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Fault Classification of a Centrifugal Pump in Normal and Noisy Environment with Artificial Neural Network and Support Vector Machine Enhanced by a Genetic Algorithm

A. Nourmohammadzadeh and S. Hartmann, Department of Informatics, Clausthal University of Technology, Germany

15. Dezember 2015

Introduction

- Condition monitoring of a centrifugal pump is absolutely necessary:
  ✓Because the role of centrifugal pumps is of great importance in many industries.
  ✓To prevent early failure and production line breakdown.
  ✓To improve plant safety, efficiency and reliability.
  ✓Pumps, compressors and piping are causes of the major equipment failure in oil and gas plants.
- Centrifugal pumps are sensitive to:
  (1) Variation in liquid condition (i.e. viscosity, specific gravity, and temperature).
  (2) Suction variation, such as pressure and availability of a continuous volume of fluid.
  (3) Variation in demand.

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- The data of a real centrifugal pump in a petroleum industry located in the south of Iran is used.
- The data consists of 7 columns, flow , temperature, suction pressure, discharge pressure, velocity , vibration and the last column is the fault class related to these features ranged from 1 to 5.

Flow	Temperature	Suction Pressure	Discharge Pressure	Velocity	Vibration	Fault Type
57	96	20	700	3.5	7.67	3
a	b	c	d	e	f	?

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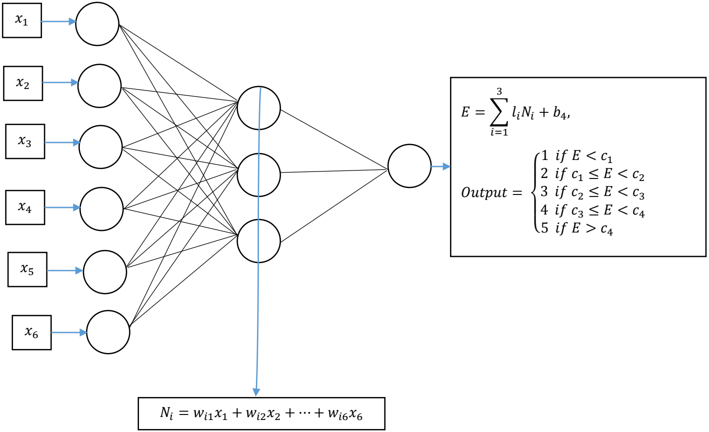
ANN Structure



Parameters

$$W = \begin{vmatrix} w_{1,1} & w_{1,2} & w_{1,3} \\ w_{2,1} & w_{2,2} & w_{2,3} \\ w_{3,1} & w_{3,2} & w_{3,3} \end{vmatrix}$$

$B = [b_1, b_2, b_3, b_4]$, $L = [l_1, l_2, l_3,]$, $C = [c_1, c_2, c_3, c_4]$.

- Choosing the best amounts for the above parameters can improve the classification performance of the ANN.
- Besides the conventional training methods, we apply Genetic Algorithm, which is a powerful evolutionary optimisation algorithm and is able to obtain solution of good qualities in real time.
- The fitness of each chromosome:

  $Fitness\ function = 1 - percentage\ of\ correct\ predicted\ classes = 1 - \frac{N_c}{N_T}$
- Other characteristics: $Population\ size = 200$, $Crossover\ percentage = 0.7$, $Mutation\ percentage = 0.3$, $Maximum\ of\ Iterations = 100$

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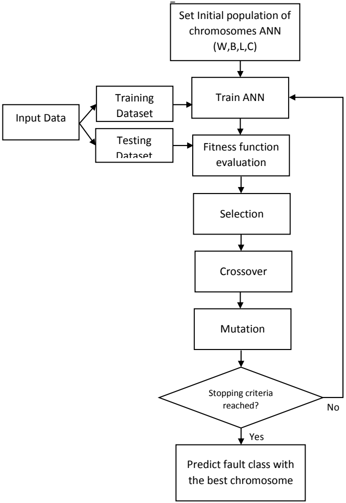

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SVM Structure

In SVM (SVC), we have a set of training input $D = \{(x_1, x_2), ..., (x_i, y_i)\}$, where $x \in R^d$ and $y \in \{-1, 1\}$ is the class label, $i = 1, ..., l$. The method seeks to find a separating hyper plane that maximises the distance to the nearest data points of each class. This goal is met by minimising the following objective function:

$$Max\ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}\varepsilon_i \quad (1)$$

$$Subject\ to\ \ y_i[W^T.\Phi(x_i)] \geq 1 - \varepsilon_i \quad (2)$$

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$$\varepsilon_i \geq 0, i = 1, ..., l$$

Considering necessary condition for optimality, one can turn the above minimization problem into the following dual form:

$$Max \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j K(x_i, x_j) \tag{3}$$

$$Subject\ \ to\ \sum_{i=1}^{l} \alpha_i y_i = 0 \tag{4}$$

$$0 \leq \alpha_i \leq C, i = 1, ..., l$$

Solving the dual problem leads to the optimal separating hyper plane as following:

$$\sum_{SV} \alpha_i y_i K(x_i, x_j) + b = 0 \tag{5}$$

And the optimal classifying rule is:

$$f = sgn(b + \alpha_i [y_i K(x_i, x_j)]) \tag{6}$$

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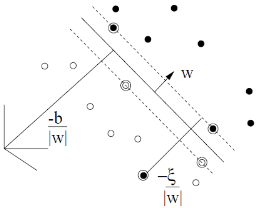

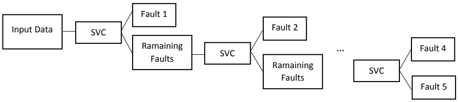

$$Polynomial : K(x_i, x_j) = (\gamma. < x_i, x_j > +s)^d \tag{7}$$

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$$Linear : K(x_i, x_j) =< x_i, x_j > \tag{9}$$

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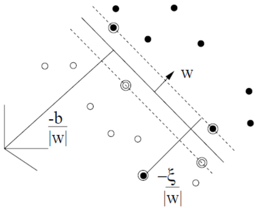

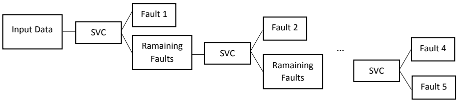

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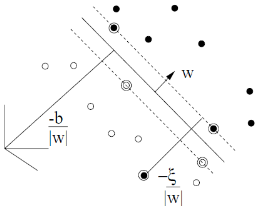

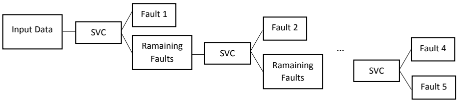

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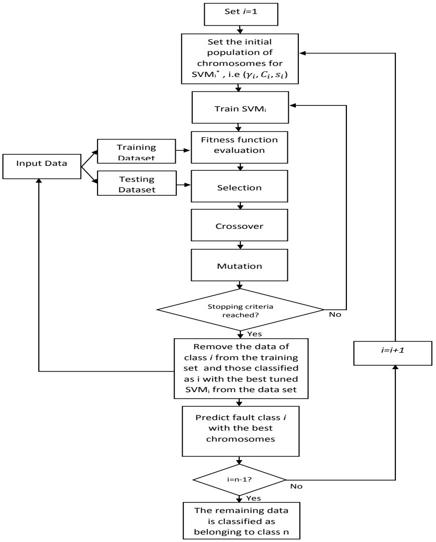
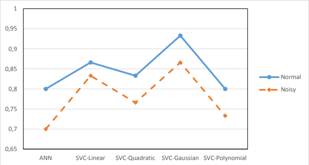


Results and Comparisons

- We have altogether 100 rows of data.
- 70% of data are randomly considered for training and 30% as testing data.
- To make the data noisy for testing the robustness of the approaches, 0.1 is added to 30% of columns 1, 3, and 6 of the data sheet.

	ANN	SVM			
		Linear	Quadratic	Gaussian	Polynomial
Normal	0.8	0.866	0.833	0.933	0.8
Noisy	0.7	0.8333	0.766	0.866	0.733



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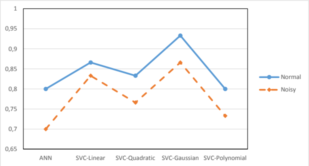

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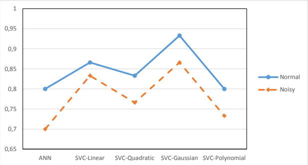

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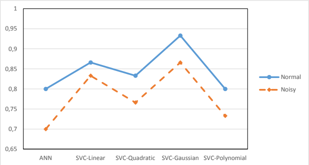

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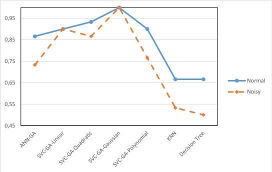
Noisy	0.733	0.9	0.866	1	0.766	0.533	0.5



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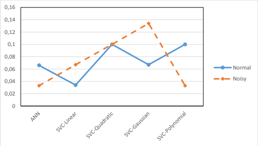

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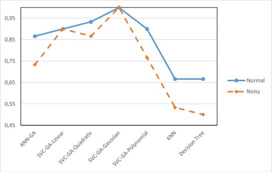

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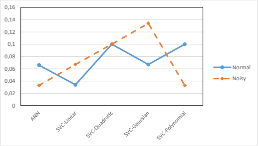

Results and Comparisions

MCNemar's test results (p-values):

	ANN-GA	SVM	ANN	Decision Tree	KNN
Normal Environment					
SVC-GA	0.1336	0.4795	0.0412	0.0044	0.0044
ANN-GA		0.6171	0.4795	0.0771	0.0412
SVC			0.1336	0.0133	0.0133
ANN				0.1138	0.0771
Decision Tree					0.7518
Noisy Environment					
SVC-GA	0.1333	0.1336	0.0077	0.0003	0.0003
ANN-GA		0.2207	1	0.0455	0.0771
SVC			0.1306	0.0026	0.0044
ANN				0.771	0.1824
Decision Tree					1

Results and Comparisions

A 10-fold cross-validation:

- The data sheet is divided into 10 even subsets.
- Each of them is once used as the test dataset and the other 9 as training dataset.
- The averages of models' accuracies (proportion of correct predicted fault types) are considered for models' validity evaluation.

	Normal Environment	Noisy Environment
SVC-GA	0.95	0.95
SVC	0.9	0.85
ANN-GA	0.85	0.75
ANN	0.85	0.8
KNN	0.6	0.6
Decision Tree	0.6	0.5

Conclusions

- GA can significantly improve the performance of the classifiers.
- SVM with Gaussian kernel function had the best accuracy in correct fault diagnosis and an excellent robustness against noise.
- SVM is superior to ANN in most of the cases.
- For future research:
  Testing the ability of other optimisation algorithms to improve ANN, SVM and other classification methods is recommended.

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Thanks a Lot For Your Attention