Machinery Fault Diagnosis and Signal Processing

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Lecture - 05
Machine Learning in CBM

This lecture is on Machine Learning for CBM. In this first week of this course, this is the fifth lecture on which we are discussing about machine learning for CBM. So, we will now give you an overview of the CBM techniques and what where it is today and what is the future, and then I will give an example as to how machine learning has been used to predict the tool ware in a metal cutting operation.

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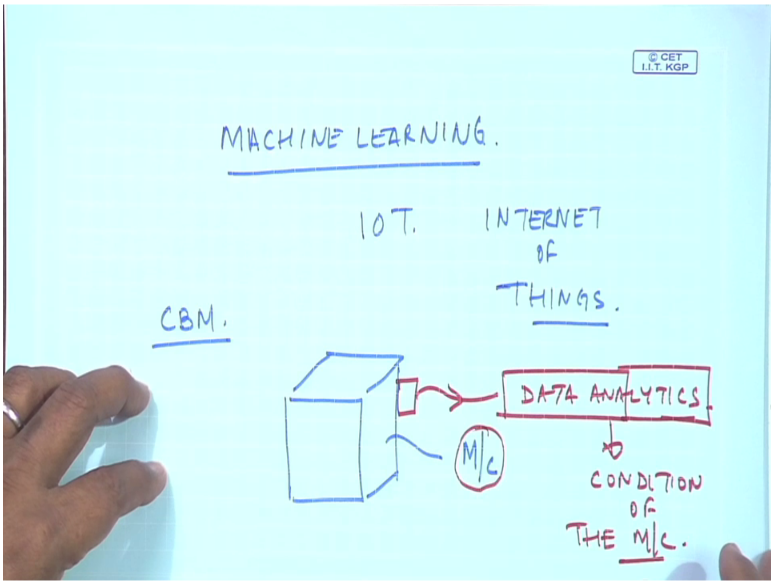

Let me tell you once we have learned about this machine learning, today the state of the art is you know you must be all hearing about internet of things. And how machine learning is helping IOT in the sense from a CBM point of view, every machine if I put or transducer, and get some data or perform data analytics, these are catchy words nowadays. So, I thought I must mention to you and then from this data analytics and machine learning, we can find out the condition of the machine and who is deciding on the machine it always need not be a blast furnace.

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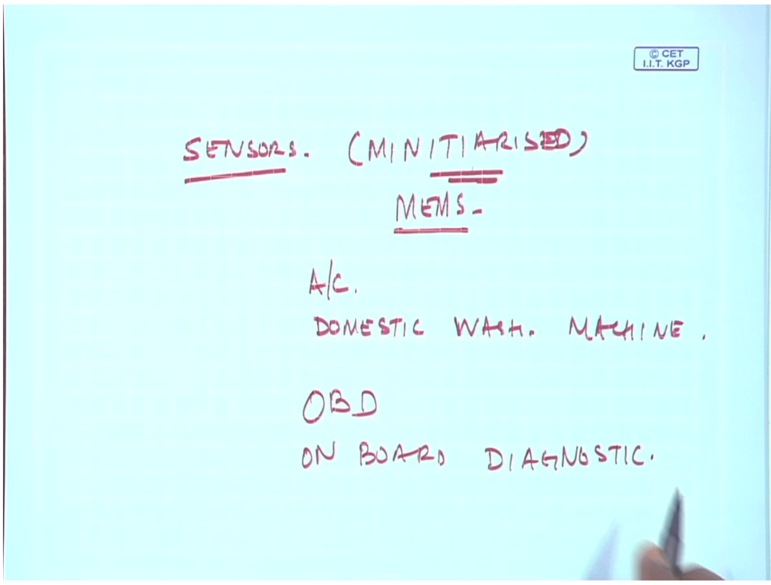

Today these sensors have become miniaturized ignore my spelling here, and then of course, like mems based sensors are there which are put on place and data could be collected, and then they could be analyzed and transmitted.

So, every machinery built a air conditioner in your room, built a domestic washing machine and so on. I always give this example in the class, so that imagine you have an air conditioner at your house and suddenly you got a knock on your door from the service technician, telling you that you know well the blower of your air conditioner needs to be looked into because that is what our service protocol or the service database indicates.

The question is a long background have a work which has happened to come to this level, imagine if a sensor was placed in the indoor unity of your air conditioner, which was monitoring the blowers performance and then if we if it was either connected to the internet. So, that all this data which has been measured by that sensor put on the blower of an air conditioner, word had conveyed this information to a central server where in data analytics was used to come up with a conclusion blower number such and such and such and such persons residence in such and such AC is having a problem, and this was perhaps you know science fiction few decades ago, but today this is a reality.

So, CBM has come to our everyday life in all aspects, built an air conditioner, built an washing machine, built an even an automobile. You know today if you go to a service station with your car the service manager would come up to you, and they will look into your engine data logger history. And then come up with some conclusions such and such engine in your cylinder needs a spark plug replacement, you would be wondering how and why.

But that is what these onboard OBD onboard diagnostic modules are there in fact, today the technology is such that you cannot sell at least in India a car in India unless it has an OBD module, there are certain protocols and so on. So, what this module does is every time your engine is running, certain parameters of the engine is already always stored in that resident memory of your vehicle. And once you go to the service station the hooking a data logger and try to retrieve that information, and tell you the condition of the car or sometimes in certain cars the system itself will tell you know you require an oil change or your brake fluid has gone down it need stopping up or your break pads of worn out they need replacement.

So, these this is where an earlier days you know if there is an abnormal sound, you drop down to the mechanic of the serviced shop and then ask them know what is the problem with your car. But today the technology is such that sensors are there almost everywhere, data has been captured by the sensor, there are robust software based on model, based on machine learning which will tell you what is the present condition what is the RUL and so on.

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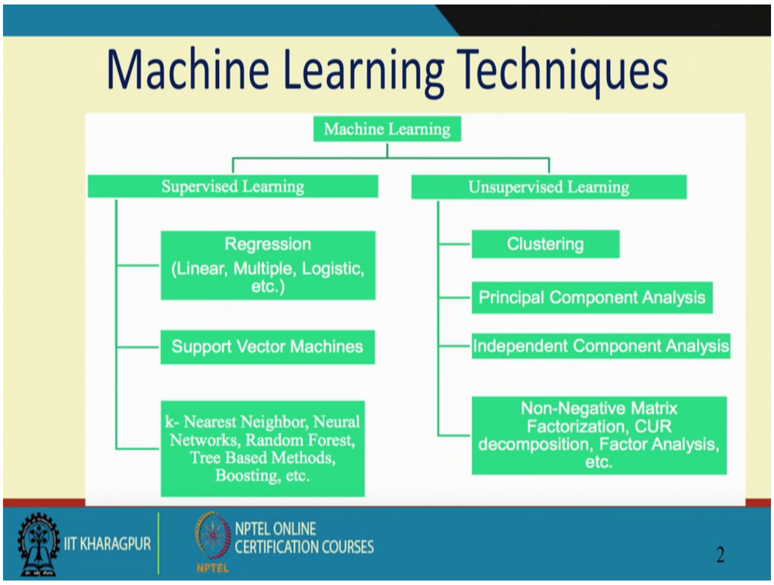

So, if I as to give you an overview of the machine learning techniques available, broadly I can classify them as supervised learning and the unsupervised learning. In the supervised learning we had this neural network random forest etcetera, which were very popular. And we also have what is known as the popularly used today is the support vector machine

So, they will map as to the in the supervised learning, they will map a plant as to what is the input conditions and what is the output conditions and come up with the plan or come up with a model and based on this model you could predict or forecast the RUL, I had given in the simple case when a system is very linear and a single system.

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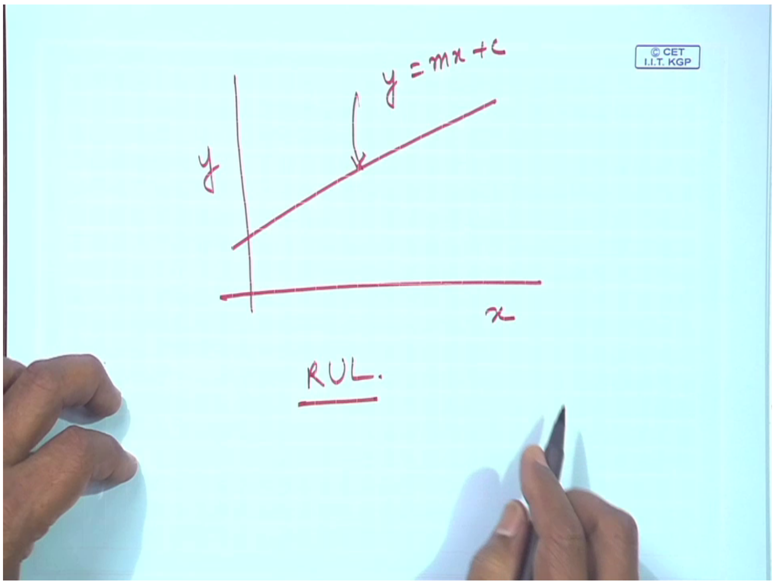

You know graph yx. So, y is equal to mx plus c, this is simple linear model. So, I can do any amount of forecasting go through such one dimensional simple linear model, but this could be complicated, that could be a polynomial fit, depending on the events and depend on the data which we have and of course, it could be multi dimensional and then the people have used support vector machines to find out.

As opposed to unsupervised learning, we can find out we can cluster the data based on a predominant trend in the data, there could be many trends or many principal components which carry relevant information, and then you can do the studies like no singular value decomposition and so on.

So, machine learning itself is actually a 40 hour lecture in any program, and then I will just with this introduction I have just given you that today everybody acamid academicians researchers and industry, people are working on developing many models based on these machine learning techniques, and they have used this to their advantage for the prediction of RUL of a component.

Because once a model is built we can have the prediction of the rul.

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Now with this I will give you a small case study as to what this machine learning can do and what we did in the past. This is something which you did about two decades ago on a case of tools we are monitoring, because in the machining operation.

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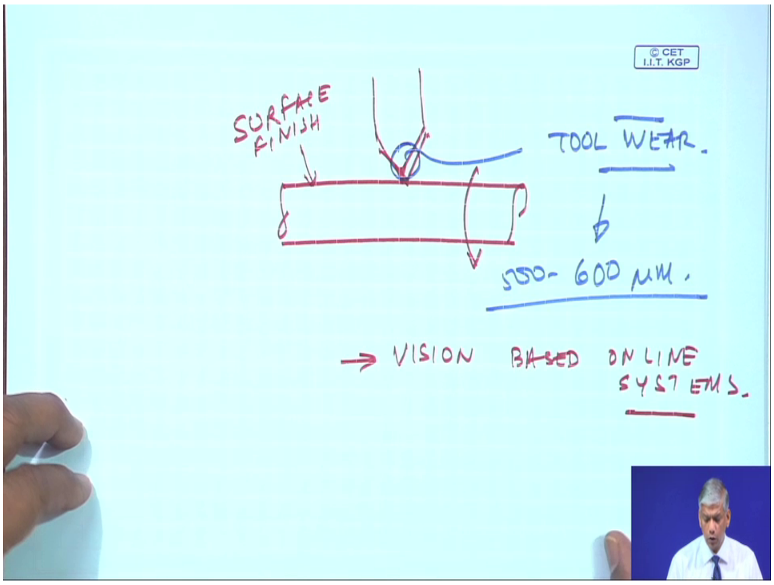

You have a cutting tool maybe to give some operation.

Now, the question is if this because of machining this cutting tool will have a tool ware; usually the tool will become blunt and there is the wear of this tool, and they say you know somewhere be around 500 to 600 micron is the amount of tool wear which could be sustained by a neat cutting tool before it is changed.

Imagine 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, you know imagine if the tool has become very blunt and instead of being sharp more cutting forces would be required more energy would be spent, on during this machining operation surface quality would change.

So, these are factors. So, there is a requirement that we can we must do an online tool mounting of course, today we have vision based systems based you know online systems, but in this example what I am going to show you is how to CBM or monitoring the condition of a spindle, which is used to rotate the cutting tool during a milling operation we could find out the tool ware.

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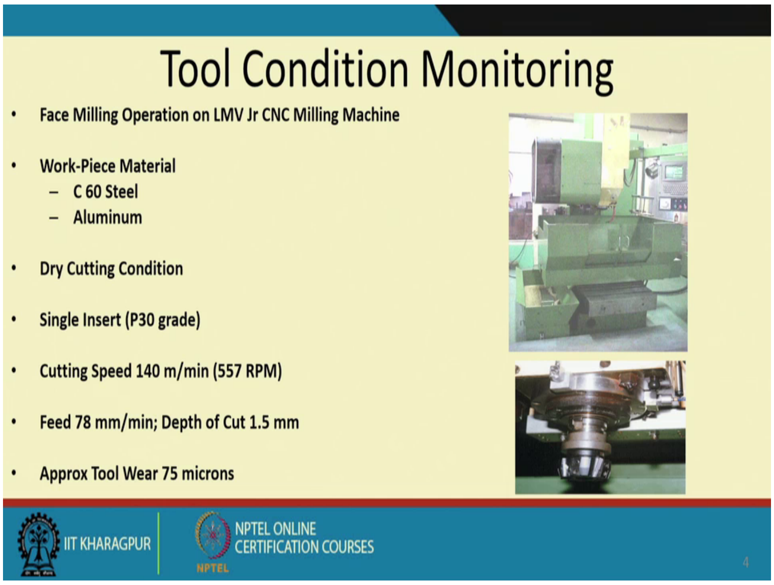

So, let me introduce you to what this is about. So, we have a machine or CNC milling machine single spindle, and then these are the conditions of the tool work piece one case there are steel and another case there was the aluminum, there was dry cutting this is single insert and we had cutting speed the spindle RPM set at 557 RPM approximate feed was about seventy eight millimeters per minute, depth of cut one point five mm and he tool wear was 75 microns to begin with ok.

So, we instrumented if you go back here we instrumented the spindle with many sensors if you can see, we are in sensor for acoustic emission for vibration, for cutting tool force for 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, and also each pass of this cutting tool operation of others come to this one.

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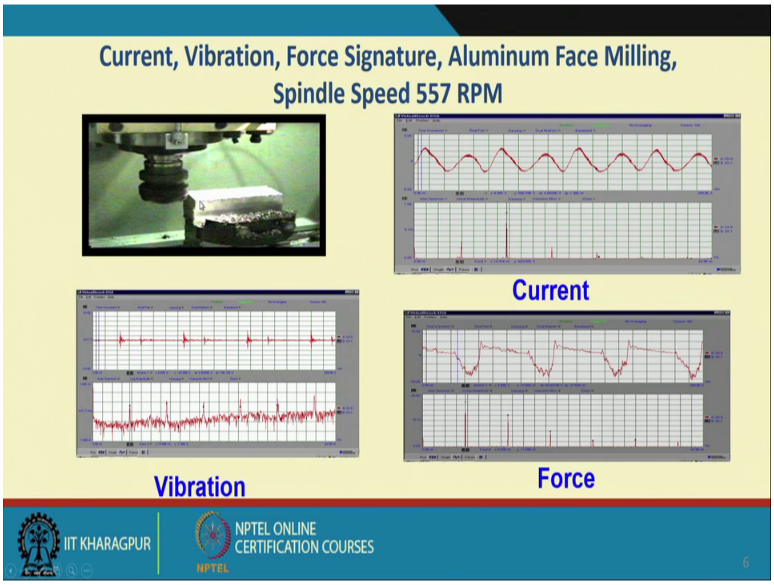

This is the aluminum then milled by this spindle which has this cutting tool single insert cutting tool it is milled. So, this did multiple passes of machining this, and in each pass we measured the tool wear off line we went, run the machine one pass measured the tool wear in a microscope and at the same time also measured the parameters like 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 as to the then in fact this is a. So, what we did.

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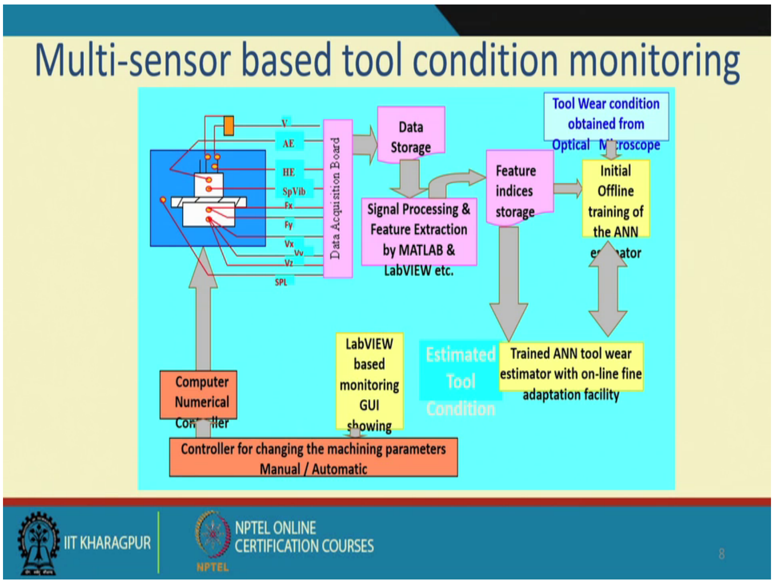

We did a multi sensor based tool condition monitoring, as to we in this machining operations we measured the acoustic emission, the high frequency, acoustic emission signals, the vibration levels, the forced levels, sound levels, the voltage current etcetera. So, everything was required I will not go to the details of how the acquisition was done something which we are going to discuss later on.

But importantly 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 may planner 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 using this si what is the time when the tool in this condition, is going to achieve 500 or 600 microphone or microns when this tool has to be replaced.

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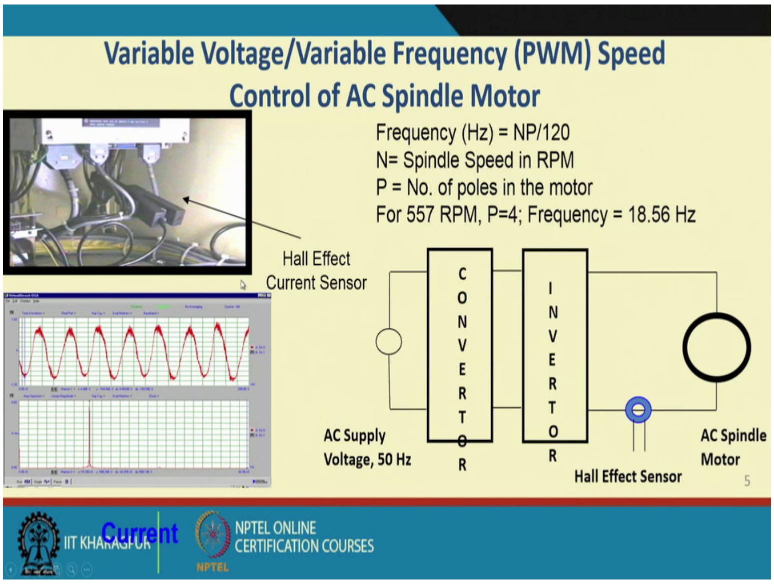

So, before I go into that I will also introduce you to our technique, wherein we measured this current through a Hall Effect sensor, this current is drawn by the spindle motor which is used for machining and as you see this is a sinusoidal signal, and there is a single frequency signal single frequency component.

And once we started machining the signal current signal quality changed, the force changed vibration change. So, we extracted features out of these sensors.

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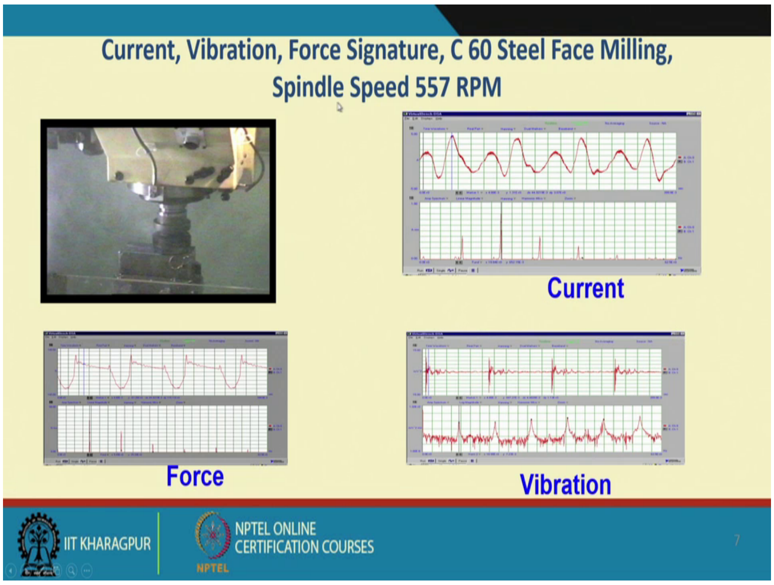

And similarly for case of machining steel and so on and then.

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We developed a.

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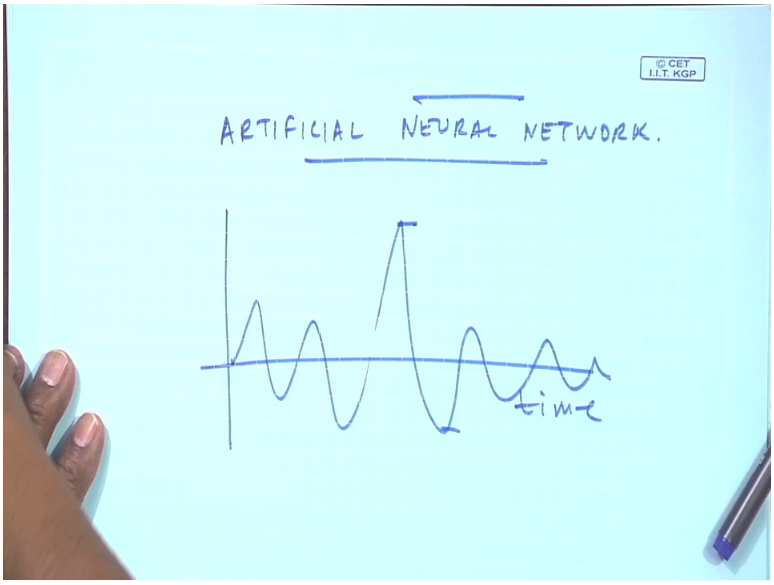

Artificial neural network model to see the robustness of the model, we took data from the machine in our lab, we measured it at a gearbox manufacturing facility also if you can see the planner machine we had the computers and the all the signal conditioners, for the force transducer for the vibration transducer and so on.

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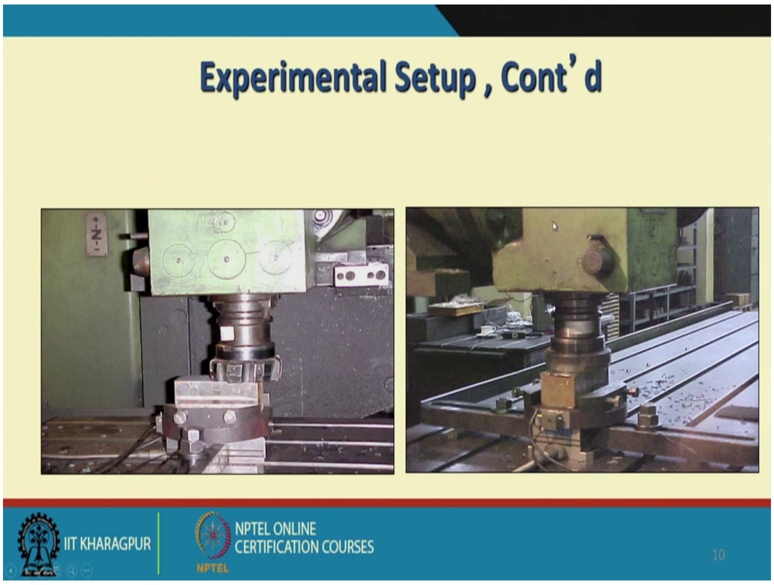

And this is another view of the cutting force dynamometer, put below the work piece and you can see this is the vibration transducer here.

So, all these parameters was simultaneously acquired.

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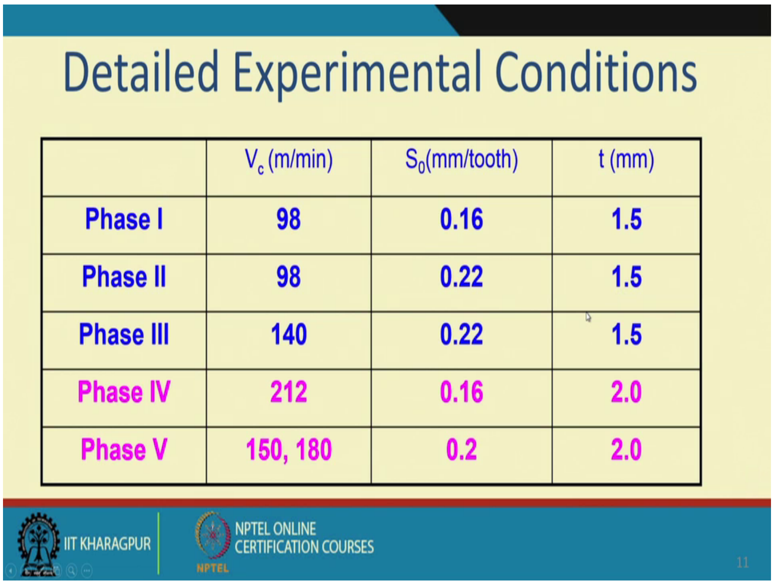

Detailed Experimental Conditions

	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

And then, these are the different we did the experiments in different phases, these are the different cutting speed velocities, the depth of cart and so on.

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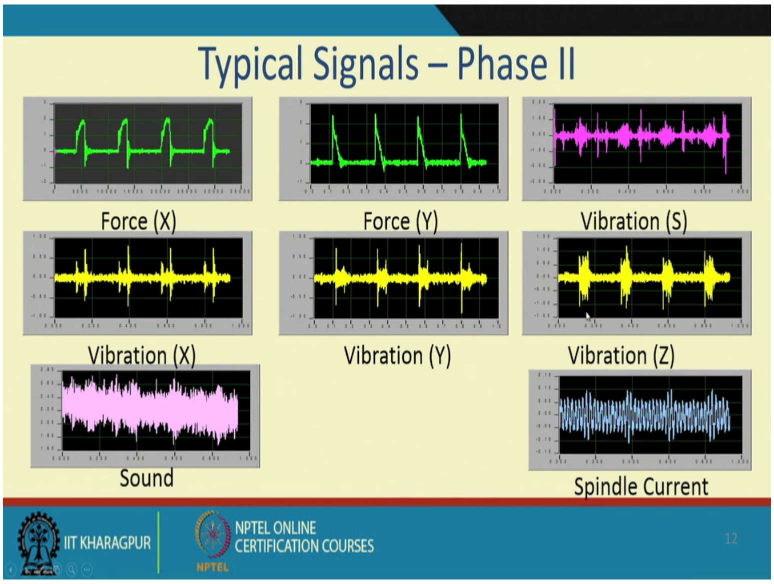

And this is the typical signal which is obtained from the sensors; force in x y z directions vibrations spindle current and so on.

So, if you look at this signal, these signals convey information as to the present condition of the machine and different types of and the different phases of the spindle voltage current and so on.

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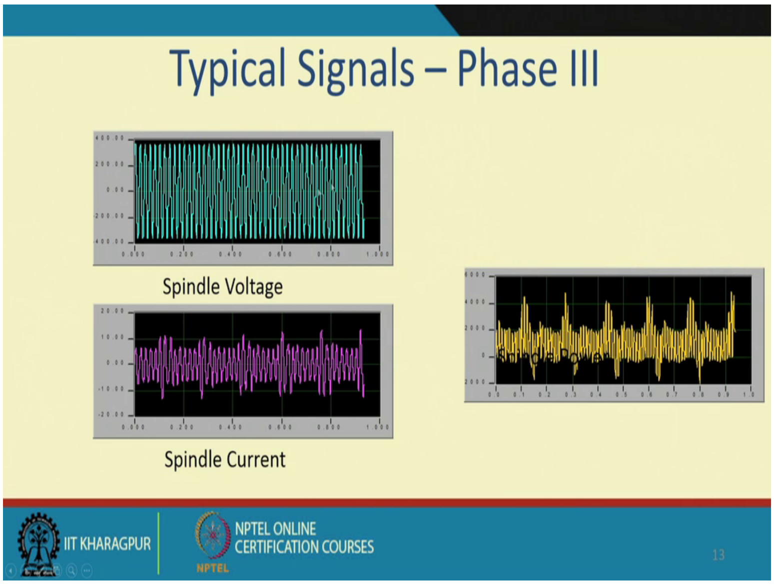

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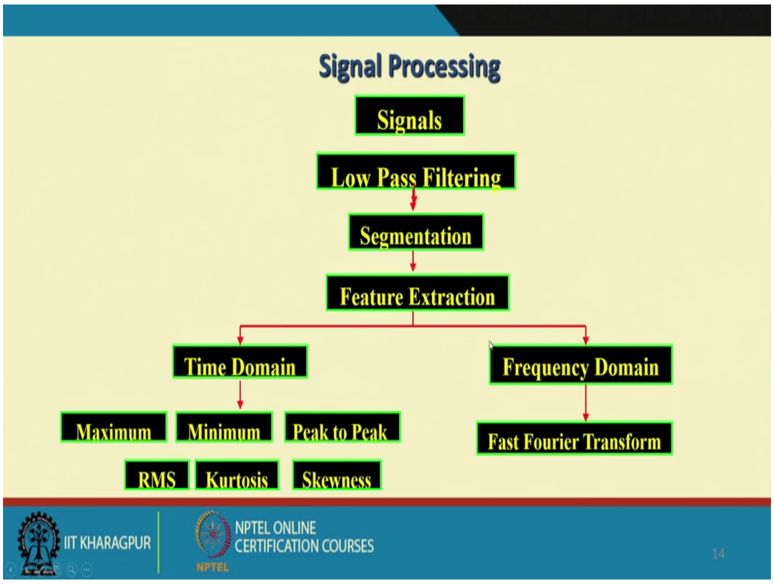

So, we did what is known as a little signal forcing a data driven. So, we did low pass filtering we remove certain artifacts from the signal, and did a time domain feature extraction these are the data analytics these are the features of the signal, if I have a signal coming from a transducer.

So, I can find out this features maximum minimum there are many features and the details of these features actually you can find in my book where in the expressions for all this you know Kurtosis Skewness (Refer Time: 17:59). In fact, we in this study we did not go into the frequency domain at all, because even in the time domain there were enough features to map to the tool ware which was measured in an offline mode.

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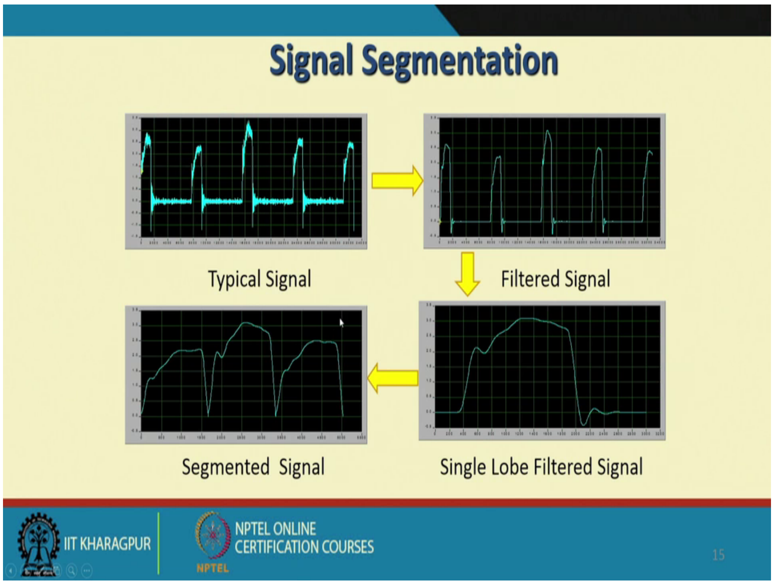

And this is what typical signal segmentation has done if you see here a typical signal there is a lot of information here and there is not much information here. So, and there is a lot of high frequency noise which was removed by filtering and will through a low pass filtering.

So, we remove this high frequency noise and then we looked into the single lobe filter single lobe looks like this, and then we join the segmented signal we clipped it remove this part clipped it remove this part clipped it and stack them together.

So, this is something one has to do in a data analytics us to signals need to convey meaningful information for signal conditioning. So, if this is done and today softwares are available which can do this for you.

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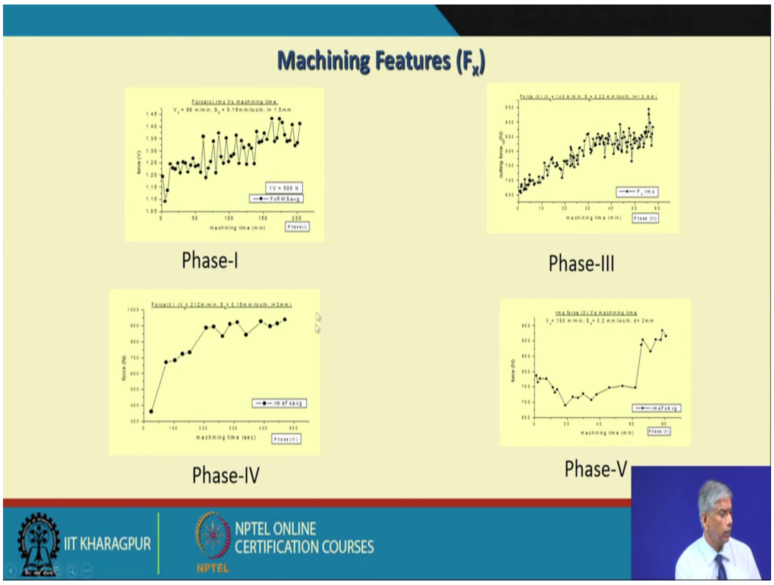

And then we looked into different in a 1, 3, 4, 5 these are the different failures of instance, where with machining time in the x axis we will see how the parameters like you know force the in different directions etcetera are changing as we will see, with the cutting tool machining time increasing the tool wear would increase.

So, what happens the forces required to cut would increase.

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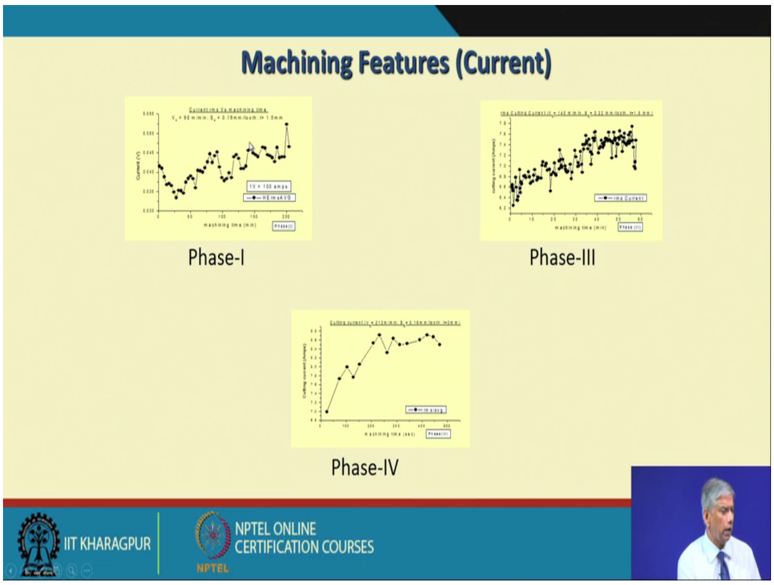

And similarly for the other parameters like the current, the motor current drawn with load increases the motor current drawn increases.

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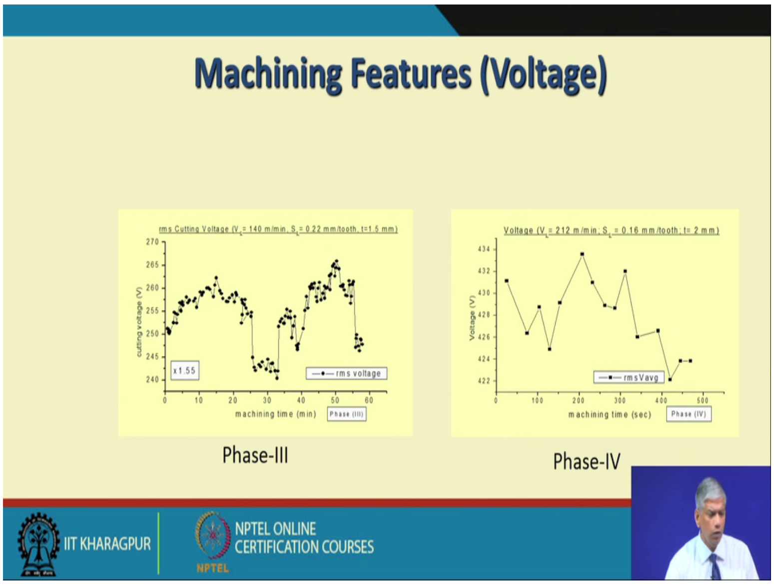

So, and similarly for the voltages, these experiments we are done over a period of you know several weeks, and we found out certain meaningful signal features is very very important.

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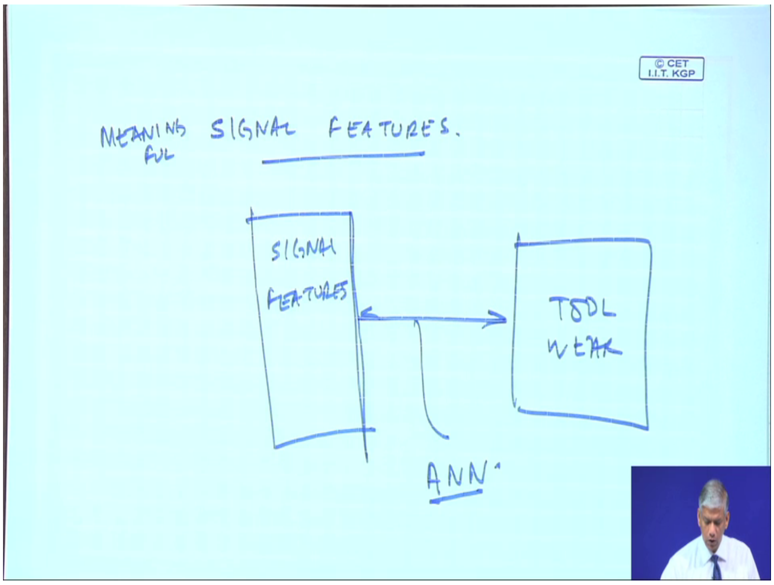

So, this request if I go back to the previous slide here, signals have been acquired from the transduces little low pass filtering to remove the noise segmenting, and then the feature extraction and use this parameters; these parameters of maximum minimum peak to peak RMS kurtosis Skewness these are nothing, but features of the signal or which relate the signal to the condition of that machine.

So, we did a map of the signal features to the actual tool ware. So, this mapping was done and then you use what is known as this artificial neural network. So, once we have a proper map we can do prediction.

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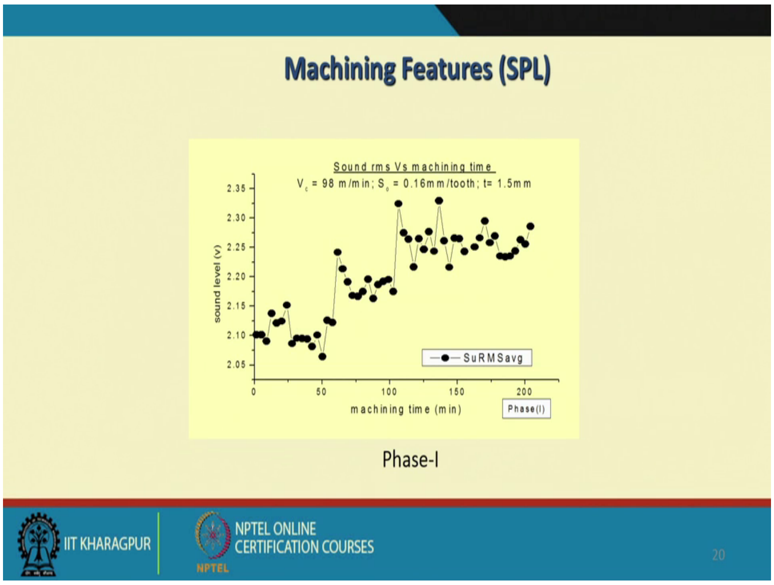

I will go into the details of the and similarly for the some pressure level that would also increase and of course, this is sound in voltage level with machining time.

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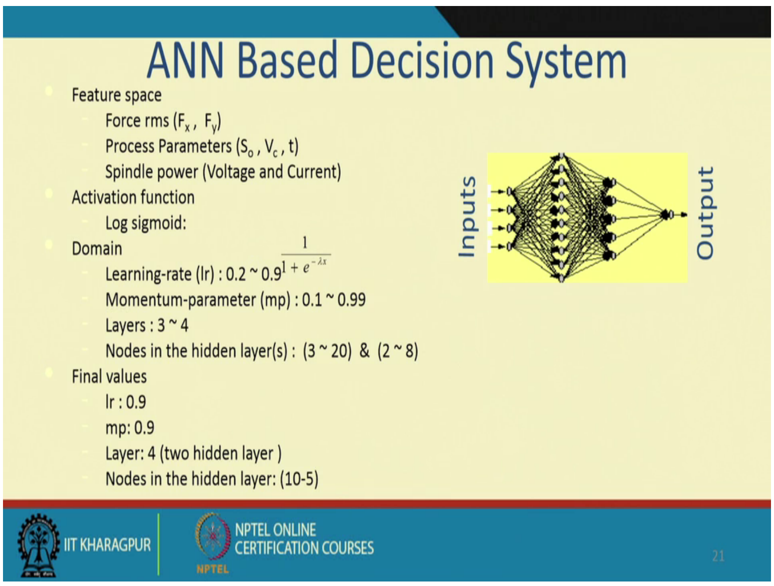

So, a typical an based decision system, we had this kind of arrangements in our model we it in the feature space we had force in Fx and Fy direction the process parameters like the speed depth of cut and the feed rate. In spindle power being the motor voltage and current and of course, we measured acoustic emission by vision because you know we are new to this area we thought we would put a lot of sensors, but then we saw that many of the sensors did not carry any meaningful information there was no substantial change with the machining time, because one with machining time or tool wear change.

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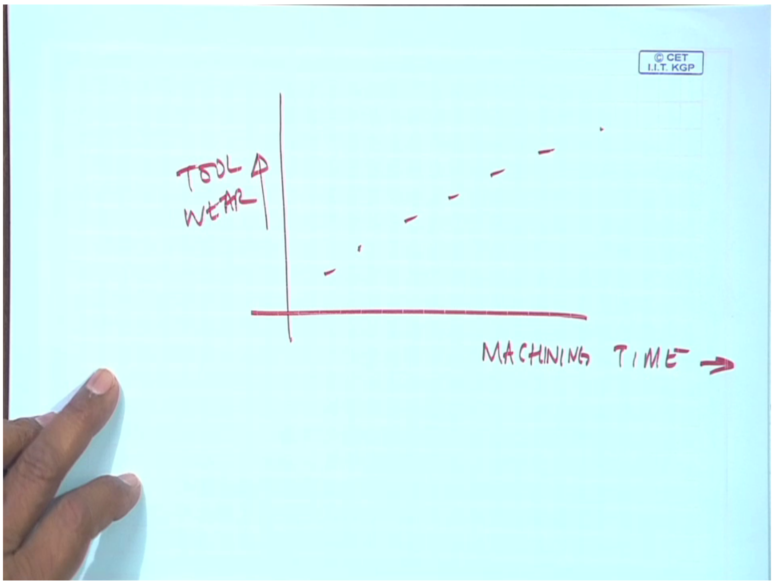

So, this kind of; so now, the other way is; what is the tool wear, to find out from the parameters measured. So, an activation function of log sigmoid was used and these are the certain parameters for the ANN and then we heard about four layers with two hidden layers. So, today this state of the art is you know such standard ANN packages are available where you know all you need to do is give the input and output.

So, once your ANN is used to train parameters that used to train, once the ANN has been properly trained, you can use it for forecasting.

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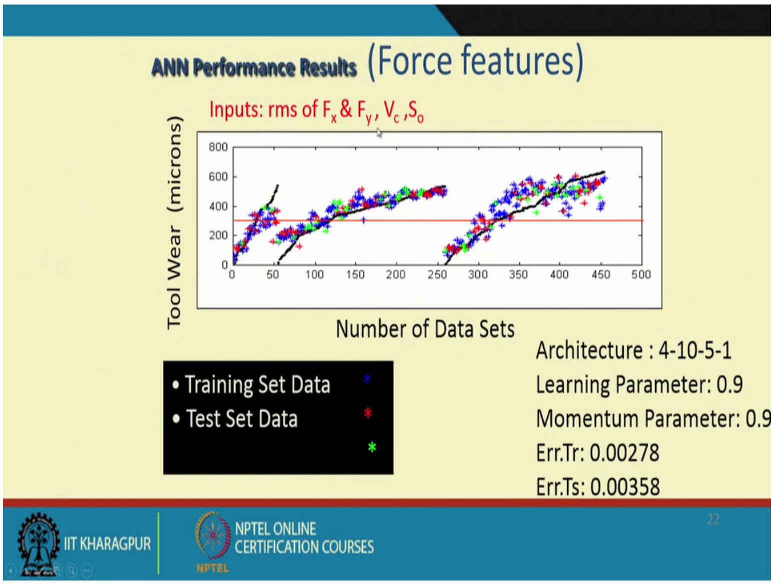

So, this is the ANN performance results in terms of the forces. So, you see the number of data sets and these are the parameters. And if you can see the tool wear, and there is a good agreement with the test data sets because they are all done at different phases and then you will see the training.

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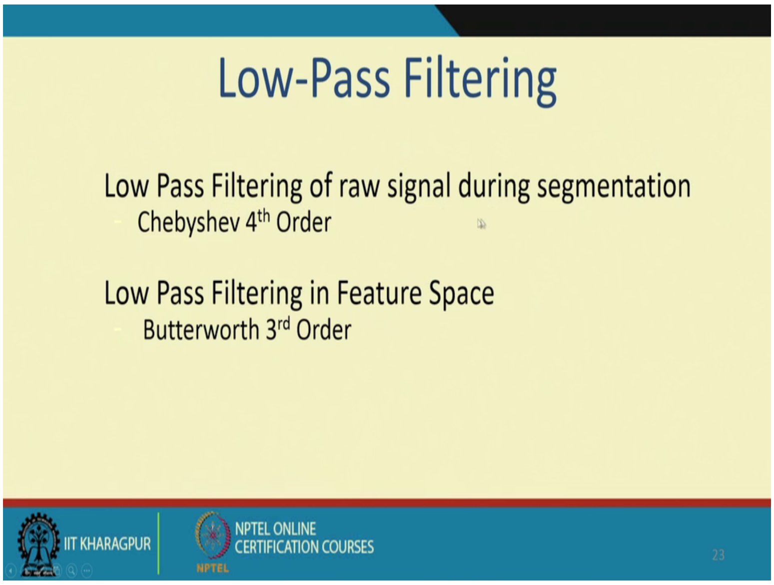

So, for the low pass filtering this was the filter order which was used.

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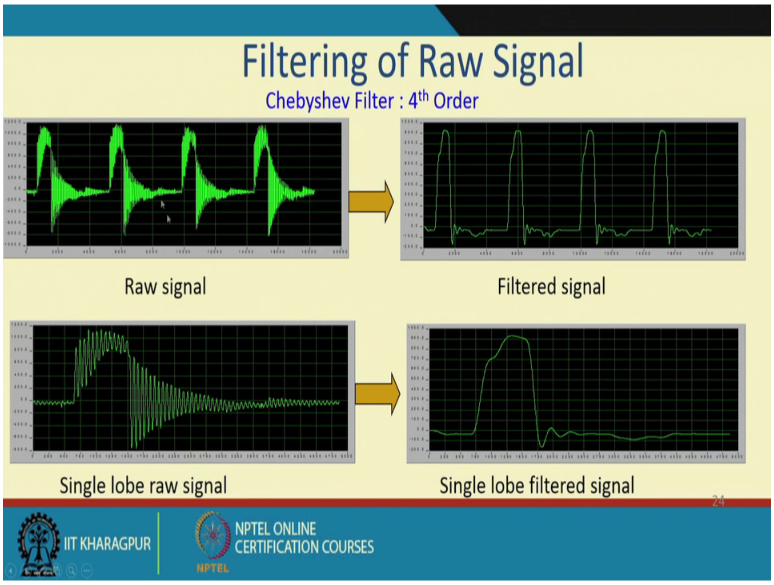

Filtering of the raw signal; so this is up to an individual how you want to do it, and this is what was used in our analysis.

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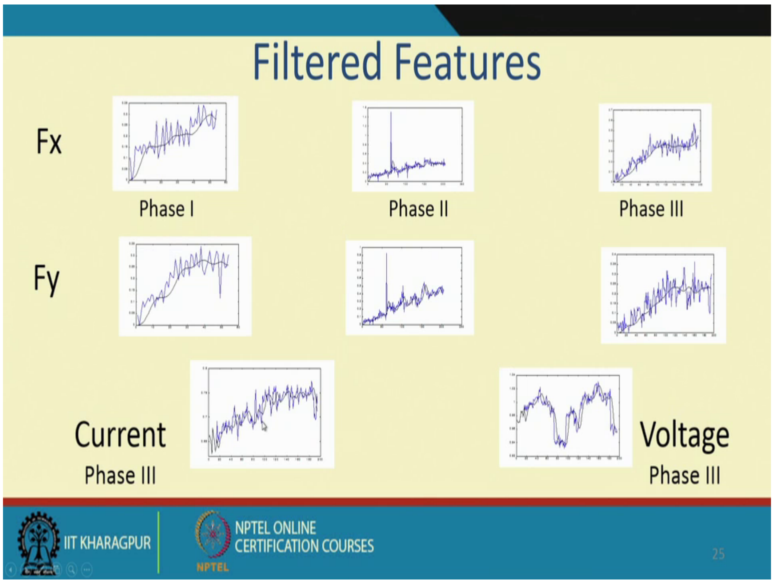

So, some of the filtered features for the forces, for the voltage and for the current.

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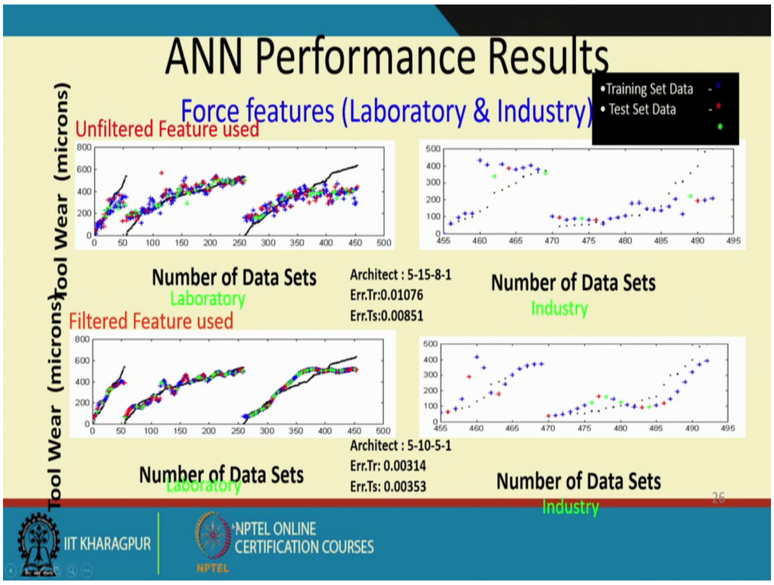

So, you see the tool wear in microns both in laboratory and in industry, we are able to predict better once we it has the filtered feature the instead of the unfiltered feature.

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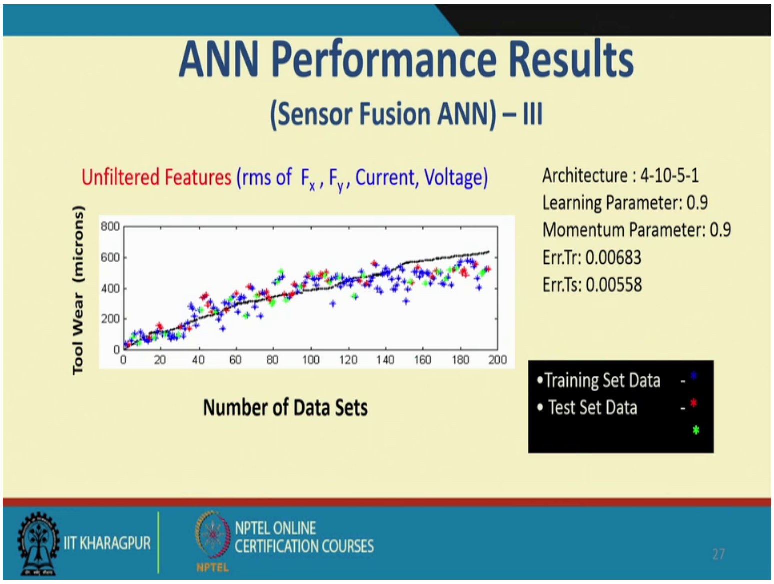

And then h with sensor fusion by sensor fusion I mean, it is just not force I took force current and voltage all of them together for having a robust model to predict the tool wear. And in fact with sensor fusion we have a better prediction. In fact, this paper is there referred to in my book.

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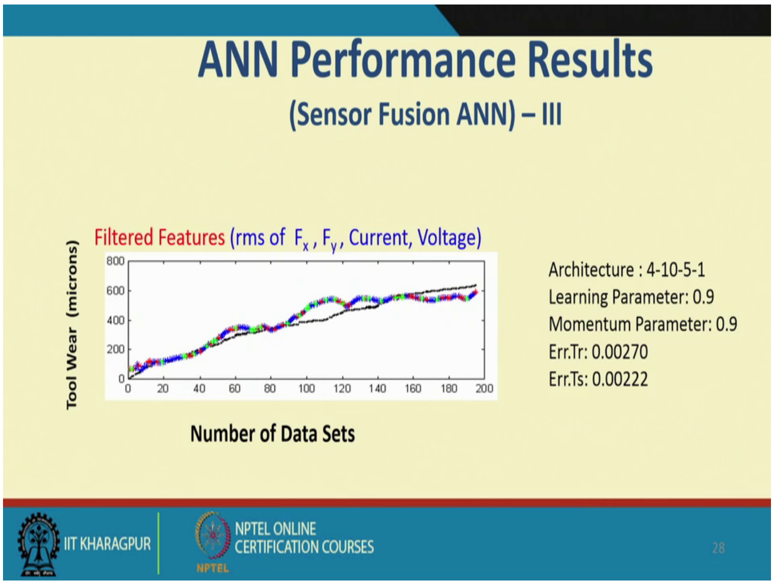

You can see that and the tool wear we can predict.

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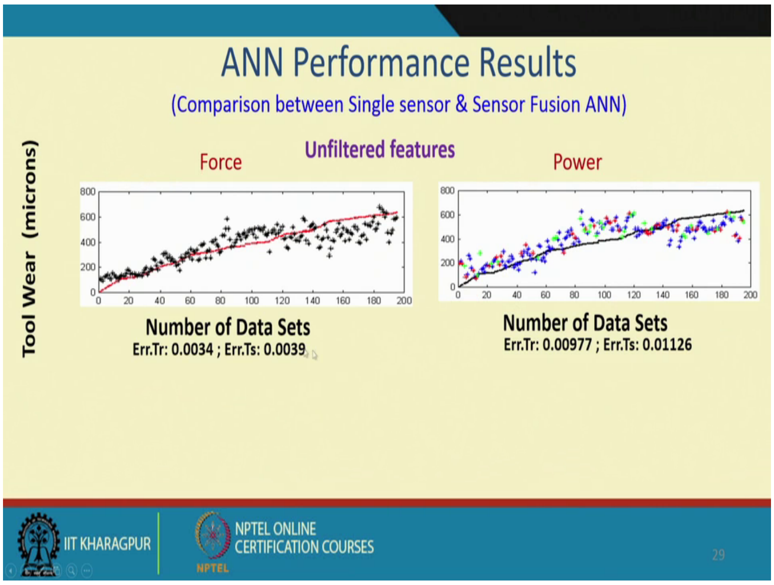

So force and power.

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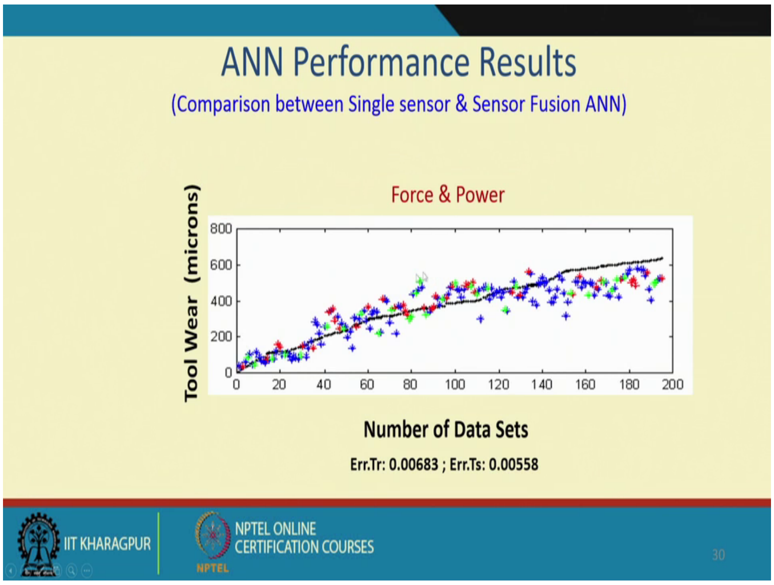

And then tool wear it could predict.

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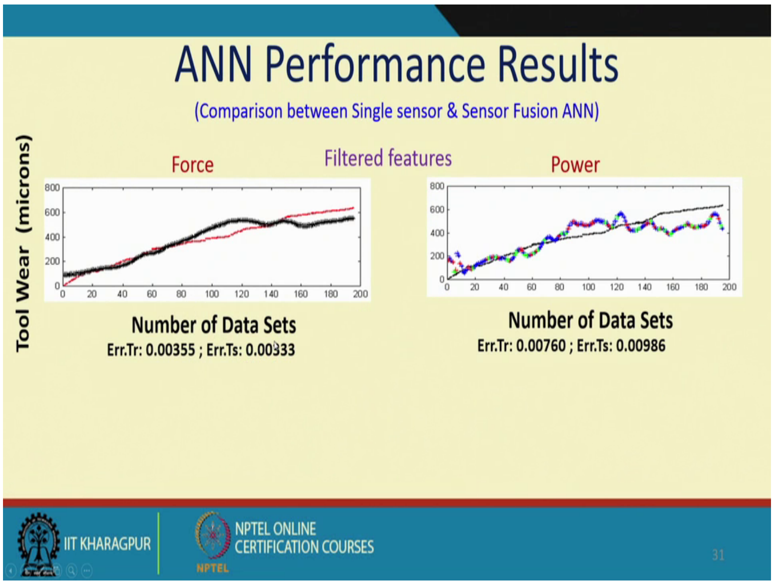

So it is single sensor and sensor fusion.

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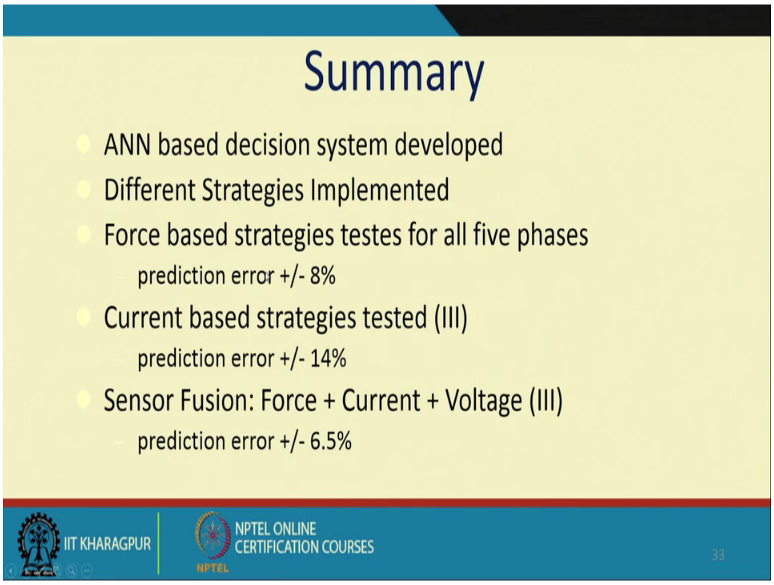

So, in summary ANN based decision system was developed different strategies implemented, force based strategies gave a prediction off with in plus minus 8 percent, only current based gave a prediction within plus minus 14 percent, but when I used force current and voltage I had a better accuracy of prediction which was within 6.5 percent.

So, with this example what I wanted to demonstrate is.

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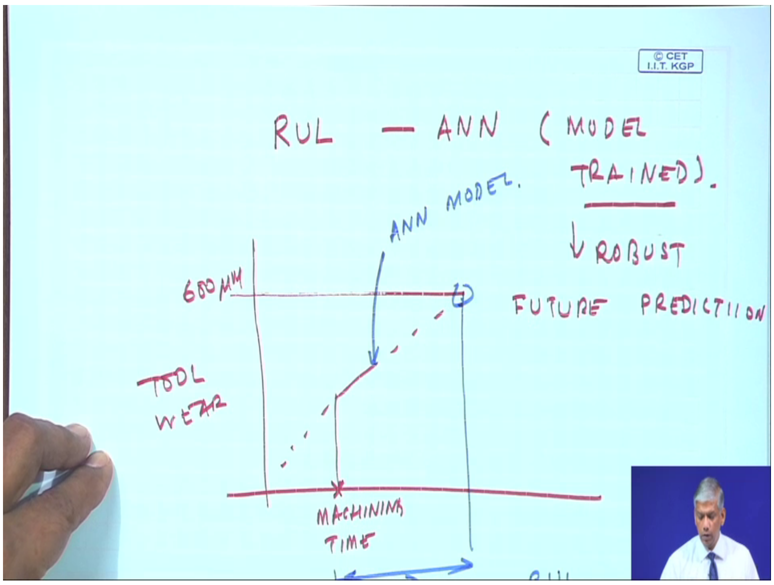

For RUL I can have ANN model, but the model has to be trained and then we robust enough to do future prediction. So, in this case if my tool wear model is something like this, I know that this is my limit of 600 micron and this is my machining time where I am today I can always if this comes from ANN model, and this model was best when we had input from force current and voltage I can always predict after how much machining time my tool needs replacement or even.

So, this was just an example of demonstrate how machine learning can be used to develop robust models and then they can be used to predict the remaining useful life of the cutting tool.

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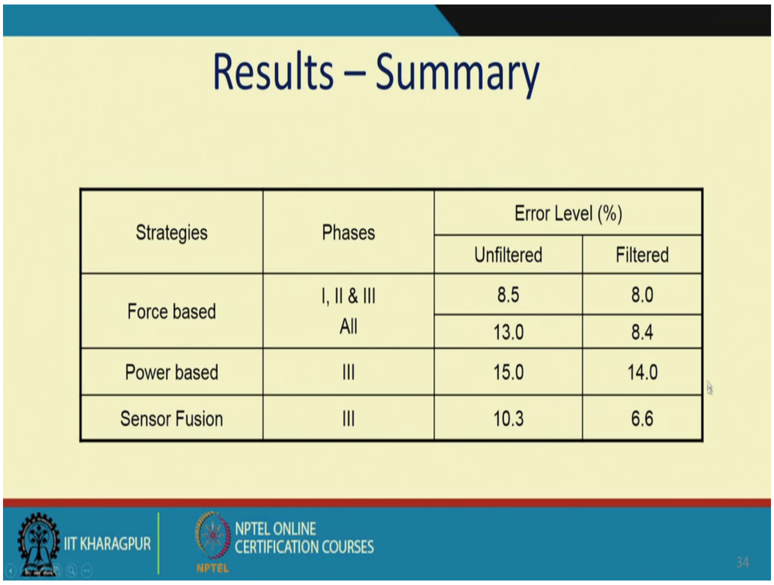

And you can see for different cases; the best was the filtered signal accurate accuracy was the best in the case of sensor fusion.

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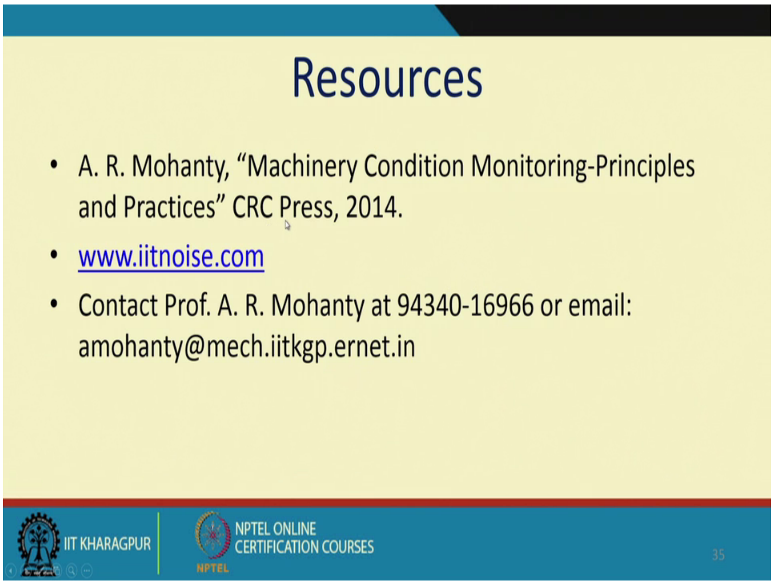

That detail of this work is given in a paper which is there in the reference of my book. And this is the first work where artificial neural network was used for tool condition monitoring and which we did that about two decades ago and it is a well sited and it is very popular way to do tool condition monitoring.

Of course now, within a good image based systems you know people have done methods to online detected tool condition monitoring just through image, but this given example how ANN could be used to develop models to predict the RUL of for the case of tool we are monitoring.

Thank you.