Machine-learning algorithms for helicopter hydraulic faults detection: model based research

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Abstract. The problem of automatic reliability monitoring and reliability-centered maintenance is increasingly important today. In this paper, we compare the accuracy of four machine learning approaches for fault detection in a hydraulic system. The first three approaches are based on SVM classifiers with linear, polynomial and RBF kernels and the last one is a gradient boosting on oblivious decision trees. We evaluate algorithms on the synthetic dataset generated by our simulation model of the helicopter hydraulic system and show that high accuracy fault detection can be achieved.

1. Introduction
The problem of robotic aircraft systems reliability and maintenance is the main concern of organizations operating them. To assess reliability and maintainability operations of the robot new intelligent maintenance methods should be developed and adopted. Such methods can be applied for monitoring the whole robotic system or only some of its parts. One of the main parts of an aircraft, that greatly affects its reliability, is a hydraulic drive system. Proposal of several fault diagnosis methods [1-3] in the last two decades created a need for their comparison and performance analysis [4-5].

One of the possible approaches for automatic condition-based maintenance of a hydraulic system is to use machine learning methods. Zhongai et al. [1] presented an overview of SVM based methods for fault diagnosis of different hydraulic system types. El-Betar et al. [2] on the basis of vibration sensor data applied SVDD (support vector data description) to detect faults in helicopter transmission. Nonlinear modifications of SVM in application to this task are studied in detail by Leuschen et al. [3]. Neural networks are also begun to be used as fault diagnosis methods [4].

2. The model of a hydraulic system
To compare the efficiency of machine learning approaches in fault detection task we used the model of Mi-8 helicopter hydraulic system [6]. The main hydraulic circuit scheme of the system is presented on figure 1 and the system itself on figure 2.
Figure 1. Hydraulic system circuit: 1 — motor; 2 — pump; 3 — reservoir; 4 — direct acting relief valve; 5, 10, 6 — inlet check valve; 7, 13 — filter; 8 — pressure regulator; 9 — indirect acting relief valve; 11, 21 — hydraulic accumulator; 12 — pressure control three way valve; 14 — outlet screen; 15 — outlet screen; 16 — hydraulic amplifier actuator; 17 — hydraulic amplifier cylinder; 18 — support; 19 — actuator; 20 — solenoid operated valve; 22 — accumulator pressure relief line; 23 — main valve; 24 — intermediate valve; 25 — executive valve.

This hydraulic system works as follows. Hydraulic fluid drifts into the pump 2 from reservoir 3 and fed into the system. Then through the check valve 5 and filter 7 flow into the pressure regulator 8, that has the following parts: inlet check valve 10, inject acting relief valve 9, main valve 23, intermediate valve 24 and executive valve 25. The pressure regulator 8 is an essential requirement to provide an idle mode for the pump 2 in case of pressure in line after it reaches the maximum configured for the system that is determined by spring tension in the command valve 23. The system has two hydraulic accumulators right after the pressure regulator that soften fluid pressure pulsations. Through the solenoid control valve 12 and filter 13 the fluid enters the inlet screen 15 that feed with energy the main actuator 19. The actuator’s 19 role is to decrease the force needed to be applied to the control handle. Hydraulic fluid returns to the main reservoir through the outlet screen 14.

The model of Mi-8 hydraulic system KAU-30B was developed as a part of research [7,8]. It uses differential and algebraic equations programmed in Matlab/Simscpe to model dynamic behaviour of the system under different command inputs.

Figure 2. Mi-8 hydraulic system: 1 - unit panel; 2 - hydraulic system KAU-30B; 3 - frequency transformer; 4 - hydraulic oil quality sensor POTOK; 5 - flow meter TDR-10; 6 - heat exchanger SA080-310-S4.
In figures 3 and 4 two block diagrams are presented: relief pressure regulator GA-77 and command control valve both implemented in Matlab/Simscape. To model the whole system each model has input and output ports for connection.

**Figure 3.** The mathematical model of relief pressure regulator GA-77 in Matlab/Simscape.

**Figure 4.** The mathematical model of command control valve in Matlab/Simscape: 1 - model of inlet check valve; 2 - model of adjustable throttle: control valve and sleeve with round holes; 3 - element that imitate control valve dead zone.

The control valve that moves under the pressure of fluid from accumulator and spring force is modeled by block 1. Physical signal of displacement from the output port of block 1 goes as input to block 2 that calculate the piston area and fluid flow through the main control valve. Sequence of blocks 3 played the role of control valve dead zone.

One of the failures in main control valve could be a loosened spring stiffness and as a consequence increased frequency of GA-77 regulator switching. This fault can be simulated by decreasing spring stiffness in the model. Also the spool could be jammed in the main valve that lead to the opposite situation, when GA-77 regulator will not be triggered and the pump will always work under the high pressure, wearing out. This simulation can be done by increasing of spring stiffness.

We have chosen for diagnostic of the system a dynamic portrait that consist of the following features: pressure after the pump, pressure in accumulator line, input pressure of an actuator, flow rate at the pump outlet, flow rate at the GA-77 outlet into the system, flow rate at the input of an actuator, absolute movement of the spool piston, absolute movement of the rod. Dataset was generated for the four cases: working condition, discharged accumulator, volumetric efficiency drop by 10% and hydraulic leakage.
In figure 5 transition processes of pressure are presented at the outlet of the pump and in the accumulator line of a working system and system with discharged accumulator. Sinusoid function was used as an input command signal to the spool with velocity of displacement equal to 40 mm/s. Simulation of actuator rod load is done by spring with stiffness equal to 215 kN/m. In the following part of the paper we present comparison results of accuracy of machine learning models in fault detection task. We use synthesized dataset for training classifiers, examples of which are shown in figure 5.

3. Classification methods for fault detection

We have applied two approaches: kernelized SVM and gradient boosting, which uses oblivious decision trees as base predictors. Support vector machines (SVM) method and its modifications are a common way to solve fault classification tasks [10, 11]. To determine characteristics of feature vectors distribution three kernels were tried: linear, polynomial and radial based function. In this work we use SVM implementation from MATLAB R2017a and CatBoost library [9] for gradient boosting.

The goal of the learning task is to train function $F: \mathbb{R}^m \rightarrow \mathbb{R}$, which minimizes the expected loss $L(F) = \mathbb{E}L(y, F(x))$. For detection of specific fault we use logloss:

$$L = -\frac{\sum_{i=1}^{N} w_i (c_i \log (p_i) + (1 - c_i) \log (1 - p_i))}{\sum_{i=1}^{N} (w_i)},$$

where $N$ is a number of samples, $w_i$ is an i-th sample weight, $c_i$ is a binary indicator of successful prediction for i-th sample, $p_i$ is a class probability of i-th sample.

4. Results

The dataset contains 6 modeled subsets of 9 timeseries: discharged accumulator scenario, volumetric efficiency drop by 10% scenario, hydraulic leakage scenario and 3 corresponding working subsets. Each subset contained 400k samples which were divided into training/verification subsets according to the 80/20 percent ratio.

All parameters of CatBoost classifier were left as defaults except the number of iterations which was set to 200. This number was decreased as it was sufficient to get very good results with much shorter time of training.

Table 1 contains the result of our experiments. It is consonant with common sense that the more sophisticated methods we use — the better are the results. Unfortunately decisions of sophisticated methods are harder to interpret and for us work as a black box, until we resort to model explanation tools. The outputs of the most sophisticated model, built by CatBoost, can be analysed with SHAP [12] approach.
Table 1. Comparison of methods for fault detection accuracy.

| Method                                | Accuracy |
|---------------------------------------|----------|
| SVM, linear kernel                    | 0.571    |
| SVM, polynomial kernel                | 0.613    |
| SVM, radial basis function kernel     | 0.853    |
| CatBoost                              | 0.993    |

According to the analysis of SHAP values in figure 6 (should be viewed in color) high oil consumption at the input of an actuator, low pressure in accumulator line and small displacement of the actuator rod are the characteristics of hydraulic leakage fault in the system.

Gas leakage from the accumulator bladder was the hardest case to distinguish for the model. All but one feature has a high impact on predictions with SHAP value greater than 0.5 with not straightforward pattern as in other cases. The most important feature for this case was the flow rate at the GA-77 outlet into the system. The second and third importance features were the flow rate at the input of the actuator and at the outlet of the pump.

Trained catboost model heavily leaned on the flow rate and pressure at the outlet of the pump, and also on the flow rate at the GA-77 outlet into the system features in the case of volumetric efficiency drop by 10% fault. The important feature was low flow rate at the outlet of the pump that varied in the interval from 26.43 to 28.26 l/min and high pressure at the outlet of the pump greater than 4.3 MPa. Four times less contribution in prediction decision did the absence of the flow rate at GA-77 outlet into the system. Other features did not significantly influence the result prediction.

Figure 6. Distribution of the impacts each feature has on the CatBoost model output. Three cases are:

a) hydraulic leakage, b) discharged accumulator, c) volumetric efficiency drop by 10%. Feature legend: A — pressure after the pump, B — pressure in accumulator line, C — input pressure of an actuator, D — flow rate at the pump outlet, E — flow rate at the GA-77 outlet into the system, F — flow rate at the input of an actuator, G — flow rate in accumulator line, H — absolute movement of the spool piston, I — absolute movement of the rod. Sample value magnitude is increasing from blue to red color.

5. Conclusion

In this work we present the results of machine learning model comparison in fault detection task based on the data of three simulated hydraulic system fault cases. The results show that machine learning methods are the right way to solve fault detection task. SVM based methods with nonlinear RBF kernel let us achieve 0.853 accuracy. More sophisticated method, gradient boosting on oblivious trees, raises classification accuracy to 0.993. The price for using sophisticated methods is their vague interpretability. This problem can be resolved with recently developed tools for model explanation such as SHAP [12] and Lime [13].

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