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Advancing Sustainable Maritime With AI/ML Enhanced Hardware-in-the-Loop Testing

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***Abstract*—This paper explores the potential of Hardware-in-the-Loop (HIL) testing and simulations in advancing sustainable maritime. HIL testing is a technique that combines physical components and a virtual real-time system. HIL is a powerful method for developing control algorithms and doing optimization for vehicles and vessels in a laboratory. By combining HIL testing with artificial intelligence (AI) and machine learning (ML), improvements in fuel and cost efficiency, emission reduction, risk mitigation, and sustainability reporting can be achieved. This study reviews literature in the maritime and related fields where AI and ML are being used to address sustainability objectives. This paper also reports the implementation of a Mechanical-level HIL (MHIL) test bench, which features a real marine engine attached to a simulation model that comprises a vessel and a hybrid powertrain. The ultimate objective of this study is to identify AI/ML-driven research opportunities for the MHIL test bench. The results reveal five potential classes of AI/ML/HIL research: data-driven modeling, optimal engine and hybrid drive control, multi-objective optimization of navigation, proactive maintenance and condition monitoring, as well as opportunities for regulation and sustainability compliance.**

***Index Terms*—Artificial intelligence, hardware in the loop, hybrid vessel, MHIL, machine learning, optimization.**

I. Introduction

Hardware-in-the-Loop (HIL) testing is a technique that synergistically combines physical components with a virtual real-time system. This powerful tool is extensively used in the development and testing of control algorithms for various vehicles such as cars, vessels, and aircraft. It achieves this by substituting physical components with simulation models in a laboratory setting. However, HIL testing stands apart from conventional simulation methods by incorporating physical components. While simulations are inherently approximations of the real system and often fall short in accurately reflecting all dynamics and degrees of freedom of their physical counterparts, the physical components integrated in the HIL environment can be identical to those deployed in the actual vessel [1], [2]. For instance, in our study, a real 4L20 marine engine (Wärtsilä) attached to a real generator is run in laboratory, whereas the vessel and its hybrid power unit are simulated. This is an example of Mechanical-level HIL (MHIL), in which loads and sources are emulated [3].

HIL testing is beneficial, because it facilitates automated and reproducible tests, thereby enhancing the reliability of the results. In addition, a wider scenario space can be covered and critical and potentially hazardous - and often overlooked - corner-cases tested. Furthermore, computational optimization methods can be applied to develop virtually any part of the system. This opens up the possibility of a fully-automated optimization loop, where software-controllable system parts are automatically developed and optimized during HIL testing [4]. In the context of our study, the primary objective was to minimize vessel emissions. To achieve this, we focused on the development of control algorithms for the hybrid powertrain, leveraging the capabilities of HIL testing.

HIL testing requires the presence of an accurate simulation model and a real-time simulator with the capability to execute it. Moreover, it is imperative that the physical and simulated components are seamlessly integrated through sensors and actuators in a way that both steady-state and transient behavior of the overall system approximates accurately its fully physical counterpart. Thus, the HIL system must undergo rigorous validation against data derived from real-world experiments. [5].

This paper discusses the possibilities to advance sustainable maritime by applying artificial intelligence (AI) and machine learning (ML) to HIL testing as well as simulations. The sustainability objectives under discussion include: improved fuel-efficiency, optimized emissions when considering also emission control areas, reduced risks, and economic sustainability. Given the multiplicity of objectives and the frequent presence of constraints, advanced optimization methods become a necessity. Thus, AI and ML approaches are beneficial and also extensively studied.

Our objective is to show the potential of HIL testing and simulations when addressing the challenge of advancing sustainable maritime. We accomplish this by reviewing articles, where sustainability objectives are tackled with AI and ML, in both maritime or related fields. This literature survey serves as an initial step in defining the research objectives for the HIL test bench, which was implemented at the Vaasa Energy Business Innovation Centre (VEBIC) laboratory at the University of Vaasa, Finland. This HIL system incorporates a large marine diesel engine integrated to a simulated vessel model, which also includes a hybrid power unit. It also offers the flexibility to use a simulated engine in place of the physical engine, enabling fully-simulated tests.

Section II provides an overview to the HIL test bench and discusses its objectives. Section III delves into the architecture of the HIL test bench in greater detail so that its potential and limitations become tangible. Section IV discusses the possibilities to apply AI and ML in the HIL test bench. This is done by scanning scientific literature for studies, in which AI or ML has been employed either in a digital twin simulations or in HIL tests. TThe examples are categorized into five key areas that encapsulate various objectives of AI/ML/HIL in maritime: enhancing the realism of models and scenarios, optimizing hybrid powertrain control, optimizing navigation, proactive maintenance, and regulation compliance. In addition to studies that concern vessels, examples from related applications areas, such as hybrid electric vehicles, are reviewed in order to find transferable knowledge. Finally, conclusions are given in Section V.

II. Objectives and overview of HIL testing

This research was done in the INTENS project. As defined on its website [6], "The INTENS project is a national consortium striving to proactively advance, promote and digitalize Finnish marine industries and beyond, with the special focus on energy efficiency and emissions of ship energy systems". INTENS, an acronym for Integrated Energy Solutions to Smart and Green Shipping, represents a collaborative effort between Wärtsilä, LUT University (Finland), and the University of Vaasa (Finland). The primary objective of the project was to build a HIL test environment for hybrid vessels in order to mitigate ship emissions. The ultimate gaol is to find optimal hybrid propulsion algorithms and design parameters, such as battery and super-capacitor size, to reduce CO_2 and other emissions (e.g., NOx) from the marine engine in real-world shipping operations.

In our research setting, the simulation part comprises a mechanical vessel model as well as an electrical vessel model, which includes a hybrid propulsion drive. The virtual parts were developed in MATLAB/Simulink. The ship engine, on the other hand, is a physical component. The HIL test bench is housed in the VEBIC engine laboratory at the University of Vaasa, where is equipped to measure actual emissions. The inclusion of a physical engine in the loop ensures the use of more realistic torque dynamics and, perhaps more importantly, provides more accurate emission estimates compared to a simulated engine.

The mechanical vessel model includes a gearbox, propeller, and hull. the electrical model of the vessel includes power take-in/power take-out (PTOPTI), batteries, auxiliary gen-sets, the load regulators, the ship's electricity load (commonly referred to as the 'hotel load'), and the hybrid drive. The block diagram of the full HIL setup is depicted in Fig. 1.

III. Implementation

A. Real-time simulator

Hardware-in-the-Loop (HIL) testing imposes stringent real-time requirements on the simulated virtual components, as multiple components need to be simulated concurrently, necessitating low simulation latency. The complexity and realism of the virtual component directly influence the difficulty in achieving low latency times. Besides the simulation and the real-time target machine, the speed of communication also impacts the latency time. Certain ultra-low latency HIL emulators have been successful in achieving latency times as low as 1 μs [7].

Speedgoat [8] is a real-time computer that is capable of hosting MATLAB/Simulink models and acting as the I/O interface between the marine engine and the vessel model. Because in our case the engine controller and engine model already run on Speedgoat, we decided to accomplish the HIL loop with a PC configured to run a Speedgoat kernel. Moreover, the PC was attached to a Modbus card that mirrors the functionality of Speedgoat. Fig. 2 illustrates the multiple communication interfaces and buses, by which signals between the physical components and real-time simulators are transferred.

B. Simulink Real-time Explorer

Simulink Real-time Explorer (SLRTEXLPR) are both products of MathWorks, designed to operate cooperatively. SLRTEXLPR can be used to send the vessel model to Speedgoat. It provides the capability to monitor all signals and parameters of the simulation model. Thus, it facilitates the tuning and adjustment of variables while running the HIL system. Moreover, it enables having data logs of the simulation values for future reference.

C. Load control

In the HIL loop (see Fig. 1), the engine generates torque, which is measured from the generator shaft. The measured torque serves as the input to the vessel model. The output from the vessel model is the resultant rpm. This is utilized as the response to the engine by modulating the load demand of the generator. In simple terms, if the engine torque - and consequently, its power - exceeds the current load demand, the vessel model gains additional kinetic energy or energy to the batteries. Following a transient period, a balance is achieved between the engine power and the load.

The vessel model controls the load via a frequency converter. However, our frequency converter does not accept rpm values as the load demand input. To address this, we used a PID controller (see Fig. 3) to convert the rpm request into a torque request. During the engine start-up phase, the vessel model is not utilized. Once the engine achieves a steady state, the vessel model is 'accelerated' until its output rpm matches the engine rpm. Following this synchronization, the vessel model can be engaged to control the load, thereby closing the HIL loop.

IV. Opportunities of AI/ML in HIL testing

The incorporation of artificial intelligence (AI) and machine learning (ML) into Hardware-in-the-Loop (HIL) testing for marine vessels holds significant potential for emission reduction and efficiency enhancement. The forthcoming examples, aimed at unlocking this potential, are substantiated by a review of analogous AI/ML applications in marine transportation and

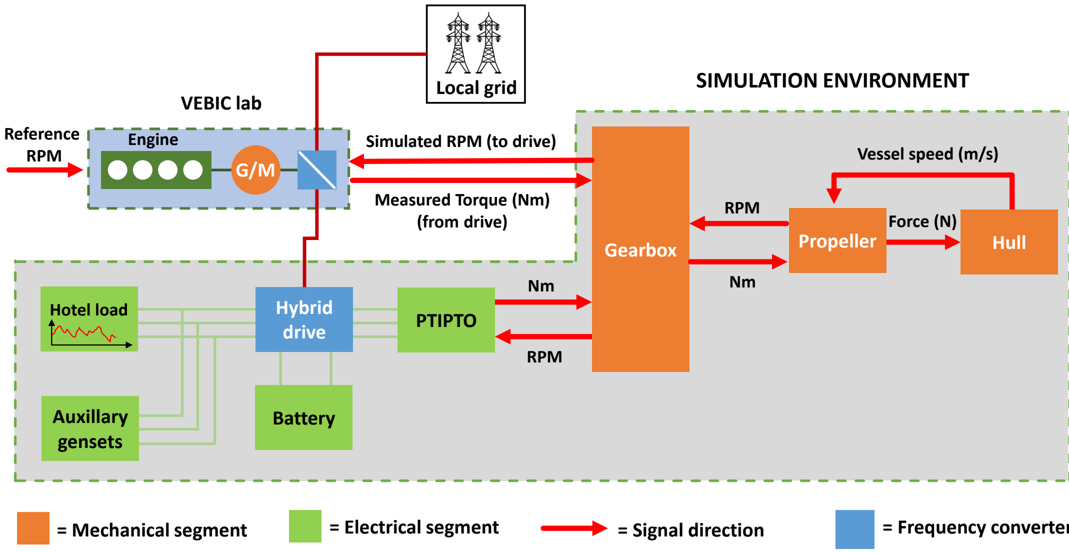

Fig. 1. Components of the HIL system.

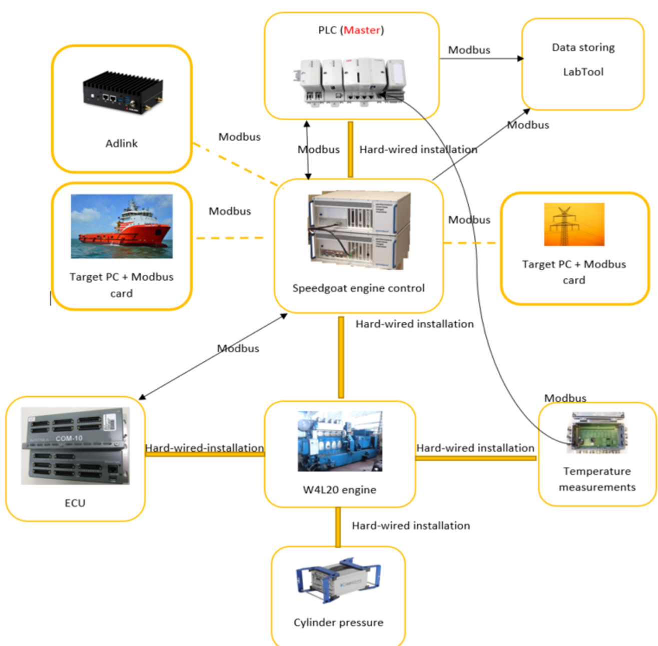

Fig. 2. Communication interfaces between sensors, actuators and real-time computers.

related fields. The examples encompass both from HIL and simulation cases.

A. Model and scenario calibration

The accuracy of the HIL system can be enhanced by dynamically adjusting model parameters. ML algorithms can learn from real-world data and adapt model parameters offline

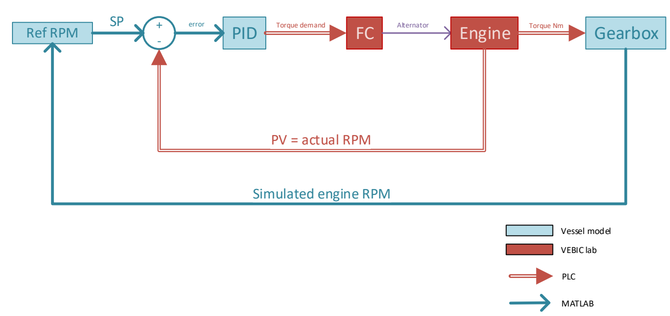

Fig. 3. Conversion from RPM demand into torque demand using a PID controller.

or during the operation of the HIL system. In the context of the vessel model, this allows for a better representation of vessel behavior under varying conditions (such as waves, currents, wind, and ice) and during transient situations. Moreover, machine learning can be used to construct parts of the simulation model, offering an alternative to first-principle models that rely on equations describing the physical counterpart.

An example how to use ML for modeling is given in Estrada et al. [9]. The article presents a method to estimate CO_2 and other emissions (CO, NO_x, etc.) using convolutional neural networks. The inputs of the neural network are engine measurements such as engine speed, air mass flow, torque, and exhaust temperature. This emission model forms part of the comprehensive simulation model of a hybrid electric vehicle that consists of, e.g., a driver model, an engine model, and an aftertreatment model. The simulation operates at a speed that is suitable for HIL testing. Hence, parts of the simulation could be replaced with physical components. The use of convolutional neural networks, as opposed to static maps or equations, is advantageous in transient situations, which occur frequently in realistic driving scenarios. The machine learning method achieves pollutant accuracies under 8.5%, while previous methods resulted in accumulate errors of 15% in frequent transient situations. Only with a model that can accurately predict both the CO_2 and other emission levels it is possible to effectively optimize the powertrain control algorithms, because reducing fuel consumption aggressively can lead to an increase in other pollutants.

Scenarios, such as speed profiles, are essential to HIL tests. They can be generated manually, based on standardized reference models, or using data-driven ML methods. Moreover, the scenarios can be static or stochastic in nature. However, with static scenarios, there exists a risk of over-optimizing the controller algorithms for specific scenarios, a phenomenon known as overfitting. As a result, even a minor alteration to the scenario could lead to a significant decline in performance.

Nyberg, Frisk, and Nielsen [10] introduced a stochastic speed profile model based on Markov chains. They used a data set that included 466 recorded drives to train the state transition matrix of the Markov chain. The state was defined by the velocity and acceleration of the vehicle. In order to have equivalent driving cycles for better comparability, in terms of objectives like mean tractive force, the Markov chain is empoyed to generate candidate driving cycles. Only candidates that closely align with the specified criteria are accepted. Finally, the driving profiles are modified with iterative algorithms to precisely match the criteria. This approach enables the generation of a diverse set of driving cycles that, while not identical, share identical statistical properties.

B. Optimal engine and hybrid unit control

With an accurate Hardware-in-the-Loop (HIL) system in place, featuring realistic simulated components and scenarios, machine learning (ML) and HIL testing can be leveraged to dynamically optimize engine control and hybrid drive strategies. This optimization aims to, e.g., minimize fuel consumption and emissions. The control strategies can proactively account for varying factors such as weather conditions, user patterns, and the state of the vessel. Moreover, the design parameters of the powertrain, such as battery size, can be controlled and optimized during the simulations and HIL tests.

Complex control optimization problems are often addressed with machine learning approaches. Optimal, data-driven control can be categorized into three distinct groups: 1) data-driven tuning of a model-based controller, 2) data-driven tuning of controllers with a fixed architecture, such as a PID controller, and 3) model-free controllers [11].

An example of optimizing a data-driven model-free controller is given by Estrada et al. [9]. They employed a reinforcement learning method, specifically Q-learning, to optimize a controller that distributes the torque demand between the internal combustion engine and the electric motor. The Q-learning algorithm maps states to actions. In this case, the states are: battery state of charge, vehicle speed, and power demand. With the optimized controller fuel consumption was reduced by 23% when compared to a reference non-hybrid vehicle. However, minimizing other pollutants is less straightforward, particularly due to the Catalyst Light-off phase. Nevertheless, it a compelling challenge for future studies.

The Q-learning method could be applied to the optimal control of the hybrid unit of a vessel. However, when dealing with continuous state variables and an increasing cardinality of the state space, the sample, computational and space complexities increase rapidly. There exist variants of Q-learning that are more efficient than the standard algorithm (e.g., [12]). Q-learning can also be efficiently implemented as hardware accelerators [13].

Simani, Farsoni, and Castaldi [14] used a neural network for optimal control of wind turbine wakes in a wind farm. The objective of wake control is to minimize the disturbances that upstream wind turbines cause to downstream turbines. The controller takes into account the wind speed and direction, as well as the turbine status. The controller was trained and tested in a simulator and validated in a HIL test bench. In this case, optimization is based on the fixed positions of the wind turbines, which makes predicting the wakes relatively easy.

Vessels also encounter many disturbances (such as changing wind, waves, ice, and other vessels) that have effects on the optimal control strategy. However, optimal control for vessels that takes these disturbances into account is considerably more complex than in the wind turbine case, primarily due to the challenge of predicting these disturbances.

C. Course control and route optimization

HIL tests can be utilized to develop AI models that optimize ship routes based on factors such as load, vessel condition, weather forecasts and ice maps. The objectives can range from improving route adherence (i.e., optimal course control, which is paramount for safe navigation), to enhancing fuel-efficiency, and reducing emissions and disturbances to local nature. Overall, vessel navigation is a multi-objective optimization problem. Hence, it is an appealing area for the application of heuristic AI methods.

Chen et al. [15] review the dynamical model for ship motion, including nonlinear terms and external disturbances. They also examine numerous studies where nonlinear controllers and control parameter optimization have been implemented to enhance ship course control under complex external disturbances. They propose an adaptive Q-learning-based controller that uses both offline learning and online adaptation. The controller includes an active disturbance rejection model based on the dynamical ship motion model. The parameters of the controller are adapted online by the Q-table.

Zvyggin and Zvyggin [16] deal with three main criteria when considering the multi-objective weather routing optimization problem of vessels: route length, risks along the route, and the number of direction changes. They suggest a graph-based algorithm to find pareto-optimal solutions, i.e., optional pareto-optimal routes. This allows to select one of the alternative routes based on tacit knowledge and preferences, such as the minimum risk or minimum fuel consumption route. They also show how to include ice motion to optimization with the aid of 3D graphs, although they had to assume a constant speed for the vessel.

Ma et al. [17] presents an optimization method that controls both the route and the vessel speed. The optimization targets to minimize costs and emissions simultaneously. As for costs, the model includes fuel costs, time-based costs, and even the capital costs of the cargo. When considering SO_x emissions the model takes into account areas where emissions are regulated. A genetic algorithms was used to find alternative Pareto-optimal routes.

D. Proactive maintenance

HIL tests can be instrumental in creating and validating AI models for early detection of emerging failures. They also facilitate the validation of condition monitoring devices and algorithms on the HIL test bench prior to their deployment. Moreover, HIL systems enable testing the effects of various faults on the rest of the system using fault insertion. Proactive maintenance requires ML algorithms that are trained on historical sensor data to identify patterns associated with impending failures, such as those in engine components, actuators, and sensors. HIL tests potentially enhance the training of these AI models, because the laboratory environment and equipment enable creating large data sets with scenarios and measurements that are not feasible with operating fleets.

Short and Twiddle [18] developed an embedded device prototype to condition monitoring of rotating machines in the water industry. The device, which is based on a physical micro controller, takes several temperature measurements and the shaft speed as inputs. It was tested in a HIL test bench against a simulated pumping device.

Gonzalez-Jimenez et al. [19] studied fault detection of induction machines. They used a software-in-the-loop approach to generate training data for ML to overcome the lack of real field data. Software-in-the-loop is similar to HIL but lacks any physical components. However, the authors were planning to validate the method with a HIL test bench.

Le, Tsai, and Le [20] developed a real-time evaluation and fault detection system for photovoltaic (PV) systems. It uses a HIL system where real-time sensor data from the PV system serve as inputs to the real-time simulation model, which is a digital twin of the physical PV system. The simulated current and power values are compared with the true values to detect faults.

E. Regulation and sustainability compliance

HIL testing can serve as a tool for validating whether components comply with regulations. It can also facilitate the development of AI models to estimate emissions without direct measurements. These models, known as virtual sensors, could potentially be utilized to ensure compliance with regulations and enable real-time reporting of emissions and other sustainability metrics. With the use of digital twins, emissions could even be predicted and reported in advance and used, e.g., for service pricing purposes.

Michna et al. [3] developed an MHIL test bench to test electric motors for cranes. The crane loads were simulated, and the test setup also allowed to control the ambient temperature. The article reports how to conduct efficiency measurements to validate the compliance of motors with standards.

Dimitrakopoulos [21] developed a virtual sensor to estimate NO_x and relative air-fuel ratio (λ value). The estimates were computed using artificial neural networks (ANN). The inputs for the NO_x estimates were: intake manifold absolute pressure (MAP), λ value, engine speed, and torque at shaft. To estimate the λ value, the ANN used MAP, engine speed, and torque at the shaft as inputs. The training data was generated using a simple test matrix of steady speeds and torques. The validation tests were conducted with more dynamic scenarios, including randomized speed and torque changes. The validation results show that recurrent neural networks could estimate NO_x emissions with $R^2 = 0.91 - 0.99$, depending on the validation experiment. However, the virtual sensor was less accurate in tracking the true λ value, with $R^2 = 0.59 - 0.94$, depending on the validation experiment. This work underscores the challenges in accurately estimating certain parameters. Hence, it highlights the need to develop better AI models for virtual sensors. This could be achieved in an MHIL environment that enables collecting large datasets from realistic scenarios.

V. Conclusion

This study explored the potential of data-driven AI/ML methodologies, in conjunction with virtual vessel models and Hardware-in-the-Loop (HIL) test facilities to advance sustainable maritime. We also detailed the implementation of a mechanical-level HIL test bench for a marine engine. Such an MHIL system can be used to load the engine using realistic vessel route scenarios, which can be learnt from data and still be stochastic in nature. This approach helps prevent overfitting when optimizing engine controls. Moreover, MHIL tests facilitates generating larger data sets from a borader input space for ML, which in turn allows creating more complex AI models.

With data-driven digital twin models, large data sets, and validation in a HIL test bench, it is possible to develop, e.g.: (i) advanced engine and hybrid powertrain controls that operate optimally and pro-actively along the planned route, (ii) condition monitoring of components for proactive maintenance, (iii) route optimization, including risk-management, and (iv) emission estimates and predictions for sustainability reporting and services pricing. Furthermore, AI methods, such as genetic algorithms, can be utilized to find Pareto-optimal solutions for multi-objective optimization problems in maritime.

When dealing with AI models, it is crucial to acknowledge the potential for biases that the models may possess or develop over time. As for HIL testing, biases can stem from various sources including data, scenarios, algorithms, as well as alterations in components, materials, and environmental conditions. First, it is essential to evaluate if data-driven approaches are indeed needed. Second, when employing AI models, regular updates and monitoring are crucial to ensure their accuracy and relevance. Moreover, the use of explainable AI models, data logging, and a human-in-the-loop are highly recommended to ensure alignment with reality and regulatory compliance.

In the future, the ideas presented in this paper ought to be implemented and tested to validate their effectiveness.

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