A Machine Learning Approach for Tracking the Torque Losses in Internal Gear Pump - AC Motor Units

Emad Ali

Bosch Rexroth AG, Bgm.-Dr.-Nebel-Str. 2, 97816 Lohr am Main, Germany
E-mail: emad.ali@boschrexroth.de

Prof. Dr.-Ing. Jürgen Weber

Institut für Fluidtechnik (IFD), Technische Universität Dresden, Helmholtzstrasse 7a, 01069 Dresden, Germany
E-mail: mailbox@ifd.mw.tu-dresden.de

Matthias Wahler

Bosch Rexroth AG, Bgm.-Dr.-Nebel-Str. 2, 97816 Lohr am Main, Germany
E-mail: matthias.wahler@boschrexroth.de

Abstract

This paper deals with the application of speed variable pumps in industrial hydraulic systems. The benefit of the natural feedback of the load torque is investigated for the issue of condition monitoring as the development of losses can be taken as evidence of faults. A new approach is proposed to improve the fault detection capabilities by tracking the changes via machine learning techniques. The presented algorithm is an art of adaptive modeling of the torque balance over a range of steady operation in fault free behavior. The aim thereby is to form a numeric reference with acceptable accuracy of the unit used in particular, taking into consideration the manufacturing tolerances and other operation conditions differences. The learned model gives baseline for identification of major possible abnormalities and offers a fundament for fault isolation by continuously estimating and analyzing the deviations.

KEYWORDS: Condition Monitoring; Pump losses; Speed variable drives; Machine learning algorithms; Neural Networks;

1. Introduction

The utilization of servo AC electric motors to drive hydraulic pumps for control tasks by varying the speed, has proven advances for better energy efficiency in comparison to valve controlled schemes. Besides energy efficiency, reliability is a much more important criteria /5/. The motivation of this work is the demand of more profitability and efficiency without increasing the costs or the complexity of the drives.

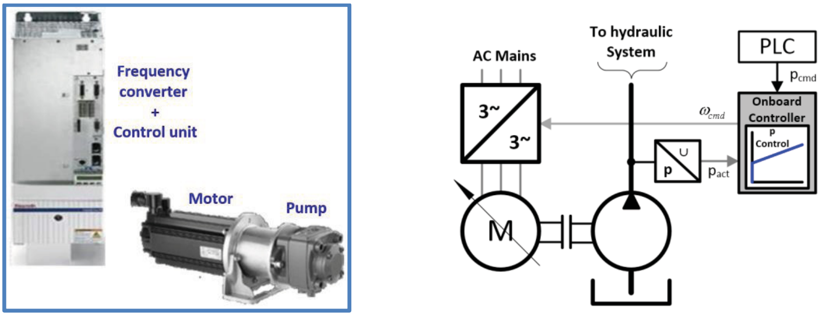


Fig. (1) Overview of the drive unit

The condition monitoring strategies in the recent research are divided, in general, into two main categories:

1. Model based techniques
2. Signal processing based techniques

The idea of the first category is based on generating analytical redundancy by using a mathematical description of the drives as a system component and estimate the deviations between calculated and real outputs as residual signals. Some studies followed the way of mathematically estimating system parameters as a derivation from the known input and output signals /2/. The residual signal in this case is the deviation in the estimated parameter. An accurate model of the system or the working fluid is mostly unknown. A description of the healthy operation by estimating the efficiency of the drive and monitoring the changes in it as evidence of faults, seems more applicable, if a suitable model about the losses of the drive is available. The authors in /12/ had established an overview about physical, analytical and numeric modelling of the pump losses and concluded that physical methods are almost impossible to establish, due to the complex physical effects inside the hydrostatic pump and the effects of the manufacturing tolerances. Numeric methods can be generally applied /12/, the POLYMOD fitting method was found to be the most accurate, but it's a pure numeric description of curves and doesn't consider all effects, for ex. temperature changes of the fluid. Furthermore, the numeric methods demand high number of measurements. Due to those requirements, the method is hard to apply for each single manufactured unit.

The second category's principle is to study the relationships between specific features of the measured signals to mechanical or hydraulic faults. This strategy offers more robustness in the application area but it was mostly combined with the use of extra sensors and additional analysis hardware. Another drawback is the lack of aspects of automation and adaptability. We propose the technique of machine learning as it implies online adaption and requires no prior information about the hydraulic system.

The paper is organized as follows. Chapter 2 illustrates a mathematical model of the unit, Chapter 3 shows the related feasibility analysis, Chapter 4 outlines the monitoring framework and Chapter 5 depicts a test of the proposed approach.

2. Mathematical Description

The case studied in this research is an internal gear pump (IGP) of fixed displacement ϑ_g /1/. Due to the effect of the compensation elements, the volumetric losses at given oil temperature are assumed to be constant, and negligibly small. The input pressure is maintained at atmospheric ($0\ bar$). Typical faults in the operation arise because of oil conditions that leads to excessive friction and causes mechanical wear.

The permanent magnet synchronous motor (PMSM) used to drive the pump is controlled by the field oriented control method. The q-current component i_q is directly proportional to the output air gap torque M_{el}.

$$M_{el} = k_m i_q \tag{1}$$

By assuming symmetrical motor construction and sine wave input stator alternating current, the dynamics of the PMSM could be represented as a first order system /9/, if no field weakening is applied

$$\frac{i_q}{U_q} = \frac{1}{R_q} \frac{1}{\frac{L_q}{R_q} s + 1} \quad , \tag{2}$$

The iron power losses explained in /3/ forms an opposite torque proportional to speed

$$M_{fe} = k_{fe} \omega \tag{3}$$

And the mechanical friction torque:

$$M_{fr} = k_{fr} \omega \quad , \quad |\omega| \gg 0 \tag{4}$$

Thus, the output motor torque is then

$$M_m = M_{el} - M_{fe} - M_{fr} \tag{5}$$

The mechanical coupling between the pump and the motor is assumed to be rigid, therefore the rotor angle and the IGP pinion position are considered to be identical. The mathematical model of pump in steady state operation is explained in /6/ :

The volumetric losses, $Q_L = C_\mu \frac{p}{\mu} + C_\rho \sqrt{\frac{p}{\rho}}$ (6)

The effective flowrate, $Q_t = \omega\vartheta_g - Q_L$ (7)

Sum of moment losses, $M_s = k_\rho \rho \omega^2 + k_\mu \frac{\mu}{h}\omega + k_p\, p + \beta$ (8)

$$M_o = p\frac{\vartheta_g}{2\pi} \quad (9)$$

$$M_{pmp} = M_o + M_s \quad (10)$$

M_{pmp} is the total torque needed to drive the pump. Clearly, M_s is dependent on speed, pressure and the working fluid, whose viscosity has a large influence on the values of both volumetric and mechanical efficiency. The effect of manufacturing tolerances is apparent in h ,Eq.(8).

The linearized model of the hydraulic operation considering all losses as control loop disturbances:

$$\dot{X} = A\bar{X} + B\bar{U} \ , \quad \bar{X} = \begin{bmatrix} \omega(t) \\ p(t) \end{bmatrix}, \quad \bar{U} = \begin{bmatrix} M_{pmp} \\ M_L \\ Q_L \end{bmatrix} \quad (11)$$

$$A = \begin{bmatrix} 0 & \frac{-1}{J}\left(\frac{\vartheta_g}{2\pi}\right) \\ \frac{E\vartheta_g}{V_{sys}} & 0 \end{bmatrix}, \quad B = \begin{bmatrix} \frac{1}{J} & \frac{-1}{J} & 0 \\ 0 & 0 & \frac{-E}{V_{sys}} \end{bmatrix} \quad (12)$$

And the observation:

$$Y = C\bar{X} + D\bar{U} \ , C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \ D = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix} \quad (13)$$

In the formulation above, $\bar{U}$ contains nonlinear terms and it’s instantaneously dependent on the states vector $\bar{X}$.

3. Feasibility Analysis

To make a fundamental analysis without a quantitative localization of the each physical quantity, the pressure controlled system was simulated as depicted in Fig. (2). The aim of this simulation is to evaluate the dynamics of the motor output torque in compensating the disturbances due to mechanical defects, or pressure pulsations. The closed loop model parameters are listed in table (1).

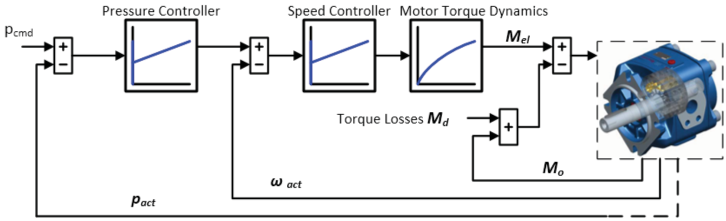


Fig. (2) Ideal pressure control loop in s-domain

Paramater	*Value*	*Unit*
Kp_p	5.23	$rad/bar \cdot s$
Ki_p	34.9	rad/bar
Kp_n	10	$Nm \cdot s/rad$
Ki_n	667	Nm/rad
K_m	1.676	Nm/A
V_{sys}	2	dm^3

Paramater	*Value*	*Unit*
R_q	0.34	Ohm
L_q	5.2	mH
J	$7E-3$	kgm^2
Z_z	12	-
ϑ_g	20	cm^3
E	$16E3$	bar

Table (1) Model parameters

The frequency response of the transfer Function ${}^{M_{el}}/_{M_d}$ is depicted in Fig. (3). Under linearized conditions and neglecting the volumetric losses.

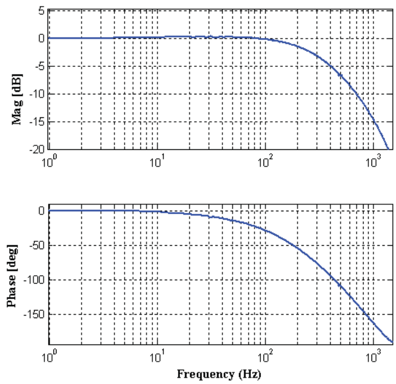


Fig. (3) Disturbance transfer function

The development of the torque losses due to changes in the fluid properties results in changes in the magnitude of the torque. For other dynamic disturbances due to for ex. pressure pulsations or mechanical defects, the bandwidth in Fig. (3), $F_b \sim 300\ Hz$. shows limited dynamic observability. Thereby, for the IGP under study, the torque pulsations due to the pressure wave could be used as a possible fault evidence. The detection capability limit is up to speed ω_{max}

$$\omega_{max} = \frac{60 \times F_b}{Z_z} = 1500\ 1/min \tag{14}$$

4. Condition Monitoring of the Drive

The field of computational intelligence had introduced many methodologies of applying Neural Network (NN) as nonlinear black box model. NN can operate simultaneously on qualitative and quantitative data and can be readily applicable to multivariable systems and they have the ability to make intelligent decisions in cases of noisy or corrupted data /2/. On the other hand, NN will not overcome the disadvantage of having no insight to the physics just as any type of numeric modeling. The proposed approach uses NN to build a description of the fault free operation through "Learning phase". The output is taken as reference for comparisons to recognize deviations as abnormalities in the "Detection phase" during operation. The algorithm estimates the thresholds of normal deviations and is able to adapt the learned reference during operation while memorizing what already learned. An overview of the framework is depicted in Fig. (4).

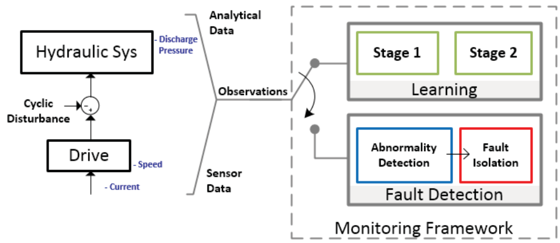


Fig. (4) The monitoring framework

This approach makes use of the fact that most of the target systems such as injection moulding, pressure casting and blow moulding machines operate repeatedly for millions of cycles. A self-learning model would enable auto supervision and minimize the need of expert operators.

4.1. Introduction

Kohonen Neural Networks (KNN) has many advantages for the aim of condition monitoring. The unsupervised way of learning, online adaptability and the excellent capability to map highly nonlinear data in multidimensional space make it a proper choice for our purpose. The basic idea is to map the available information about operation states to finite nodes (neurons) and track the changes through the process.

From the mathematical point of view, KNN is an art of projection from a set of given data items $\in \mathbb{R}^n$ onto a regular, usually two-dimensional grid /7/. A model m_i is associated with each grid node as depicted in Fig. (5). Those models are computed by the KNN algorithm. A data item will be mapped into the node whose model is most similar to it, i.e. has the smallest Euclidean distance from the data item in some metric /8/.

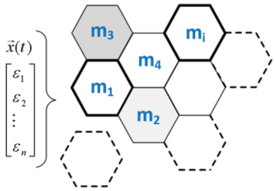


Fig. (5) The array of nodes in a 2D grid

Consider input vector $x(t)$ of n variables:

$$x(t) = [\varepsilon_1(t), \varepsilon_2(t), \varepsilon_3(t), \dots \varepsilon_n(t)] \tag{15}$$

And let m_i be the model that belongs to the node i of a map of size k and it's arbitrary initialized as:

$$m_i(t) = [w_{1,i}(t), w_{2,i}(t), w_{3,i}(t), \dots w_{n,i}(t)] \tag{16}$$

The structure of m_i is kept constant for all nodes whereas the parameters for each node are to be adapted. The training of the KNN performs an iterative adaption in the form:

$$m_i(t+1) = m_i(t) + \alpha(t) h_{ci}(t)[x(t) - m_i(t)] \tag{17}$$

As $\alpha(t)$ is a correction factor and the subscript c indicates the node that has the minimal Euclidean distance D_c to the input vector $x(t)$.

$$D_i = \|x(t) - m_i(t)\|, for\ i: 1 \to k$$

$$D_c = \min\ (D_i) \tag{18}$$

The node m_c is called the winning neuron, whose model will be updated to be closer to the input vector. Other map nodes in the neighborhood of m_c would be updated by a function $h_{ci}(t)$ as a kind of smoothing kernel /8/. A typical use of the neighborhood function is the Gaussian. The training is performed unsupervised in a sequential or batch way. After training is complete, the map is used to estimate the winning node, named then as the best match unit (BMU), whose response alone will define the map's reaction. The BMU is thus the output of the cost function that minimizes the quantization error Qe

$$Qe = \|x(t) - m_i\| \tag{19}$$

The author in /13/ had basically investigated the usage of KNN (also known as Self Organizing Maps) for condition monitoring by classification and parameter estimation, and in /4/, two maps structure was designed to assess the prediction of maintenance requirements of valves.

4.2. Learning and Detection

As stated in chapter 3, the torque losses can be considered as a health indicator at each operational state. The resulting built KNN map is in fact a quantized description of the behavior with no extrapolation or interpolation capability. The algorithm of the classical KNN algorithm does not give any further information about the nature/ properties of the fault /7/. We aim to extend this algorithm by injecting two matrices R, S to enable fault localization.

The learning phase is divided into 2 stages as depicted in Fig. (6). The first stage is identical to the usual KNN, where the nodes are clustered to model all similar input vectors and build the optimal code book matrix CB as outlined in Eq.(15-19).The second learning stage builds recursively a matrix R which registers the nearest input in the Euclidean space that each node optimally models, $x^*(t)$. The matrix R assess the localization of symptoms and the last vector $n+1$ assigns the normalized fault free deviation in each element of (t) . A further matrix S is constructed to track the sequence of the matching nodes at each state during the process.

$$CB = \left.\begin{pmatrix} w_{1,1} & w_{1,2} & \dots & w_{1,k} \\ w_{2,1} & w_{2,2} & \dots & w_{2,k} \\ \vdots & \vdots & \vdots & \vdots \\ w_{n,1} & w_{n,2} & \dots & w_{n,k} \end{pmatrix}\right\} \begin{matrix} m_1 \\ m_2 \\ \vdots \\ m_k \end{matrix} \quad , \quad R = \begin{pmatrix} \varepsilon^*_{1,1} & \varepsilon^*_{1,2} & \cdots & \varepsilon^*_{1,n} & \Delta\varepsilon_1 \\ \varepsilon^*_{2,1} & \varepsilon^*_{2,2} & \cdots & \varepsilon^*_{2,n} & \Delta\varepsilon_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \varepsilon^*_{k,1} & \varepsilon^*_{k,2} & \cdots & \varepsilon^*_{k,n} & \Delta\varepsilon_n \end{pmatrix}$$

$$\Delta\varepsilon_i = \max_{j:1\to k}\left(\left|\frac{\varepsilon_{i,j}(t)-\varepsilon^*_{i,j}}{\varepsilon^*_{i,j}}\right|\right) \quad , \quad S = [m_{(t1)} \ \ m_{(t2)} \ \ \dots] \tag{20}$$

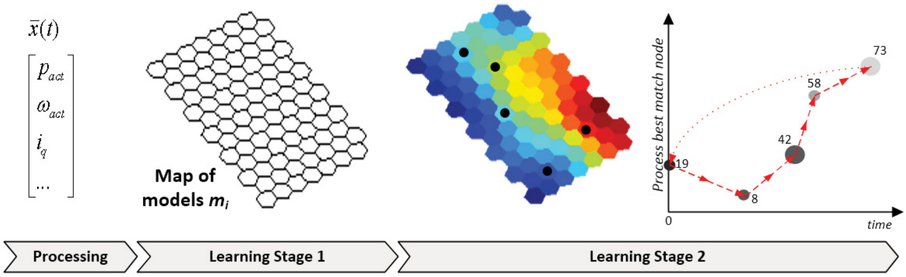


Fig. (6) Learning phase (example)

Fig. (6) shows the learning for a 5-states process. A map 13x7 is used in stage 1 to learn possible operation points and in stage 2, the black dots depict the BMUs for target process. The color scheme is considered as similarity indicator between the nodes. Vector S is depicted graphically on the right side.

In the detection phase, the matched nodes for each steady state are determined using the cost function of minimizing Qe. Thereafter, the activated nodes and the order of activation are compared to vector S in order to detect the abnormalities in the process. The symptoms are recognized by comparing the deviation of each element i in $x(t)$ to $\Delta\varepsilon_i$. Faults can be related to symptoms by diagnostics algorithm such as fuzzy inference system. Various symptoms of rotary machines are introduced in /14/. This is a focus for future work and is mentioned here to get an overview of the method.

4.3. Input Variables Space

For the case of study, the input vector $x(t)$ contains statistical properties of the discharge pressure, motor speed, torque and in addition, the spectrum of torque signal in low band < 300 Hz. That's to limit the analysis to the readily available signals and dynamic capability of the control loop.

It should be here notified that vibration measurement is mainly suitable for detecting mechanical failures and especially in the case of bearings faults but in recent years, it has been attempted to use in fluid power systems but with weak success /11/. In addition, the frequency analysis of vibration or audio emissions demands the installation of extra sensors and suitable acquisition system which again would be not economic.

4.4. Benefits and Drawbacks

The proposed approach constructs a low dimensioned space of normality about the healthy operation and has many advantages, among these:

- Semi unsupervised way of learning
- Scalability for any number of available variables, as the length of $x(t)$ is not set as constant
- Fusion of human expert knowledge in the fault isolation
- Online adaption capability
- Able to map new processes without losing the experience about the states learned
- Automatically set the threshold of variables fluctuations statistically

On the other side, the healthy operation must be clearly defined by human operators in order to activate the learning. A typical choice is the first operation hours of the machine. Any faults in this phase would be unfortunately learned as healthy. Further major drawbacks:

- Need of new initialization in case of component replacements or after changing the control parameters
- Suitable only for bounded stable control loops
- High number of arithmetic operations
- No interpolation or extrapolation capabilities

5. Fundamental Test

Using the simulation model described in chapter 2 and 3, a test scenario is done by increasing k_p only, Eq. (8). A constant load flowrate $Q_t = 0.1\ dm^3/s$ is assumed. Thereby the drive reaches the same pressure at the same speed but by exhibiting more torque. In practical sense, this depicts friction increase in bearing.

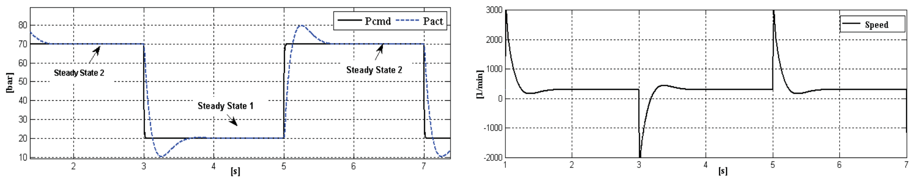
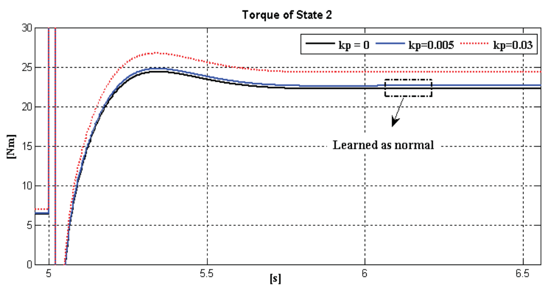


Fig. (7) Test process

The steady state operation is defined as : ${dp_{cmd}}/{dt} = {dp_{act}}/{dt} = {d\omega}/{dt} = 0$. The observations vector is limited to $x(t) = [p, \omega, M_{el}]$. The model map is a 6x6 grid using the toolbox available in /10/. We set $Qe\ =\ 0.01$ and the test cycle comprises 2 steady states, Fig. (7). The BMUs found are the nodes 9 and 22. Therefore, the matrix R contains only 3 nonzero columns. The results are depicted in Fig. (8).



$$R_{3x36} = \begin{pmatrix} & 20 & & 70 & & 0 \\ \cdots & 300 & \cdots & 300 & \cdots & 0 \\ & 6.36 & & 22.3 & & 0.023 \end{pmatrix}$$

$$\boldsymbol{S} = [22\ 9]$$

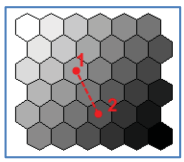


Fig. (8) Steady state at various k_p

Note that, because of the absence of noise and other practical uncertainties, $\Delta\omega, \Delta p$ are estimated $=\ 0$ in the simulation. By the abnormality detection of the non-learned case ($k_p = 0.03\ \frac{Nm}{bar}$), the matching nodes remain the same at the presence of fault but with an increment in Qe. The symptom is localized as the normalized deviation = 0.108 is greater than the learned, 0.023, which indicates the change in the bearing friction.

6. Summary and outlook

The application of recent condition monitoring methods, involves many difficulties, either because of the lack of a reference about the healthy behavior of the drive or because of unavailability of accurate information about the system components. Due to economic drawback, the utilization of extensive sensors is not possible. This paper mainly contains two topics. The first one is a feasibility analysis of using motor torque measurements as possible evidence of faults, besides pressure and speed signals. For that aim, it has been found that the torque dynamics can be beneficial especially at low speeds. In the second topic, the paper proposes a new condition monitoring approach based on machine learning technology. The approach benefits from the fact that the target process would be repeated frequently for many times in typical industrial applications. A new algorithm is proposed to learn the normal variations in the torque demands of the hydraulic drive during the first operation in the target machine and track the losses for each state thereafter. The approach is based on Kohonen neural networks and it comprises an extension for identifying the fault symptoms quantitatively. To ensure the effectiveness and demonstrate the idea, a simple test case with simulation software shows positive results for the cases of increase in the bearing friction.

Future works are to be done on real units as the algorithm can be implemented for a microcontroller. The case studied was focused on internal gear pumps driven by a servo synchronous motor. In fact, the technique is a general concept and can be used for other pump types and for tracking other losses and it can be scaled to cover any available evidences of faults. The diagnostics part is left for future work to relate the symptoms to mechanical or hydraulic faults.

7. Nomenclature

x	Observation vector
Qe	Quantization error
u_q, i_q	Input motor voltages and actual current in q coordinate respectively
L_q, R_q	Stator inductance and resistance in q coordinate respectively
J	Total rotary inertia

ω, θ	Rotor rotational speed and position
M_{el}, M_m	Air gap generated and output mechanical torque respectively
M_{fr}, M_{fe}	Torque losses in the motor due to friction and iron losses respectively
k_m	Motor torque constant
k_{fe}	Iron losses, torque factor
k_{fr}	Motor mechanical friction factor
p	Discharge pressure
Q_t, Q_L	Total and leakage flowrates respectively
ϑ_g	Pump displaced volume per revolution
C_μ, C_ρ	Empirical factors to estimate the volumetric losses
M_o, M_s	Pressure and losses torque in the pump respectively
M_{pmp}	Total torque needed to drive the pump
μ, γ	Fluid dynamic and kinematic viscosity
ρ	Fluid absolute density
$k_{l0}, k_{l1}, k_\rho, k_\mu, k_p, \beta$	Empirical parameters to calculate the torque losses in the pump
h	Clearance between mechanical components
V_{sys}	Hydraulic circuit volume
E	Fluid Bulk modulus
Ki_p, Kp_p	Configuration parameters of the pressure loop controller
Ki_n, Kp_n	Configuration parameters of the speed loop controller
Ki_I, Kp_I	Configuration parameters of the current loop controller

8. References

/1/ Bosch Rexroth AG. *Internal gear pump, fixed displacement*. RE 10227/12.10.

/2/ Calado, J., Korbicz, J., Patan, K., Patton, R. J., and Sá da Costa, J. 2001. Soft Computing Approaches to Fault Diagnosis for Dynamic Systems. *European Journal of Control* 7, 2-3, 248–286.

/3/ Gerling, D. 2015. *Electrical machines*. *Mathematical fundamentals of machine topologies*. Mathematical Engineering. Springer, Berlin.

/4/ Gonçalves, L. F., Bosa, J. L., Balen, T. R., Lubaszewski, M. S., Schneider, E. L., and Henriques, R. V. 2011. Fault Detection, Diagnosis and Prediction in Electrical Valves Using Self-Organizing Maps. *J Electron Test* 27, 4, 551–564.

/5/ Helduser S. 2008. Development Trends in Electrohydraulic Drives and Controls.

/6/ Ivantysyn, J. and Ivantysynova, M. 2003. *Hydrostatic pumps and motors*. *Principles, design, performance, modelling, analysis, control and testing / Jaroslav Ivantysyn and Monika Ivantysynova*. Tech Books International, New Delhi.

/7/ Kohonen, T. 2001. *Self-organizing maps*. Springer series in information sciences, 0720-678X 30. Springer, Berlin, London.

/8/ Kohonen, T. and Honkela, T. 2007. Kohonen network. *Scholarpedia* 2, 1, 1568.

/9/ Schröder, D. 2007. *Elektrische Antriebe*. Springer-Lehrbuch. Springer, Berlin

/10/ *SOM Toolbox*. http://www.cis.hut.fi/projects/somtoolbox/. Accessed 17 Nov 2015.

/11/ Nykänen T.; Ellman A.U. 2003. Methods for On-Line Condition Monitoring of a Fixed Displacement Hydraulic Motor. SICFP.

/12/ Kohmascher T.; Murrenhoff H.; Rahmfeld T.; Skirde E. 2007. Improved Loss Modeling of Hydrostatic Units: Requirement for Precise Simulation of Mobile Working Machine Drivelines. IMECE2007.

/13/ Zachrison, A. 2008. Fluid Power Applications Using Self-Organising Maps in Condition Monitoring. PHD, Linköping University.

/14/ Lei Y.; He Z.; Zi Y. 2009. Application of an intelligent classification method to mechanical fault diagnosis. In Expert Systems with Applications 36 (6), pp. 9941–9948.