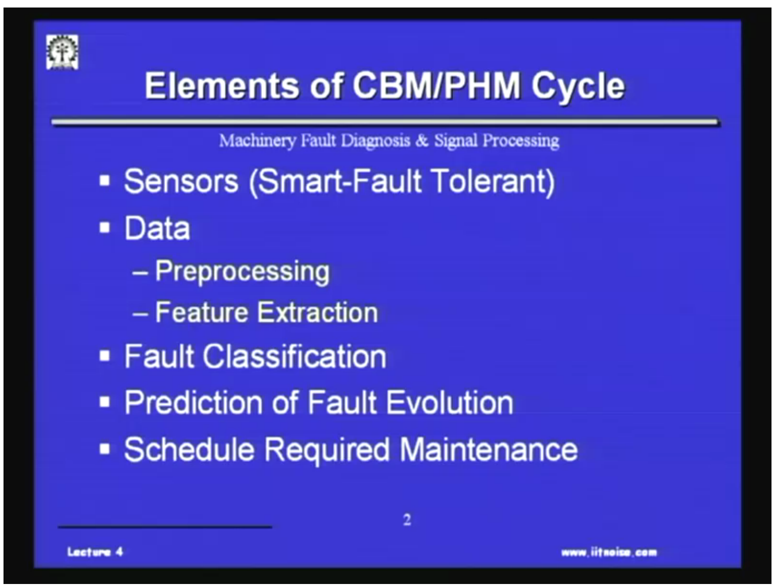
Machinery Fault Diagnosis and Signal Processing
Prof. A R Mohanty
Department of Mechanical Engineering
Indian Institute of Technology-Kharagpur

Lecture 04
Principles of Maintenance Fault Diagnostics and Prognostics

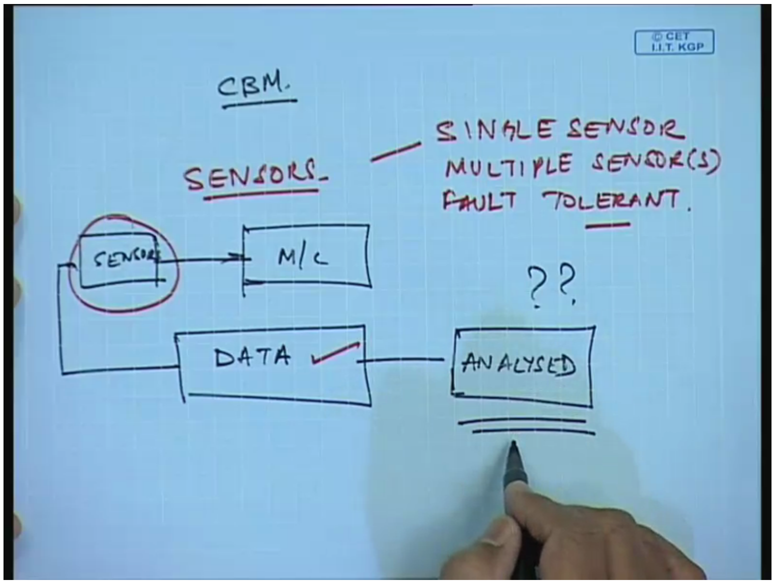
In this lecture, you are going to speak about Fault diagnostics and prognostics. As we already know that in this course, we are focusing mostly on CBM. That is condition based maintenance. We will see, what are the definitions of diagnostics? And what is prognostics. And how do we estimate the remaining useful life of a machine, because of the fact that, you know, once we maintain a machine. We would like to see or predict by certain tools how long this machine is going to last, before we totally remove it out of service.

(Refer Slide Time: 00:51)



So, the essential elements of CBM or the prognostics health management cycle are as follows:

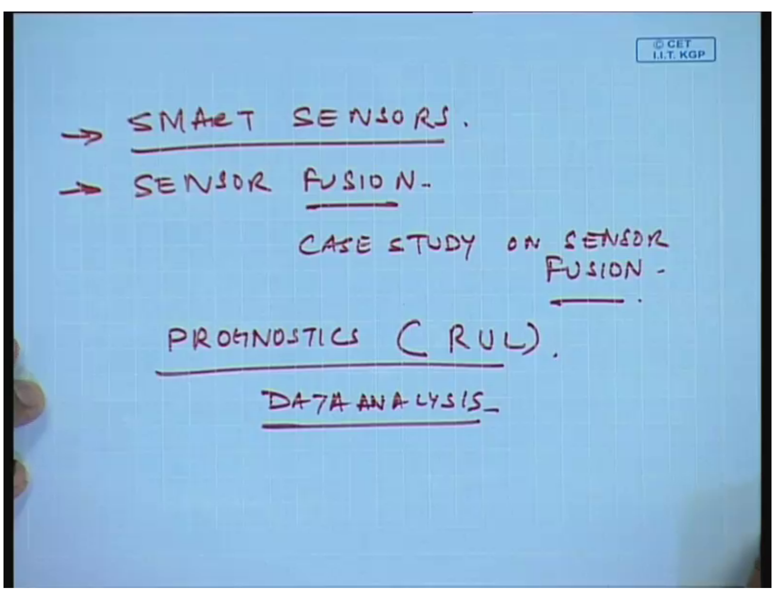
(Refer Slide Time: 01:03)



As you all know, the most important features are the sensors around a machine. And then, these sensors are going to provide us data which has to be analyzed. And all our decision is based on this analysis. But in the modern days, CBM, the trend is towards that, in this sensor, whether I can do with single sensor, whether I should have multiple sensors, whether these sensors are fault-tolerant, etcetera.

Because as you know, everything in this CBM depends on the data collected by the sensor, in the, to begin with, if the sensor itself is faulty and it is providing us wrong data; our analysis will be totally wrong.

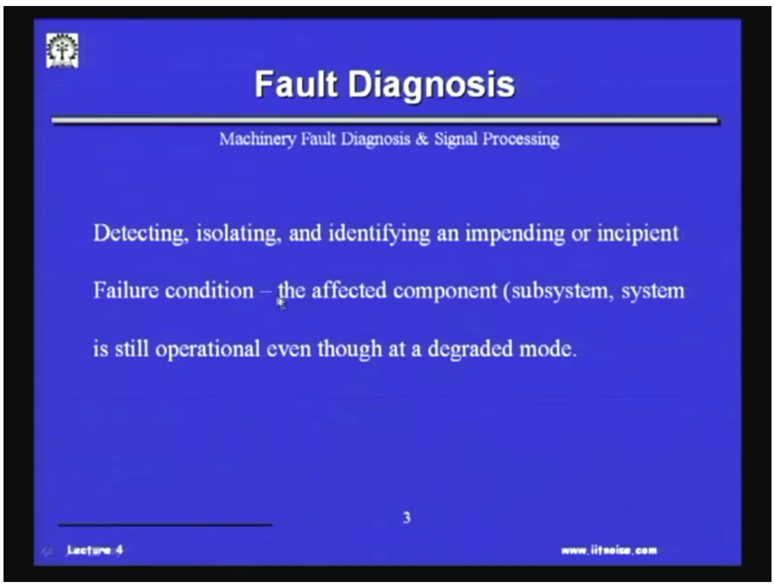
(Refer Slide Time: 02:30)



So, the most important feature of what these sensors, nowadays, are used in CBM are what is known as smart sensors, ok. And topics like sensor fusion whether a single sensor will do or multiple sensors are to be used. And then, of course, towards the end of this lecture, I will give in a short case study on sensor fusion. And how we will see the remaining useful life of a cutting tool can be corrected by using sensor fusion.

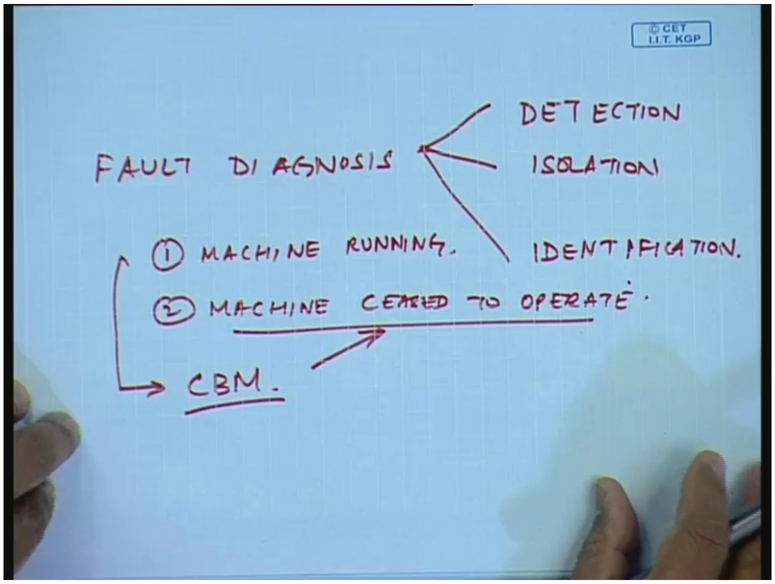
Now, once we have the data coming from this sensor we can classify the faults and also then try to predict how the fault is going to evolve. And then, if necessary we will go for maintenance. So, the prognostics or estimation of the remaining useful life depends on my data analysis.

(Refer Slide Time: 03:49)



So, before we move to the next sections, I would like to give you a definition of Fault Diagnostics which is detecting, isolating and identifying an impending or incipient failure condition - the affected component subsystem, system is still operational even though at a degraded mode. So, the fault diagnosis encompasses detection, isolation and identification.

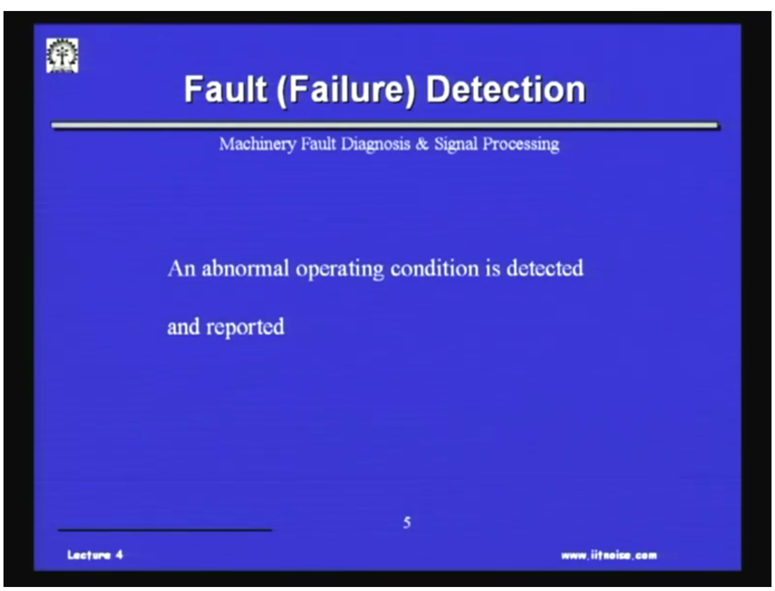
(Refer Slide Time: 04:21)



Fault diagnosis has three important components: one is detection, other is isolation and other is identification. And also, and fault diagnosis is also used to detect isolate and identify a component or system that has ceased to operate. So, in one case, we have the machine still running. Machine running; in other case, we have machine cease to operate. As I was telling in the last class, you know, CBM is not good for a machine which is not operating.

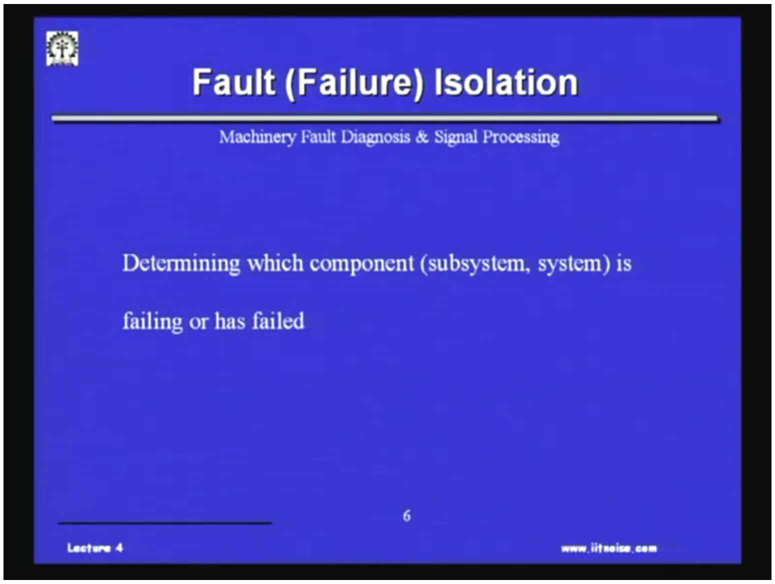
So, we will use mostly CBM for a case when the machine is running. So, to define fault detection it is known as an abnormal operating condition which is detected and reported.

(Refer Slide Time: 05:40)



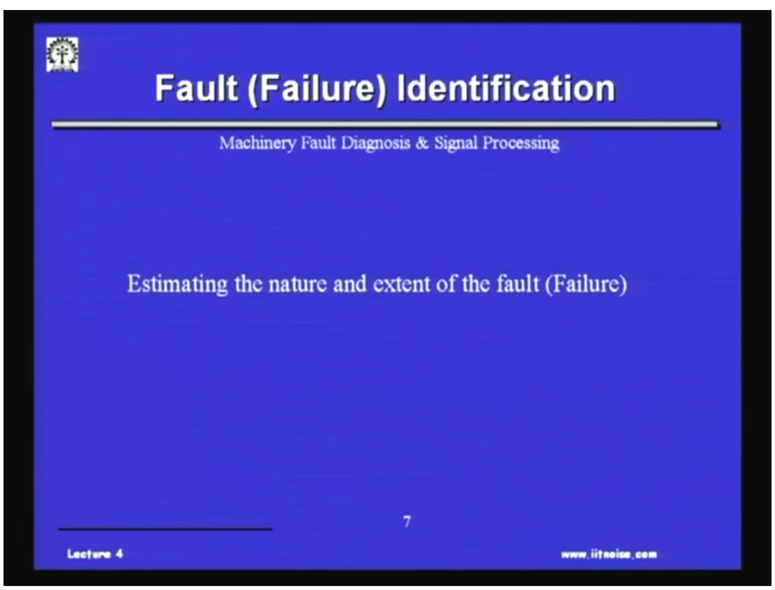
So, this is the definition of fault or failure detection; that is, an abnormal operating condition which is detected and reported. We will see the mathematical techniques, how such faults can be detected, can be isolated, can be identified, and so on in the subsequent sections.

(Refer Slide Time: 06:01)



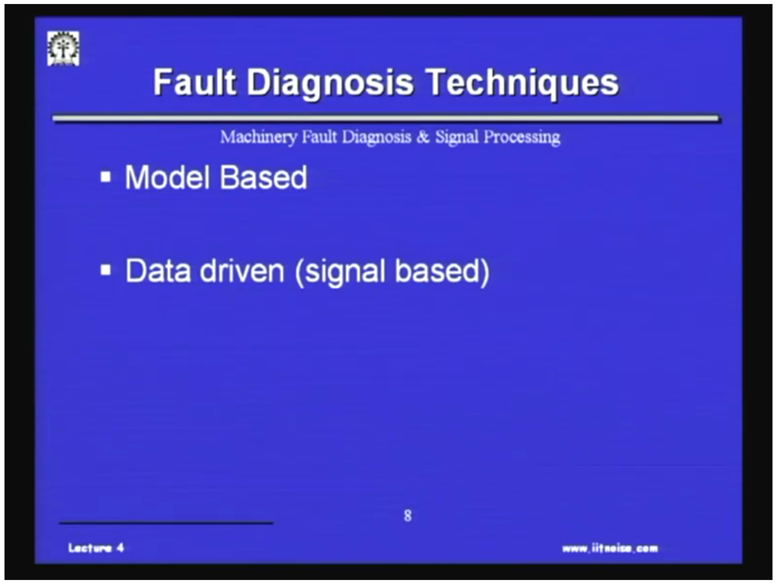
And next is the fault failure isolation. So, determining which component subsystem or system is failing or has failed.

(Refer Slide Time: 06:17)



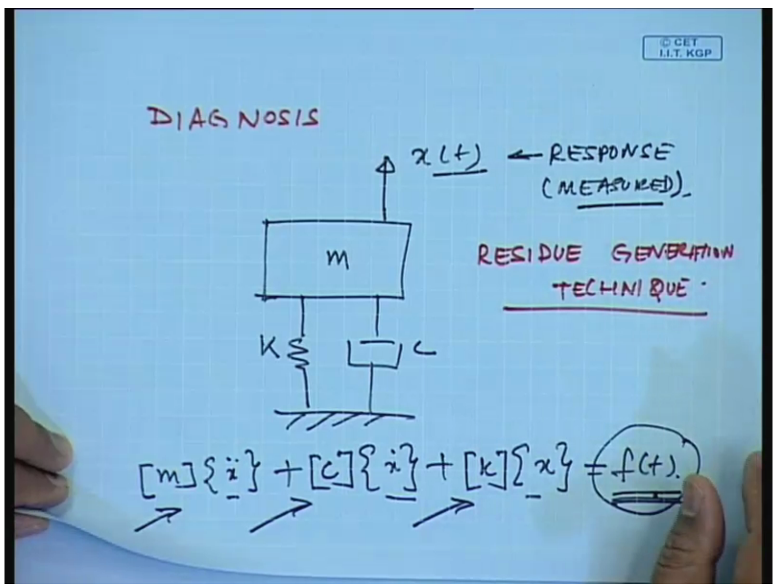
Next is the fault failure identification. That is estimating the nature and extent of the fault.

(Refer Slide Time: 06:25)



The question is, how do we diagnose these faults?

(Refer Slide Time: 06:30)

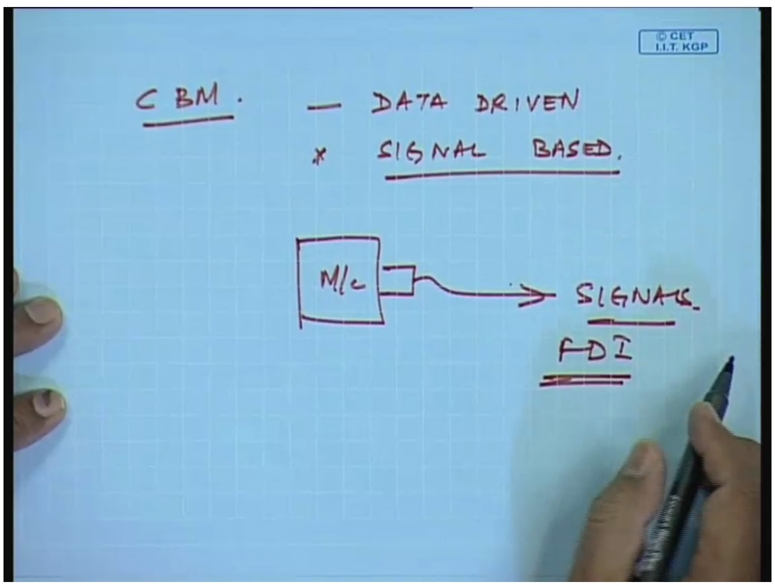


Diagnosis, traditionally, are done by two important methods: one is the model-based method and other data-driven or signal based method. In model-based methods people use certain mathematical models like the, from the physics of the problem and modulus techniques, they have a mathematical technique known as: For example, I will give you a simple, simple example here. Suppose, I have a system, a simple mass spring dashpot system; and I have got certain response because of a fault in it.

So, I can write the equation of motion of this system. And because of some force, I am going to get a response, though, I have written is that a vector and shown a single degree of freedom system; But we could generalize that a system having a lot of m and k and seasoned can be written in such a matrix form. And this force is what is creating the response in which we are measured; response which is measured.

And once I had the response measure and if I have some estimate of this mc and k I can through this equation find name of this force. If this force is abnormal, if the force is more than what is necessary I can say a fault has occurred in the system. And this could be done by what is known as the residue generation technique. In the model-based system, one such method is the residual generation technique.

(Refer Slide Time: 08:52)

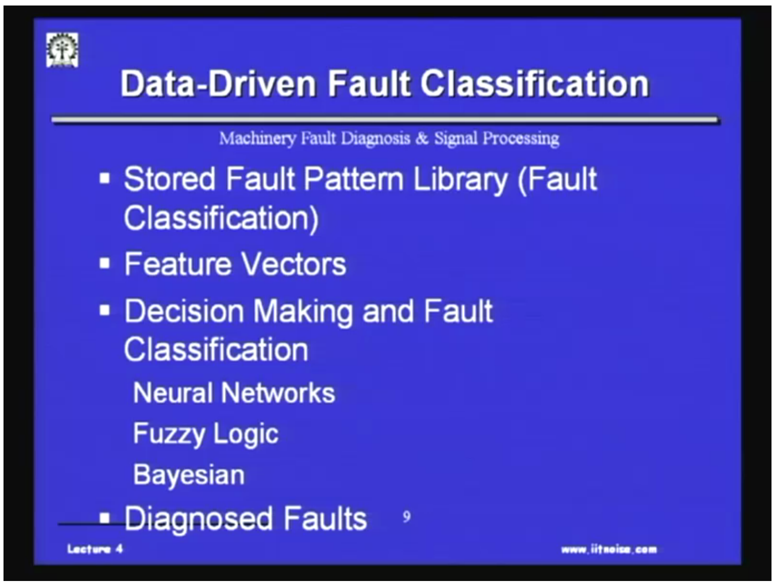


However, in the present course on CBM our focus will be towards mostly data-driven or which is also otherwise known as signal based, okay. Because this is very easy to understand in the sense I have a machine. I put a sensor and I get my signal. And everything is the total FDI is done based on this signals. And that is traditionally people do such kind of FDI or CBM in the industry and this is very easy to do, compared to the model-based technique.

Wherein you require, in the model based technique you require a lot of computation, a lot of physical understanding of the system for complex large systems; that has become very difficult to model the entire complex system. So, traditionally people have been using mostly the data driven or the signal based technique. And in this course we will be focusing our attention mostly towards signal based techniques.

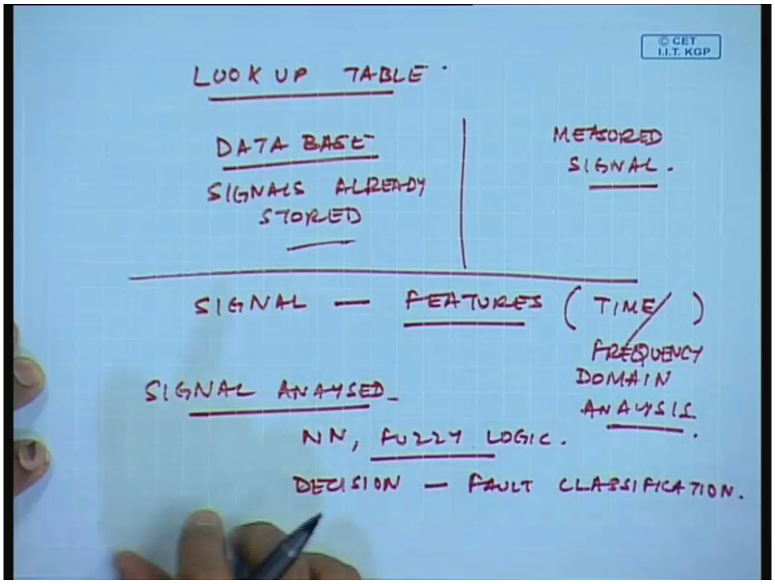
Though, while we are on this topic, I will also tell you some of the model based techniques other than the residual generation techniques, which are used in, in the industry; or are practiced by maintenance engineers to do fault detection or identification in the machinery.

(Refer Slide Time: 10:24)



Before I go to the model based fault diagnostics, I should mention to you that this data-driven fault classification is actually done on or done by many methods. One is stored fault pattern library and then we have a fault classification. For example, something like a lookup table.

(Refer Slide Time: 10:52)

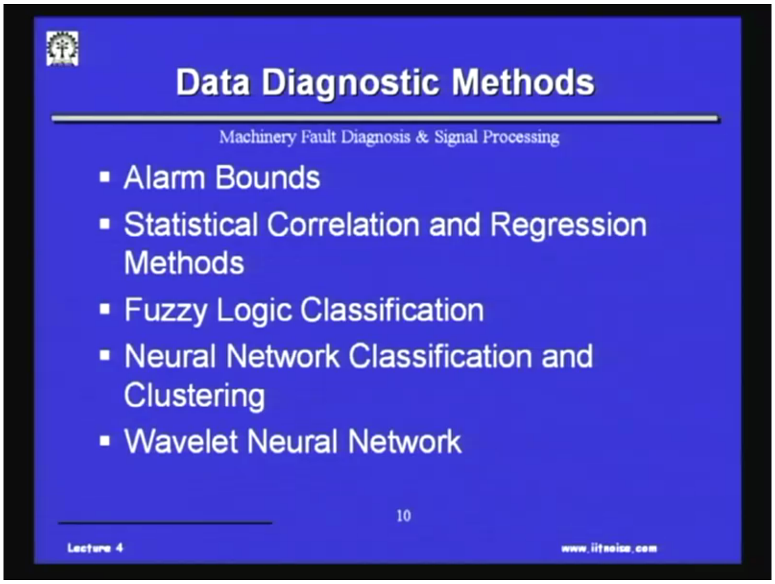


We compare in a database, signals already stored with the measured signal. If the deviations are large, we can pretty safely say a fault has occurred. And that is this feature vectors, now, we can in this signal, what are the features to be studied? I will focus more on this when I talk about the time domain and frequency domain analysis. But to do a fault classification there are nowadays many techniques.

One is the neural network based method which is very widely used in the industry, the fuzzy logic and the Bayesian system. And then, these are mostly reliability and probability based models. And then, the fault can be diagnosed. So, in a data-driven fault classification, there are techniques where in this signal analyzed based on certain neural network, based on fuzzy logic.

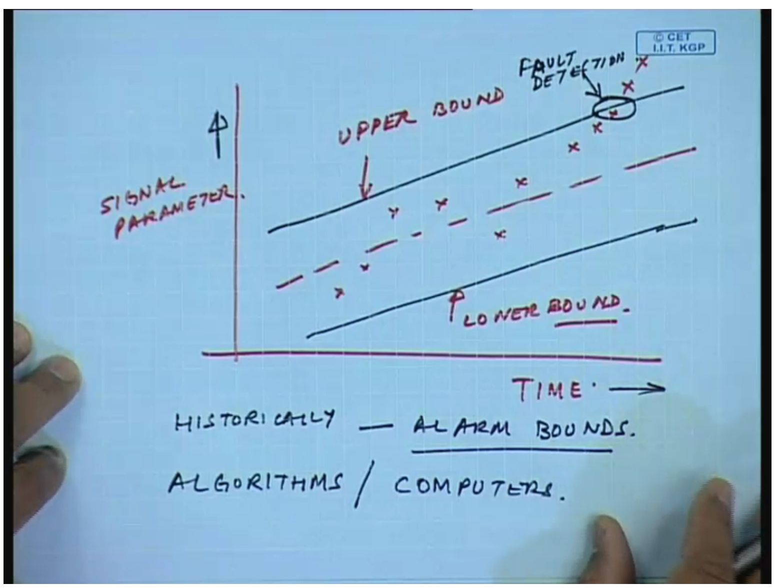
And a decision is made on the fault classification, could be, by fault classification I mean that there faults are of two different types one is severe, one is normal or one is something which we can live with. So, such decisions can be made by neural network systems. And I will give you an example as to how this kind of study can be done for different machines. We have a case study for a cutting tool monitoring situation.

(Refer Slide Time: 13:17)



And this data diagnostic methods, there are many ways by which this data can be diagnosed one simple way is;

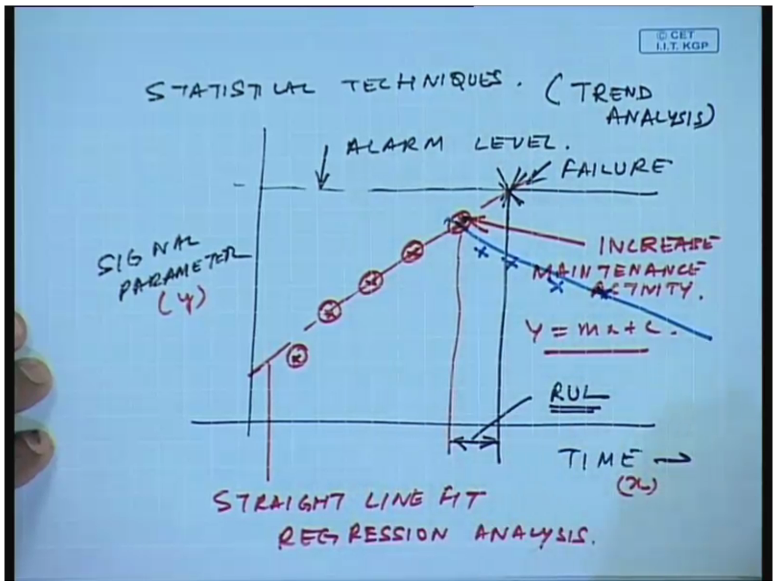
(Refer Slide Time: 13:27)



Say for example, which time we have a certain signal parameter which we are monitoring. Say for example, I know with time these are my upper and lower bounds so what could be happening that my system parameter, etcetera. So, this is the upper bound and this is the lower bound. I can set the limits of this upper and lower bound within the plus minus 3 Sigma values of the measured parameter.

And I can be only alarmed that a fault has occurred in such a situation, fault has been detected. So, simple alarm bounds can be used. And then, in fact, fault can be detected and traditionally or historically in the industry people are using such alarm bounds, okay. And then, you know you can detect a fault. But, nowadays, with the availability of many Algorithms and fast computers, many new methods of fault diagnostic methods have evolved. And we will discuss few of them here.

(Refer Slide Time: 15:42)



Many statistical techniques are available. I will give you one simple example of a regression analysis. For example, with time, I know that this is the signal parameter and this is my alarm level. That means if the signal will increase beyond this level, I will be alarmed about the condition of the machinery. For example, what I could do is suppose I have measured with time these are the condition of my signal.

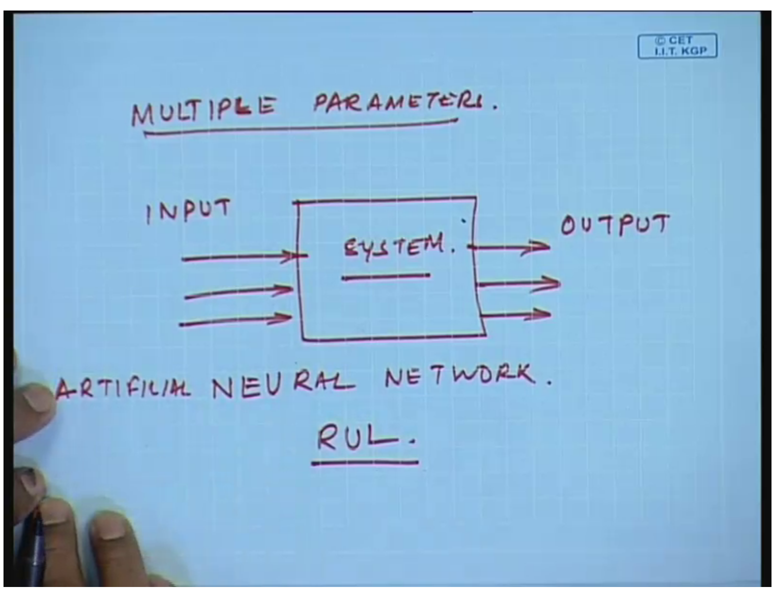
So, statistically what I could do is, I could do a simple regression analysis. And suppose my measurement has been done only at these points, okay looking at the past data and taking the present data, I could do a straight line fit; where you know, $y = mx + c$ is the equation to this curve here. This is y and this is x, okay. But this is a single component I could have multiple coefficient.

But, the most important parameter of this is what I mean this condition of this machine and I know the equation to the straight line, I can always find out the remaining useful life from the past data. And this has been also known as what is known as the trend analysis in the industry. That means looking at the past data, measuring the present data, I can come up with an regression and an estimate, when this machine will have a failure.

So, there are many software available with lot of database where this kind of data are stored. People do simple regression analysis and can predict the failures. And even in an industry, if these kinds of measurements are done, this is going to give us a lead time before I do my maintenance, so that I know the remaining useful life. So, I have this kind of our lead time before the failure occurs to take corrective measures I could perhaps now because of this trend I could increase the maintenance activities.

So that I can reduce the failure and subsequently maybe this levels could come down and with time you can take corrective measures. And that was just a simple example using the straight line regression analysis of linear fits.

(Refer Slide Time: 19:38)

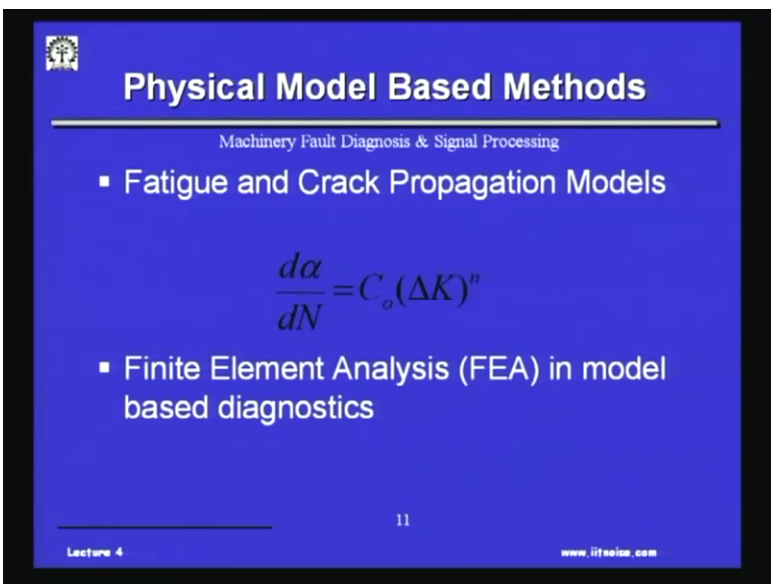


But nowadays when multiple parameters are involved, it becomes impossible to find out a straight line fit. And many of the relationships between the input to the system, so such an analysis it becomes very difficult humanly to measure know what are the input parameters, output parameters. So, people use what is known as a neural network or artificial neural network to find out a relationship between the input and output.

And come up with models as to what kind of output levels will be predicted with as a function of time. And then, we can estimate the remaining useful life, by such a technique there are many methods of RUL estimation. One is the fuzzy logic classification other is the neural network classification. And next one is wavelet neural network. In this course, we will not be focusing into more in more on model based fault diagnostics or using neural network and other tools.

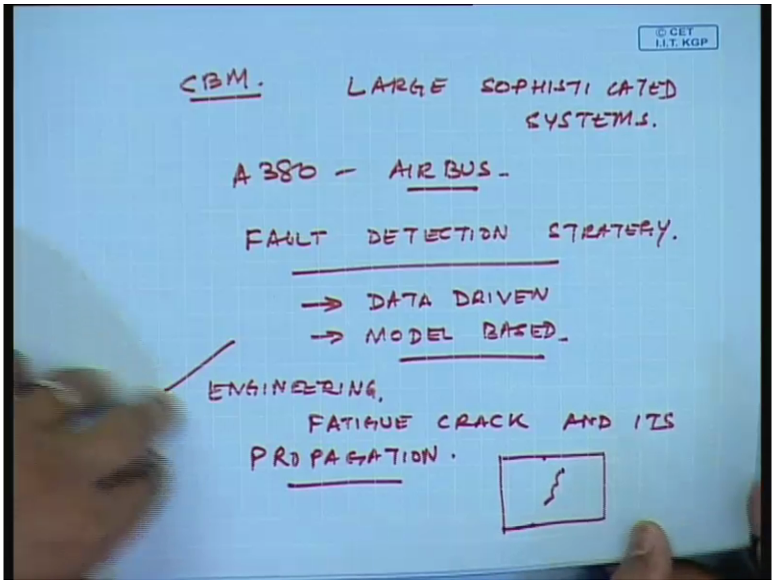
But mostly, since it is a very basic course on machinery for diagnostics and signal processing, we will be mostly spending our time on the fault detection through the, looking at the alarm levels, looking at the past history, looking at the look up tables, looking at the historical data. And then try to correlate the fault condition with the present signature. And that is what we are focused in this course.

(Refer Slide Time: 21:43)



Now, that we have some idea regarding the data based fault detection methods.

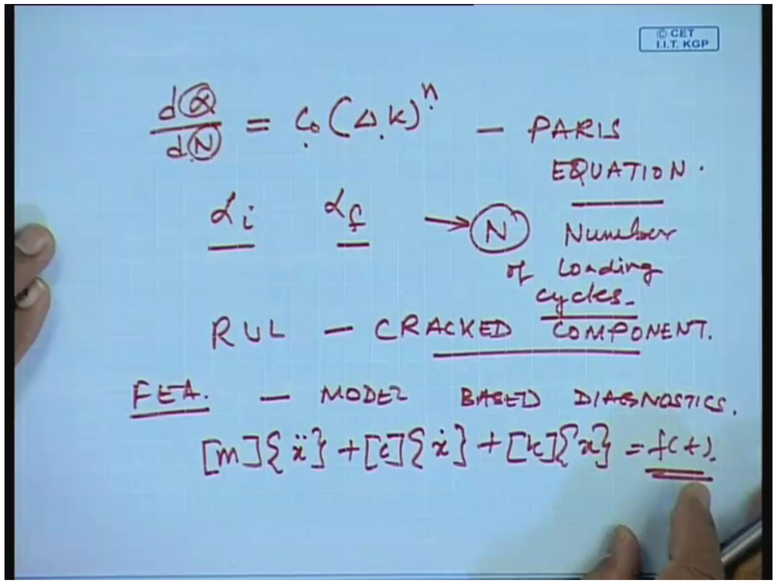
(Refer Slide Time: 21:57)



I will also tell you about the certain physical model based methods which are used in well CBM and maybe in large sophisticated systems. For example, an Airbus A380, there are many, many systems. It is a very, very complex systems and what kind of fault deduction strategy is to be used. So, this could be a combination of data driven and also a model based.

One very fundamental problem in engineering is, be it cement mills, be it gearboxes, casings etc is the development of fatigue, crack and its propagation. So, once a crack has developed on a machinery component, say some crack on a machine component, the next question is, always people have in their mind is, how long is this crack going to be there; can my machine still run under this crack condition, etc.

(Refer Slide Time: 23:51)



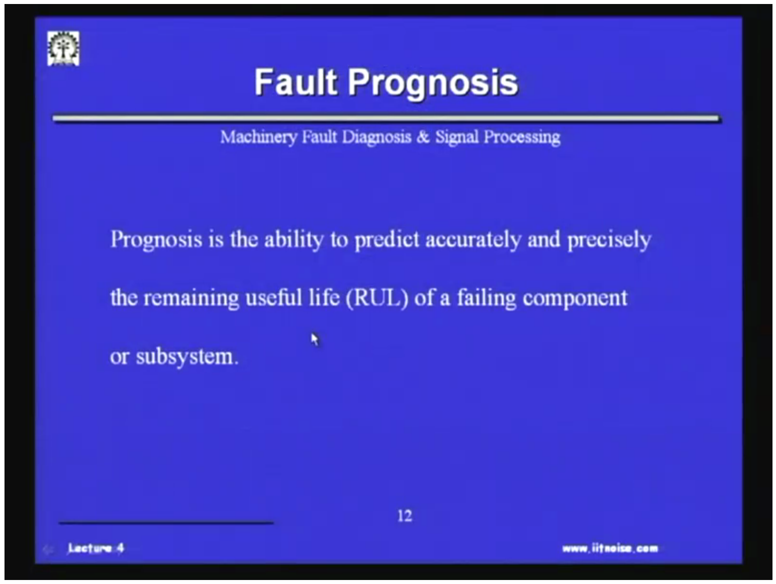
And the most important equation to this is this crack growth parameter with the number of cycles of operation C naught is an material property and n is also an material property and this is known as the famous various equation. From such an equation, we can always estimate the, is the crack length or dimension for crack this is the number of cycles, the material property, this is the stress intensity level and this is again a material property.

We can decide on how many number of cycles this machine can be loaded before a crack grows from an initial length to a final length. And then, once N is estimated, we can then decide on the RUL for a crack component, okay. This being a basic course, I will not go into details of all this because this will require lecture on fatigue failure and fatigue mechanic, fracture mechanics. But I will just want to mention to you that such techniques are available for the crack growth development.

And then, once we know the final crack length which our machine can be subjected to, we can decide and we can estimate the number of loading cycles. And thus know the time remaining useful life of the machine. Another very important model based techniques which people use is the FEA. So, if you have been used in model based diagnostics, so what we can do, you know, you should go back to that same equation, I was talking about, simple FEA model of the system can be developed.

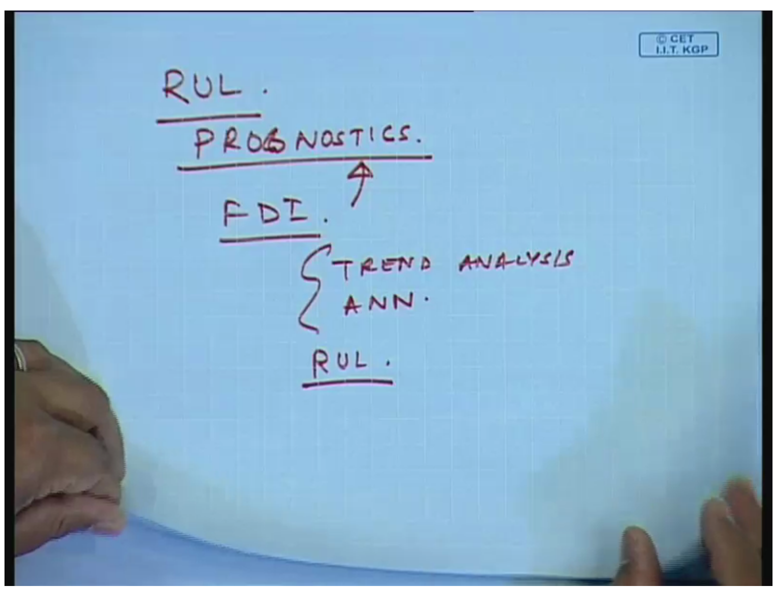
And this force can be estimated. And then, the model based fault diagnostic procedure or strategy can be developed for the fault detection.

(Refer Slide Time: 26:25)



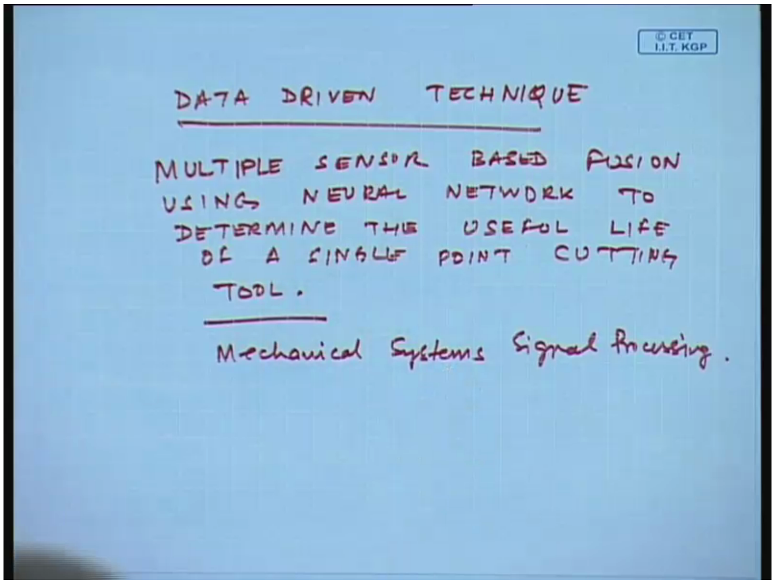
Now, once we know, have an idea regarding the fault detection, fault Diagnostics, fault isolation identification. And once we have understood our system.

(Refer Slide Time: 26:38)



The most important parameter is the RUL and what is actually known as the fault prognostics. So, prognosis is the ability to predict accurately and precisely the remaining useful life of a failing component or subsystem; because once default has been detected and isolated, the next question is, this prognostic's to estimate the remaining useful life. And all these mathematical tools of trend analysis, artificial neural network, etcetera, could be used to predict RUL, okay.

(Refer Slide Time: 27:32)

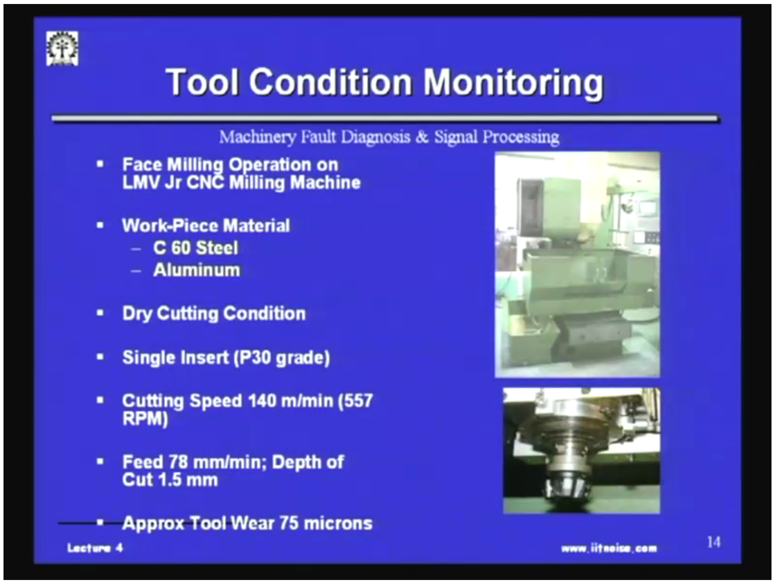


Now, with this, what I would like to do is, I will show you an example as to how this model based or data driven technique based technique can be used for fault detection in the machine.

(Refer Slide Time: 27:55)

So, we already talked about a tool we are monitoring case study in fact and this was a project which we did in IIT about a decade ago. And this was sponsored by the Department of Information Technology here.

(Refer Slide Time: 28:08)

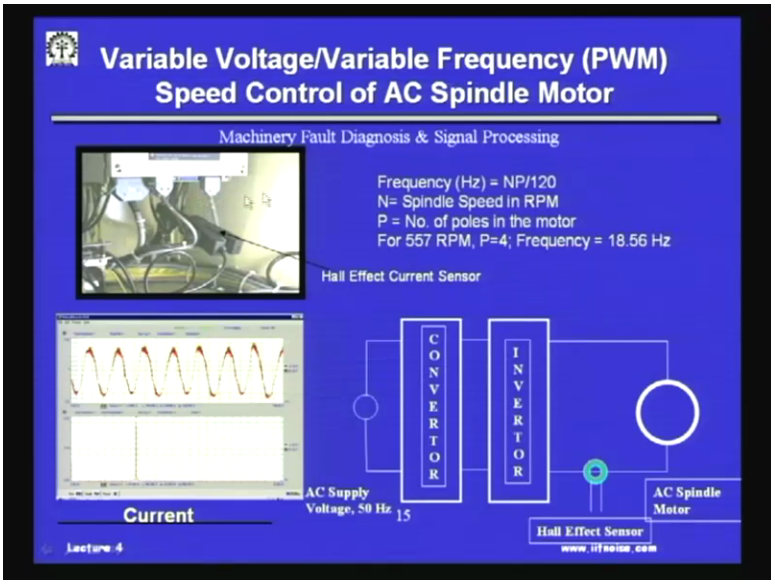


This project was to estimate the effect of multiple sensor based fusion, using neural network to determine the useful life of a single point cutting tool. In fact, in this example, I mean, this work has actually been published by the in the Journal of mechanical systems signal processing and the details of this could be found in that reference. But here, let me tell you what this tool condition monitoring is about.

We have a face milling operation being done on a machine. We use two cases or work material. One was the steel and another was the aluminium. There were no cut introduced. It was dry cutting condition there was a single cutting tool in this insert. And the cutting speed approximately was at 140 meters per minute or 557 RPM of the spindle feed and depth of cut was 1.5 mm maintain lists. And the approximate tool where was 75 mic.

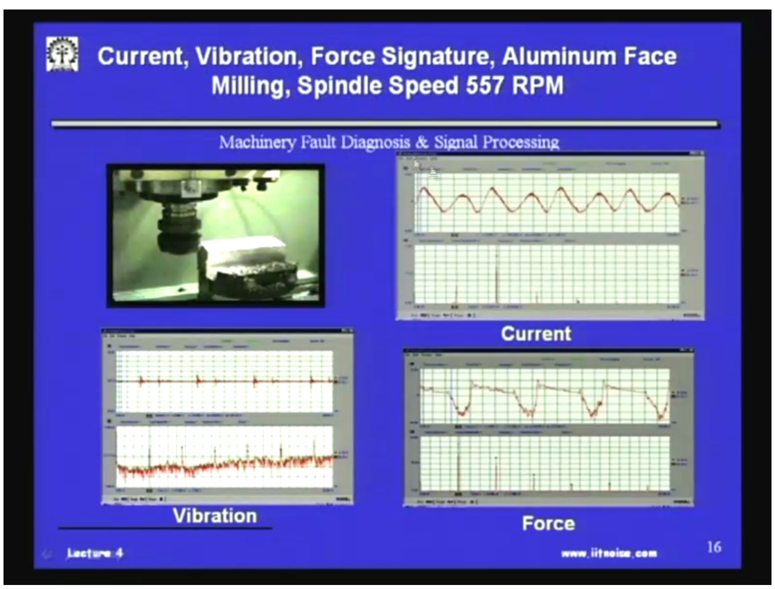
In such a condition, this instrument of this milling machine was instrumented with a cutting tool first dynameters was instrumented with the acoustic emission sensor, with vibration sensor, the microphone, etcetera. And also the current driving, current being supplied to the spindle motor was also monitored.

(Refer Slide Time: 30:29)



So, I will show you this current which was being supplied to the spindle motor was measured using a Hall Effect sensor because this had a variable frequency drive and one this rpm was 557 rpm, the correspondent to a frequency of 18.56 Hertz and if you look at the current which is being measured by the Hall Effect sensor, which is driving the spindle motor. You will see this current to be a sinusoidal signal and then a single frequency is shown in this current.

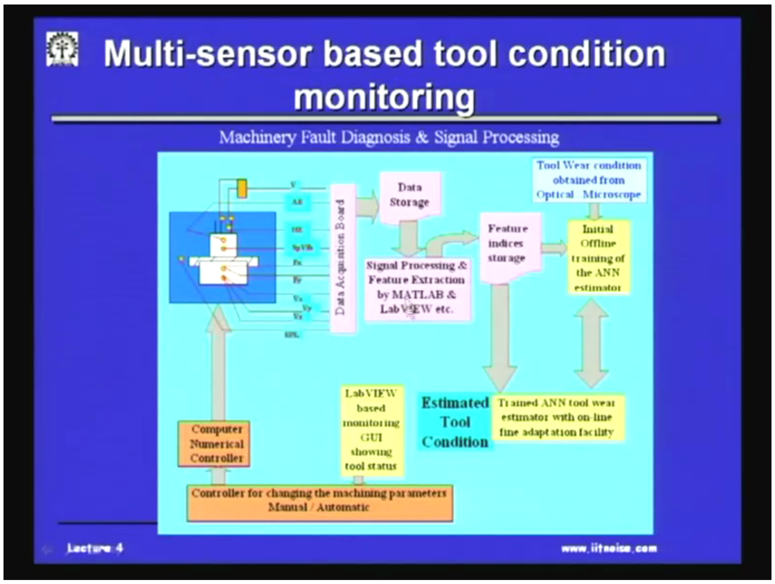
(Refer Slide Time: 31:03)



Next is, when we try to Mel aluminum with tri cutting conditions and try to measure the vibration, the cutting force and also the current. And current also gets modulated because the node on the spindle motor. And then, you can see the sidebands of the current. I will not go into details. But these are the features which could be extracted from these signals around this machining process being current force and vibration

And once we tried to machine steel in the same conditions, the cutting forces, the vibration levels and the current modulations are high and which is reflected in such a plot here.

(Refer Slide Time: 31:52)



Now, with this kind of analysis, we thought that why not we instrument this machine with many more sensors, which are more than required. Like voltage acoustic emission, vibration cutting force in X, Y, Z direction, sound pressure level. And then, we have a data acquisition system where when we do a signal processing and feature extraction by certain software. And then, also try to; in the offline stage measure the tool we have conditioned by a microscope.

So, we have the actual conditions. And then, they have an offline condition of the tool cutting tool wear. And then, we through artificial neural network, we could try to estimate the tool wear. And then, try to find out at what tool wear and what is the remaining useful life of the tool, when we say, it will feels about under 500 microns etcetera. So, how much time it would take for the tool to fail.

And this analysis was done through all the sensors taken together in the artificial neural network because it would be humanly impossible or physically impossible to have a mathematical model based system wherein all these parameters are taken in and compared to the tool wear. Rather we thought of using artificial neural network and which is very powerful in the sense it is a black box, which relates pretty well to the output level condition and the input level to the system.

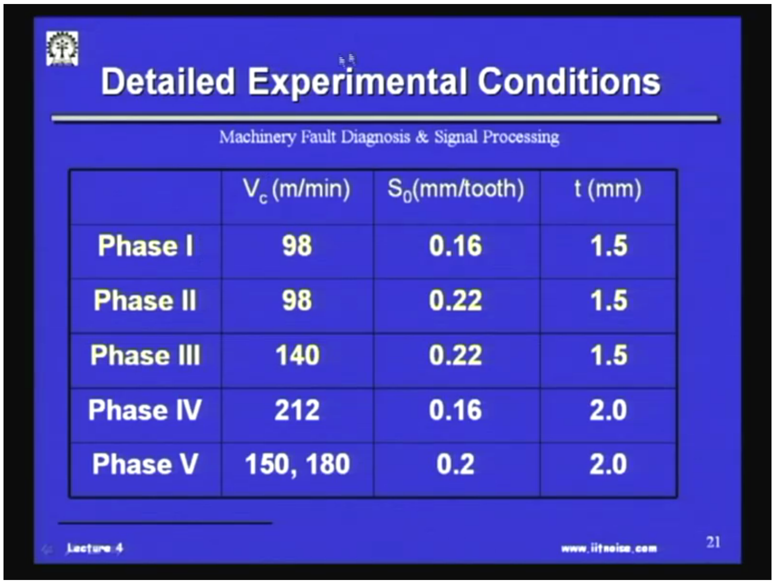
(Refer Slide Time: 33:32)

These experiments were done also the same tool used at a very, very higher cutting tool, depth of cut to bring in failure, quickly. And such levels were done in an industry, where the actually force level, the cutting speeds, the depth of cut rates are very, very high.

(Refer Slide Time: 33:57)

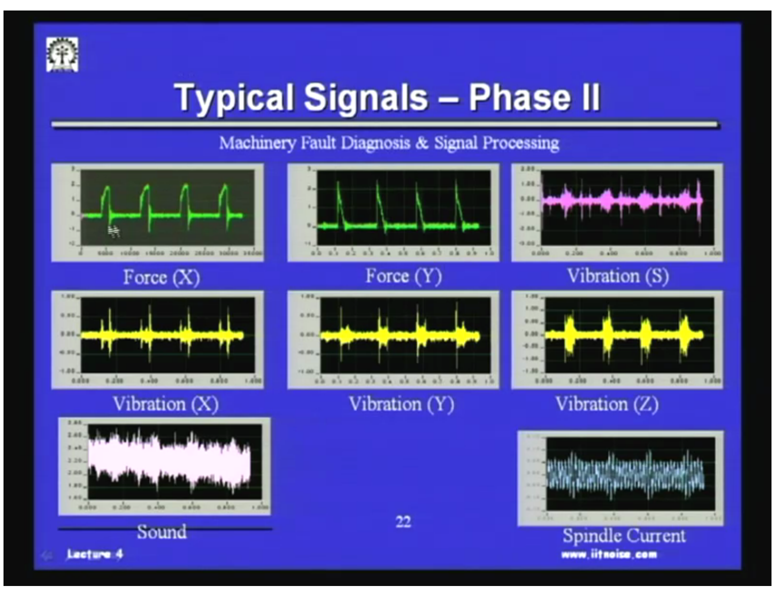
And then, you can see in the same industry, how this spindle is being sent is being monitored through; and vibration sensor here, through a force sensor sitting on here, behind the, just below the work piece.

(Refer Slide Time: 34:17)



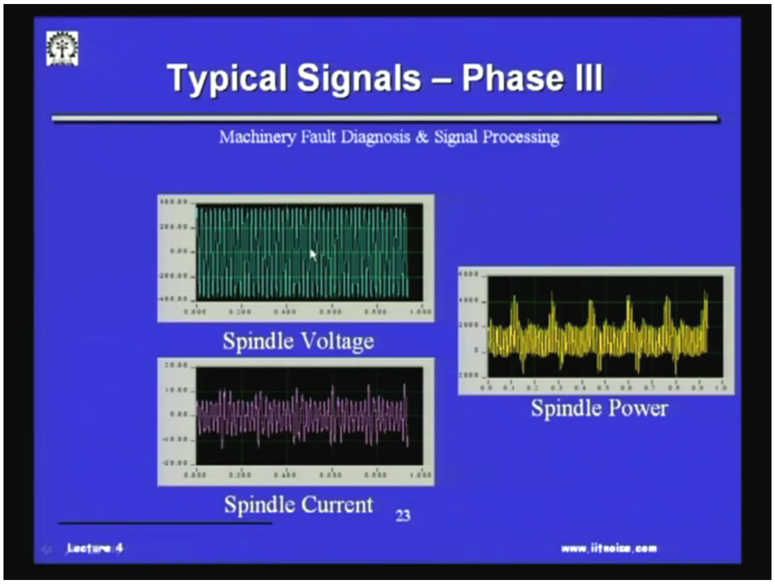
And these three phases, you will see the detailed experimental conditions for such an estimation cutting speed, depth of cut and then, and you see there are these three phases, which were done in the laboratory, and then the CVR phases were done in the industry.

(Refer Slide Time: 34:40)



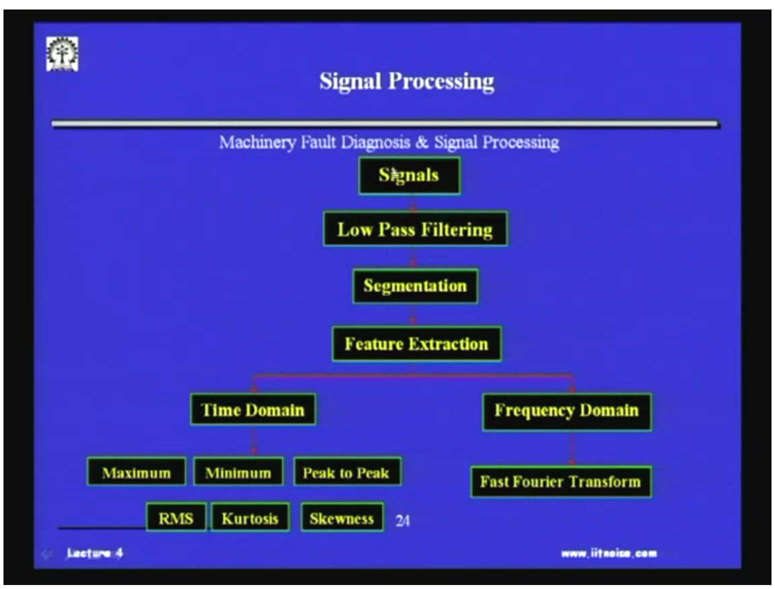
And these are the typical values of the forces which we are measured. In the laboratory force, in the X component, Y component, because this is a milling operation, every cut there is to be a force increase and decrease, where some of the spindle, X,Y and Z direction; and then, in the sound level and the spindle current.

(Refer Slide Time: 35:02)



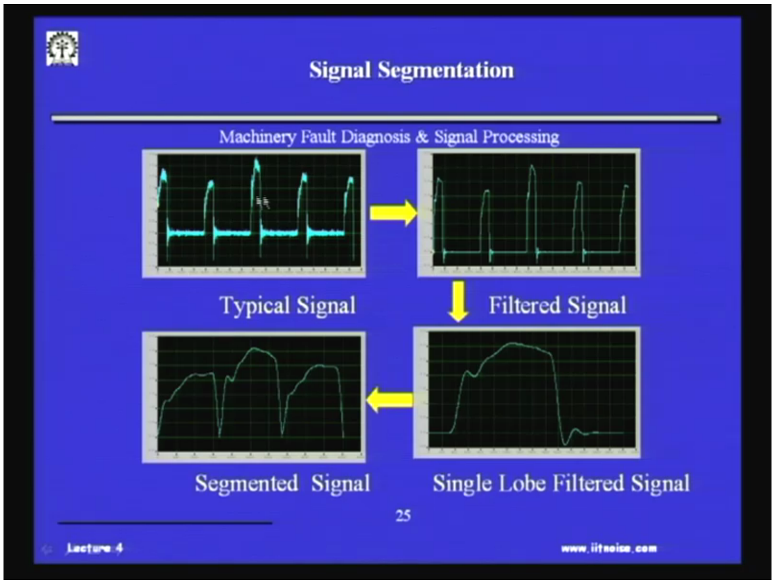
Once we also measure the spindle voltage and current, we can multiply them to get the spindle power and these are all functions of time.

(Refer Slide Time: 35:10)



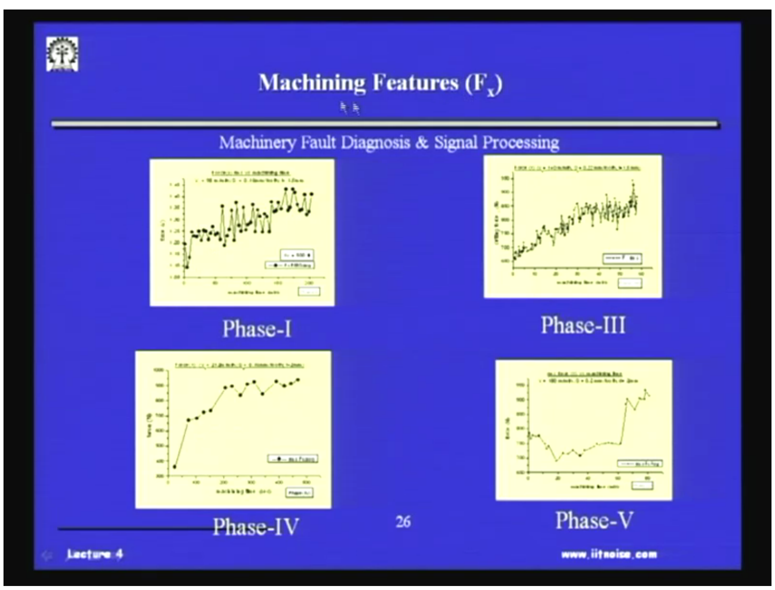
Once the signals are obtained, we could do some sort of a feature extraction. And this is entirely done in a data driven method, where you can do a time domain analysis or a frequency domain analysis. But, right now, we will focus our attention into the signals in the time domain only.

(Refer Slide Time: 35:31)



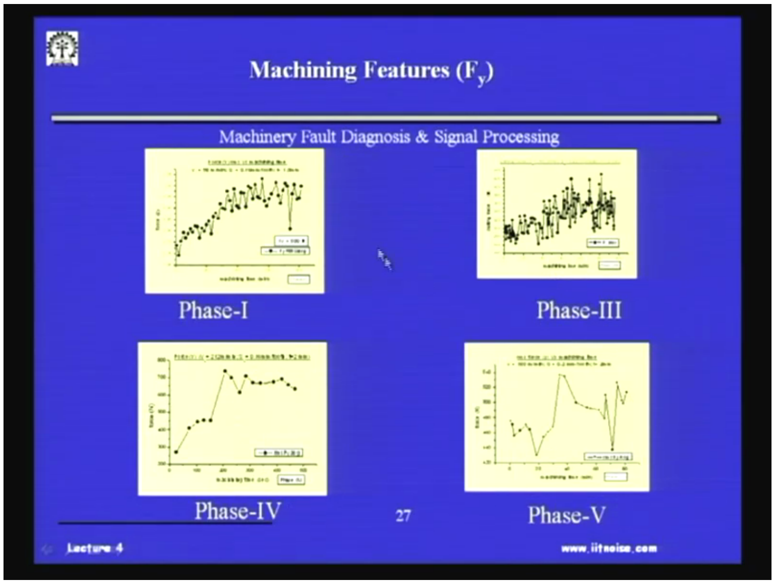
And typical signal, we may do some sort of a feature extraction by having a typical signal. We have to filter it, to remove the high-frequency noises. And then, we have the lobes brought together. Segmented signal will remove this and these processes and bring in these loops. And Then, we can again filter it, so, feature can be extracted from the signal, low filtered signal.

(Refer Slide Time: 35:58)



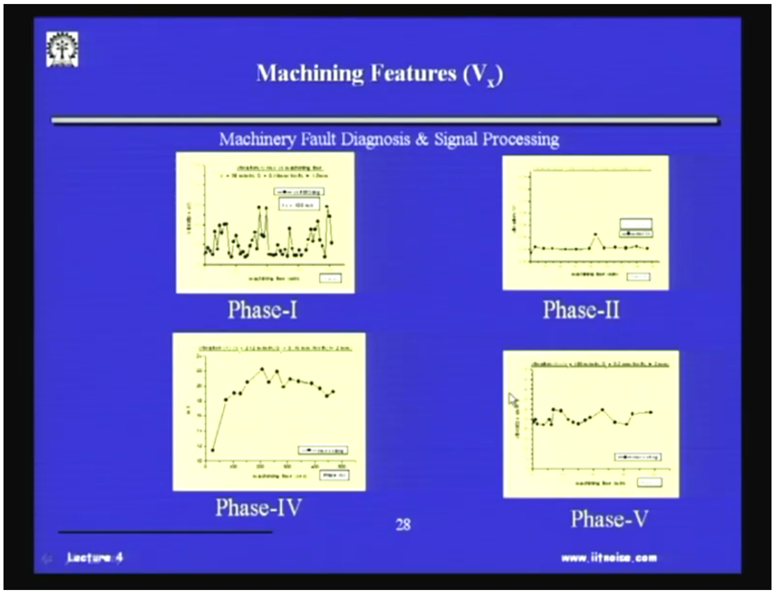
And then, in this condition, we try to monitor the machining features being effects in this condition, for different conditions of the machining time ok. And how the four different conditions, these forces varies, according force effects as a function of time for all the different conditions. And these are actually estimated by neural network.

(Refer Slide Time: 36:25)



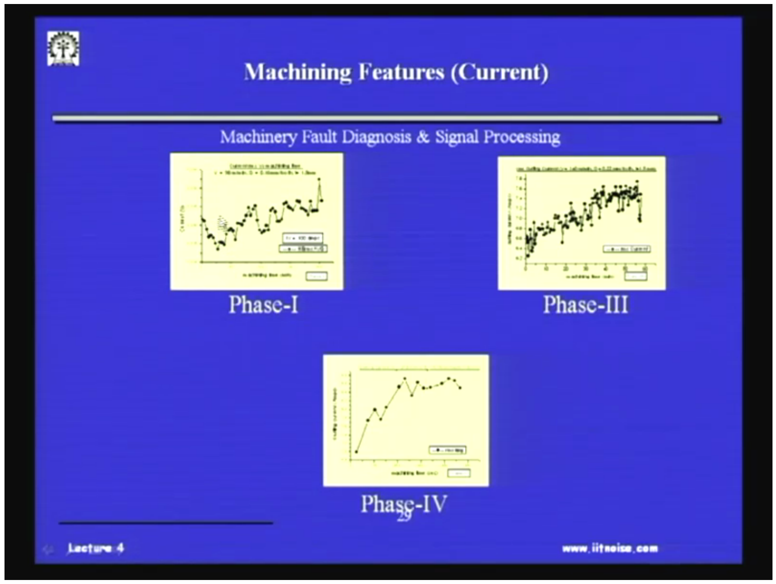
Similarly, for Fy, prediction in the laboratory, and then, prediction in an industry;

(Refer Slide Time: 36:34)



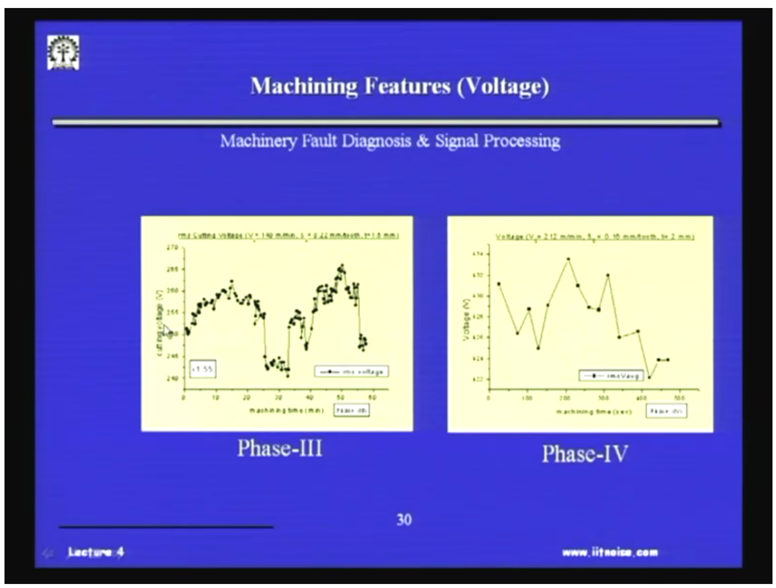
Similarly for the evaluation in the Vx direction, we have again machining time, because once we know that the levels are higher or not allowable, then, we can also always predict the remaining machining time, by which this current will has to be replaced.

(Refer Slide Time: 36:56)



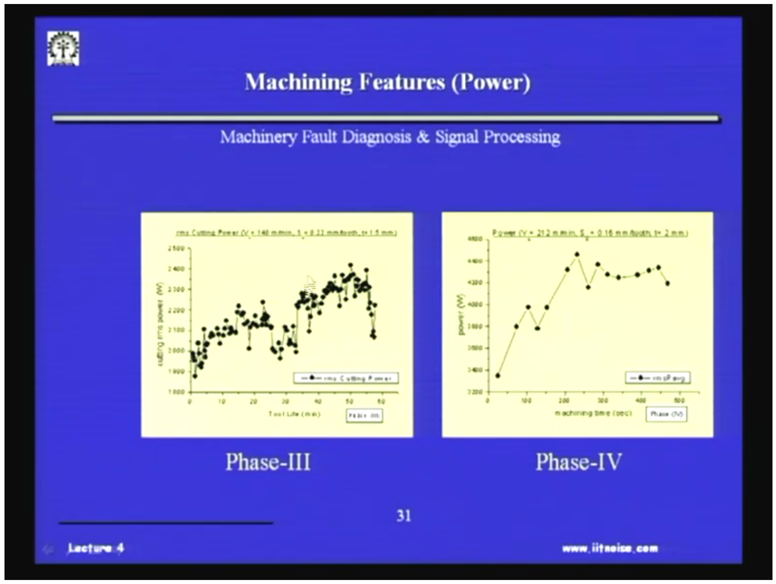
And this is for the current again machining time for different phases.

(Refer Slide Time: 37:02)



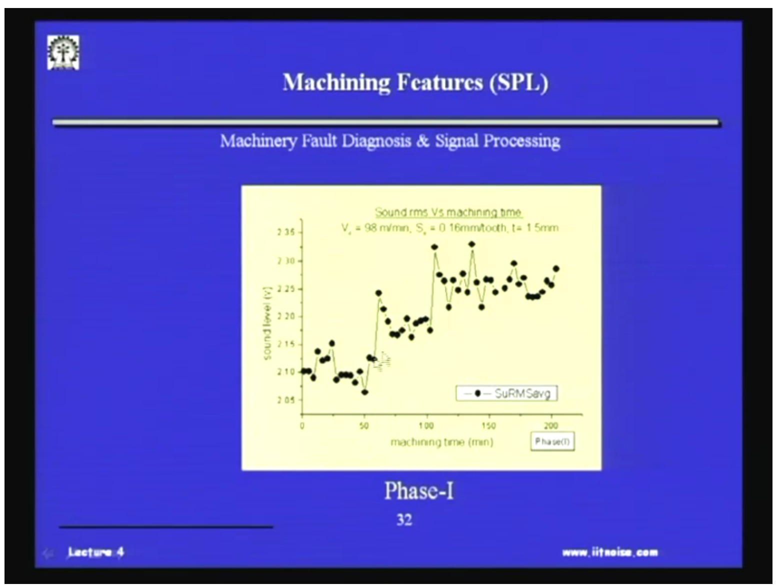
This is for the machining feature of the voltage. So, all these features could be extracted and it is up to you or us how to decide on what kind of signal features to extract or use for our data driven fault detection.

(Refer Slide Time: 37:20)



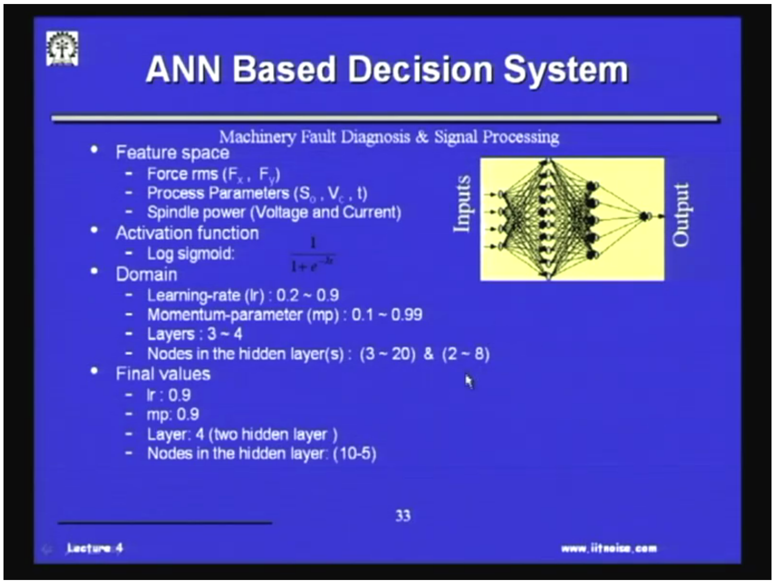
And this is for the power.

(Refer Slide Time: 37:27)



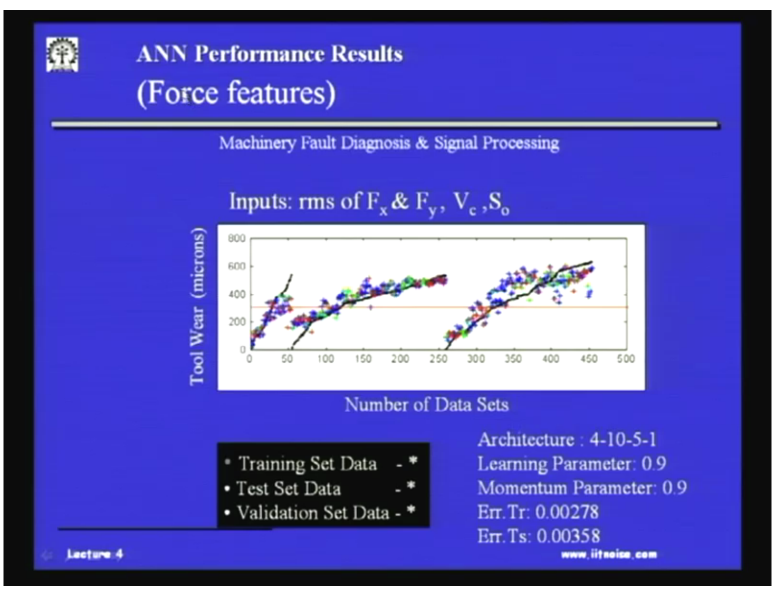
And similarly, for the sound pressure level.

(Refer Slide Time: 37:30)



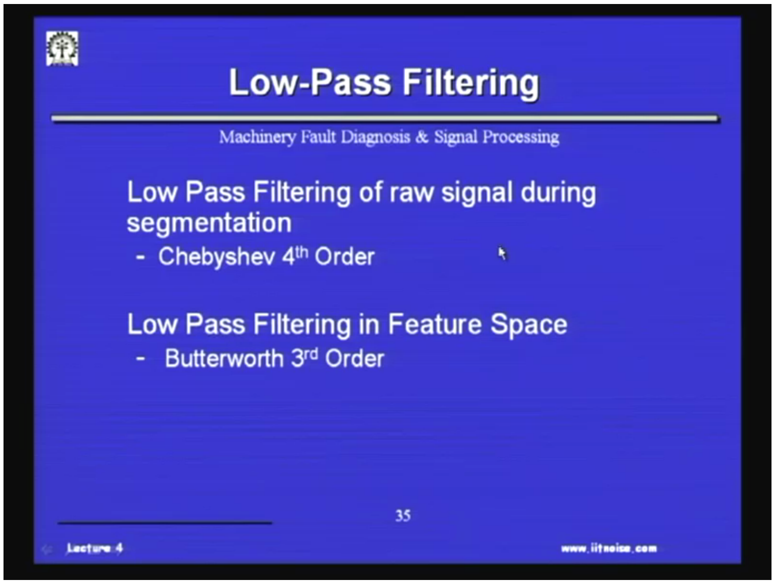
Now, once we have all this data and the features extracted, we now will decide, on what to do with this kind of data. So, as I was telling you, in the artificial neural network based for distant system, we have certain amount of inputs and certain amount of output. In this case, the inputs were the RMS force in X, Y Direction, the process parameters like the depth of cut, the machining time, cutting speed, etcetera, spinning rotation and then, the spindle power. And then, we used artificial neural network with these conditions and try to develop an model.

(Refer Slide Time: 38:18)



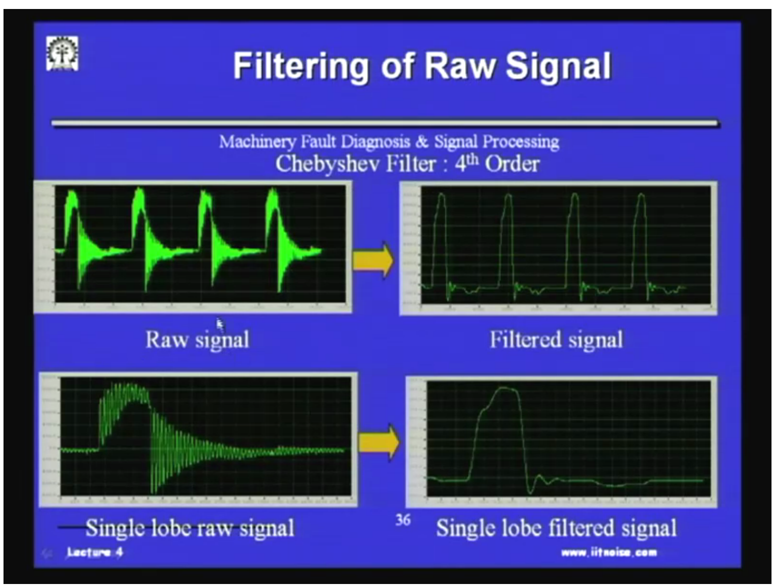
And just to predict the force features, we took number of data sets and the inputs are Fx, Fy, Vc, So, we could estimate the tool wear. In the sense, certain amount of training is done; test data values and then validation were also done. And we can estimate that what is the, this is the training with the test data and we have a good set of training data with the measured values. So, we have established on allowable or out; so, a reliable neural network model for doing such prediction.

(Refer Slide Time: 39:02)



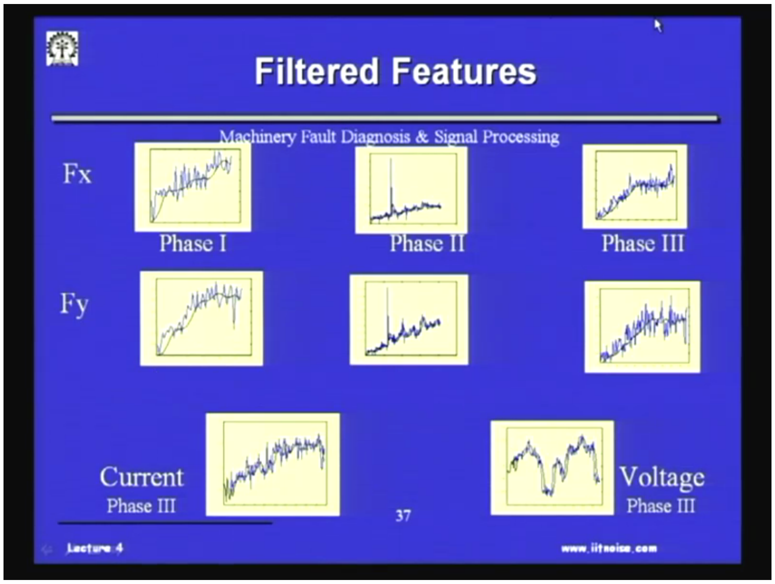
And just to tell you that the filtering was done through Chebyshev 4th order filter and in for the raw signal and the feature space it was Butterworth 3rd order filter.

(Refer Slide Time: 39:14)



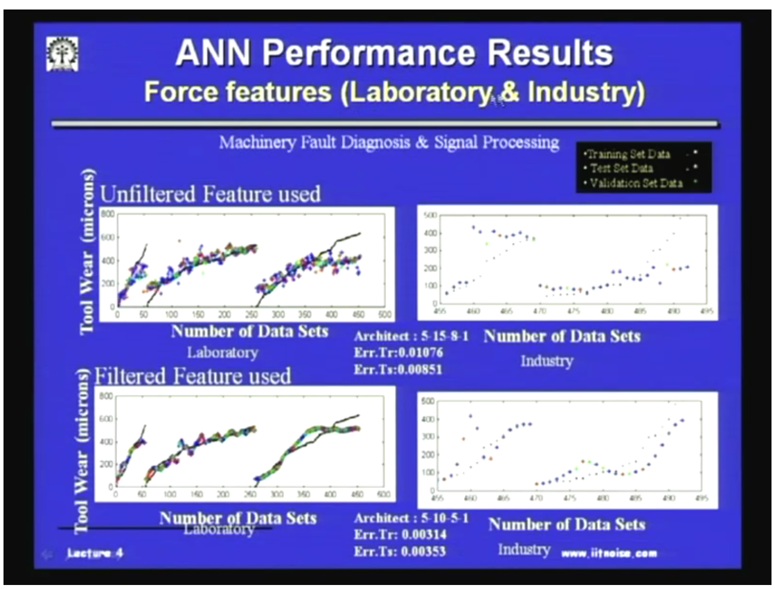
So, raw signal, filtered signal and then single low filtered signal.

(Refer Slide Time: 39:21)



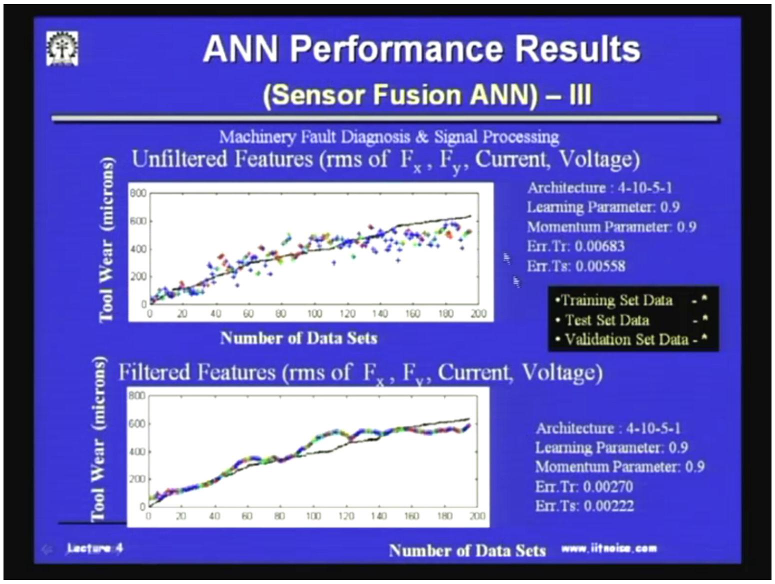
So, once the filtered features were used, we in phase 1, phase 2, phase 3 and these are the cutting forces and then the current. And we could have the training of the neural network by these inputs.

(Refer Slide Time: 39:38)



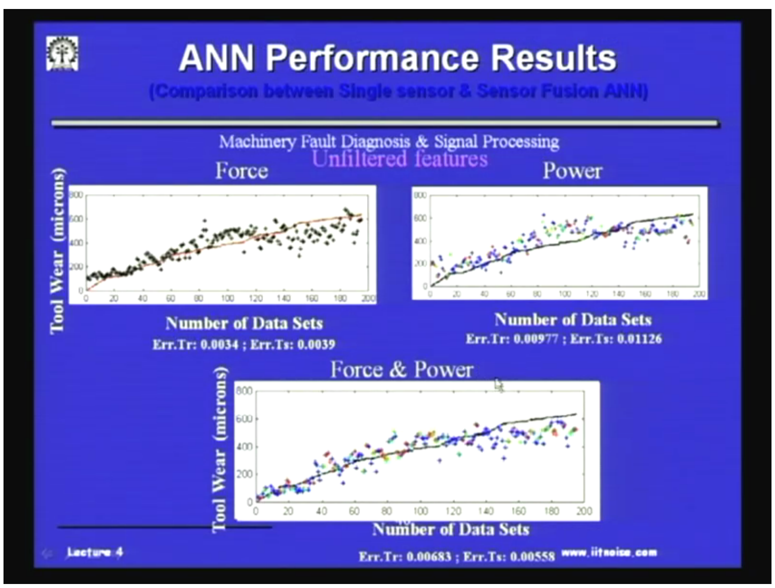
So, once we have the laboratory and Industry results, I, we could estimate the two lower microns in microns for the laboratory case and for the case of the industry. And we will know at what levels that this tool is to be replaced only through a, such a model.

(Refer Slide Time: 40:02)



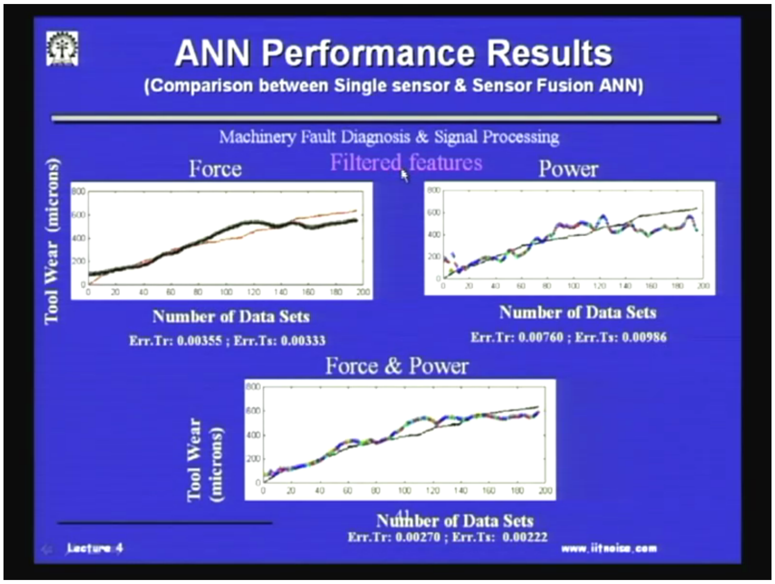
Again, we did again the sensor fusion in sense, not relying on, just only on Fx, Fy, or current by taking all of them together, okay. And then, we are trying to estimate the tool wear for the different cases. Different parameters have been used and then we could do a better estimation of the model.

(Refer Slide Time: 40:33)



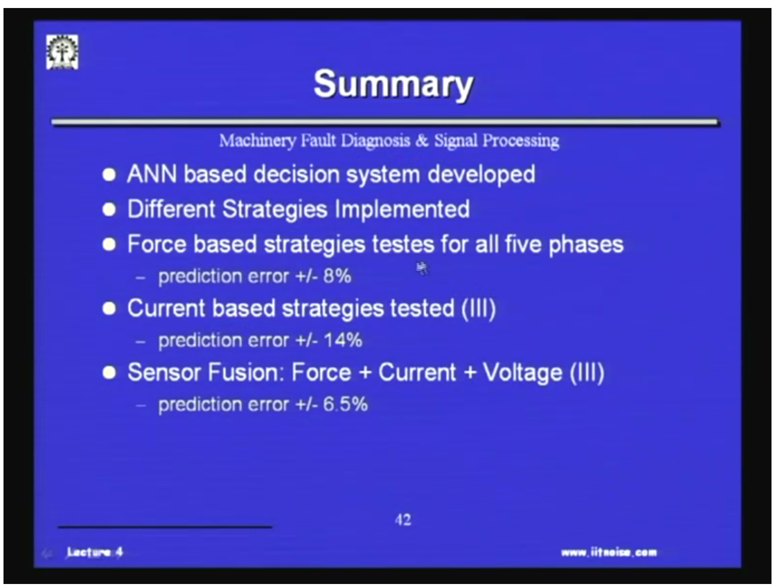
With unfiltered features, somehow, sometimes, the stator is more. So, while using artificial neural network for a data-driven, fault detection techniques, it is always necessary that we do some amount of signal pre-processing, before applying such models.

(Refer Slide Time: 40:55)



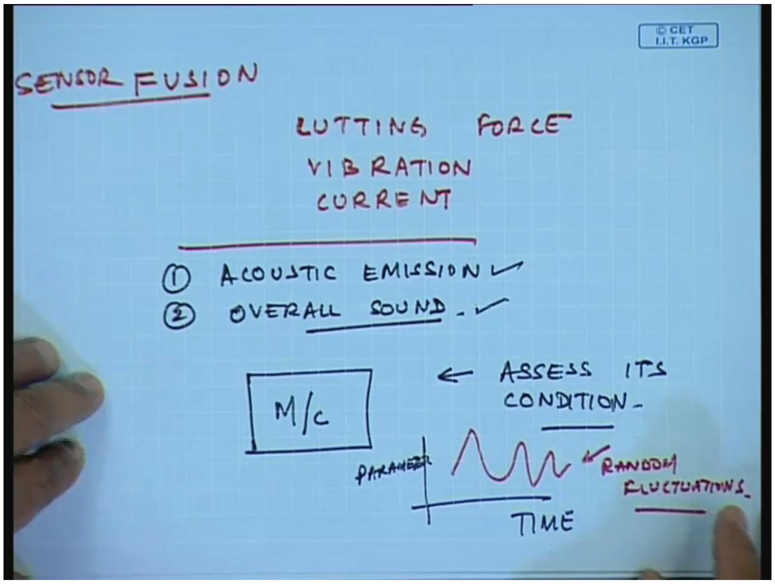
And once we will do the filtering. You see these variations are much smoother. And then, we have a better prediction.

(Refer Slide Time: 41:05)



So, in this, ANN systems developed, different strategies were implemented and forced based strategies and for all these five phases gave us a prediction error.

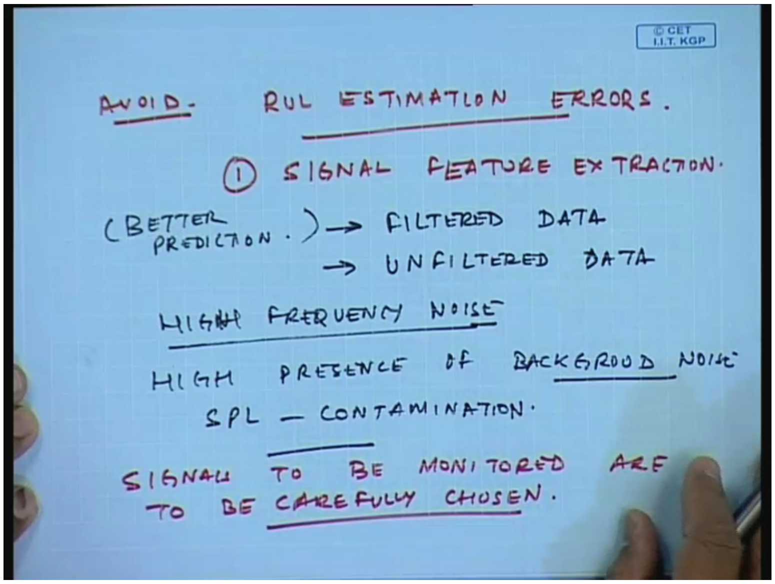
(Refer Slide Time: 41:36)



We have sensor fusion. We could have cutting force, we could have the vibration and we have the current ok. Now, right in the beginning, I had told you that we are also using parameters like the Acoustic emission, overall sound; because for a machine, while we are trying to assess its condition, we were pretty liberal in terms of, in terms of the sensors and instruments to be used.

And then, really the process of measurements, we saw that some of the parameters which are being provided or measured did not correlate well with the observations. And there are certain random fluctuations okay.

(Refer Slide Time: 43:34)

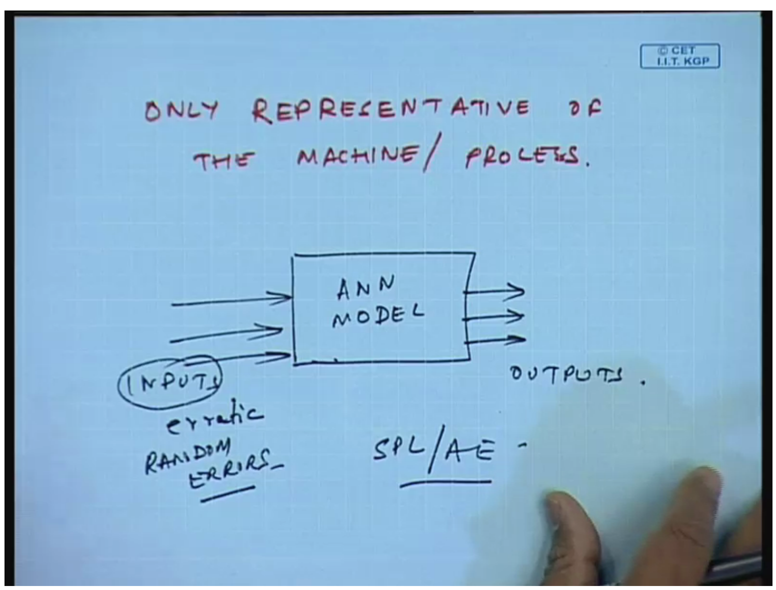


Now, to avoid RUL estimation errors; we did couple of things, we did signal feature extraction; in one case, there was filtered data and there was unfiltered data. So, once we have the filtered data, it eliminated the high frequency noise. And then, we once, we had the unfiltered data, the prediction was very good. And we had a better prediction. And we also avoided using the acoustic emission and the overall sound in the measurement method, because the predictions were not up to the mark.

And in fact, I will go back to one of the slide before, for example, they focus my attention here. There are wide amount of variations in the sound level with machining time. And there is not a strong correlation between the measured sound levels, of course, when a voltage level given here to the machining time. And such a feature was actually not used because as you know sound gets easily contaminated from the background noise, because of high presence of background noise.

SPL contamination occurs so, the signal to be monitored or to be carefully chosen. That is very important. So, in this experiment of ours, actually we then, we measured acoustic emission and overall sound. And in the later stages, we did not use them for the estimation of the artificial neural network because of the fact that they were contaminated.

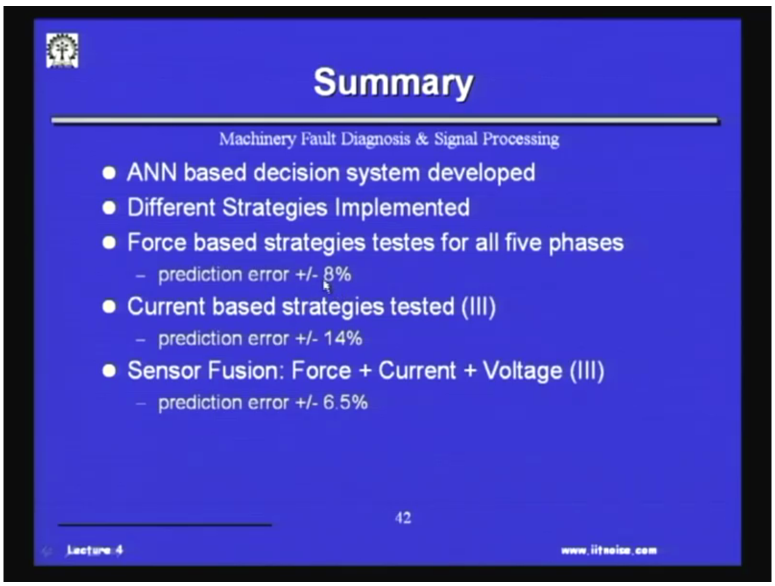
(Refer Slide Time: 47:09)



And then, we are not giving in signals which are only representative of the machine or the process because I was telling you, on ANN models, if certain levels of inputs are given. And I obtain an output, if certain inputs are very erratic, having a lot of random errors. I would not say that ANN model will not be able to predict the output correctly. But I would like to have a robust model which would eliminate certain random errors. So, in this case we decided not to use the SPL and the acoustic emission signals.

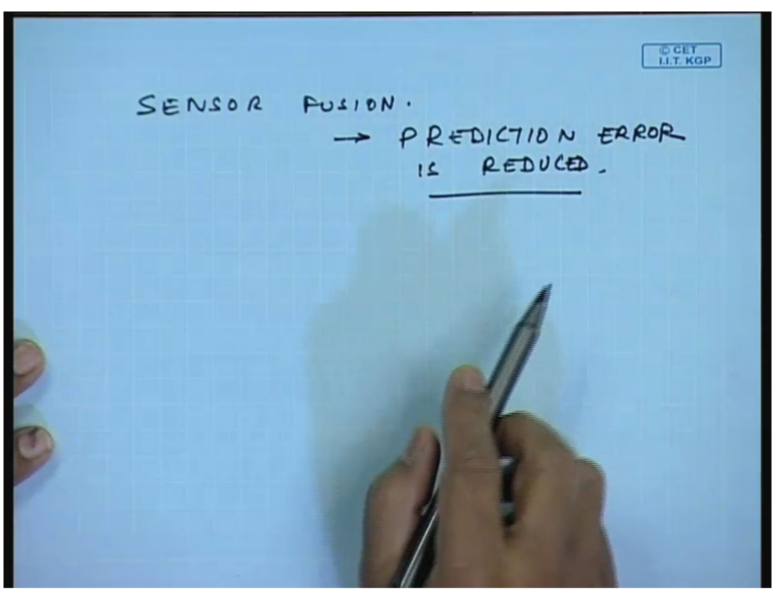
And then if you go back to the cases of, when we used Fx, Fy, current and voltage the predictions are much better compared to just measuring just the forces.

(Refer Slide Time: 48:42)



So, sensor fusion is also very important in the sense.

(Refer Slide Time: 48:46)



That in this example, you will see when the first min strategy tests where for all five phases are conducted the prediction was a percent of 8%. But only, when current based strategies were used, the prediction error was 14% which is very high. But when we used sensor fusion, using force, current and voltage, the prediction was within 6.5%. So, prediction error is reduced, okay. So, in summary to do, fault detection, isolation and identification, two important strategies are used.

One is the model based fault detection method. And now that is the data driven or the signal based detection technology. And in the example, we saw that sometimes a combination of them is used. Sometimes just a feature extraction followed by a data analysis and then using a mathematical tool like a neural network can be used, to predict the remaining useful life of the Machine component.

The example, we which we discussed, we talked about the cutting tool single point cutting tool. And then, we decided that this single point cutting tool can have a remaining useful life, predicted on the neural network model. And in the case of cutting tool, we used till the remaining is for life as 350 micron. For example, I always get this question used by friends in the industry, which is the right time to remove a cutting tool from the machining operation?

Because and sometimes people do this from the workers experience. The operator they know, they, they are experienced that the work piece parameters, the word per surface furnace is not up to standard. So then they are saying that something wrong with the cutting tool; it is time to change the cutting tool, out of experience, out of the machining time, people have developed the strategies.

But, if such simple neural network based models could be developed, wherein we just monitored the machining parameters or the tool vibration or the cutting dual force put it in a neural network; a chip, in fact, nowadays modules are available with programmable functions for neural network. In all this database has been measured by signals can be put into this chip. And this chip is going to give you a periodic warning has to know when this cutting tool is to be replaced and so on.

So, fault prognostics or diagnostics has come a long way than the historical data from just an overall alarm level. And the today's world we talked about using model based fault reduction techniques using artificial neural network is in wavelets and other signal processing techniques, for doing a more robust detection of faults in systems and of course, estimating the remaining useful life.

(Refer Slide Time: 53:00)

And then, in this example, which we saw: So, our sensor based fusion for filter data also gives you the best value, okay. Unfiltered and filtered. So, sensor fusion is another area which is being used for a robust fault detection and identification in machineries. Thank you.