Supervision systems course

Chapter - 03: Machine Learning in CBM

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Outline

Introduction

This chapter delves into Machine Learning for Condition-Based Maintenance (CBM). We'll provide an overview of CBM techniques, explore its current state, look at future prospects, and examine how machine learning is enhancing the Internet of Things (IoT) from a CBM perspective. We'll illustrate this with an example involving the use of transducers for data collection and analytics. Additionally, we'll showcase a case where machine learning is applied to predict tool wear in metal-cutting operations. Today, sensors have significantly evolved and become more compact, with the advent of MEMS-based sensors, facilitating data collection, analysis, and seamless transmission.

Machine Learning in CBM

- The Internet of Things (IoT) is a concept that refers to the interconnected network of physical objects, devices, and sensors, each embedded with technology and capable of communicating with each other and with central systems over the Internet.
- The Internet of Things, often abbreviated as IoT, is a technological paradigm that has gained significant prominence in recent years. It represents a vast network of everyday objects, machines, and devices that have been enhanced with sensors, software, and connectivity features, enabling them to collect and exchange data over the internet.
- sensors have come into the spotlight recently due to a major development in the Micro-Electro-Mechanical Systems (MEMS)

The key components of IoT are:

- Physical Objects: These can be anything from household appliances and vehicles to industrial machinery and wearable devices.
- Sensors: These are integrated into the objects to monitor and collect data about their surroundings. Sensors can measure various parameters, including temperature, humidity, location, motion, and more.
- Connectivity: IoT devices are equipped with communication capabilities, allowing them to transmit data to central systems or other connected devices. Common communication protocols used include Wi-Fi, Bluetooth, cellular networks, and low-power wide-area networks (LPWAN).

The key components of IoT are:

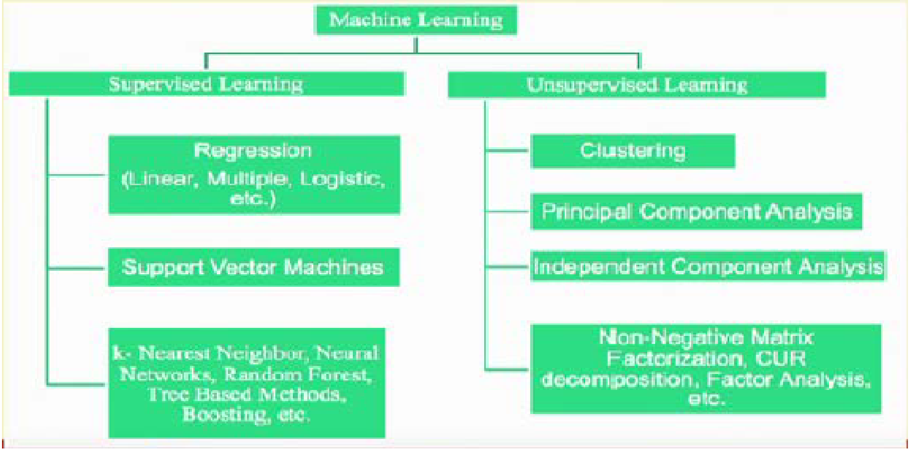
- Data Processing: The data collected from IoT devices is processed, analyzed, and often stored in the cloud or other centralized systems. Advanced analytics and machine learning techniques are used to derive insights and patterns from the data.
- Action and Automation: IoT systems can trigger actions based on the data collected and analyzed. For instance, a smart thermostat can adjust the temperature in a room based on occupancy and environmental conditions, or an industrial machine can automatically shut down when a fault is detected.

IoT has found applications in various domains, including smart homes, healthcare, agriculture, transportation, manufacturing, and more. It offers numerous benefits, such as improved efficiency, enhanced convenience, and real-time monitoring and control. However, it also raises important considerations related to privacy, security, and data management, which must be carefully addressed as IoT continues to proliferate.

Example on IoT

- Picture this scenario: You have an air conditioner at your home, and unexpectedly, a service technician arrives at your door. They inform you that, based on their service protocol or the data in the service database, they need to inspect the blower of your air conditioner.
- When you visit an automobile service station with your car, the service manager will approach you and review the data logged in your engine's history. From this, they'll draw conclusions, such as the need to replace a spark plug in a particular cylinder. You might find yourself wondering about the "how" and "why" of this assessment, all thanks to the (OBD) onboard diagnostic modules.

Machine Learning Techniques



supervised learning

supervised learning

In the realm of machine learning, supervised learning is a prominent approach. Among the various algorithms used, three notable ones are neural networks, random forests, and support vector machines (SVM). These algorithms serve as powerful tools for mapping input data to desired output and constructing predictive models. Let's delve into each:

- **Neural Networks**: Neural networks are computational models inspired by the human brain. They consist of interconnected layers of artificial neurons that process and learn from data. Neural networks are highly versatile and can handle complex relationships in data, making them well-suited for tasks like predicting Remaining Useful Life (RUL).

supervised learning

- **Random Forest:**: Random forests are an ensemble learning technique that combines multiple decision trees. They are adept at handling large datasets and provide robust predictive models. Random forests are known for their ability to capture intricate patterns and relationships in data.
- **Support Vector Machine (SVM)**: SVM is a supervised learning method that excels (exceed) in binary classification tasks. It finds an optimal decision boundary that maximizes the margin between classes in the input space. SVM can also be used for regression tasks and is valuable for predicting RUL in various applications.

These algorithms take historical data, where input features are correlated with the RUL, and create models. These models serve as a blueprint for forecasting RUL in new, unseen data. They can be applied to linear systems or more complex systems, offering flexibility for a wide range of predictive maintenance tasks. The accuracy and performance of the model depend on the algorithm chosen and the quality and relevance of the input data, which is crucial in the realm of predictive maintenance.

Unsupervised learning

Unsupervised learning

Unsupervised Learning is a category of machine learning where the algorithm is trained on data without explicit supervision or labeled outcomes. Unlike supervised learning, where algorithms learn from a dataset with predefined labels or target values, unsupervised learning deals with unstructured data and aims to find patterns, relationships, or structures within the data without prior knowledge or guidance. It's particularly useful when you want to explore and understand data, identify hidden patterns, and discover underlying insights.

Unsupervised learning

Here are some key aspects of unsupervised learning:

- Clustering: One common application of unsupervised learning is clustering, where the algorithm groups similar data points into clusters. K-means and hierarchical clustering are popular clustering algorithms. Clustering can be used for customer segmentation, anomaly detection, and image segmentation, among other tasks.
- Dimensionality Reduction: Unsupervised learning techniques like Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) reduce the dimensionality of data while preserving its essential features. This is valuable for data visualization, feature selection, and simplifying complex datasets.

Unsupervised learning

- Anomaly Detection: Unsupervised learning can identify anomalies or outliers within a dataset. This is crucial for fraud detection, network security, and quality control in manufacturing.
- Density Estimation: Algorithms such as Gaussian Mixture Models (GMM) estimate the probability distribution of data, allowing for modeling complex data distributions. Density estimation is used in applications like natural language processing and image analysis.
- Representation Learning: Unsupervised learning can learn meaningful representations of data without explicit labels. Autoencoders, for example, are neural network architectures that learn to encode and decode data efficiently, often used in deep learning applications.

Unsupervised learning

- opic Modeling: In natural language processing, unsupervised learning can discover topics within text data. Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NMF) are popular techniques for topic modeling.
- Recommendation Systems: Collaborative filtering is an unsupervised technique used in recommendation systems to suggest products, services, or content based on user behavior and preferences.

Unsupervised learning is exploratory in nature and is essential for understanding the inherent structure of complex data, even when there is no clear guidance on what to look for. It has applications in various fields, including data mining, image and speech recognition, biology, and social network analysis.

Case Study

Tool wear monitoring

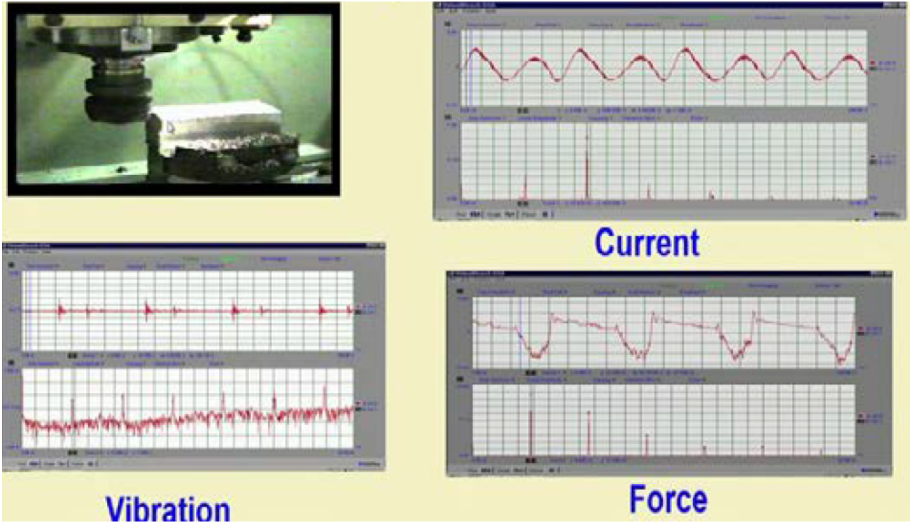
(is the gradual failure of cutting tools due to regular operation)
If there was no way to monitor cutting tool wear and this tool had become blunt. So, this is going to affect the surface finish of your machining. Another case is if the tool has become very blunt and instead of being sharp, more cutting forces would be required, more energy would be spent, on doing this machining operation, and surface quality would change.

Tool Condition Monitoring

- CNC milling machine
- Work Piece Material
  - Steel
  - Aluminum
- dry cutting Condition
- single insert
- Cutting speed 140m/min
- Depth of cut 1.5mm
- Approx Tool wear 75 micron; Tool wear: is the gradual failure of cutting tools due to regular operation. Tools affected include tipped tools, tool bits, and drill bits that are used with machine tools.

Tool Condition Monitoring

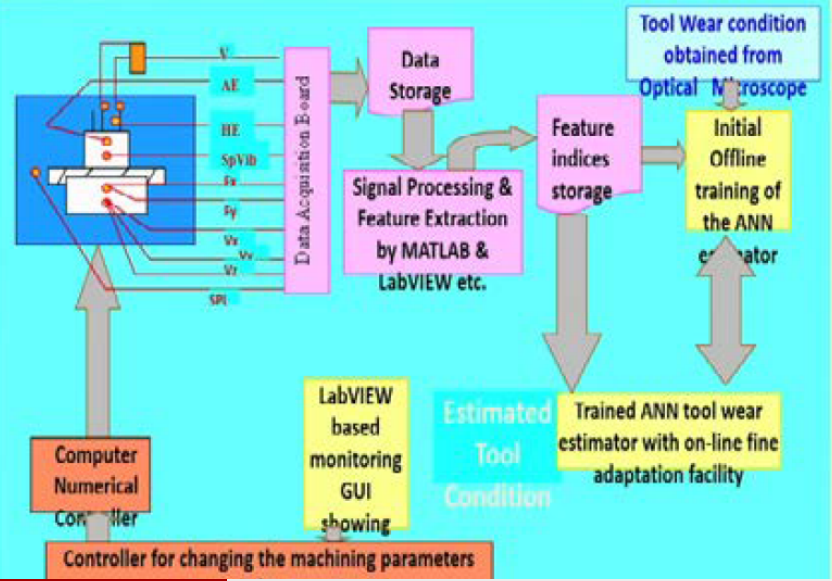
We instrumented the spindle with many sensors, having a sensor for acoustic emission, vibration, cutting tool force, the sound radiated and for the motor current being drawn by the spindle motor, and so on. So, we tried to indirectly measure many parameters out of this machining.


Current
Vibration
Force

Current, Vibration, Force Signature, Aluminum Face Milling, Spindle Speed 557 RPM

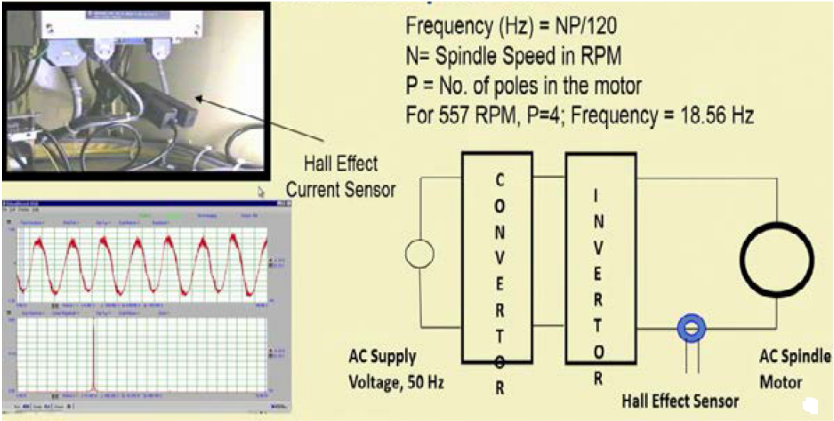
In the previous stage, we run the machine one pass and measured the tool wear in a microscope at the same time we measured the parameters like the current drawn by the motor, the force of the tool dynamometer the vibration induced, and so on and then we made actually a neural network mapping.

Multi Sensor based tool condition monitoring

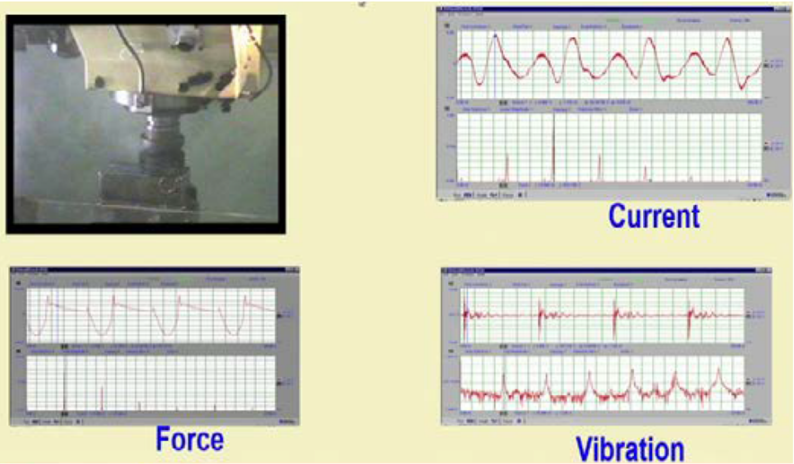


We did a multi-sensor-based tool condition monitoring, we measured the acoustic emission, the high frequency, acoustic emission signals, the vibration levels, the force levels, sound levels, and the voltage-current, at the same instance, we measured the tool wear in a microscope. So, we did an initial offline training of the artificial neural network estimator, wherein we mapped these parameters the signal features obtained from all the sensors to the actual tool wear and did a neural network model, and that is one of the machine learning algorithms. So, once my model was successful we could always find out and forecast the time when the tool in this condition, is going to achieve 500 or 600 microns when this tool has to be replaced.

Variable Voltage/Variable Frequency PMW Speed Control of AC Spindle Motor



Current, Vibration, Force Signature, C60 Face Milling, Spindle Speed 557 RPM



Experimental Setup at a Gear Box Manufacturing Facility

Experimental Setup Cont'd

This is another view of the cutting force dynamometer, put below the work piece and you can see this is the vibration transducer.

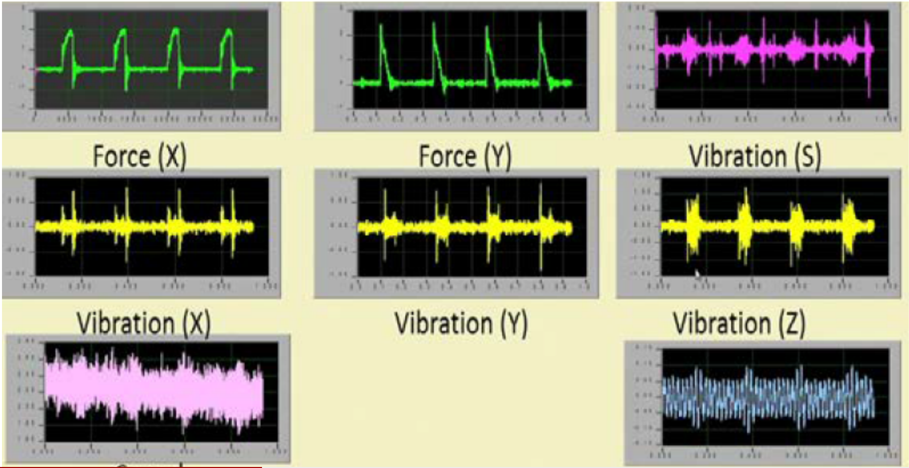
Detailed Experimental Conditions

These are the different phases for the different cutting speed velocities, the depth of cutting, and feed rate.

	V_c (m/min)	S_0(mm/tooth)	t (mm)
Phase I	98	0.16	1.5
Phase II	98	0.22	1.5
Phase III	140	0.22	1.5
Phase IV	212	0.16	2.0
Phase V	150, 180	0.2	2.0

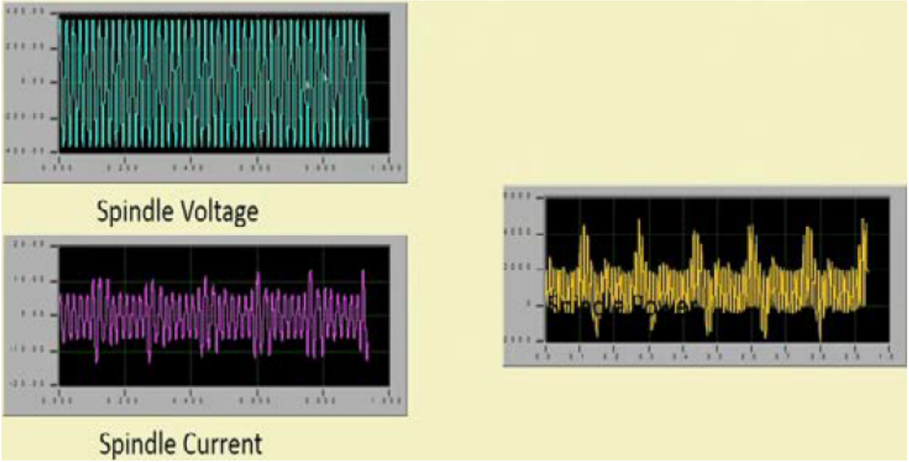
Typical Signal Phase-II

This is the typical signal which is obtained from the sensors; force in x y z directions, vibrations, spindle current, and so on. So, these signals convey information as to the present condition of the machine.

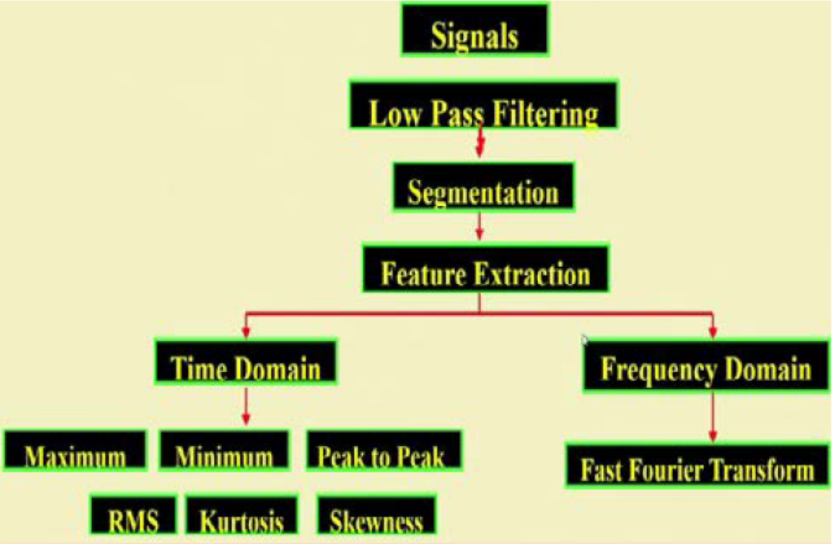


Typical Signal Phase-III

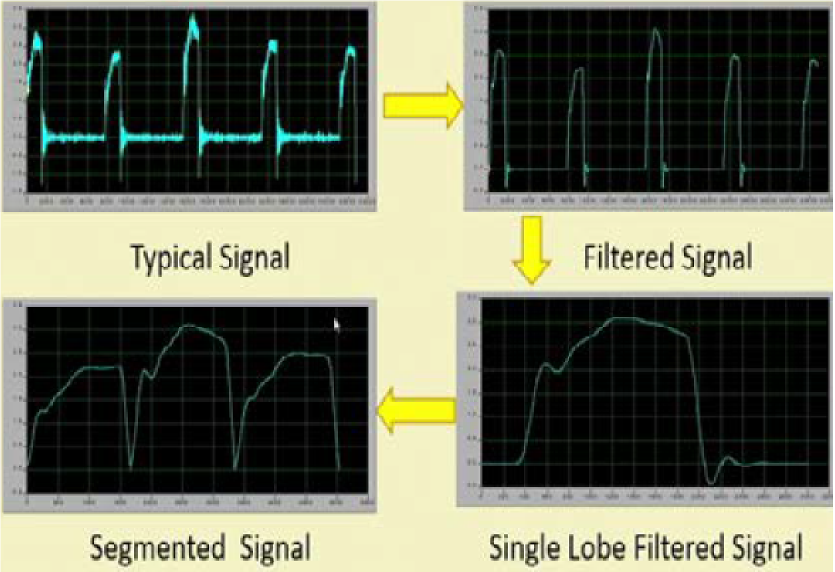
These are the spindle voltage and current in Phase-III



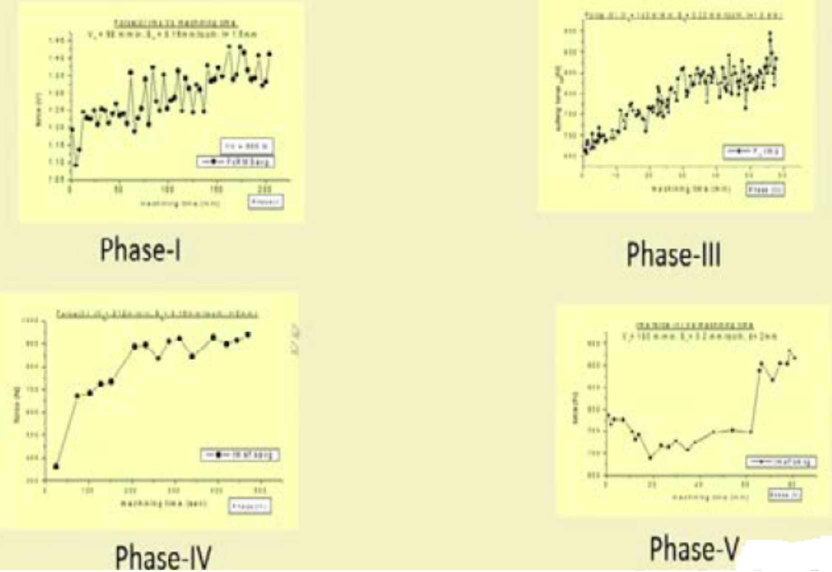
Signal Processing



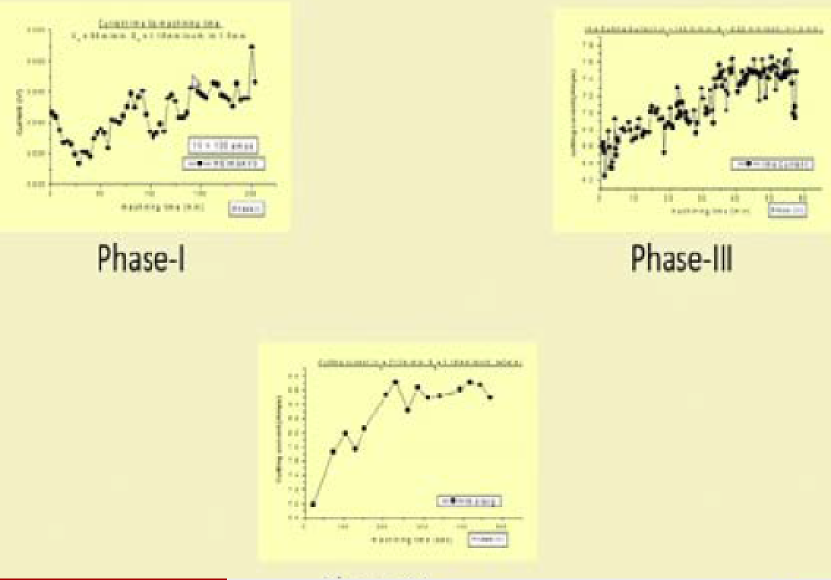
Signal Segmentation



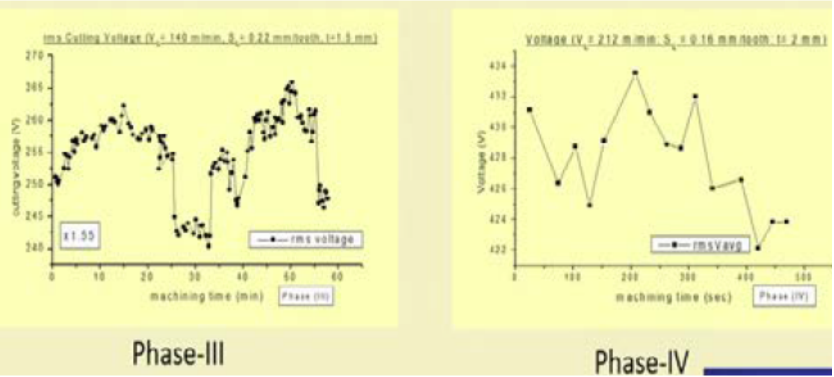
Machining Features (Fx)



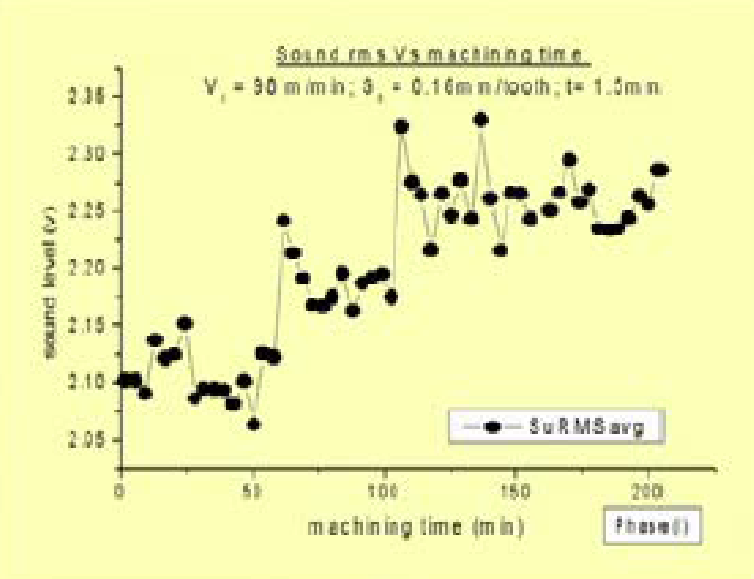
Machining Features Current



MachiningFeatures Voltage



Machining Features SPL



ANN Based Decision System

Feature space

- Force rms (F_x , F_y)
- Process Parameters (S_o , V_c , t)
- Spindle power (Voltage and Current)

Activation function

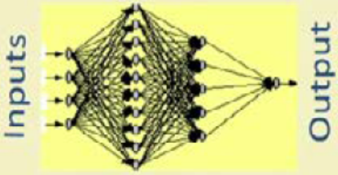
- Log sigmoid: $\frac{1}{1+e^{-\lambda x}}$

Domain

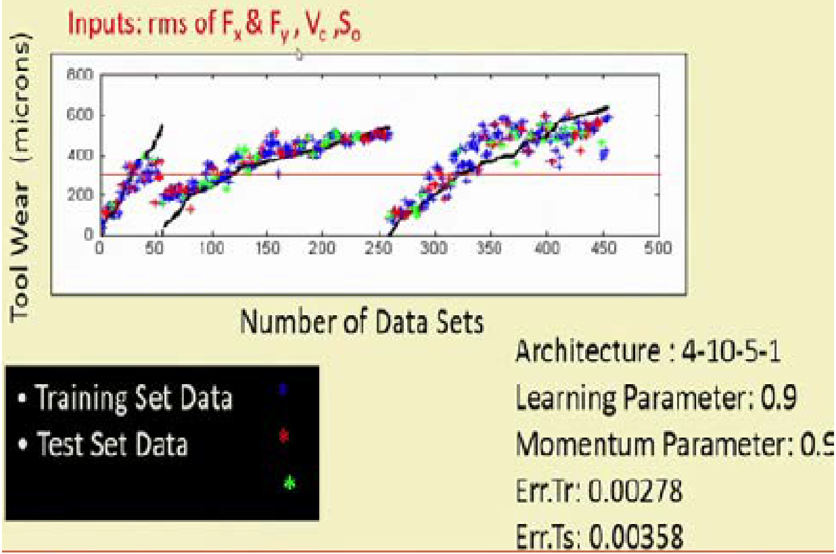
- Learning-rate (lr) : 0.2 ~ 0.9
- Momentum-parameter (mp) : 0.1 ~ 0.99
- Layers : 3 ~ 4
- Nodes in the hidden layer(s) : (3 ~ 20) & (2 ~ 8)

Final values

- lr : 0.9
- mp: 0.9
- Layer: 4 (two hidden layer)
- Nodes in the hidden layer: (10-5)



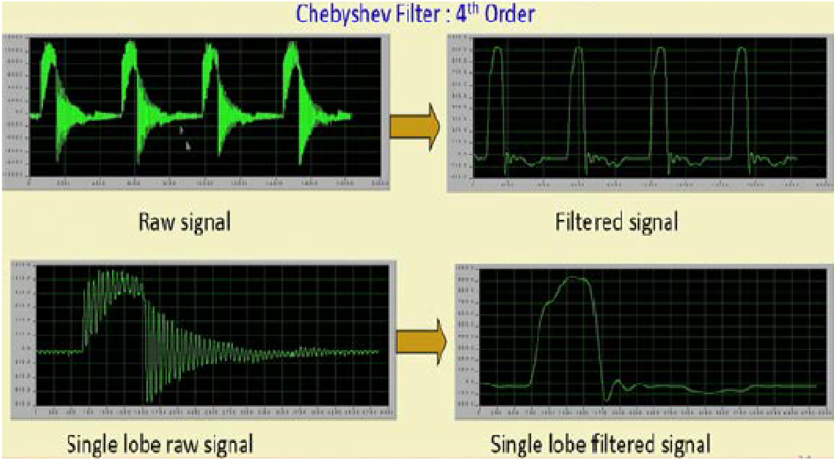
ANN Performance Results (Force Features)



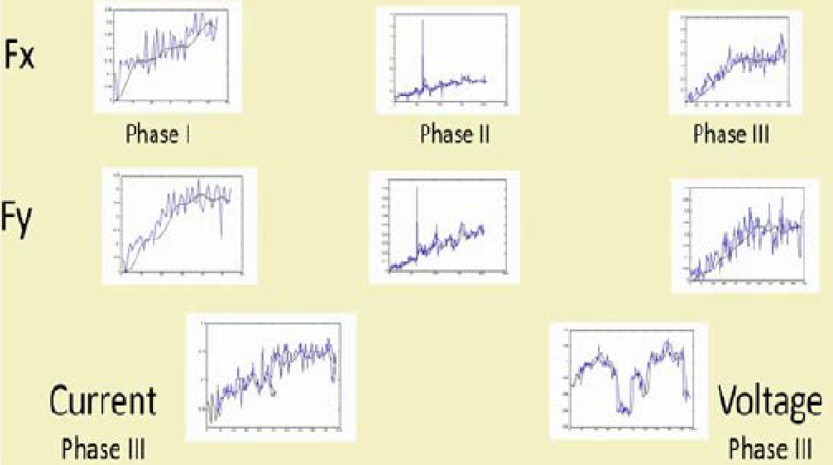
Low-Pass Filtering

- Low-Pass Filtering of raw signal during segmentation chebyshev 4th order.
- Low-Pass Filtering in feature space Butterworth 3th order.

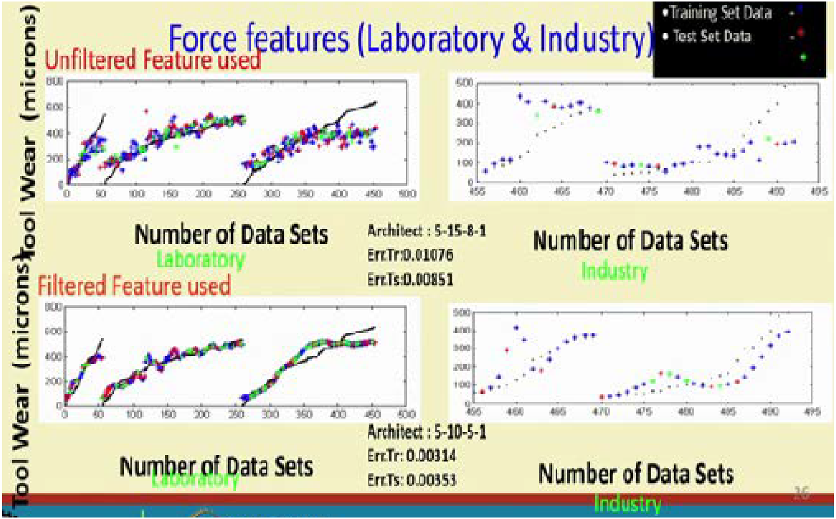
Filtering of Raw Signal



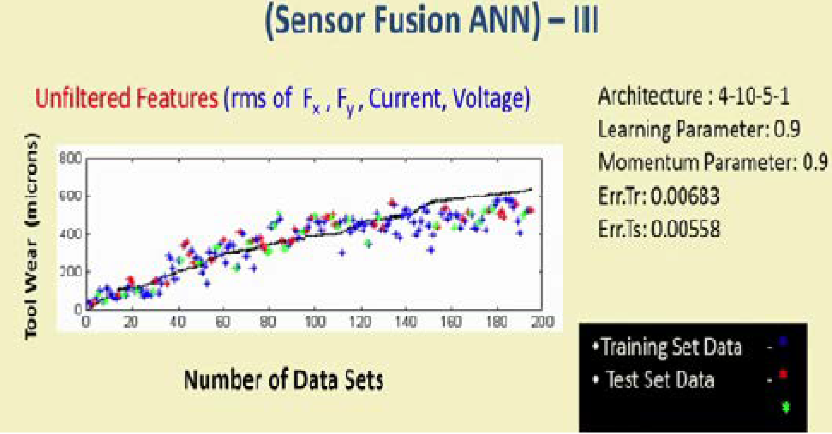
Filtered Features



ANN Performance Results



ANN Performance Results



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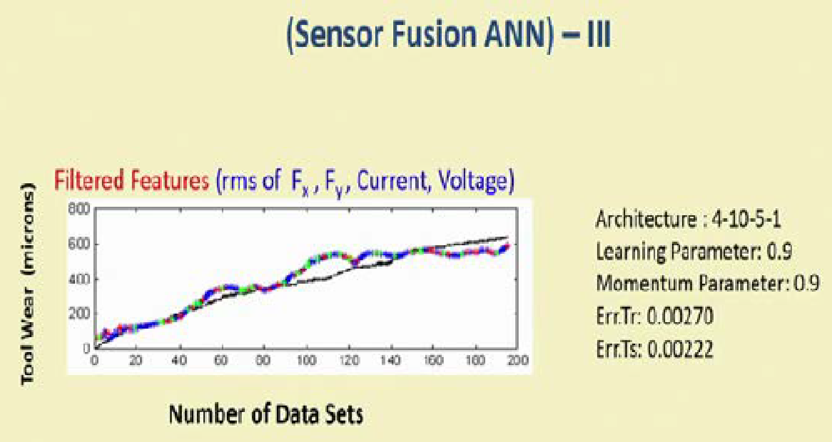

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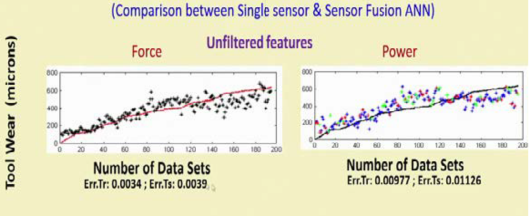

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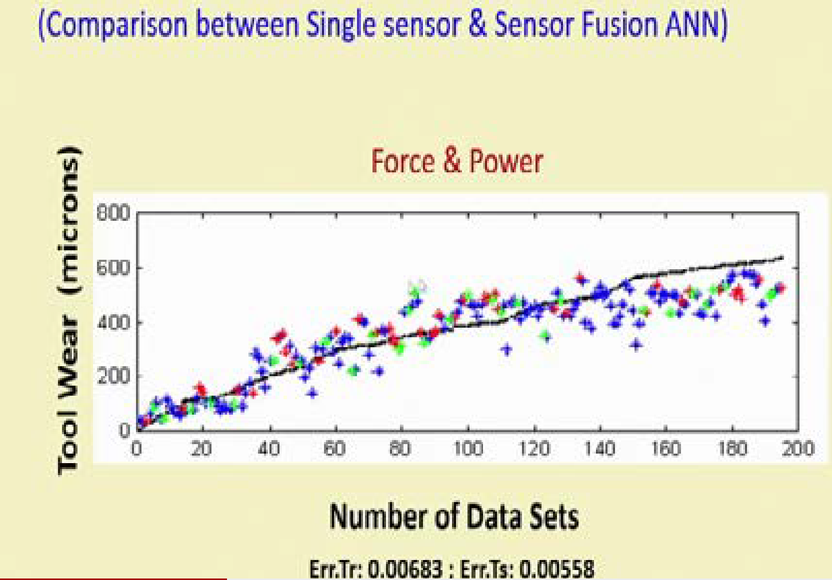

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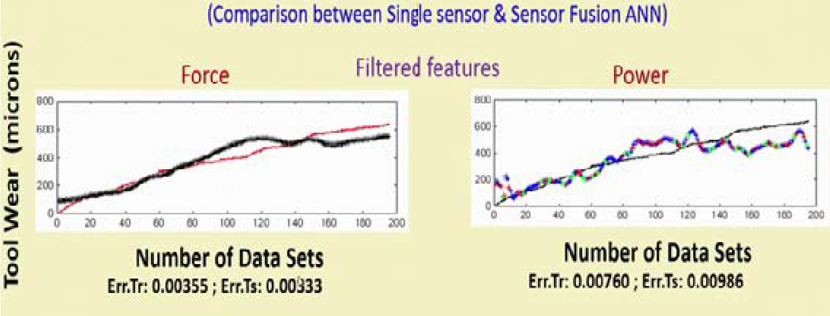

Summary

- ANN based decision system was developed.
- Different strategies implemented.
- force-based strategies gave a prediction off within $\pm$ 8 %.
- Current based strategies testes (III) prediction off within $\pm$ 14%.
- Sensor Fusion: Force + Current+ Voltage (III) prediction off within $\pm$ 6.5% .

Results-Summary

Strategies	Phases	Error Level (%)	
		Unfiltered	Filtered
Force based	I, II & III	8.5	8.0
	All	13.0	8.4
Power based	III	15.0	14.0
Sensor Fusion	III	10.3	6.6

Thank You!