for the accident, so if any one of them had not occurred, the accident would have not happened /30/. This observation is in line with the "Swiss cheese" model.

Dekker /31/ criticized "Swiss cheese" model and stated that the model's assumptions of independency and linearity between the levels is not realistic. Ren et al. /12/ pointed out that “Swiss cheese” model is only a theoretical framework, not an actual investigation technique and it does not contain information on how it should be applied to real world problems. For that purpose Human Factors Analysis and Classification System (HFACS) was developed describing “what the ‘holes in the cheese’ really are so they can be identified during accident investigations” /32/. Originally developed for the U.S. Navy and Marine Corps, HFACS has also been applied to commercial /33/ aviation.

In marine domain, accident analysis of 46 ferry accidents was conducted in Washington State Ferries risk assessment /8/ in order to analyze the role of human and organizational error. Found errors were categorized by Reason’s taxonomy into two types of unsafe activities: unintended errors and intended violations. All human errors that were found had been unintended. /8/

5 HUMAN RELIABILITY ANALYSIS

5.1 1st and 2nd generation HRA methods

The influence of human element on a failure of a system can be included in probabilistic risk assessments using HRA, Human Reliability Analysis/Assessment. In the guidelines of Formal Safety Assessment (FSA) /16/, which is a PRA method for marine domain developed by International Maritime Organization, it was described how to fit HRA into FSA process. FSA guidelines also stated that the proposed HRA guidance, which was very similar to FSA process, "should be used wherever an FSA is conducted on a system which involves human action or intervention which affects system performance" /16/.

The early methods of HRA were based on the assumption that humans make errors because of their inherent deficiencies /34/. With this assumption, the human error probability can be estimated mainly based on the task characteristics, and the environment where the task is being performed has only minor influence on human failure /34/. These methods have been called as first generation HRA methods. 1st generation methods have been criticized: table 5 presents some weaknesses listed by Kristiansen /35/. Second generation HRA techniques were developed in order to overcome the deficiencies in first generation methods. Hollnagel /36/ stated that with the development of modern technology human work has changed from manual skills to more cognitive nature, and because of this HRA techniques must also be updated. In second generation methods the importance on environment such as design, maintenance, and management, is acknowledged and the major role on human failure has been given to task environment instead of the human's task /15, 34/.

There exist a large number of HRA techniques, some being very domain-specific, mostly developed in the 1980s /15/. An example of the probably best-known first generation method, THERP, and a second generation method, CREAM, are described in the following subchapters. Descriptions and comparisons of some of the other HRA techniques can be found, e.g., in /15/.

Table 5. *Weaknesses of 1st generation methods presented by Kristiansen /35/*

Weaknesses of 1st generation HRA methods
Scarcity of data
Lack of consistency in treating errors of commission
Inadequate proof of accuracy
Insufficient treatment of performance-shaping factors
Inadequate treatment of dynamic situations
A mechanical view of humans
Quantitative rather than qualitative focus
High level of uncertainties
Inadequate identification and understanding of error causes
Lack of systematic analysis of task structure
Inadequate provision of error reduction strategies

5.2 THERP

Technique for human error rate prediction (THERP) /37/ is widely used tool for providing human reliability data for PRA. THERP was originally developed for nuclear power industry. In the FSA guidelines /16/, THERP and HEART /38/ were listed as be applicable methods for marine domain.

The basic assumption in THERP is that the operator's actions can be modeled as an equipment item such as a pump or a valve. The four steps of THERP are /37/, cited in /23/

1. Identifying of the system components that may be influenced by human error
2. Analyzing the related human operations
3. Estimating the relevant human error probabilities (HEPs) using available data and expert judgment
4. Estimating the magnitude of effects of human errors
5. Recommending and evaluating changes

At the third step, the probability of a certain erroneous action can be derived with the equation /37/, cited in /23/

$$P_{EA} = HEP_{EA} \sum_{k=1}^{m} PSF_k \cdot W_k + C \qquad (1)$$

, where

P_{EA} is the probability for a specific erroneous action,
HEP_{PA} is the basic operator error probability of a specific action,
PSF_k is numerical value of *k*th performance shaping factor,
W_k is the weight of PSF_k,
C is numerical constant, and
m is the number of *PSF*s.

The basic HEPs are predefined values of human error probabilities and they are listed in the THERP Handbook /37/. Basic HEPs are assumed to be independent of their context so they can be applied to different domains /39/. The performance shaping factors describe the effect of context on the basic human error probability /15/. PSFs have been classified into external PSFs, stressor PSFs and internal PSFs /15/. They are presented in table 5. The values for the PSFs are also listed in the THERP handbook. The total effect of PSFs on failure probability is calculated as a weighted sum, as can be seen in equation 1. This means that the PSFs are assumed to be independent /15/. In THERP each human action is divided into tasks and subtasks and they are presented in HRA event tree /15/. HRA event tree is binary so that each action can be either successful or failed one with a certain probability summing to 1 /15/.

In a tanker grounding model /35/, THERP was expanded to consider management and organizational factors also. This was done by introducing MOFs, Management and organizational factors, which influenced the PSFs. The relationships between PSFs and MOFs were based on expert judgment. /35/

Hollnagel /15/ stated that in modeling human behavior the event tree approach used in THERP does not make sense, because cognitive acts cannot be separated into subtasks as easily as manual actions. He also criticized the separate use of PSFs that would suggest context independency of the model by itself. /15/

Table 6. *PSFs in THERP /15/*

External PSFs			***Stressor PSFs***		***Internal PSFs***
Situational characteristics	**Job and task instructions**	**Task and equipment characteristics**	**Psychological stressors**	**Physiological stressors**	**Organism factors**
Architectural features Quality of environment (temperature, humidity, air quality and radiation, lighting, noise and vibration, degree of general cleanliness) Work hours/work breaks Availability/adequacy of special equipment Shift rotation Organizational structure (authority, responsibility, communication channels) Actions by supervisors, co-workers, union representatives, and regulatory personnel Rewards, recognitions, benefits	Procedures required (written or not) Cautions and warnings Written or oral communications Work methods Plant policies	Perceptual requirements Motor requirements (speed, strength, precision) Control-display relationships Anticipatory requirements Interpretation Decision-making Complexity (information load) Narrowness of task Frequency and repetiveness Task criticality Long- and short-term memory Calculational requirements Feedback (knowledge of results) Dynamics vs. step-by-step activities Team structure and communication Man-machine interface factors	Suddenness of onset Duration of stress Task speed High jeopardy risk Threats (of failure, loss of job) Monotonous, degrading or meaningless work Long, uneventful vigilance periods Conflicts of motives about job performance Reinforcement absent or negative Sensory deprivation Distractions (noise, glare, movement, flicker, color) Inconsistent cueing	Duration of stress Fatigue Pain or discomfort Hunger or thirst Temperature extremes Radiation G-force extremes Atmospheric pressure extremes Oxygen insufficiency Vibration Movement constriction Lack of physical exercise Disruption of circadian rhythm	Previous training/experience State of current practice or skill Personality and intelligence variables Motivation and attitudes Knowledge required (performance standards) Stress (mental or bodily tension) Emotional state Sex differences Physical condition Attitudes based on influence of family and other outside persons or agencies Group identification

5.3 CREAM

Cognitive Reliability and Error Analysis Method (CREAM) is one of the best-known 2nd generation HRA methods that was presented by Hollnagel /15/. Hollnagel stated that human actions occur in a context, so the effects of context on human behavior must be included in a model describing human performance /15/. CREAM can be used in retrospective accident analysis or in qualitative or quantitative human performance prediction related to PRA /15/. For retrospective accident analysis, a specified marine domain version of CREAM called BREAM (Bridge Reliability and Error Analysis Method) has been developed /40/. BREAM combines CREAM's rather static environment that includes aspects of organization and team work the dynamic environment of CREAM's adaptation to road traffic, DREAM (Driving Reliability and Error Analysis Method) /40/. In this chapter the application of CREAM for quantitative human performance prediction, i.e. assessing human failure probabilities for the needs of a PRA, is described.

For human failure probability assessment CREAM can be done in two steps with basic and extended method. Basic method assesses the overall performance reliability and the outcome will be an estimate of the probability of performing an action incorrectly for the task as a whole. The extended method uses this outcome to take a closer look at the parts of the task that should be investigated more precisely. /15/

5.3.1 Basic method

The first step in the basic method of CREAM is to identify the safety scenario or event that will be analyzed /15/. After the event sequence is constructed, the common performance conditions (CPCs) are assessed /15/. CPCs describe the effects of context and differ from THERP's PSFs for having a larger role on the outcome than just an adjustment on the final probabilities /15/. The nine CPC are listed in table 7. In BREAM CPCs suitable for marine domain were introduced /40/.

For each of the CPCs, a set of discrete possible states has been defined. For the adequacy of organization, for example, the states are {very efficient, efficient, inefficient, deficient}. For each state of all CPCs, the expected effect on performance reliability is described using an identical set of states {improved, not significant, significant}. /15/

Initial assumption in CREAM is that the CPCs are not independent. According to Hollnagel, this is more realistic assumption than the independence of PSFs assumed in THERP /15/. The proposed dependencies are presented in table 7. Because of the dependencies, the expected states may have to be adjusted. This is done for those CPCs whose expected state is "not significant" and that are depended on at least two CPCs. If at least all but one of the affecting CPCs (or, for "Crew collaboration quality", both "Adequacy of organization" and "Adequacy of training and experience") have the same effect, the expected effect on performance reliability of the CPC in question will be changed to match the expected effect of the affecting CPCs. /15/

Table 7. *CPCs and the dependencies between them /15/*

CPC name	Affected by
Adequacy of organization	-
Working conditions	Adequacy of organization , Adequacy of MMI and operational support, Available time, Time of day, Adequacy of training and experience
Adequacy of MMI and operational support	Adequacy of organization
Availability of procedures / plans	Adequacy of organization
Number of simultaneous goals	Working conditions, Adequacy of MMI and operational support, Availability of procedures / plans
Available time	Working conditions, Adequacy of MMI and operational support, Availability of procedures / plans, Number of simultaneous goals, Time of day, Crew collaboration quality
Time of day (circadian rhythm)	-
Adequacy of training and experience	Adequacy of organization
Crew collaboration quality	Adequacy of organization, Adequacy of training and experience

Based on the adjusted expected effects on performance reliability, a combined CPC score can be expressed as /15/

CPC score = (number of reduced, number of not significant, number of improved)

In Contextual Control Model, which is the human cognition model in CREAM, the human failure probability is assessed based on the degree of control that the persons have over the situation. The degree of control is divided into four control modes: scrambled control, opportunistic control, tactical control and strategic control. Some features of the control modes are presented in table 8. The control mode can be estimated based on the CPC score and the plot presented in figure 4. For example, if the CPC score is (2, 0, 5) then the control mode is scrambled. For the control modes, general human failure probability intervals have been assessed, and they are also presented in table 8. /15/

Table 8. *Features of the control modes in CREAM and the corresponding human failure probability interval /15/*

Control mode	Features and possible causes	Human failure probability interval
Scrambled control	Next action is unpredictable, little or no thinking involved, high task demands, unfamiliar and unexpectedly changing situation, complete loss of situation awareness	1.0 > p > 0.1
Opportunistic control	Very little planning, actions are often based on perceptually dominant or most frequently used features, context is not clearly understood , time is too constrained	0.5 > p > 0.01
Tactical control	Performance based on limited scope of planning, follows a known procedure or rule	0.1 > p > 0.001
Strategic control	Global context and higher goals are considered, efficient and robust performance	$0.01 > p > 0.5 \cdot 10^{-5}$

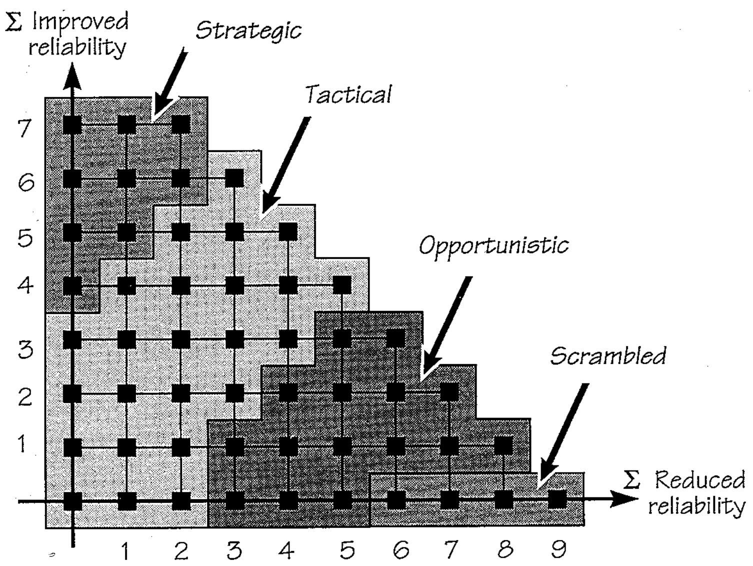

Figure 4. *Relations between the CPC score and control modes. The number of improved reliability CPCs (0..7) is on vertical axis and the number of reduced reliability (0..9) on the horizontal axis /15/*

Instead of getting an interval for human failure probability, Fujita and Hollnagel /41/ presented a model for calculating a mean failure rate. Calculations were based on the CPC score of the application in question and an expert judgment estimate for mean failure rate when the number of reducing conditions is equal to the number of improving conditions /41/. Konstandinidou et al. /42/ presented a fuzzy classifier based on the basic CREAM method. In order to include the uncertainty of the specification of CPCs, Kim et al. /34/ presented a probabilistic approach for assessing the control mode in CREAM. The CPCs were presented as probability distributions, and the probability distribution of the control mode was derived using Bayesian networks /34/.

5.3.2 Extended method

Hollnagel stated that the extended method of CREAM needs to be done in cases where the general action probability derived with the basic method is unacceptably high or when the uncertainty is unacceptable large. The extended method consists of three steps. The first step is to build a profile of the cognitive demands of the task by refining the description of event sequence identified in basic method. Cognitive activities are identified from a list of characteristic cognitive actions presented in /15/. These activities are then described using four cognitive functions: observation, interpretation, planning, and execution. The relations between the cognitive activities and functions are presented in /15/. After the description on each cognitive activity in terms of cognitive functions, the cognitive demand profile for the whole task (or its major subtasks) can be calculated by summing the occurrences of each cognitive function. /15/

The second step is to identify the likely cognitive function failures. These are selected from a list of failures related to the cognitive functions. The list is presented in table 9. Third step is to assess the failure probabilities for the identified cognitive function failures. The nominal values of the probabilities, presented in table 9, are adjusted to consider the effects of CPCs identified in basic method. The adjustment factors can be found in /15/. /15/

Table 9. *Generic cognitive function failures and their nominal probabilities in extended CREAM /15/*

Cognitive function	**Potential cognitive function failure**		**Nominal CFP**
Observation errors	O1	Observation of wrong object. A response is given to the wrong stimulus or event	$1.0 \cdot 10^{-3}$
	O2	Wrong identification made, due. to e.g. a mistaken cue or partial identification	$7.0 \cdot 10^{-2}$
	O3	Observation not made (i.e., omission), overlooking a signal or measurement	$7.0 \cdot 10^{-2}$
Interpretation errors	I1	Faulty diagnosis, either a wrong diagnosis or an incomplete diagnosis	$2.0 \cdot 10^{-1}$
	I2	Decision error, either not making a decision or making a wrong or incomplete decision	$1.0 \cdot 10^{-2}$
	I3	Delayed interpretation, i.e., not made in time	$1.0 \cdot 10^{-2}$
Planning errors	P1	Priority error, as in selecting the wrong goal (intention)	$1.0 \cdot 10^{-2}$
	P2	Inadequate plan formulated, when the plan is either incomplete or directly wrong	$1.0 \cdot 10^{-2}$
Execution errors	E1	Execution of wrong type performed, with regard to force, distance, speed or direction	$3.0 \cdot 10^{-3}$
	E2	Action performed at wrong time, either too early or too late	$3.0 \cdot 10^{-3}$
	E3	Action on wrong object (neighbor, similar or unrelated)	$5.0 \cdot 10^{-4}$
	E4	Action performed out of sequence, such as repetitions, jumps, and reversals	$3.0 \cdot 10^{-3}$
	E5	Action missed, not performed (i.e., omission), including the omission of the last actions in a series (“undershoot”)	$3.0 \cdot 10^{-2}$

6 MODELING HUMAN FACTORS IN ACCIDENT CAUSATION

6.1 Introduction

In marine traffic risk assessments an estimate for the probability of human failure has been obtained different ways. In some risk assessments or software such as /43, 44/, the human elements in accident causation have not been studied or modeled in more detail but the value for human failure probability has been derived from a previously conducted risk assessment or other literature source. Also when analyzing human reliability with THERP-technique, the fixed values of basic operator error probabilities and performance shaping factors listed in the THERP Handbook are used /15/.

As it is mentioned in the introduction chapter of this report, in some of the earliest collision and grounding probability estimations the causation probability was estimated based on the difference in accident frequency and the geometrical probability of an accident. Fujii /45/ calculated "the probability of mismaneuvers leading to collision to fixed object or grounding" in Japanese waters this way and found the value to be about $2 \cdot 10^{-4}$. In Øresund Link project's calculations for a grounding scenario as a result of human failure and collisions with a lighthouse /46/, this value was used as a human failure probability and a reference to Fujii's study was made, thus making an assumption that the "probability of mismaneuvers" was equal to human failure probability.

Drawing human error probability for the needs of a PRA from previous studies or based on the difference in accident statistics and geometrical probability may save some effort, but then the actual human elements in accident causation are not addressed at all, as opposed to constructing a model for the estimation. Getting a number value for the probability of human factors as an accident cause is only one outcome of a model, the acquired model structure itself and the dependencies of the parameters may be even more important. In this chapter input data sources and Bayesian networks for modeling human factors in accident causation are described and some examples from marine domain are presented.

6.2 Data sources

6.2.1 Introduction

For constructing a model for estimating the probability of human failure in accident causation, information is needed on how the human failure has been originated and what are the probabilities of occurrence of these elements leading human failure. Hollnagel /15/ commented that human errors cannot be observed directly, only by observation of human behaviors. The human behavior observation can be done using accident descriptions or statistics, self observation or diary-keeping of errors that have happened in everyday life, questionnaire studies, simulator studies, or expert judgment /23/. In the following subchapters the most commonly used input data sources for human factor modeling in marine domain are described.

6.2.2 Accident registrations and databases

Data from marine traffic accidents happened in the past can be gathered from accident databases, accident reports, or published accident statistics of from certain areas and time periods. Data collection from accident databases is applicable especially if the information is stored in numerical format using fixed categorization. Accident reports are in text format and their usage typically requires some human effort in extracting information from the text.

All marine accidents except the ones happened to pleasure boats must be reported according to the Maritime Act. Accident database DAMA consists of marine casualty reports given to Finnish Maritime Administration. All reported accidents of Finnish vessels and accidents of foreign vessels on Finnish territorial waters are listed in DAMA from the year 1990 on. Very minor accidents such as small dents from ice assistance situations, pleasure boat accidents or accidents that have not been reported are not included in DAMA-database. /47/

In DAMA there exist several fields for each accident case, such as fields for accident vessel's name, gross tonnage, nationality, event type, and location. In reality, many fields have been left blank. One of the fields is the primary cause of the accident. The options for causes are divided into the following eight main groups /48/:

1. External factors not related to the accident vessel
2. Vessel layout and structure
3. Technical failures
4. Factors related to equipment use and positioning
5. Factors related to cargo and handling of cargo or fuel
6. Communication, organization, instructions and routines
7. Persons, situation assessment, action
8. Other causes

These groups consist of several subgroups. The subgroups of groups 6 and 7, the ones related to human and organizational factors, are presented in table 10.

Table 10. *Subgroups of human and organizational factors cause groups in DAMA-database /48/*

Communication, organization, instructions and routine	**Persons, situation assessment, action**
No/insufficient instructions	Inadequate qualification for the task (education, degree etc.)
Operational procedures not known/not trained enough	Inadequate practical experience (work experience, familiarity of waters, equipment use etc.)
Insufficient safety instructions	Task/activities poorly planned (cargo, night navigation, route plan, anchoring etc.)
Safety instructions known but not followed	Available warning aids not sufficiently used
Safety instructions not followed during welding	Optional navigational systems not used. Wrong assessment of lights etc.
Welding lead to fire though safety instructions followed	Navigational aids or publications not exploited
Safety equipment testing instructions not followed	Position of own ship not fixed properly, position not marked in chart
Safety equipment not used	Misunderstanding of other vessel's movement or intentions
Too low level of organizing/instructions/knowledge	Misunderstanding of own vessel's movement or intentions
Checking/maintenance instructions not followed	Trying to perform task in unfavorable conditions
Stability not known/no approved stability calculations	Did not stay in right side of the lane/water area
Inappropriate management style, personnel issues etc.	Situational speed too high
Undermanned vessel or bridge	Sickness, lack of sleep, excessive workload etc.
Unclear distribution of liabilities or tasks	Fell asleep on watch
Bridge routines insufficient/not defined	Alcohol or other substance
Bridge routines not followed	Other personnel factor
Charts/other publications not updated	
Errors in co-operation/procedures with a tug, land organization etc.	
Other factors related to organization, safety instructions, routines or communication	

In Finland the Accident Investigation Board located within the Ministry of Justice investigates and reports "all major accidents regardless of their nature as well as all aviation, marine and rail accidents and their incidents" /49/. The Board investigates how the accident happened and what were the causes, consequences and rescue operations. Several marine traffic accident reports of accidents from 1995 on are available at Accident Investigation Board's web pages. /49/

Accident investigation reports were used in the study of performance shaping factors in navigation accidents in the Royal Norwegian Navy /50/. For evaluating the presence of patterns in the accidents, cluster analysis was performed to the data /50/. Accident reports were also used when the role of human and organizational error was analyzed in Washington State Ferries risk assessment /8/ and in an investigation process where marine accident reports published by authorities of several countries were used for estimating occurrence probabilities and consequences of human factors by creating so-called "cause parameters", describing the ways how the studied human factor item had appeared, and "result parameters", describing the resulted accident types and seriousness of injuries and damages, of the studied human factor /14/. Leximancer, a text-mining software for automatically analyzing content of text documents /51/, was used for examining the role of lack of situation awareness in marine accident causation from accident reports /19/. Results got with Leximancer tool were comparable to manual analysis of reports /19/.

At the moment there exists no standardized accident-reporting format in the marine domain. Accident databases are scarce, there are differences in format between countries and they are not easily available, if even existing /14/. According to Reason /23/, the reliability of accident reports can be questioned, since they will always have a simplified presentation of the events and are mostly concerned with attributing blame. Accidents with no injuries are underreported, more severe accidents are investigated in more detail and a high risk of bias is present when using accident investigation reports as data /50/. It is also very unlikely that the chain of causes and their interactions that had lead to a certain accident would be occurring identically again in another accident /14/. Harrald et al /52/ stated that the collected marine accident data is not detailed enough for a human error assessment and suspected that it unlikely will ever be. Therefore they emphasized the need for data from 'near miss' situations for more advanced modeling and risk assessment /52/.

6.2.3 Simulator studies

Reason /23/ stated that the most powerful technique for studying human error is to study particular error types under controlled laboratory conditions. In marine traffic studies this can be done using shiphandling simulators. According to Harrald et al. /52/, the advantages of simulator use are the possibility to observe human error occurrence in simulated hazardous situations, uniformity that can be attained in data collection by using trained observers and the possibility for questioning the participants to confirm the types of errors made. Experiences can be recorded using video or audio recorders so that domain experts can analyze the behavior /21/. The fact that the environment and situations are totally simulated and, at least some part, different from normal situations, is the problem of using simulators in human factors studies /21/. Ship bridge simulators have been used in studies of officers' collision avoidance behavior /22/, cited in /23/, /24/.

6.2.4 Expert judgment

If no hard data is available for constructing the model, the probabilities and/or dependencies of the model parameters can be based on opinions of a group of domain experts. In modeling human factors in marine traffic accidents, relevant and extensive data is difficult to find and the use of expert judgment is very common. There are several ways to find the probability estimates with expert judgment such as performing pair-wise comparisons, using ranking procedures or acquiring the numerical estimates directly or indirectly from the experts /15/.

Some examples of marine traffic accident risk studies that used expert judgment in human factors assessment are Prince William Sound risk assessment /52/, North Sea risk assessment /53/ and Åland Sea FSA study /54/. For example, in the Åland Sea FSA study carried out by VTT, an expert workshop with six experts were organized in order to assess the influences of risk control options to situational awareness of bridge officers /54/. The risk control options were also identified in expert workshops /54/.

6.3 Bayesian network as a modeling technique

6.3.1 Introduction to Bayesian networks

Bayesian networks are directed acyclic graphs that consist of nodes representing variables and arcs representing the dependencies between variables. Each variable has a finite set of mutually exclusive states. For each variable A with parent nodes $B_1,\ldots, B_n$ there exist a conditional probability table $P(A \mid B_1, \ldots, B_n)$. If variable A has no parents it is linked to unconditional probability P(A). /55/

Bayesian networks are used to get estimates of certainties or occurrence probabilities of events that cannot or are too costly to be observed directly. For identifying the relevant nodes and the dependencies between nodes, and constructing the node probability tables, both hard data and expert opinions can be used and mixed. Possible disagreements between the experts' opinions on the probabilities can be included in the model by adding nodes representing the experts. /55/

Bayesian networks can also be used as an aid in decision-making under uncertainty. These networks, called influence diagrams (IDs), include a couple of extra nodes in addition to the oval-shaped chance nodes: rectangular-shaped decision nodes and diamond-shaped utility nodes. A decision node has states that are describing the options of a decision. Links from a decision node to the chance nodes describe the impacts on network variables. Utility nodes are used in computing the expected utilities or "usefulness" of the decision alternatives. They have neither states nor children but can express the utility of a decision for example in Euros. /55/

Bayesian networks have been applied in several fields, including risk analysis of military vehicles /56/, modeling the operational accident causation in railway industry /57/, and the reliability of search and rescue operations /58/. They have been used in modeling nuclear power plant operators' situation assessment /59/. In Aviation System Risk Model (ASRM) presented by Luxhøj /60/, human factors in aviation accidents were assessed using Bayesian networks and HFACS human error framework. In 2006, utilization of Bayesian network at step 3 of Formal Safety Assessment was suggested in a document /61/ submitted by the Japan body of maritime safety to the IMO Maritime Safety Committee.

6.3.2 Learning Bayesian networks

When constructing a Bayesian network, the structure of the network may be known for example by a domain expert opinion but the probability values of states of nodes may be unknown. Or there may not be expert judgment available and then the network structure may also be unknown. If there is some data available, the network structure and the parameter could be learnt from it. If the data set used as a basis in parameter estimation is complete, i.e. it does not contain missing values, the estimation can be done with maximum likelihood estimation or with maximum a posteriori estimation. If the data is incomplete, EM-algorithm can be used. For the network structure learning, constrained-based or score-based methods can be used. These are described, e.g., in /55/. /55/

In a study for predicting football match outcomes /62/, the results from a Bayesian network based almost exclusively on expert opinions were compared with the results from four machine learning techniques: a decision tree learner, a naïve Bayesian learner, a Bayesian network whose structure and node probabilities were learnt entirely from data, and a K-nearest neighbor learner. The expert Bayesian network gave the most accurate predictions of the outcomes /62/. In the study it was stated that in addition to impressive performance when built by a reliable domain expert, the merits of expert Bayesian network were the simplicity of building the model and the ability to perform well with little learning data /62/. Latter feature is important if the model was applied to a domain with scarce data, such as marine traffic accident data.

Hu et al. /63/ used accident data in learning a Bayesian network structure and parameters for ship traffic risk assessment. Naïve Bayes classifier was used as a learning method for network structure learning /63/. The structure after learning is presented in figure 5. When the network structure had been learnt, the probability values for network parameters were estimated using equation /63/

$$P(a_j \mid x_i) = \frac{n_c + m \cdot p}{n + m} \tag{2}$$

, where

n was the total number of training examples for which x_i occurred,
n_c was the number of training examples for which a_j occurred,
p was the prior estimate of the probability to be determined and
m was a sample size constant.

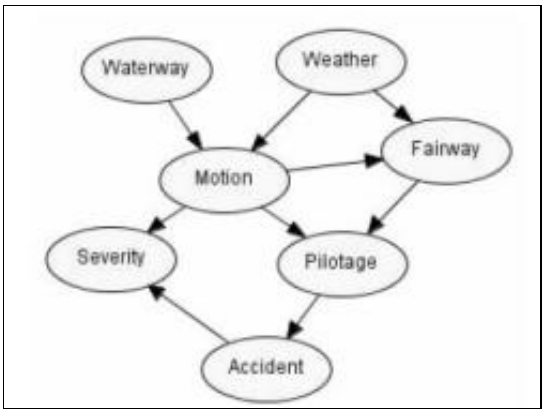

Figure 5. *Bayesian network structure learnt with a naive Bayes classifier from ship traffic accident data /63/*

6.3.3 Object-Oriented and Dynamic Bayesian networks

Fragments of a Bayesian network that are identical in structure and probability table can be instantiated. These generic fragments will then be called classes, and an instance of a class will be an object (as in object-oriented programming). An interface to the class can then be included into the main network. A network that consists of objects is called object-oriented Bayesian network (OOBN). With OOBN the visual representation of the network becomes simpler, and so-called information hiding can be achieved. /55/

If the modeled system is evolving under time, its state can be modeled at each time step 55/. This can be easily done using OOBNs so that the output variables are the variables which have children at later time steps and the input variables are parents from earlier time55/. If the structures and probability tables of the time slices are identical, the model is called dynamic Bayesian network /55/. Dynamic Bayesian networks have been applied, e.g., in modeling pilot's decision-making in air combat simulation /64/.

6.3.4 Applications to human factors modeling in marine risk assessments

Traditional tools of PRA, such as fault and event trees, have been used in modeling human failure in marine domain, e.g., in /53/ and /65/. In recent years, the use of Bayesian networks has become more popular and in this chapter some examples from marine domain are briefly described.

In a FSA study of large passenger ships conducted by DNV /66/, Bayesian networks were used for estimating the probability of failure and the consequences given critical course towards shore or collision course. Slightly modified, separate networks for tanker and bulk carrier groundings were used again in a FSA of electronic chart display and information system (ECDIS) /67/. Structures of the networks were examined by domain experts for ensuring relevance of model parameters. When available, statistical data was used as input to node probabilities. For acquiring input for nodes with no statistical data available, expert workshops were organized. Bayesian networks for grounding and collision models were in large parts similar except that nodes related to communication between vessels were added to the collision model. A simplified overview of the network structure for grounding model is presented in figure 6. The nodes in figure 6 are only illustrative and they were not the real nodes of the more detailed actual model. In the model, safety culture had an impact on nodes relating to navigator's personal condition, work conditions, and management factors. Each of these influenced the performance of the navigator. Network also included nodes for the possibility of some sort internal or external vigilance such as from a pilot or a VTS operator. The loss of control probability leading to grounding was influenced by the performance of the navigator, extra vigilance and steering failure. Collision probability was influenced by loss of control and communication with another vessel. /66, 67/

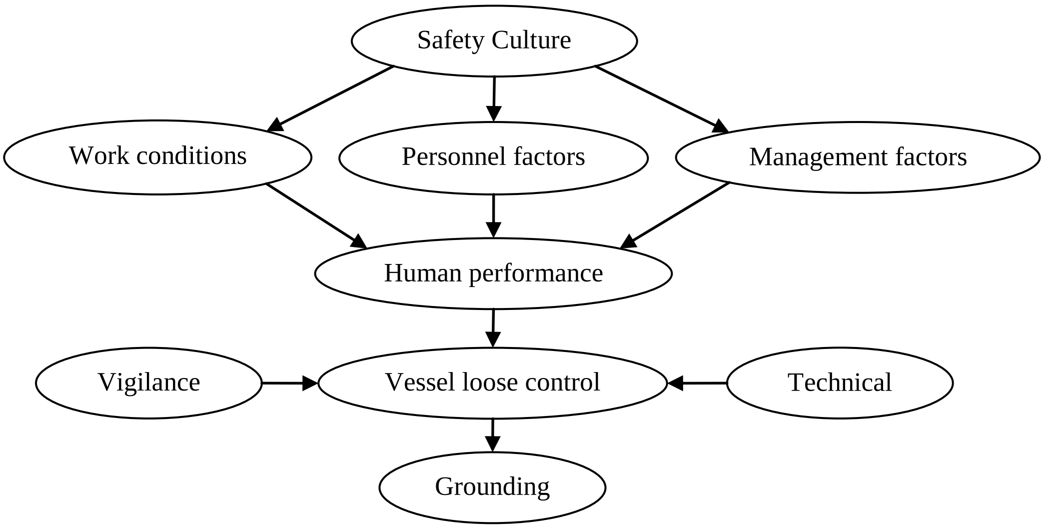

Figure 6. *Simplified overview of a loss of control part of grounding network in ECDIS safety assessment. In addition to loss of control, vessel must had a course towards shore in order to ground /67/*

In Øresund marine traffic risk and cost-benefit analysis /68/, Bayesian networks were used in grounding and collision frequency estimation. A separate subnetwork was constructed for modeling human error, which was then inserted as an instance node in accident frequency estimation network. The human error network is presented in figure 7. In this model, the probability of human error depended on fatigue, accident, absence, distraction, alcohol and man-machine interface. The presence of VTS had an influence on absence, distraction and alcohol. Output node was the probability of human error. The failure probability values, based on literature, were order of 10^{-4} and were modified at specific locations because of the influence of external conditions, such as VTS presence and awareness of sailing in difficult waters. It was stated in the report that for the purposes of the analysis, this model, constructed only of few nodes and arches, was considered detailed enough. /68/

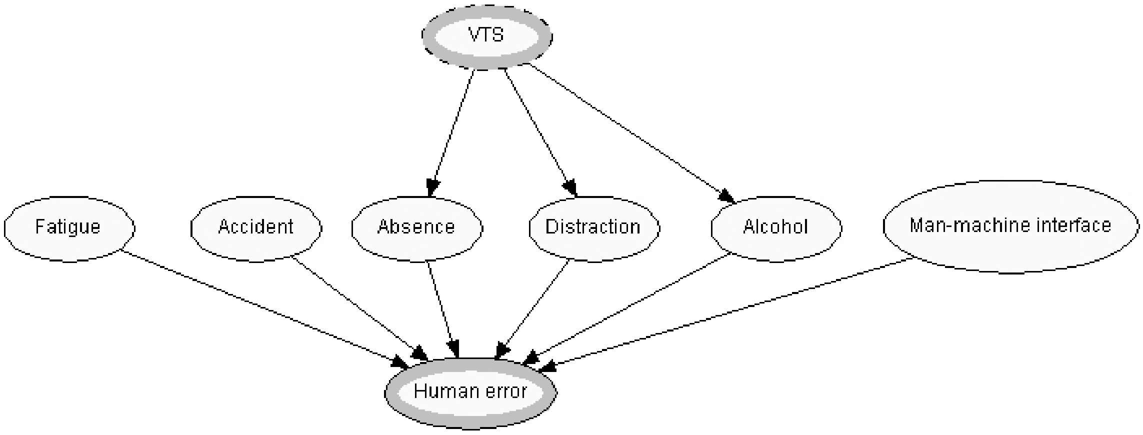

Figure 7. *An example of modeling human error in marine traffic with a rather simple Bayesian network /68/*

In Åland Sea FSA study /54/, Bayesian networks were used in modeling the effects of risk control options on causation factor. The actual causal factor was not modeled with a network but the value $3 \cdot 10^{-4}$ was used as a baseline causation factor. Based on expert opinion, an expected reduction coefficient was estimated with a Bayesian network. The reduction coefficient was influenced by OOW's awareness on own ship and on surrounding traffic. These awareness parameters were influenced by the risk control options. Values for causation factor for the risk control options were obtained by the product of baseline causation factor and the reduction coefficient. /54/

Loginovsky et al. /69/ introduced an object-oriented Bayesian network model for assessing the impact of ISPS code on workload and crew performance onboard. Dependencies and parameter values for the network were based on survey among seafarers, statistics and expert data from security training courses. /69/

In the context of a system reliability analyzer tool for a naval command and control system, a Bayesian network was used for estimating the performance of human operators and technology components /70/. The network was based, e.g., on Reason's and Hollnagel's theories of human error, performance shaping factor tables in the THERP manual, and experimental data. Input nodes were classified into four categories: 1) task, 2) technology properties, 3) operator/personnel qualities, and 4) human and system operational environment conditions. Expert judgment was used in designing the network structure and constructing the probability tables. Properties of human agents were taken from training data and job descriptions. The network is presented in figure 8. /70/

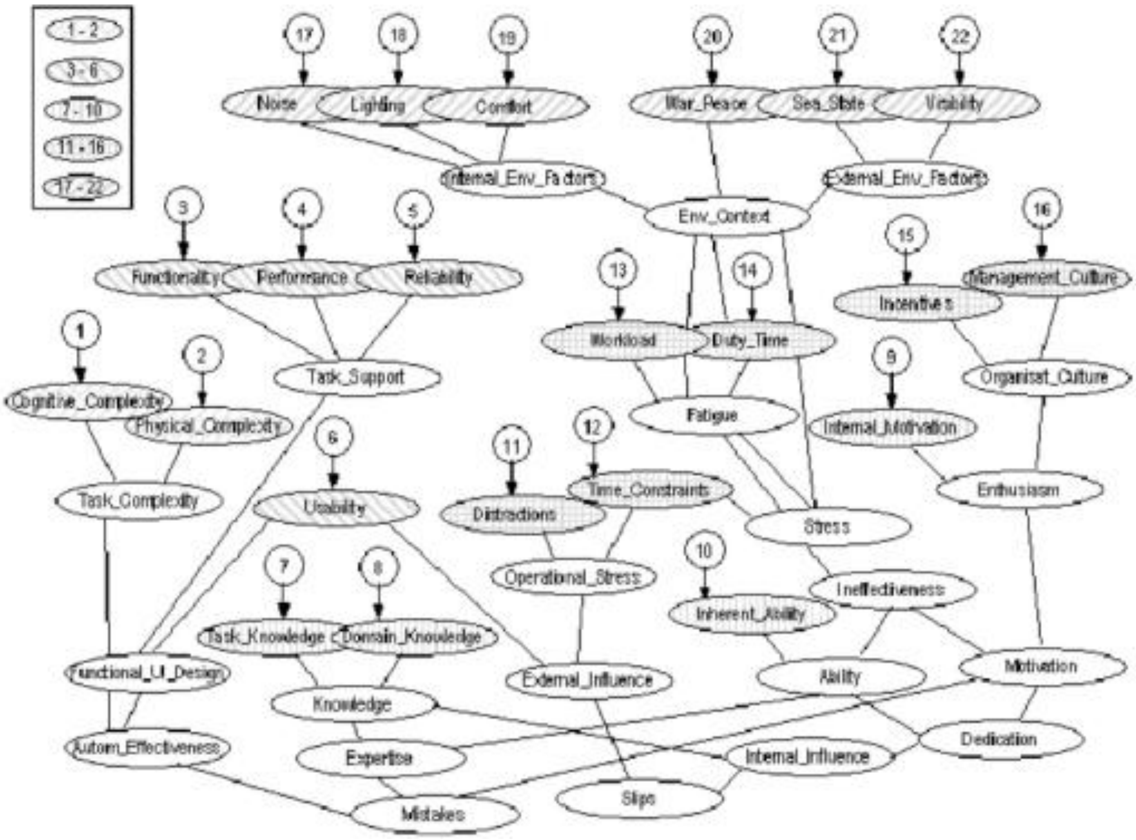

Figure 8. *A Bayesian network for predicting the reliability of a human agent in naval command and control system used within a system reliability analyzer tool /70/*

In Fast-time numerical navigator developed in Safety at Sea project /71/, whose simulation results were suggested to be used for collision and grounding frequency prediction /72/, Bayesian networks were used in route execution and collision avoidance maneuvering /73/. The simulation was constructed as a multi-agent system and a Bayesian network for route execution handled a single agent's proceeding through their mission. The output from the route execution network was the updated value for ship's current heading. The network for collision avoidance described the logic used to evaluate each ship-ship encounter from one ship's point of view, the 'artificial intelligence' in one ship. The output from collision avoidance network was the probability of taking evasive action. No specific nodes for technical failures or human errors were included in the collision avoidance model as such. Their influences could be present in other parameters' uncertainty, but for most of the network nodes, states or probabilities were not described in the study. /73/

Trucco et al. /74/ used Bayesian network as an extension to a fault tree analysis for collision, grounding, contact and striking occurrence probability estimations. In the fault trees representing different hazard scenarios, the top event was the accident to be considered, such as "collision in open sea", and basic events (BEs) were the potential causes for the top event, such as "confused by other ships movements". The Bayesian network was used for modeling the organizational structure of marine transport system. The influence of organizational factors on the probability of occurrence of a single basic event, given a specific configuration of critical human and organizational factors, was estimated with the basic

Bayes theorem. A fictitious variable called “organizational scenario variable” was used for connecting the Bayesian network and the fault tree. The states of the organizational scenario variable Ω_k were the j mutually exclusive combinations of states of those variables of the Bayesian networks that influence the basic event under consideration (BE_k). For the BE example “confused by other ships movements” the organizational scenario variable was defined by the combinations of states of Bayesian network variables “crew and personnel performance”, “traffic density” and “hazard/failure identification”. /74/

The occurrence probability of both technical and human BE_k given $\Omega_{j,k}$ was calculated as /74/

$$P(BE_k \mid \Omega_{j,k}) = \frac{P(\Omega_{j,k} \mid BE_k) \cdot P(BE_k)}{P(\Omega_{j,k})} \qquad (3)$$

, where

$\Omega_{j,k}$ was the jth state of the organizational scenario variable representing the influence of human and organizational factors on BE_k,
$P(BE_k \mid \Omega_{j,k})$ was the posterior probability of occurrence of BE_k given $\Omega_{j,k}$,
$P(BE_k)$ was the prior probability of occurrence of BE_k,
$P(\Omega_{j,k})$ was the probability of state j of the k organizational scenario variable and
$P(\Omega_{j,k} \mid BE_k)$ was the degree of belief in the occurrence of $\Omega_{j,k}$ given the occurrence of BE_k.

$P(BE_k)$ was suggested to be estimated by statistical analysis of historical data or by predictive model. Expert judgment was used in order to estimate the value of $P(\Omega_{j,k} \mid BE_k)$. $P(\Omega_{j,k})$ was estimated through the Bayesian network given a marginal distribution for the root nodes. The proposed linkage between a Bayesian network and a fault tree is presented in figure 9. /74/

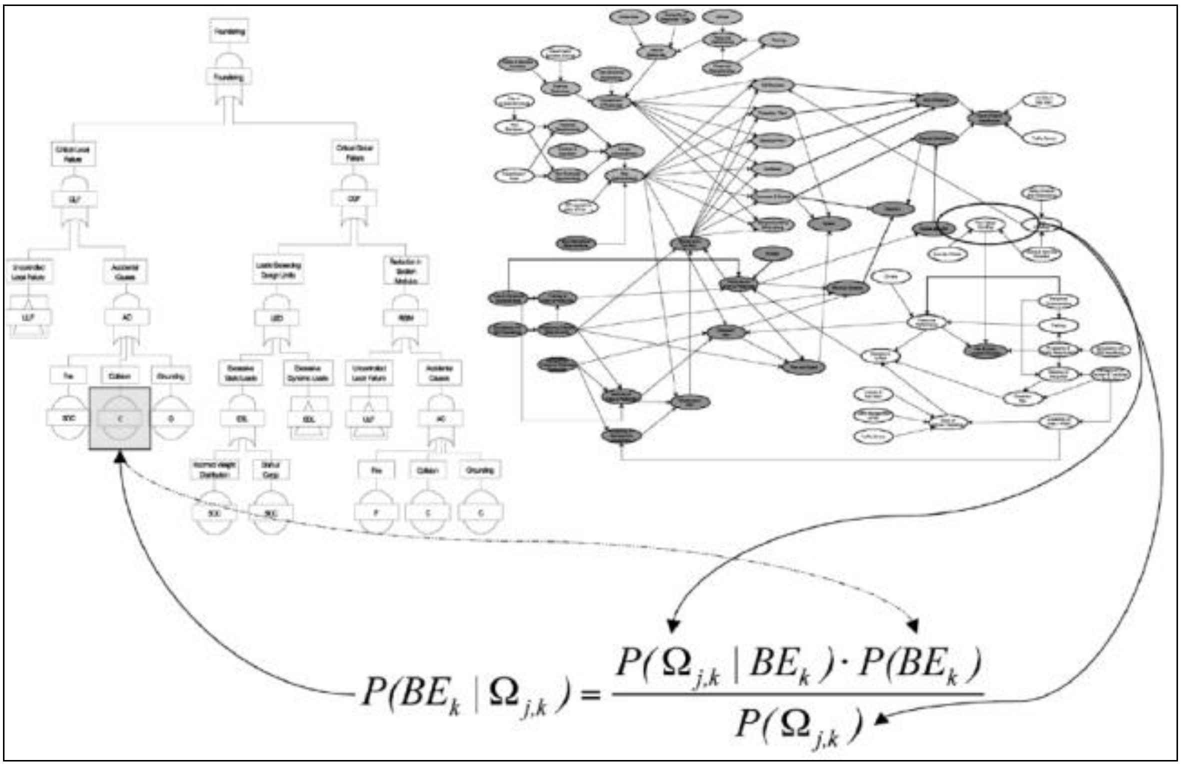

Figure 9. *The linkage between a Bayesian network and a fault tree for taking human and organizational factors into account in marine traffic risk modeling proposed by Trucco et al. /74/*

Eleye-Datubo et al. /75/ proposed fuzzy-Bayesian networks for assessing human performance in marine and offshore risk assessment. The model linked fuzzy logic and Bayesian networks and could be applied to nodes whose uncertainty was a combination of inherent vagueness and randomness. The following performance shaping factors were used as input to the model: available time, stress and stressors, experience and training, complexity and workload, ergonomics and human-machine interaction, environmental effects, the quality of operating procedures, language and culture, morale and motivation, operator fitness for duty, and work processes. Based on the PSFs and their relationships determined by simulation and expert opinion, a fuzzy set for human performance was obtained as the fuzzy output. The elements of the set were {very poor, poor, below average, average, good, very good, excellent}. The conversion from fuzzy membership to probability value for each element was determined with mass assignment formalism. The obtained probability distribution could then be inserted into a Bayesian network. /75/

Ren et al /12/ proposed a methodology for modeling causal relationships that used Reason's "Swiss cheese" model jointly with a Bayesian network. The proposed model was applied to an offshore safety assessment, considering only human and organizational factors. Potential failure factors that were identified in the case study of a collision between a FPSO and a shuttle tanker or a support vessel were personal injury/loss, shuttle tanker collision with FPSO, support vessel collision with FPSO, drive-off, miss position, over control of the vessel, improper procedure, misjudgment of the distance, rule-based errors, knowledge-based errors and safety culture based errors. The 11 factors were categorized to five different levels in the risk analysis hierarchy. The levels were consequence level, accident level, incident level, trigger event level, and root cause level. Categorization and addressed causal relationships between the factors can be seen in figure 10. In the model the human and organizational factors were identified as the root causes and could be triggering unwanted events to happen. Probabilities regarding all nodes of the network were based on expert opinion and fuzzy membership functions were used to describe these probabilities. Fuzzy values were then transformed into crisp numbers using f-weighted valuation function for conducting the Bayesian analysis. /12/

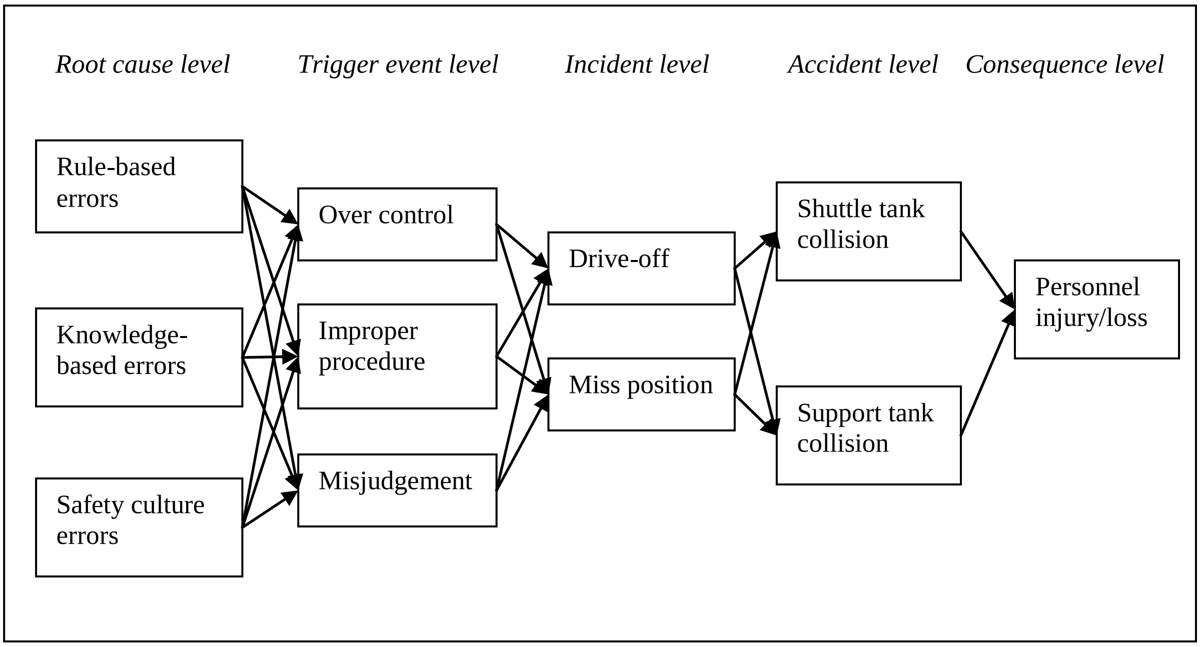

Figure 10. *The Bayesian network model of the collision risk of a FSPO and a shuttle tanker or a support vessel /12/*

7 SUMMARY

The purpose of this literature review was to describe the state-of-the-art in modeling human and organizational factors in marine traffic accident causation. Especially the use of Bayesian networks and ways for modeling human factors in marine traffic in the Gulf of Finland was studied.

Nowadays it is understood that accident occurrence is the result of multiple causes having complicated interrelations. Human failure has roots deeper in the organization and the accident causation cannot be thought as just one human error made in bridge. Human failure has been cited to be the cause of the majority of marine traffic accidents and thus its modeling should be included in probabilistic risk assessments. As human failure is complicated, ambiguously defined, and still not completely understood process, the modeling can be tricky. The following difficulties in human and organizational factors risk analyses have been identified /6, 12/:

- Great variation in definition of human and organizational factors
- Questions of ecological validity
- Inadequate or imprecise data, small sample sizes
- Difficulties in selecting usable methods for measuring human factors and determining interrelations of those measures, lack of outcome measures for assessing the influence of a certain behavior or condition, e.g. a measure for the influence of fatigue to accident data.
- Conventional risk assessment methods might not be suitable with human and organizational factors because of subjective and vague nature of terms
- Retrospective nature of studies
- In interview studies, validity issues rising from administering items to subjects in their second language

Human failure in marine domain has not been studied as much as in other domains such as aviation. Data from other domains could be used in calibration of the models, but it’s suitability for marine domain is questionable, since there are large differences between domains, e.g., in safety cultures. In marine domain, improvements in quality and availability of near-miss situation reporting would be very beneficial for modeling human failure.

Bayesian network approach has been adapted in several risk assessments, also in few cases from marine domain. The benefits of using Bayesian networks in modeling are that they are easily understandable, complicated causal interrelations and dependencies of model parameters are clearly visible, and the effects of risk-control options to accident frequencies can be done easily. Bayesian networks are acyclic graphs, so compromises in modeling may have to be made in order to avoid cyclic influences. Modeling the interrelations of human factors may be difficult and information on prior and conditional probabilities of the network may be difficult or impossible to obtain. As mentioned already, this is a challenge common to all quantitative modeling approaches, not just of Bayesian networks.

In a light of theories of human error and accident causation, the human failure models used in marine traffic risk assessments have been rather simple and incomplete. If different Bayesian network models are compared, it can be seen that some parameters that exist in one network are lacking from another, and vice versa. It also seems that the expert groups used in constructing of many models' structures or probability tables had been biased either to marine domain experts or human factor specialists, but not both.

In the future, a model for human factors in accident causation in marine traffic of the Gulf of Finland will be developed for risk assessment of the Gulf of Finland's marine traffic. In normal winter at least the eastern part of the Gulf of Finland will be wholly covered by ice. Navigation in ice differs in many ways from open sea navigation and has multiple risks. In a report of incidents and accidents in the Baltic Sea during winter 2002-2003 /76/, causes for damages to ships were listed. Some of these causes related to winter navigation were /76/:

- Colliding with ice edges with high speed
- Ship-ship collision when moving with short lead in ice channel and the first ship gets stuck in ice
- Collision with an icebreaker during assistance
- Contact with ice channel edges when turning
- Stuck in compressive ice due to moving ice field
- Darkness and snowfall
- Inexperienced crew in winter navigation

In none of the human failure model descriptions found in the literature, the challenges that winter navigation proposes to human performance was discussed. Since the majority of ship-ship collisions in the Gulf of Finland have occurred in ice conditions /5/, these factors must be included in a model for assessing the human failure probability in the marine traffic of the Gulf of Finland. Expert groups of marine domain and human factors specialists will be used in constructing the model so that the properties of the traffic in the Gulf of Finland will be reflected appropriately in the model. In order to acquire hard data for the model, ship simulator tests will be conducted in the future.

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