Automatic "A Sample" Acknowledgement

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Abstract

This project develops a decision-support tool to identify whether an oil sample is at an acceptable quality. An acceptable oil sample, known as an "A sample", contains no contamination and has experienced relatively low deterioration. Oil samples are sent to WesTrac from companies who utilise their Caterpillar equipment. They process over 400,000 oil samples per year. These samples are tested using a number of techniques and the results assessed by fluid analysts (or Interpreters). The implementation of the decision-support tool and the associated software will help to screen the "A samples" out of the manual analysis, thus reducing the number of samples that the Interpreters have to analyse. This will allow them to focus on the low quality oils (B, C and X samples) requiring higher-order analysis. This paper presents a mapping of the decision making process, the training method and the results of this training. The support tool was applied to five oil compartments and analysed approximately 90% of the "A samples" correctly for each one.

1. Introduction

WesTrac is one of the largest Caterpillar equipment dealers in the world by sales volume. In conjunction with equipment sales and service, WesTrac also has business units responsible for quality assurance, contamination control and equipment management. Their Perth based facility is responsible for oil testing and analysis for all Caterpillar equipment in Western Australia, New South Wales, Australian Capital Territory and northern China. This oil lab processes over 400,000 samples a year (30,000+ per month); -and this number is increasing. There are currently seven Interpreters employed at WesTrac's WA office, which means that each Interpreter has to analyse 50,000+ samples annually.

The current interpretation utilises a set of rules and experience to identify the oil sample's suitability for component use. The data comes from a series of tests with the results represented as numerical values of each parameter. Examination of the element history of each compartment for a particular component allow for trends to be formed by correlating the number of fluid hours the oil has been used for, with the element levels that correspond to each fluid hour reading. Elements are ranked as either A, B, C or X samples, in order of decreasing oil quality based on their PPM value and corresponding oil hour value. The fluid analysts can also include an information (**i**) button to alert the customer that they have supplied incorrect oil information (eg. Oil type/grade, fluid hours etc.)

- **A Sample:** The oil is of an acceptable quality and the customer should continue to use this compartment, as well as continuing to take samples at consistent intervals
- **B Sample:** There is a minor problem with the component. The customer should be cautious and continue to monitor the component, taking samples at regular intervals.

- **C Sample:** There is a significant problem with the component. The vehicle needs to be repaired or serviced as soon as possible, as well as taking samples at shorter intervals.
- **X Sample:** There is a serious problem with the component. The customer needs to stop operating the vehicle immediately otherwise failure will occur. The vehicle should be repaired and serviced ASAP. Another oil sample should be taken soon after the repair to determine whether the problem has been corrected.

Approximately 30-40% of the tested samples are 'A samples'.

The Interpreters use WesTrac's automated interpretation system, *Oil Commander,* to assist them with their diagnosis. This system alerts the Interpreters if oil samples contain any parameters which exceed their allowable PPM limit. For example; if the iron levels exceed 20 parts per million for an engine oil sample, *Oil Commander* will mark the sample as sub-par.

A limitation of this system is that it does not take into account how an oil characteristic is 'trending'. This means that for a particular vehicle, an iron level of around 30 PPM could be its regular concentration which would indicate that the oil sample is satisfactory; however the system will flag it as unsatisfactory.

2. Neural Networks

For the modelling approach, two potential options were considered in this project; neural networks and fuzzy logic. Both these options could be used to generate accurate results for this project, however Neural Networks were settled on as they have been applied for many situations in the past. The following literature review provides evidence as to why Neural Networks were chosen for the development of this decision-support tool.

Artificial neural networks are models whose primary function is to simulate intelligent behaviour by copying the process by which biological neurons in the human body work. They originate from artificial intelligence (AI) research but differ in the way that they act to imitate the "how they work" of biology rather than AI's method of copying the "why do they work" (Livingstone, 2008). This intelligent mode of operation enables the use of a neural network model in this case as the project aims to simulate oil analysis the way the fluid analysts do.

A number of studies have been conducted which base themselves around using neural networks to analyse real world situations and/or problems. A study conducted by Jalali-Heravi (2008) utilised neural networks to predict the activities of a series of aromatic sulphides based on previously accumulated data. A decision support tool was constructed also in 2008 by Larder, Wang and Revell which would help guide doctors in providing future therapy to a patient based on the mutational patterns of the HIV virus. Both these studies (among others) provide significant evidence that neural networks can be used specifically for the purpose of this project. As it is concerned at constructing a decision support tool to predict oil grades based on past data, these studies can be used as a basis for constructing the model in the neural network software.

3. Modelling Process

The complete modelling process is described below:

1. Identification of the problem: what are the limitations of the current oil analysis system in place at WesTrac, why do we need to overcome these limitations and what results can be expected from this project?
2. Obtaining background knowledge: Research possible ways to overcome these limitations and chose an appropriate solution.
3. Data selection: Extract and analyse data sets from Oil Commander to identify existing trends and relevant input parameters.
4. Modelling process: Import the data into the modelling software and train the network. Training requires the user to manually set the operational parameters of the network in order to optimise the accuracy of the results. Figure 1 illustrates the modelling process using the *NeuroShell Classifier* software program.
5. Results: Analyse the output results from the software. Determine whether the results are acceptable or not and alter the program's settings to increase accuracy.

This project used a neural network software package, *NeuroShell Classifier,* to train oil data sets taken from wheel bearing compartments. It utilises a Back Propagation Neural Network to train the data and produce results. Wheel bearing data from various Off-Highway Trucks was exported from Oil Commander into the *NeuroShell* program. Once this data was imported, the following procedure (shown in figure 1) was used to train the neural network.

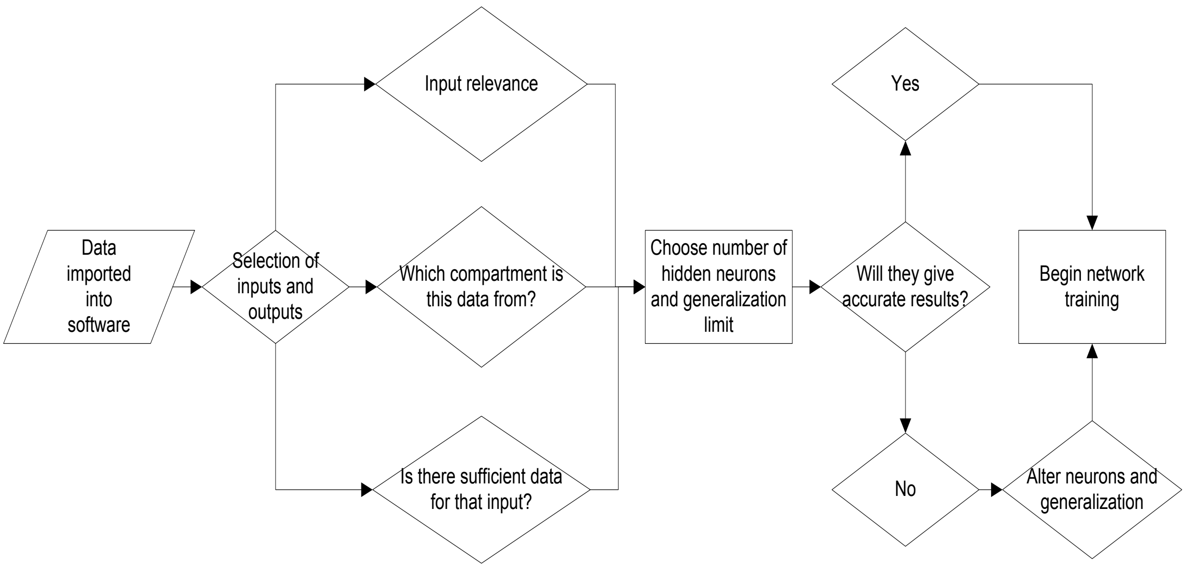

Figure 1: Summary of a neural network modelling process.

Figure 1 illustrates the process of the actual modelling utilising the neural network software.

4. Results and Discussion

Before any modelling results could be obtained, the oil analysis procedure that the analysts use was mapped out. By determining this procedure, inputs from each of the data sets could be determined based on their relevance in producing a final oil evaluation grade.

As stated in section 2, the function of a neural network is to evaluate data in an identical fashion to how a human mind would. Multiple results were taken from one data set to illustrate the increasing accuracy of the network and to also demonstrate the relevance of each input parameter. For the wheel bearing data set, a total of 892 samples were used to create the model, consisting of; 714 training and 178 validating samples. Every time the program trains a network, it changes the samples used in its training and validating ranges. This means that the accuracy of the network is applicable for all 892 samples, rather than the same 178 validating samples.

Table 1 displays the changing accuracy of each model as the number of inputs is increased. The '**Actually are "A samples"**' column are the amount of actual acceptable samples that were also classified as acceptable samples by the network.

Table 1: Progressive accuracy of the neural network software

No. of inputs	Classified as "A samples"	Actually are "A samples"	% Accuracy
3	83	71	85.5
4	80	70	87.5
5	81	71	87.7
6	82	71	86.6
7	74	66	89.2
8	77	68	88.3
9	70	64	91.4
10	72	63	87.5
11	73	63	86.3

(Note: this model was trained using 80 hidden nodes and 50% generalisation.)

Initially starting with 3 inputs (Iron levels, number of oil hours and viscosity) the model was trained and validated to determine the accuracy of the model. As the number of inputs increased, the accuracy of the model exhibited a rising trend. The following nine inputs displayed the highest degree of accuracy: oil hours, iron, viscosity, PQ index, silicon, copper, ISO6, ISO14 and oxidation level. Once nitration and sulfation limits were introduced in the inputs, the accuracy of the model declined. This could mean that these inputs have a larger range of values which would influence the final oil evaluation grade.

Table 2 summarises the training criteria, optimum inputs and accuracy of the network in analysing the other compartments.

Table 2: Summary of different oil compartments

Compartment	Opt. No. of Inputs	Training Samples	Validating Samples	Classified as "A"	Actual "A"	Accuracy %
Wheel Bearings	9	714	178	70	64	91.4
Final Drives	8	725	181	167	149	89.2
Hydraulic Systems	13	734	183	144	128	88.9
Transmission Systems	12	728	182	148	141	95.3
Steering Systems	10	716	179	118	104	88.1

NeuroShell Classifier uses probability values to classify a data sample. For this project, the program determines the probability of a sample being an "A sample". As an example, let's say an "A sample" has the following probabilities:

- P(A) = 0.4
- P(Not A) = 0.6

The program analyses the sample and sees that it contains characteristics for which the oil could be a classified as either an "A sample" or not. Even though the oil had been evaluated as an A sample by the Interpreters, the program determines that it is in fact a "Not A" sample and gives it that classification. Each analyst has different methods of evaluating samples and will sometimes produce differing evaluation grades for the same sample. The software program can be thought of as another analyst and will also sometimes provide conflicting results with what the analyst gave it.

Multiple attempts were made to increase the accuracy of the model; however they had a mostly negative effect on the system. One method that was trialled was to increase the number of hidden nodes used to train the model. The program can generate a maximum of 150 hidden nodes for training. When a network containing 8 inputs was trained using 150 hidden nodes, there was a 1% increase in accuracy in the "A sample" analysis, but when 9 inputs were used the model showed a 6% drop.

NeuroShell Classifier contains two strategies of network training. The results illustrated by table 1 were generated from the "Neural" training strategy. This strategy operates by generating a layer of hidden nodes to increase the accuracy of the network. Each of these hidden nodes is attached to a certain "Weight". These weights are used by the software to determine the importance of each input and the relationship between the inputs and outputs. As the network trains, the weighting of each node is altered over and over to produce increasingly accurate results. The program allows for the generation of up to 150 nodes in the hidden layer before the training is complete. The "Genetic" strategy functions in a similar manner to its counterpart, but instead of generating nodes until the node limit is reached, this strategy focuses on creating "groups" of solutions to the optimisation problem. It works by ranking the inputs by relative importance with respect to the desired output. Once ranked, these inputs are then "bred" with each other (even cutting out the less important inputs altogether) until a suitable outcome is reached. It is quite similar to the way natural selection works to overcome mutations. Figure 2 compares the accuracy of the model using the "Neural" and "Genetic" training strategy (using 9 inputs at 50% generalisation).

	Actual "A"	Actual "Not A"	Total	Positive Predictive Value
Classified as "A"	64	6	70	91.43%
Classified as "Not A"	15	93	108	86.11%
Total	79	99	178	

	Actual "A"	Actual "Not A"	Total	Positive Predictive Value
Classified as "A"	72	9	81	88.89%
Classified as "Not A"	7	90	97	92.78%
Total	79	99	178	

Figure 2: Comparison between Neural (left) and Genetic (right) training strategies.

Genetic training strategies are usually applied when the amount of data relative to the number of inputs are quite large. They require more time to learn a network but generalise the data better than the Neural training strategy. For this project, the Neural training strategy is used due to the small amounts of available data for each compartment.

5. Conclusions and Future Work

The results discussed in section 4 demonstrate that neural network models can be sufficiently utilised to classify oil samples. By correctly identifying the most significant inputs, appropriate training strategies and relevant data, a sufficient model can be constructed which can classify oil samples to 90% accuracy. Even though 100% accuracy is most desirable, if 9 out of 10 samples are correctly identified as "A samples" that leaves the Interpreters only 1 out of 10 "A samples" that will require further investigation.

Once modelling with *NeuroShell* has been completed, the project can be further developed by implementing neural networks with WesTrac's coolant analysis. This coolant analysis still relies on Oil Commander which will enable it to be easily adapted from the oil analysis. A user manual will also be constructed so that any WesTrac personnel can use *NeuroShell* for future projects.

6. Acknowledgements

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