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Real time fault detection in hydraulic system for wheel loader application

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Abstract.

This paper presents the development and implementation of a real-time simulation model for the hydraulic implements of a wheel loader, with a focus on fault detection applications. The model replicates the behavior of the hydraulic system controlling the boom and bucket, incorporating components like load sensing pumps, control valves, and double-acting actuators. It was engineered for real-time performance without sacrificing accuracy, making it suitable for embedded systems. After the validation phase - performed using experimental data from a sensor-equipped wheel loader - the model was then deployed on an embedded platform, where it processes live sensor inputs and compares predicted actuator positions with actual measurements. Significant deviations can indicate faults such as leaks, wear, or sensor drift, allowing early detection and operator alerts. This approach enhances safety and reduces downtime. Ultimately, the model functions as both a virtual sensor and diagnostic tool, and its methodology is applicable to other electro-hydraulic systems promoting wider adoption of virtual simulation in off-highway equipment.

Keywords. Fault detection, real-time, digital twin, virtual model, off-highway equipment, hydraulics.

1. INTRODUCTION

Construction and off-highway machinery are becoming increasingly automated and sensorized, so simulation technology offers a powerful approach for enhancing operational reliability and predictive maintenance [1].

Fault detection in hydraulic systems, particularly for heavy-duty mobile machinery such as wheel loaders, is essential for ensuring operational reliability, safety, and productivity. The main fault detection methods [2] for mobile equipment and hydraulic systems can be classified as follows: Model-Based methods [3][4], which utilize mathematical or physical models to predict expected system behavior and detect faults by comparing measured signals with model outputs; Data-Driven methods [5][6][7], which employ statistical or machine-learning techniques to identify anomalous patterns in sensor data without relying on explicit physical models; Signal-Based methods [8][9], analysing time-domain or frequency-domain characteristics of pressure, flow or vibration signals; and Hybrid approaches [10], such as Digital Twin [11][12]frameworks that combine model-based and data-driven techniques by integrating physical models with real-time data.

In the frame of model-based fault detection methods, the main approaches are the following: Parity Equation-Based Detection [13] describes the use of parity equations (analytical redundancy) in mobile hydraulic systems to generate residuals and identify faults through threshold-based deviations; Nonlinear Observer with Adaptive Robustness [4] introduces a nonlinear adaptive robust observer addressing uncertainties and disturbances for detecting sensor faults, fluid contamination, and supply pressure deviations; Interactive Multiple Model (IMM) Filters [14] Applies IMM filtering with smooth variable-structure filters to detect and isolate friction and leakage faults in hydraulic actuators; Multi-Model Observer-Based Diagnosis [15] utilizes a bank of parallel models (observers) representing normal and fault conditions where the model with minimal output error indicates the current system state; Comprehensive Parity-Space and Observer Approaches [16] presents a unified treatment of observer-based residual generation, parity-space techniques, Kalman filters, and isolation strategies in a state-space framework.

Traditional maintenance approach on off-highway vehicles is time-based, that means preventive actions are scheduled regardless of the actual condition of the components [17][18]. Time-based approach relies on routine inspections and replacements, which can lead to unnecessary system downtimes and inefficiencies.

The target of this project is failure and predictive maintenance analysis and observation using a hard real time model integrated on physical vehicle electronic control unit (ECU) during standard manoeuvres. In this paper the focus is on the high-pressure circuit of a wheel loader, a heavy-duty construction machine equipped with a front implement used for digging, lifting and transporting bulk materials like soil, gravel, or debris.

In fluid power systems, the application of a failure detection systems can significantly enhance operational reliability, safety and productivity. These techniques can be implemented across various components such as pumps, valves, and motors, enabling early detection of wear or malfunction, preventing failures that could compromise safety.

The condition monitoring of single components inside a hydraulic circuit is described in many papers using different techniques. Raduenz et Al. in [19] describe a method for condition monitoring and fault detection on proportional valves based on spool position and supply current monitoring to detect deviations from healthy behavior, while Kumar et Al. in [20] investigated the condition monitoring of hydrostatic transmission by developing a detailed mathematical model of the system and the analysis of the effects of the loss gap that leads to state the pressure/flow deviation as a key indicator for the fault detection. Applications to hydraulic pumps can be found in [9] and [21]. In particular [9] investigates the use of wavelet analysis for real-time health diagnosis of hydraulic pumps, focusing on pulsation discharge pressure signals rather than vibration signals. Traditional methods (limit checking, spectrum analysis, logic reasoning) struggle due to high noise levels and low signal-to-noise ratios in pressure signals. The proposed method uses wavelet decomposition that provides sub-band signals with distinguishable features; patterns and amplitudes of wavelet coefficients correlate with defect types and this method works on-line in real time without affecting pump operation thus providing robust fault detection in hydraulic systems.

Paper [21] introduces a deep learning approach for anomaly detection in hydraulic piston pumps with demonstrated improvements in diagnostic accuracy. Additionally, in the context of wheel loader applications, [7] proposed a fault diagnosis of a Wheel Loader, but instead of using model based fault detection it exploits a hierarchical approach based on artificial neural networks (ANN) and fuzzy logic in order to identify the subsystem of the vehicle affected by the fault and the type of fault with inputs from 24 sensors.

Building upon this background, the present paper integrates model-based fault detection with a real-time embedded Digital Twin deployed on the vehicle's ECU. This hybrid strategy leverages both physics-based modeling and data-driven insights, thereby enhancing robustness and minimizing false alarms due to noise or disturbances. A time-counter mechanism further filters transient anomalies, ensuring that only persistent deviations above threshold levels trigger fault alerts.

In this activity, a dynamic model of the hydraulic circuit controlling the boom and bucket actuation was developed to simulate the subsystem's behavior under real operating conditions. The simulation model includes key elements such as Load Sensing (LS) pump, control flow valves, and hydraulic double acting actuators. The model was designed with real-time computational efficiency as a core requirement, without compromising model fidelity. This enables its deployment on embedded hardware ensuring responsiveness suitable for continuous monitoring in live operation.

To validate the model, experimental data were collected from instrumented wheel loader operating under various load conditions and duty cycles. Sensor data, including cylinder pressures, actuator displacements, and control inputs, were used to calibrate and correlate the simulation model. The simulation results demonstrate a good degree of correlation with the measured system behavior, confirming its suitability for use as a real time replica.

The correlated model was implemented on a real-time embedded computing platform. The model receives live input signals from the machine's onboard sensors and computes the expected positions of the boom and bucket in real time. This virtual output is continuously compared with actual position measurements of the actuators. Deviations between the predicted and measured positions provide a basis for fault detection. Differences beyond predefined thresholds may indicate potential faults such as hydraulic leakage, actuator wear, sensor drift, or electronic control system anomalies. By analysing these deviations, the system can notify the operator of emerging issues. This early fault detection capability enhances safety, reduces unplanned downtime, and contributes to the overall robustness of the machine.

The proposed solution thus acts as both a virtual sensor and a diagnostic tool in heavy machinery. The work demonstrates how physics-based modeling, when combined with real-time computation and sensor integration, can lead to significant advances in machine reliability. The methodology and implementation described in this paper are generalizable to other systems, not only electro-hydraulic, promoting wider adoption of virtual simulation in off-highway equipment.

2. DESCRIPTION OF THE SYSTEM

2.1. Wheel Loader

The Wheel Loader considered in this work is a Case 821G, see Figure 2.1, which main characteristics are listed in Table 2.1.

Figure 2.1. Wheel loader Case 821G

Table 2.1. Main vehicle features

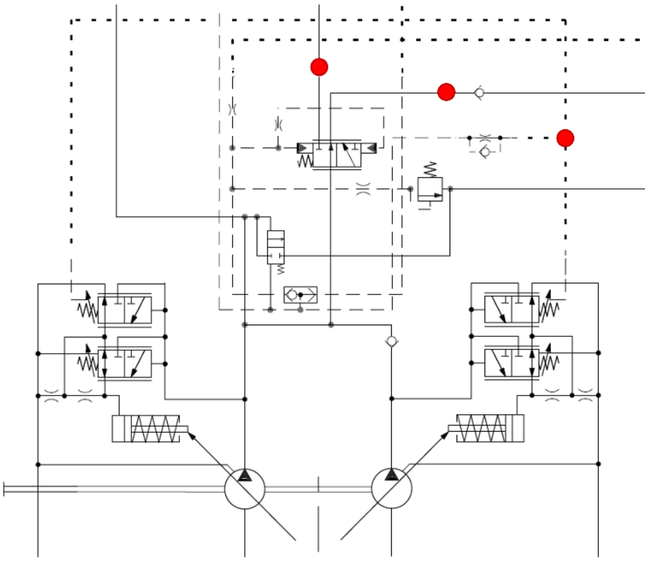
Maximum Engine Power	172 kW
Hydraulic Pump	Tandem, variable displacement
Maximum Oil Flow	236 l/min

2.2. Documentation

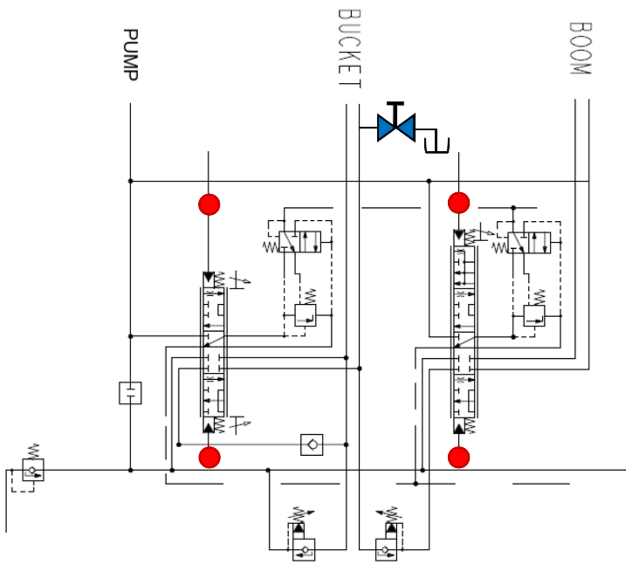
The following Documentation is the starting point for the work:

- Hydraulic Schematic
- Mechanical Design 3D drawings
- CAN Configuration
- Electric/Electronic Interface

The main parts of the high-pressure hydraulic circuit of the vehicle are shown in Figure 2.2.



(a)



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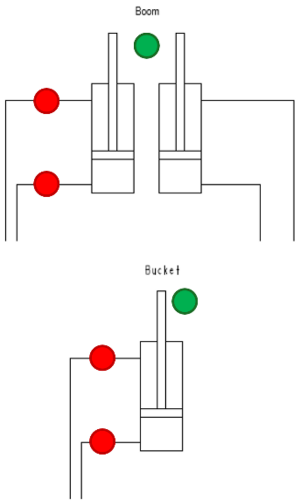


(c)

Figure 2.2. ISO drawings of main components: (a) CCLS hydraulic twin pumps; (b) Directional valves; (c) Boom and bucket cylinders. Red dots indicate the position of pressure sensors; green ones the displacement sensors.

It is a Load Sensing system fed by two twin variable displacement pumps, that work with two slightly different values of pump margin to ensure the pumps works in sequence, Figure 2.2a. A priority valve is present to provide oil first to steering, the most critical function; the excess flow goes to the implement, boom and bucket. In the case study vehicle, the boom has two cylinders, while the bucket just one, Figure 2.2c. Directional valves are placed to control the flow to boom and bucket, Figure 2.2b: they are hydraulic piloted valves, actuated by a pilot pressure signal provided by electronically controlled valves. These are actuated by the electric signal of the joystick and generate the correct pilot signal to move the spools of the directional valves. In this way, the movement of the driver can control the movement of the implement.

2.3. Procurement and Physical Installation

In order to acquire the needed measurements, the vehicle has been set up with sensor installation. Then a preliminary verification of possible installation issues is made, to ensure that the measurement equipment is correctly in place.

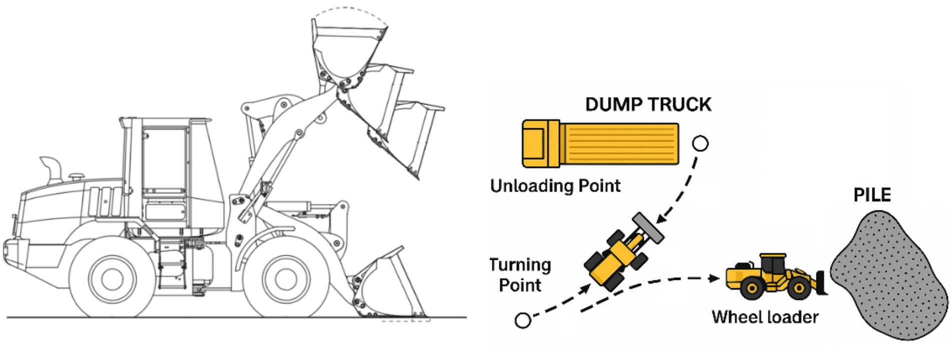
Several sensors were installed on the wheel loader; their position is indicated with a spot in Figure 2.2:

- Pressure sensors (red dots) to measure: boom and bucket pressure in both side of the cylinders; pilot pressure on directional valves, load sensing pressure and pump delivery pressure.
- Electric signals provided by joystick.
- Linear transducers (green dots) to measure the cylinders displacement of boom and bucket. Cable transducers were chosen since the displacement of the hydraulic cylinders is on the order of hundreds of millimeters, see Figure 2.3.

All vehicle CAN signals have been acquired. The sampling rate is 1000 Hz to capture even the fastest system dynamics.

Figure 2.3. Detail of bucket cylinder with displacement sensor installed.

The tests performed are aligned with the standard test procedure of Roading/Transport and Y Cycle. The Wheel Loader implement movements are schematized in Figure 2.4, see the Service Manual of CASE 821G and [22].



(a) (b)

Figure 2.4. (a) Wheel Loader implement movements. (b) Scheme of an Y loading cycle.

2.4. Physical Test

The next step is the physical test on the vehicle equipped with all the needed sensors. The test is led following a Test Procedure, which defines how to perform typical maneuvers such as Roading, Transport and Y Cycle, [22].

3. SIMULATION MODEL

3.1. Model Description

A model of the hydraulic circuit of vehicle has been developed in Matlab/Simulink environment, focusing on the hydraulic high-pressure circuit of front implement (Boom and Bucket). The model consists of the hydraulic power supply unit (Hydraulic Pumps), the pilot pressure valves, the directional valves and the implements actuators (Boom and Bucket cylinders), see Figure 2.2.

All components have been carefully parametrized by combining information obtained from component catalogs, suppliers, or by drawings from internal company documentation. Then the model has also been tuned to match the experimental data.

In more details, the pump model includes volumetric and hydromechanical efficiencies and the absolute and differential compensators are modeled to have a correct prediction of the swashplate angle and its related dynamics. The pump speed is an input to the model and it is calculated from the engine speed (available from CAN) as:

$$\omega_{Pump} = \omega_{Engine} \cdot R \tag{3.1}$$

where R is constant ratio of the pump drive.

The flow rate provided by the pump is calculated by the model as follows:

$$Q_{Pump} = \alpha \cdot V_d \cdot \omega_{Pump} \cdot \eta_v(\omega_{Pump}, \Delta p_{Pump}) \tag{3.2}$$

Where α is the fractional displacement of the pump, V_d the nominal displacement and η_v the volumetric efficiency expressed as a function of speed and pump differential pressure Δp_{Pump}.

The electronic valves that generate pilot pressure signals are pressure reducer valves: they reduce the upstream pressure of a low pressure line in order to maintain the desired pressure value to correctly pilot the directional valves. The model of such electronic valves contains the real software characteristics used in production to achieve the actual relation between joystick actuation and pilot pressure. During the simulation, the actual current signals – wired from the joystick - are used as input of this model subsystem.

The directional valves (including the post compensator) are modelled using the orifice equation:

$$Q_{Valve} = C_d \cdot A \cdot \sqrt{\frac{2 \cdot |\Delta p_{Valve}|}{\rho}} \cdot sign(\Delta p_{Valve}) \tag{3.3}$$

Where C_d is the discharge coefficient (assumed 0.7), A is the metering area, Δp_{Valve} the differential pressure and ρ the oil density. The metering areas of both the main spool and the compensator are provided by supplier to accurately calculate the flow rate across the valves. The differential pressure Δp is given by the difference between the pump pressure and the pressure signals of sensors on boom and bucket actuators.

The displacement of the boom/bucket cylinders is computed from the valve flow by:

$$x = \frac{1}{A_{Cylinder}} \int Q_{Valve}(t) dt \tag{3.4}$$

where $A_{Cylinder}$ is the area of the cylinder.

A picture of a portion of the Matlab/Simulink model is shown in Figure 3.1 with a focus on variable displacement twin pumps, directional valve, compensator and bucket cylinder.

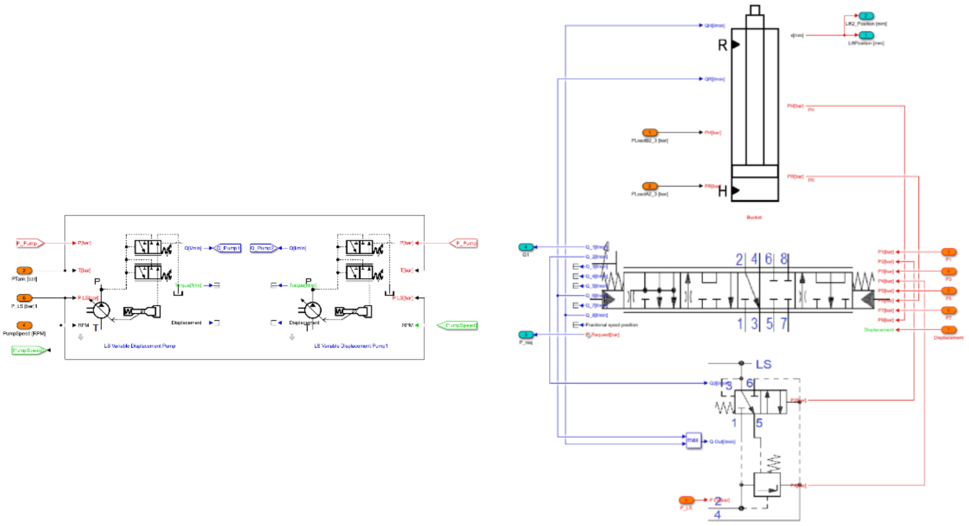


Figure 3.1. Sketch of Simulink model with twin LS pumps, directional valve, compensator and bucket cylinder.

3.2. Model Validation

The model was validated through experimental data, replicating a Y cycle. The graphs in Figure 3.2, show the comparison between experimental data and simulation results of the boom and bucket displacements over time. The y-axes are normalized using a reference value for confidentiality reason.

The correlation between the experimental and simulated curves is high enough for the fault detection purpose. Considering only the bucket and its rising phase, which is the movement studied in this work (falling phase is neglected for fault detection), the maximum deviation between the two curves does not exceed 5%. This deviation is small enough for the purposes of fault detection activity, confirming the robustness of the model and its ability to reproduce real-world behavior.

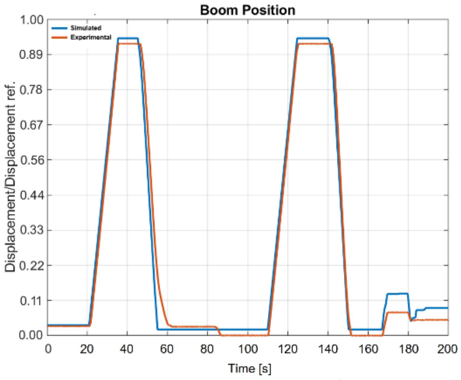


Figure 3.2. Comparison between simulation results and experimental data of Boom and Bucket position.

3.3. Hard Real Time Model on ECU

The validated Simulink model was first discretized then converted and deployed on the vehicle ECU by integrating it within the ECU software. The model in the ECU is able to run in real time and some checks have been done to verify that the results are the same as the Simulink model. The Figure 3.3 shows the bucket position over time, simulation in Simulink in dashed line and real time model with solid line.

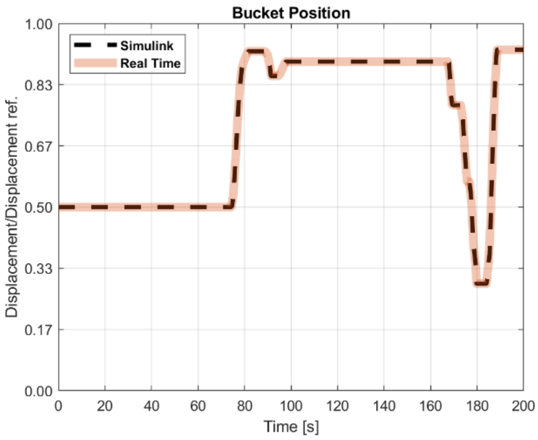


Figure 3.3. Comparison between Simulink simulation and real time model of bucket position.

4. Failure Detection

Most of the claims on Wheel Loader about the implement regard a slowdown of the cylinders and one of the root causes can be the external drain on Boom or Bucket.

4.1. Physical Test with induced Failure

The study focused on leakage failures because it represents the wear of various components inside the machine, such as directional valves, fittings and hose connections, as well as internal leakage of hydraulic cylinders due to seal wear. During the life of an off-highway vehicle, harsh working conditions and severe environments can lead to damage to some of these components.

In order to test if the mathematical model is able to recognize a possible failure an additional experimental activity was performed, inducing a slowdown only on the bucket. To achieve this, a 3-way valve was inserted in the circuit between the directional valve and the cylinder, Figure 2.2b, to drain oil to the tank so inducing a leakage in the circuit: in this way, a lower amount of oil is sent to the actuator and so the bucket movement is slower. Figure 4.1 shows a 3D image of the 3-way valve highlighted by a circle placed on the bucket hose.

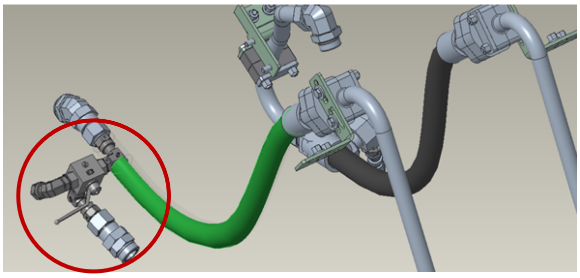


Figure 4.1. CAD representation of 3-way valve positioned on the bucket hose.

The effect of the induced external drain leads to a slower movement of the bucket. To test the model accuracy, several valve openings were set to achieve different bucket speed variations, representative of the cases that can occur during the useful life of the machine. Therefore, the valve opening was set by monitoring the average bucket cycle time on a Y-cycle. In this section, the results are shown for two limit cases according to internal criteria. Taking as reference the simulation output of the bucket position in healthy condition, when a high drain is set then the cycle time increases up to 80% of the lifting time; when a small drain is set then the cycle slowdown is lower and the cycle time increase is about 10% of the lifting time, see Figure 4.2 where axes are normalized using a reference value for confidentiality reason.

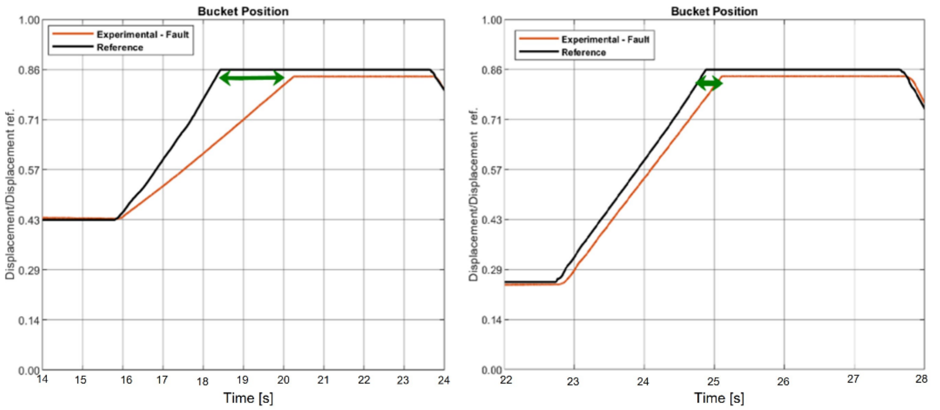


Figure 4.2. Bucket position in case of high and low drain with respect to healthy condition.

The fault detection algorithm checks the kinematic of the bucket between experimental measurement and the simulation results of the Hard Real Time Model. A flowchart of the algorithm is shown in Figure 4.3. When a deviation in the speed of the bucket movement is detected, the algorithm is able to assess whether this is happening during the bucket actuation by monitoring the rising pilot current. The procedure also checks the time interval of the deviation with respect to the manoeuvre time (obtained by the pilot current): this prevents that numerical speed deviations trigger a fault detection. Monitoring the speed instead of the position of the actuator, leads to a higher accuracy since any position offset due to numerical deviations of the model are neglected therefore avoiding false positives in fault detection. Threshold values were estimated accordingly internal criteria and are confidential.

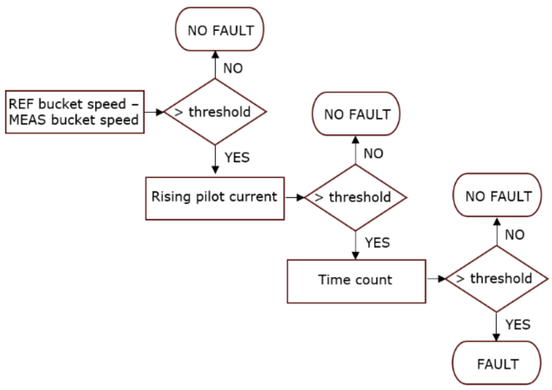
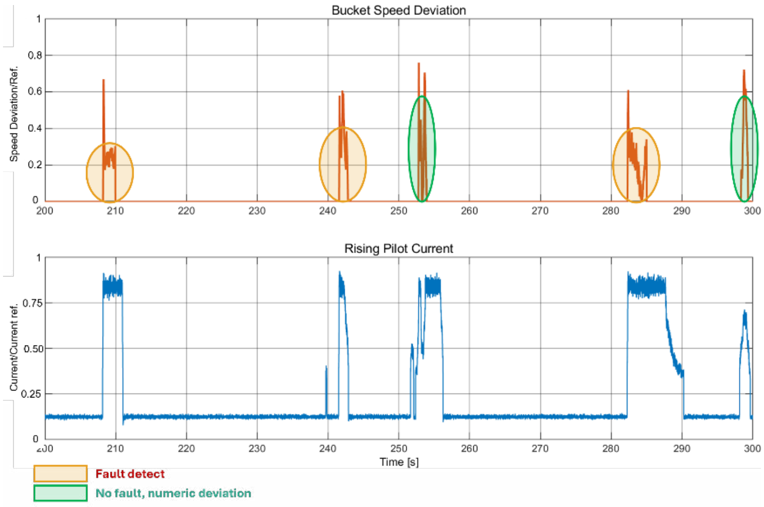
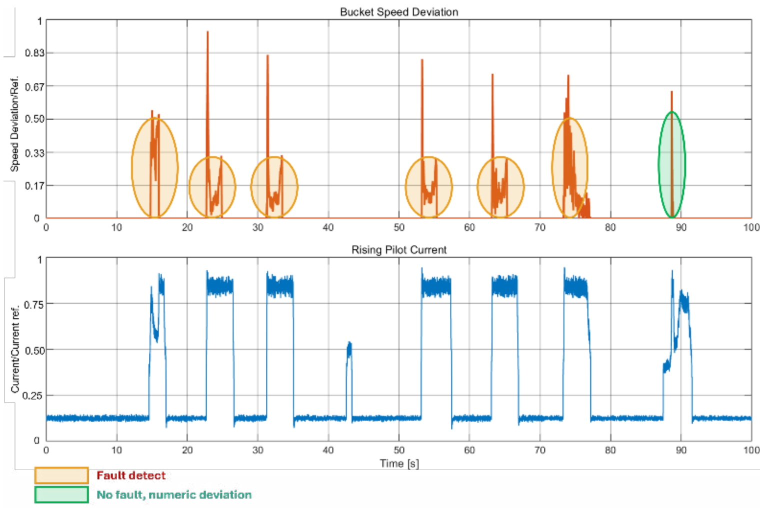


Figure 4.3. Flowchart of fault detection algorithm.

The tests are presented in two conditions: high and low drain. Figure 4.4 (a) shows the plot of the bucket speed deviation together with the rising pilot current (linked to the manoeuvre time) in the high drain condition while (b) is related to the low drain condition. The external drain valve has a constant opening during the entire manoeuvre. The described algorithm detected the faults in correspondence of the parts of the signal highlighted within the yellow circles, since both the speed deviation and the rising pilot current time thresholds are reached. The speed deviations highlighted with green circles are due to numerical deviations and are not detected by the algorithm because the rising current time threshold is not reached.



(a) High drain condition



(b) Low drain condition

Figure 4.4. Bucket speed deviation together with the rising pilot current in the high drain condition (a) and in low drain condition (b).

The study was limited to the bucket cylinder: once verified the effectiveness of the proposed approach in detecting faults in a hydraulic circuit, the methodology can be extended to the boom cylinder as well. Considering the study of a single actuator allowed to reduce the experimental tests, which are the most expensive part from an industrial perspective, without losing the generality of the methodology. Since the methodology proved promising, the aspiration is to extend the analysis to a greater number of actuations and a wider range of fault types.

5. Conclusion

This paper presented the exploitation of a real time model deployed on real ECU of a wheel loader for fault detection purposes. The development and implementation of a real-time simulation model for the hydraulic implements of a wheel loader is the basis to replicate in real time the behaviour of the healthy system.

The proposed model is deployed on a real-time embedded computing platform, acquiring live data from onboard sensors to estimate boom and bucket positions. These estimates are continuously compared against measured actuator positions. Deviations exceeding predefined thresholds serve as indicators of potential faults, including hydraulic leakage, actuator degradation, sensor drift, or control system anomalies. This model-based fault detection framework enables early anomaly identification, enhancing operational safety, reducing unscheduled downtime, and improving system reliability.

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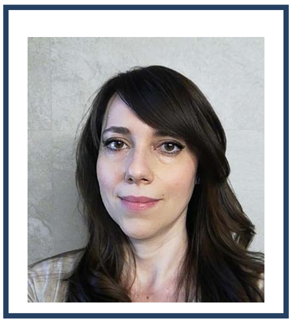
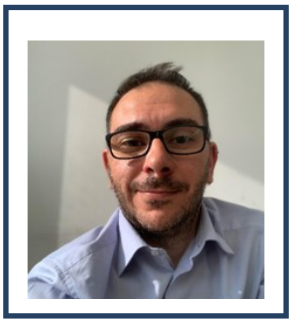
Biographies

Fabio Scolari received the bachelor's and master's degree in mechanical engineering in 2016 and 2018 respectively, and the PhD in Industrial Engineering in 2022 from University of Parma, Italy, with a dissertation on tribological improvement of hydraulic pumps with texture surfaces. He is currently working as system modelling engineer at CNH. His research areas include simulation, hydraulic system modelling, fuel economy analysis, high performance systems in off-highway vehicle applications.



Federica Grossi received the bachelor's and master's degree in electronic engineering in 2003 and 2006 respectively, and the PhD in Electronics and Telecommunications in 2010 from University of Modena and Reggio Emilia, Italy, with a dissertation on dynamic modelling and control of hybrid vehicles. She is currently working as senior system modelling engineer at CNH. Her research areas include modelling, simulation, software development, fuel economy analysis, high performance systems in automotive and off-highway vehicle applications.



Francesco Pintore received the bachelor's and master's degree in mechanical engineering and the Ph.D. in High Mechanics and Automotive Design & Technology from University of Modena & Reggio Emilia, Italy. He is Manager of High-Performance System Simulation at CNH. He is responsible for High Fidelity 0D/1D model development, looking on entire vehicle performance evaluation, interfacing and providing modelling support to multiple Teams across CNH. He is also responsible for interfacing Modelling Team with electrification, Hydraulics, Driveline and Powertrain Teams across the Company's entire agriculture and construction product portfolio.

Ciro Mariniello received the master's degree in Automation Engineering from University of Sannio in 2011. He started to work in 2011 as Control system engineer with Segula as a resident engineer in Magneti Marelli, in 2012 he started to work in CNH as system modelling engineer, in 2013 he became System modelling European manager. Currently working as System modelling & Dynamic simulator Manager within DA&S Department in CNH.