Gold Mine Dam Levels and Energy Consumption Classification Using Artificial Intelligence Methods

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***Abstract*— In this paper a comparison between two single classifier methods (support vector machine, artificial neural network) and two ensemble methods (bagging, and boosting) is applied to a real-world mining problem. The four methods are used to classify, thus monitoring underground dam levels and underground pumps energy consumption on a double-pump station deep gold in South Africa. In terms of misclassification error, the results show support vector machines (SVM) to be more efficient for classification of underground pumps energy consumption compared to artificial neural network (ANN), and surprisingly, to both bagging and boosting. However, in terms of other performance measures (i.e., mean absolute error, root mean square error, relative absolute error, and root relative squared error) artificial neural networks yield good results. In terms of underground dam level classification, SVM outperforms all the other methods with artificial neural networks (once again) having the best overall performance when other performance measures other than misclassification error are considered.**

***Index Terms*— Support vector machines, energy monitoring, ensembles, neural networks, bagging, boosting, gold mines, de-watering system, and underground pump stations.**

I. INTRODUCTION

South Africa is the major economic nation on the African continent. Mining has been the pillar of the South African economy for many years and has indeed contributed significantly to the economy and welfare of the country [1]. In fact, the mining sector is a major electricity power consumer in South Africa. It consumes nearly 23% of the total power generated [2]. In spite of this, little studies have been carried out on monitoring, controlling, analyzing, and predicting energy consumption and underground dam levels [3].

In deep gold mines, de-watering system, or clear-water pumping system is vital for mining process especially for cooling different mining levels and mining purposes. It is very essential to monitor and observe the underground dam levels for the safety of miners and pumps, as well as the pump power consumption in order to decrease the electricity cost [4].

The clear-water pumping system mainly consists of pumping stations with dams on certain underground levels, and in some cases fridge plants. The water being pumped from underground is water already used for mining purposes [5].

A typical layout of the clear-water pumping system is illustrated in the
Figure 1.

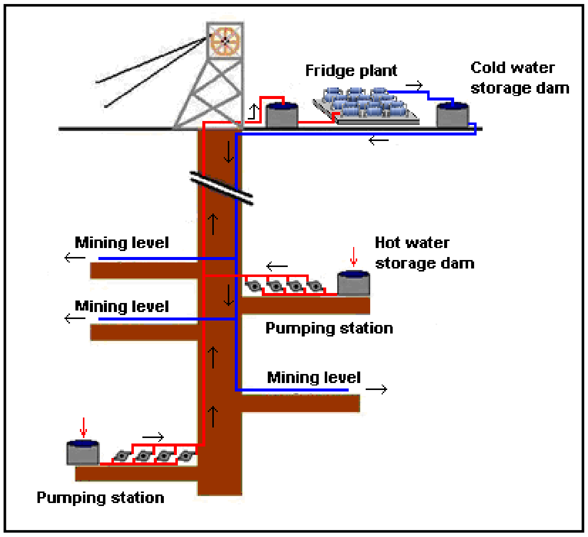

Fig. 1: Typical layout of a clear-water pumping system

In the deep mines, underground dam levels must be monitored to ensure the dam's water level stays within safe limits, in order to prevent flooding or damage. These critical maximum and minimum levels are determined by the mine personnel. This water cycling system is relatively large energy consumer, and therefore may represent an opportunity for energy optimization and therefore cost savings [6]-[7].

Recently, a great deal of interesting research work has been done in the area of machine learning and artificial intelligence for prediction, classification and optimization purposes, in fields such as robotics, management and statistical sciences. There are several systems and methods that have been developed to monitor and control the underground de-watering systems [6]-[7], but none of them uses state-of-the-art machine learning (ML) or artificial intelligence methods. Presently, there have been several applications for ML, the most significant being data mining. ML has also been successfully applied to improving the efficiency and accuracy of systems and the design of sophisticated machines [7]. Other ML applications include classification and prediction tasks, for example, to monitor and predict how a given system would behave according to the present inputs and factors in terms of energy demand [8]. This work was undertaken to investigate the feasibility of using machine learning and artificial intelligence in certain aspects of the mining industry. If successful, artificial intelligence systems could lead to improved safety and reduced electrical energy consumption.

Ensembles or multi-classifier methods have recently become as a popular learning method, not only because of their straightforward implementation, but also due to their superb predictive performance on practical problems [22]. An ensemble comprises a set of individually trained classifiers (for example decision trees or neural networks) whose predictions are combined when classifying unique instances. Ensemble methods purpose is to improving the predictive performance of a given statistical learning or model fitting technique. The general principle of ensemble methods is to construct a linear combination of certain model fitting method, instead of using a single fit of the method [23]. Previously, researches have shown that an ensemble is often more accurate than any of the single classifiers in the ensemble. Bagging and Boosting are two relatively new but famous methods for creating ensembles [16].

The major contribution of the paper is the comparison between two robust single classifier methods (artificial neural networks and support vector machines), on the one hand, against two well-known ensemble strategies (bagging and boosting) in terms of their ability and accuracy to predicting underground dam levels and pump energy consumption in a South African mine. The comparison between these algorithms is applied on a double pump station in a deep mine in order to determine the best method (in terms of predictive accuracy) that the mine could apply when monitoring underground dam levels and pumps energy consumption.

The layout of the paper is as follows: section 2 gives a mine layout situated in South Africa. In Section 3 methods used in the current investigation in the paper are briefly described. Comparative experiments on dam levels and energy consumption databases are presented in Section 4 followed by the major results in Section 5. Section 6 contains concluding remarks.

II. MINE LAYOUT

Mine A is situated in the North West of South Africa. Mining operations at this mine shaft have ceased and the shaft is only being used to pump underground water.

Figure 2 shows the pumping system layout. The mine has two main pump stations:

- 27 level pump station has 5 pumps. Each pump is rated at 2.75MW at a flow rate of 190 l/s. The total underground dam capacity is 3 ML. Note that pump number 5 is permanently off, thus it was not considered in the experiment.
- 12 level pump station has 7 pumps. Each pump is rated at 3.30MW and can pump at 190 l/s. The total underground dam capacity is 3 ML at this level.

Water is directly pumped from the 27 level underground dam to the 12 level underground dam then to the surface dam. From the surface dam, the water is used in the neighboring farms and industry.

The surface dam level was not monitored because it has sufficient capacity to accommodate all the mine water without any risk of flooding as the water is directly pumped out of it to farms [5].

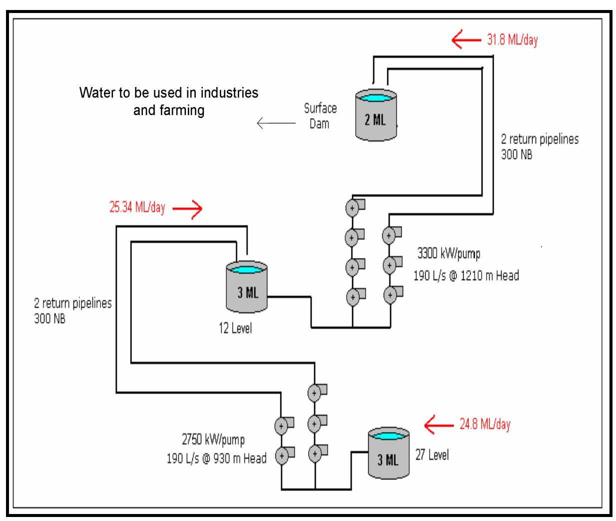

Fig. 2. Mine A clear-water pumping system [5]

III. MACHINE LEARNING ALGORITHMS

1- Individual Classifiers

A. Artificial Neural Network (ANN)

The first algorithm to test is ANN. Neural network is one of the significant components in Artificial Intelligence (AI) [20]. It has been studied for many years with the objective of achieving human-like performance in several fields, for instance speech and image recognition, as well as information retrieval. [16]. Basically, an artificial neural network is a system on its own that receives an input, process the data, and delivers an output [11]-[19].

Multilayer Perceptron (MLP) is a network of perceptrons. A perceptron is the simplest neural network representing a linear hyper-plane within instance space [12]. MLP's can be used to solve complex problems. Each MLP contains an input layer that contains at least one hidden layer and an output layer. A layer is an arrangement of neurons that include hidden ones which do not have any connection to the external sources [13]. An MLP is typically built as a back-propagation neural network. In a back-propagation neural network, the error is fed back to the same neuron [17]. The neuron output is the threshold weighted sum of all inputs from the previous layer. This process is continued iteratively until the error can be tolerated or reaches specific threshold. Activation functions use the input into the neurons to compute the output, which is comprised of weighted sums of the outputs from the previous layer [13]-[17].

B. Support Vector Machine (SVM)

Support Vector Machine method (SVM) is finding application in pattern recognition, regression estimation, and operator inversion for ill-posed problems [12]-[20]. Support vector machine classifier (SVM), or as it is called SMO in the Waikato Environment for Knowledge Analysis (WEKA), can be used to solve two-class (binary) classification problems. These classifiers find a maximum margin linear hyper-plane within the instance spaces that provides the greatest separation between the two classes [18]. Instances that are closest to the maximum margin linear hyper-plane from the support vectors are correctly classified [13].

Among the possible hyper-planes, SVMs choose the one where the distance of the hyper-plane from the nearest data points (the "margin") is as large as possible [14]. Once instances from the support vector have been recognized, the maximum margin linear hyper-plane can be created [14].

2- Multiple Classifiers

A. Bagging

One popular way to obtain multiple classifiers is through Bagging or Bootstrap aggregating, proposed by Breiman in 1996 to improve the classification by combining outputs of classifiers that are trained using randomly-generated training sets [21]-[22].

Bagging is a "bootstrap" multi-classifier method that generates individuals for its ensemble by training each classifier on a random redistribution of the training set [15]. Each classifier's training set is generated by randomly drawing, with replacement, X examples – where X is the size of the original training set; many of the original examples may be repeated in the resulting training set while others may be left out [23]-[21]. Each single classifier in the ensemble is generated with a different random sampling of the training set [15].

B. Boosting

Boosting algorithms have been proposed in the machine learning literature by Schapire and Freund [24]. Boosting includes a family of methods. The focus of methods is to produce a series of classifiers. The training set used for each member of the series is chosen based on the performance of the earlier classifier(s) in the series [21]. In Boosting, examples that are wrongly predicted by previous classifiers in the series are chosen more often than examples that were correctly predicted. Thus Boosting attempts to generate new classifiers that are better able to predict examples for which the current ensemble's performance is poor. Note that in Bagging, the resampling of the training set is not dependent on the performance of the earlier classifiers [15]-[19].

IV. EXPERIMENTAL SET-UP

Data for underground dam levels were collected for a period of three months by using pressure transmitter fitted on the dams. This pressure transmitter is connected to a programmable logic controller's (PLC) fixed on the pump station, then via fibre optics to a supervisory control and data acquisition (SCADA) system to log the data on a spread sheet. It logs a value every two seconds. Data for pumps energy consumption were logged for three months using a power logger mounted on the pump control panels, and connected to the underground PLC's and then to the SCADA on the surface at the control room. This data represents the run time status for each pump, where 1 value denotes pump is on status, and 0 is off status. Each pump has a specified power capacity, as mentioned above which determines the amount of power consumption.

In this experiment the WEKA software is used to classify the mine data (power and dam level) using ANN, SVM, Bagging ensemble and Boosting ensemble algorithms. For the simulation purposes the data was averaged over 30 minute's intervals. For all the algorithms default parameters are used. WEKA is a software which was developed at Waikato University in New Zealand. It is a collection of open source of numerous data mining and machine learning algorithms [9]-[10].

Starting with the pumps energy data, for both 12-level and 27-level pumps the data were joined, trained and tested as one pump station level. This data were tested on a neural network of 28 sigmoid nodes for energy data experiment using WEKA, and each uses sigmoid function as the activation function. This 28 sigmoid network could incur complex classification process, nevertheless, WEKA software determines the optimum network needed depending on the data nature and size. The data were split into 80% for training, and 20% for testing intervals for energy consumption. For 12-level dam level, the ANN model includes 13 sigmoid nodes, and 8 sigmoid nodes for 27-level. Number of instances is 744 (sum of weights) and attributes are 12 (pump1-27, pump2-27, pump3-27, pump4-27, pump1-12, pump2-12, pump3-12, pump4-12, pump5-12, pump6-12, pump7-12, and class). As mentioned before the pumps are directly linked to the dam level, so the attributes here represent the pump running status (on, off). The class represents, in case of energy consumption test, the total energy consumed by the pumps.

The SVM model includes classifier for each class and attribute, each of these classifiers comprises a number of kernel evaluations for each class. The data split for energy consumption was 80% to train and 20% to test.

Bagging ensemble algorithm and Boosting ensemble algorithms are used to train the data. The data split was, 80% to train and 20% to test for both algorithms, as in the previous methods. In Bagging model, several trees were constructed, each of different size to train and test the data. For Boosting method, one classifier was used.

For underground dam level's data. Each level (12-level and 27-level) data were trained and tested separately. The maximum and minimum dam levels for both levels in this mine were provided by the mine's shaft engineer. For 27-level the maximum is 85% and the minimum is 20% and the same for 12-level underground dam. The data is categorized in classes for simulation. Table 1 illustrates the classes for 12-level dam levels.

TABLE 1: 12level dam level classes

Description	Dam level percentage	Class
Pump damage risk	>25%	1
Low	25%-39%	2
Medium	40%- 67%	3
High	68%-80%	4
Critically high (flooding risk)	>80%	5

Table 2 shows 27-level underground dam level percentages and classes.

TABLE 2. 27LEVEL DAM LEVEL CLASSES

Description	Dam level percentage	Class
Pump damage risk	<24%	1
Critically low	24%-30%	2
Low	31%-42%	3
Medium	43%-69%	4
High	70%-78%	5
Critically high	79%-85%	6
Dam flooding risk	>85%	7

Energy data are categorized for classes as shown in Table 3. The energy data represent the energy consumed by the underground pumps for both 12-level and 27-level pump stations.

TABLE 3. ENERGY CONSUMPTION CLASSES

Energy Level (kW)	Description	Class
0	No Energy Consumption	0
2750	Very Low Energy Consumption	1
3300	Low Energy Consumption	2
5500	Relatively Low energy Consumption	3
6050	Medium Energy Consumption	4
6600	Medium Energy Consumption	5
8250	Medium Energy Consumption	6

8800	Medium Energy Consumption	7
9350	Medium Energy Consumption	8
11550	Relatively High Energy Consumption	9
12100	Relatively High Energy Consumption	10
12650	High Energy Consumption	11
14850	High Energy Consumption	12
15400	Very High Energy Consumption	13
18150	Very High Energy Consumption	14

V. EXPERIMENTAL RESULTS

The number of instances for energy data is 744 instances. Table 4 shows the number of instances (count) and weight distribution for each class for all levels energy consumption classes.

TABLE 4. CLASS LABELS AND WEIGHTS

Energy Level (kW)	Description	Class
0	No Energy Consumption	0
2750	Very Low Energy Consumption	1
3300	Low Energy Consumption	2
5500	Relatively Low energy Consumption	3
6050	Medium Energy Consumption	4
6600	Medium Energy Consumption	5
8250	Medium Energy Consumption	6
8800	Medium Energy Consumption	7
9350	Medium Energy Consumption	8
11550	Relatively High Energy Consumption	9
12100	Relatively High Energy Consumption	10
12650	High Energy Consumption	11
14850	High Energy Consumption	12
15400	Very High Energy Consumption	13
18150	Very High Energy Consumption	14

After specifying the classes and the split to train percentage, the data was processed by WEKA to determine the most suitable neural network and support vector machine that achieved the maximum correctly classified instances.

Table 5 shows SVM and ANN achieving higher accuracy for energy consumption classification compared to Bagging (Bag) and, in particular Boosting (Bos). In fact, in terms of all, but two, performance measures, there is no significant difference in performance between SVM and ANN at the 4 % level of significance. However SVM is the most accurate classifier among the four used classifiers.

TABLE 5. PUMPS ENERGY CONSUMPTION PREDICTION RESULTS

Description	ANN	SVM	Bag	Bos
Misclassification error	1.34%	**1.071%**	12.08%	62.416%
Mean absolute error	**0.0044**	0.109	0.025	0.101
Root mean squared error	0.04	0.228	**0.106**	0.223
Relative absolute error	**4.406 %**	109.02%	23.93%	94.16%
Root relative squared error	**18.136 %**	103.62%	46.58%	97.71%

It can be noticed that Boosting method has the poorest performance. That is because in this particular experiment boosting was not possible and only one classifier was used. Results for 12-level dam level classification are shown in Table 6. All four methods have almost the same accuracy with SVM is relatively more accurate with minimal changes in root mean squared error.

TABLE 6. 12-LEVEL DAM LEVEL PREDICTION RESULTS

Description	ANN	SVM	Bag	Bos
Misclassification error	46.30%	**45.63%**	47.65%	46.98%
Mean absolute error	**0.179**	0.216	0.186	0.186
Root mean squared error	**0.306**	0.320	0.306	**0.306**
Relative absolute error	**96.21%**	115.63%	99.80%	99.80%
Root relative squared error	100.24 %	104.85%	**100.19 %**	100.25%

For 27-level dam level classification results, all four methods performed with similar accuracy, with nominal change in root mean error as shown in Table 7.

TABLE 7. 27-LEVEL DAM LEVEL PREDICTION RESULTS

Description	ANN	SVM	Bag	Bos
Misclassification error	42.95%	42.95%	42.95 %	42.95%
Mean absolute error	**0.232**	0.2695	0.242	0.239
Root mean squared error	0.346	0.360	0.348	**0.34**
Relative absolute error	**95.38%**	110.77 %	99.49%	98.51%
Root relative squared error	**99.30%**	103.33%	99.92%	99.48%

VI. CONCLUSIONS

In this paper, the problem of dam levels and energy consumption monitoring using Artificial intelligence algorithms in a gold mine dam in South Africa has been researched. From the results it can be seen that SVM is the most accurate classifier of energy consumption out-performing ensemble strategies such as bagging and boosting. This is rather surprising since ensembles have been shown by both statistical and machine learning researchers to improve classification accuracy of, say, an individual classifier. In terms of dam level prediction poor performances of all the methods is observed with SVM yields the most accurate performance. However, when other performance measures are considered other than misclassification error, ANN exhibits good overall accuracy rates. The application of different types of classifiers and ensembles in various mines in South Africa could yield consistent results that may be superior to the use of one mine alone. Further work will examine the use of other machine learning algorithms (classifiers) such as decision trees, instance-based learning, logistic regression (discrimination), naïve Bayes classifiers and association rules in terms of their ability in addressing the prediction problem. Other South African mines will also be considered.

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