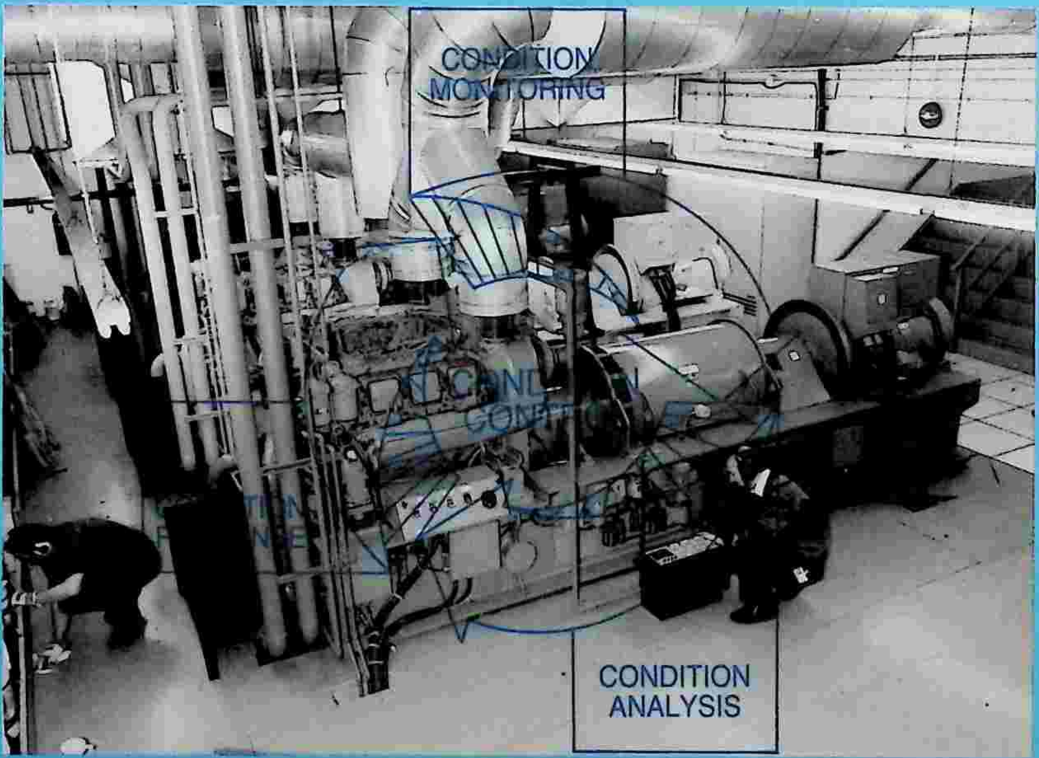
CONDITION MONITORING

Editor

J.R. McEwan



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ELSEVIER APPLIED SCIENCE

Chapter 13

MODEL OF A FUZZY LOGIC EXPERT SYSTEM FOR REAL-TIME CONDITION CONTROL OF A HYDRAULIC SYSTEM

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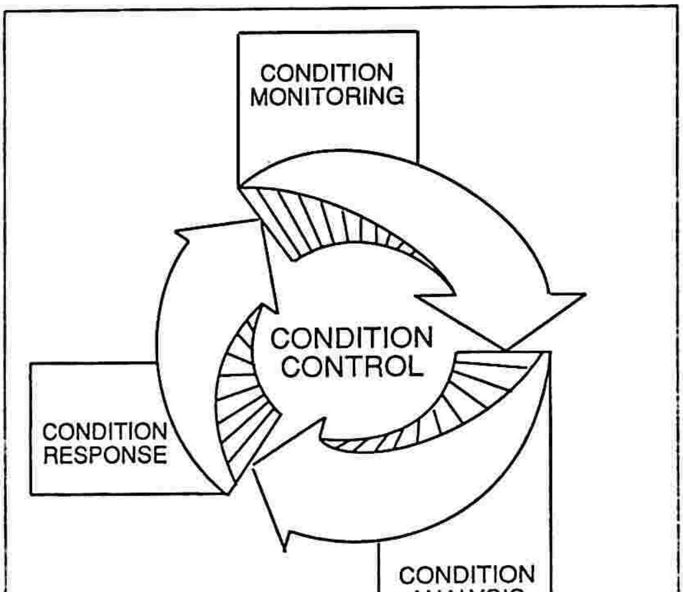
ABSTRACT

Condition control is defined as the interactive processes of condition monitoring, condition analysis, and condition response. A model is presented which employs the use of expert systems to achieve real-time condition control of a hydraulic system. The approach focuses on the use of fuzzy logic to achieve machine intelligence to monitor and analyze pre-degradation 'incipient' failure and impending conditions. Also discussed are the corresponding real-time 'reactive' condition responses, coupling system control with condition control.

1.0 INTRODUCTION

Condition control is defined as the interactive processes of condition monitoring, condition analysis, and condition response as shown in Fig. 1 [1]. As a closed-loop system, condition control assesses system state and then identifies, prescribes, and administers the response requirement. Not stopping there, the process involves monitoring the system's 'reactive response' after each response iteration, measuring the error, and as required, commissioning another response. The response closes the loop and is the operative element. At the heart of the condition control model is an expert system, which governs and directs the cognizant reasoning and decision elements. The approached preferred by the authors is fuzzy logic.

Figure 1. Condition control concept.



The basic components of the condition control model are described below.

1.1 Condition Monitoring

While the field of condition monitoring has become increasingly established as an information technology, its function serves only as the 'acquisition' component of the condition control expert system. Therefore, it is recognized as essential but incomplete. In a real test system, sensors and transducers must be used to communicate information such as the following to the expert system: noise, velocity, flow, speed, pressure, contamination, temperature, force, acceleration, strain, vibration, time elapse, torque, humidity, composition, power, efficiency, eeration, wear debris, displacement, duty cycle. These condition-dependent parameters are often the carriers of the recognizable symptoms of an ailing component or machine misapplication.

1.2 Condition Analysis

The expert system, (later described), resides in the computer and performs the condition analysis. Less efficiently (and accurately), the condition analysis could well be performed without the expert system or even the computer. The rising level of system diagnostic and failure knowledge will serve as the condition reference from which the analysis will draw. Such analysis methods and results as the following might be expected:

- Trend/Pattern Recognition
- Condition Diagnosis
- Condition Prognosis
- Wear-Mode Analysis
- Failure Mode Analysis
- Comparative Analysis
- Residual Life Estimation
- Incipient Failure Condition
- Impending Failure Condition
- Fault Localization

While it can be said that the purpose of the analysis is to recognize a fault 'on condition', such fault may not relate to the system but may instead be rooted in the application, or even the method of operation. Therefore, the analysis might recommend/commission corrective action that is not maintenance related.

1.3 Condition Response

Increasingly, hydraulic system designs include microcomputer controllers to dictate the movement of motors and actuators. Many such work-end 'guidance systems' employ adaptive control, PID control, and/or fuzzy logic control which make an ideal interface to a smart 'condition' controller (see Fig. 2). For instance, when the two are interfaced, certain computer administered condition responses might call out changes in speed, load, acceleration, temperature, flow, pressure, or duty cycle to correct an incipient fault or condition aberration.

The two principle types of controller directed responses are (see Fig. 3):

Controller-To-Controller Avoidance (CCA) Responses
Here the condition controller directs the system controller to alter the mode or level of operation to avoid a threatening or noxious condition.

Figure 2. Intelligent controller-controller interface (ICCI) system.

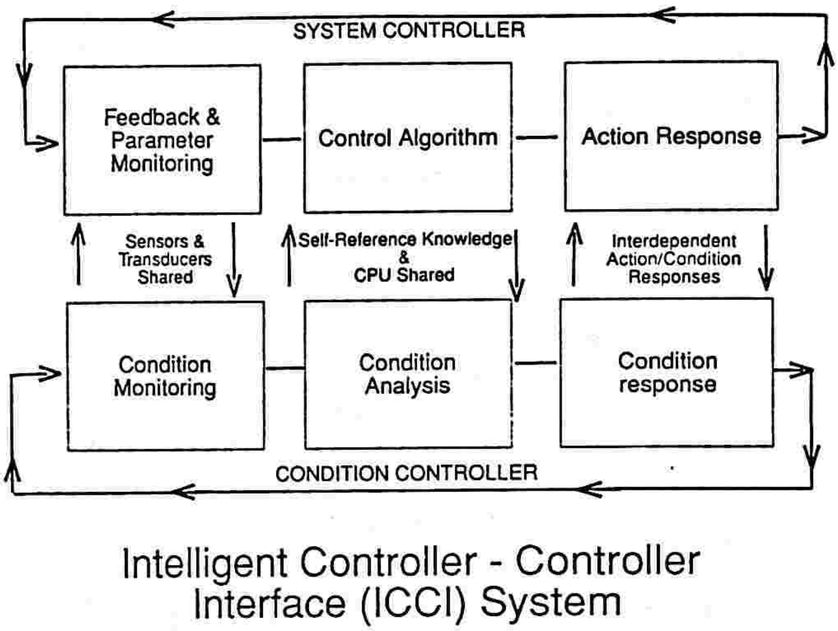
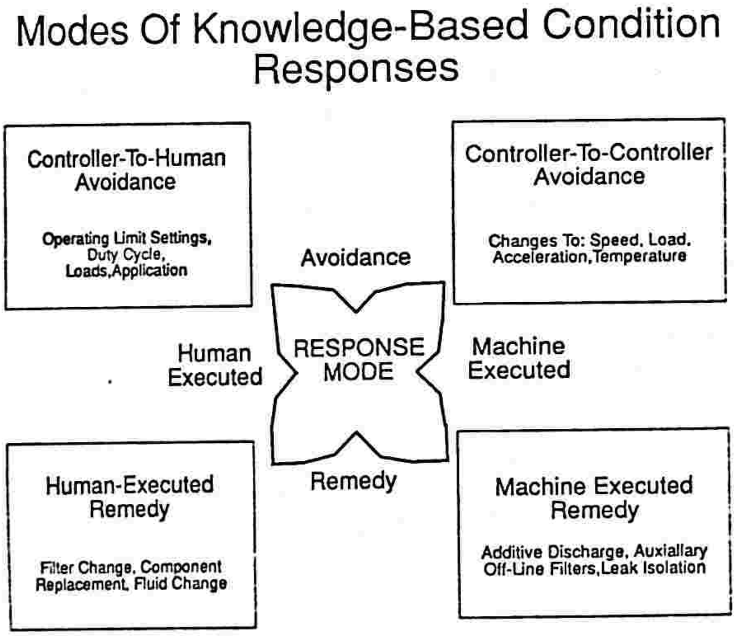


Figure 3. Modes of knowledge-based condition responses.



Machine-Executed Remedy (MER) Responses
With MER Responses, a fault has been localized and the remedy is prescribed and totally carried out by the system. For example, the fault might be high fluid contamination and the remedy might be turning on an auxiliary off-line filter.

The benefits of intelligent controller-controller interface (ICCI) systems that provide for CCA and MER responses are many:

- Responses are machine executed and immediate, without human interface or delay.
- Responses react to incipient faults.
- The machine becomes much more application, environment, and operator adaptive.

In addition to computer-controller administered responses, the expert system will alert operators or technicians to required responses not under its control. A well conceived expert system will direct the technician to root-cause actions, not symptom-based actions.

The two types of human executed responses are (see also Fig. 3):

Controller-To-Human Avoidance (CHA) Responses
In this case, the controller advises the operator to avoid a certain manner of operation, duty cycle, application, etc. Unlike the CCA response, here the controller depends on the operator to articulate its instructions.

Human-Executed Remedy (HER) Responses
In many cases, an adverse condition must be remedied by a technician or mechanic. With HER responses, the fault is localized, hopefully in the incipient stage, and the required corrective action is communicated. Examples of possible action requests are:

- Filter change
- Component replacement
- Fluid change
- Ingression point correction
- Design change
- Installation error
- Misalignment

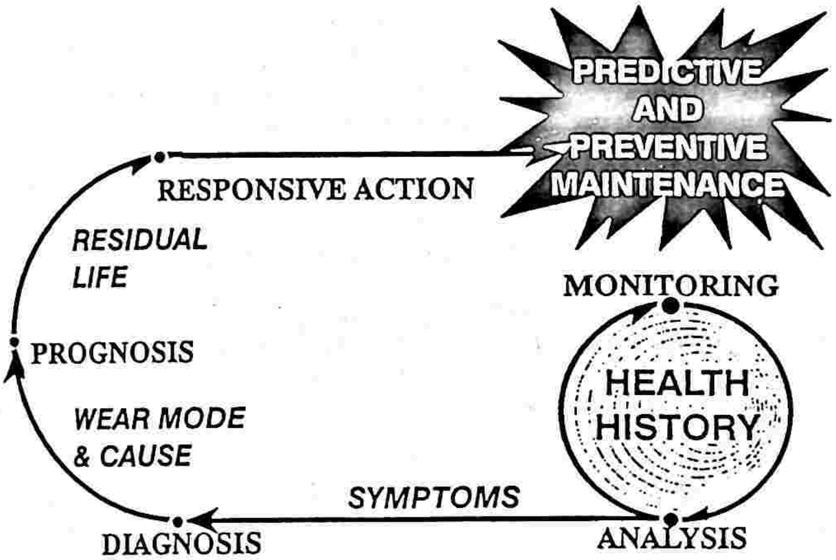
After each response has been implemented, the expert system measures the system's effect to the response and assesses the error. The error is the difference between the desired effect and the actual measured effect. Depending on the error, additional responses may be commissioned.

1.4 Expanding the Model to Achieve Real-time Condition Control

As stated previously, machine condition control is defined as three major activities: monitoring, analysis, and response. Further, in order to accomplish the predictive and preventive maintenance (PPM) for a machine, the analysis portion can be subdivided further into three sequential steps: symptoms analysis, condition diagnosis, and condition prognosis.

Figure 4 illustrates this for machine condition control. In the first stage, machine condition is monitored, as previously described. Symptoms, which are the performance abnormality of a machine from the intended design behavior, are then analyzed. If there are no symptoms or abnormalities observed, the cycle of condition monitoring/symptom-analysis continues to establish the health history of a machine. This grows the important knowledge base.

Figure 4. The process of machine condition control.



Next, diagnosis is the act or process of identifying the machine condition according to the symptoms observed. In essence, the objective of diagnosis is to localize the cause or causes responsible for a set of symptoms. The diagnosis and information are further processed to achieve prognosis, which forecasts the future condition of a machine or component. Restated, prognosis is the process of interpreting the situation in terms of the residual life. Based on the prognosis results, responsive action is determined and issued to avoid the fault(s) or to remedy the abnormalities.

1.5 The System Approach to Condition Control

In the context of the evolving field of artificial intelligence, expert systems are making the single greatest commercial contribution. Unlike common rule-based programs, an expert system takes advantage of both the art and science of decision making, reflecting the needs of the terrestrial world in which we live. And, their use is particularly adapt to performance monitoring and system diagnostics as would be prescribed for a hydraulic system.

2.0 FUZZY LOGIC APPROACH TO COMPUTING UNCERTAINTY FOR CONDITION CONTROL

Conventionally, predictive and preventive maintenance is usually accomplished using a fairly rigorous form of inverse logic, whose basis depends almost entirely on a general understanding of the subject system [2]. For instance, when a hydraulic actuator gradually becomes powerless (symptoms), it is possibly due to excessive internal leakage resulting from the presence of abrasive contaminants (cause) in the fluid which damaged critical surfaces. By knowing the fluid contamination level and the component contamination sensitivity characteristics, the residual life of the component can be executed and proper action prescribed to avoid the failure. Obviously, the extent and knowledge involved in the PPM process depend highly on experience. That is to say, the conventional PPM process is an art, rather than a science, and it is even farther away from being a technology.

One of the major reasons that the PPM process has been stagnated at this state-of-the art is mainly due to the large role that imprecision and uncertainty play in characterizing the experience of the machine condition control expert. The expert generally gathers knowledge about the machine from critical quantitative data (e.g., gauge readings, laboratory test results and past history) as well as qualitative information (such as is gained from the three 'S's'-sight, sound, and smell) [2]. The knowledge obtained from each source bears various degrees of uncertainty. In quantitative data acquisition, the accuracy of measurement depends mainly on sensor characteristic and calibration. No sensor available today can provide 'exact' information to truly represent machine condition. In other words, each quantitative measurement has its own precision limit. Therefore, if the values of critical parameters measured are around the borderline between normal and failure, the decision making for PPM is then solely dependent on the expert's subjective judgement. An experienced person can make a reasonable and often accurate decision than a less experienced one although the set of quantitative data used for analysis is identical.

In regard to qualitative information, the degree of uncertainty and imprecision is even higher. A person may exaggerate or underestimate the machine condition he gained from his 'feeling.' Further, this information is usually described using linguistic terms that are rather vague, such as the machine becomes very noisy but the temperature is normal. Obviously, what is needed is a model which characterizes the expert's logic in solving problems. Theoretically speaking, it is to identify or develop a strategy that the engineering commonsense knowledge can best be mathematically manipulated to provide the necessary information for decision making.

For several decades, researchers have found that fuzzy logic is a very effective way to handle uncertain and imprecise information. The fuzzy approach is based on the premise that vague information can be approximately reasoned using a strict mathematical framework–the fuzzy set theory. Numerous technical papers and text books have been published to illustrate the detail of the fuzzy set theory and applications since it was introduced by Professor Zadeh in 1965. It is not the intent of this paper to give a tutorial on fuzzy set theory. However, it is worth noting the conceptual differences between the fuzzy approach and the conventional approach in process modeling and reasoning described below.

2.1 Knowledge Processing and Fuzzy

Strategies for process modeling, reasoning and computation normally employ the three most commonly used mathematical approaches:

- Deterministic Knowledge
- Probabilistic Knowledge
- Possibilistic Knowledge

Deterministic knowledge is based on the well defined system structure and rigorous physical laws or equations available in text books or research reports to solve problems. The usefulness of such knowledge depends on the system's ability to make it machine and condition specific. Probabilistic knowledge is mainly gained from a statistical process on the belief that for every event there is a probability occurrence. To establish a probability model for predicting the frequency of certain events to occur requires a reasonably large amount of repetitive tests. Possibilistic knowledge, on the other hand, focuses primarily on imprecision or uncertainty which is intrinsic in natural languages and man-made machines. Imprecision here is meant to express a sense of vagueness rather than the lack of knowledge about the value of a parameter, as in tolerance analysis [3]. In other words, the possibilistic model is dealing with process 'fuzziness' not 'randomness.'

To illustrate the difference between the above three mathematical approaches, consider a simple example of diagnosing the flow degradation of a pump. Assume that the pump is operating under a condition which will result in a 5% flow degradation after 100 hours of operation. From a deterministic standpoint, pumps which are identically designed and operate at the same conditions should show the same flow degradation; that is, 5% degradation after 100 hours of operation. it is a crip number—5%, neither 4.9% nor 5.1%. However, both the probabilistic and possibilistic approaches describe the flow degradation of pumps in terms of a distribution junction. Table 1 shows the

Table 1: Various Approaches of Flow Degradation Analysis

Flow Degradation (%)	0	1	2	3	4	5	6	7	8	9	10
Deterministic	0	0	0	0	0	1	0	0	0	0	0
Probabilistic	0	0	0	0.1	0.2	0.6	0.1	0	0	0	0
Possibilistic	0	0	0.4	0.5	1	1	0.8	0.6	0	0	0

Table 2: Data Used for Fuzzy Analysis

Parameter Measured	Units	Initial	500 hrs.	1000 hrs.
System Pressure	bar	70.00	69.90	69.80
Pump Inlet Pressure	cm Hg	19	19	19
Actuator Motion	cm/sec	5	4.75	4.25
Fluid Contaminant	#/ml > 10μm	10	70	220
Fluid Viscosity	cSt	10	9	8.5
Fluid Temperature	°C	65	65	65

example data illustrating the differences between them. Note that the possibility distribution represents the degree of satisfaction that a person believes the flow degradation may occur after 100 hours. It is extremely possible (membership grade of 1.0) that the flow degradation is 4% or 5%, and fairly possible (grade of 0.8) that it is 6%, and so forth. It depends solely on the person's experience and common sense. On the other hand, the probability distribution might have to be determined by testing 100 pumps.

Defining a fuzzy membership function to represent the uncertainty of an event, plus constructing the fuzzy relational matrix to correlate the degree or strength of relation or interaction between fuzzy set elements are two major activities prior to applying the possibilistic approach to accomplish machine condition control. Membership functions are based on human senses and opinions which are subjective but can not be assigned arbitrarily. Dubois and Prade [4] suggest some ideas and methods for selecting membership functions, as follows:

- Exemplification
- Reformable prototypes
- Implicit analytical definition
- Use of statistics
- Relative preferences methods, comparison of subset and filter function

Among these methods, it is found that the implicit analytical definition has an advantage of ease in hydraulic system condition control [5].

The implicit analytical definition method assumes the membership function is an S-shaped, continuous and differential function. In practice, the shape of the function can also be any shape such as the U-shaped, triangular, or trapezoidal to best describe the condition under study.

The relational matrix, in essence, is a causality relationship between the effort and reaction of events. The strength (grade) of the causality can be obtained by heuristics, experiences, experiments, or implicit analytical methods. Note, the grades are subjective, uncertain, but not random.

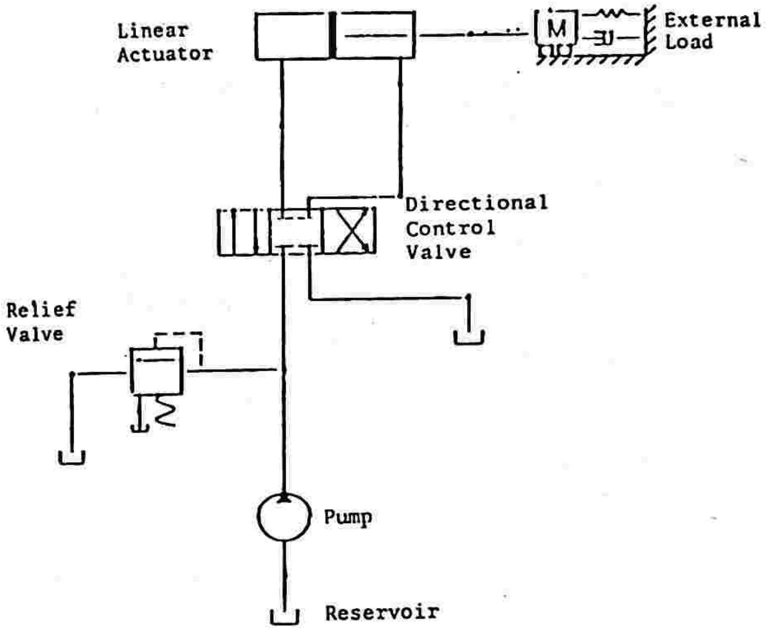
2.2 Applying Fuzzy to Hydraulic System Condition Control

To illustrate the process of applying fuzzy logic to machine condition control, consider a simple but representative hydraulic system as shown in Fig. 5. The system consists of a pump, a relief valve, a directional control (D.C.) valve, a linear actuator and a reservoir. Assume the following parameters are of interest to a specific application.

- System Pressure
- Pump Inlet Pressure
- Actuator Motion
- Fluid Contamination
- Fluid Viscosity
- Fluid Temperature

Appropriate sensors are installed on the system and the status is monitored accordingly. Table 2 shows the data obtained at initial, 500 hours and 1000 hours after the initialization of operation. The monitored data are continuously fed into the fuzzy inference engine where the Fuzzy Symptom Matrix (FSM) resides. An example of an FSM is illustrated in Table 3. The FSM relates the symptoms with a fuzzy membership grade value. For example, it assumes that the fuzzy value is 0.0 for normal sys-

Figure 5. Example of hydraulic circuits.



tem pressure (i.e. the pressure is equal to the designed pressure P_0), and 0.25 for pressure over or under 10 percent of P_0. In this paper, the normalized fuzzy number is used which means it ranges from 0 to 1 to stand for the strength of the expert's perception (membership grade value) on an event. It also assumes, for the simplicity of example demonstration, that the membership function is linear. In other words, for the value of the parameters not shown in Table 2, it can be obtained by linearly interpolated using the most nearby two values. For instance, if the system pressure is 15% higher than P_0, then the membership grade value is calculated from (0.25/10%, 0.75/25%) which is 0.42.

According to the above mentioned assumptions, a resultant symptom matrix (RSM) can be obtained by substituting the values in Table 2 into the related cell in Table 3. A RSM is shown in Table 4. It is also assumed that no diagnosis will be performed if the value of the membership grade is less than 0.5. Hence, the diagnosis must be performed at the 1000 hour period according to the data shown in Table 4. It indicates that the actuator's motion and the fluid contaminant level are abnormal.

To effectively carry out the diagnosis, a fuzzy matrix to correlate the influences (causes) to component abnormality (say, the ICA matrix) is required. Table 5 shows an ICA matrix including pump, actuator and relief valve. The membership grades for a directional control valve and a reservoir are assumed to be the same as the relief valve for demonstration purposes. The influences of concerned are:

- Structure
- System Pressure
- Pump Inlet Pressure
- Fluid Contaminant
- Fluid Viscosity
- Fluid Temperature

Table 3: The Fuzzy Symptom Matrix

Symptoms	Units	Fuzzy Rating				
		Very Low	Low	Normal	High	Very High
System Pressure	% P_o	.75 -25%	.25 -10%	0 P_o	.25 +10%	.75 +25%
Pump Inlet Pressure	cm. H_g	1.0 35-75	.50 15-35	0 0-15	0 atm	0 atm
Actuator Motion	% V_o	.75 -15%	.25 -5%	0 V_o	.25 5%	.75 15%
Fluid Contaminant	#/ml >10μm	0 1	0 10	0 50	0.50 150	1.0 500
Fluid Viscosity	% μ_o	1.0 -100%	0.50 -50%	0 μ_o	0.50 50%	1.0 100%
Fluid Temperature	%T_o	1.0 -5%	0.25 -2%	0 T_o	0.25 +2%	1.0 +5%

Table 4: The Resultant Symptom Matrix

Symptoms	Units	Normal Condition	Fuzzy Rating		
			Initial	500 hrs.	1000 hrs.
System Pressure	bar	70.00	0.0	0.0	0.0
Pump Inlet Pressure	cm H_g	15	0.1	0.1	0.1
Actuator Motion	cm/sec	5	0.0	0.25	0.75
Fluid Contaminant	#/ml > 10 μm	500	0.0	0.10	0.60
Fluid Viscosity	cSt	10	0.0	0.10	0.15
Fluid Temperature	°C	65	0	0	0

Note that the quality of the structure of the component depends on the workmanship, and it can only be expressed verbally. It is assumed that a good structure has a value of 0 while a poor structure has a value of 0.5, namely, a poor structure has a higher tendency correlating to pump failure than a good one. It is also noted that the Omega value is used to represent the contaminant sensitivity of a component per NFPA-RST-3.9.18-1976 and Beta Ten filtration model. A component that has an Omega of 2 means it requires a Beta 10 of 2 filter to protect the pump for 1000 hours service life if the external ingression rate is 10^8 particles greater than 10 micrometers per minute. The higher the Omega value, the more sensitive the component is to the contaminant wear.

Table 5: The Influence to Component Abnormality Matrix

Components	Influences	Units	Fuzzy Rating				
			Very Low	Low	Normal	High	Very High
Pump	Structure	Verbal	1.0 bad	0.5 poor	0.25 fair	0 good	0 excellent
	System Pressure	% P_o	0.75 -20%	0.25 -10%	0 P_o	0.25 +10%	0.75 +25%
	Inlet Pressure	cm H_g	1.0 35-70	0.5 15-35	0 0-15	0 atm	0 atm
	Fluid Contaminant	Omega	0 1-1.01	0.01 1.01-1.1	0.1 1.1-2	0.5 2-10	1.0 10-100
	Fluid Viscosity	%μ_o	1.0 -100%	0.5 -50%	0 μ_o	0.5 +50%	1.0 100%
	Fluid Temperature	% T_o	1.0 -5%	0.25 -2%	0 T_o	0.25 2%	1.0 5%
Actuator	Structure	Verbal	1.0 bad	0.5 poor	0.25 fair	0 good	0 excellent
	System Pressure	% P_o	0.75 -20%	0.25 -10%	0 P_o	0.25 +10%	0.25 +25%
	Inlet Pressure	cm H_g	0.25 35-70	0.05 15-35	0 0-15	0 atm	0 atm
	Fluid Contaminant	Omega	0 1-1.01	0.01 1.01-1.1	0.1 1.1-2	0.5 2-10	1.0 10-100
	Fluid Viscosity	%μ_o	1.0 -100%	0.5 -50%	0 μ_o	0.5 +50%	1.0 100%
	Fluid Temperature	% T_o	1.0 -5%	0.25 -2%	0 T_o	0.25 2%	1.0 5%
Relief Valve	Structure	Verbal	1.0 bad	0.5 poor	0.25 fair	0 good	0 excellent
	System Pressure	% P_o	1.0 -20%	0.5 -10%	0 P_o	0.5 +10%	1.0 +20%
	Inlet Pressure	cm H_g	0.50 35-70	0.25 15-35	0 0-15	0 atm	0 atm
	Fluid Contaminant	Omega	0 1-1.01	0.01 1.01-1.1	0.1 1.1-2	0.5 2-10	1.0 10-100
	Fluid Viscosity	%μ_o	1.0 -100%	0.5 -50%	0 μ_o	0.5 +50%	1.0 100%
	Fluid Temperature	% T_o	1.0 -5%	0.25 -2%	0 T_o	0.25 2%	1.0 5%

Constructing the Fuzzy Diagnosis Matrix (FDM) requires information regarding component structure and its Omega value. Again, for demonstration purposes, it is assumed that all components have a 'good' structure while the relief valve which has only a 'fair' structure. The Omega values are 8, 2, 2, and 4 for pump, relief valve, directional control valve and actuator respectively. With these assumptions and Table 5, the resultant fuzzy diagnosis matrix is obtained and shown in Table 6. Then, by summing all the membership grade values of each row and write them in the right column. The resultant totals will indicate the degree of criticality of component towards failure. Similarly, by summing all the membership grade values of each column to the bottom row, the degree of criticality of component's failure is identified. From Table 6, we can conclude that the critical component most likely to induce a very low actuator motion (see Table 4) is the pump (a value of 0.68) and the critical influence is the contamination effect (a value of 0.81).

Table 6: The Resultant Fuzzy Diagnosis Matrix

Component	Structure	System Pressure	Inlet Pressure	Fluid Contaminant	Fluid Viscosity	Fluid Temperature	Sum of Raw Fuzzy Values
Pump	0	0	0.1	0.48	0.1	0	0.68
Relief Valve	0.25	0	0.05	0.10	0.1	0	0.50
D.C. Valve	0	0	0.0	0.10	0.1	0	0.20
Actuator	0	0	0.01	0.23	0.1	0	0.34
Reservoir	0	0	0.0	0.0	0.1	0	0.10
Sum of Column Fuzzy Values	0.25	0	0.16	0.81	0.5	0	

The fuzzy manipulation for both condition prognosis and condition response is similar to the diagnosis just described except the final objective is to determine the residual life of the critical component and the response to remedy or avoid failure. The relational matrix of component residual life can be obtained from expert's opinion or from implicit analytical method. For example, in the example shown in this paper, the critical condition is contaminant induced pump wear. The residual life can be obtained by finding the difference between the predicted pump service life and the amount of operation already obtained. Fig. 6 [6] illustrates a nomography which is commonly used in the field to predict pump service life in terms of the pump Omega value and its fluid contamination level. These two parameters are measurable. Note that there is no definite equation available to calculate the pump service life. The data shown in Fig. 6 is obtained from critical test data and from expert judgement. According to Fig. 6, a Fuzzy Prognosis Matrix (FPM) for a pump can be formulated and shown as in Table 7. For instance, one of the symptoms identified (Table 2) is high fluid contamination level (220 particles per milliliter greater than 10 micrometers), and the pump Omega value is 8, which is also high. Hence, from Table 7, it can be found that the expected service life is normal. By fitting the nomograph with an

Figure 6. Pump life versus contamination level of fluid.

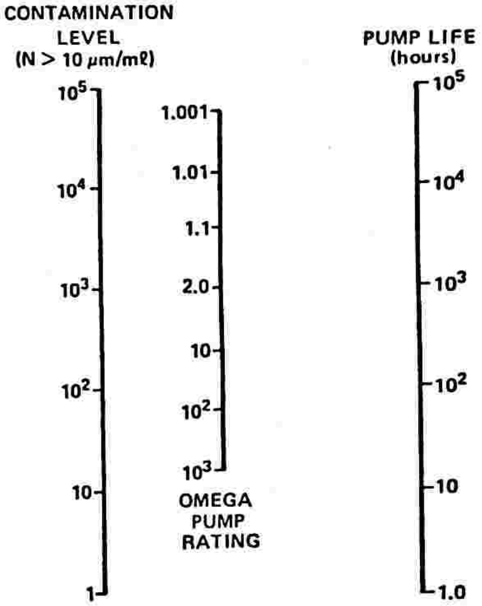


Table 7: A Fuzzy Prognosis Matrix

Pump Omega Rating	Fluid Contamination Level (#/ml > 10μm)				
	VL (1-10)	L (10-50)	N (50-150)	H (150-500)	VH
VL (1-1.01)	VLG*	VLG	VLG	VLG	LG
L (1.01-1.1)	VLG	LG	LG	LG	N
N ((1.1-2)	VLG	LG	LG	N	ST
H (2-10)	VLG	LG	N	N	ST
VH (10-100)	LG	N	N	ST	VST

Note:

1. * indicates the approximate service life.
VLG: Very Long (10^5 hours); LG: Long (10^4); N: Normal; (10^3); ST: Short (10^2); VST: Very Short (10)

2. VL: Very Low; L: Low; N: Normal; H: High; VH: Very High

appropriate membership function, then by the fuzzy calculation, the pump service life is approximately 1100 hours. Thus, the residual life is 100 hours (1100 minus 1000 hours already used). It may also require that the sum of the values of the probability distribution be one. No such limitation for possibilistic distribution is needed.

The response can be machine executed or human executed or both. In this example, in order to maintain a satisfactory actuator velocity, the speed of the pump (critical component) should be adjusted (machine executed) to provide adequate flow rate to the actuator. However, because the critical influence is contamination, to maintain pump service life, the contaminant must be removed from the fluid; so the condition response might be to commission the system filter to be improved or replaced (human executed).

Fig. 7 [6] shows a nomograph designed per expert experience. Similar to the process of prognosis, Table 8 is a Fuzzy Response matrix (FRM) to aid in the selection of a

Figure 7. Pump life versus system filtration ratio.

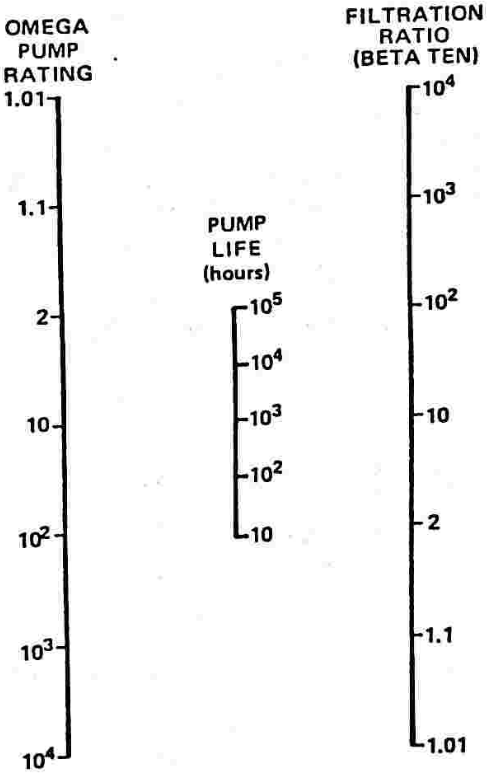


Table 8: A Fuzzy Response Matrix

Pump Omega Rating	Filtration Ratio (Beta Ten)				
	VL (1-1.01)	L (1.01-1.1)	N (1.1-2)	H (2-10)	VH (10-100)
VL (1-101)	N*	LG	VLG	VLG	VLG
L (1.01-1.1)	ST	N	LG	VLG	VLG
N (1.1-2)	VST	VST	N	LG	VLG
H (2-10)	VST	VST	ST	N	LG
VH (10-100)	VST	VST	VST	ST	N

Note:

1. * Indicates the approximate service life
VLG: Very Long (10^5 hours); LG: Long (10^4); N: Normal (10^3); ST: Short (10^2); VST: Very Short (10)
2. VL: Very Low; L: Low; N: Normal; H: High; VH: Very High

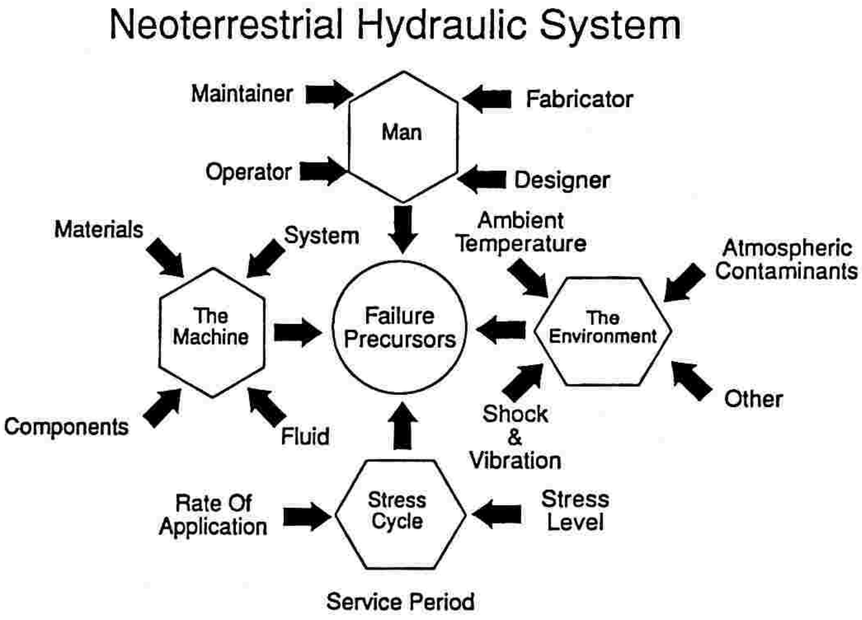
filter to properly protect the pump such that the desired service life can be guaranteed. the filtration ration (Beta Ten) of a filter can be obtained in the laboratory (ISO 4572).

Suppose that it is desired to have a pump service life of 1500 hours which implies that the predicted pump residual life of 100 hours (per prognosis) should be extended to 500 hours. From Table 8, it is found that for a pump having an Omega value of 8 (high) and if it is desired to operate for 1500 hours (long service life) requires a filter having a very high filtration ratio to protect it. From the fuzzy calculation, the filter required should have a Beta 10 of 15 or higher to meet the service requirement.

2.3 'Adaptive' Knowledge-Based Condition Control

Today's hydraulic systems are neoterrestrial inasmuch as they are modern, man-made 'imperfect' machines (see Fig. 8). While this fact, in one sense, is mundane, in another sense it points to the essence, if not the key, to the successful application of knowledge-based expert system for condition control.

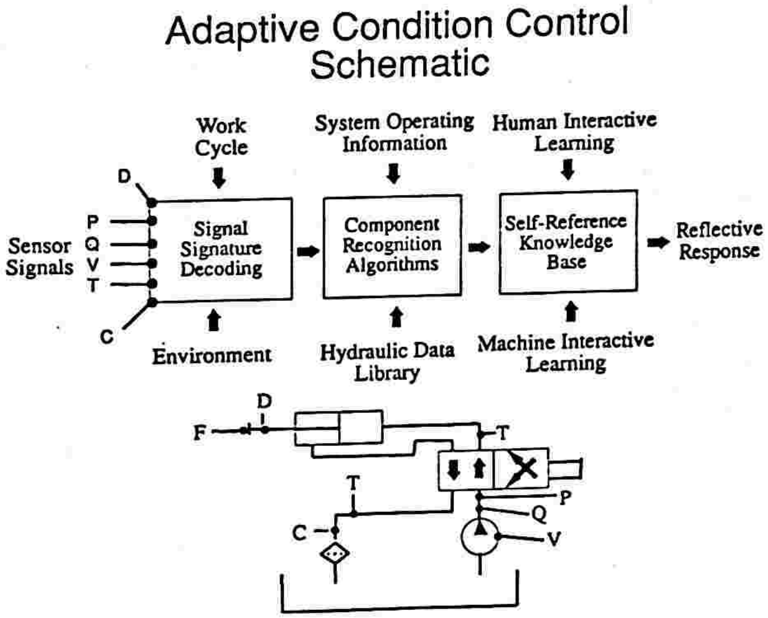
Figure 8. Neoterrestrial hydraulic system.



In order for an expert system to succeed in a neoterrestrial domain, it must be 'adaptive.' Restated, it must have the capacity to learn its system domain and environment and adapt to it. Without adaptivity, expert condition control would clearly fail in the face of the shear magnitude of the number of system types, applications, and environments.

Adaptive means establishing a self reference knowledge base, exhibiting reflexivity as things change, and alerting the human-interface to the need of critical information otherwise unavailable through machine-learning channels. Using signal signature deciphering, an adaptive system will orient itself to the presence and location of system components such as pumps, motors, valves, cylinders, and filters. See Fig. 9.

Figure 9. Adaptive condition control schematic.



3.0 SUMMARY

The concept of condition control has been defined as the interactive processes of condition monitoring, condition analysis, and condition response. The use of a knowledge-based expert system employing fuzzy logic is proposed as a means to achieve real-time condition control of a hydraulic system. Four specific categories of condition responses are defined to both avoid and remedy fault conditions.

It is proposed that the expert condition controller interface the system controller to gain several synergistic benefits. Also essential is the ability of the system controller to be adaptive and establish a self-reference knowledge base.

In conclusion, the authors feel that knowledge-based expert condition controllers represent an inevitable direction of hydraulic system design technology. It is further believed that condition control and system control should be linked to insure 'on-condition' responses to system anomalies.

4.0 REFERENCES

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