Deep Learning in Manufacturing

–"When Ernst Met LeCun"
Team 6

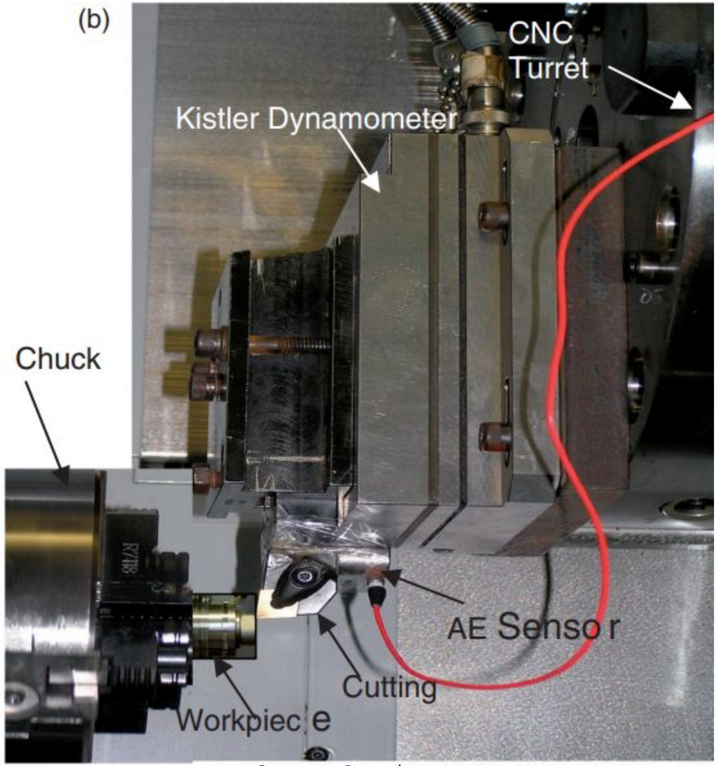
Motivation and Overview

Some broad problems in manufacturing (specially machining):

- Input Parameters are based on intuition and experience.. may be suboptimal
- Previous Tool and machine health monitoring techniques are:
    - Not accurate
    - Take a lot of time
    - Offline
    - Requires more human intervention
- Output parameters cannot be estimated accurately

Sensor Data Acquisition & Processing

- -→ Cutting Force
- -→ Acoustic emission
- -→ Vibration
- -→ Power consumption
- -→ Spindle Current
- -→ Product Quality



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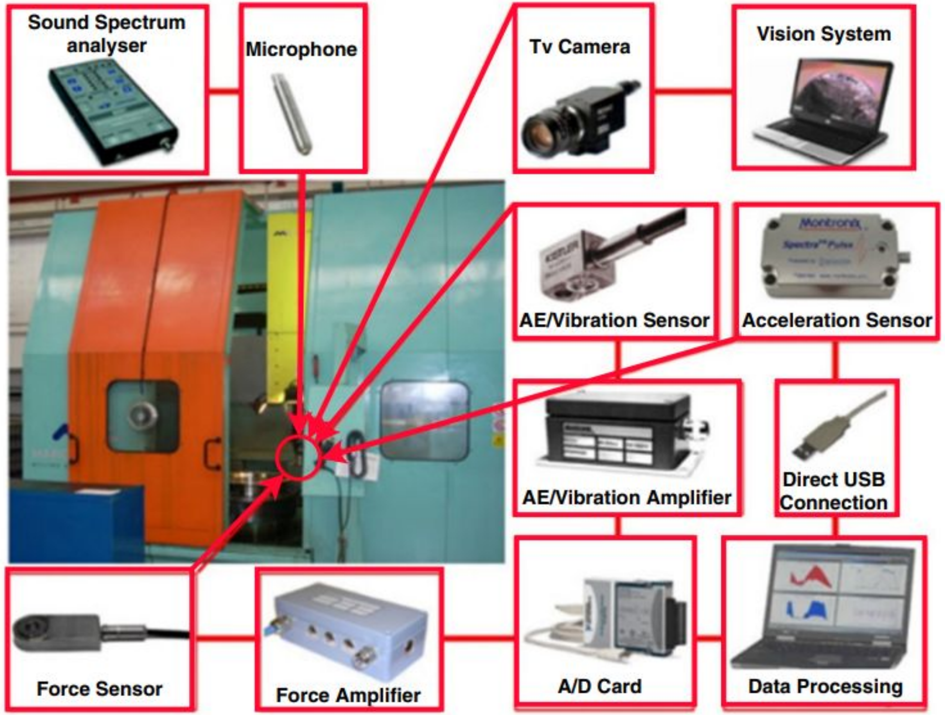
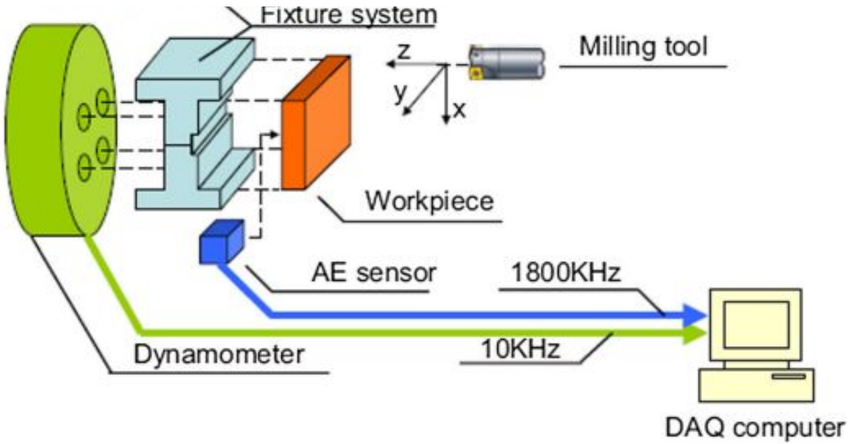


Cutting Force:

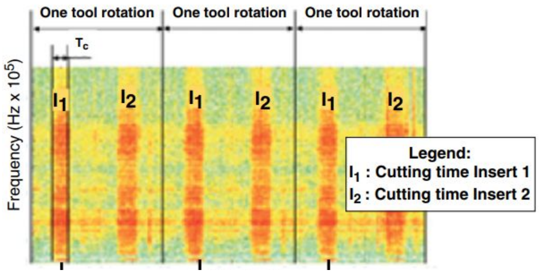
- **Sensor used**: Dynamometer | Indirect
  Data format: time, convert in frequency domain , transformed using FFT
- **Sources of Cutting Force** : Depends on cutting parameters, tool wear and when tool loses it sharpness it increases
- **Interests** : By measuring tool wear or breakage can be monitored
- **Result**: Allow us to establish relation between tool wear and breakage

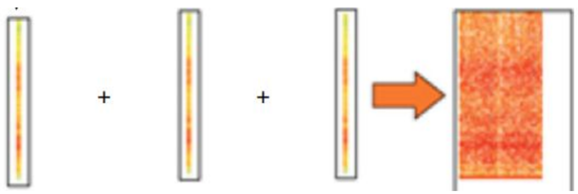


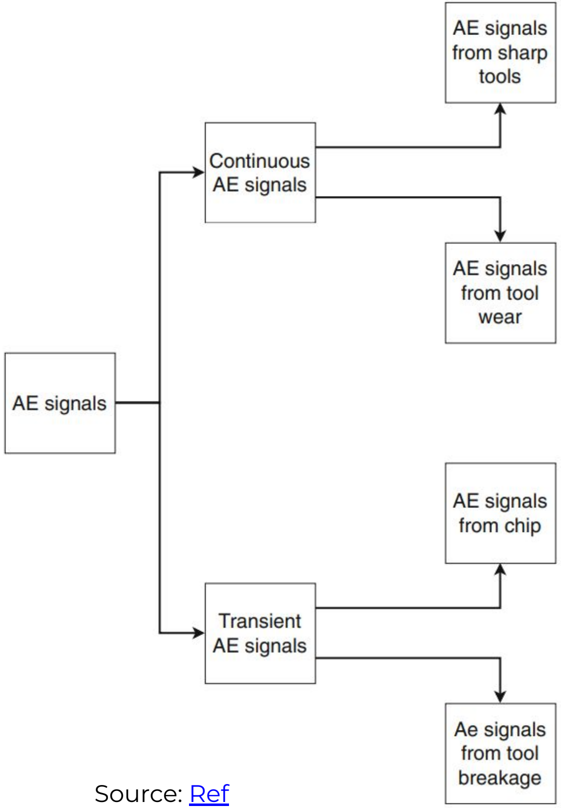
Source: [Ref]

Acoustic Emission

- Radiation of the elastic waves in the solids
- Generated when the w/p experiences plastic deformat
- **Sensor :** Acoustic emission transducer or microphone
- Indirect (or online) monitoring
- **Processing:**
  1. Transform to time-frequency domain using STFT
  2. Determine cutting time for each tool
  3. Extract the bands of tooth engagement
  4. Combine bands to obtain dense spectrogram



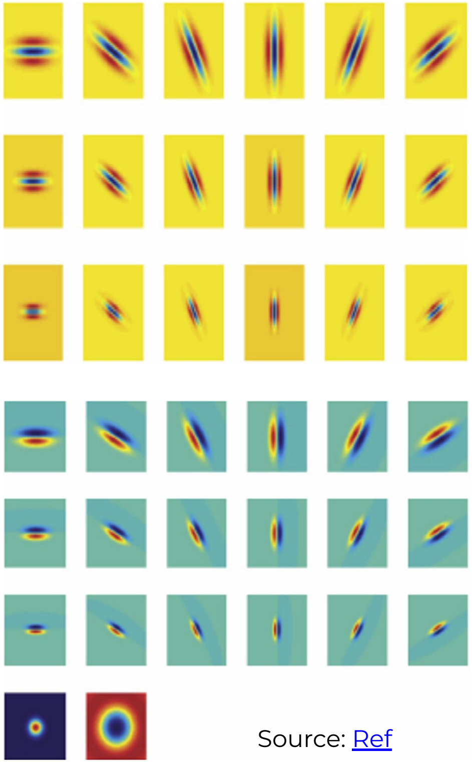




Source: [Ref]

Vibration

- **Sensor used**: Accelerometer
- **Sources of Vibrations**: unbalanced rotating component, inertia forces of the reciprocating parts, kinematic fault of drives
- **Processing**:
  a. Transform to time-frequency domain using STFT
  b. General features of interest: VE about mean (represents chatter), TVE (represents wear)
  c. Spectrographs are scanned using the appropriate filters to extract 2D texts for each predefined frequency band.
- Proposed features works best with fuzzy C-means classifiers



Source: [Ref]

Other types of sensory data:

For Direct Tool Condition Monitoring:

- Optic Sensor
- Displacement

For Indirect Tool Condition Monitoring:

- Surface Roughness of product
- Temperature of tool

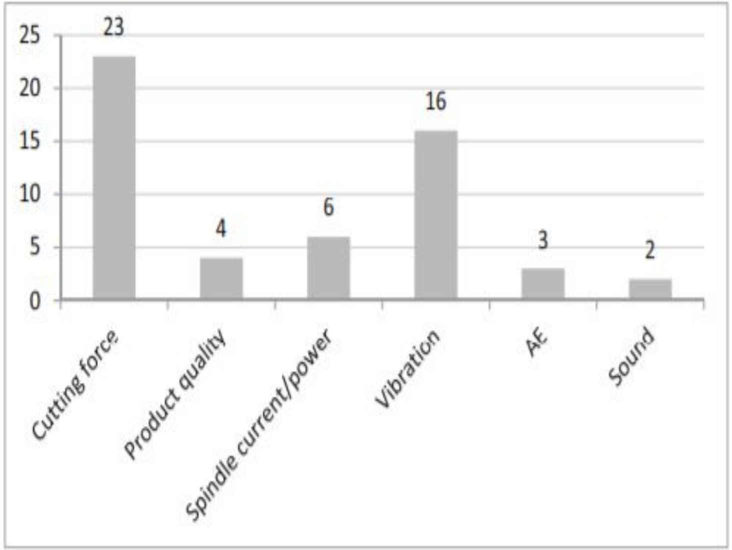


Fig. 2 Frequency of various CM parameters in 38 published papers

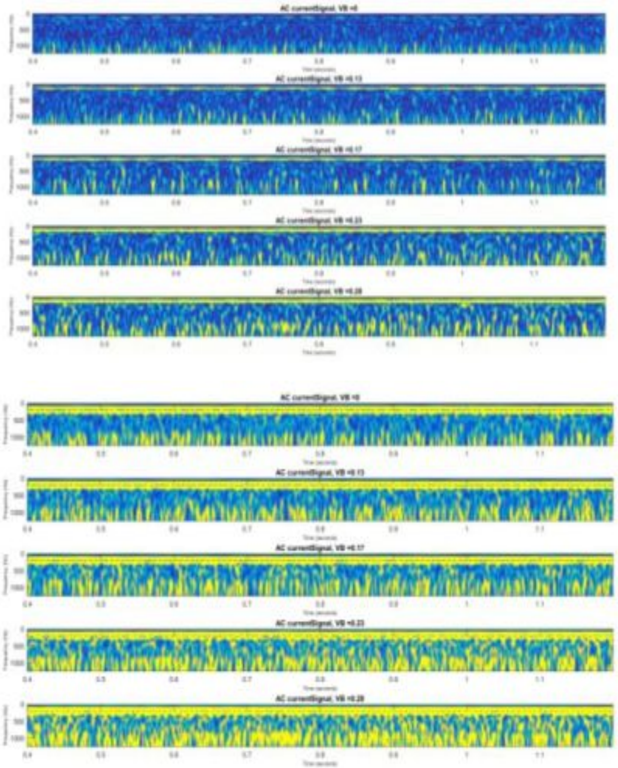
Source: [Ref]

Non-Deep Learning ideas & their limitations

TEAM 6

Aghazadeh F, Tahan A, Thomas M (2018)

Tool Condition Monitoring Using Spectral Subtraction Algorithm and Artificial Intelligence Methods in Milling Process



Aim: Tool condition monitoring for milling operations using spindle current

Method:

- Descriptor signal: spindle current in time-frequency domain using WT
- WT of a healthy signal (one with no tool wear) is also obtained beforehand
- Feature = extracted WT-healthy WT (spectral subtraction). Fed into regression model (Decision Tree performs best, 91% accuracy) to estimate the flank wear

Non-Deep Learning ideas & their limitations

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Srinivasan A, Dornfeld D, Bhinge R (2016)
"Integrated vibration and acoustic data fusion for chatter and tool condition classification in milling"

Aim: Demonstrate that **integrated vibration and acoustic** sensor provide reliable results

Method:

- Input feature: vibration and acoustic data; Classification with linear SVM
- Chatter detection: Features - Acoustic SC, VE about mean
  - Accuracy with only SC: 95.78 % ; only VE: 98.46%; Combined: 99.87 %
- TW detection: Features- SC, ASE, VE about mean, total VE
  - Accuracy with only SC: 72.9 % ; only VE: 56.9 % ; Combined: 96.97 %

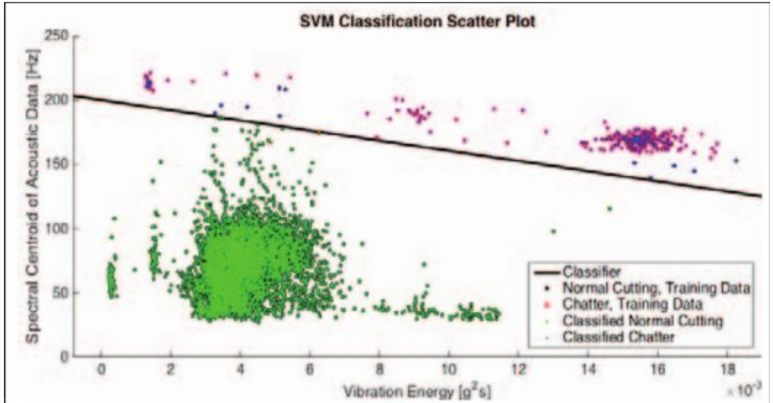


Figure 4: Scatter plot for SVM classification on combined acoustic and vibration data

***Note**: *all the accuracies mentioned are on training data*
SC - spectral centroid ; VE - vibration energy
ASE - Acoustic Spectral Energy

Towards Deep Learning

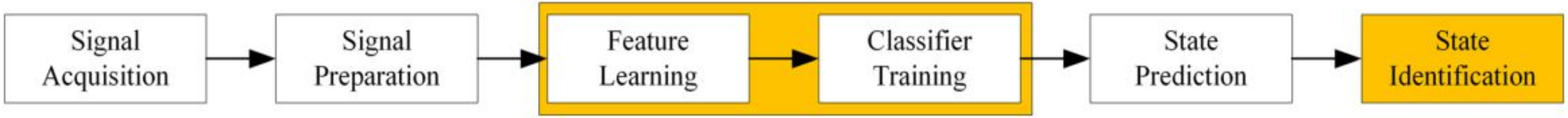
- Process Monitoring
- Estimation of Process parameters
- Optimization

Process Monitoring

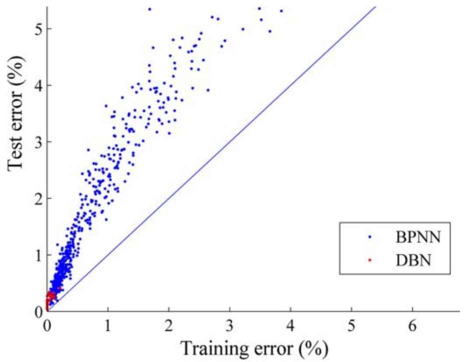
Zhang, Sun et al. (2019)

Automatic feature constructing from vibration signals for machining state monitoring

- <u>Aim</u>: To predict machining state (idling moving, stable cutting, chatter)
- <u>Sensors</u>: Accelerometers



- Deep belief networks(DBN) for AFE with two step training
- Shallow classifier model to predict the state
- Voting strategy considering current and past states
- Can protect the workpiece from serious chatter damage



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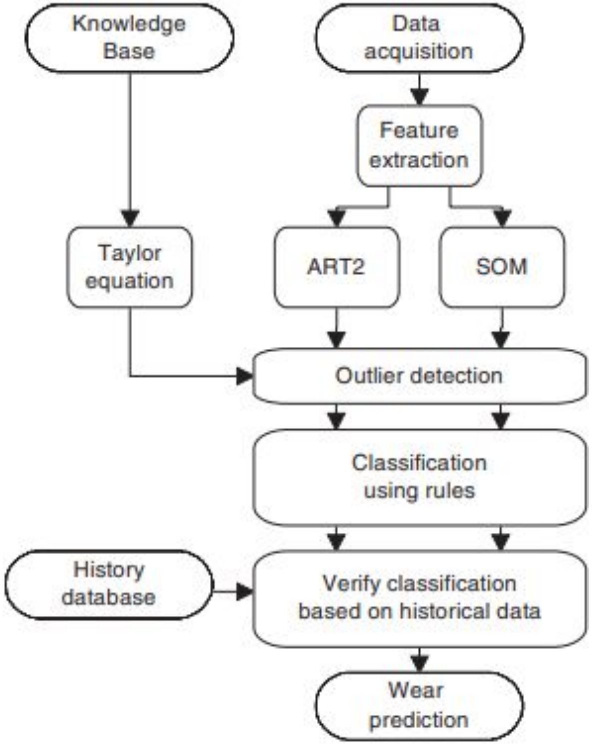
Process Monitoring

Silva , Wilcox al. (2006)

Development of a system for monitoring tool wear using artificial intelligence techniques

- Turning machine
- Input : vertical vibration, sound emission, cutting force & spindle current
- Use of hybrid intelligent system, based on an expert system and 2 NN.
- NN classified abnormal and normal operating states,
- Misclassifications were filtered out through a rough estimator – **Taylor's tool life** model

Output : Tangential and feed forces -strongest features but condition variant.



Process Monitoring

Jia, Lin et al. (2018)

A neural network constructed by deep learning technique and its application to intelligent fault diagnosis of machines.

- Sensors and Input : Accelerometers (Vibration Signals)
- Normalized sparse autoencoder(NSAE) - attempts to learn features from raw data automatically

  Model background:
- Builts Local Connection Network by input, local , feature & output layer.
- Use NSAE to locally learn meaningful features & to obtain shift-invariant features
- For gearbox data set testing accuracy 99.43 % and for bearing 99.92%

  Future Scope : Optimization techniques such as PSO can be used to adjust parameter of NSAE- LCN

Estimation of Process Parameters

- Prediction of parameters which usually can be accurately calculated only after the process is completed.
- Mathematical models couldn't capture all the complexities

Serin et al. (2017)

Estimation of parameters for the free-form machining with deep neural network

- Created dataset using a turn-mill machine
- 5 hidden layer deep neural network
- Input: Stepover, Depth of Cut, Feed, and cutting speed
  Output: Specific energy consumption, MRR, Surface Roughness
- Average error: 0.44% (SEC), 1.5% (MRR), 0.38% (RA)
  The errors decreased significantly even small number of epochs completed

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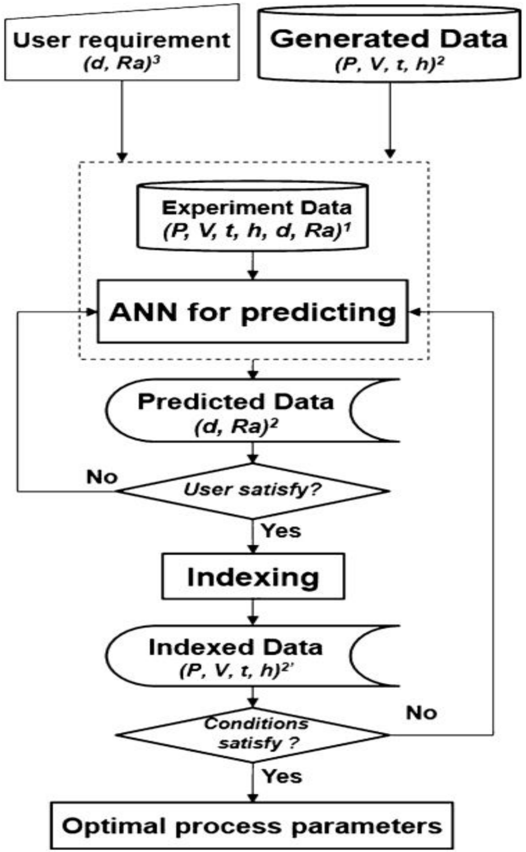
Optimization

Hong, Chang et al. (2020)

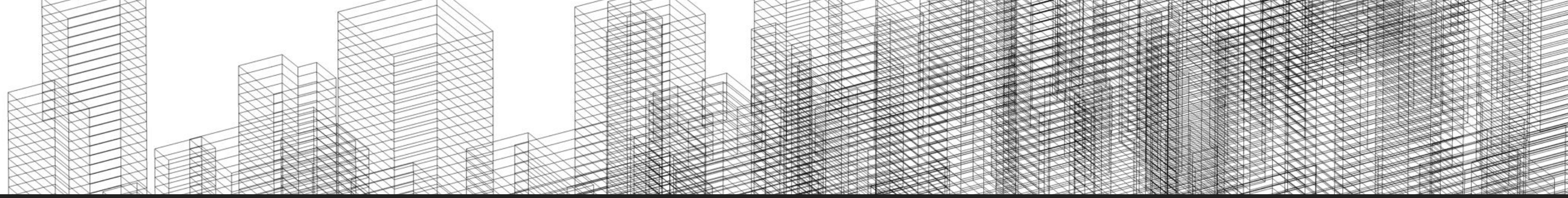
Optimization of selective laser melting process parameters for Ti-6Al-4V alloy manufacturing using deep learning

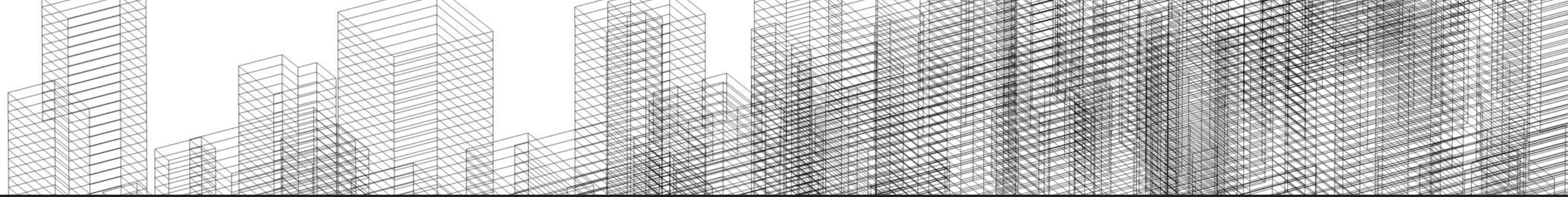
- Supervised DL as a core function
- Input: process parameters
- Output: product relative density
- 4 optimal process parameters:
    - laser power = 180W,
    - laser scanning speed = 900mm/s,
    - layer thickness = 20um,
    - hatch distance = 80um.
- Output = 99.8 % of relative density.



Our ideas

- Improving input parameters using Deep Encoder-Decoder architecture
  - Input: the machining parameters
  - Output: improvised machining parameters
  - Aim: Slightly change the parameters to optimize time and cost
  - Loss to be minimized: Reconstruction Loss + Financial Cost + Time Cost
  - The relative priority of these losses will be user defined
- Generative model for predicting temperature distribution
  - Dataset of thermal images captured during machining
  - Input: Machining parameters
  - Output: Generated image showing the temperature distribution





Thank you!

Outline

1. Overview (1 slide) (teeno)
2. About Machining and the requirement of DL (Motivation) (teeno)
3. explanation of direct and indirect monitoring (online and offline)
4. Sensor data acquisition and processing (sensor, what it measures, whether it is direct or indirect, and how the data is processed) (one slide for each sensor and processing and one extra slide for listing the remaining sensors)
5. Non-dl techniques ([8],[78],[94]) (to motivate DL)
6. TCM or Machine monitoring ([84], [86], [96]) (GG)
7. Estimation of parameters ([79], [ref1], [ref2]) (HD)
8. Optimization (provided we find papers) (or our ideas) (SG) [1 - 2 slides]
9. (or other category)
10. Potential future applications (2 / 3 slides) (main review me there are some ideas or our own ideas)
11. Our suggestions (2 slides)

Sensor Data Acquisition & Processing

Direct

- Offline process
- Data acquisition has to be done by interrupting the process
- Causes delay in manufacturing
- Estimation methods are generally based on traditional techniques

Indirect

- Online process
- Process monitoring can be done without interrupting the process
- Parameters can be tuned in case of any anomaly detection
- No much literature for online monitoring, requires DL techniques for estimating process parameters

Other types of sensory data:

For Direct Tool Condition Monitoring:

- **Optic Sensor**: Digital image of the tool is processed to calculate wear parameters
- **Displacement**: distance between the tool and workpiece can indicate the wear

For Indirect Tool Condition Monitoring:

- **Surface Roughness of product**: As tool wears out, roughness of the surface increases
- **Temperature of tool**: Since high temperatures are produced during machining, it can cause high tool wear

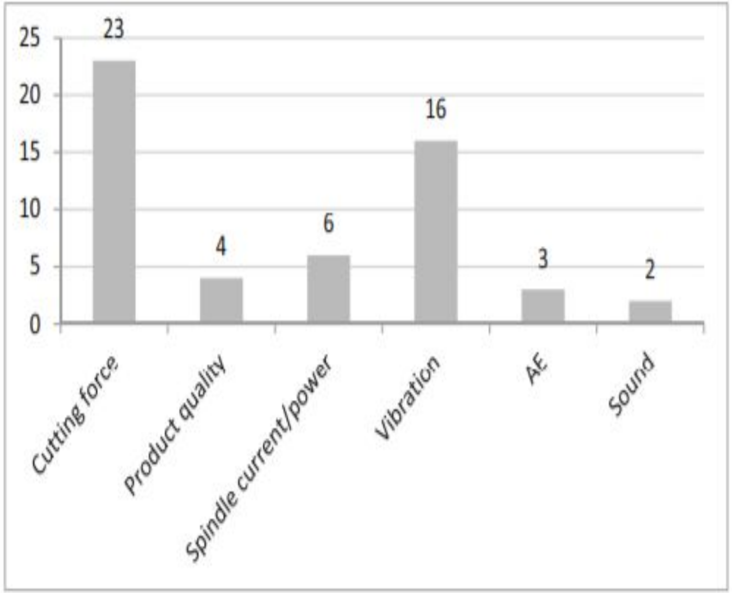
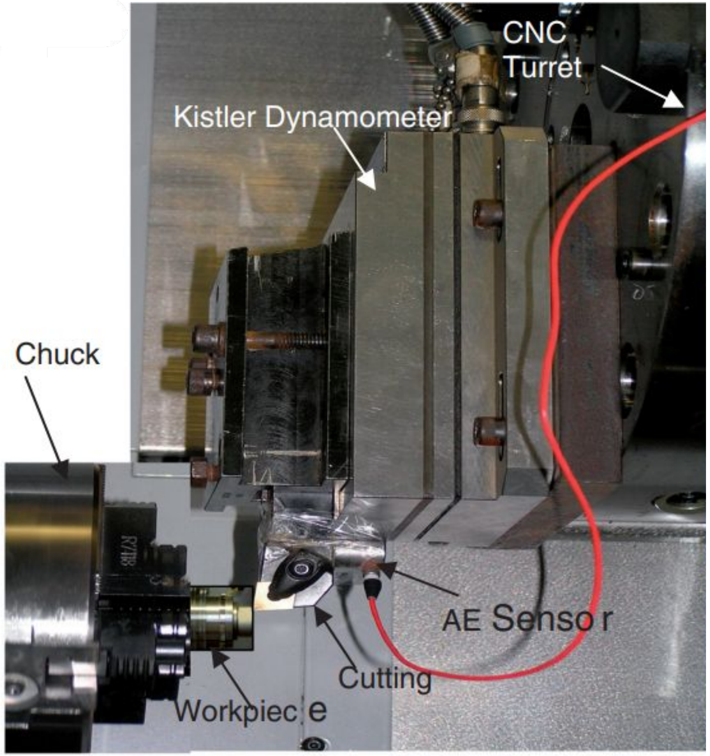
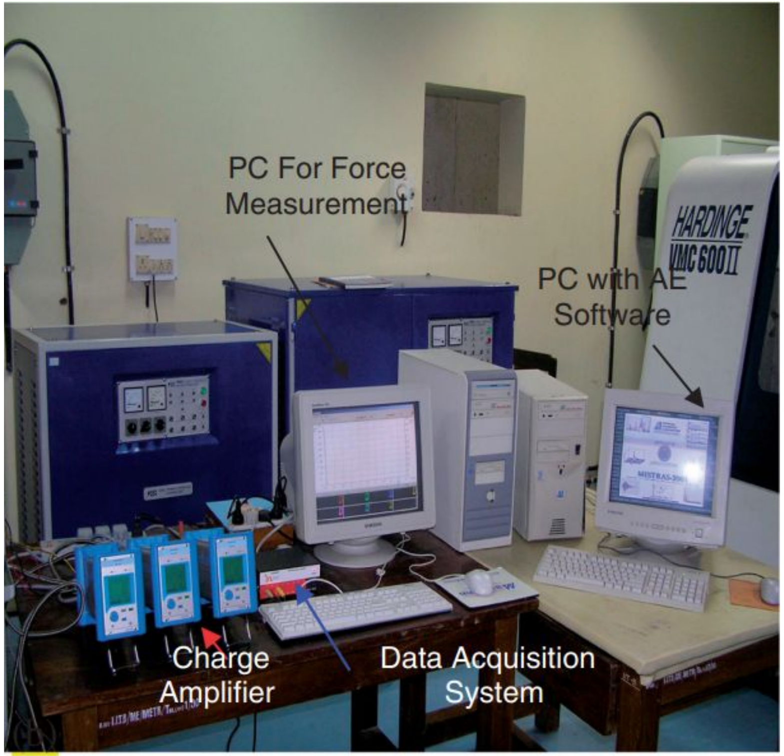


Fig. 2 Frequency of various CM parameters in 38 published papers

Experimental set-up:





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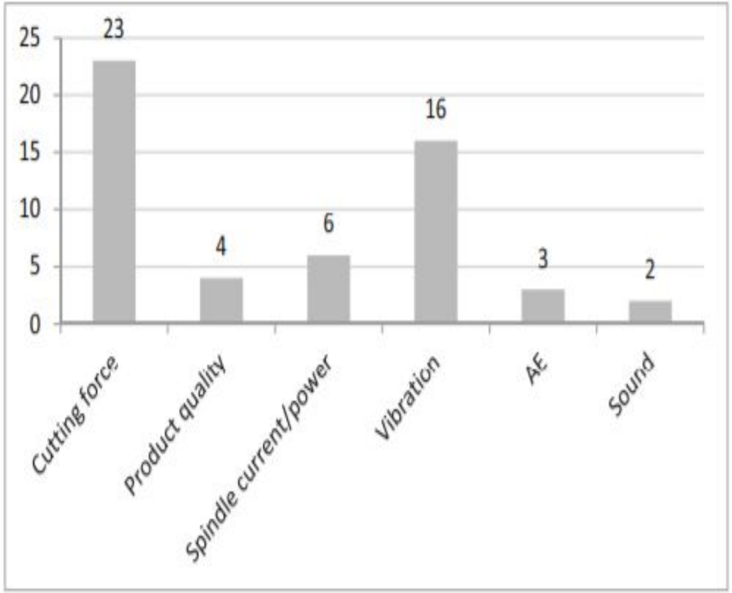

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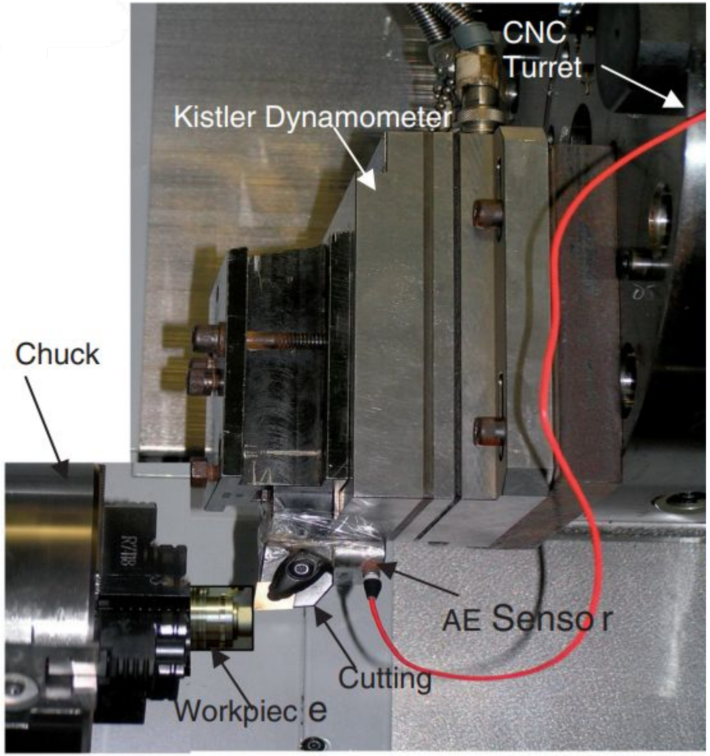

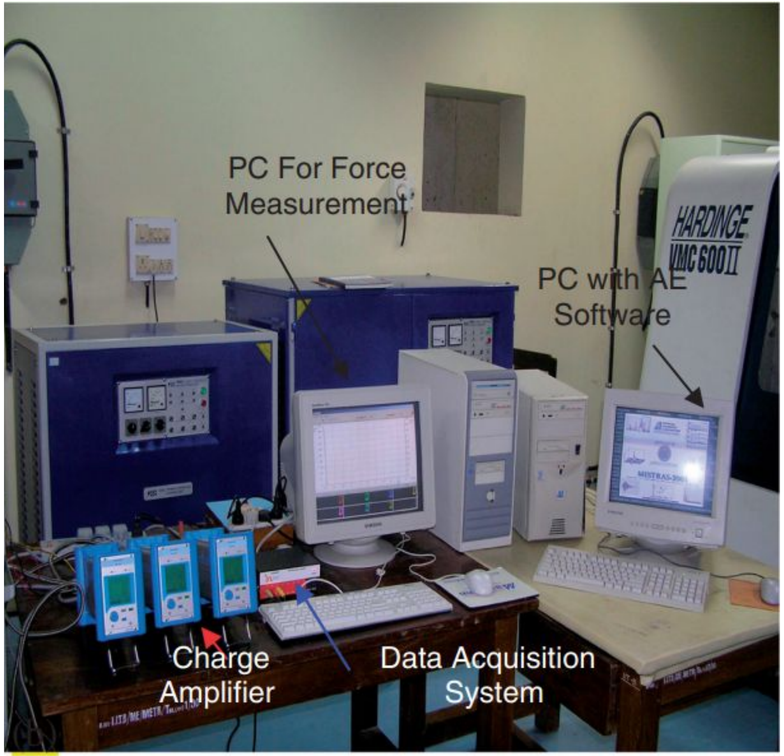

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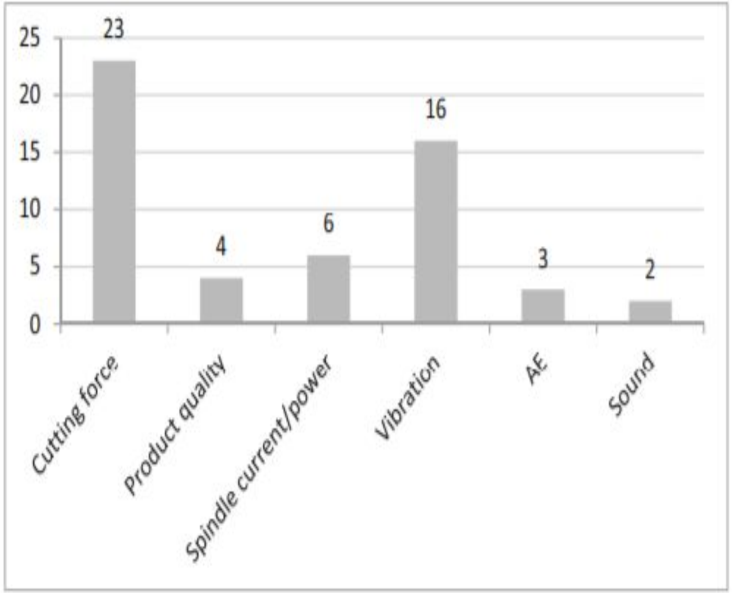

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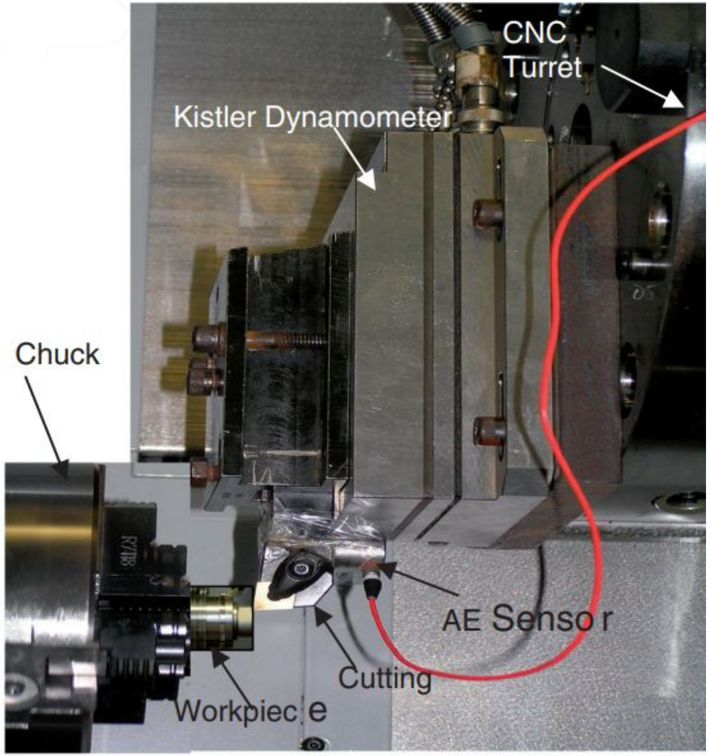

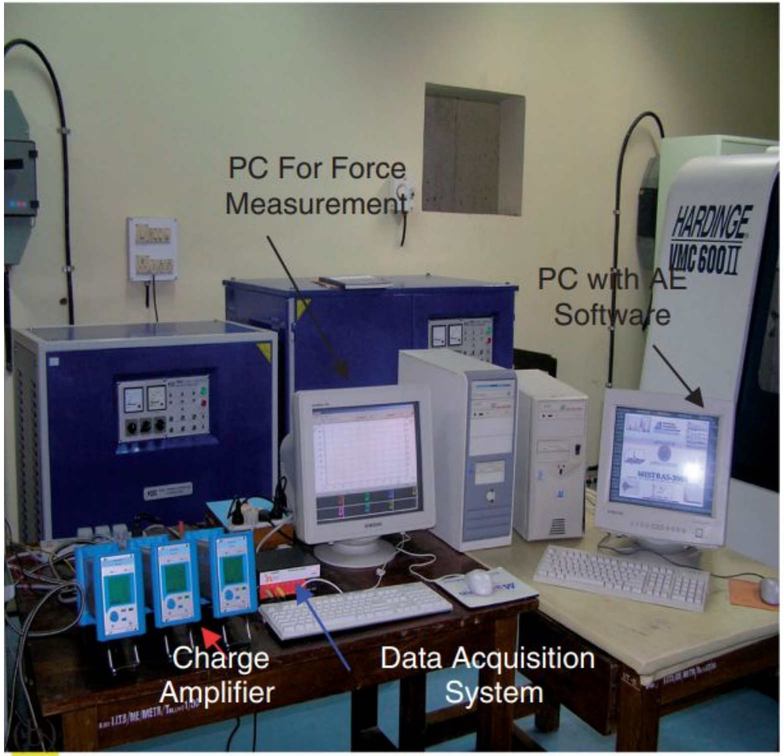

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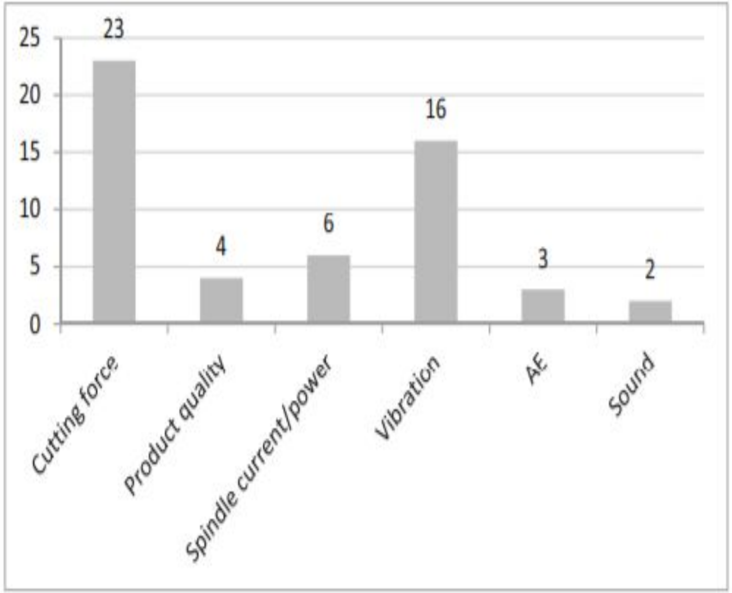

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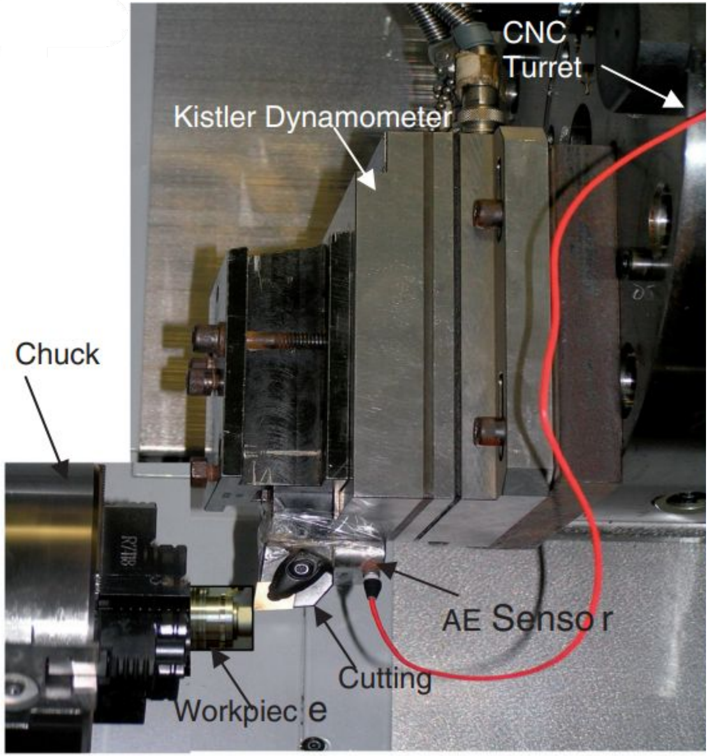

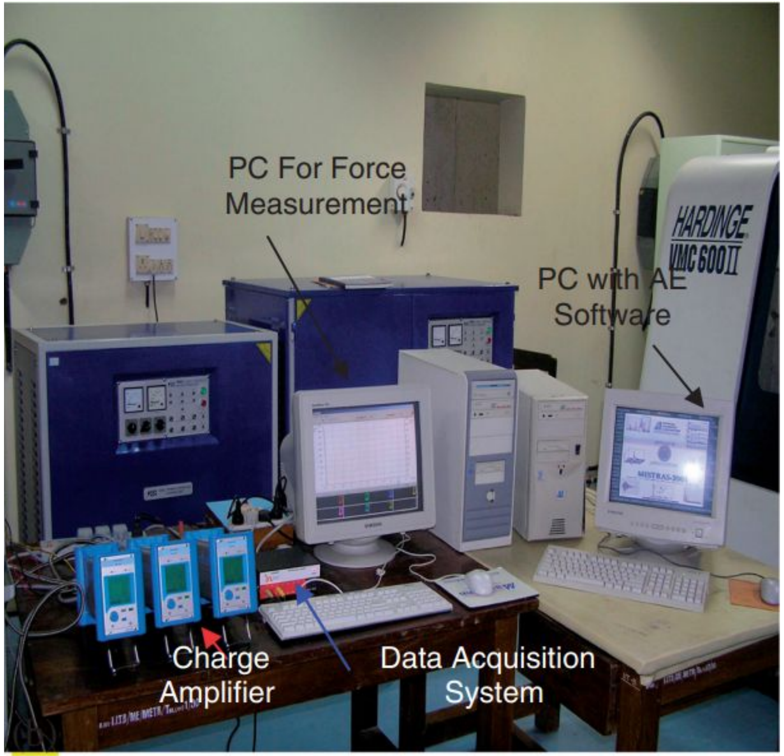

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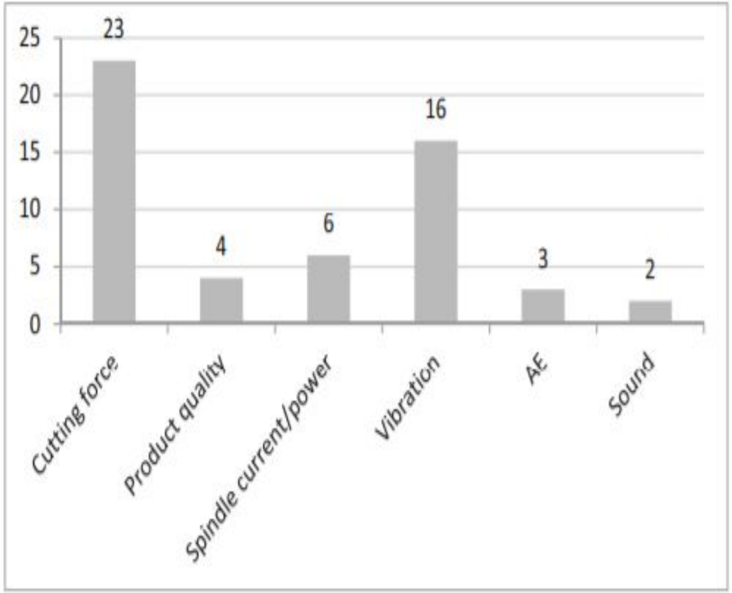

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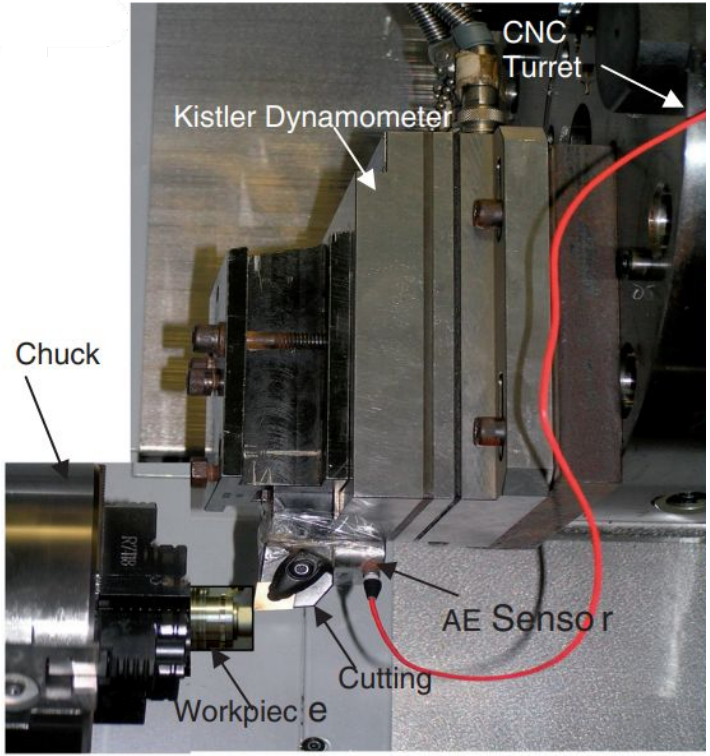
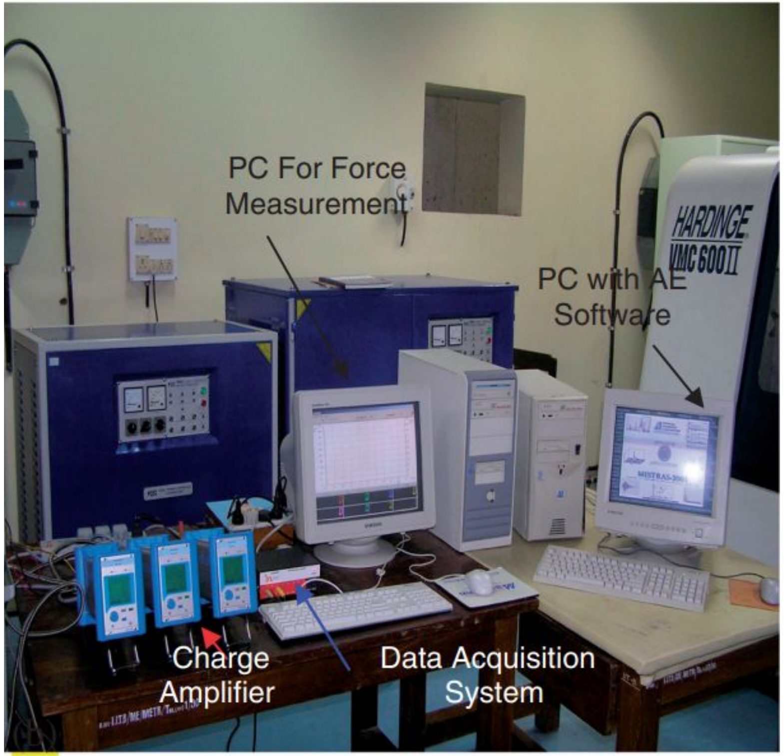
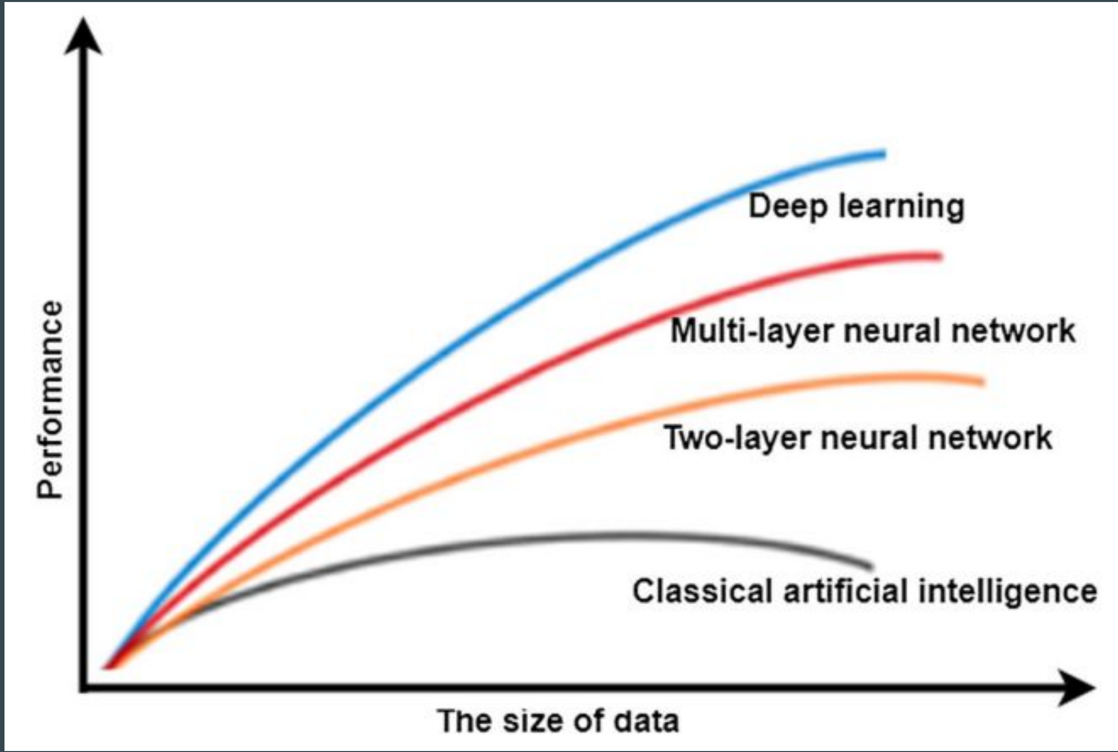




General Fields/topics being researched:

1. Machine tool; TCM!
2. Parameter Optimisation
3. Product Quality Prediction



Rough points on the slides

- Ideas of using AI to improve manufacturing dates back to the ___ (e.g 90s)

Random ideas

- At least one or two pictures for each paper (which is the highlight of that paper, unique to that paper)
- Start with non-deep learning methods
- Potential category: TCM
- Potential category: Optimization of Manufacturing using DL
- Potential category: non-DL techniques
- Potential category: bearing/shaft related stuff (backup)
- Combine 86 with 84
- Keep 94 before or after 84
- Find atleast 2-3 papers which do a comparative study between non-dl and dl methods for the same process

Actual Slides from here...

Sensor Data Acquisition and Processing

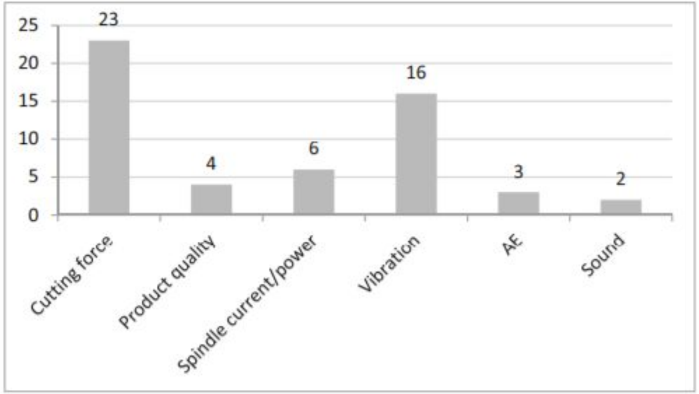
Acoustic Emissions (AE):

#keypoints: What exactly is this data? How is the data measured? What processing is done on it? (both traditional methods and as a feature for DL methods...)

#transformation methods: time -> frequency domain; FFT, WT, STFT (acc to the desired signal type)

Sensor Data Acquisition and Processing: Overview

The types of TCM	Process parameter (input signal)	Transducer	Measurement (output signal)
Direct (offline)	Optical/vision	Optical instruments such as CCD camera or optic sensor	The concentration and size of the tool wear
	Electric resistance	Voltmeter	Junction resistance between tool and workpiece
	Displacement	Micrometer, pneumatic gauge, displacement transducer	The distance between tool and workpiece
	Acoustic emission	Acoustic emission transducer, microphone	Acoustic wave
Indirect (online)	Vibration	Accelerometer	Vibrations occurred in tools and machine tool
	Cutting force	Dynamometer or strain gauges	Cutting force of the main spindle during the machining
	Cutting temperature	Thermocouples	Temperature of the workpiece and the main spindle
	Electrical current	Amperemeter or dynamometer	Current or power consumption during the machining
	Surface roughness	CCD camera or fiber optic sensor	Surface roughness of the machined surface



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SMART MACHINING

So far, we have been focusing on conventional machining processes for TCM. Here on, we will be reviewing both..

Processes Reviewed in this PPT: Milling, Turning, Drilling

#Random points

process parameter optimization for cost reduction through energy consumption predictions, and product quality enhancements through predictions of surface roughness, cutting force, and workpiece deformation. For such purposes, a popular choice was also SVM, but other algorithms, such as Gaussian process regression (GPR),47,48 Nondominated sorting genetic algorithm II (NSGA-II),49 and other statistical methods were also used

In non-conventional processes, due to the issue of low productivity, one of the main purposes was process parameter optimization for maximizing the MRR

References and Citations :

1. Serin, G., Sener, B., Ozbayoglu, A.M. et al. Review of tool condition monitoring in machining and opportunities for deep learning. Int J Adv Manuf Technol 109, 953–974 (2020).
2. Hsieh, WH., Lu, MC. & Chiou, SJ. Application of backpropagation neural network for spindle vibration-based tool wear monitoring in micro-milling. Int J Adv Manuf Technol 61, 53–61 (2012).