Online risk modelling of autonomous ships with experimental results

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Introduction

Automation is the process, often computerised, that implement a specific and predefined method to execute certain operations without a human controlling it[1]. A number of industries have started to implement autonomy on different levels, where particularly the maritime industry is experiencing substantial changes and opportunities. The potential of autonomy is larger today, due to a considerably progress in the field of sensors and computer power. Increasing level of autonomy in the maritime industry, may lead to safer solutions and more cost efficient operations. However, autonomous vessels are a relatively new concept, thus challenging the way vessels are designed, tested and introducing new challenges related to verification and safety[2]. A large amount of accidents and fatalities in the maritime industry are due to human error. With increased autonomy level for the vessels, errors introduced by fatigue, lack of knowledge and organisational failures can be reduced.

Objective and scope

The scope of the thesis is to develop an online risk model in order to replace the decision-making and risk assessment, today preformed by the officer on watch at the bridge. The main scientific contribution of this thesis is to demonstrate a decision model for an continuously unmanned ship, CUS. The decision model developed, will be integrated into the control system, of the ship model CS Enterprise I. Following, the model will be tested in simulation and hardware-in-the-loop. Lastly, full scale testing will be performed in the Marine Cybernetics laboratory.

Method

A Bayesian belief network is developed in . The objective of a BBN is to identify all risk influencing factors or hazards that might increase the probability for the critical event. The network created consists of nodes and directed arcs, indicating state, relationship and condition of the relevant factors. Each node in the BBN contain an variable consisting of two or more possible states. In this BBN the critical event is *Collision*, where *fuzzy logic* is utilised in order to define 'High risk' and 'Low risk' of collision. The network consist of 22 nodes which influence the probability of collision. These 22 nodes are divided into two subgroups:

1. Sensor failure and situation awareness.
2. Environmental and power.

The *decision* algorithm proposed is developed in order to distinguish four different decisions, where the purpose is to avoid collision. Depending on the probability of collision and detected scenarios, an action is chosen.

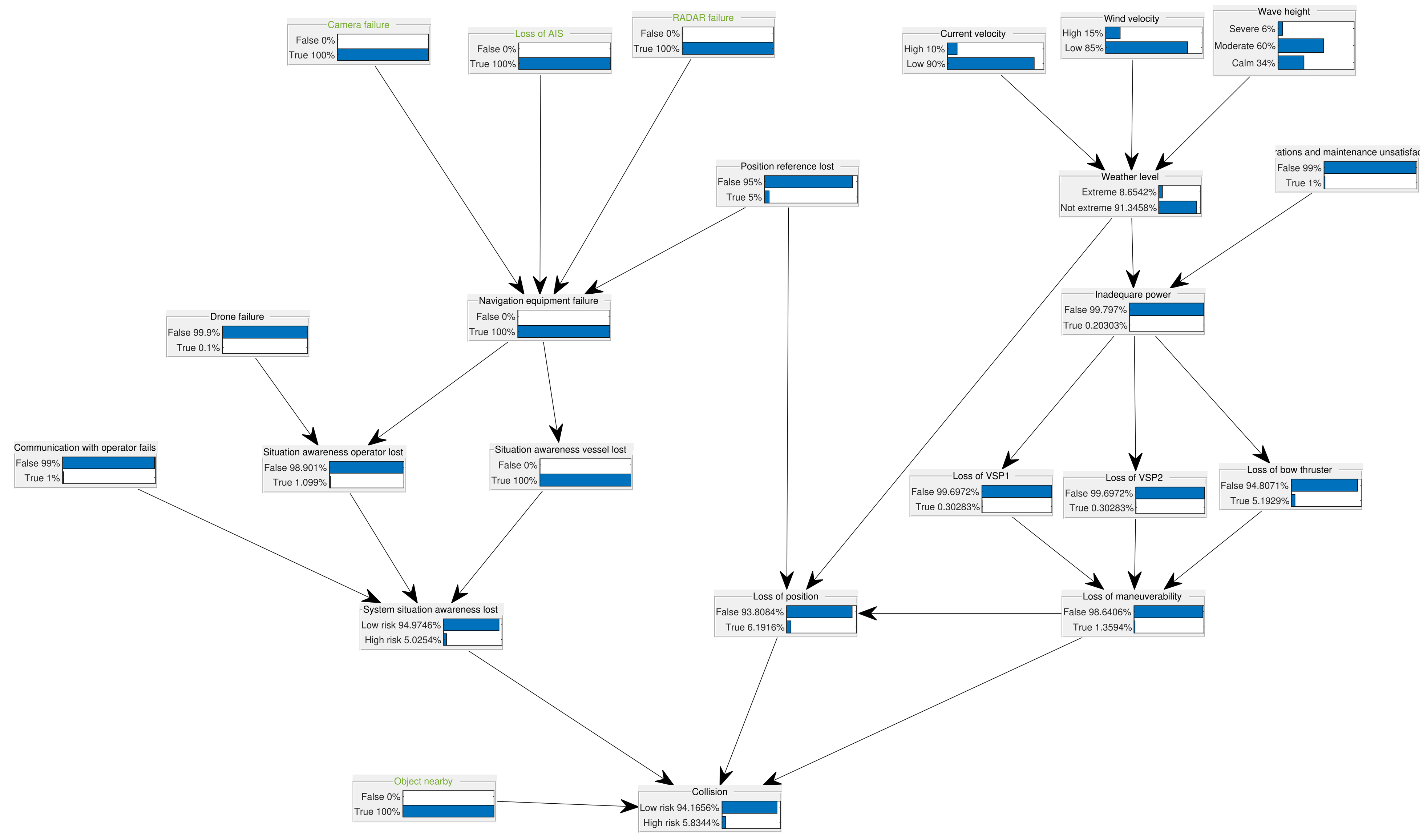
References

[1] Rødseth, Ø. J. and Nordhal, H.'Definitions for Autonomous Merchant Ships'. In:Norwegian Froum For Autonomus Ships (NFAS) (2017), pp. 1-21

[2] Utne, I. B and Sørensen, A. J. and Schjølberg, I.'Risk management of autonomous marine systems and operations'. In:ASME 2017 36th International Conference on Ocean, Offshore and Arctic Engineering

Simulation and experiments

Three different scenarios are simulated and tested in full scale. Scenario I is presented in this poster. Scenario I is developed in order to illustrate the concept of how an online risk model can be used in context with an continuously autonomous vessel, and in particular how a shore control center, SCC, can be alerted and commanded to take over the steering of an vessel. This scenario consist of a DP operation, where the vessel is changing setpoint from the vessel's current position to the waypoint $[2, 0, 0]$.

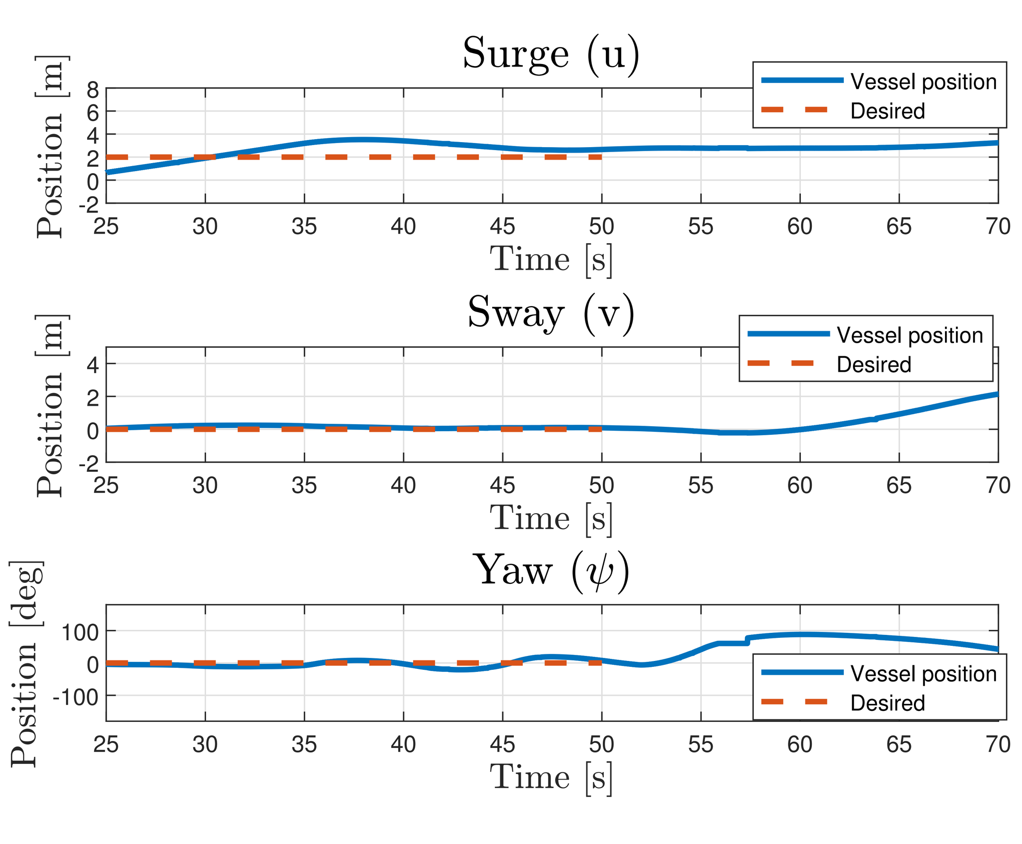


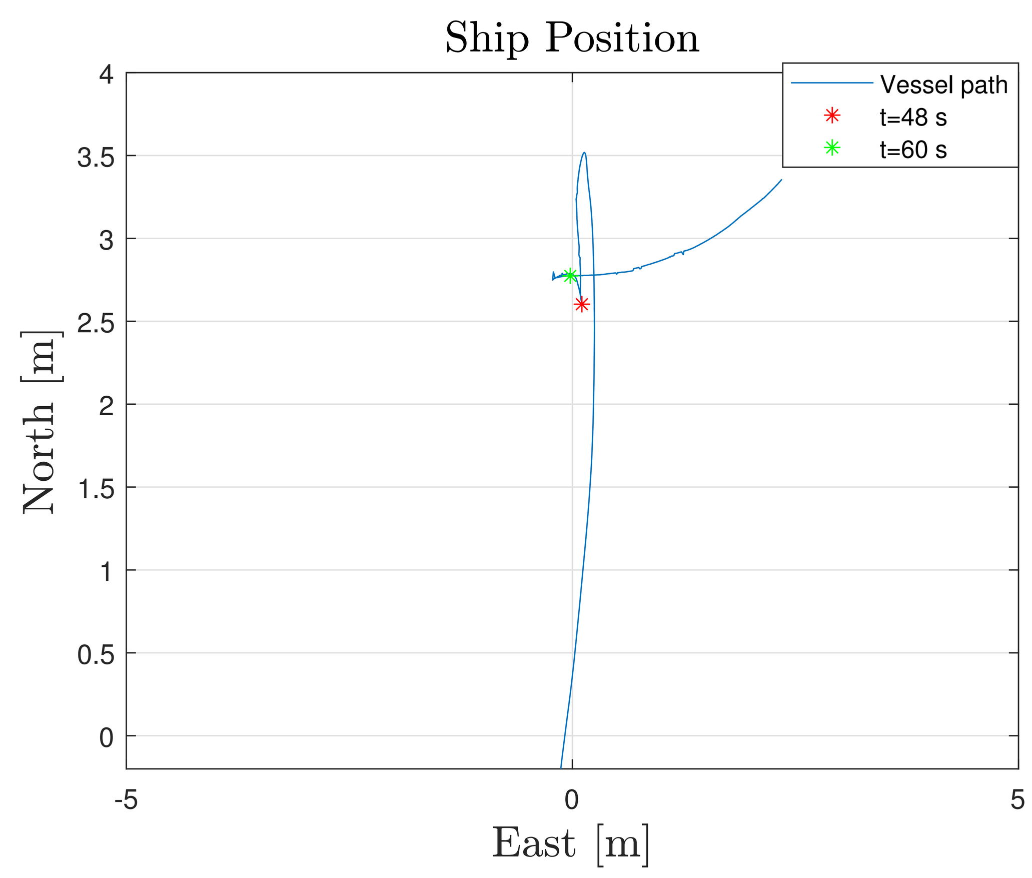
Results and Conclusion

The connection between GeNIe and the hardware in the laboratory did not connect successfully. Hence, the BBN illustrated is from simulation in Simulink. However, the probabilities calculated during simulation in simulink was implemented into the model when preforming laboratory experiments. The vessel is given the identical setpoint in simulation, HIL testing and laboratory testing. However, in full scale testing in the laberatory the start point was approximately [-2, 0, 0]. The BBN shows that after 50 seconds, a RADAR failure occurs and the probability of 'High risk' of collision is increasing to 6%. Consequently, the decision part of the ORM successfully alerts the operator at the SCC. Hence, the SCC is given fully command of the vessel. The results from simulation of the BBN is shown in the table below.

Time [s]	Node	Belief	'High Risk' of Collision	Decision
5	Object nearby	True	2%	-
20	Camera failure	True	2%	-
30	Loss of AIS signal	True	2%	-
50	RADAR failure	True	6 %	Control SCC

In the left plot, the surge movement from LAB is displayed. The vessel reaches its setpoint after 45 seconds. Compared to the results from simulation and HIL, the settling time is longer during model scale testing. After 50 seconds the online risk model is noticing loss of situation awareness on the vessel. Hence, the operator is given command of the vessel. I.e. manual control of the vessel with the Sixaxsis controller. In figure the path of the ship model during testing is illustrated. Accordingly, it can be seen that the operator is manoeuvring the vessel away from the previous position where the probability of collision had 'High risk' of collision. I.e. away from the detected object. The vessel is given positive sway force. Thus, moving in East direction according to NED.





The online risk model proposed demonstrates that it is able to make decisions in order to reduce the risk of collision. Three different scenarios have been tested in simulation, HIL and full scale in the marine cybernetics laboratory. Further work, would be to include additional all relevant factors in the BBN, and to extend the decision algorithm to account for other scenarios.