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Research Article

AI-Enabled Simulation-Based SIL Setup For Motor Controllers: Enhancing Software Testing Efficiency

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ABSTRACT

In the automotive domain, the trend of ECUs becoming central units facilitating deployment of functionalities sliced up across domains and their interlinking makes MC soberly complex. Some typical functionalities, as examples, are driven control and safety, electrification of the powertrain, and driving assistance. This phenomenon also led to a sharp increase in testing these MCs. Incidents such as those recently seen in highly and fully automated driving automobiles show that rigorous testing of such MCs for readiness to be released to the field is an exponentially increasing challenge. To cope with the MC wiring complexity and its handling efforts, hardware-in-the-loop testing devices are increasingly used to test MC software functionality. Incidentally, many MC customers often first test dumps of the MC software in their software integration labs or they use simulators known as models. The challenges of increasing the number of test cases to pass for the release candidate and the amount of test runs are similar.

Keywords: AI-Enabled Simulation-Based SIL Setup for Motor Controllers, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, VehicleReliability

1. Introduction

emphasizes the growing importance and undeniable benefits of big data usage across various sectors. Collecting and processing data from numerous sources comparatively faster leads to more efficient operations, resulting in big data creation and usage trends in every aspect of the economy. However, integrating big data analytics into any organizational strategy involves risks, especially when it comes to sensitive data protection. One of the industries that has faced a lack of theoretical methods to continuously improve cybersecurity is big data analytics systems, especially when the data is distributed and processed in real-time. However, protecting the confidentiality, integrity, and availability of data is a challenge for cybersecurity governance across the entire system. Furthermore, this paper emphasizes information assurance with the main data analysis stages: classification, prediction, pattern recognition, clustering, policy development, decision support, risk analysis, and security testing which are crucial for modern online services.

Security is all about ensuring that the controlled asset remains in a certain state where data integrity is considered to be a subset of confidentiality and privacy control, which have been proven to be achieved if in place together with availability. Thus, confidentiality and privacy are fighting against unauthorized disclosure and unpermitted reception of data, respectively, while integrity focuses on unauthorized modification. Conversely, as an essential criterion for security, the availability gives the guarantee that the controlled asset would be able to perform the required operations as expected without any impediment. A reliable certification system will not only benefit network operators but also end-users, enhancing trust in the resulting processed data. Therefore, to realize the true potential of big data analytics, in a manner that is sensitive to data protection, most importantly, a security benchmark is needed to support data assurance across all data processing stages. Without a measurable data security benchmark, engineers may easily ignore this important part of scientific research, analysis, and development in parallel with security, testing, and improving new big data platforms. Therefore, incorporating diverse network equipment, data processing operations, and

equipment capabilities into the general big data framework, infrastructure security, and data protection are critical during the entire process.

Cybersecurity attacks continue to rise and threaten individuals, organizations, and governments worldwide. Despite this, the wide and explosive nature of big data has not been leveraged to address or counteract this problem tremendously. To counteract the dynamic nature of this attack landscape, the need for innovative approaches to bolster security is urgent. Machine learning, artificial intelligence, and systematic cybersecurity approaches are the foundational elements that are essential to that. Security across a broad range of applications is a major issue due to the interconnected and complex nature of the World Wide Web today. Innovations in cyber security are urgently needed to contribute to these newly evolving security threats effectively. On top of using machine learning and AI to detect cyber attacks, we need data-driven intelligence with the following features:

Finding unknown threats to help organizations adapt to low-signal attacks. Intelligent decision-making for action inside and around the network. More sophisticated analysis for post-mortem analysis of attacks. Moreover, large-scale datasets are still data that can be used to enrich and reinforce this process, enabling more advanced feature extraction for more accurate and better decision-making. Lastly, it is essential to monitor and collect data in a structured way. Tools without structured data are hard to maintain, and the model will not be able to correlate features without a clear view of the network landscape.

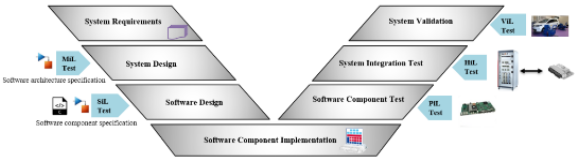

Fig 1: V-cycle of model-based software development process with the test phases

1.1. Background and Significance

Cybersecurity measures have become an omnipresent method of ensuring organizational protection. These measures are even more relevant in today's age of big data where organizations must have robust cybersecurity strategies in place. While this is necessary, our approach to cybersecurity in general is largely reactive. Given the dynamic nature of technology, cybersecurity is a moving target and our strategies are often inadequate to protect our systems from new and emergent cyber threats. In this paper, we discuss key strategic methods that organizations need to consider to have a robust cybersecurity strategy. The overarching goal is to provide proactive rather than reactive approaches to cybersecurity.

The goal of this paper is to provide an exhaustive discussion of the various data-driven approaches that organizations can leverage to improve their cybersecurity posture. With the advent of big data, there is great interest in exploiting analytics-driven tools and decision aids to sense as well as assess evolving cybersecurity threats. However, despite the recognized big data opportunity, the data analytics field for cybersecurity is still evolving; there is a genuine lack of ecosystem partnerships among cyber-domain experts, data science experts, and end-users who are enveloped in complex big data cyber-protect decision-making. This paper explicitly connects the link between cybersecurity and data science practices and gives a detailed review of available big data methods.

test harms the agile development and in-the-loop-type verification methods. This research proposes the use of AI-based automation during the set-up and multi-core architecture work, thereby reducing the time-bound delays. Such optimization can help improve the effectiveness of software testing, which, in turn, will improve the overall drive development efficiency.

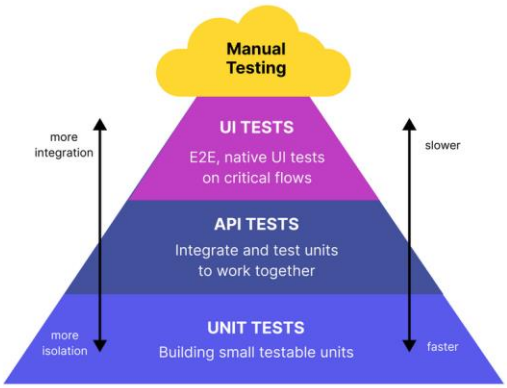

Fig 2: Testing Tools and Frameworks

1.2.Research Objectives

The major research objectives associated with this research study are listed below: - To deploy a simulation AI solution for a full motor controller high-level C code virtually used for Hardware-In-the-Loop Testing, to

replace faulty components with predicted behavior modules based on machine-learning algorithms. - To demonstrate a reduced manual effort and automated fault insertion method for integrating AI/ML advanced technologies in virtual Hardware In The Loop (HTL) testing processes (before the physical motor is produced). - To accelerate the automated fault insertion, setup, and results of the virtual HIL using simulation models to increase product maturity and timely deliveries. - To encapsulate 43 scenarios, each of which contains 10-70 safety metric components (brake pedal, throttle pedal, transmission position sensor, front camera, front radar, side camera, side radar, steering angle sensor, and wheel slip sensor). - To portray a process that enables verification and validation (V&V) for safety-level critical systems, while demonstrating enhanced fault insertion failures in singular components, reducing test automation scripting time and test setup for the automation framework, and improving test accuracy.

2. Literature Review

The leading trend in system design has been shifting from costly and time-consuming prototype-based design to early testing of the control algorithm based on a complete system model. Most motor control applications have a rich toolbox for simulation and code generation. However, by intensively using hardware-in-the-loop setups for motor control, a considerable waste of resources was realized concerning the postprocessing and the parametrization of the control algorithms. Software-in-the-loop (SIL) testing is a well-known technique to enhance software development efficiency and effectiveness. Therefore, a problem that is growing exponentially is the need to run simulation-based SIL systematically on high-fidelity models, translated from the motor controller code.Simulink is a general-purpose tool for modeling, simulating, and analyzing dynamic systems. It supports automated code generation of embedded software, enabling real-time control, signaling, and testing from the controller to the physical hardware. Despite the many Simulink tools on the market capable of code generation, Model-Based Design, automated code generation, SIL, hardware-in-the-loop (HIL), and configuration management tools, there is no tool specifically designed to bridge the gap between design-time tests on SIL at the algorithm level, based on a complete precise system model with all controller functionalities, and the growing need for testing for uncertainty management based control. Moreover, the demand for accurate and fast simulation systems with hardware-in-the-loop embedding arises as a consequence of the design and simulation functionalities embedded in a standardized and familiar integrated environment.

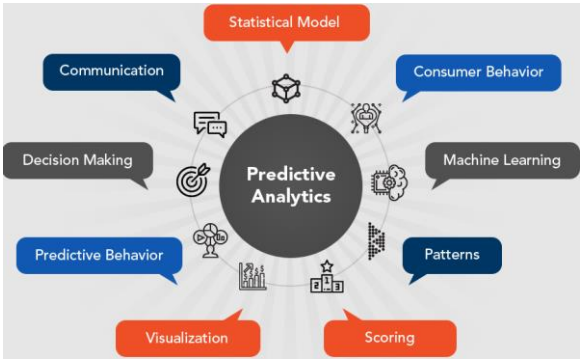

Fig 3: Predictive Analytics and Data-Driven Development

2.1. Simulation-Based Testing

In comparison with Hardware in the Loop (HIL) setup, software testing through Model in the Loop (MIL) and Processor in the Loop (PIL) offers faster turnaround time and better code coverage. Simulation-based software-in-the-loop (SiL) supports early functional testing, default, robustness, and safety verification of motor-controller development. It also allows fast debugging of model artifacts. It's an efficient and cost-effective way to carry out a large number of tests. The main benefit of SIL is continuous and automatic application testing in the CI/CD DevOps chain, offering quick feedback to developers. SIL brings the possibility of very early application testing, almost immediately after the artifact's software construction. Furthermore, we perform the SIL test at multiple levels. Firstly, low-level implementation modules are tested by their isolated configuration. Then, these implementations are collaboratively orchestrated using a high-level Ivy. The Mechanical and Motor workload software modules are tested. The server applications enable the state of processing of each module and gather the results.SIL enables the rapid validation of system features. Simplified or hypothetical models are used for rapid testing before replacing them with a detailed ECU plant model. A stopband filter or hardtop prototype is used to simulate flow and enable the synchronization of mechanical and motor software interfaces. Motor command IAMs are simply simulated module inputs and workloads are the simulated outputs. The server software modules fulfill the role of ECU plug systems, enabling the gathering of data/results. To develop SIL, a SIL framework was the element that allowed easy-to-build new software platforms quickly and enabled the identification of defective modules. SIL improvements stabilize the quality and robustness of Sil's workflow between each job, make it more responsive, and increase its degree of parallelism. SIL performance improvements: reduced performance impact on hardware; the reduced-time impact of architecture tests;

richer software configuration. SIL meets the software criteria with performance requirements, breaks firmware with a minimum turnaround time for developer software maintenance, and supports simulated system testing.

2.2. Software-in-the-Loop (SIL) Testing

While testing embedded software for motor controllers, which are highly hardware dependent, development times can be significantly reduced and the range of cases covered can be extended by creating a suitable virtual environment provided by simulation-based SIL testing. Software testing is vital not only to ensure that the software installed in vehicles and the devices embedded in vehicle systems are functioning properly with minimal defects but even more importantly, to foster and disseminate a culture of quality and integration of software systems. With the growing complexity of automotive software, the relevance of testing is increasing rapidly and eventually causing a high workload in system testing. Given the fact that Industry 4.0 is accelerating the integration of software, hardware, systems, and different suppliers towards developing more integrated products, the relevance of the complexity of testing during software development for motor controllers is increasing rapidly.Software-in-the-loop testing is a technique used in embedded software testing. Software-in-the-loop testing is an automotive prototype-based system used with deployable production software. Software-in-the-Loop testing is used to verify that the controllers are ready for deployment and can be tested within a virtual engine using Simulink models and Processor-in-the-Loop. Around the same time, additional manufacturing cost savings can be achieved by automating the process. With the development of Software (S-W), hardware (H-W), model-in-the-loop (MIL), processor-in-the-loop (PIL), and hardware-in-the-loop (HIL) techniques (often combined as system layer/embedded software), designed models and simulations, designed and fully embedded software developed for motor controllers must be validated through System-in-the-Loop tests. From S-W, H-W, MIL, PIL, and HIL types of tests, a procedure improvement is system testing.

2.3. AI in Software Testing

The application of artificial intelligence (AI) techniques has opened doors to applying AI as an effective approach to optimize the software testing process. This exploration aims to develop various AI-based systems to automate different phases of software testing. Also, AI has come up with creating processes so that they can be controlled automatically. In the AI phase, usually, the AI models are produced using the stock data. As the data is pelted with millions of information, it automatically produces a standard model. Similarly, the stock data predicts the trends. By applying data mining and analysis algorithms, patterns are drawn. This builds reusable assets; branded problem-solving repositories can be designed for automatically answering typical queries. Repetitive and most analytical maintenance tasks are evaluated and they can be improved. Prime Operations Company often creates AI-based systems that involve automatic retrieval and interpretation of information.Traditional algorithms have typically been used. For instance, generating test models and extrapolating algorithms for test automation have already been developed and used. With the recent rise in data-rich software testing and development, the potential of AI to improve software testing has increasingly been recognized. The latest international software testing standard, ISO/IEC/IEEE 29119, has introduced a new keyword titled "intelligence - especially artificial intelligence" to describe the broad spectrum of AI-driven techniques applied to software testing.

3. Methodology

As part of the ideation process, the central idea was to minimize the manual effort for the current setup. Different stakeholders in the project, including Sales, Customers, Applications, Hardware, and Control, were interviewed and the challenges and gaps in the offline and online system integration process concerning the used infrastructure were chalked out. The roles and responsibilities of each stakeholder were clearly defined. A current-state analysis was done on the process, tools, challenges, and other dependencies by involving the stakeholders. The process implementation was carried out with the support of a Core Process Development Checklist. The efficiency of the entire process implementation was estimated with the utmost care for Sales, Customers, Applications, Hardware, and Control, as well as for the organization.The rear and chassis dynamometers in the dyno test cells are capable of controlling different hardware-in-the-loop models of various electronic control units such as sensing devices, MCUs, and codes that are embedded in the electronic control units. The models used are RCP, dSpace Simulink, Python, E-python, System C, LABCAR RCP, ETAS, and other data acquisition tools. Any of the customer-required control algorithms or customer-requested targets must be varied either with the help of expert knowledge-based support or via hardware-in-the-loop testing. The automation controller, control interface parameters, external sensors interfacing, sensor condition validation, and parameter and threshold updating as discussed with the respective stakeholders at the planning phase must complete the race. Minimizing the manual efforts and the time consumed in performing these tasks can significantly help in enhancing the execution speed of the offline and online products under test.

3.1. AI Algorithms for Simulation-Based SIL Setup

The task of simulation has been a key enabler for verifying models for motor controllers implemented in simulation-based SIL setups. In this section, AI-based algorithms for accelerating simulation-based testing to reduce SIL setup time are discussed. The idea is to create an AI-based software tool that can automatically configure a model simulation, and use several algorithms or state-of-the-art works from literature to improve

your configuration method. Heuristic-modified methods which use genetic algorithms with a discrete choice method are efficient and can get the expected results.For two-order models, multi-exponential methods have been implemented. The first algorithm is based on the genetic algorithm. The use of genetic algorithms to solve optimization problems is not designed for resolving combinatorial optimization problems – problems with integer variables in decision space. The integers are hard to operate with, and genetic algorithms do not require solving another problem, such as linear programming problems, to satisfy the constraints. In this method, binary coding, initialization, selection, and crossover and mutation algorithms are used to create a valid combination. The GA is also used to simulate an effective resolver applied to the target signal. The first and second algorithms, proposed and verified, will be compared to test function approximations and to artificial neural networks to check the reliability of both methods.AI-enabled simulation-based Software-in-the-Loop (SIL) setup for motor controllers represents a significant advancement in software testing methodologies, particularly in enhancing efficiency through AI algorithms. This approach leverages artificial intelligence to optimize simulation parameters, streamline scenario generation, and enhance the accuracy of motor controller behavior emulation. By employing AI, the SIL setup can autonomously identify critical test scenarios, thereby reducing manual effort and accelerating testing cycles. Furthermore, AI algorithms continuously learn from simulation results, enabling adaptive adjustments to testing strategies and improving the overall robustness of motor controller software. The integration of AI in SIL setups also facilitates real-time anomaly detection and fault injection, crucial for evaluating the resilience of motor controller software under diverse operating conditions. This capability not only enhances software reliability but also reduces development costs and time-to-market. Moreover, AI-driven SIL setups enable comprehensive performance evaluation across a spectrum of operational parameters, ensuring motor controllers meet stringent quality standards before deployment. As AI continues to evolve, its role in SIL setups promises to revolutionize software testing by offering deeper insights into complex system behaviors and enabling proactive identification of potential issues. Ultimately, the synergy between AI algorithms and simulation-based SIL setups marks a transformative leap forward in optimizing motor controller development processes and ensuring superior software performance in real-world applications.

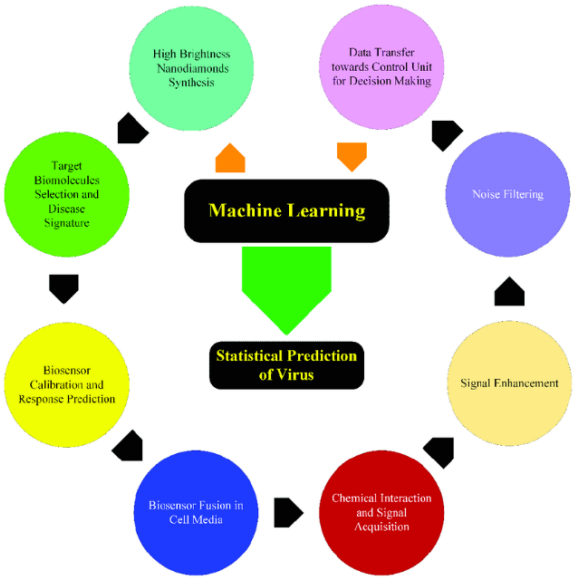

Fig 4:Data flow diagram for the proposed model of AI-integration with FND biosensing for SARS-CoV-2 prediction

3.2. Integration of AI with SIL Setup

AI-enabled SIL setup introduces the process of integrating Artificial Intelligence (AI) with the existing SIL setup. This process involves the usage of modern Python libraries to train a Deep Q-learning Reinforcement model based on input and output motor controller datasets. This model is used to generate training patterns for testing of a motor controller. Along with this, analysis of test results is done using statistical and reinforcement learning methods. By creating and implementing this AI-enabled simulation-based SIL setup, a novel approach for testing motor controllers has been established. The traditional SIL-based setups like the inverter HIL setup and hardware-based SIL setup use Simulink models and dSPACE hardware for validating motor controllers.

The selection of calibration and optimization parameters is done based on knowledge of the domain and successful motor controller testing data with SIL and PIL simulations. The key to the proper testing of the motor controller is the generation of proper test patterns. Based on user inputs, the AI model is trained and is used for the selection of input vectors, number of iterations, and other testing parameters. After completion of the testing, ML model results are stored for future reference. The sigmoid function is used to predict the output and the activation function is used to decide the saturation of the output signal. The correlation between the output signal prediction and KW signal prediction is used to finalize the test vector for motor controller tests.

All parameters with boundary values are tested for the motor controller. The reinforcement learning algorithm computes the optimal policy where the ML model finds the optimal actions (select proper test patterns) by evaluating the Q (quality) value for each possible move.
AI-enabled simulation-based Software-in-the-Loop (SIL) setup for motor controllers represents a transformative approach to enhancing software testing efficiency. By harnessing AI algorithms within simulation environments, this methodology optimizes the validation process for motor controller software. AI algorithms facilitate dynamic scenario generation, allowing for a broad spectrum of real-world conditions to be simulated accurately and efficiently. This capability ensures comprehensive testing coverage, identifying potential issues early in the development cycle. Moreover, AI enables adaptive testing strategies by autonomously adjusting simulation parameters based on real-time feedback, thus improving the accuracy and reliability of test results. The integration of AI into SIL setups also streamlines regression testing, reducing manual effort and accelerating the identification of regression issues across different software versions. Furthermore, AI-driven anomaly detection enhances fault tolerance evaluation, enabling motor controllers to operate robustly under diverse operational scenarios. Overall, AI-enabled simulation-based SIL setup for motor controllers not only enhances software testing efficiency but also fosters innovation by pushing the boundaries of simulation realism and accuracy, ultimately leading to safer and more reliable motor controller software in industrial applications.

3. Case Study

In the present work, a detailed effort has been initiated to achieve SIL 2 compliance according to IEC 61508 for the most advanced industrial PCB designed in-house. Below is a detailed case study representing the present effort. The given reference is an automotive-oriented design, and similarly, any other industrial domain PCB can leverage this approach and use the same.The control part of this exterior flap of a car comprises an H bridge, which can handle the load of any type of actuator. In this case, this specific reference design module is designed with 4 relays (TA25DU) in the H bridge. The onboard power supply IC U4 is designed such that low inductive steers are connected to the load. Additionally, a mandatory free-wheeling diode is given to have an external connection to avoid thermally induced failures in TA25DU.Trigger circuitry is also designed onboard such that a microcontroller can control it. The microcontroller is designed with an onboard USB to UART, and the open drain outputs of the microcontroller ensure the directional H bridge requirement.

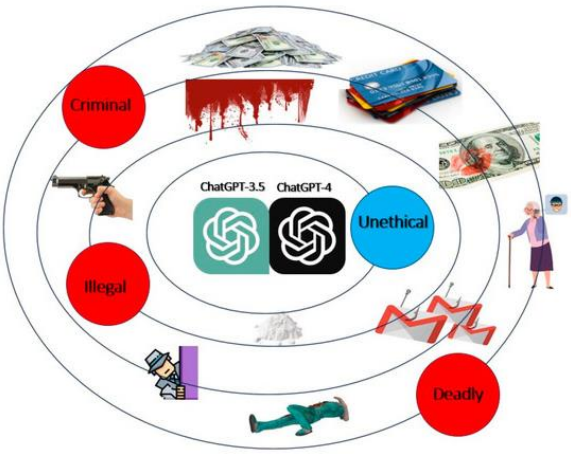

Fig 5: Case study road map

4.1. Experimental Design

The effectiveness of the AI-enabled auto-configuration features of the proposed virtual setup depends on the robustness and effectiveness of the base configuration that is used to prepare the model. Therefore, it is essential to perform laboratory experiments with a variety of practical scenarios such as inverter faults, boosting, and changing loads. Moreover, the test setup should be able to provide the mixed line power quality scenarios as required for mission-oriented testing.In simulations, several input parameters such as the set output current, reference modulation index, and load that affect the results of the simulation have default values based on the smooth behavior of the inverter model. After the survey of these parameters, the parameter ranges and an appropriate algorithm can be developed to find the parameter values to get similar responses with the available simulation data.The response signals used to conduct online simulations are generated by performing experimentation and simulation both on a real-time digital simulator, where various fault scenarios can be easily developed for the components tested.The developed method can be extended for the case where the open-loop and closed-loop responses are different or unique values for the parameters in both loops. The main issue here is that open-loop commands do not have enough responses for every condition of the two loops, so due to real-time issues, online parameter changes are not feasible. Retraining for the specific second loop

becomes the solution in these sorts of problems.The addition of a load board with dynamic loads and a rectifier with passive elements make the mixed line power quality testing difficult. The characteristic of the rectifier will prevent the simulation result from representing the power factor or active power response of the corresponding test that reflects the motor controllers' line-side input current to voltage dynamics.

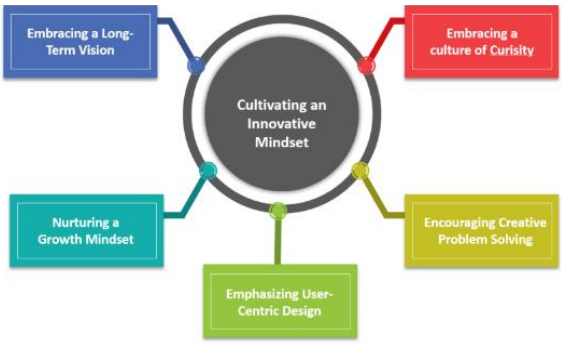

Fig 6: Principles of cultivating an innovative mindset

4.2. Results and Analysis

The AI agent is implemented and executed in UI Automation in conjunction with the existing AUTOSAR Adaptive Virtual Machine setup. Figure 8 shows the UI Automation console settings used to implement the assembly of required components. The AI agent inspector developed for On-WOL setup generation is shown in the figure. The inputs include a trigger-list file containing the trigger names, description tags, and the file path to place the generated source files. Parsed JSON data, application logic, and source template plugins are run on the AI agent, as well as loaded to form a decision tree for the respective trigger. A JSON file corresponding to the trigger is then generated using the AI agent and is placed in the folder diagram as shown in the figure.The WOLF classes, modules, and data tags, with internal signals, are then auto-generated for the On-WOL setup development. For the developed AI agent to auto-generate the source files, relevant trigger information is retrieved from the leaked ARXML files and/or CSV files generated from the previous On-WOL setups. The trigger information schema must be well structured so that the AI agent extracts the trigger details from metadata files. The code-generating process needs to be repeated once a change is required in the source files following any design changes. If changes are major, the decision tree might produce errors during auto-generation, requiring model retraining or the introduction of new nodes in the tree. The ARXML or the CSV files that contain trigger information help the AI agent better learn and retrieve the basic information for the module's functions.

4. Discussion and Future Directions

In this work, we have developed AI-based algorithms for the setting up of simulated motor controllers for hardware-in-loop (HIL) setups. These AI-enabled algorithms will significantly reduce the time and effort required to develop HIL-based SIL setups. In the initial implementation of the setup, the creation of hardware-in-loop (HIL) interfacing software concerning the actual motor and its controlling unit takes a significant amount of time. It may also require significant control software changes to utilize the HIL test environment. The proposed solution provides a simple and powerful boundary condition verification test that allows the developers to run MIL verification tests in the HIL environment without requiring any additional creation of control software or logic changes. As shown in the results section, the CPU load of the plant model was observed to increase when the AI-based data highway setting algorithm was used.The setting-up of the simulated plant or plant models for hardware-in-the-loop-based controller testing has significant complexities and can take a significant amount of time. In the initial stages of HIL setup creation, the AI tool data capturing will thus help in a rapid setting up of the HIL system. The need for high fidelity in the model is also one of the key requirements for HIL system validation. The usage of these AI-based setup verification tools will help in rapid change and setup validation. Post lockdown, the AI-based capturing of data points from these HIL systems is promising to facilitate rapid transfer learning algorithms. In this current work, we have utilized the Bayesian optimization-based algorithms to aid in virtual setting estimation. There exists an understanding that AI-based algorithms always serve as black boxes, but we would like to encourage hyperparameter tuning for simulation and validation-related model settings. If the model performances improve, such AI-based models can eventually be used for setup validation purposes. In the future, we plan to conduct extensive drift analysis on existing AI-based algorithms and explore newer algorithms such as random forests, artificial neural networks, and supervision algorithms for identifying the data highway setting for control software.

5.1. Key Findings and Implications

The study involved identifying a solution for enabling the execution of controller source code into the machine code directly efficiently generated from Simulink for GPIO control of industrial motor controllers at a

predefined clock. The study shows that the auto-generated source code can be called in three Executable Functional Mockup Units adopted to Controlled Software Packaged based on the application-specific execution rates. The GPIO port can be replaced with specialized models of serial and Modbus, and the microcontroller can be replaced with the SoC (System on Chip) controllers, which would be one enhancement of the proposed work. The field of the detailed study provides application possibilities in electrification, but the concept can be equally extended to HVAC, SmartGrid, and others. The proposed research is still undergoing further fine-tuning to get maximum performance in software debugging ways similar to the optimization of the neural network models.

Fig 7: Software Testing and Quality Assurance Services

5.2. Potential Applications in Industry

AI and ML applications have been of interest in several other areas of the automotive industry, besides autonomous vehicles and ADAS. We believe that the simulation-based AIES for SIL setup using machine learning algorithms can be applied in several areas of the industry to speed up the testing process. In concept, it can be used in scenarios where parameter estimation procedures are used. These parameters can be stress inputs, time-varying road conditions, or just the different races the vehicle has driven. Machine learning algorithms present potential in vehicle energy management owing to their self-adaptive nature through learning from the condition and history of the object. The machine learning applications of AI event prediction, in identifying sensor faults, or permanent magnet failures, predictive maintenance, and fault detection of a motor are associated with electrification.In a slightly broader sense, ML and AI can find applications in classical vehicle simulation software used by engineers, where several inputs are given to test out a model's output. Many times, the tasks are repetitive and time-consuming testing sequences and can be made easier and optimized through ML for that model. This optimization, design of experiments, and other such applications of ML can indeed reduce test durations, the cost of test equipment, and above all, the time the product reaches its end consumer. It helps in substantially reducing the design cycle, optimizing the product faster, and remaining competitive, ensuring a faster time to market.

5. Conclusion

Technological advancements in key inhibiting factors of software development have been one of the critical reasons for recent advancements in digital applications. In addition to this, real-world applications bring forth increased requirements due to a multiplicity of use cases and proprietary system confidentiality. Consequently, derivative tests that balance time, skill, and accessibility are becoming increasingly important. However, for safety-related system debugging at early V-model setup, the sub-SA test strategy is indeed underrepresented. Due to the high complexity of real-world system interfacing for knowledge-based remote diagnostics, external devices are only mapped for end-consumers in the motor controller domain. Consequently, this results in a significant cost-efficiency drop in the context of system quality at very low fault-injection rates.

In line with advanced user interfaces, this paper proposes and implements an AI methodology for systematic fault analysis and a formally structured SIL setup. First, we demonstrate the proposed method on a sub-SA setup at the motor controller domain, including a synthesis of strategies for cost-optimized system interfacing. Next, in software-in-the-loop simulation tests of a realistic motor controller use case, a relevant subset of the SUT model is systematically tested. Then, we verify our strategy, assuming only safe input range data and suitable similarity constraints, to successfully cover functional ranges that would otherwise remain blind spots

for the SA. Finally, the remaining system interfacing could be improved by demonstrating that the accuracy of the input diagnostics was high when returning simulated data. In short, this paper signifies that real-time data horizon condition-dependent hardware in the loop tests finds a pre-SIL candidate in the form of cheap new technologies. In the automotive domain, in-virtual testing could significantly contribute to cost optimizations, particularly since a greater share of these assemblies will neither be re-used nor contain exposed protection chains.

6.1 Future Trends

With evolving technology, it is anticipated that the dependency on computationally expensive models will be reduced. However, with advancements in artificial intelligence, the complexity of the issues solved concerning the SIL requirement using detailed models like the motor-inverter systems will increase. Detailed and computationally expensive models of the RSL will be utilized by the AI, and an autoencoder or similar approach will be used to determine the SIM-State, effectively reducing the RSL demand. Using AI, the SIM will learn to resume time from the SIM-State bypassing the testing required to get to the SIM-State. The parameterization of the testing will most likely be done by the operations, without requiring the designer to add substantial new code, making the operations the expert.

The AI-enabled SIM setup for MCs we designed could be enhanced by using domain adaptation and transitive learning. In the initial stages, simulation results were unavailable, and hyperparameters like allowable learning error for each loss and the importance of each loss needed to be set experimentally. It is anticipated that with hundreds of projects using this process, the correct hyperparameters could be provided by the AI. In the initial stages, low simulation error could be set up before dropping out the actual sensor and control. Over time, the SIM could use the RSL and SIM-State as training data for the AI, learning control, estimation, and sensor and motor performance. DNNs within the AI could be trained to a high level of performance using the auto-encoder technique, with lots of training data generated by one high-level model evolution.

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