Comparison of Machine Learning Techniques in Prognostic Maintenance of Hydro Power Plant Subsystem

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Abstract

With the advent of time, automation is becoming an inevitable component of human lives. Our homes, industries, offices, market areas, etc. are being mechanized and human power is slowly being replaced by machines. Although it has increased the system efficiency manifold, but the probability of system breakdowns has also increased, since machines are more susceptible to faults. Hence, a continuous monitoring system is therefore required. Many techniques have since been devised for better maintenance of machines throughout their operation so as to increase their useful life. This paper presents the use and comparison of two different machine learning techniques for fault sensing ahead of time and prognostic maintenance of a turbine System. The data is acquired from the turbine of a hydro power plant installed in Dargai, Malakand Agency, Pakistan. The machine learning techniques compared in this paper for fault sensing and prognostic maintenance of a turbine system are support vector machines and artificial neural networks.

Keywords—Prognostic maintenance, Remaining Useful Life (RUL), Support Vector Machines (SVM), Hydropower Plant, Turbine, Artificial Neural Networks (ANNs).

1 Introduction

Machines and mechanical equipment have taken over majority of the labor. The tasks that were once done by humans are mostly done by machines now. They have provided ease and utility in many parts of human life. Whether it is domestic home tasks, or office task, from industry to power generation, from food processing to products manufacturing factories, mechanical equipment are the major and essential feature, without which majority of processes will cease to act. With all the advantages of machine taking over humans, there come some disadvantages too. Machines are susceptible to errors and faults and with time they worn out. They need to be constantly monitored and maintained for smooth operation. Researches have been conducted to increase the life time of mechanical systems and improve the efficiency of machines. Many maintenance techniques are devised to keep system running efficiently. One of these that involve Machine Learning Techniques and Artificial Intelligence is “Prognostic Maintenance” [1].

Prognosis is a term that is opposite to diagnosis. The faults are predicted even before their occurrence [2]. Prognostic maintenance is a technique that keeps a check on machines and mechanical system by notifying about the events and faults before they take place. The damages and physical conditions about a machine can be found out using sensors’ measurement [3].

One of the most necessary mechanical and electrical systems invented in the history of industrial revolution is the “turbine engine”. A turbine is a machine that utilizes a certain form of energy to generate electrical. In Pakistan, the one of the most important means of electricity generation are Hydropower Plants. Second to electricity generation through thermal, Hydropower plants generate most of the electric power in Pakistan. There is an utmost necessity to keep the turbines and plants running in the most efficient condition to power up the majority areas of Pakistan.

In this paper, various faults and sensors data was collected from 81 MW Malakand III Hydropower project, installed at Dargai, Malakand Agency, Pakistan. Algorithms based on ANNs and SVM were developed for the Prognostic Maintenance of turbines and the data was analyzed and tested on both these algorithms.

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2 Literature Review

Artificial intelligence is the backbone of prognostic maintenance. Techniques like Artificial Neural Networks (ANNs) and Support Vector Machines (SVM) can model a state of the art prognostic maintenance systems. There are many examples in literature that uses Machine Learning techniques for fault detection in various machines.

One of the techniques being discussed in this paper in ANN. McCulloch and Pitts (1943) are considered to be the pioneers of neural network based model for neurocomputation. Initially, they were just simple models that used to perform simple logical and arithmetical operations. Further, Perceptron came into working when Rosenblatt (1958) mapped input to random output using Perceptron [4]. ANNs have been increasingly used in machine technology and with time they are improving efficiently. ANNs are considered to be one of the most powerful Machine Learning techniques. Many advanced variations of ANNs are also being used in different cases of Prognostic Maintenance. For example, in a case of Gas turbine, wavelet neural network was used for fault diagnoses [5]. The other machine learning technique that is used in this research is Support Vector Machine. SVM is a machine learning technique that has a less complicated approach than ANNs. They were developed around 1950s. They are currently most famous classifier being used because of their relatively easier and clear approach. In real world problems most of the classifications are not linearly separable. SVMs deal with such problems very efficiently [6]. Even multi-class models can be easily modeled using support vector machines. From detailed analysis it was decided that SVM and neural network were specifically better approach for pattern detection in the data. Moreover, prognosis has been done using this approach is many other cases [7].

2.1 Prognostic Maintenance

Prognostic maintenance is a technique in which future health of an entity is estimated in terms of remaining useful life (RUL). Current condition and previous health condition is used for the future prediction [8]. Prognostic maintenance is the opposite of "diagnostics", where reasons of a fault or event are found by the analysis of the event. But diagnostics approach is inconvenient and inefficient in mechanical systems. The occurrence of fault leading to diagnosis can increase the maintenance cost as well as halting of processes decreases the output and efficiency of a system [9].

Prognostics maintenance has been used in medicines since long. The current condition of a patient as well as family history can predict the conditions one might have in future, if no treatment is done [10]. Similarly, prognostics is done for mechanical equipment to foresee a fault that is about to happen. The health of products and systems is monitored to provide warnings and avoid a catastrophic failure in advance. Physical or mechanical degradation such as cracking, corrosion, increase in resistance, etc. are the triggers that tell us about the fault to occur [11].

Some mechanical systems are very much complex like power generation systems. They are a complex mixture of mechanical and electrical system. As complexity increases, the systems are more prone to faults. Machines like gas turbines, hydro power subsystems, etc. needs to be replaced from conventional fault diagnosis to intelligent prognostics systems with the help of artificial intelligence and machine learning techniques [12].

Various machine learning techniques can be used to design a model, that with the given data, it produces efficient results. The comparison of how data is manipulated, how efficiently a system is trained with the considered technique, how accurately can it predict a fault, etc. determine the suitability of a proposed technique for the better prognostics of systems. Many variables can be used to determine the efficiency of prognostic techniques including time, accuracy, precision, speed of data retrieval etc. [13]. The two most efficient techniques that are being compared in this paper are ANNs and SVM.

The paper is distinct from the previous published work as ANNs have not been yet used in Hydropower plants. As well as the data set used for modeling the classifier is acquired from Pakistan's local hydropower plant which is not used in previous work.

2.2 Artificial Neural Networks

Number of interconnected processing units, or neurons are the basic elements of ANNs. ANNs are based on the concept of a human brain. They try to process information similar to the way a human brain does and on that basis a model is being made. ANNs have the capability to learn and train themselves as well as organize the information. ANNs have been used in industrial equipment and efficient results have been achieved. In a case of machine maintenance, ANN was used to make a model for the vibration signal diagnoses [14]. A much accurate prediction can be made from a model that has been trained using ANNs. They have an ability to predict faults way before the occurrence and that is why they are being used in prognostic maintenance, since it gives adequate time for the essential maintenance steps to be taken.

2.3 Support Vector Machines

SVM is a classification technique used in Machine Learning. Different groups of data are classified on the bases of their features using best possible split technique. The widest separation between different groups is determined. The line which splits the data in the best possible way is called a "Hyper plane". The distance between the two extreme samples from both the groups (in case of two classifications) is called support vectors. This distance is as far as possible between the support vectors and Hyper plane [15]. As the margin between support vectors and Hyper plane is maximum, this makes the split between the data best possible. The function that transforms training data vectors into higher dimensional space is called kernel function [16]. In a case of a "Roller Bearing Fault Detection" SVM was used. Vibration Acoustic Emissions were used as one of the feature in that model [17]. Concepts like e-maintenance of mechanical systems are introduced, as artificial intelligence techniques are being employed in industry. One of such example is a research made on an operating thermal power plant where SVM based model was used to detect turbine failures [18].

Both the techniques are used efficiently for the pattern detection and fault analysis in previous work. Various algorithms were used such as genetic algorithm etc. but in our case we are using cluster grouping in SVM and pattern recognition algorithm in ANN [19].

3 Methodology

The process of Prognostic Maintenance of a turbine system using machine learning techniques and comparisons of ANN and SVM algorithm was distributed in the following steps:

1) Data acquisition from the Hydropower plant
2) Data analysis and extracting the key variables
3) Making datasets for computation
4) Modeling the classifier using SVM and ANN for the dataset
5) Comparison of both the models
6) Evaluating the final result based on the comparisons

3.1 Data collection

During the project, a hydropower plant, 81 MW Malakand III Hydro Power project, was visited. Maintenance and operation, issues, demands, working and other attributes of the hydropower plant were studied. The data gathered was generated by a system named SCADA, installed at the power house. SCADA stands for "Supervisory Control and Data Acquisition". SCADA is a system that controls various industrial processes. It can control them locally as well as remotely. It consists of devices like sensors, actuators, pumps, valves, motor, etc. SCADA also converts data from analog to digital and vice versa.

The data acquired from the SCADA was in the form of Log sheets of excel/CSV format. It consisted of temperature, vibrations, and other physical attributes of various unit of turbine across a time period of 8 months. There were different sheets for different variables/features and different generating units. A total of three (03) Turbines were installed at the project; Unit1, Unit 2 and Unit 3. Each sheet contained data collected over a time span of 24 hours with an interval of 1 hour. In Figure 1, an example of Primary data gathered from SCADA system of 81 MW Malakand III Hydro Power Plant is shown. Sensors record the temperatures from various components of turbines after a constant time interval and stores in CSV format. Specifically in this example, two components of a turbine i.e., thrust bearing and turbine bearing's temperature is shown in the form of each component various pad's temperature. The temperature is controlled by oil and water cooling.

3.2 Dataset

A dataset was created from the data acquired through SCADA. Data was first analyzed and the key feature from the data was extracted. The log sheets were divided into mainly two types of data. One set of data consisted of the time and date on which the turbine had fault recorded and it was shut down and the other set of data consisted the features and attributes recorded from sensors on a particular date and time. Comparison of both kinds of data shown that temperature of various units of turbine had the most impact on the faults of turbine and eventually the shutting down of the system. Therefore, temperature readings of various units were considered the key feature for both the algorithms. Each feature in every example was converted into the same unit and same range. In the end, the final modified data set consisted of 4488 samples of temperature of two units of turbine system.

3.3 Support Vector Machine (SVM)

Initially, to pre determine the number of clusters within this multidimensional dataset K-mean clustering was used. In our algorithm, K was found by the elbow curve method. The graph obtained flattened out at 3.5 so the number of clusters were used as 3.

After the K-mean clustering, training of the classifier

Malakand III Hydropower Station

Unit 3-Log Sheet 2(Temperature)

Start: 18-03-01 0:00:00

Item / Time	Thrust Bearing											Turbine Bearing											Air Cooler							
	Pad								Oil		Outlet water	Pad								Oil		Outlet water	Inlet				Outlet			
	1	2	3	4	5	6	7	8	Hot	Cool		1	2	3	4	5	6	7	8	Groove	Slot		1	2	3	4	1	2	3	4
	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C	°C
0:00	58.6	59.8	47.2	23.6	49.6	59.1	32.3	46.7	23.26	51.42	19.5	41.1	40.6	36.7	38.7	38.2	38.1	39.5	-19.1	38.63	39.89		29.3	24.9	24.7	33.2	45.2	44.5	44.1	44.7
1:00	58.6	59.9	47.2	23.6	49.6	59.1	32.3	46.7	23.26	51.52	19.5	41.3	40.7	36.7	38.8	38.2	38.2	39.6	-19.1	38.74	40.69		29.6	25.1	24.8	33.3	45.1	44.4	44.1	44.7
2:00	58.5	59.7	47.1	23.6	49.5	58.9	32.2	46.6	23.26	51.42	19.4	41.3	40.7	36.8	38.8	38.3	38.2	39.6	-19.1	38.84	40.69		29.5	25	24.6	33.3	45.2	44.5	44.1	44.7
3:00	58.5	59.7	47	23.6	49.4	58.9	32.1	46.6	23.26	51.31	19.18	41.4	40.9	36.8	38.8	38.4	38.3	39.7	-19.1	38.84	40.42		29.4	24.9	24.5	33.2	44.9	44.3	43.9	44.4
4:00	58.3	59.6	46.9	23.6	49.3	58.7	31.9	46.5	23.26	51.2	18.97	41.6	40.9	36.8	38.8	38.3	38.2	39.7	-19.1	38.84	40.16		29.1	24.6	24.2	32.8	44.7	44	43.7	44.1
5:00	58.2	59.4	46.8	23.6	49.1	58.6	31.8	46.3	23.26	50.99	18.86	41.4	40.8	36.7	38.6	38.1	38	39.5	-19.1	38.63	40.16		28.9	24.3	24	32.6	44.3	43.8	43.4	43.9
6:00	58.2	59.4	46.7	23.6	49.1	58.6	31.7	46.2	23.26	50.99	18.32	41.6	41.1	36.9	38.8	38.3	38.2	39.7	-19.1	38.84	40.42		28.1	23.9	23.7	32.1	43.8	43.1	42.7	43.3
7:00	61	62.7	49.4	23.6	52.4	61.3	31.8	49.4	23.26	53.89	18.32	45.2	42.4	36.4	38.1	37.7	37.6	39.3	-19.1	38.52	40.16		29.1	24.3	24	33.5	46.5	45.7	45.3	45.8
8:00	61.5	63.2	49.9	23.6	53.1	61.8	31.9	50.1	23.26	54.53	18.11	45.7	43.3	37.3	39	38.5	38.5	40	-19.1	39.17	41.75		30.4	24.9	24.5	34.7	49.1	48.6	48	48.5
9:00	60.9	62.5	49.3	23.6	52.3	61.1	31.5	49.3	23.26	53.67	17.68	43.6	41.9	36.6	38.1	37.5	37.5	39	-19.1	38.2	39.89		30.4	24	24.5	35.1	50.7	49.8	49.5	50
10:00	60.8	62.2	49	23.6	52	61.1	31.2	49	23.26	53.46	17.36	44.2	42.2	36.8	38.3	37.9	37.9	39.3	-19.1	38.52	39.89		30.8	24	24.2	35.1	50.8	50	49.5	50.2
11:00	60.4	62.1	48.8	23.6	51.9	60.8	31	48.8	23.26	53.35	17.25	44.3	42.4	36.9	38.5	38.1	38	39.5	-19.1	38.74	40.42		30.7	23.8	24	35	50.6	49.8	49.4	50.1
12:00	60.6	62.8	48.8	23.6	51.9	60.9	31	48.8	23.26	53.35	17.14	44.7	42.4	37	38.6	38.1	38.1	39.6	-19.1	38.84	40.16		30.9	23.8	24	35.1	50.7	49.9	49.4	50.1
13:00	60.4	61.8	48.6	23.6	51.6	60.8	31	48.5	23.26	53.14	17.14	41	41	36.7	38.1	37.3	37.1	38.4	-19.1	37.88	39.63		31	23.8	24	35	50.6	49.8	49.4	50.1

Fig. 1: Dataset for temperature of Unit 3.

was done. SVM implementation was done with the Sci-kit in Python. The same dataset was used in this implementation. The data was preprocessed by dividing the data into attributes and labels and further dividing the data into training and testing sets. The labels generated by the k-means algorithm were passed to SVM. The figure shows a plot of the Support Vector Machine (SVM) model trained with a dataset that has been dimensionally reduced to two features. The lines separate the areas where the model predicted the particular class that a data point belonged to. This plot shows the decision boundary of the SVM. It is clear from this plot that the SVM model has correctly separated most the data points successfully with the occasional data point being misclassified.

3.4 Artificial Nueral Networks (ANN)

The second algorithm used for the classification model was ANN. The data set used was exactly the same that has been used for SVM classification.

The basic concept used in ANN classification was that there is a pattern in temperature recording that leads to the fault. The pattern was noted as the gradual increase and then crossing the threshold value. The dataset was modified according the classifier. Temperature samples were stated against the current condition of turbine whether the turbine is on or not. The neural network classifies the input features into target categories. A feed-forward network was used to classify vectors. The output layer has an S shape transfer function to limit the outputs between minimum and maximum limit.

The data selected for the model was an input matrix of 2×4488 elements and target vector of also 2x4488 elements showing the status respective to the features of turbine. The target set has either a 1 or 0 in each column that shown 1 for on in first column and 1 for off in second column. The dataset is modified as shown in the Figure 3. Some of the samples are shown in the figure. The entire data set was divided into training, testing and validating data. 70% of the data was used for training, 15 percent for testing and 15% for validating. The number of hidden neurons was 10 per layer. The neural network was trained using scaled conjugate gradient back propagation. The network once trained was tested by confusion matrix and receiver operator characteristic, discussed in the next section.

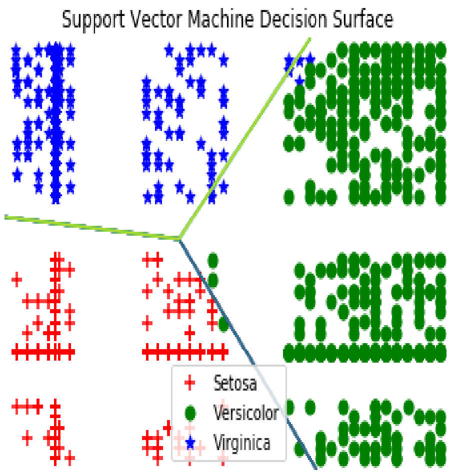
4 Results & Comparisons

The data obtained from Hydropower plant's turbine system was used to train and test the classifier model based on SVM and ANN. The comparison standards used were as follow:

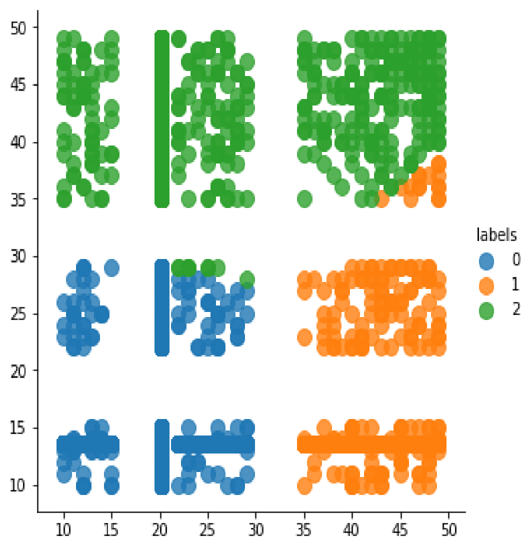
1) Confusion matrix
2) Error percentage
3) Data classification

4.1 Confusion Matrix

The confusion matrix produced through SVM is shown in Table 1. There are 1010 points in the first class (label 0) all of which are classified as label 0. Similarly in second row there are 433 points in class 1, all of them are marked correctly. In last row total points are 353 of which one is classified as class 1 and the rest 352 are correctly classified. This confusion matrix is overly accurate which is not possible in real life data. This shows that SVM did not correctly considered the errors present in the pattern leading to faults. The confusion matrix obtained through Neural Network Model is shown in the Figure 4. This confusion matrix is very detailed showing the training, validation and



((a))



((b))

Fig. 2: SVM decision boundary. The data set was divided into 3 classes labeled as 0, 1, and 2 according to difference in features by SVM.

	Class 0	Class 1	Class 2
Class 0	1010	0	0
Class 1	0	433	0
Class 2		1	352

TABLE 1: SVM confusion matrix

```
Turbine_status =

 Columns 1 through 20

   1    0    1    1    0    1    1    1    1    1
   0    1    0    0    1    0    0    0    0    0

 Columns 21 through 40

   0    1    1    1    1    1    0    1    0    1
   1    0    0    0    0    0    1    0    1    0

 Columns 41 through 60

   1    1    1    1    0    0    1    1    1    0
   0    0    0    0    1    1    0    0    0    1
```

((a))

```
Temperature_Inputs =

 Columns 1 through 12

  20.1500   20.1500   20.1500   25.0000   11.0000
  25.0000   48.0000   13.5900   28.0000   48.0000

 Columns 13 through 24

  20.1500   39.0000   49.0000   38.0000   20.1500
  13.5900   26.0000   13.5900   13.5900   13.5900

 Columns 25 through 36

  20.2600   20.1500   49.0000   20.1500   11.0000
  13.5900   13.5900   22.0000   13.5900   45.0000
```

((b))

Fig. 3: Temperature Inputs and Turbine status corresponding to the respective temperature Input.

test matrices also. The results obtained from this matrix are that the percentage of correctly classified samples is on average 96.5%. The value obtained from the neural network model is more realistic and in accordance with the test data.

4.2 Error percentage

The error percentage of SVM model was 0.06 which is not possible practically. This result further proves the point that SVM model did not notice the small changes in pattern. While the error percentage in neural network model came out to be 3.6% which is considerably fair according to the test data.

Fig. 4: Neural network confusion matrixes

4.3 Data Classification

A comparison point that was noticed during experimentation phase of this research was that SVM classified the data into 3 clusters using the elbow curve method. So in classification a considerable amount of test data that comprises of temperature reading was classified into neither off nor on group. Which is a huge drawback of SVM for this data since the project is dealing with a turbine. A turbine can either be off or on. And the test data should decide between the binary classification of 1 or 0. There must not be a grey area.

4.4 Comparison Results

From various comparisons, it was concluded that a classification model based on Artificial Neural Network is more suitable than Support Vector Machine for the prognostic maintenance of a turbine system installed in a Hydropower plant.
SVM could not detect small pattern changes that lead to fault detection. SVM classifier produced overly accurate results since due to data unsuitability to the model. Since SVM classifier didn't consider the on and off status of the turbine, it made the classifier unfit for this kind of data set. Moreover, neural network classifier produced fairly accurate results. The algorithm devised proved to be better since it considered the turbine operational status as well. Also ANN model detected small changes in pattern, which is the most crucial part in the research of Prognostic Maintenance of Hydropower plant.

From the results derived, a practical maintenance system based on ANNs can be easily devised using microcontrollers and embedded systems. Actuators and sensors will detect temperature rise pattern in turbine components. Classification machines based on ANNs will detect the temperature readings crossing the threshold level and alarming the engineers and quality control officers about the current situation of the turbine. Fixing the fault beforehand will save the complete halting of the system since a component will be overheated and burnt if the fault is not predicted beforehand. This will reduce the maintenance cost too.

5 Conclusion

Using Artificial intelligence techniques, we can make our machines more efficient and less susceptible to break downs. There can be many ways in which various Machine learning techniques can be employed to predict faults and errors beforehand. Specifically in a developing country like Pakistan, the power outage can affect its economy a lot. So, devising the better algorithm that can reduce the breakdown of power plants should be the target. According to the data obtained from a local power plant and testing it on the two most popular ML techniques, it was concluded that Artificial Neural Network proved to be more efficient to model a prognostic maintenance system in turbine system of a hydropower plant as compared to Support Vector Machine classifier.
Moreover, the future work in this field can greatly enhance the industrial efficiency. This research targeted a hydropower subsystem but it can be taken further to oil power plants, nuclear power plants, even automation industries and many more mechanical systems.

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