APPROACH TO THE SIMULATION OF AGEING OF ENVIRONMENTALLY COMPATIBLE FLUIDS IN HYDRAULIC SYSTEMS

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Abstract

This article describes a concept for the lifetime prediction of fluids used in hydraulic networks that has emerged from sub-project A3 concerned with "ageing behaviour of ecologically compatible precursor materials" within collaborative research centre (SFB) 442 at the RWTH Aachen University, Germany. This concept is focused around a neural network that implicitly contains the ageing properties of the fluid. The complex of loads imposed on the fluid by the hydraulic circuit is processed in such a way that it can be used as the input for the neural network when described by appropriate characteristic values.

Keywords: oil ageing, lifetime prediction, environmentally compatible fluids, neural networks

1 Introduction

The analysis of the ageing behaviour of ecologically compatible lubricants constitutes part of a research project concerning "environmentally compatible tribo-systems by means of suitable composites and precursor materials, using the machine tool as an example" conducted by collaborative research centre 442. The collaborative research centre 442 was established at RWTH Aachen University in 1997. The involved institutes, with disciplines ranging from chemistry and medicines to mechanical engineering and material science, enable a new approach to redesign ecologically compatible tribosystems. The applications for these tribosystems range from power transfer to forming processes. They not only contribute towards functional performance, but also exert a significant influence on the economic and ecological balance of the technical systems. These are affected to a particular extent by the high eco-toxicological risk potential of the mineral-oil-based precursor materials containing additives. This is because the precursor materials may leak into the environment and give rise to contamination problems. More broadly speaking, however, enormous amounts of resources are also being wasted as a consequence of improperly handed lubricants. Collaborative research centre 442 has therefore defined the development of new tribological contacts as one of its objectives. The lubricants used for this should be unrefined and unfortified, wherever possible. The functions performed by the additives in conventional contacts are transferred to newly developed coating systems on the surfaces of the friction contact pairs (Murrenhoff, 2004). Figure 1 illustrates the adopted course of action.

The Institute for Fluid Power Drives and Controls (IFAS) is involved in the collaborative research centre with the subtask "Ageing Properties of Ecologically Compatible Lubricants". The investigation of ageing mechanisms (Zhang, 2004), the development of appropriate test methods and testing of the ageing stability of new developed lubricants (Schmidt, 2003) are focuses of the conducted research. It is intended to make knowledge acquired within the collaborative research centre available to the user in the form of an expert system. As far as the ageing behaviour of the developed lubricants is concerned, this is to be achieved by the simulation of ageing of hydraulic fluids in hydraulic circuits. This paper describes the proposed concept of this simulation. It shows how characteristic values and simulation approaches on laboratory scale can be combined to implement a simulation to for ageing in hydraulic circuits. It describes the state of progress and the lasting steps necessary to finally set up and verify the simulation tool.

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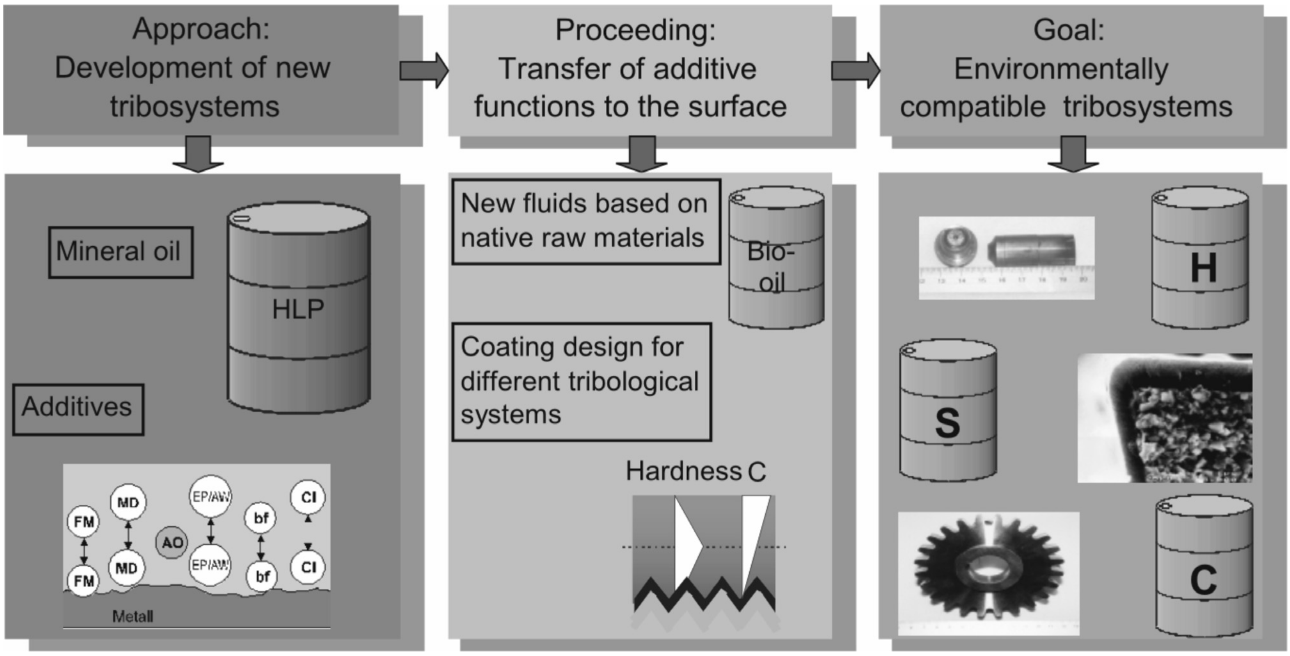

Fig. 1: *Course of action adopted within collaborative research centre 442*

2 Using Neural Networks to Simulate Ageing

In the context of lubricants, the term "ageing" refers to a change in the useful properties of the fluid as a result of chemical reactions during the time spent in storage and in use. The most important changes to the fluid's characteristics affect its viscosity, acid content, foaming behaviour, air release capability and anti-wear properties. But they also affect the colour, odour and ecological compatibility of the fluid. Compared with the condition of the fluid when new, these alterations to the fluid's characteristics lead to changes in the characteristics of the system as a whole. An increase in viscosity exerts a direct influence on leakage losses and on the efficiency of the system. An increase in the acid content may give rise to a higher corrosion level and a greater proportion of ageing products may cause damage to seals. A reduction in the anti-wear properties of the fluid shortens the lifetime of the system components. The aged fluid is replaced by fresh fluid as a consequence of these changes. As costs are incurred for the fluid itself and by the restriction on the system's availability, it is obvious that an improvement in the ageing stability of the fluid exerts a direct influence on the economic efficiency of the system.

The ageing processes taking place in the fluid attack on two different levels because of the compound character of the lubricant. Firstly, the additives used are subject to a decomposition process, and secondly, the fluid basestock itself is susceptible to ageing processes (Mang, 2001). As the development work carried out within collaborative research centre 442 is focused around unfortified lubricants, this article is primarily concerned with the ageing of ester-basestocks. The main decomposition mechanisms acting on the basic fluid are autoxidation and hydrolysis. These are described in greater details by Zhang (2004), for example.

In this respect, artificial neural networks are capable of simulating complex relationships following a training phase. The ability has already been used successfully in a number of fluid technology applications (Mundry, 2002). The basic element of a neural network is a neuron, as shown in Fig. 2. This consists of a weighted addition of its input variables x_i and the addition of a constant Θ. The sum is then used as the input for a function. This may be a simple linear function, a signum function or another similar function, according to the type of neuron (Demuth, 2002). This function then determines the output value of the neuron directly. Different network structures may be produced by combining several of these neurons. One possible arrangement is the multilayer perceptron network (MLP network), whereby the neurons are arranged in layers (Demuth, 2002). The neurons within one layer are not connected to one another. However, all of the inputs for the neurons in a layer are linked to all of the outputs in the previous layer. Furthermore, a three-layer network containing the input variables for the network in the first layer, neurons with a Sigmoid function in the second layer and a neuron with a linear function in the third layer, is capable of reproducing even complex functions in linearised form, section by section. The weighting factors w_i and constants Θ in the various neurons are used to adapt the network to the task in hand. There are various ways of optimising these unknown factors and one of them is the back-propagation algorithm (Demuth, 2002). This stipulates input and output values for the network and calculates the neutrons' parameters from these. The network's "training" therefore requires data which must be obtained in the course of experimental testing. The training data records then form the points in a grid which the neural network uses to approximate a function.

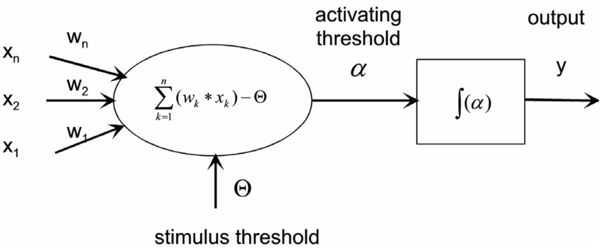

Fig. 2: *Schematic representation of a neuron*

The neural network method has already been successfully used to simulate the ageing of environmentally compatible lubricants (Schmidt, 2003; Murrenhoff, 2004). The laboratory-scale system simulates the influence exerted by the saturation level of fatty acids on the lifetime of the fluid in an oxidation test. The term "saturation" refers to the different fatty acids which are forming the triglyceride which were simulated. Usually the fatty acids consist of 18 carbon atoms. If a fatty acid contains no carbon double bond, it is called saturated or named C18:0. One double bond means single unsaturated or C18:1 and two or more are called as multi unsaturated or C18:2 (Schmidt, 2003). Double bonds are a weak point within the fatty acid regarding oxidation and thus ageing stability (Zhang, 2004). Native triglycerides contain different amounts of different fatty acids. This is referred to as the fatty acid distribution which can be determined by means of gas chromatography and mass spectroscopy. During the process of manufacturing the fluids on the basis of native triglycerides, influence is selectively exerted on the distribution of saturated, monounsaturated and polyunsaturated fatty acids for this, thereby achieving a broad spectrum in the distribution of fatty acids. The oxidation stability of the fluids produced in this way is examined in an oxidation test that is similar to the rotary bomb test according to ASTM D 2112. It involves heating 35 g of the test fluid up to the test temperature (110 °C and 120 °C) in an oxygen atmosphere of 6.2 bar without adding water or any catalysts. The test vessel rotates throughout the test and the pressure of the oxygen atmosphere is measured. Oxygen is used up during the ageing process taking place in the fluid and there is a drop in the pressure inside the closed test vessel. The time that passes between the maximum pressure reached as a result of heating the specimen and a 1.75 bar drop in pressure constitutes a measure of the oxidation stability and is also regarded as being the lifetime of the fluid.

The lifetimes of the mixed fluids, with the respective distribution of fatty acids broken down into saturated (C18:0), monounsaturated (C18:1) and multi unsaturated (C18:2) fatty acids, and the test temperature make up the components of 113 training data records. These are used to both optimise the weighting factors of an MLP network with 40 neurons in the concealed layer and one neuron in the output layer and to monitor the simulation quality of the network outside the training points. 75 % of the test data demonstrated an error of less than ± 10 %.

Trained in this way, the network was then used to calculate the lifetimes of fictitious fluids. Figure 3 shows the notional amounts of each fatty acid for the 16 fictitious oils which were used as input for the trained neural network. These 16 different distributions of fatty acids were varied systematically in order to investigate the influence of the degree of saturation. The simulated lifetimes are shown in Fig. 4. A pronounced lifetime-reducing influence of the multi unsaturated fatty acids is evident as the decrease of the amount of multi unsaturated fatty acids causes the , as well as the typical lubricant dependence of lifetime on temperature to such an extent that the lifetime is halved when the temperature is increased by 10 K (Schmidt, 2003).

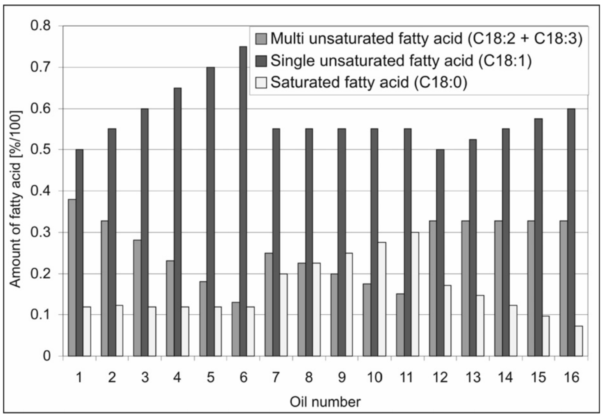

Fig. 3: *Systematic variation of the fatty acid spectrum*

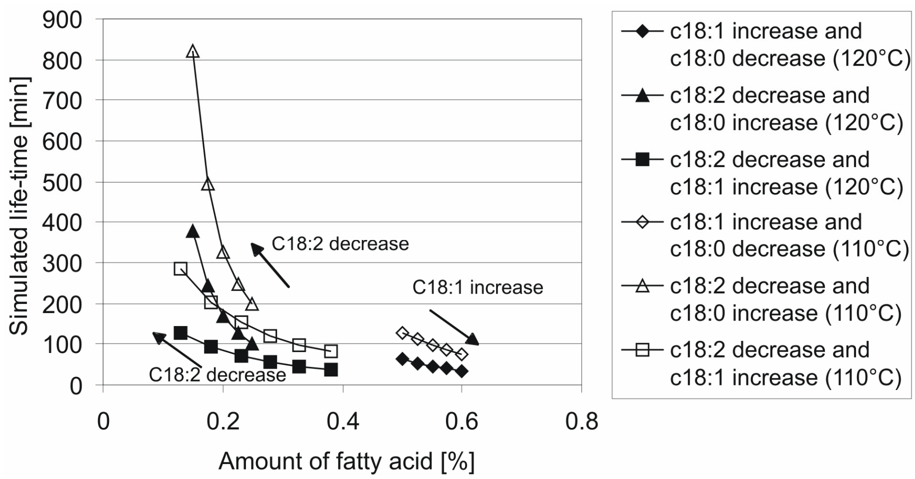

Fig. 4: *Simulation results*

3 Simulation of Ageing for Hydraulic Circuits

It is intended to make knowledge acquired within the framework of redesigning tribosystems available to the user in the form of an expert system. As far as the ageing behaviour of the developed lubricants is concerned, this is to be achieved by translating the successful use of artificial neural networks on laboratory scale into the simulation of ageing of hydraulic fluids in hydraulic circuits. This will offer hydraulic system design engineers a tool which enables them to design ageing-optimised hydraulic circuits by simulating the ageing behaviour. In addition to this, it also offers a means of using the ageing prediction to determine intervals for analysis or replacement of the fluid.

A neural network is to be used to predict the lifetime of the fluid in a hydraulic circuit in the same way as for the simulation of ageing on laboratory scale. This should simulate the ageing characteristics of the fluid and the associated reaction to the complex of loads acting on it. The simple structure of the load acting on the fluid in the laboratory is at odds with the much more complex load structure in a hydraulic circuit. The constant temperature load in the rotary bomb test becomes an uneven distribution of heat in the system when leaving the laboratory scale. Temperature distributions in hydraulic systems are described by Kempermann (1999) for example. The oxidation test does not simulate shearing loads of the type that occur in areas where there are considerable differences in flow rate, as is the case when fluid flows through orifice plates, for example, or the catalytic materials that accelerate ageing like those used in pumps and motors. Furthermore, the large number of possible hydraulic circuits, ranging from simple pump-motor combinations right through to more bifurcated systems with numerous consumers, give rise to a number of differences. This means that, compared with the simulation of ageing on laboratory scale, there are many additional variables that describe the structure of the hydraulic circuit and the load acting on the fluid and these must also be taken into consideration.

The simulation structure shown in Fig. 5 is used in order to be able to use the ageing simulation for these variable requirements. A distinction must first be made between the necessary training of the neural network shown above and the actual simulation application shown below. The simulation is divided into two possible paths: one of these beginning from an existing circuit diagram and the other beginning from an existing system. The velocity k of chemical reactions is a function of temperature T, activation energy E_A , universal gas constant R and the pre-exponential factor A in accordance with the Arrhenius equation (Eq. 1).

$$k = Ae^{-E_A / RT} \tag{1}$$

Compared with other factors a dominance of the thermal influence on ageing is evident in many previous studies (Kempermann, 1999; Werner, 2001; Schmidt, 2003; Zhang, 2004). It is therefore important to know the way in which heat is distributed throughout the system and this is determined by means of a thermal simulation or by measuring the heat in the various partial volumes V_i within the system. The pressure values p_i for the partial volumes can also be determined at the same time. As the size and number of partial volumes generally vary from one hydraulic circuit to another and a neural network always requires a constant number of input variables, the temperature and pressure distribution values obtained by simulation or measurement must be processed in an appropriate manner.

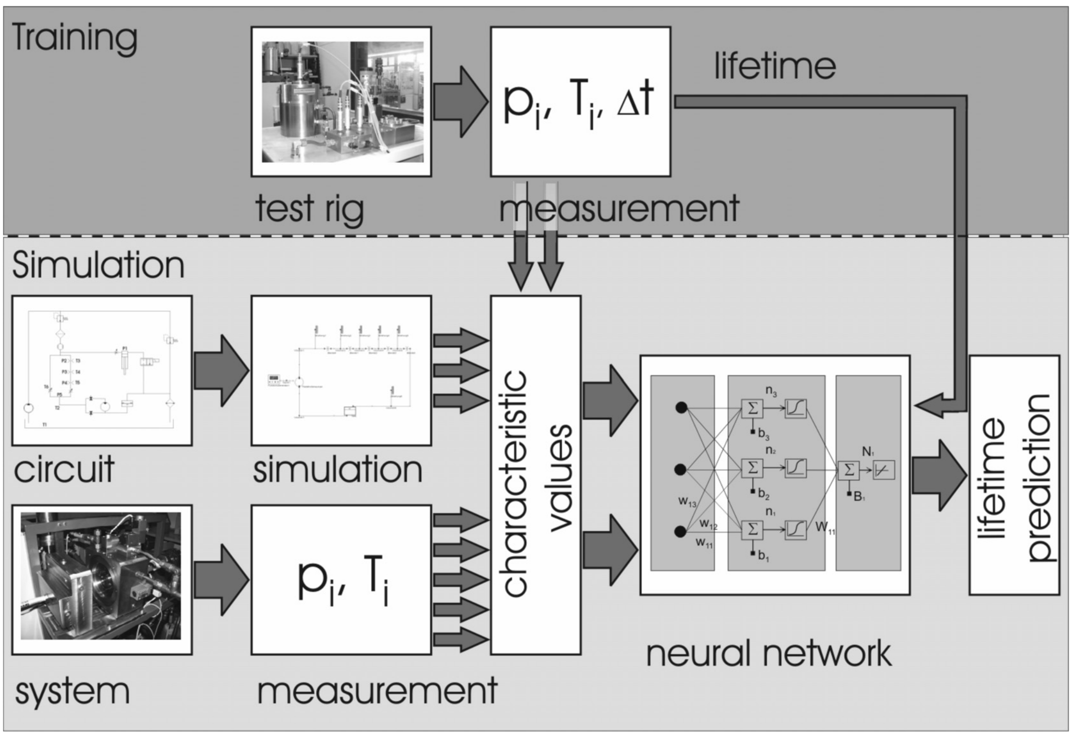

Fig. 5: *Ageing simulation structure*

This is done by generating suitable characteristic values, which combine the temperature distribution values and constitute characteristic variables for the structure of the circuit. These characteristic values are therefore the input variables for a neural network, which calculates the lifetime prediction as a function of the complex of loads acting on the fluid. While the load acting on the fluid is described in the characteristic values irrespective of the fluid's properties, the neural network implicitly contains the oil-specific ageing properties.

Training is necessary in order to optimise the initially unknown weighting factors for the neural network. This is shown in the upper part of Fig. 5. Different hydraulic circuits are selectively simulated on suitable test rigs for this and the distribution of temperature and pressure are measured. Characteristic values are generated from this data and specified as the input variables for the neural network. The lifetime of the fluid is determined experimentally for each configuration by means of ageing tests. The measured lifetime serves as the specified output variable for the neural network. These output variables can then be combined with the appropriate input variables, enabling the use of algorithms to optimise the weighting factors.

4 Ageing Simulation Elements

4.1 Thermal Simulation

In its capacity as an integral element of ageing simulation, the purpose of the thermal simulation is to obtain information about the distribution of heat throughout the planned system. The circuit diagram is mapped in DSHplus [N.N., 2001] with "thermohydraulic elements" for this. These special elements contain systems of equations for the heat balance. Thermal parameters must therefore be given in addition to the normal hydraulic parameters. One of these is the heat transmission coefficient α which, in conjunction with the size of the component surface, is required to determine the flow of heat over the surfaces of the component. The heat transmission coefficient combines radiation and convection fractions. The second thermal parameter, the heating time constant, is defined as being the time that passes before an increase in the temperature of the fluid can be measured on the surface of the component. It therefore describes the thermal conductivity indirectly and determines the component's heating-up behaviour. As this paper is primarily focused on the static temperature of the hydraulic circuit, the heating time constant is of secondary importance in this respect.

The following procedure has been used to determine the heat transmission coefficient of a component:

- Representation of the studied component using a suitable basic form that is equivalent in thermic terms and analytically solvable, or an experimentally derived model, such as a horizontal or vertical plate, vertical / horizontal cylinder, cube, parallelepiped or sphere,
- Determination of "characteristic length L" of the heat transmission problem, i.e. the mean reference diameter d_m for a horizontal cylinder or a reference height L_H (vertical plate) and the resulting heat-dissipating surface A,
- Determination of the mean surface temperature ϑ_w of the component and the heating time constant (measured), the material reference temperature ϑ_{mat} in accordance with the heat transmission law (usually $(\vartheta_w + \vartheta_\infty)/2)$) and the material parameters λ or v for ϑ_{mat},
- Calculation of the Grashoff quotient Gr, Prandtl quotient Pr and Rayleigh quotient Ra,
- Application of a heat transmission law that describes the respective heat transmission problem ($Nu = f\ (Ra^m,\ Pr)$), determination of the Nusselt quotient Nu (non-dimensional heat transmission coefficient) and the convective heat transmission coefficient α_k,
- Determination of a heat transmission coefficient α_{rad} that relates to the driving convective temperature drop (ϑ_W - ϑ_∞) for the transmission of heat by radiation and
- Formation of a total heat transmission coefficient α_{tot} by means of additive superimposition of the convective and radiation-specific heat transmission coefficients α_k and α_{rad}.

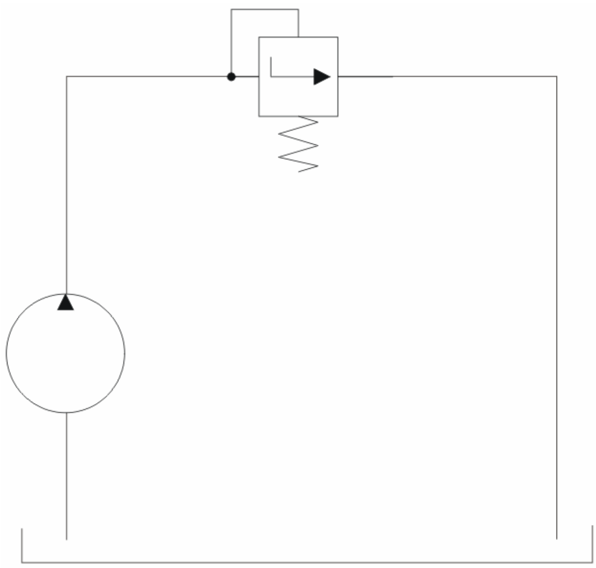

Fig. 6: *Simple circuit*

Once the necessary heat transmission coefficients have been determined according to the procedure described above, a simple circuit comprising pump and pressure control valve, as shown in Fig. 6, can be carried over into a DSHplus simulation model as shown in Fig. 7. DSHplus is a commercial software tool to simulate hydraulic circuits, N.N. .(2001). In this model, the pipelines are represented by suitable restrictors. The heat is dissipated via special heat dissipation elements rather than directly through the component. Figure 8 shows a comparison between the simulation and a measurement of the temperature characteristic within the respective partial volume. It is evident that the

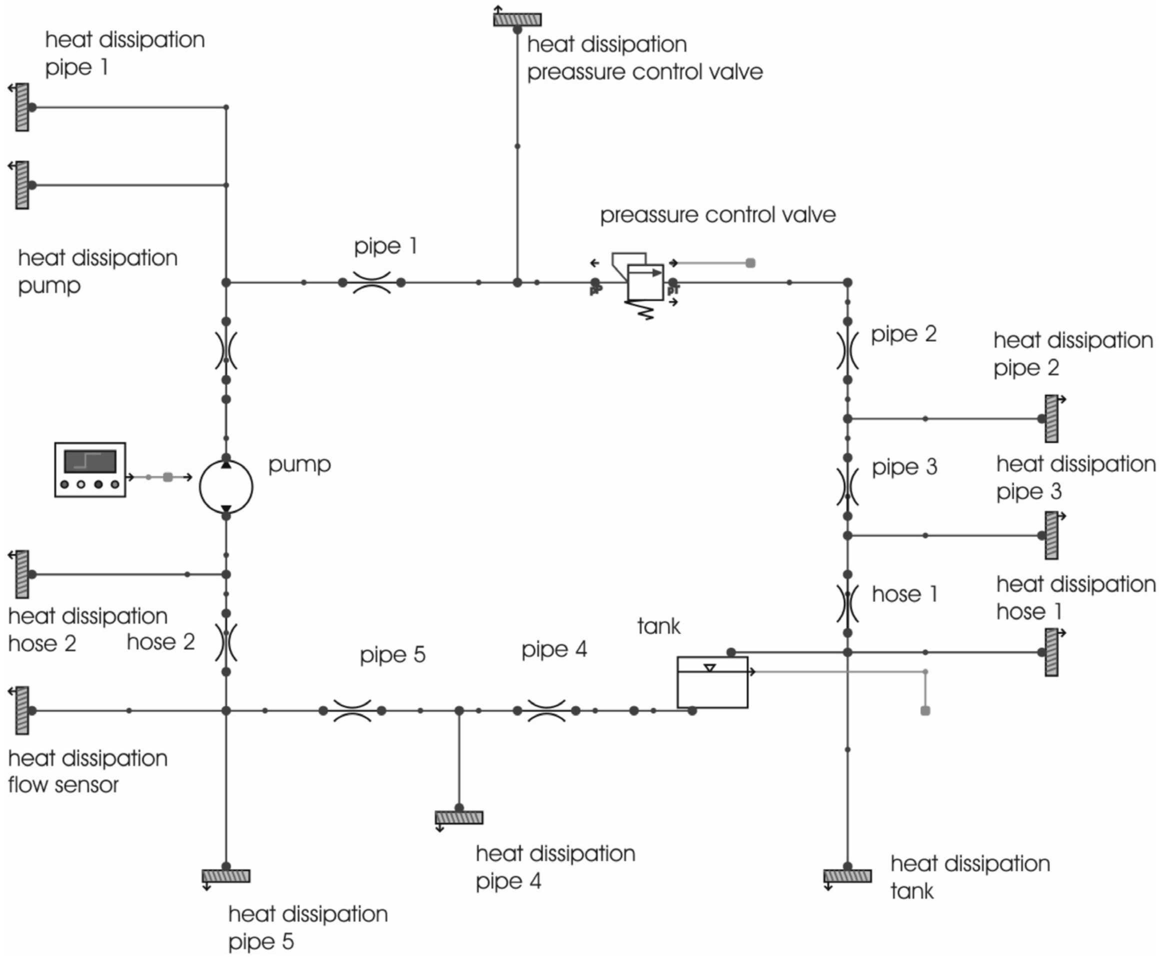

Fig. 7: *Thermal simulation model in DSHplus*

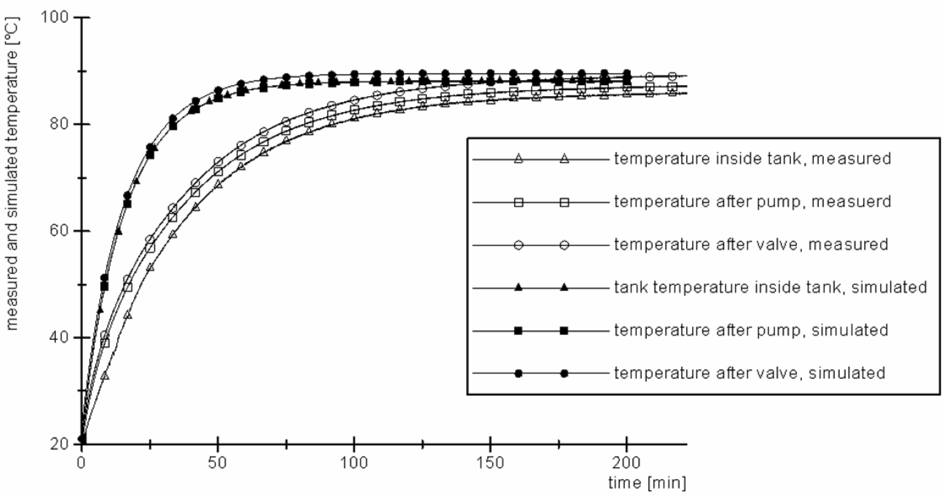

Fig. 8: *Comparison between measured and simulated temperatures*

measured and simulated final temperatures are achieved with a maximum deviation of 2 K. This proves the method of determination of the heat transmission coefficients and the simulation model as suitable to calculate the static temperature distribution within the hydraulic system. To simulate the dynamic temperature distribution resulting from changing operation modes as they occur in real systems, the time constants, which describe the time dependency of the heating-up, have to be adapted.

4.3 Generation of Characteristic Values

Characteristic values are generated to process the various structures from different hydraulic circuits and the temperature and pressure distribution data of varying complexity based on these in such a way as to ensure that suitable input variables are available for the neural network. Simple characteristic values are used initially, describing the load acting on the fluid with global parameters. These include the maximum temperature, the circulation rate, Eq. 2, that relates the volume flow of the pump to the existing volume of fluid, and the volume-related power loss, Eq. 3, which links the proportion of power introduced into the system by the conversion of heat.

$$Q_{\mathrm{v}} = \frac{Q_{\mathrm{Pump}}}{V_{\mathrm{tot}}} \tag{2}$$

$$P_{\mathrm{v,v}} = \frac{P_{\mathrm{an}} - P_{\mathrm{ab}}}{V_{\mathrm{tot}}} \tag{3}$$

The volume-related mean temperature, Eq. 4, and the volume-flow-related mean temperature, Eq. 5, offer possible ways of describing the distribution of temperature without any knowledge of the fluid.

$$\overline{T_{\mathrm{V}}} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} T_{\mathrm{i}} V_{\mathrm{i}}}{V_{\mathrm{tot}}} \tag{4}$$

$$\overline{T_{\mathrm{Q}}} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} T_{\mathrm{i}} Q_{\mathrm{i}}}{Q_{\mathrm{tot}}} \tag{5}$$

These mean temperatures do not allow for the increasing load acting on the oil as the temperature rises, however. This means, for example, that a small partial volume flow through a small partial volume at high temperature only leads to a slight increase in the two mean temperatures, in spite of the associated extreme load and possible damage to the fluid. Kempermann (1999) developed a load coefficient $f_{\mathrm{b,i}}$ on the basis of the Arrhenius equation (Eq. 1). This describes the way in which the lifetime of an oil sample is determined by the temperature to which it is exposed.

$$f_{\mathrm{B,i}} = k_{\mathrm{B}}^{\;T_{\mathrm{i}} - T_{\mathrm{Ref}}} \tag{6}$$

In Eq. 6, k_{B} describes the change in lifetime and T_{Ref} a reference temperature. To enable application of this load coefficient with respect to hydraulic systems, the system-related load coefficient $f_{\mathrm{B,\,tot}}$ is defined, which adds the load coefficients for the various partial volumes in the system with their volume shares together as a weighting factor (Eq. 7).

$$f_{\mathrm{B,tot}} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \frac{V_{\mathrm{i}}}{V_{\mathrm{tot}}} f_{\mathrm{B,i}}}{\sum_{\mathrm{i=1}}^{\mathrm{m}} \frac{V_{\mathrm{i}}}{V_{\mathrm{tot}}}} \tag{7}$$

This system-related load coefficient has proved expedient in the investigation of forestry equipment (Kempermann, 1999) and was supplemented by the volume flow in the respective partial volume by Werner (2001). The load coefficient described above is only suitable for application in the processing of data for the neural network to a limited extent as it already allows for the lifetime-temperature behaviour of a specific fluid. The system-related load coefficient approach may be used as the basis for development of other characteristic values, however, which are not specific to a particular fluid and are also capable of mapping the elementary increase in load as the temperature rises. In this respect it would appear expedient to use Euler's quotient e instead of the k_{B} value. If the temperature in the partial volume is related to a reference temperature in addition to this, the result is the exponentially weighted load coefficient shown in Eq. 8, whereby quotient $V_{\mathrm{i}}/Q_{\mathrm{i}}$ is a measure of the period during which the fluid is exposed to temperature T_{i}.

$$f_{\mathrm{e,t}} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \frac{V_{\mathrm{i}}}{Q_{\mathrm{i}}} e^{\frac{T_{\mathrm{i}}}{T_{\mathrm{ref}}}}}{\frac{V_{\mathrm{tot}}}{Q_{\mathrm{tot}}}} \tag{8}$$

Apart from the characteristic values for temperature distribution described above, other characteristic values are needed in order to describe the structure of the circuit. It would appear expedient to use the number of orifices in the system with the pertinent differences in pressure as a measure of the shearing load acting on the fluid. Tribological contacts in pumps and motors constitute catalysts with respect to ageing, which means that the surface area of a contact can also be used as a characteristic value (Schmidt, 2003). A distinction can therefore be made between a set of hydrostatic gears with a pump-motor combination and a system comprising pump and cylinders.

4.5 Training Test Rig

Special ageing test rigs have been set up at the IFAS in order to have a sufficient high volume of data for network training. The flexible connection facilities of these test rigs offer a means of mapping a large number of different circuits and examining their respective ageing characteristics. Figure 9 shows the hydraulic circuit diagram for the test rigs. The so-called resistor unit can be seen on the left-hand side, comprising three screw-in orifices and a restrictor connected in parallel. Various hydraulic circuits can be simulated by varying the orifices and the throughput characteristics of the restrictor and orifices. There is a tribometer on the right-hand side. It consists of one static and one rotating disc, which are pressed together with a defined load. Both discs contain grooves in their contact surfaces which allow the hydraulic fluid to enter the tribological contact and interact with the surface materials. The concept of adding such tribometers to oil ageing tests was used by Schmidt II, 2003. The cylinder is used to press the two discs together and one of these is driven by the fluid motor. The fluid flowing back into the motor is used to lubricate the mating surfaces of the two test specimens. Different characteristic tribosystems with their respective ageing influence can be introduced into the system by varying the test discs, the surface pressure and the relative velocity. The test rig has been designed in such a way as to enable the measurement of pressure and temperature distribution. Combined with regular testing of such fluid properties as viscosity and total acid value and the resulting lifetime, suitable training data records are produced for the neural network. Figure 10 shows an example of the viscosity characteristic as a function of test duration. The circuit used for this corresponds to that shown in Fig. 6, the maximum temperature amounts to 72 °C and the maximum pressure is 70 bar. The fluid is an unfortified synthetic ester, which reached the end of its lifetime after 624 hours.

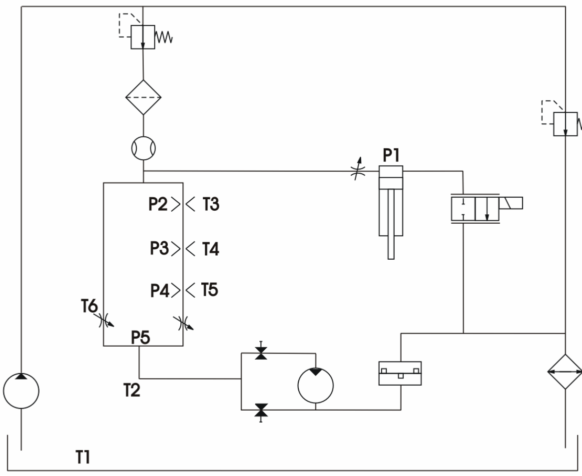

Fig. 9: *Circuit diagram of the ageing test rig*

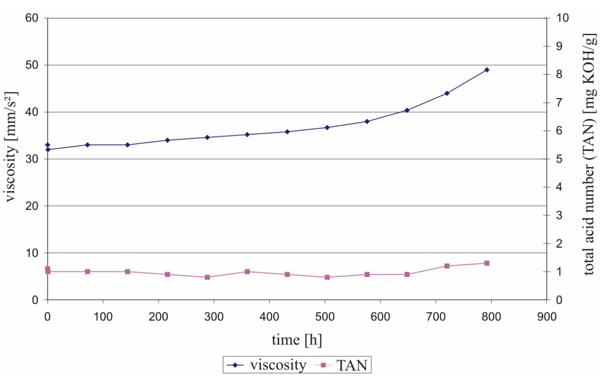

Fig. 10: *Ageing test with a simple circuit*

4.6 Neural Network

A multilayer perceptron (MLP) network with four inputs, 40 neurons in the concealed layer and one output has proved to be expedient for lifetime predictions on laboratory scale. This simple network structure and the available training algorithms proved to be very satisfactory and a decision has therefore been made in favour of using the same network structure to simulate ageing in hydraulic networks. Mundry (2002) uses networks with three inputs and 15 neurons, as well as 13 inputs and 22 neurons. There are between 1.7 and 10 neurons in the concealed layer for each input in the networks described above. The advantage of finer discretisation of the approximated function with a larger number of neurons in the concealed layer is offset by the disadvantage of the larger number of weighting factors to be optimised and the associated need for more training data. The exact number of neurons for the network used to simulate ageing in circuits will therefore require optimisation according to the results of training and verification. Analogous to the example shown in the test rig chapter 4.5 ageing tests have to be conducted to form a suitable database for the training of the neural net. There for pressure and temperature values will be varied as well as the parameters of the tribological contacts. For each set of parameter an ageing test will performed. The resulting lifetime together with the characteristic values of one test run will form one point of data for the neural network to approximate the ageing function. The database for the ageing simulation on laboratory scale as described in chapter 2 consists of 113 data sets. When a similar size of the database is archived, the neural net work will be set up and trained. During this process different numbers of neurons in the proposed multilayer perceptron net will be evaluated. After training and verification of the net the whole ageing simulation concept has to be verified by an ageing test executed on a test rig which was not involved in the set up of the training database. Due to the time necessary to complete an ageing test the size of the database does not yet allow a training of the network. Thus results of simulations of the neural network and a comparison with performed test runs can not given by now.

5 Summary and Prospects

This article describes a concept for the lifetime prediction of fluids used in hydraulic networks that has emerged from sub-project A3 concerned with "ageing behaviour of ecologically compatible precursor materials" within collaborative research centre (SFB) 442 at RWTH Aachen University, Germany. This concept is focused around a neural network that implicitly contains the ageing properties of the fluid. It is based on the experience that has been made with the ageing simulation of oil samples in an oxidation test. The two main elements of the concept are a neural network and a set of characteristic values. The complex of loads imposed on the fluid by the hydraulic circuit is processed in such a way that it can be used as the input for the neural network. There for appropriate characteristic values were suggested to describe the temperature loads of the fluid. A thermal simulation has been set up to simulate the temperature distribution within a hydraulic system as an input to the characteristic values.

To finally set up the neural network and verify the simulation concept a training database for the net has to be generated. There for ageing tests are conducted. This will be continued to archive a appropriate distribution of parameters. The work currently being performed includes the generation of other training data records for optimisation of the network's weighting factors. These will then constitute the basis for a future implementation and training of the network.

6 Acknowledgement

The work described in this article makes up part of sub-project A3 of the research project concerning "environmentally compatible tribosystems by means of suitable composites and precursor materials, using the machine tool as an example" conducted by collaborative research centre 442 at the Institute of Fluid Power Drives and Controls (IFAS) at RWTH Aachen University. This collaborative research centre is sponsored by the German Research Committee (DFG) and the authors would like to thank the DFG for its financial support.

Nomenclature

A	Pre-exponential factor
k	Reaction velocity
E_A	Activation energy
p_i	Pressure in partial volume i
T_i	Temperature in partial volume i
T_{ref}	Reference temperature
Q_i	Volume flow in partial volume i
V_i	Partial volume i
x	Input variable of a neuron
y	Output variable of a neuron
W	Weighting factor in the neuron
Θ	Displacement summand in the neuron
α	Activation value in the neuron
α	Heat transmission coefficient
Nu	Nusselt quotient
Gr	Grashoff quotient
Pr	Prandtl quotient
Ra	Rayleigh quotient
P_{an}	Driving power
P_{ab}	Useful power
$f_{b,i}$	Load coefficient
k_b	Fluid-specific basis for load coefficient $f_{b,i}$
Δt	Lifetime
R	Universal gas constant
L	Characteristic length
d_m	Mean diameter
L_H	Reference hight
A	Surface
ϑ_W	Surface temperature
ϑ_{mat}	Material reference temperature
ϑ_∞	Air temperature in a distance
λ	Heat conductivity of the fluid
ν	Kinematic viscosity of the fluid
α_K	Convective heat transmission coefficient
α_{rad}	Radiation heat transmission coefficient
α_{tot}	Total heat transmission coefficient
Q_v	Circulation rate
Q_{pump}	Volume flow of the pump
$P_{v,v}$	Volume related power loss
V_{tot}	Total volume
$\overline{T_v}$	Volume-related mean temperature
$\overline{T_Q}$	Volume-flow-related mean temperature
Q_{tot}	Total volume flow
$f_{B,tot}$	System-related load coefficient
i	Index to the partial volumes
n	Number of patial volumes of a system
$f_{e,t}$	exponentially weighted load coefficient

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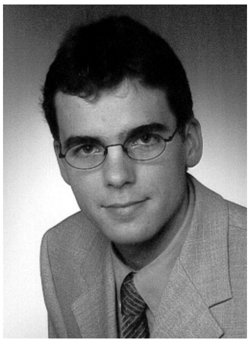

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