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Resilience Assessment Of Liquid Hydrogen Bunkering Systems

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In an era dominated by growing concerns over climate change, emerging decarbonization technologies are assuming a central role in shaping a more environmentally conscious future. Among these innovations, liquid hydrogen (LH_2) has emerged as a promising zero-emission fuel with vast potential to transform many economic sectors (Qazi, 2022). While several industries are exploring how to include LH_2 into their processes, the marine sector stands out as a vital domain for its uptake (Ustolin et al., 2022). However, as LH_2 adoption gains momentum, it is crucial to stress the need of a thorough systemic risk and resilience assessment. Evaluating bunkering systems' ability to withstand challenges, adapt to evolving conditions, and ensure uninterrupted functionality is paramount in the context of risk assessment, where conventional approaches fall short in addressing the post-failure phase of complex systems. As such, in the current study a quantitative resilience evaluation of a LH_2 bunkering system has been performed using Dynamic Bayesian Networks (DBNs). DBNs account for the dynamic and probabilistic features of resilience, in which the engineered system, human and organizational factors, and external disruptions are involved (Khakzad, 2015).

The resilience metrics adopted to conduct the analysis is the one proposed by (Tong et al., 2020), that defines resilience as "*the probability of a system's functionality state sustaining a "high" state (S1) or restoring to a "high" state from a "low" state (S4) during and after the occurrence of disruptions in the operation of a system within a specific time*". To deeply understand this definition, details regarding resilience attributes and their conceptualization with respect to functionality are provided in the following.

Basically, a resilient system has four attributes: absorption, adaptation, restoration, and learning. The innate capacity of a system to withstand and endure a disturbance is known as absorption. Adaptation is the system's capacity to adjust to a disturbed environment, regaining the lost functionality without the necessity of external restoration efforts. Restoration represents the ability of a system to support external actions to fix the damages caused by the disturbances and return to a new normal state, while learning consists in the ability of improving future system responses to disturbances thanks to past experience integration. Four functionality states (S1, S2, S3, and S4) are used to quantify resilience and the transition rates among the states are determined based on the system's absorption, adaptation, restoration, and learning abilities at each period following Markov Chain rules. Based on this, (Tong et al., 2020) developed a DBN model for describing the change of functionality state of a system under the influences of resilience attributes and disruptions.

In the following, the DBN model is applied to a case study concerning LH_2, to demonstrate its potentialities in supporting the implementation of resilience in LH_2 bunkering operations.

The case study aims to quantitatively assess the resilience of a bunkering system based on the metrics outlined in Section 2. Figure 1 (a) shows the DBN developed with the GeNIe software (GeNIe Modeler, 2024) to perform the analysis. The main system disruption consists in the failure of the flexible hose used for the LH_2 transfer and it is assumed as always occurring with a state defined as “YES”. Then, the safety barriers of the system are considered to define the influencing factors of the resilience attributes (Zinetullina et al., 2020). In this case, absorption and adaptation are influenced by the release prevention and detection barriers of the system, respectively. Instead, the factors affecting the restoration ability are equipment maintenance and replacement, preliminary measures, human reliability, and management culture. In the network, all root nodes entering the resilience attributes nodes are characterized by a state defined as “HIGH”. Learning affects all the three attributes, and its state is defined as “HIGH” as well. To define the Computational Probability Tables (CPTs) among parents and child nodes, all the impacting factors are considered with the same probability of altering the child nodes.

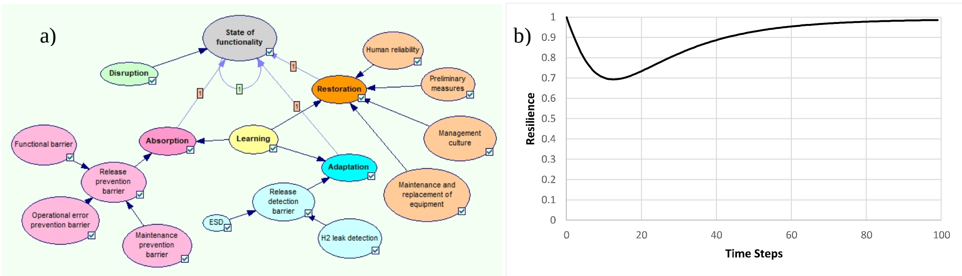

Fig. 1. (a) The DBN model for bunkering resilience assessment (GeNIe Modeler, 2024); (b) The dynamic resilience curve.

The DBN model was computed for 100 time steps, and the conditional probabilities for the four states of reliability were assigned in the CPT of the “State of Functionality” node applying the data from (Tong et al., 2020). The dynamic resilience curve is then obtained by summing S1 and S4 probabilities, as stated in the definition of resilience; see Figure 1 (b). The resilience of the system varies over time until it stabilizes at about 80 min with a new resilience of 98.5%. The rapid decline of the resilience at 12 min is associated with the disruption due to the LH_2 leakage, and the further increase in resilience is due to the system’s adaptation and restoration attempts. The learning capability of the system would contribute to increased absorption, adaptation, and restoration capabilities, facilitating the achievement of higher levels of system resilience.

This work delves into the imperative of addressing resilience assessment, emphasizing the intricate intersection between climate change mitigation and the robustness of emerging technologies to strongly delineate a sustainable path for the maritime industry. The resilience profile obtained by the case study supports the estimation of bunkering systems’ ability to withstand uncertain disruptions, monitoring their performance variation, assessing the effectiveness of safety measures, and identifying potential design and operational improvements.

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