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CI-MCMS: Computational Intelligence Based Machine Condition Monitoring System

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***Abstract*—Earlier around in year 1880's, Industry 2.0 marked as change to the society caused by the invention of electricity. In today's era, artificial intelligence plays a crucial role in defining the period of Industry 4.0. In this research study, we have presented Computational Intelligence based Machine Condition Monitoring system architecture for determination of developing faults in industrial machines. The goal is to increase efficiency of machines and reduce the cost. The architecture is fusion of machine sensitive sensors, cloud computing, artificial intelligence and databases, to develop an autonomous fault diagnostic system. To explain CI-MCMs, we have used neural networks on sensor data obtained from hydraulic system. The results obtained by neural network were compared with those obtained from traditional methods.**

***Keywords*—Computational Intelligence, Machine Condition Monitoring, Industry 4.0, Hydraulic System**

I. Introduction

In the last decade, with the increasing technological advancements, there had been an exponential rise in the use of technology in manufacturing. With the onset of Industry 4.0 or the Fourth Industrial Revolution, the paradigm changed in the industries, specially manufacturing [1]. Researchers were able to define possible technological framework to fulfill the goal of Industry 4.0. One of the major aims of industries and manufacturing units is to reduce the operation cost and get the best output at the same time i.e. to increase the efficiency of the system. Often, there is a high negative impact created by uncertain machine tool breakdown. An industrial breakdown of even 1-2 hour can highly impact the timeline and efficiency of the system. Such breakdowns are most of the time caused because of some minor auxiliaries, like motor, cooling unit, etc. [2] One of the ways to assure efficiency is to make sure that the machinery in the industries is working fine enough. There are a couple of factors that decide the overall performance and efficiency of machinery which include initial cost, life efficiency, maintenance cost, and other operating costs. To ensure this, regular check or assessment of the machinery is essential. The process of monitoring machine parameters to detect developing faults is referred to as Machine Condition Monitoring (MCM). These machine parameters differ and depend on the type of machinery. The general evaluation parameters for MCM are Temperature, Current, Vibration, Motor RPM, Wear Debris, Oil Analysis and Acoustic Emissions [3]. In the last few years, with digitization and an increase in the sensor-based approach, there has been a significant increase in the amount of data by various organizations and industries. Researchers have found out ways to use this data to understand, analyze, and improve the performance of the system. Such an approach is also used in Healthcare [4]. Various sensor-based gadgets are used to record continuous health data of the patient which is finally used to diagnose the onset of various diseases. For MCM, a network of sensors is deployed on the peripheral of machinery to record corresponding parameters. Then these parameters are closely monitored to diagnose developing faults in the system. Earlier this monitoring process was carried out manually where a person was employed to study the sensor data to monitor the working of machinery periodically. But there are many complexities associated with human monitoring and demands for high expertise in the field. It also undergoes various mathematical complexity in deducing the system performance from the sensor data. Researchers often found the integration of various monitoring systems very difficult [5]. However, in today's era, due to development in the field of Machine Learning and Intelligent System, these problems can be addressed easily. Various algorithms and methods can be used to design an automated approach for Machine Condition Monitoring, eradicating most of the prior complexity. Various researchers have designed a machine learning-based automated approach to monitor machine condition and to detect developing faults using the sensor data.

II. Literature Review

The concept of Prognostic and Health Monitoring (PHM) using sensor data is not new and has been practised for a long time [6]. By the early of the decade, the data received from machines by the sensors was modelled using the concepts of advanced mathematics or statistics. The initial work in this domain was carried out by Stanley [7] in 1938, when he developed a 3-phase model using phase variables for monitoring the condition of the induction motor. The domain of MCM gained popularity after this. Computational Intelligence (CI) is another term interchangeably used with Machine Learning. CI is an umbrella term used to describe all the AI based paradigms in computational domains. Recently, researchers have also

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implemented CI based models for MCM. In a review paper [8], authors have deeply discussed about the potentials goals with Industry 4.0. Authors have described about the lack of assessment methodologies in most of the sector under Industry 4.0 without which the expected transformation is difficult. We have discussed about various tech-stack that makes up most of the part to achieve the end goal. Machine Learning, Sensor based system and data science is one of the most disruptive technologies to bring the expected transformation. In [9], Balachandar et. al. collected data and analyzed it using machine learning approaches. In the study, Aluminium alloy was used for experimentation by using vibration analysis techniques signals were captured for good and faulty conditions of the tool. Statistical information was extracted from the raw vibration signatures and selection of features was carried out. The selected features were then classified using the Best first tree (BFT) classifier. The best first tree produced 93.07% as the classification accuracy. Similarly, in [10], the researchers have implemented the C4.5 machine learning algorithm, a decision tree classifier, on the training data. In [11], authors have majorly used advance mathematical and fuzzy tools to formulate condition monitoring models. They performance obtained is significant and provides base to model described in this paper. [12] has also used CI based methods for Machine condition monitoring. The research showcases anomaly detection based approach for fault diagnostic. The research also put forwards various application of intelligence machine condition monitoring system in industry.

III. CI-MCMs

In this paper, we have tried to present CI-MCMs paradigm (Computational Intelligence based Machine Condition Monitoring System). CI-MCMs is an artificial intelligence based architecture for automated monitoring and analyzing machinery in industry. The MCM parameters and architecture differ for different types of systems. “Fig. 1” demonstrates a general architecture of the CI-MCMs. CI-MCMs is a cloud based architecture in order to support real-time transfer of stream of sensor data. The CI model is also deployed on the cloud service. Thus, as the sensor data reaches the cloud hosted database, the CI model runs through the data to detect anomaly, if any. The results of the prediction are sent to client-side device in real time. At client side, a designated person can monitor the dashboard flexibly to asses the functioning and condition of the industrial machinery.

The goal with CI-MCMs is not limited to any set of intelligent algorithm or application. Depending on the type of machinery, different sensors are required. Each sensor records information in it’s own pattern i.e. frequency, type of information, size of information, etc. Thus, in such a variable data scenario a single set of algorithms cannot guarantee success. Further in this research study we have particularly used MCM for monitoring of hydraulic system. We tried implementing multiple CI algorithms like linear algorithms and different types of feed forward Artificial Neural Network (ANN) with certain variations. Further, we have compared the

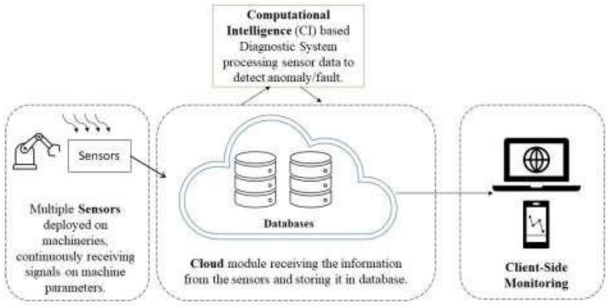

Fig. 1. CI-MCMs architecture

performances of those algorithm to analyse which works best for Hydraulic system. Use of MCM for Hydraulic systems has gained significant popularity lately. This is due to the high operational cost of such a system. Using MCM, sometimes leads to saving a high cost and time, thus making the use of such systems popular amongst the hydraulic system industries. This research also presents various other statistical methods and analysis on the same. It is important to note that MCM on Hydraulic system is one such application of the CI-MCMs architecture.

IV. Data & it’s pre-processing

The data set used in this paper, which is a publicly available data set on kaggle [13], was collected via a hydraulic test bench which simulated different component conditions of cooler, valve, internal pump, hydraulic accumulator and also assessed the overall stability [14]. There are different sensors deployed across the test bench namely multiple pressure sensors, motor sensors, temperature sensors, etc. “Fig. 2” illustrates various input features of the data set with corresponding details. As it can be seen in the figure, there are multiple attributes being measured by each sensor. Specifically, the pressure sensors, motor power sensors and volume flow sensors measure about 6000 various attributes. Considering such many parameters to the model might become undesirable. Thus, we took the mean value of all the attributes for a corresponding sensor at specific data points. This helped in reducing the number of parameters from 48000 to 15 whilst retaining the significance of data and reducing the complexity at the same time.

V. Methodology & Experiment

We have constructed three different classification modelsfor the dataset. Each model has it’s own unique approach towards the problem. The first model uses the concept of Logistic Regression, a go-to method for binary classification problems, while, the other two models are built on the concept of artificial neural networks (ANN). The only difference between the architectures of the two ANN models is Principal Component Analysis (PCA), a method used to reduce dimensions in the input data. Further, the total sample size for our dataset is 2205 rows and 16 sensor features. After running a covariance function code on the entire dataset, we took 5 most important

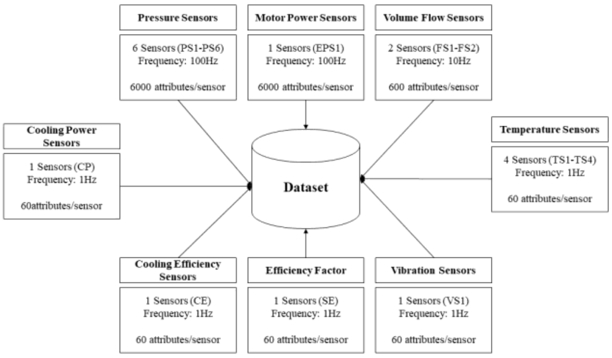

Fig. 2. Stream of input data in the data set which is further passed to the model

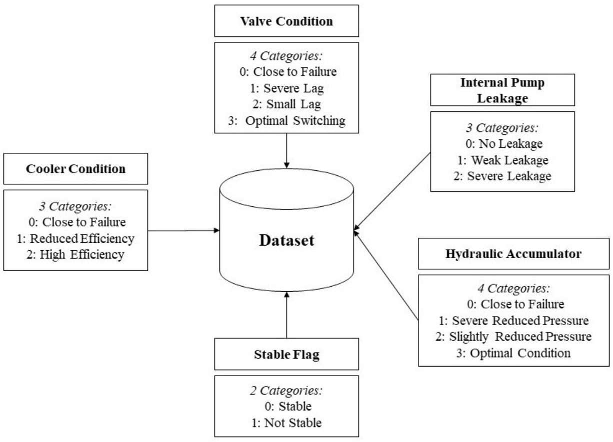

Fig. 3. Stream of input data in the data set which is further passed to the model

features - Cooler Condition, Valve Condition, Internal Pump Leakage, Hydraulics Accumulator, Stable Flag, and used them for analysis. To perform the covariance, a heat map was also generated to check correlations between the input and the output features. The idea behind generating the heat-map was to see if we could find any unique linear co-relation between the input and the output features. Before the training model, we used a default split ratio of 80 to 20, where 80% of data went into training and 20% went in testing. Further, the number of iterations was decided based on the accuracy results, for example, we set 75 epochs for Cooler Condition as it gave 100% accuracy with just 75 iterations (Refer “Table. I”).

TABLE I
FEATURE WISE NUMBER OF EPOCHS FOR TRAINING

Output Feature	**Epochs**
Cooler Condition	75
Valve Condition	100
Internal Pump Leakage	200
Hydraulic Accumulator	200
Stable Flag	100

The first ANN model has an extra block of code for

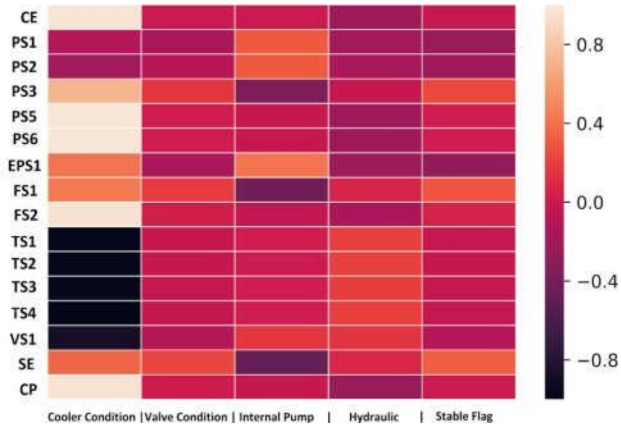

Fig. 4. Correlation heat map matrix between all input and output features

performing PCA on the inputs followed by two fully connected Dense layers with 128 and 64 neurons respectively. The activation function used in the first layer is LeakyReLu while the second layer uses ReLu and finally the output is passed through the softmax function depending on the number of classes for each feature. The idea behind applying PCA, before feeding it to the fully Dense layers, was to reduce the dimension of the input layer. PCA takes in the inputs and finds a new set of dimensions that are orthogonal and have high co-variance with respect to the outputs. In simple terms, it tries to summarize the data by finding linear correlations between the input and the outputs. On the other hand, the second model was constructed without applying PCA by feeding the input layers to the first Dense layer. Once the models were ready, they were run through a set number of epochs, ranging from 50 to 100, depending on the accuracy achieved. For the second ANN, everything remains the same except no PCA is applied. The input data is directly fed into the first Dense layer with 128 neurons. In order to compare the performance of Artificial Neural Networks (ANN) over basic classification models, we implemented Logistic Regression (LR) algorithm on the same data set on same input and corresponding output features. The design process was simple; feed the input data to the to LR function and run the program. With regards to the analysis of the results, we used ‘accuracy’ metrics from Keras library, where accuracy metrics basically compares the true sample point with the predicted sample point. For instance, if true points are (2, 3), and the predicted points are (2, 4), the accuracy is 50%. Further, accuracy metrics are easier to understand and gave us high accuracy, and therefore in this paper, we have used ‘accuracy’ metrics for the models. “Fig. 4” demonstrates the correlation matrix.

VI. RESULTS & DISCUSSION

On observing the results from all the three models, we concluded that the ANN model with the PCA implementation gave the best results. (Refer to “Fig. 5” and “Table. II”) In-fact, Cooler Condition, Internal Pump Leakage and StableFlag

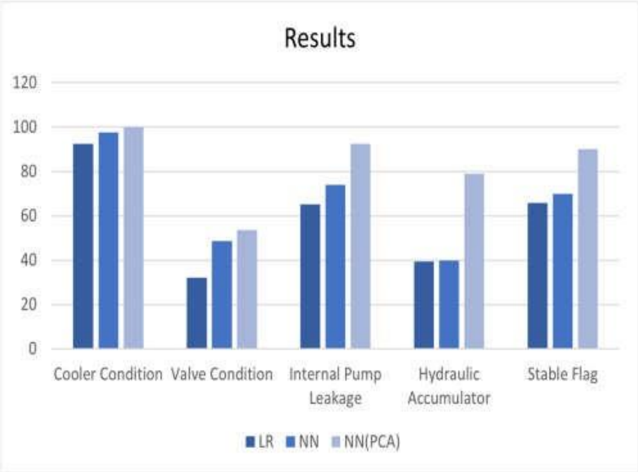

Fig. 5. Results from two different approaches:(1) The dark blue bars show accuracy of Logistic Regression model (2) The medium blue bars show accuracy without PCA (3) The light blue bars show accuracy with PCA; clearly, we observe that the Neural Network model with PCA delivers better results.

TABLE II
ACCURACY OF THE IMPLEMENTED MODELS ON 5 DIFFERENT OUTPUT FEATURES

Output Feature	**LR**	**NN**	**NN (PCA) n = 3 ***
Cooler Condition	92.45%	97.61%	99.99%
Valve Condition	32.04%	48.61%	53.52%
Internal Pump Leakage	65.08%	74.01%	92.41%
Hydraulic Accumulator	39.40%	39.88%	78.93%
Stable Flag	65.90%	69.89%	90.06%

had highest accuracy of 99%, 92.4% and 90.06% followed by Hydraulics Accumulator at 78.93 and Valve Condition at 53.52% respectively. ANN without PCA implementation gave lower but still promising results; for instance, Cooler Condition and Internal Pump Leakage had higher accuracy of 97.61% and 74.01% compared to the accuracy of Hydraulics Accumulator, Stable Flag and Valve Condition. When it came to Logistic Regression, except for Cooler Condition which had highest accuracy of 92.45%, the rest of the output features had lower results with Valve Condition and Hydraulics Accumulator being the lowest with 32.04% and 39.40% respectively. ANN are best suited when it comes to multi-dimension data. Moreover, the research shows that shallow neural networks with ample numbers of neurons in the hidden layers are sufficient to accurately model on a data set which has high correlation. This also mean that engineer with just basic knowledge of Machine Learning concepts can implement a small neural network with a of hidden layers and get promising results.

VII. CONCLUSION

With innovation of new technology, mankind has always witnessed a transformation in the economy, society, education and in general the industry. At some point in the timeline, such changes become a necessity for the industry. Otherwise, it begins to disrupt the traditional methods. In this paper, we have introduced CI-MCMs architecture and have implemented one of it's application. Such automated fault diagnostic systems increase the production efficiency and significantly decreases the machine operating costs. Data is the new oil, and thus the data collected via sensors, as discussed in the architecture, can be used to extract lots of valuable information. The neural network-based model implemented in this research study produced great accuracy. Thus, are reliable to be used at real time in the industry. The information obtained from t h e data can also be used for purposes other than what was discussed in this paper. It is evident that future manufacturing will be more intelligent and will comprise of more automated modules. Thus, there is lot of scope improving this current CI- MCMs architecture. In future, we wish to work on creating model for sudden accident avoidance on production supply line. The model should be able to predict if there is an upcoming accident or shortage. Thus, shall be able to run the safety (anti-accident) module in advance. This implies that the advanced MCM module under CI-MCMs will be the topic of the following paper we intend to produce.

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