Combining Control and Monitoring in Mobile Machines: the Case of an Hydraulic Crane

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The widespread use of electro-hydraulic (EH) technology of the last decades has led to important improvements in the control features, safety and performance of hydraulic machines. However, limited work exploited the use of the EH control features for condition monitoring. This paper proposes a neural network based diagnostic algorithm that takes advantage of the parameters of a controller developed for the case of an independent metering hydraulic system. The reference application is a truck loading crane available at the authors’ research center. The results show how the proposed methodology is effective to detect faults (the faults considered pertain to the pump, the metering valves and the cylinder), with a limited number of sensors.

Keywords: Control, Diagnostic, Independent Metering, Hydraulic Cranes, Mobile Hydraulics

Target audience: Mobile Hydraulics, System Diagnostic, Control

1 Introduction

The widespread use of electro-hydraulic (EH) technology of the last decades has led to important improvements in the control features, safety and the performance mobile applications. The hardware (electronic control unit, sensors) which is used for control functions can be exploited to implement strategies for Prognostics and Health Management (PHM), which would bring important benefits, such as increased reliability and safety, optimal condition based maintenance of the hydraulic systems.

Therefore, the integration of EH control with diagnostics/prognostics techniques can make the EH technology more appealing even for hydraulic applications traditionally resistant to the adoption of electronic control. The integration of diagnostic and prognostic features in EH systems also enables condition based maintenance strategies, which is more effective than the classic time-based maintenance.

Researchers in the area of diagnostics have proposed several approaches, which can be divided into two main categories: model based approaches and data driven methods (Figure 1). As the words suggest, a model based approach relies on the development of a mathematical model of the system representing its health status. The comparison between the output of the model and those of the real system leads to the diagnostic analysis, which gives a diagnosis of the system health. Good examples of this methodology can be found in [1-2]. On the other hand, data driven approaches are the most popular in research because they don’t require the derivation of a mathematical model of the machine, which is always a challenging task for complete EH systems. Data driven approaches require a first offline step, in which a proper identification of the system features allows for the training of a classifier. Once the classifier is trained, the data driven algorithm can run online on the machine giving the diagnosis of the system through the classifier. Although a data-driven method does not require the derivation of a mathematical model of the system, it strongly relies on the availability of experimental data. This might represent an important drawback, because it might be difficult to produce experimental data in faulty conditions for training purposes. Good examples of data-driven approaches applied to hydraulic systems can be found in [3-4].

This paper contributes to the topic of combining EH control strategies with PHM, and proposes a solution for the diagnostic of the entire hydraulic system, enabling the fault detection of the main hydraulic components. The novelty of the proposed approach is that the diagnostic algorithm is not only based on sensors installed on the machines, but it also uses controller parameters as additional indicators of the health status of the machine.

![Model based approach](image1)

**Figure 1**: Block diagrams of the model based approach and the data-driven approach for diagnostic algorithms.

The reference machine used to demonstrate the potential of the proposed approach is a hydraulic crane for truck applications instrumented at the authors’ research center. The hydraulic system chosen for proving the effectiveness of the proposed diagnostic method is an EH (independent metering system, which is different from the open-center system that equips the commercial version of the reference machine) independent metering systems are known for presenting control challenges, and for this reason they are particularly suitable for the proposed method which combines control features with conventional sensors for diagnostic purposes.

In [5], the authors formulated and experimentally validate a numerical model of the reference machine. A control strategy for the independent metering systems was also synthesized and the simulation results proved the effectiveness of the control technique. The controller was model based, and the uncertainties of the model parameter where handled through a PI controller. The parameters of the PI were found by means of an optimization procedure. The value of the cost functions used for the optimization were also found to be correlated to the health condition of the machine. This past work put the basis of the present effort, which proposes a diagnostic algorithm to evaluate the health status of the system. Thus, the diagnostic algorithm constitutes the element of novelty of this work. The proposed diagnostic method uses as inputs not only information coming from the sensors installed on the machine, but also information coming from the cost function used to define the controller parameters. The input parameters are then used within a neural network, which is able to provide outputs indicative of the faults. As selected faults considered for the analysis, the case of pump degradation, cylinder degradation and selected valve faults will be considered. After a proper training of the neural network, examples of significant results are shown.

2 Reference Machine

The reference machine considered in this work is a truck loading crane with a maximum capacity of 5 t, based on the commercial product Atlas 125.1 A4 (Atlas Maschinen GmbH 1996), shown in Figure 2. This machine is installed on a concrete base at the Maha Fluid Power Research Center of Purdue University. The crane arm is operated through 4 hydraulic actuators: the swing, the main boom, the outer boom and the telescopic actuator. In
This study, the proposed diagnostic strategy was applied to the outer boom actuator, whose movements involves both resistive as well as overrunning load phases.

![Reference machine, ATLAS 125 1.44, installed at the Mahi Fluid Power Research Center](image)

The hydraulic circuit of the reference machine is based on a post-compensated Load Sensing (LS) system, implemented through cartridge independent metering valves provided to the authors by Hydromatik. Compensators are present at each meter-in control section, and permit an easy control of the velocity of each actuator, while meter-out sections are used to counter-react overrunning loads. A simplified schematic of the system is shown in Figure 3. In more details, the hydraulic circuit can be divided into 4 main sections, the flow supply unit, which is essentially a fixed displacement pump (a gear pump of 19 cm³/r), an unloading valve that permits to pressurize the pump to the level of the LS signal, the independent metering valves manifold and the actuator. All the actuators present in the reference machines are connected in parallel downstream the unloading valve; however, for the sake of clarity Figure 3 shows only the reference actuator. The hydraulic circuit is controlled by the Data Acquisition System (DAQ) NI cRIO-9030 equipped with only pressure sensors \(p_{a1}, p_{a2}, p_{a3}\), which are enough to show the diagnostic potentials of the proposed diagnostic procedure.

![Hydraulic circuit of the reference machine: partial schematic showing only one actuator (outer boom) (image)](image)

A complete numerical model of the machine is used, implemented with the AMESim commercial software. This model has been derived and experimentally validated in /5/. Within this work, the same model will be used to validate the proposed diagnostic algorithm, as described in the following sections.

## 3 Control Strategy

The controller used for the independent metering system of Figure 3 is presented in this section. The controller constitutes an essential part of the diagnostic algorithm that will be described in section 4. For this reason, although the derivation of the controller was the main subject of /5/, for completeness this section describes the essential elements of the controller. However, the reader can refer to /5/ for more details on the controller and its experimental validation.

### 3.1 Control Synthesis

The EH post compensated LS independent metering architecture of the hydraulic circuit of Figure 3 requires a proper controller to guarantee a proper and safe functioning of the machine. As widely explained in literature /6-8/, at least two different cases need to be considered: resistive and overrunning loads.

In the case of resistive loads, the meter-out valve can be fully-opened to reduce energy consumption of the machine, and the controller can set the opening area of the meter-in orifice that works along with the compensator to eliminate possible interference with other actuators. For the case of overrunning loads, a more complex control strategy is required. The working principle of the controller can be easily explained from the simplified schematic of Figure 4, where only the extension case is considered in the case of overrunning load. The retraction case can be derived with a similar procedure.

Being the system based on LS compensators (Figure 3), the pressure drop \(\Delta p\) across the meter-in valve (valve 1) can be in first approximation assumed constant. For a simplistic model of the system, the compensator can be excluded, as shown in Figure 4.

The force applied at the cylinder, can be derived from the force balance at the cylinder in Equation (1):

\[
F_{cyl} = p_{a1} \cdot A - p_{a2} \cdot A + m_{eq} \cdot x_{eq}
\]

Where \(A\) and \(a\) are respectively the piston area and the rod side cylinder area, \(m_{eq}\) is the equivalent mass of the rod, \(x_{eq}\) is the linear acceleration of the cylinder, \(p_{a1}\) and \(p_{a2}\) are respectively the pressure in the piston chamber and in the rod chamber of the cylinder and \(F_{cyl}\) is the force acting on the cylinder.

From the force balance at the cylinder, a reference pressure \(p_{ref}\) can be calculated at the rod chamber to exactly balance the load, allowing the pressure in the piston chamber to reach zero-gauge pressure. A reference pressure \(p_{ref}\) needs to be introduced to avoid cavitation in the piston chamber, before calculating \(p_{ref}\) with Equation (2).

\[
p_{ref} = p_{a1} + \frac{A}{a} (p_{ref} - p_{a2})
\]

As mentioned before, the actuator velocity is set from the meter-in portion of the system, according to the LS principle, therefore Equation (3) needs to be always satisfied.

\[
x_{eq} = \frac{Q_{in}}{A} = \frac{Q_{out}}{a}
\]

Afterwards, considering the two orifice equations, the meter-out command can be easily derived. Its control law is described in Equation (4).
\[ u_{\text{out}}(t) = A_{\text{out}}^{-1} \left( \frac{\Delta p}{A} \left( p_{\text{ref}} - p_t \right) A_{\text{in}}(u_{\text{in}}(t)) \right) \]  

Where \( A_{\text{in}}(u) \) is the area function of the meter-in valve and \( A_{\text{out}}^{-1}(u) \) is the inverse area function of the meter-out valve.

The value of the first term of the cost function \( CF_1 \) represents how much the pressure in the piston chamber is below a reference pressure \( p_{\text{ref}} \) (a low pressure level above atmospheric, such that cavitation is avoided with a certain margin).

The value of the second term of the cost function \( CF_2 \) represents how much the pressure in the chamber of the cylinder (connected to the meter-in) is higher than the reference value \( p_{\text{ref}} \). Therefore, this term is created to reduce the energy consumption of the machine, having the goal to minimize it.

The weights \( \alpha_1 \) and \( \alpha_2 \) are needed to give a priority to the cost function related to the cavitation phenomena since if cavitation occurs in this kind of machines, safety needs to be guaranteed.

The value of the cost functions will be afterwards used for the diagnostic algorithm proposed in section 4.

4 Diagnostic Algorithm

The diagnostic algorithm is based on a neural network (NN) approach (Figure 6), defined in Equation (8).

\[ y_j = f \left( \sum_p w_p x_i \right) \]  

Where \( y_j \) represent the \( j \) output of the neural network, \( x_i \) represent the \( i \) input of the neural network and \( w_p \) represents the neurons of the neural network.

The advantage of the NN approach is given by the fact that the system is considered as a black box; after a proper training the NN will be able to detect the faults in the hydraulic system.

The output \( y_j \) of the NN are defined as faults of the hydraulic system, and in this work four faults were considered, leading to four outputs of the neural network. The choice of the faults considered to prove the effectiveness of the procedure was arbitrary, although realistic fault instances were considered.

Each fault was simulated by changing the corresponding parameter, as shown in Table 1.

| Volumetric efficiency [-] | 0.95 | 0.55 | 0 - 1 |
| Cylinder friction [N] | 1000 | 10000 | 0 - 1 |
| Meter-in/Meter-out limiter [-] | 1 | 0 | 0 - 1 |

Table 1: Parameter considered for the representation of the fault in the reference machine.
the valve. This somehow simulated a phenomenon like a spool blockage. A zero value would represent a full blockage condition, while a unit value represents the healthy condition of the component.

All the four considered faults were defined as output of the NN, as values between 0 to 1, where 0 represents the healthy condition of the component, and 1 the faulty condition of the component.

The input \( x_i \) of the NN, are based on the readings from the sensors available on the machine. In this work, a time-domain analysis has been chosen to extract characteristic features as descriptive statistics as mean. The time synchronous average has been chosen to reduce and remove noise and effects from other sources, to enhance the signal component of interest. The features are defined in Equation (9).

\[
x_i = \frac{1}{N} \sum_{n=0}^{N-1} x(t + nT),
\]

where \( x_i \) represent the feature, \( N \) the number of samples, \( T \) the sampling period. The mean of the sensor signals was performed on the signals during the operating condition for which the input command is not zero. Therefore, the input information comes only from the useful trend of the operating condition.

Beyond the input coming from the three pressure sensors, the NN also receives the information coming from the cost functions and the control inputs. This creates a relationship between the value of the fault and the performance of the controller.

As described in section 2, the pressure sensors are located at the outlet of the pump and in the two cylinder chambers. These pressure sensors are required also by the independent metering control algorithm described in section 3. In addition, the NN takes as input also the control output \( u_{sol} \) and the value of the cylinder pressure. Other than these four inputs, the cylinder pressure \( p_A \) is used to calculate the other three inputs \( CF, CF_1 \) and \( CF_2 \), as shown in Figure 6.

Summarizing, the resulting neural network consists of 7 input features \( x_1 \), 4 outputs \( y_2 \) and 8 neurons \( w_p \) composing the hidden layer.

The neural network is trained with an offline supervised learning, meaning that the training consists of input patterns as well as their correct results in the form of the precise activation of all output neurons.

5 Results

5.1 Case Study

Crane loading cranes are usually mounted on tracks and are folded before the operator utilizes them. Therefore, before operating the machine, an unfolding process is always executed, leading at least to the partial extension of the main boom actuator and the outer boom actuator. This repetitive condition perfectly suits the needs of a diagnostic function, and for this reason it was chosen as the reference condition to test the algorithm proposed in this work. The considered unfolding consists in two phases (Figure 7): the first one is the main boom extension or unfolding until the main boom reaches an angle \( \phi_1 \); the second phase represents the outer boom unfolding, until the outer boom reaches the angle \( \phi_2 \).

For this work, only the second phase (outer boom extension) was considered due to a more interesting behaviour from the controller point of view. In fact, this phase presents both resistive and overrunning load conditions. An example of the acquired signal from the pressure sensors on the machine is shown in Figure 8. The mean of the signals is then calculated and the value is fed to the neural network.

5.2 Neural Network Training

As shown in Figure 1, the data-driven method requires a first phase of training off-line. A total of 85 training cases are considered. 5 cases of healthy conditions, while for each fault a total of 20 cases are considered, with an increase value from 0 to 1 and step size of 0.05. A white-gaussian noise is added to simulate more realistic
conditions where other variables (environment temperature variations, sensor noise, etc.) might affect the sensor outputs.

The results from the training are shown in Figure 9. Each plot represents a single output $y_j$ from the neural network. On the horizontal axis is represented the case number, starting from a healthy condition, each fault is being analysed separately. The first twenty cases represent a linear degradation of the pump. The following cases represents the meter-in (MI) fault, followed by the cylinder fault and the meter-out (MO) fault. In blue is represented the target value, therefore the real fault value affecting the component, and in red there is the output obtained from the neural network.

$MSE_j = \frac{1}{N} \sum_{i=1}^{N} (y_j - y_{ij})^2$  

(10)

The mean-squared error of the training phase is shown in Table 2.

<table>
<thead>
<tr>
<th>Fault</th>
<th>Pump Fault</th>
<th>Meter-in Fault</th>
<th>Cylinder Fault</th>
<th>Meter-out Fault</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>2 $\cdot$ 10$^{-4}$</td>
<td>0.002</td>
<td>7 $\cdot$ 10$^{-4}$</td>
<td>0.009</td>
</tr>
</tbody>
</table>

Table 2: Mean-squared error of the training case.

5.3 Neural Network Validation

To validate the neural network and to simulate an online case, a different set of cases was considered. In this validation set, the fault percentage is 0, 0.25, 0.5 and 1. This set of faults is reduced in order to test the ability of the network to recognize the correct percentage of fault after being trained. Also in this case, each fault parameter values was artificially modified with the addition of white gaussian noise, in order to not compare the same exact simulation and to simulate a real application. The results are shown in Figure 10.

<table>
<thead>
<tr>
<th>Pump Fault</th>
<th>Meter-in Fault</th>
<th>Cylinder Fault</th>
<th>Meter-out Fault</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>6 $\cdot$ 10$^{-4}$</td>
<td>0.004</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Table 3: Mean-squared error of the validation case.

The detection of the meter-out fault is instead the one that has more issues, although the mean-squared error evaluation could be acceptable. This problem of the neural network for detecting the meter-out fault comes from the particular case study considered in this research. This is also confirmed in Figure 11, which shows the input fed to the neural network, for two reference faults: the meter-out one (not properly detected) and the pump one (one of the faults properly detected). It can be noticed that with an increasing pump fault level, the feature related to the pump pressure fed to the neural network sees a linear decrease. On the other hand, when the meter-out fault occurs, the pump pressure feature has a jump at the value of 0.6 as meter-out (MO) fault. This derives from the
fact that a small intensity of the fault is not affecting the system. This is mainly due to the meter-out control. When the fault has a small intensity, there is almost no effect in the acquired signals. Only when the intensity of the fault is high enough to affect the meter-out control performances, the effect of that is a big increase of the system pressure, due to the valve characteristic. Operating the machine with small loads, a small change in the input creates a big change in the pressure drop across the valve, coming from the area characteristic of the valve. This is seen also in Figure 8, where there is a big discrepancy between the healthy condition and the faulty condition in the pressures. This discrepancy is present in all the input selected for the neural network, therefore the neural network is not able to separate all the level of faults of the meter-out valve. This explains the problem of the neural network detecting the meter-out fault condition. In this case study, due to the jump of the input features to the neural network, a good training cannot be performed. This problem could be solve giving at the meter-out fault only a digital value between 0-1, representing the healthy condition or the faulty condition, but being not capable of describing intermediate values between 0-1.

Figure 11: Plot of the input given to the feature related to the pump pressure in the case of increasing fault for the meter-out (MO) fault and the pump fault.

6 Summary and Conclusion

This paper presents a new diagnostic algorithm able to detect faults in an EH system, using information coming from the sensors, and added information coming from the controller, such as the control input and the value of the cost functions. The reference case is a hydraulic crane, and the unfolding operation is considered as reference for the diagnostic evaluations. The proposed algorithm is synthesized considering only the outer boom actuator, which present both resistive and overrunning conditions; additionally, only certain faults (pump volumetric efficiency degradation, cylinder friction, metering valve openings) were considered. However, the proposed procedure could be extended to more general cases with a proper modification of the topology of the neural network used to estimate the faults. Only three pressure sensors were utilized for the diagnostic function; two of these sensors are necessary for the proper control of the independent metering system. In this way, the use of more expensive sensors (such as flow meters or position sensors) is avoided. This is an important result achieved thanks to the capability of the neural network training algorithm to recognize the trends in the available input signals in case of faulty conditions.

Results from a detailed model of the machine shows good performance of the network. Limitation of this approach are related to the difficult prediction of the meter-out valve health condition, which cannot be predicted with a proper resolution by the neural network. While the other faults can be predicted with good accuracy at all cases, the meter-out valve fault is predicted only according to a pass/fail fashion.

The proposed method can be considered as a valuable diagnostic algorithm for mobile equipment, where a power unit (power supply), a regulation unit (proportional valves) and a user unit (hydraulic cylinders or motors) are always present, leading to a diagnosis of the main components of the hydraulic system.

7 Acknowledgements

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Nomenclature

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>EH</td>
<td>Electro-hydraulic</td>
<td>[-]</td>
</tr>
<tr>
<td>PHM</td>
<td>Prognostic and Health Management</td>
<td>[-]</td>
</tr>
<tr>
<td>LS</td>
<td>Load-sensing</td>
<td>[-]</td>
</tr>
<tr>
<td>LSPT</td>
<td>Load-sensing post compensated</td>
<td>[-]</td>
</tr>
<tr>
<td>MI</td>
<td>Meter-in</td>
<td>[-]</td>
</tr>
<tr>
<td>MO</td>
<td>Meter-out</td>
<td>[-]</td>
</tr>
<tr>
<td>( F_{\text{cyl}} )</td>
<td>Force acting on the hydraulic cylinder</td>
<td>[N]</td>
</tr>
<tr>
<td>( P_{\text{a}}, P_{\text{b}} )</td>
<td>Respectively pressure at the bore side and at the rod side</td>
<td>[bar]</td>
</tr>
<tr>
<td>( P_{\text{a}}, P_{\text{b,ref}} )</td>
<td>Respectively reference pressure at the bore side and at the rod side</td>
<td>[bar]</td>
</tr>
<tr>
<td>( \dot{x}<em>{\text{cyl}}, \dot{r}</em>{\text{cyl}} )</td>
<td>Respectively linear velocity and acceleration of the hydraulic cylinder</td>
<td>[m/s-m/s²]</td>
</tr>
<tr>
<td>( Q_{\text{in}}, Q_{\text{out}} )</td>
<td>Entering and leaving flow at the hydraulic cylinder ports</td>
<td>[m³/s]</td>
</tr>
<tr>
<td>( A_{\text{in}}(x), A_{\text{out}}(x) )</td>
<td>Respectively meter-in and meter-out orifice area</td>
<td>[m²]</td>
</tr>
<tr>
<td>( p_{\text{p}} )</td>
<td>Pump outlet pressure</td>
<td>[bar]</td>
</tr>
<tr>
<td>( p_{\text{r}} )</td>
<td>Tank pressure</td>
<td>[bar]</td>
</tr>
<tr>
<td>( u_{\text{in}}, u_{\text{out}} )</td>
<td>Meter-in and meter-out command</td>
<td>[-]</td>
</tr>
<tr>
<td>( CF )</td>
<td>Cost function</td>
<td>[-]</td>
</tr>
<tr>
<td>( \alpha, \beta )</td>
<td>Cost function weights</td>
<td>[-]</td>
</tr>
<tr>
<td>( NN )</td>
<td>Neural network</td>
<td>[-]</td>
</tr>
<tr>
<td>( x_{i} )</td>
<td>( i ) - Neural network input</td>
<td>[-]</td>
</tr>
<tr>
<td>( y_{j} )</td>
<td>( j ) - neural network output</td>
<td>[-]</td>
</tr>
<tr>
<td>( w_{k} )</td>
<td>( k ) - neural network neuron</td>
<td>[-]</td>
</tr>
<tr>
<td>( u_{\text{in}}, u_{\text{out}} )</td>
<td>Respectively meter-in and meter-out command</td>
<td>[-]</td>
</tr>
</tbody>
</table>
References


