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ESTIMATION OF GAS-LIQUID FLOW PATTERNS UTILIZING MACHINE LEARNING METHODS

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Abstract. *In recent years, several published works use models based on artificial neural networks (ANN) to estimate the gas-liquid flow patterns; however, only few compare the accuracy of different algorithms such as support vector machines (SVM), decision trees (DT), random forests (RF) and nearest neighbors (KNN) with experimental data. Based on a large experimental database available in the literature for gas-liquid flow in pipes, consisting of different diameters, fluid properties and pipe inclination, an accuracy comparison is performed with five different algorithms. Results show that the SVM algorithm presented the best accuracy, achieving 90.03% of accuracy in correctly predicting the flow patterns.*

Keywords: *machine learning, two-phase flow, gas-liquid flow, flow patterns*

1. INTRODUCTION

Gas-liquid flow occurs in several areas of industry, such as petroleum, chemical, geothermal and nuclear. The analysis and the good understanding of the flow patterns are of extreme importance for the design of new installations in the industry. The literature has several examples that show neural networks proving to be very effective in predicting flow patterns, but only few studies are devoted to accuracy analysis of different machine learning algorithms through comparison with experimental data.

Osman (2001) worked with a three layer back-propagation neural network. Superficial fluids velocities, temperature, pressure and fluids properties were used as inputs.The model predicted correctly the flow regime for more than 97% of the data points. Ozbayoglu and Ozbayoglu (2009) compared and tested several ANN methods, with different numbers of neurons and layers, to estimate flow patterns of two-phase flow through a horizontal and annular pipe. In this work, it was showed that an artificial neural network could predict flow patterns within a error margin of $\pm 5\%$.

Al-naser *et al.* (2016) used an artificial neural network for flow pattern identification in horizontal pipes, utilizing the Reynolds numbers of the fluids as input.Their model achieved more than 97% accuracy in classifying flow patterns. Azizi *et al.* (2016) worked with ANN in order to predict void fraction of gas-liquid flow in horizontal and inclined pipes, adding the pipe inclination angle as input. Using a multilayer perceptron, by trial-and-error, 96% of the data utilized in this work were within a 5% error band.

Ozbayoglu and Yuksel (2011) analyzed the the accuracy of different algorithms such as nearest neighbors, decision trees, neural networks and support vector machines.The SVM method showed the best results, with an accuracy of 92.49% and predicting correctly seven different flow regimes.

The present work compares several methods of machine learning, from the ones that are most utilized in the literature (ANN, SVM), to others that are not so common (KNN,RF,CT).The accuracy score and the standard deviation of each method is calculated using a k-fold cross validation test. The models created using these methods are used to generate flow pattern maps, so they can be also compared graphically.

2. METHODOLOGY

2.1 Experimental Data

A dataset of 1293 points, collected from Barnea and Shoham (1982) is used in the present work. Pipe diameters of 0.025m and 0.051m and inclination angles of 0, -1, -5, -10, -30 were used to validate the methods.

2.2 Methods

This work uses five different methods, support vector machines (SVM), artificial neural networks (ANN), decision trees (DT), random forests (RF) and nearest neighbors (KNN), given the input dataset.The data are separated into 60% for the training set and 40% for the test set. It is used a k-fold cross validation test in order to test the accuracy of each model.

SVM work looking for the best fit line, called hyper-plane, to separate two or more classes of data. ANN try to mimic the human neurons and the relation between them in order to make interpolations. It has at least three layers of artificial neurons that are interconnected. The first layer is the input layer. The neurons in this layer send information on to the second layer, called hidden layer, which in turn sends the output to the third layer. In the hidden layer, the neurons transform the input (fluid velocities, pipe diameter and inclination angle) into output (flow patterns).

In machine learning, DT are a binary method of classification, that consist in making a series of splitting in the data based on the input values. RF are an ensemble method of machine learning, made from multiple decisions trees. This technique is used to avoid overfitting, that is, when your model fits well the input data but it cannot make predictions on new inputs. KNN methods make a prediction of a new data point, based on the closest distances from the inputs of your dataset.

In this paper, it is used 4 types of inputs to train the methods: superficial water velocity, superficial gas velocity, pipe diameter and pipe inclination angle. All the methods were trained with the same type of inputs.

3. PRELIMINARY RESULTS

The results shown below are related to a limited experimental dataset, using only the data presented in Barnea and Shoham (1982).

Table 1 shows the accuracy (score) and the standard deviation of each tested method. ANN, RF and SVM presented similar accuracy values, of about 90%. SVM presented the best accuracy result, although just slightly better than ANN and RF, and the lowest standard deviation. The results provided by KNN and DT were significantly worse. The use of a bigger dataset will probably help to identify critical situations for which one technique may be better that the others.

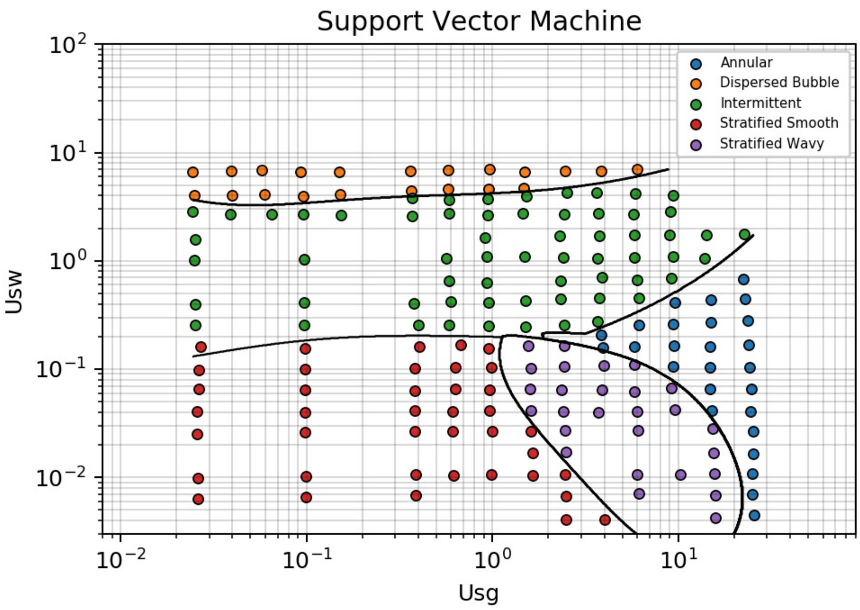

Figure 1. Transition lines - Support Vector Machine

Table 1. Accuracy of each method and standard deviation, based on data of Barnea and Shoham (1982).

Classification Methods	Score	Std. Dev.
KNN	81.05%	4.36%
SVM	90.03%	1.95%
ANN	89.04%	2.08%
CT	85.96%	4.80%
RF	89.81%	4.07%

One can see in Figures 1, 2 and 3 the flow-pattern transitions boundaries obtained using SVM, ANN and RF, respectively. The dots are experimental data and the lines are the results of the test. The boundaries obtained via SVM and ANN are fairly similar. On the other hand, RF produced transition boundaries rather different from the other techniques and

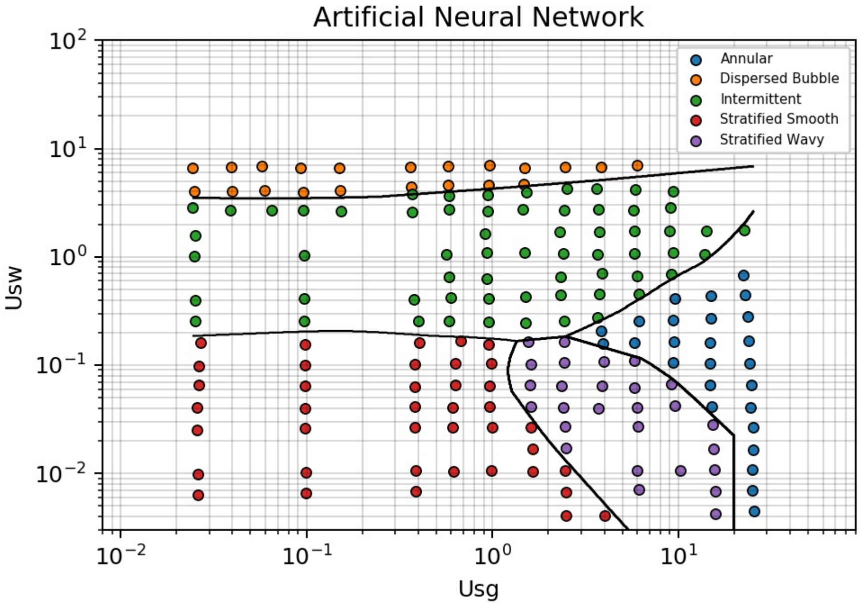

Figure 2. Transition lines - Neural Network

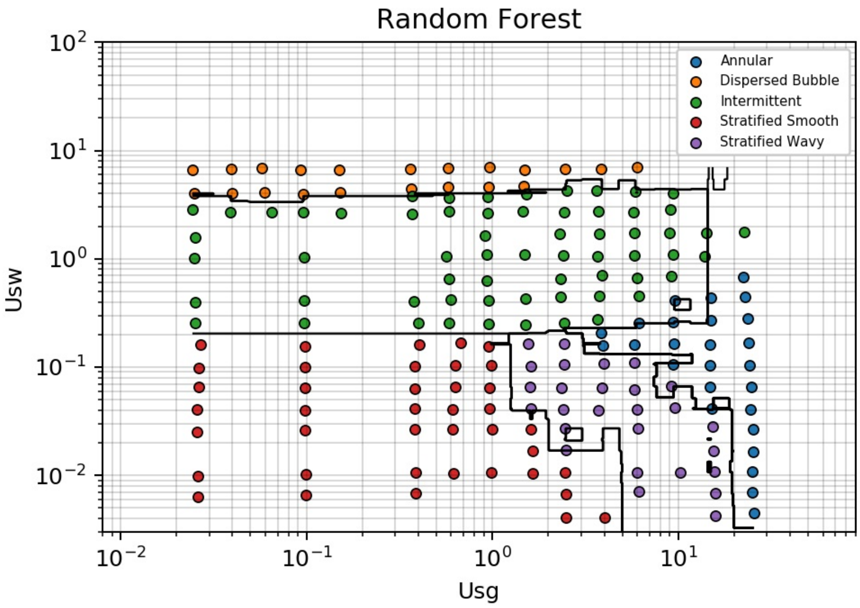

Figure 3. Transition lines - Random Forest

some spurious small regions that clearly do not have any connection with the observed flow patterns. Once again, the use of a bigger dataset is expected to result in a more accurate mapping of flow patterns.

4. CONCLUSIONS

According to the preliminary results, the support vector machine (SVM) method achieved the highest degree of accuracy in comparison with the other methods, correctly predicting 90.03% of the data with the lowest standard deviation of 1.95%. It can be seen from the generated flow maps that the support vector machine and the artificial neural network presented smoother and more realistic curves in comparison with the random forest method.

5. ACKNOWLEDGEMENTS

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