CLASSIFICATION OF MACHINE OPERATIONS BASED ON GROWING NEURAL MODELS AND FUZZY DECISION

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ABSTRACT

In this paper, a novel approach to analysis and classification of complex machine operations is presented. The available data sets from different machine operations are first compressed and saved in the form of neural models that are called compressed information models (CIM). Here an original algorithm for unsupervised learning is proposed. It creates the so called growing neural models in a sense that the number of neurons is gradually increasing (growing) during the learning process, until predetermined model accuracy (the "average minimum distance") is satisfied. The proposed algorithm has much faster convergence compared with the classical neural-gas learning that uses preliminary fixed number of neurons.

A special Knowledge Base classification scheme is also proposed in the paper. It uses a fuzzy decision block for computing the difference degree between each CIM in the Knowledge Base with the CIM of the current machine operation. The fuzzy inference procedure uses two parameters for comparison the CIMs, namely the decision the Center-of-Gravity and the General Size of the CIM.

An example for classification of 45 specially generated operations from a diesel engine of a hydraulic excavator is used to demonstrate the whole proposed technology and its applicability. This fuzzy classification scheme is also able to discover new operations that significantly differ from all previously known operations.

INTRODUCTION

Many industrial systems and complex machines, such as chemical and power plants, hydraulic excavators and other construction machines often work under different operating conditions, depending on the load, raw material characteristics, ambient temperature etc. Basically, such machines and systems are equipped with different sensors that are used for data acquisition in order to provide information about the daily operation of the system. This information is obtained in the form of large "raw data sets" which are further used for different types of *off-line* analysis, such as performance evaluation, classification and fault diagnosis, in order to detect possible deterioration trends or malfunctions and make respective decisions.

The example, shown in the following Fig. 1. is from different operating conditions of the turbo diesel engine of a hydraulic excavator. It is easy to notice that each operation form a kind of "cloud" in the parameter space with specific shape and location in the space.

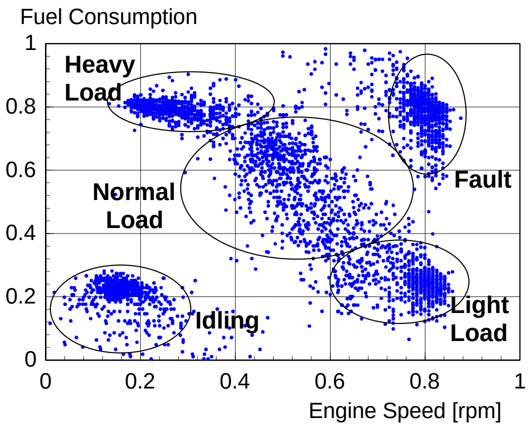

Figure 1: Example of Five Diffeent Operations of a Turbo Diesel Engine

However if many operation data are collected over a long period of time (many days or months of operation) it is not easy task even for an experienced operator to analyse and classify them into a number of predefined groups of typical operations or as "new" or even "strange" (possibly abnormal or faulty) operations. The complexity of the problem arises from the fact that we have to analyse, compare and classify huge data sets to each other rather than classify single patterns (single data points in the feature space), as in the standard classification problem (Bishop, 1995; Bezdek et al. 2005). In the sequel of this paper we explain a novel approach to classification of large data sets. It is based on a preliminary information compression by use of special unsupervised learning algorithm for neural models, combined with fuzzy decision procedure for computing the difference degree between the neural models.

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INFORMATION COMPRESSION BY USE OF NEURAL MODELS

When a large number of “raw” data are collected for each machine operation, it is a good idea to initially preprocess by converting the raw data set into a more compact form, further called *compressed information model* (CIM). However such *information compression* procedure should be done carefully so that to preserve as much as possible the original data structure and the local density distribution of the data in the high dimensional parameter space.

The learning methods for information compression generally belong to the group of the competitive unsupervised learning methods and algorithms (Bishop, 1995; Kohonen, 2001; Martinetz et al. 1993; Kasabov, 2001; Fritzke, 1994). Widely used are the Self-Organized (*Kohonen*) Maps (Kohonen, 2001) and the Neural Gas Algorithm (Martinetz et al. 1993; Fritzke, 1994). Because of their unsupervised nature, these methods are pure “data-driven” learning techniques, which try to locate the neurons from the neural model in the densest area of the input space.

As a result of the unsupervised learning, the large amount of *M* data is replaced by much smaller number of *N* neurons (*N* << *M*) in the same parameter space.

An example for such information compression of a raw data set consisting of *800* two-dimensional data (*M = 800*; *K = 2*), into a neural model with *N = 32* neurons is shown in Figure by using the newly proposed growing Neural Gas algorithm. This algorithm is explained in the next section.of the paper.

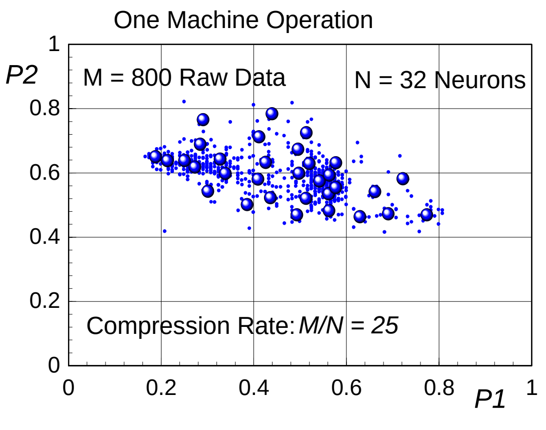


Figure 2: Illustration of Data Compression by Unsupervised Learned Neural Model with *32* Neurons

The trained neural model is further used as a compressed information model (CIM) of the original raw data set. In order to compare two CIMs and find the *similarity degree* (or the *difference degree*) between them (i.e. between the respective raw data sets), we introduce here the following two parameters: 1) the weighted *center-of-gravity* COG and 2) the *average size* AS of the CIM.

1) The weighted *center-of-gravity* COG is a point in the *K*-dimensional space, computed in the following way:

$$COG(j) = \sum_{i=1}^{N} C_{ij} g_i \Big/ \sum_{i=1}^{N} g_i\,,\ j=1,2,...,K \qquad (1)$$

Here $C_{ij}, j=1,2,...,K$ denotes the *center* of the *i*-th neuron in the *K*-dimensional parameter space and $0 < g_i \le 1,\ i=1,2,...,N$ are the *normalized weights* of the neurons, computed as:

$$g_i = m_i / M\,;\ i=1,2,...,N \qquad (2)$$

where $m_i \le M,\ i=1,2,...,N$ is the number of all data points, $\mathbf{x}_s, s=1,2,...,m_i$ for which the *i*-th neuron is a *winning neuron* (i.e. the neuron with the shortest *Euclidean* distance to all of these data points). Please, note that $\sum_{i=1}^{N} m_i = M$ and therefore $\sum_{i=1}^{N} g_i = 1$.

2) The *average size* AS is a *K*-dimensional vector $\mathbf{Z} = [z_1, z_2, ..., z_K]$ with each element computed as double “average distance” between all the neurons *N* and the COG of the model, for each dimension, i.e.

$$z_j = \frac{2}{N}\sum_{i=1}^{N}\left|C_{ij} - COG(j)\right|,\ j=1,...,K \qquad (3)$$

The physical representation of the awerage size AS in the *2*-dimensional space (*K=2*) is a rectangle with size $z_1 \times z_2$. A more general form of evaluating the size of the CIM is the so called “general size” GS, which is represented by the diagonal of this rectangle. In the K-dimenisonal space its computation is as follows:

$$GS = \sqrt{\sum_{j=1}^{K} z_j^2} \qquad (4)$$

In order to evaluate in some way the “quality” of the neural model, produced by the unsupervised learning, we have introduced (Vachkov, 1996a, 196b) the notion of the “Average Minimal Distance” *AVmin* .It is computetd as a mean of the distances between all *M* data points and their respective “winning neurons” *n**:

$$AVmin = \frac{1}{M}\sum_{i=1}^{M}\sqrt{\sum_{j=1}^{K}\left(C_{n^*j} - x_{ij}\right)^2} \qquad (5)$$

AVmin serves is a convenient *quality measure* of the neural model, since it shows “how well” the model represents the real structure in a sense of *local density distribution* of the data from the original data set. A trained neural model that has small *AVmin* represents in a better way the original (raw data) structure, compared with another model that has bigger *AVmin*. However in order to achieve a higher model accuracy, we need a larger number of neurons *N* and more computation time..

When a standard unsupervised learning is used for creating the neural model, such as the classical Neural Gas algorithm (Martinetz, 1993; Vachkov, 2006), the number *N* of the neurons is fixed (pre-determined) before the learning. Therefore the model accuracy in terms of *AVmin* will be known only after the end of the learning.

THE GROWING UNSUPERVISED LEARNING ALGORITHM

It is obvious that the standard Neural Gas learning algorithm with fixed number of neurons N cannot guarantee an optimal solution to the problem of "true information compression".

In the so called *growing neural model* (GNM), proposed in (Vachkov, 2006b), *AVmin* serves as a feedback for the *current quality status* of the neural model. This feedback is important for the subsequent decision whether to add new neurons or to stop learning.

For each neuron $n, n=1,2,...,N$ a K-dimensional subspace, called *Voronoi Polygon* (Martinetz, 1993; Fritzke, 1994; Vachkov, 2006a, 2006b) can be defined, where n is a *winning neuron* for a certain number of data from the whole data set.

The *growing-type* of the Neural Gas learning algorithm presented here, performs a sequence of *learning epochs*, during which the "model quality" is gradually improved, by adding constant number of neurons (usually only one) at each epoch, until the predefined quality *AVmin* is reached.

According to the general concept of the algorithm, the *local quality* of the neural model in each *Voronoi* polygon $n, n=1,2,...,N$ of the current model is evaluated by computing the so called *Mean Distance* MD_n between the n-th "winning neuron" and all m_n data points in this polygon, as follows:

$$MD_n = \frac{1}{m_n}\sum_{i=1}^{m_n}\sqrt{\sum_{j=1}^{K}\left(C_{nj}-x_{ij}\right)^2} \qquad (6)$$

This distance gives useful information about "how good" is the neural model in this particular area of the space. Then the *Deviation* between the *desired* Average Minimal Distance *AVmin0* and the *computed* Mean Distance (6) for each polygon in the following way:

$$DEV_n = \begin{cases} MD_n - AVmin0, \text{ if } MD_n > AVmin0; \\ 0, \text{ otherwise}; \qquad n=1,2,...,N \end{cases} \qquad (7)$$

The *Voronoi* polygon with the biggest deviation $DEV_{\max}$ will be the first (most urgent) candidate for correction, by receiving (at keast) one additional neuron.

The main computation steps of the Growing-type Learning Algorithm are given below.

The algorithm starts with a small initial number N_o of neurons: $N = N_o \geq 2$.

Step 1. Perform the standard *fixed-type* neural-gas learning algorithm as in (Vachkov, 1996a) by using the complete set of all M data. As a result, the centers of all N neurons in the K-dimensional space $[C_{i1}, C_{i2},...,C_{iK}]$, $i=1,2,...,N$ are determined;

Step 2. Analyse the performance of the current neural model with N neurons for the complete set of M data by computing *AVmin* from (5).

Step 3. Check for the stopping condition: **If** $AVmin \leq AVmin0$, **then** the algorithm stops (a satisfactory neural model with N neurons is created); **otherwise** continue to Step 4.

Step 4. Analyse the current model-quality of each *Voronoi* polygon, as follow:

- Compute the *Mean Distances* MD_n, $n=1,2,...,N$ for each neuron by using (6);
- Compute the *Deviations* DEV_n, $n=1,2,...,N$ by (7);
- Sort the deviations DEV_n for all N neurons in a *descending order*, from $DEV_{\max}$ to $DEV_{\min}$.
- Then the following decision is made: "The model quality of the *Voronoi* polygon where the neuron n^* with the highest deviation: $DEV_{\max} = DEV_{n^*}$ is located, should be improved by inserting one or more *additional neurons* in its area." Therefore, define the number $m_{n^*} < M$, as well as the list of all data points in this polygon n^*.

Step 5. Growing Step: insert a small number of neurons $N_{ad} \geq 1$ in the area of polygon n^* for further learning. The initial positions (centers) of these additional neurons are set to coincide with randomly selected data from the same polygon. In the most often cases, *only one* additional neuron is inserted in the polygon n^*, i.e $N_{ad} = 1$.

Step 6. Perform again the *fixed-type unsupervised learning* algorithm as in Step 1, but for the highly reduced case of only $N_{ad} + 1$ neurons and for the subset of only m_{n^*} data points, which are located in this Voronoi polygon n^*.

Note that the old neuron from this polygon is also included in this reduced number of $N_{ad} + 1$ neurons that have to be trained.

Step 7. Update the total number of the neurons for the current neural model: $N \leftarrow N + N_{ad}$ and Go to Step 2.

An illustration of how the proposed growing-type learning algorithm works is given in the following Fig. 3. Here the first two consecutive epochs are only shown, starting with an initial number of $N_o = 2$ neurons and adding one new neuron ($N_{ad} = 1$) at each consecutive Epoch. With a pre-deermined accuracy of *AVmin0 = 0.02*, the growing neural gas algorithm runs *31* epochs in total and finally produces a growing neural model with *N = 32* neurons. This model was already displayed in Fig. 2 from the previous Section.

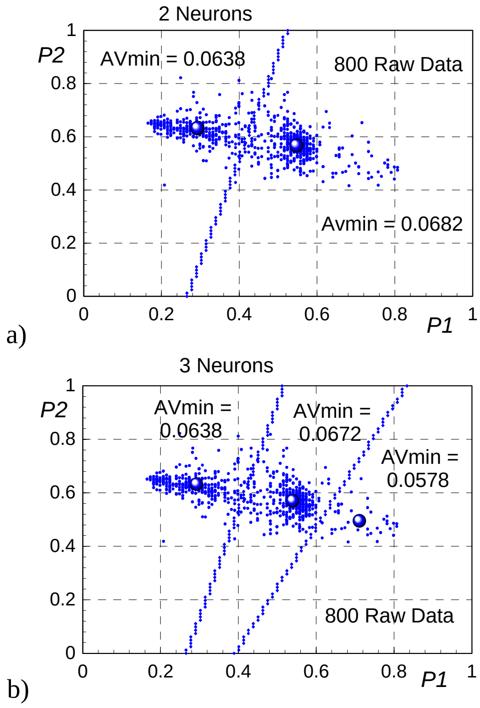


Figure 3:Illustration of the first two Epochs from the Growing Neural Gas Algorithm

The next Fig. 4. shows te convergence of the growing-type neural gas learning algorithm for the same example. As seen, the *AVmin* steadily decreases with the number of neurons (number of Epochs).

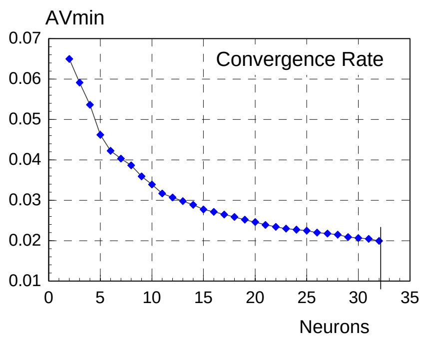


Figure 4: The Convergence Curve of the Growing Neural Gas Algorithm with the Epochs (Neurons)

THE FUZZY DECISION BLOCK FOR CLASSIFICATION OF OPERATIONS

By use of the above learning algorithm, many available data sets from different operations could be compressed as respective CIMs for a consequent comparison, evaluation and classification. Here the fuzzy systems for pattern recognition and classification are quite flexible and therefore widely used for such purpose (Bezdek, 2005).

In this paper we propose a specialized Knowledge based Fuzzy Inference system (called Fuzzy Decision Block) for classification of compressed operations (CIMs). The block diagram of the system is shown in Fig. 5.

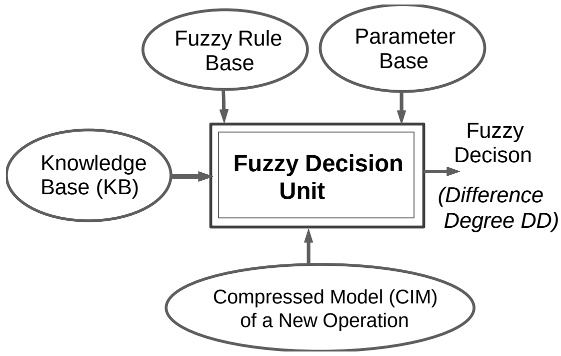


Figure 5: Block Diagram of the Proposed Knowledge based Fuzzy Inference System

Here the Knowledge Base KB consists of a collection of CIMs for *typical* (known) operations of the machine, while the new operation (to be classified) is presented as an additional CIM, as shown in the Figure.

The Fuzzy Rule Base (FR Base) and the Parameter Base in Fig. 5. are necessary elements of the Fuzzy Inference system, which makes a fuzzy evaluation by computing the *Difference Degree* (*DD*) between the CIM from the new operation (denoted as Model *A*) and each of the CIMs from the KB (denoted as Model *B*). We assumed here a *two-dimensional* fuzzy inference procedure: $D = \mathbf{F}(X1, X2)$ which uses the following two parameters, namely the *Center-of-Gravity Distance* (*X1*) and the *Model-Size Difference* (*X2*), as shown below:

$$COGD_{AB} \equiv X1 = \sqrt{\sum_{j=1}^{K}[COG_A(j) - COG_B(j)]^2} \quad (9)$$

$$MSD_{AB} \equiv X2 = \sqrt{\sum_{j=1}^{K}[Z_A(j) - Z_B(j)]^2} \quad (10)$$

The assumed in this paper FR Base is shown in Fig. 6:

Fuzzy Rule Base: $D = \mathbf{F}(X1, X2)$

X2 (Model Size Difference) \ X1 (COG Distance)	VS	SM	MD	BG	VB
VB	DIF	DIF	VDIF	VDIF	VDIF
BG	DIF	DIF	DIF	VDIF	VDIF
MD	SIM	SIM	DIF	DIF	VDIF
SM	VSIM	SIM	SIM	DIF	DIF
VS	EQ	VSIM	SIM	DIF	DIF

Figure 6: The Fuzzy Rule Base for Fuzzy Decision

An example of one concrete Fuzzy Rule is given below:

IF(***X1*** is *SM* AND ***X2*** is *BG*) **THEN *D*** is *DIF* (11)

Here the following *5* linguistic variables were assumed for the input parameters ***X1*** and ***X2***:
VS = Very Small; *SM* = Small; *MD* = Medium; *BG* = Big and *VB* = Very Big.

The consequent ***D*** in the fuzzy rule (11) denotes the fuzzy set for the Degree of Difference *DD* which includes the following *5* linguistic variables:
EQ = Equal; *VSIM* = Very Similar; *SIM* = Similar; *DIF* = Different; *VDIF* = Very Different.
Triangular membership functions for the input parameters *X1* and *X2* were assumed, as shown in Fig. 7.

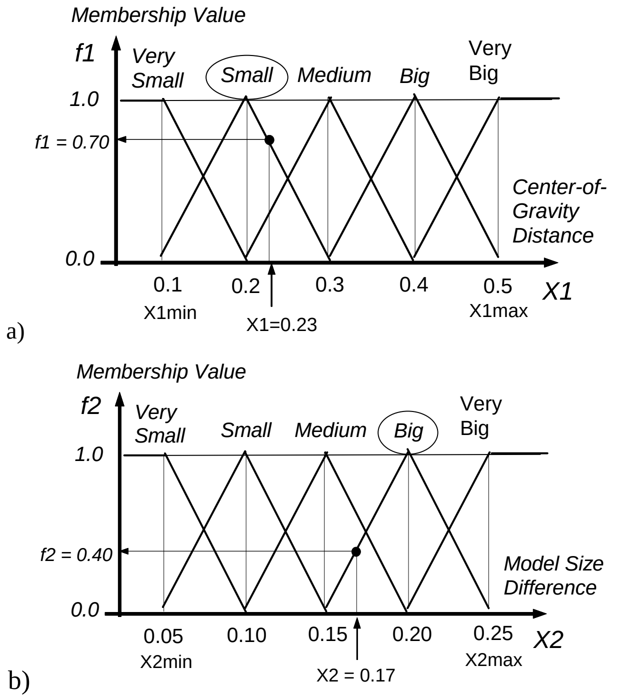


Figure 7: Triangular Membership Functions for the Input Parameters *X1* and *X2* of the Fuzzy Decision

The standard *product-operation* for fuzzy inference, as well as the *weighted average* method for defuzzification were used here for the final computation of the *difference degree* DD.(details omitted).

CLASSIFICATION OF OPERATIONS FROM A TURBO DIESEL ENGINE

In this Section we show how the whole technology, consisting of information compression and fuzzy decision works for classification of various operations of a turbo diesel engine of a hydraulic excavator. For this purpose we use the available data from *4* main operations of the diesel engine under different loads, namely: *Light Load (LL)*, *Normal Load (NL)*, *Heavy Load (HL)* and *Idling*. In addition, data from another (possibly faulty) operation was also used, named as *Fault*. Therefore all these *5* core operations were included in the Knowledge Base of the classification system., according to Fig. 5.

Various operations for classification were produced by slightly moving the original data sets for *LL*, *NL* and *HL* to different locations in the parameter space. We also changed their spread (size) by a special simulation program. Finally, *45* operations in total were obtained, (including the *LL*, *NL* and *HL*), as shown in Fig. 8.

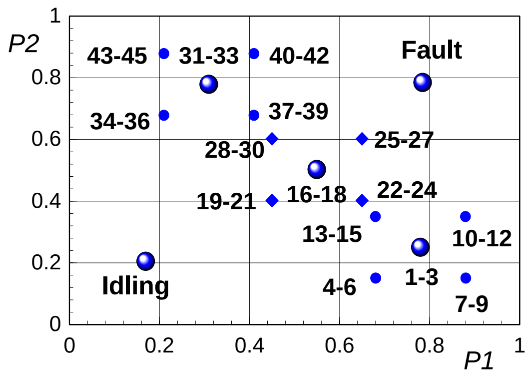
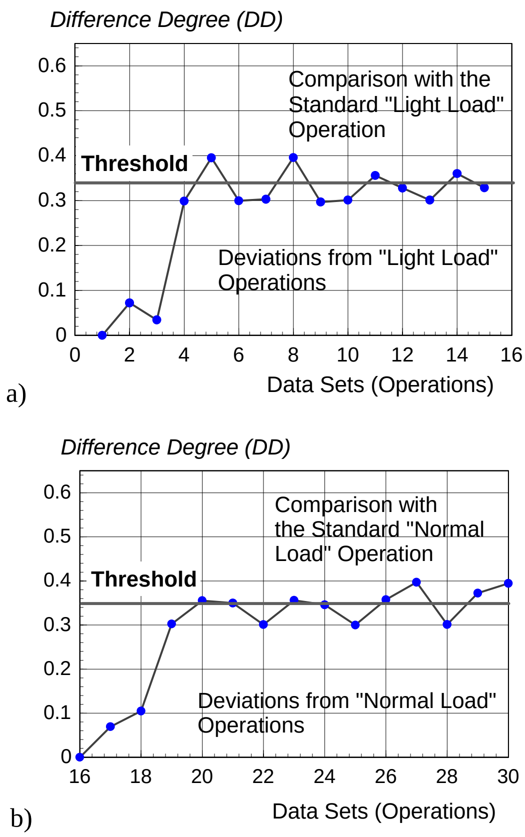


Figure 8: Locations and Numbers of all Operations used for the Classification

Large ball-type curve symbols in Fig. 8. denote the five *core operations* (from the Knowledge Base), while all other *12* curve symbols with smaller size denote the *deviated operations* by simulation. The deviation of the COG for the *LL*, *NL* and *HL* was by amount of $+\alpha$ and $-\alpha$ for *P1* and by $+\beta$ and $-\beta$ for *P2*, with $\alpha = 0.1$ and $\beta = 0.1$. In addition, the general size *GS* of each operation (including the main operations *LL*, *NL* and *HL*) has been changed twice, as follows: a *smaller* size *GS1 = 0.8GS* by *20*% and a *larger* size *GS2 = 1.2GS* by *20*%. The main *3* operations *LL*, *NL* and *HL*, with normal size GS are numbered in Fig. 8. as *1*, *16* and *31*, respectively. .

The results from the classification are shown in the next Fig. 9., separately for the cases of *LL*, *NL* and *HL*.



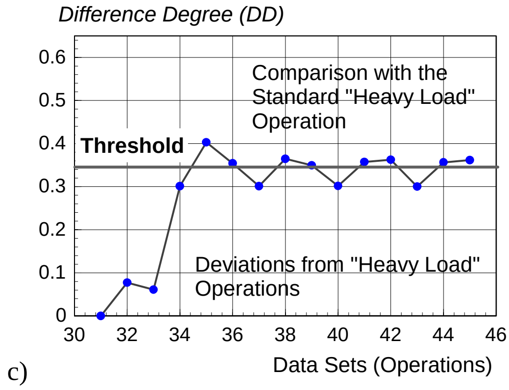


Figure 9: Classification Results for All Operations: a) *Light Load*; b) *Normal Load*; c) *Heavy Load*

A *threshold* of *0.35* was set in this case for classifying the operations in two groups, as follows: *belonging* to the respective main operation (when the *difference degree DD* < *0.35*) or *not belonging* to this operation (if *DD* > *0.35*). We leave the sensitive choice of the threshold to the experience of the human operator.

In Fig. 10. two additional (artificially generated) operations are shown, named as *Op_X* and *Op_Y*. They have unknown status and (as seen) are largely different from the main operations: *LL*, *NL*, *HL*, *Idling* and *Fault*, but may have some similarities with some of them , namely: *Op_X* is somewhere between *HL* and *Idling*; *OP_Y* is somewhere between *LL* and *Fault*.

Our classification system produced the following result: *Op_X* is the closest to *HL* with *DD* = *0.52*, but the assumed threshold of *0.35* "rejects" this decision; Op_Y is the most closest to *LL* with *DD* = *0.66*, but it is also rejected by the given threshold. Therefore, these two operations are finally classified as "new" and quite different operations. They could be included as "new members" of the enlarged Knowledge Base for classification of future operations. Thus the Knowledge Base will gradually grow (as *cumulative experience*).

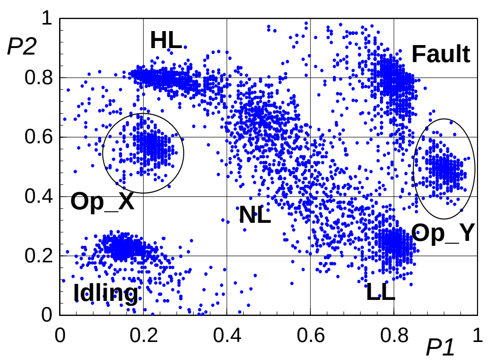


Figure 10:Two Additional (Unknown) Operations

CONCLUSIONS

In this paper we presented a new two-stage approach to classification of large data sets from different machine operations. First of all the data sets are converted into compact neural models (CIMs) by the growing neural gas learning algorithm. Then the CIMs from new operations are compared with those from a preliminary created Knowledge Base of typical operations. The difference degree *DD* between them is computed by a specialized fuzzy decision block.

The future research in this direction is aimed at improving the "plausibility" of the classification by appropriately tuning all the internal parameters.

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