

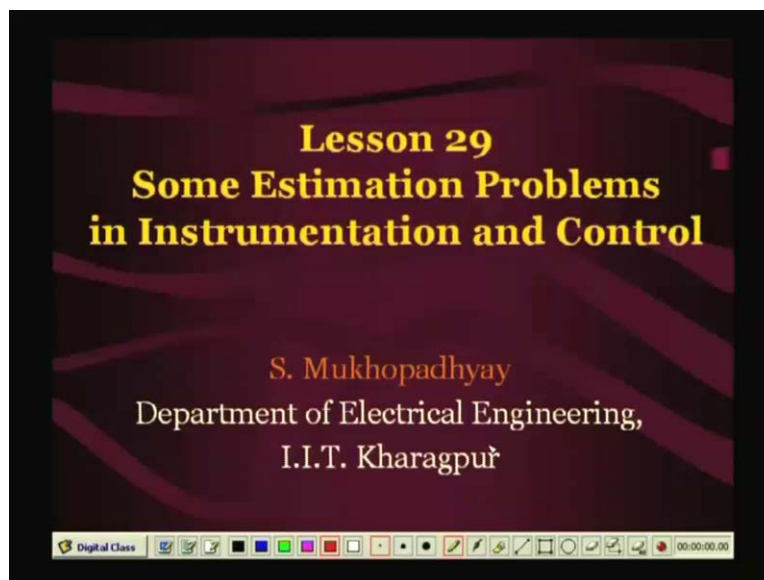
**Estimation of Signals and Systems**  
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**Lecture - 29**  
**Some Estimation Problems in Instrumentation and Control**

Ninth lecture of the course on estimation of signals and systems, we have nearly come to the end of our journey. We have studied, in this lecture series some estimation problems; like signal estimation using input output models, state estimation, system identification which is actually a system model estimation problem.

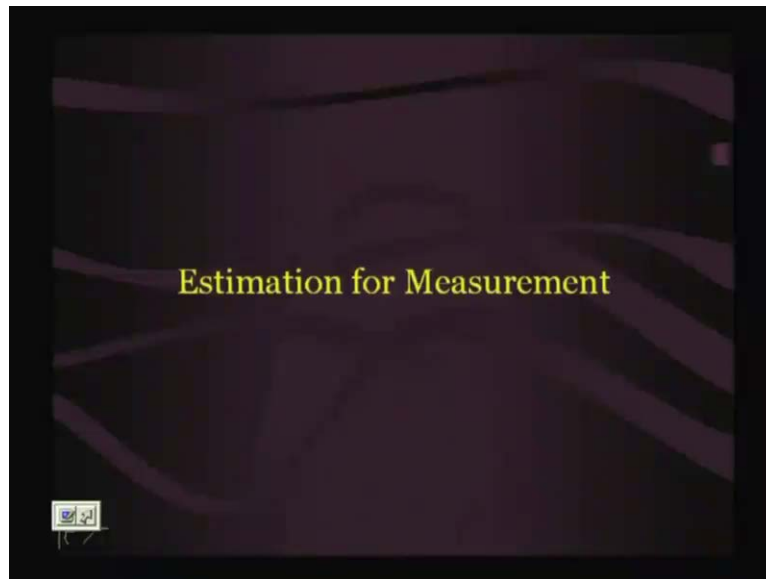
Today, before we near-about to end, this is the pre-final lecture the series; so I thought that, we have studied the lot of algorithms, some some mathematics equations, I thought we will give you at one shot a flavor of applications and also discuss, some of the problems which we have not really treated in depth. So, this is just to give you a flavor of those problems and also to discuss certain industrial applications of these; so that at one go, I can I can you know, kill be kill two birds.

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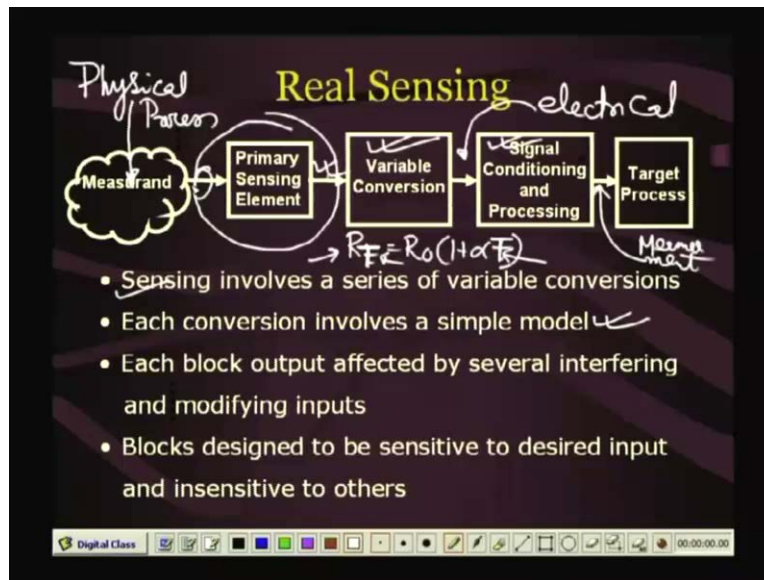
So, today we are going to discuss, some applications of estimation in industrial instrumentation; means in instrumentation and control. So, first let's talk about the measurement problem; that is the basic objective is that, we want to measure some quantity for some purpose.

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One of the very common purposes is to measure quantity for control; we will discuss such an application later but you also measure quantities, for various kinds of industrial operations. So, today let us first look at, what estimation technology can do for for for measurement?

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For measurement, we typically the first thing that is used, is called an a is called as sensor, typically it is called as sensor. So it is a device, so what does it do? This picture discusses that. So, so here we have some Measurand; which is a which is a which is a which is a physical process, so it is a physical process may be it. We are we are we are interested in measuring, some temperature pressure, strain, whatever.

There is usually a primary sensing element which is a sensor, which actually due to the lets say; due to temperature and expansion of liquid is caused and this expansion of liquid is the basic principle of this sensing element, which we called the thermometer or the liquid in ball thermometer. Now, usually this effect that is that the that the temperature produces, is not very you know easy to measure, we can we can we can of course see it, as we do in a normal clinical thermometer but there is often a need for converting this form, which is a which is let's say linear expansion into other form.

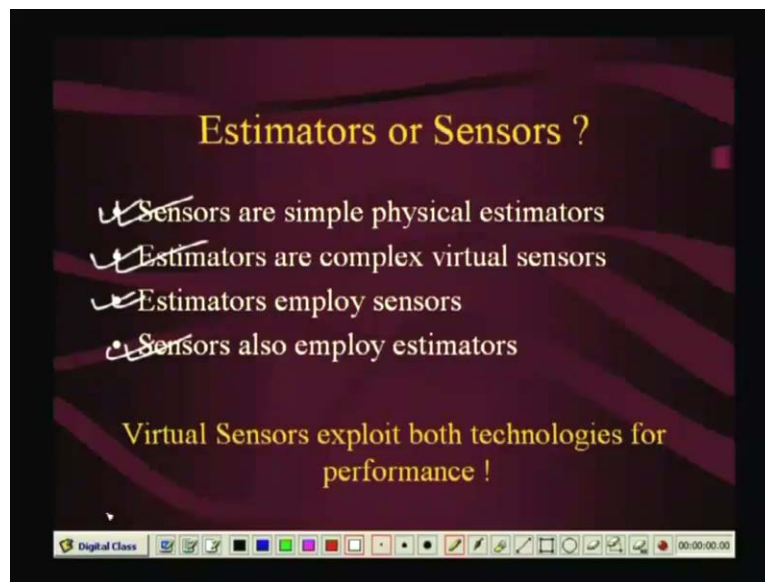
For example, if you have resistance temperature detectors then temperature produces change in resistance, which needs to be converted to other forms. Like for example, that resistance has to be put into a circuit, to produce voltage. So, this primary sensing element, goes through a series

of may goes through a series of variable conversions and after that may go for various signal conditioning and processing units, by which the the form of the signal is improved. Generally, by this time when it is come here, the signal is generally electrical in nature, voltage, current. So, in the signal conditioning and processing circuit, we improve the signal quality in terms of amplitude, in terms of we we filter it etcetera.

And finally, here we have the measurement which we shall use in our target process. So this is a this is what we generally, understand as a sensor. So, sensing involves a series of variable conversions and each conversion; remember that each conversion involves a model. For example, the change in the resistance of a nickel sensor, due to temperature change is given by the standard equation; that is  $R_T$  is equal to  $R_0 [1 + \alpha T]$ , right. So, this is the simple model or rather for  $T$ ,  $T$  is the temperature. So, this is the simple model which relates the  $T$  to the resistance at  $T$ , its capital  $T$ , alright.

So, each conversion actually involves a simple model, at each block output but however remember; that these is is is I means is not that simple, so these these these block outputs, we we may think that this output is is actually only dependent on these but in in practice, it will be affected by so many other quantities. So, there will be what is known as, interfering and modifying inputs, which degrades the quality of the measurement and a lot of effort is actually spend by engineers, to make this blocks insensitive to these disturbance and this disturbance, the interfering and modifying inputs. So, how does, so as we shall see that, in this regard estimation can help a lot, right.

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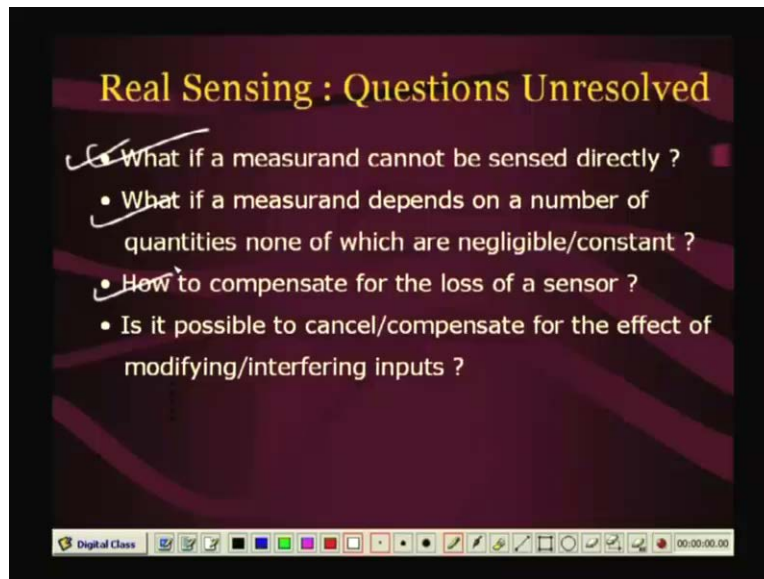
So, the question is the same, in a sense now that we understand estimation, we know that estimation is basically the computation of one quantity from another quantity, using a model right; so odd sensors very rudimentary estimation. So for example, sensors are simple physical estimators. So, you actually sense the resistance change and from that, you can estimate the temperature, right.

So, so in that sense sensors are simple physical estimators. So, if that is so then we can say that; estimators can become very complex virtual sensors; if you use complicated models which involves the number of inputs and if you want to reject, noise, disturbance, interfering and modifying inputs, then it acts like a complex sensor while remember that, that that the estimators must must compute one quantity from another. So, where were their input quantity come from?

So, often the input quantity come from other sensors; so hence so so estimators often use sensors themselves, need they need sensors. And sensors, some complex sense; for example, typical example is the example of a radar sensor, so it gets many measurements which are noisy and and inherently it provides, it it actually employs sensor estimators, within its signal processing schemes, right. So, estimators and sensors in that sense very close and very similar quantities.

And if we consider, so here today we shall see some quick examples of estimators, which are used as sensors for measurement and gives several benefits, right.

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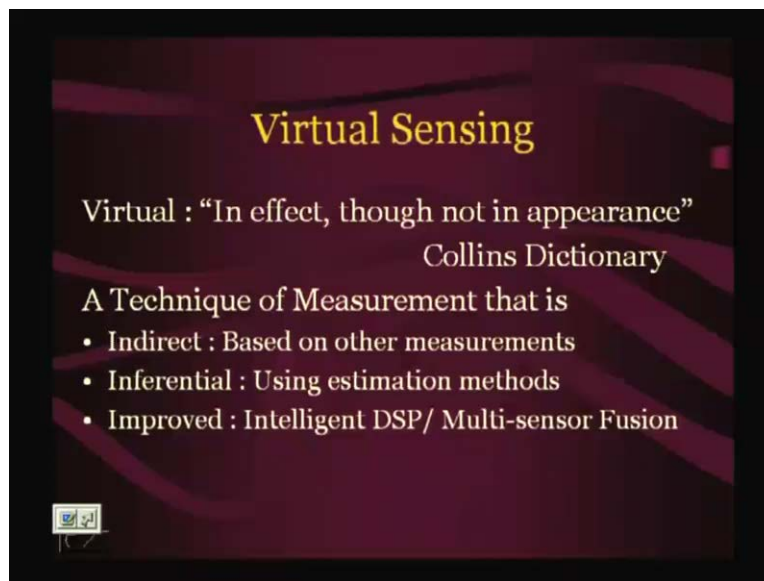
So, and real sensing that is the conventional sensor, that we use have some drawbacks, and they cannot answer some questions. For example, what if a measurement cannot be sensed directly? We shall show today, that there are some, in some cases you may be interested to measure a quantity, which cannot be measured in the situation that the measurement is decided in, right, so in that case, what you do?

Similarly, what if a measure measurand depends on a number of quantities? So, in that case, you you is not depended on only one quantity, right. So, then how to compensate for the loss of a sensor; suppose, you know this is a this is a typical problem in control, that control will requires very a sensor. So, if we lose a sensor while we are working, can we make up for using the other sensors? That is a that is that is an important question, for some in some cases.

And is it possible to cancel or compensate, for the effect of modifying and interfering, inputs? We want to improve, the quality of our measurement and we want it to; since we wanted to infer,

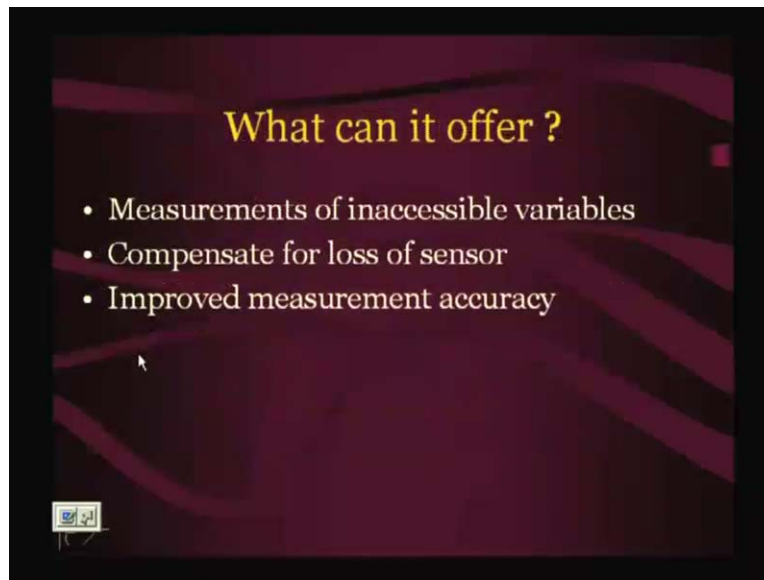
infer the desired input, we want the measurement to be unaffected by interfering and modifying input. So, the question is can we do that? We shall see that, estimators can answer these questions, okay. So we introduce, what is something which is known as a virtual sensing which is basically, estimating a quantity. So in that sense, since you are computing its value, it is a kind of measurement, so but it is not real.

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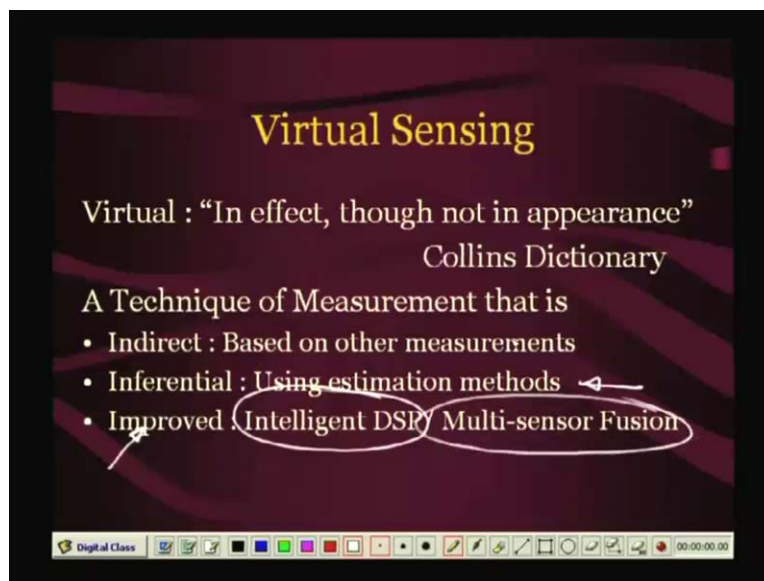
So, as usual I checked up in a dictionary and found that, virtual means; in effect but not in appearance. So, while it does not, it may not appear to be a sensor in conventional sense, it will give you a value for that for the quantity; so in effect, it will give you a measurement, right. So, in that sense, estimators can be virtual sensors. And this virtual sensing is actually a technique of measurement that is indirect. So, it is based on other measurements which you make with conventional sensors. It is inferential, so

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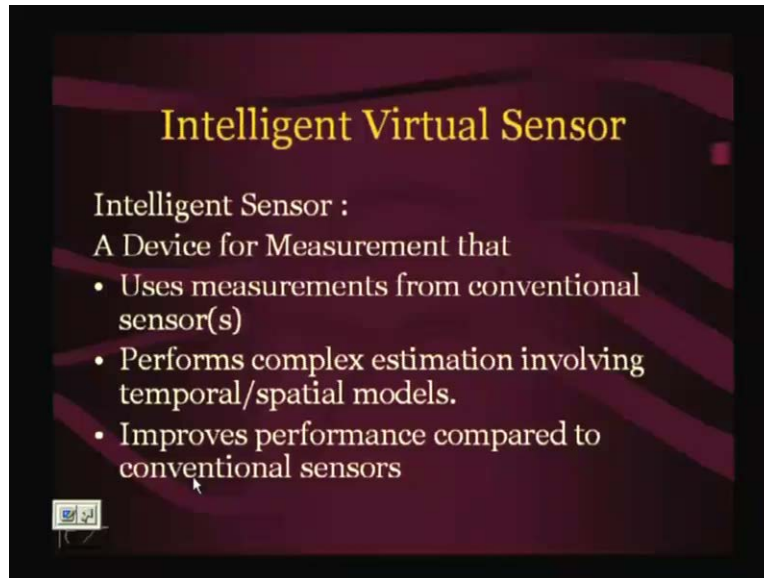


Previous, so so so it is inferential, because it infers, estimates the quantity. So, it essentially uses an estimation method and its its often quite improved; in the sense that it can cancel the effects of



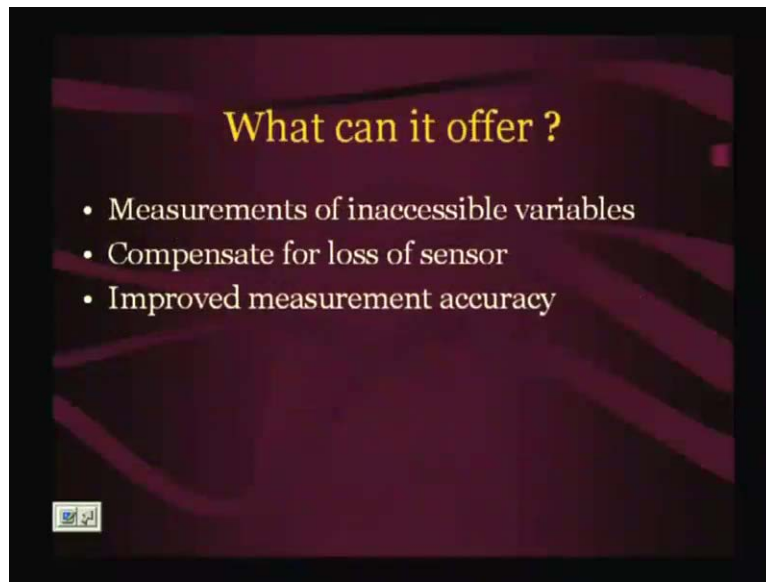
noise and it can improve the quality of estimation by using intelligent digital signal processing algorithms. Many of which we have learnt, in our course and also sometimes by using multi-sensor fusion, that is making, using more than one physical measurement; you can we can improve the quality of the measurement. So, we are going to see, how that works out?

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So, I will keep this slide, so an so an intelligent virtual sensor is nothing but a device; that makes a measurement from number of, could be a possible a number of conventional sensors, employs an estimation algorithm and improves performance compared to conventional sensors.

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So, estimation can what can it offer? It can offer measurements of inaccessible variables; variables which cannot be measured directly, will will will present, this in an example. It can compensate for loss of sensors; we will also see an example. And it can give, improved measurement accuracy, we have already seen that; we have we have already seen, in the case of Kalman filtering, for example I mean Kalman filter is a burning example, where a filter can give you, I mean vastly improved estimation of estimates of velocity and acceleration from position measurements.

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### Image-based Measurement of Fluted Ingots in Steel Plant

- Compute lengths of cut to maintain weight between 518-525 kg
- Front view for cross-sectional area – use of multiple polynomials
- Top view(s) for slope
- Commissioned in Wheel & Axle Plant, DSP

So, for example, let me first start with a very simple example. This is an example where you know, I have been involved with this work; where we were required to, require to measure you know, there is there is a there is a cylindrical ingot which you can see, here in this picture. This is an ingot, it is a it is a cylinder. You can see its cross section; it is actually made of steel. Now, the railway wheels are made out of these ingots, in the Durgapur Steel plant of SAIL.

So, they have to cut a certain you know, the the the ingot is long; so, they generally cut into three into three pieces and they were required to cut it into, the right weight because railways has a requirement that, its wheels must be often between this to this vehicle, which is a fairly string and accuracy. In in in in five hundred kgs, you need to have an accuracy of plus minus three point five kgs, which is not not not so simple to achieve.

So, what was required is that; they used to normally people cut it according to, some you know thumb rule that it must cut it at some length, but but but because of mould dimension variation, this can give, quite a bit of rate variation. If the weight is less than 518, then the then that particular piece has to be rejected. If it is more than 525 then, you have to cut out that piece of iron, generally using machining; which takes a lot of machine time and energy.

So, so it it it uses, it it it it I mean involves a lots of resource. So, what we were asked to do is that; can you can you estimate the cut length for each individual, ingot, online? That is while the while the operator is working, give him an ideas to, at what length you should cut using a saw.

So, what we did is that, we actually put two cameras; so the so the ingot was put on a, you know on a on a on a roller roller platform, so the ingot is on the platform and and and you would put one camera on the front. So, you get this picture, you get this front face. And then you have one camera on the top, so you get this top view. And then you take pictures. So, you get a image, you get two images, from one from this, these are the two images.

Now, from this images you have to find out that, what is the area; firstly, what is the area of this particular ingot and you also need to find out, that what is the what is the what is the, that is you need to find out that at what there is a this ingot is actually, a there is there is actually a taper. It it it is not seen, but actually the ingot cross section is, this is an exaggerated view, there is a two, three, degree angle taper.

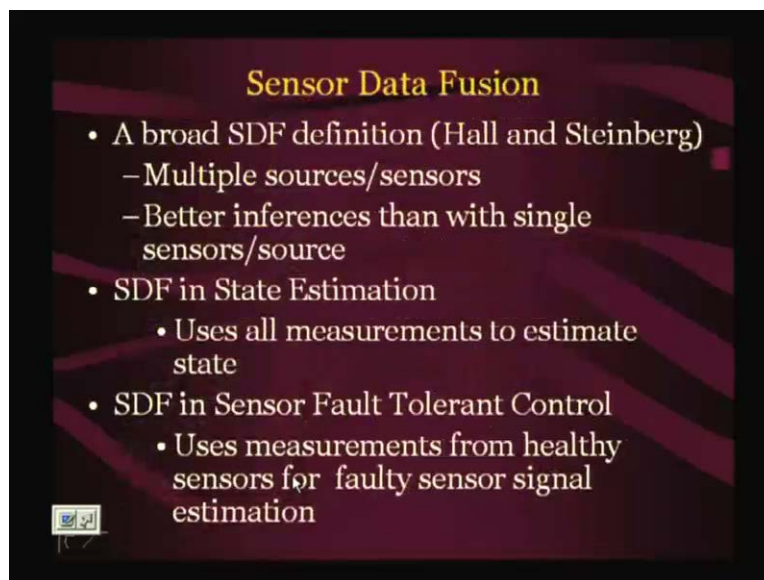
So, you need to really estimate the, you need to really estimate this taper angle theta, to be able to know that, if the if the area is A here and if the taper is theta then what should be the then where you should cut, so that this will give you a particular mass, assuming a certain density. So, we did that. So you know, you see this is here, I can tell you that this is a two dimensional signal processing because it is an image and there are various kinds of estimation involved.

For example, you have to have a very accurate estimation of the edge. We must remember, that if if this in this in in in in this algorithms; if you make a an error of two three pixels, so pixel is one picture cell then you can have, a half a kg to one kg variation in the in the weight of the ingot. So, it has to be very very accurate. So, all these edge detections, these edges had to be detected for actually getting this angle, use uses a very sophisticated two dimensional signal estimation, using using image processing techniques.

So, after you can do that, we we actually implemented this scheme and could could achieve this kind of accuracy. So, let's say this is an estimation, where we are measuring the the volume of the ingot. Now, is the volume of the ingot measurable by any easy way, no not at all. So, if you really wanted to measure the volume, you you can you can you can have a detailed mechanical measurement scheme which is going to take more much more time.

So, here we had a scheme which is which is which is a very simple, just place the ingot on the roller, take two pictures, immediately, within seconds the the estimation algorithm can tell you, that what should be the what should be the cut length here; such that this this volume will be a given volume, right. So, this is our first example.

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Coming to, let's, look at next example; we will skip this slide.

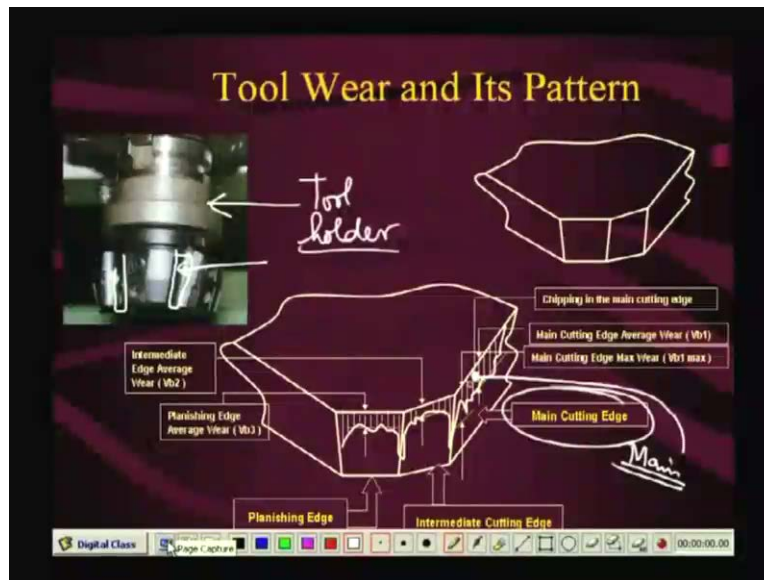
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So, we are going to see another case study where we want to measure; this is this is also work with which we were involved and we had it involves, I mean quite detail estimation. And we had actually implemented between on a on a machine and have actually we tried in an in an industry. So you see, what was the problem? The problem was the estimation of tool wear using sensor fusion; sensor fusion means that, we make many measurements and then combined those measurements to make, to compute, another quantity.

So, if you use number of measurements and generally as we shall show that, it it leads to an improved accuracy, right. So, we will look at this case study of on-line tool condition monitoring. So, the so the problem is to estimate the tool wear; while the tool is cutting metal, without removing the tool, without stopping the machine operation accurately, right.

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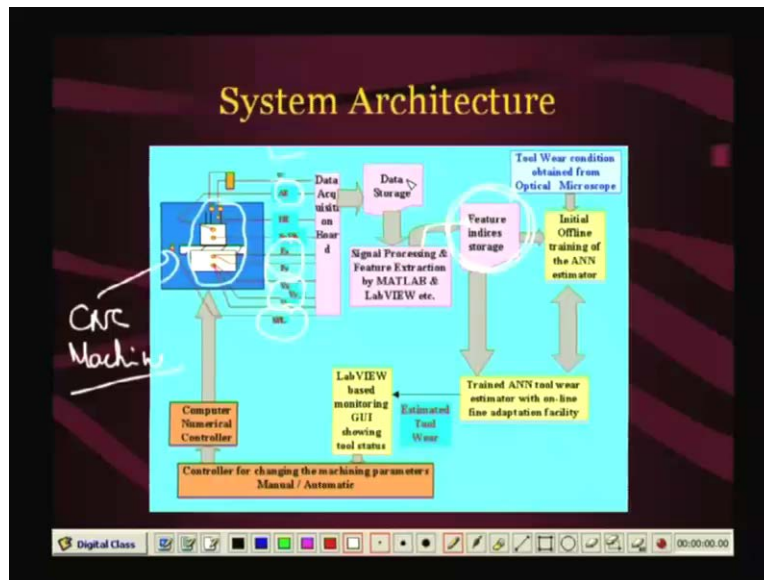


So for doing that, so you know, this is the picture where, you have a this is a face milling machine. So you can you you you, so you actually put tools here, here you can put a tool, here you can put a tool. This is called a holder, tool holder and these are the tool bits and they this somewhat looks like this, I mean the the cutting edge. So, this these are the parts which actually rub against the metal and therefore they get warned; you can see that they are worn.

So, the problem was to find the wear in this, this this is the main cutting edge, main cutting edge. So, the problem was to find the wear in this main cutting edge. So, typically speaking, you can if you want to, what is what is the other way of measuring this wear? The other of measuring this wear is; to take out the tool bit, put in an optical microscope and actually measure the wear on the microscope.

It will be it can be of the order of hundred two, hundred three, hundred four, hundred microns. Instead of that, we could do that; we are interested in estimating the wear while the machine is cutting without, removing the machine at all, so that the operator knows that; at what time you must replace the tool bits, so that the quality of this surface of the machining, and the cutting dimensions remain very accurate, right. So, that was the objective.

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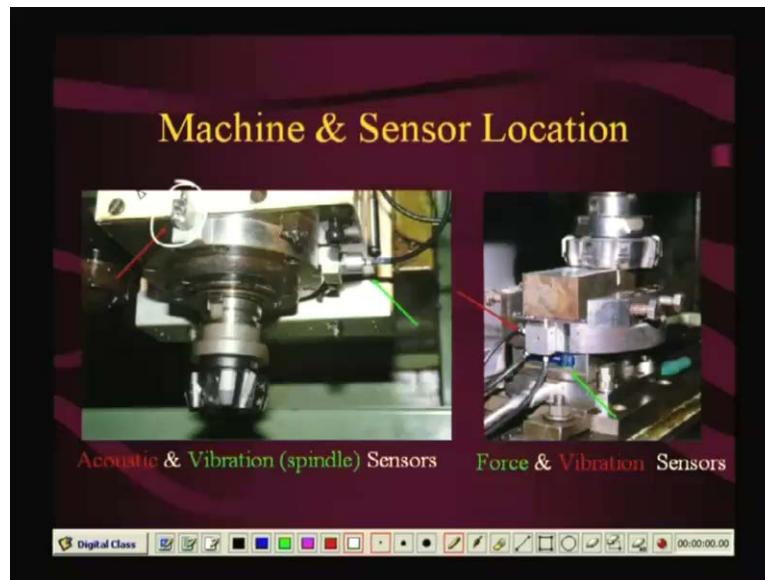
So, so so you see this was the the the architecture of the system that, we implemented, right. So we have we have a, this is our machine, C N C machine. So, we put a number of sensors here, so we take voltage, we take vibrations, we take forces F X F Y, we take vibrations V X, V Y, V Z. We take what is that; acoustic emission, sound pressures level various various kinds of measurements we do. So, we actually instrumented the machine with a with a number of sensors. We take the data and then as we shall see that, we need to process the data.

So, here we start processing the data and actually, calculates some features from the data. And we try to construct an estimator; in this case, we have used what is known as artificial neural network which will look at the features and will estimate tool wear.

So, so that was the idea, right. So let's see, how that is done.



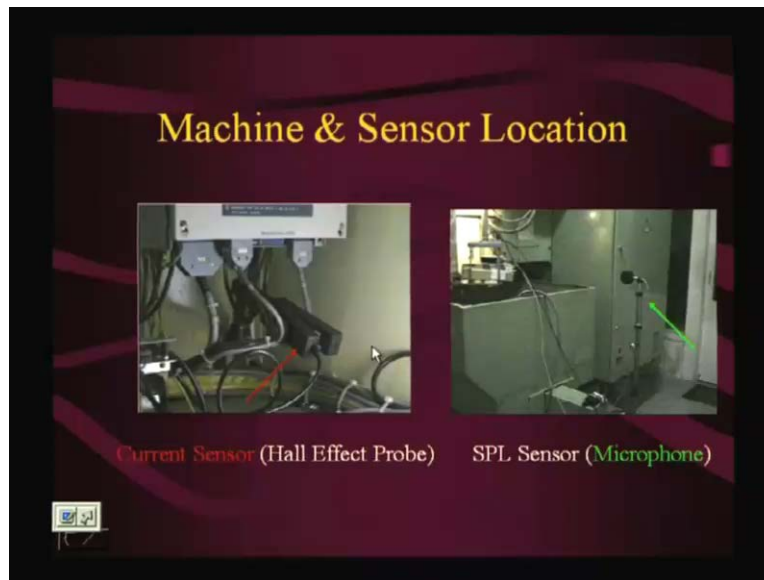
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So, these are you know, some of the point some of the points, we actually put the physical sensors. So, you have an acoustic sensor here which is which, senses very high frequency internal vibration, you should cracks etcetera, inside the thing. We did not we are not going to talk about that too much.

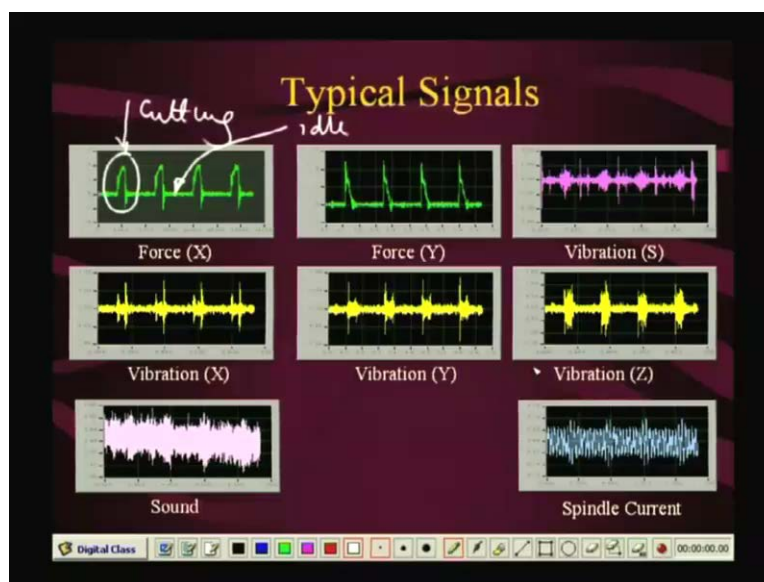
These are the these are the vibration sensors on the spindle which is rotating and these are these are the most important sensor; they give very accurate readings, they are called by force sensors but they are very expensive and they are very difficult to maintain in a typical industrial manufacturing environment. These are another sets of vibration sensors.

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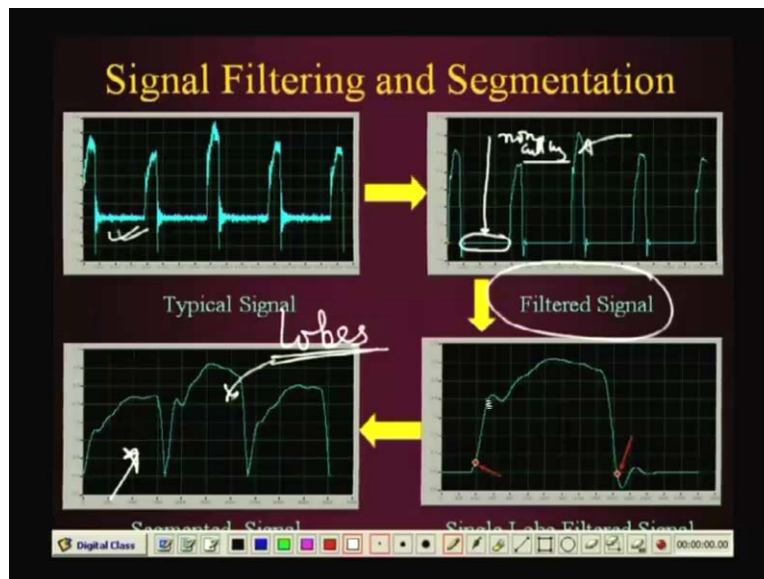
So, we have some current sensors, you know current sensors sensing is very simple, compared to force sensing. So as we shall see that, we can we we wanted to see whether rather than using force sensor, whether we can use a current sensor and then estimate the wear. So, that we can find the technology which is which is implementable much much cheaper than using a force based technology.

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So, we go ahead and so these are some of the signals. So, see the, we actually these signals are obtained by putting only one tooth, in in the in the tool holders; so, therefore you can see that here the, this this is the period where the where the tooth is cutting metal and this is the period when the tooth is idle or not engaged with the metal. So, the forces are immediately coming down to in a small level. So as we so, these are the various sensors signals force in the X direction, Y direction, vibration and vibration in X Y and Z direction and sound presence and spindle current, right.

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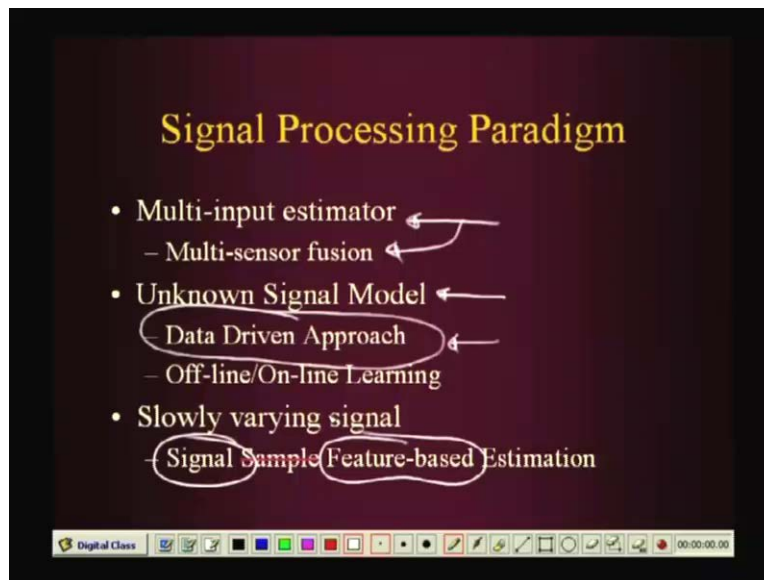
So, first thing, look at the look at the look at the kind of signal processing, that we are going to do on this. So, you first have you know, this is the this this is the original signal. So, it has noise as we can see. So, first of all we have remove noise by filtering. So, this is you know, we want to keep the lobes and we want to remove the noise. If there that, you can as you can easily easily make out, they were well separated, so so so normal fixed filter does the job. So, we got the filtered signals.

Next, we noticed that these are the parts which are non-cutting, where the so therefore; these these parts do not keep an information. They keep information, the parts which give information

about the status of the tool of the cutting parts. So, we first remove the non-cutting parts and then we get this, in a what what we call the the segmented signals these. It turns out. So, now that is there is there is a collection of lobes, so these are the lobes.

So, we actually our feature were were were were based on this lobes. So, we calculated for example, you can calculate the area of the lobe, right. So, you have to identify the end points and the beginning points of the lobe and then calculate the feature corresponding to the lobe; then you have one lobe after another coming and, you have to estimate the tool wear in terms of these feature of the lobe, right. So, that was the objective.

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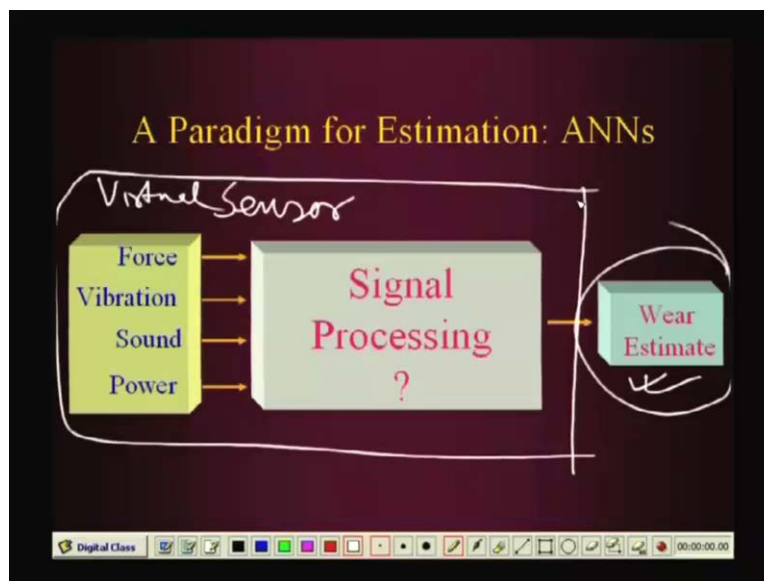


So to so now, we once we have these features, we have to set up an estimator, right. So, first of all we we make, we first of all saw that in this case; you must have multi you must have a multi input estimator, because you want to have multi sensor fusion. Secondly, your signal model; that is it is very difficult to establish from mechanical engineering theory, what is the what is going to be that, how the tool wear is actually affected by or rather how the wear of a tool manifest itself in terms of vibrations in X and Y directions or in terms of forces or or or currents? No, analytical models are available, some **unistic** models are available.

So, we want to use the data driven approach, where the model itself, we do we do not have any idea about, the the the so called model structure; remember that, whenever we need estimation, we we we generally used a model actually generally, chose a model structure. So, we have we have discussed again all pole models, pole zero models, all zero models I I R, F I R, etcetera. So in this case, since the model structure is model structure is known, we need to adopt a structure which can really model, which is a reflexive, which can model data from various types. So, that was our major motivation for choosing a anon because we did not know, what it is going to be, okay.

So so we chose this data driven approach and we also found out, that in this case the signals are the the signals are very fast varying, that is you get signal from sample to sample at may be thirty kilo hertz, but the tool wear is actually a very slow process; so therefore, we need not, we should not set up a model based on signals, signal sample values because between the the wear between two signal samples values going to be so low, that it will it will be very difficult to estimate anything. So, we thought that we will instead; we will create the estimate, create the estimator in terms of the feature of the lobe, right.

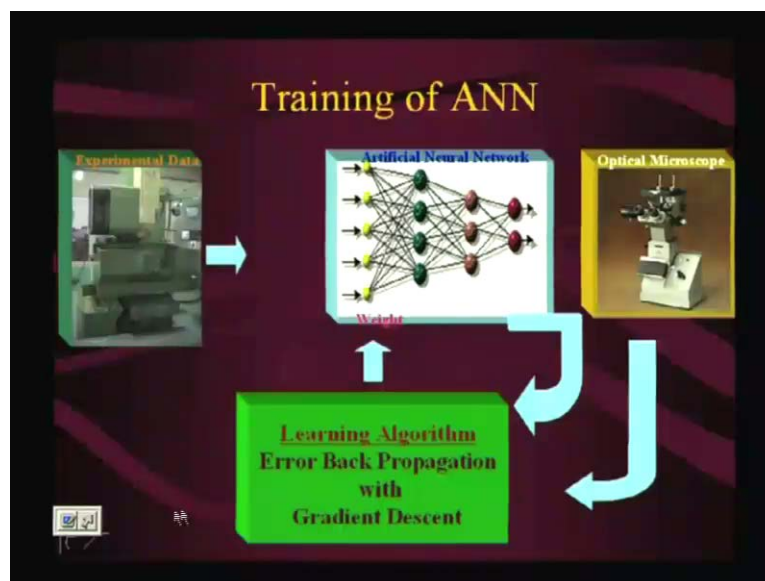
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So, so this was the basic architecture; that is we took the signals in terms of its features and then we we have to do a signal processing, so that we get a we get an estimate of the wear. So, as if this as if this becomes a sensor, this becomes a virtual sensor which gives us a measurement of the wear.

So we used an an artificial neural network, which looks like this. And we got some very good result.

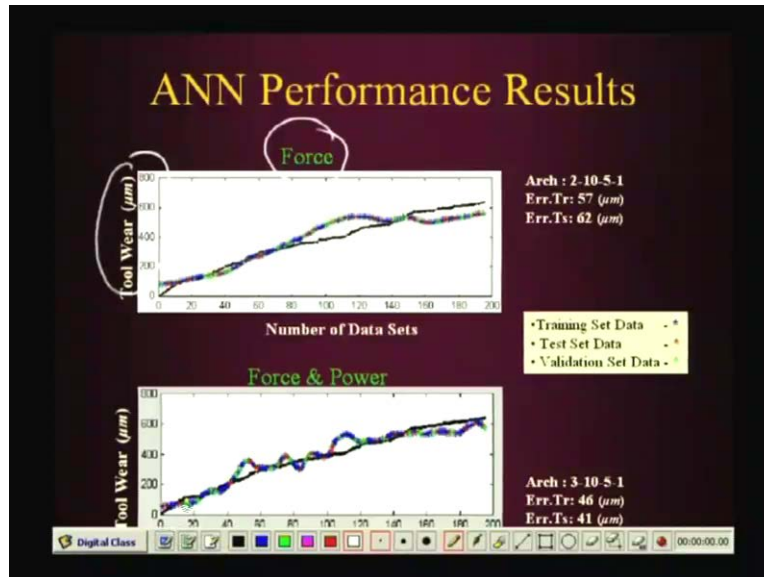
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So, we will see, so actually what we have to do now? Now, the point is that we have to in this case; you are using an using an artificial neural network, which means that you have to choose the structure of the network and you have to choose the parameters of the network. So, that is a process which is called training. So, we did this training. So, you create a create a good number of experimental data, you actually measure the wears using microscope and then you try to train or optimize your model weights; such that the model is is able to, give you a wear value which is the which is the true value, which is established using an optical microscope.

So, we use a typically, we use a perceptron and we use an error, error back propagation approach for training the training the percept perceptron. We got some fairly good results.

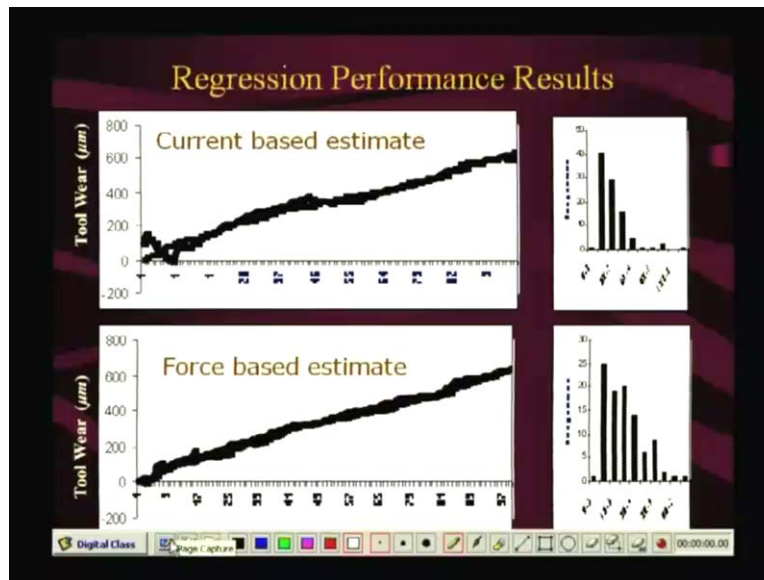
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So, here is A N N performance results. See, that based on only based on force, if tool wear is estimated using a neural network; this is these are the estimates and this these are the estimated and this is the true black one, is the true value. On the other hand, if you use force and power as is the case here, you can you can you can see; that the estimation is perhaps slightly better, okay. So, it shows that, if you include another signal some, the estimation quantity is likely to improve.



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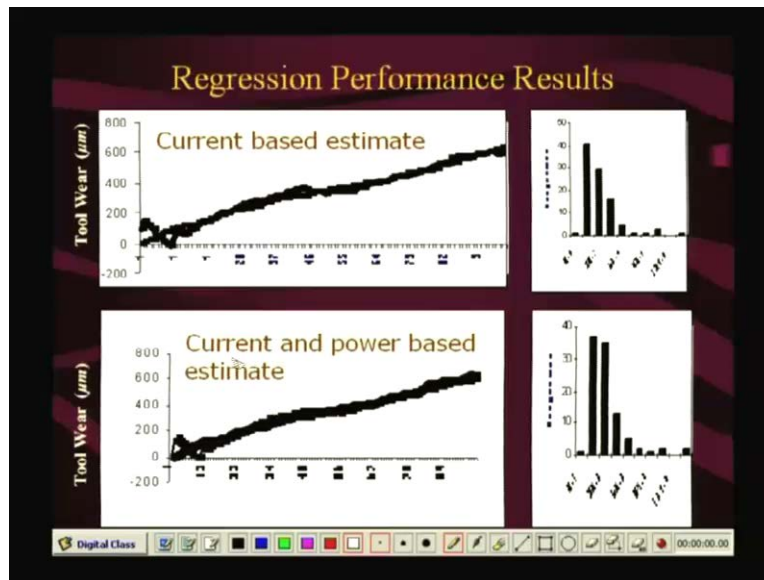


Having them or I mean, having obtained our results for for artificial neural networks. We had also tried, estimating the, estimating the wear based on based on regressions. And in this case, first thing I would like to show is that using regression; see this is the current based estimate, so we use currents and we got this graph. So, you can see that, that it its it can it can it can estimate the actual tool wears, fairly fairly well.

On the other hand, force based estimates are; indeed slightly better than this but only slightly, these are very comparable estimates with force based estimates. So, the first thing is established is that, that using an estimator or a model you can you can replace a costly measurement and still get very good quality measurements.

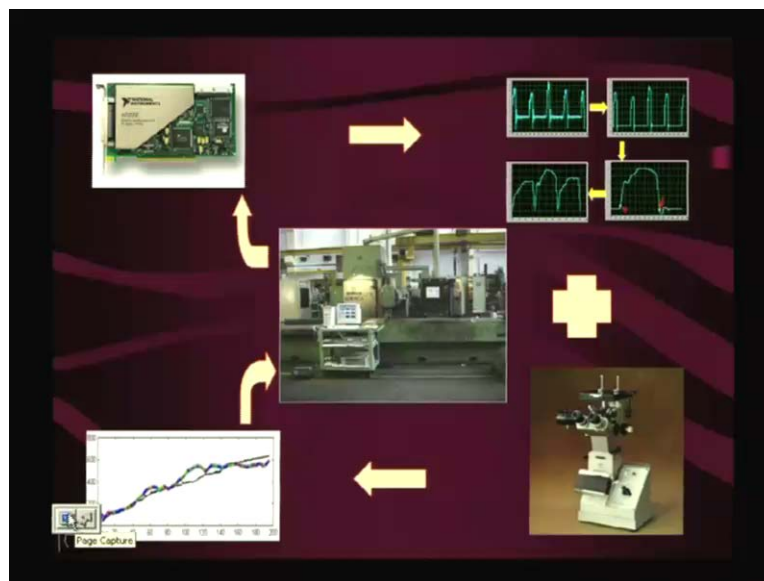


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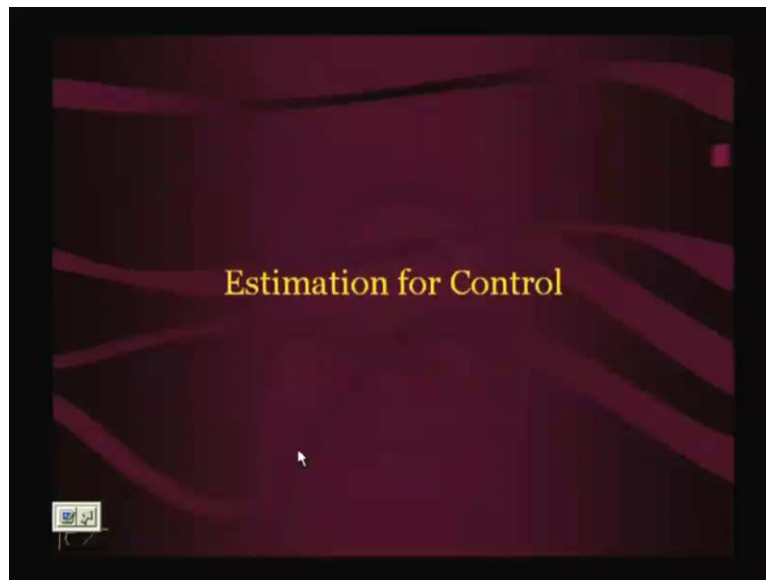
Similarly, again the the advantage of having sensor fusion in terms of accuracy is shown. So, you have current based estimates here, here you have current and power based estimates. So, it turns out that the current and power based estimates are somewhat, straightly not much; but still somewhat improved over the force based estimates or only current based estimates.

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So, that closes this. So, you see that we had, this is this is the picture where, this is the picture where we actually had taken taken our set up to actually an factory; and we have done some measurements and we could estimates the tool wear there.

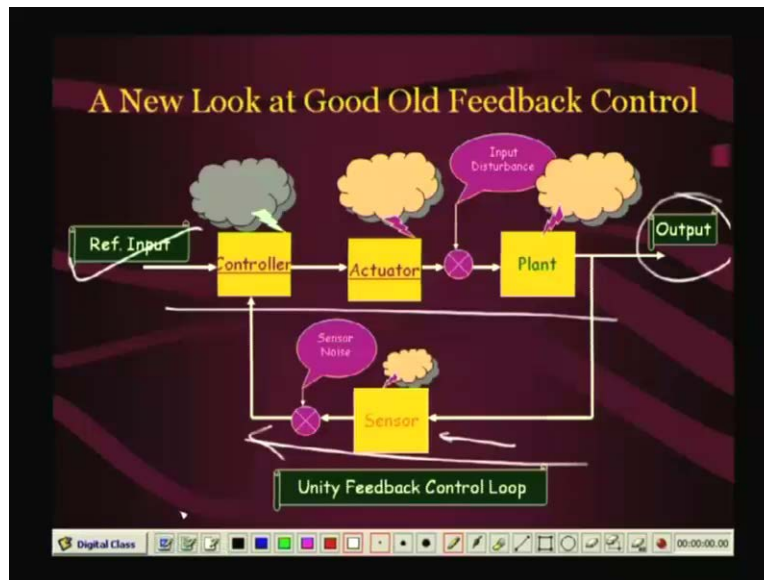
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Now, we discuss another small case study which is which is which is estimation for control. So, so what did we see in the last case study? That we we wanted to measure tool wear, which is a very inaccessible quantity in the sense that; it cannot be measured by or you do not have any technique to measure it, while the tool is cutting but we took some relatively simple algorithms. Let me, let me simple measurements from sensors and we set up a model and we and we and we build an estimator which gave a fairly correct value of the tool wear, based on those measurements and online; while the machine is cutting, it can it can predict as to what the present value of tool wear is. So, that is what estimation can do to the field up measurement.

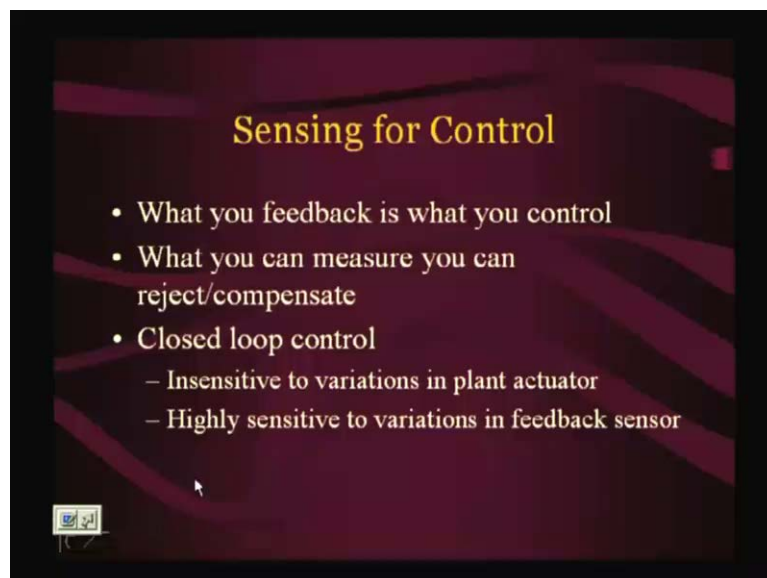
Now, for control you must I mean, estimation are estimation are generally used; again in sense of measurement because because for most control there has to be a feedback. So, that feedback is essentially sensing and we shall see an application of an estimator to ensure that, the feedback never stops even if the sensor fails, right. So

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So, this is the what I said, the good old feedback control structure. Here, you have the reference input. And here is the here is the feedback; this is the feedback, through the sensor. And this is the for fold path. It turns out that all these elements, are actually susceptible to failure, they have disturbed, they they actually get disturbances and noises; so that affects the output. In in particular, if there is the failure of let us say, the sensor then the feedback loop will be opened simply. And there are certain facts about the controller that we should mention is the following.

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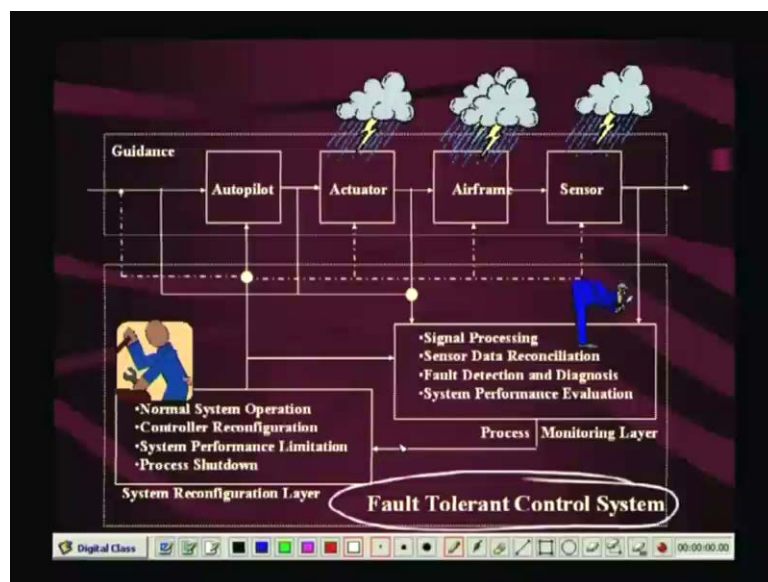


Remember, that what your feedback is what you control. So, in a control loop, if you add a one volt bias to the to the sensor then if there is bias or if there is any kind of noise in sensor; exactly the same type of noise will actually appear at the output. So, the so so the control system is actually, traditionally, a lot robust with respect to the forward path element characteristic.

Like even in the actuator, even if the actuator bandwidths falls by little bit or by some amount, even then the loop performance generally will be maintained but it is extremely sensitive, to the to the feedback path; so, if there is anything wrong with the feedback path, immediately the effect of that will will will will appear at the output. This is the property of feedback control. So, first thing, I said is that what you feedback is actually is what you control.

And what you can measure, what you can, if you can if you can compute something, then you can reject or or compensate, right. And this is what I said a closed loop control is insensitive to variations in plant or actuator but highly sensitive to to variations in feedback sensor. So, now let's consider the the following problem.

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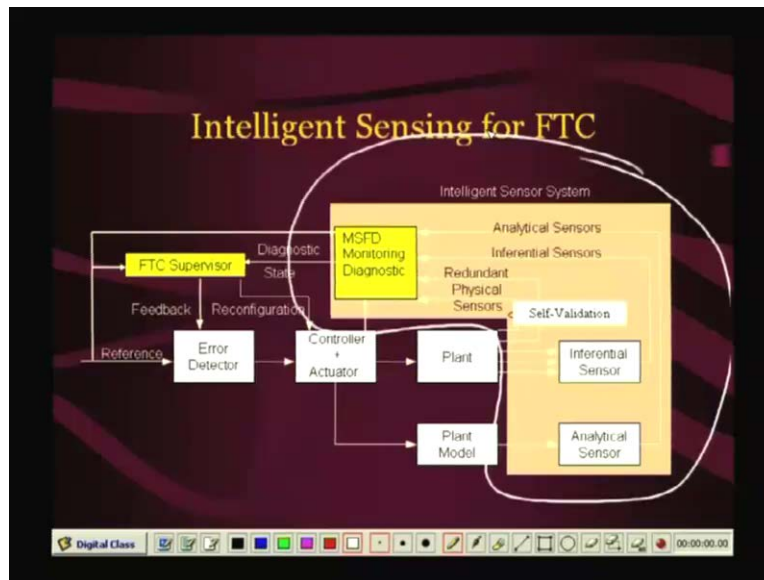
This is the problem of constructing a fault tolerant control system, that is it is the control system and it will be so intelligent robust; that even if some components in it fail using the effect, using the available level of redundancy if another healthy unit is there etcetera, it will be able to control the systems still and will not lead to system catastrophic failures. Some amount of performance can be loss but the system will not suddenly collapse, okay. So, that is called fault tolerant control and.

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So, now in now in fault tolerant control, they can be, it depends on where it faults are. So, that the fault can be in sensors, the faults can be in the in the actuators or they can be in the controller itself. In the in the for this lecture, we are not concerned with you know this this controller faults etcetera; and I mean, so we will not be considering that. We are mainly in this lecture we shall show, that how using, if you have a sensors fault then and if you can detect it, we can actually save the the operations for many very critical systems.

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So, what happens is that, we need to sense a lot of quantities and we need to consider always; see the basic problems is to understand is to understand, whether the system now is behaving like its normal model. So, you need to compare things. If, it was a normal model and if I receive this input, what is the output that I am likely to receive, likely to give out, am I giving that out? If if they are roughly matching then I am normal, if I am if it is not matching then I am not normal.

So, there are lots and lots of senses used, have to be used; so a whole thing called intelligent sensor system must be put in place, which is a combination of some sensors, some of the some of which are very trivial and easy to put, and electronic processing of signals to to obtain better quality measurements.

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**Redundancy for Detection**

- Detection : "Odd one out"
  - It takes at least two, (preferably 3 or more) to find the odd one
- Types of Redundancy
  - Physical : Triplex Sensor Voting
  - Analytical : Model based Residual Generation

!!!  
a, b, c

This is an idea which says that; if you have if you want to detect, whether whether something is failure, you need redundancy because you need another copy of a signal with which you are going to compare. Unless, you have a redundancy, you cannot compare a signal with something and you cannot therefore; say that that that whether this signal is behaving, coat un-coat, normal, right. So, therefore detection is actually the problem, of detection is actually the problem of finding the odd one out. And to find the odd one out, it takes at least two but even sometimes with two; we cannot detect which one is the odd one, so therefore we we we often need three, right.

And then there are so, this odd one out is the basic principle of detection, which is an which is a kind of estimation problem. So, you see what is the problem? The problem is a is not a value computation problem, like in the previous class case. It is a simpler problem, in the sense that that we only need to classify. So based on the measurement; that whether the system is, right now in a faulty state or or in a whether it has suffered a failure or not, right.

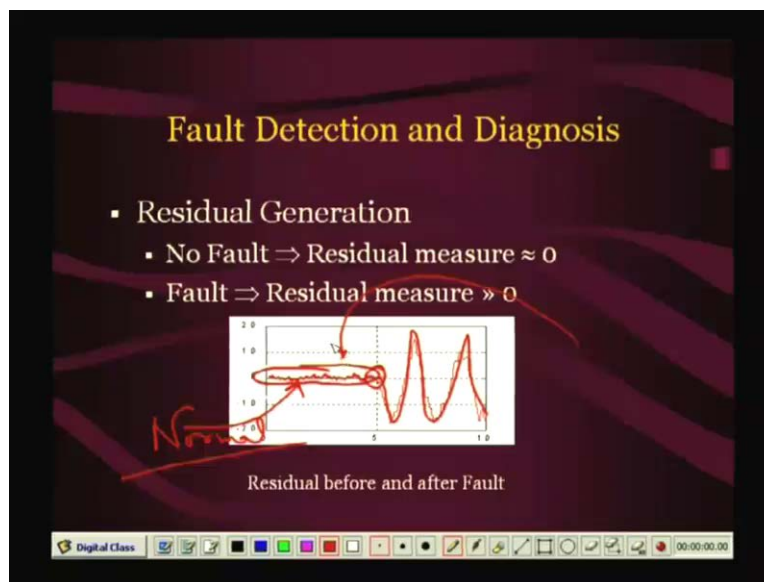
So for that, we this this detection problem; this kind of redundancy which is which is needed for detection, can be created in various ways. For example, you can have a physical redundancy,



when you actually, for every measurement of variable you put three sensors. So, you put three sensors, they give value, a, b, c. So, if a is significantly different from b and c, then then a is faulty. So, by the simplest simple strategy, you can detect many faults but the problem is that for for everything, you are going to put three sensors now. So, so that is going to cost in terms of money, weight, space which are very critical in in some application, such as aerospace.

So, the question is that whether, we can generate this redundancy without using a copy but rather by computation using a model. So, such redundancy creation is called, analytical redundancy.

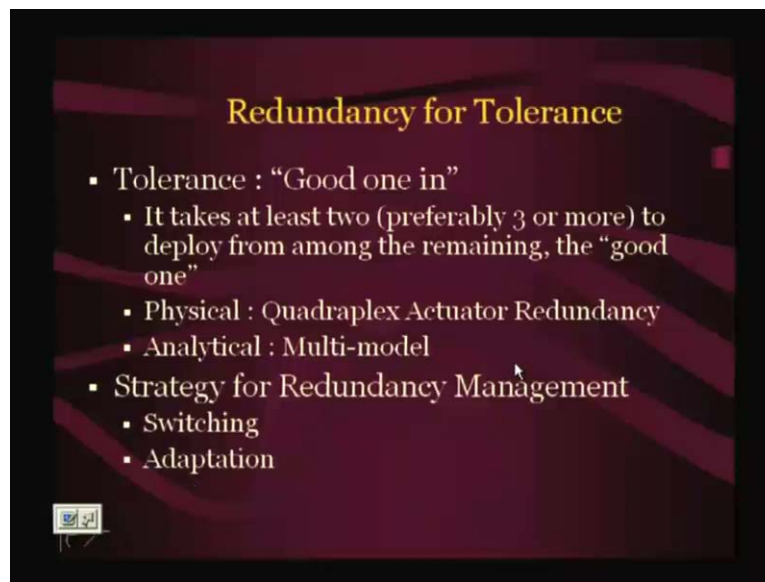
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So, using now, using this two signals we want to create another signal, which is, which you called a residual; such that as long as the system is normal, see so the system is normal here , this is normal, so the residual is very small. Actually, this is this is actually; it will be something like this is a, it will be it will not be a very small quantity. And the moment there is a fault then this residual will rise to a large quantity, so that one can easily understand, that that that there is a fault. So, actually the a a lot of problems of detection is actually concerned with creating such a signal, right.



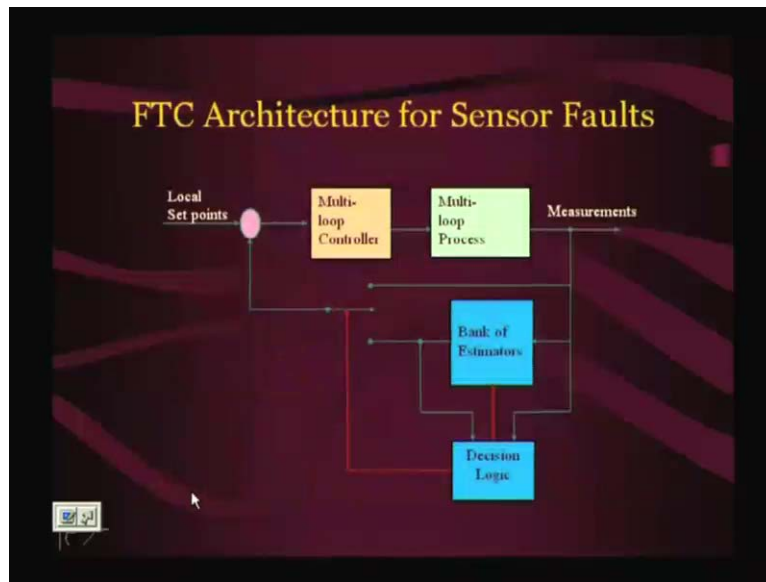
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So, similarly while you need redundancy for detection, you also need redundancy for tolerance because tolerance is actually; basically tolerance is bring the good one in, detection is get the get the odd one out, and tolerance is to bring the good one in. So, obviously you you will you will you will have to have a good one and in many cases, it turns out you see, you cannot you can create information from models and computation, but you cannot create energy.

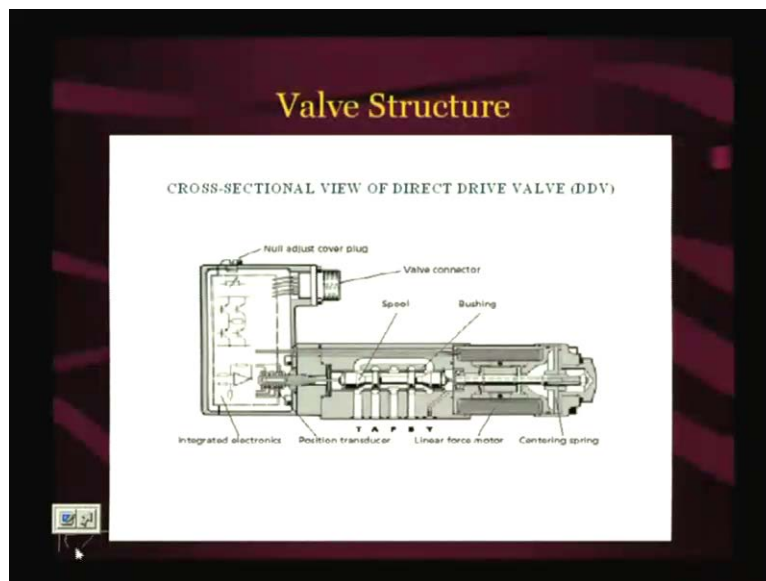
So, in many cases; if you if you if you want particular device like, an actuator has failed, you cannot really tolerate that fault, unless you have some sort of redundancy available in your system. Now, it turns out that in many cases; redundancy is generally available and and all we need to know is, how to how to deploy that redundancy, intelligently. So, therefore we need, we often have redundancy and we have we need to use it.

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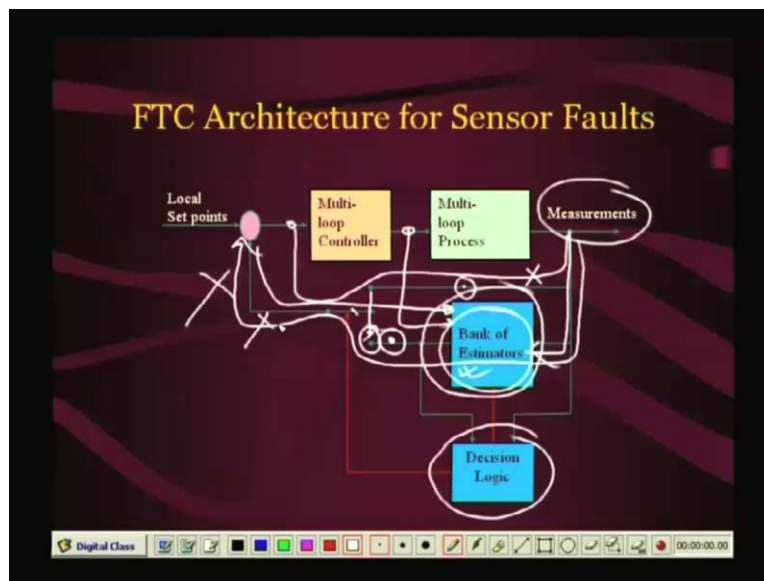


So, okay so, let's go directly to an example. So, one of the one of the but sensor fault, which we are going to discuss; mainly are are we have interesting because of the fact, that sensor faults, so what is the what is the sensor fault? What is the sensor doing? See the sensor, is actually, I am sorry.

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So, the sensor is actually feeding back signal like this. Now, if it is faulty, if it is faulty if there is any fault here; suddenly this loop path will be broken, it will be broken and this will become open loop. They will completely destroy the control. So rather than that, if we have a bank of estimators, this could be Kalman filter, there could be observers, there could be artificial neural networks, there could be various kinds of models which will estimate this quantities.

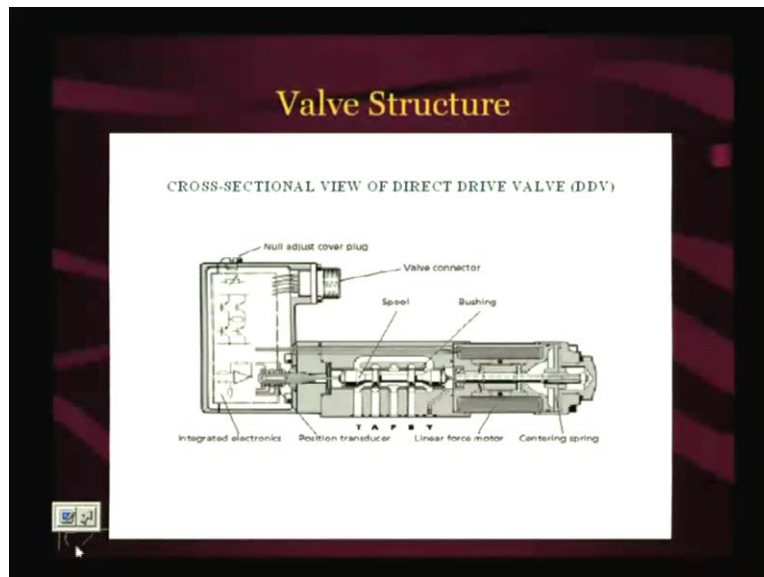
So, it will take the measurement as input, it will also take these these various plant signals as as inputs, so it may it will take these things also. And then it will try to, first of all detect whether any sensor is failed faulty, and then if it is faulty; it will try to, it will try to compute that signal based on many other measurements. See, we are assuming, normally in a process there could be various, there could be large number of measurements; it is not that there is there is only one sensor.

So, the question is that, can we construct the estimators such that, we can calculate the value of a particular sensor without using that sensors. And it turns out that, we can, right. So, once we can do that then then we have we have no problem; because if we can detect that, the failure and if

we can compute the value of this fail sensor then we need to simply flick our switch from here to here.

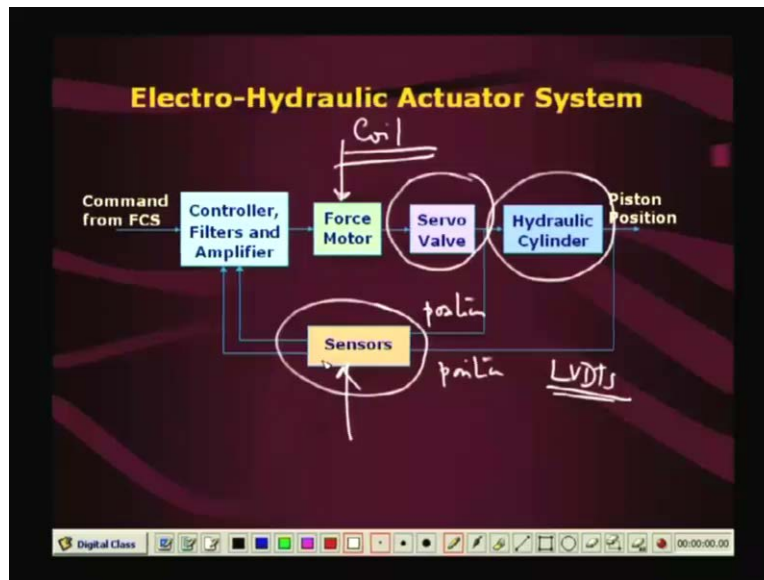
So, now the feedback path of the control loop is going to be, is going to be closed like this. So so the controller does not understand this difference at all, that whether it is coming through this path or whether it is coming through this path. It gets the feedback, so therefore it can maintain performance, okay.

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So, now we are going to show an example of that happening, which is the which is for a you know this is an aircraft actuator. Now, these are very very powerful devices; they can create tones of pressure. So, and they are very precise and fast. So, therefore they are obviously; you know a closed loop device, otherwise they cannot be controlled, so much power cannot be controlled in in open loop.

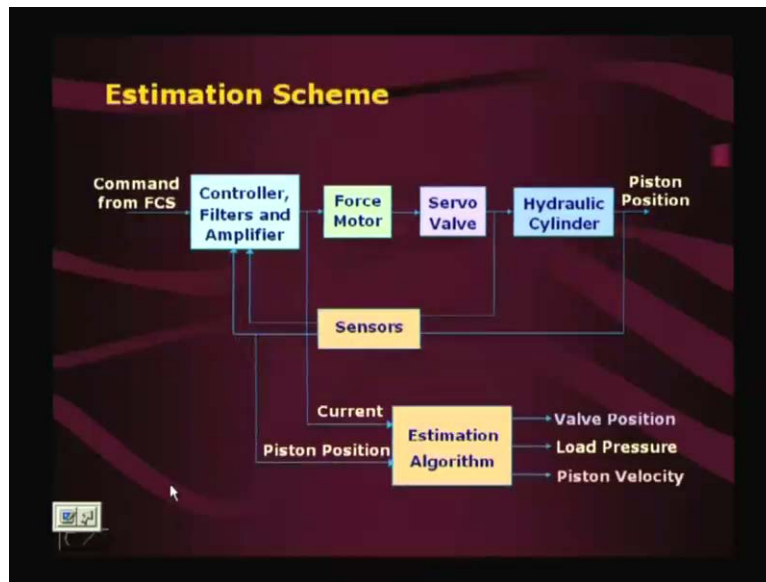
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So, this is the block diagram of that actuator system which is electro hydraulic; in the sense that, in the sense that you have this is a hydraulic servo valve, this is the hydraulic power piston. So, using, these are the sensors which sense position, the servo valve full position and the piston ram position, they are basically LVDTs. So, they gave the feedback to the controllers and the controller drives; what is known as the which is which is nothing but a coil.

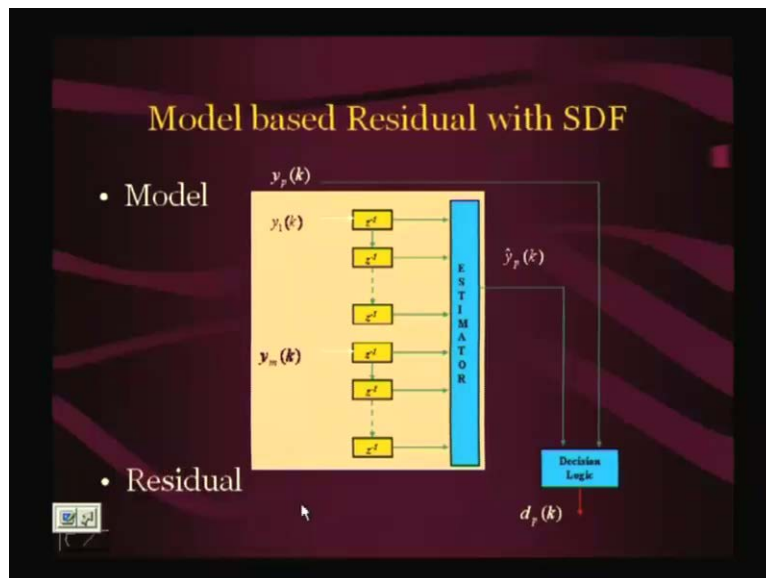
So, this coil can move this servo valve very minutely. Once and servo valves have huge amount of gain, so once the servo valve is moved even a little bit; there is a there is a lot of force generated in the in the hydraulic chamber, right. So, you see that this is the this is an actuator but we the actuator itself is in a closed loop system, and therefore you have a sensors within the actuators and we are considering the failure of such sensors.

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So, what we do is, we first produce an estimation algorithm; which gives us the valve position load, pressure piston, velocity.

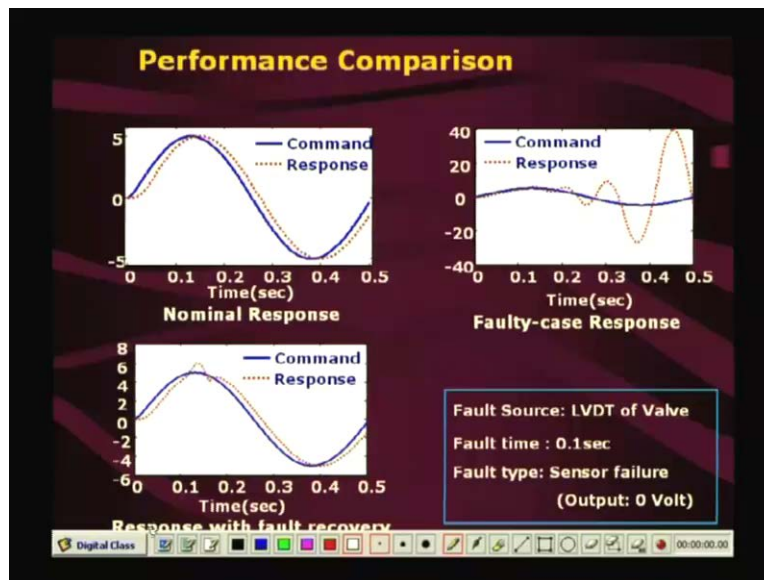
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So, you see that, what you are going to do is you are going to feed these measurements; and their past values into an estimator. And then so so the whole idea is that, suppose you have the suppose you have the **peads ((00:47:56 min))**; the the estimated which is supposed to estimate the p ((00:47:59 min)) measurement, then you feed all the measurements into the into the estimators, only thing is that the general case is  $y_i$  and  $i$  is not equal to  $p$ .

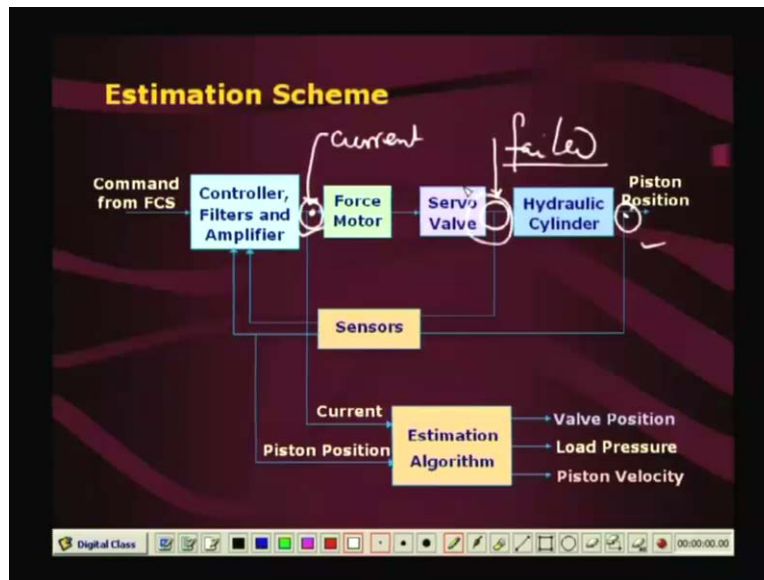
So, excepting  $y_p$  you send all of these to the estimator and then it generates an estimate of  $y_p$  but  $\hat{y}_p$ ; and then you compare these and use in a decision logic to understand whether the the  $p$  f sensor is actually healthy or not, okay.

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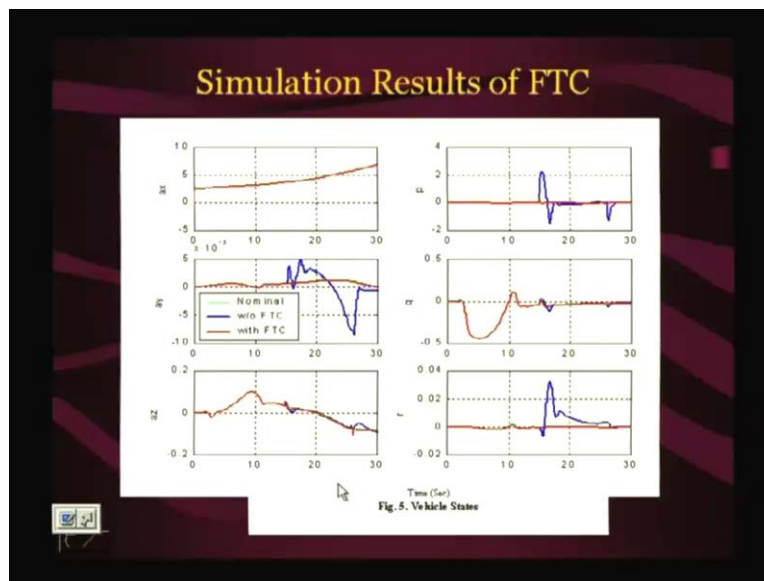
So in this case, see we are we are we are showing some cases; in this case, this is the performance of the actuators. So, the blue is the command and the red is the response. So, clearly the response is following the command.

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Now, if one of the sensors fails. In this case in this case I think, in this case what we assume is that; this sensor has failed and we wanted to create this sensor from this, this is current current and this is ram position. So, using these two measurements; so whether we can estimate these spool positions that is what we tried.

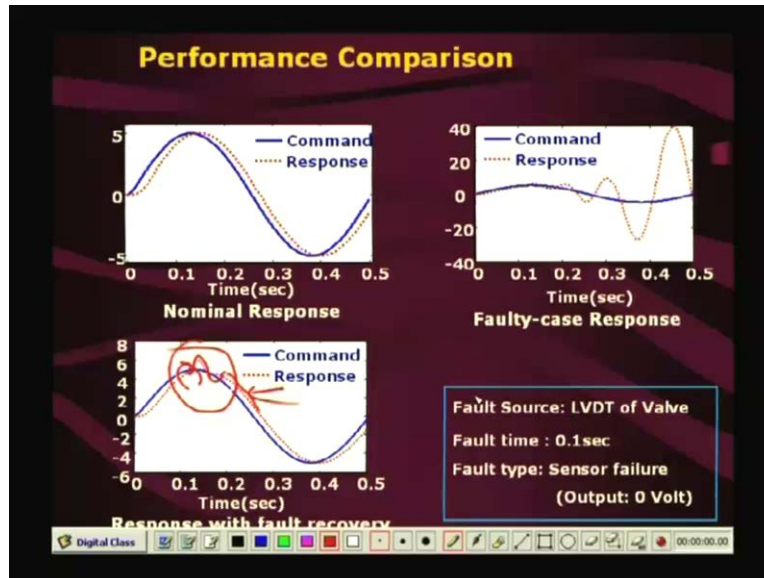
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This is the simulation which says that, if the so you know.

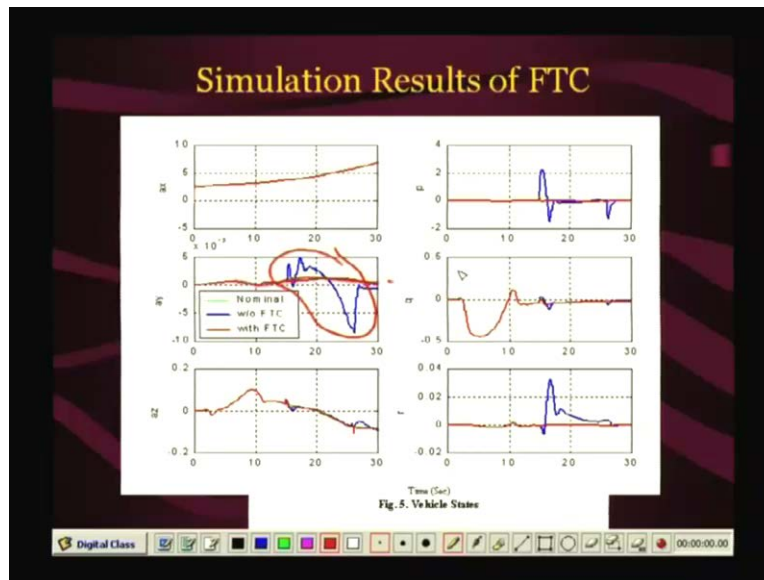
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So, you see that if one of the sensors in this case, if whether LVDT; that is the position on the spool sensor if it fails, that if the value become zero then immediately the actuator response becomes unstable. So, you can understand, that that this actuator; if it is if it is part of any aerospace vehicle then, that vehicle will will also go, may also go unstable, it will create disturbance, it move away from where it was going and things like that.

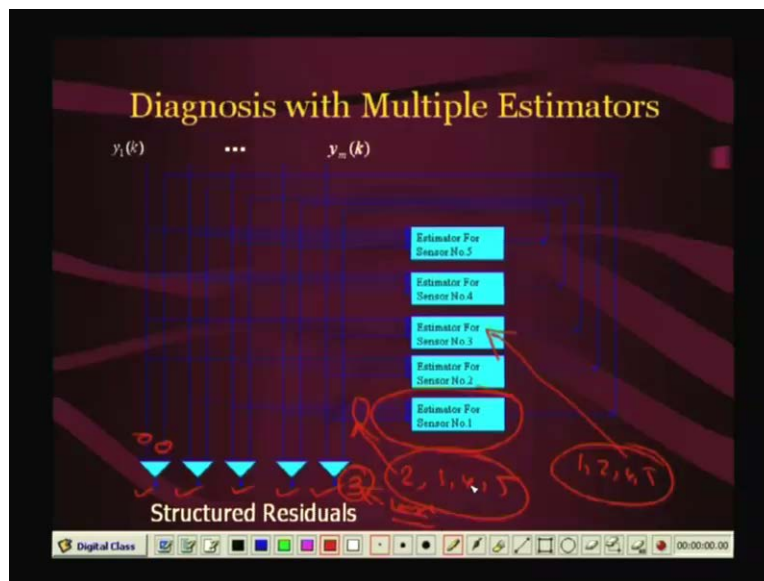
While, if you use the simple faulty response algorithm; using an observer and it turns out that, this is the this is the this is the performance. So, here the fault occurred. So, there is some initial transient but then the signal has been estimated and which is set back; therefore it starts following the pattern, again.

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So, this is the this is actually, this actuator was made a part of a full missile model; and then we wanted to see, that if such a fault occurs in the actuator then what happens to the missile. And it turns out that, you see without the fault tolerance control the the signals, that are they are they are actually quietly differ from, what the desire levels of signal should be.

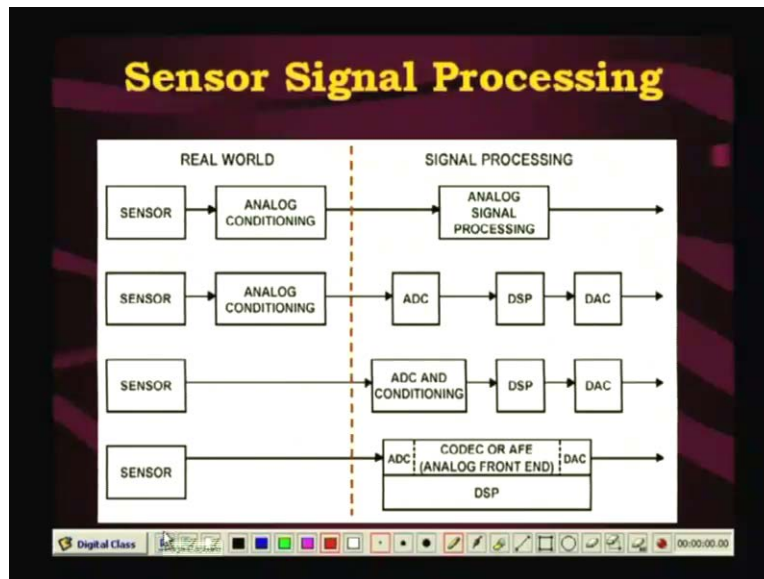
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So, we will skip these. And so you see that, if you want to if you have many such estimators then we need to create multiple such estimators. Just note that for example, say estimator number one; estimator number one uses measurements 2, 3, 4 and 5. Estimator number three, uses 1, 2, 4, and 5, so it uses all the others, other than the other than it's that that particular sensor. And then it and then it it compares, the estimate with the measurement and they are they are from ingots, the it gets the the various residuals. And therefore, suppose you find, that the third residual is large right or the fifth residual is large. So, we can easily find out that, which is the sensor which is failed.

So, this is the way, so this is called diagnosis; which is one step ahead of detections, which says that you you it is it is not enough to find out which is the, that that that something has failed but rather than you can also tell which one has failed, so that is called diagnosis.

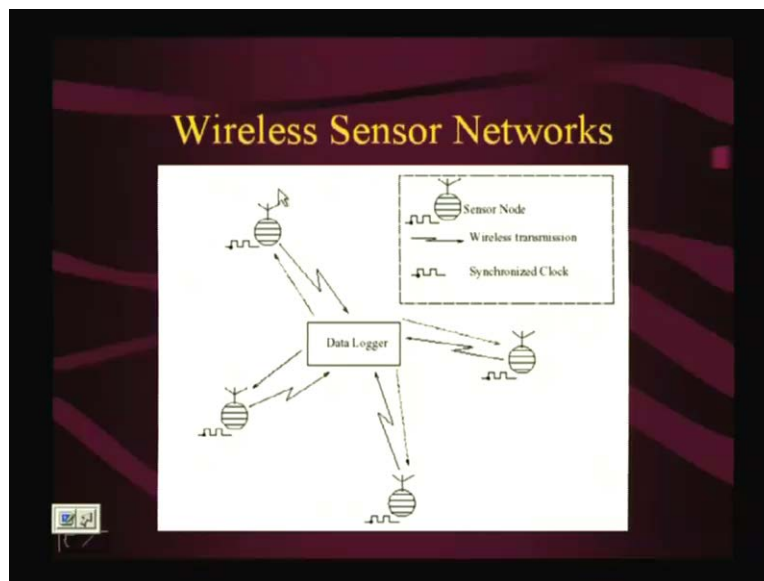
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So, you see that so we were basically; let's let's try to reflect because we are going to end that. So, if we see that using estimators; we can improve quality of estimates, we can estimate quantity which which we cannot measure directly, we can even estimate values wethere the whether whether sensor has failed and these these become very important in certain applications

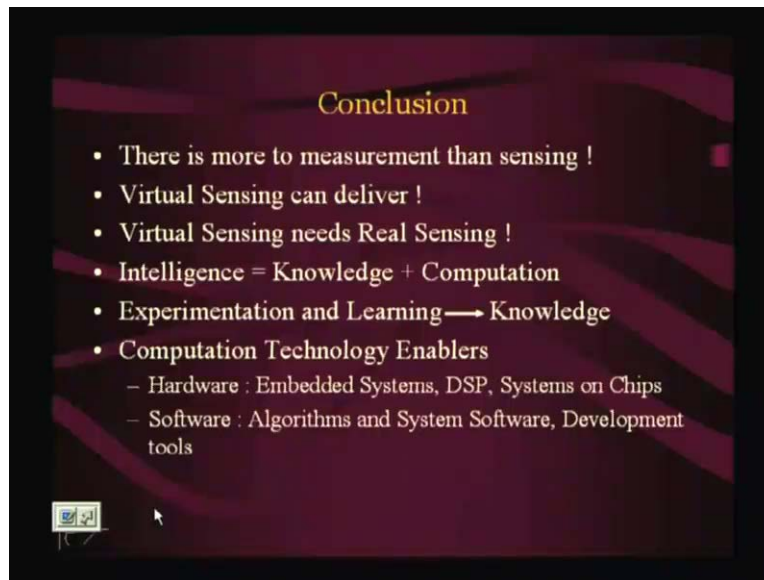
using estimation. And not only that, modern electronic technology for example, this is a slide on sensor signal processing; all these computations estimators can be now today integrated with sensors, using technologies such as MEMS and VLSI design. So, we can put these estimators on chips and we can make the part of the hardware. Then they are not the is not that, we have to put big big computers here and there, right.

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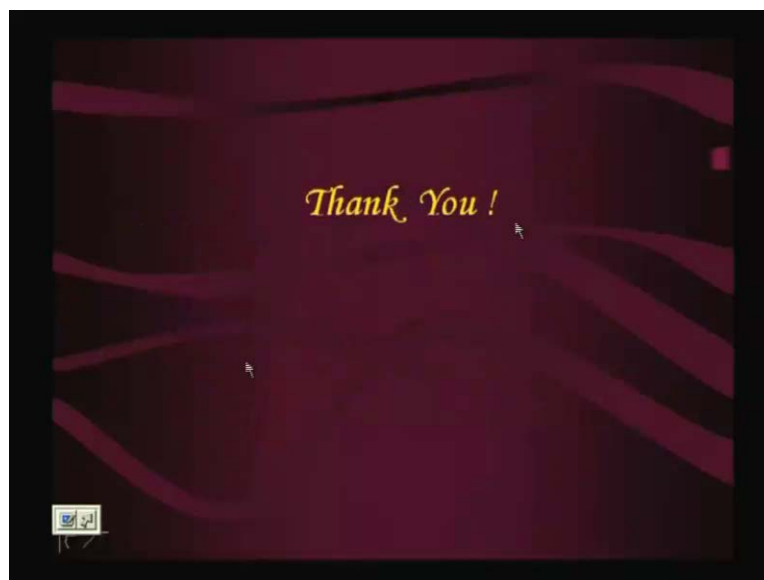
So, that makes these technology very real and we can have we can have such sensor, which can actually communicates. So, using multi sensor fusion is now easier; you can actually fuse sensors of different locations and they can make, wireless communication with each other. So such schemes are going to come and therefore use of algorithms is going to explode and this is the this is the point, that I am try to make that; here is estimation theory which can really contribute to this quality of measurement.

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So, finally we come to the conclusion slide and which says that, there is more to measurement than sensing. So, measurement is not only just physical sensing by a sensor; but using lot of algorithms, most many of which is much of which is actually estimation.

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But at the same time, remember that virtual sensing, really needs, I am sorry.

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**Conclusion**

- There is more to measurement than sensing !
- Virtual Sensing can deliver !
- Virtual Sensing needs Real Sensing !
- **Intelligence = Knowledge + Computation**
- Experimentation and Learning → Knowledge
- Computation Technology Enablers *Models*
  - Hardware : Embedded Systems, DSP, Systems on Chips
  - Software : Algorithms and System Software, Development tools

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So, virtual sensing really needs, real sensing and its needs that. And now basically we want we are trying to create, intelligence within the devices; which comes from knowledge and which comes from computation. So, knowledge will come from experimentation and learning, that is the these are the models which you want to set out, without the models no estimation algorithm will work. So, you have to for pilling the models, you need to be experimentation. And computing can be done today using the technology enablers in hardware and software. So, this is what, this is the point I wanted to make, today. Thank you very much.