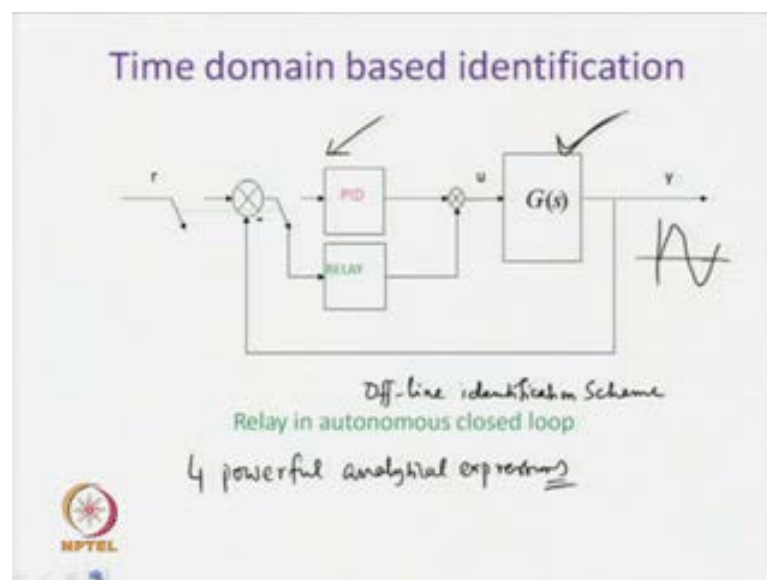


Advanced Control Systems
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Module No. # 03
Time Domain Based Identification
Lecture No. # 16
Review of Time Domain based Identification

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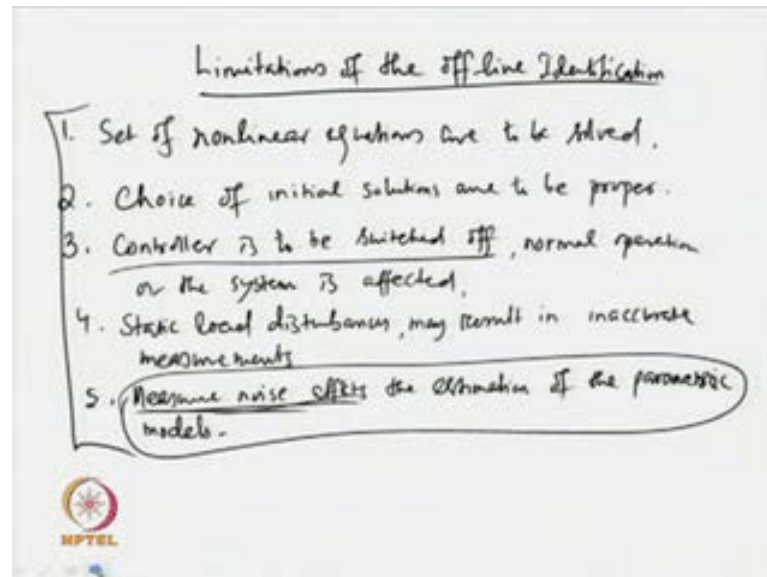


Welcome to the lecture titled review of time domain based identification. In this lecture, we shall discuss about some issues related to time domain based identification. Also using some statistical measures, measurement error effects on the model parameter estimations will also be described. In the offline identification scheme, we have already discussed earlier, offline identification scheme. Why it is called the offline identification scheme? When the relay is switched on that time the controller remains out of the loop. And when the controller is in action, relay remains out of the loop that is why, this scheme is known as the offline identification scheme.

Then how identification is accomplished, the limit cycle waveform is obtained, and analysis of the limit cycle waveform results in 4 powerful analytical expressions - **analytical expressions**. And now, solving the set of analytical expressions, it is possible

to identify the dynamics of a real time process, in the form of transfer function models. Now, the transfer function models can assume various forms.

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Now that will not discuss again rather, we shall see the limitations of this identification scheme. So, the measure limitations of the offline identification scheme are: First, you need to solve a set of non-linear equations using some non-linear equation solver. So, a set of non-linear equations **equations** are to be solved. And solution of the non-linear equation requires you to choose proper initial values or initial settings, while trying to solve the set of non-linear equations. So, choice of initial **initial** solutions, **choice of initial solutions** are paramount importance; means choice of initial solutions are to be proper.

Next controller is to be switched off, **controller is to be switched off** while conducting the identification test or relay experiment. That means, the process operation will get disturbed. So, when the controller is switched **switched** off, normal operation of **normal operation of** the system closed loop control system is affected. Now in the phase of presence of static load disturbances, we may get inaccurate pix or the measurement of the limit cycle output may yield in accurate measurements. So, static load disturbance may result in inaccurate measurements, and lastly the measurement noise **measurement noise** affects the estimation of the parametric models **parametric models**.

So, measurement noise results in inaccurate measurements, and which in terms may yield higher estimation errors or the parameters may be estimated in accurately. So, these are the five important limitations, we have with the offline identification scheme. In spite of that, for each in analysis **analysis**, and for each in identification - offline identifications are often chose or selected.


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Presence of Measurement Noise

The identification error due to measurement noise can be quantified by the following standard deviation

$$\sigma_Q = \sqrt{\sum_{i=1}^n \left(\frac{\partial Q}{\partial P_i}\right)^2 \sigma_{P_i}^2}$$

where $Q = f(P_1, P_2, \dots, P_n)$, σ_{P_i} = standard deviation of the variables (measured quantities) of the function f and σ_Q = standard deviation of the estimated parameter, Q .



Now, since measurement noise plus an important role; it will be nice to see the estimation errors result in due to measurement noise. So, the presence of measurement noise relates to error in measurements, which indirectly gives identification error. And the identification errors, can be quantified by using some statistical measure, such as the standard deviation. So, the standard deviation for the estimation error can be given by this expression. What is that? Sigma Q is equal to square root of sum of i equal to one to n del Q upon del P i square sigma P i square. What are Q, P, and sigma - sigma is the standard deviation.

Now Q is a function of the parameters of the transfer function model, sigma P i is the standard deviation of the variables, those have there in the explicit or inexplicit expressions, those are to be used for identification of transfer function models. Now, sigma Q is the standard deviation of the estimated parameter that is Q.

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Suppose $T = \sigma/\tau$

$$\sigma_T = \sqrt{\left(\frac{\partial T}{\partial \theta}\right)^2 \sigma_\theta^2 + \left(\frac{\partial T}{\partial \tau}\right)^2 \sigma_\tau^2}$$

FOPDT $\Rightarrow G(s) = \frac{K e^{-\theta s}}{T_1 s \pm 1}$

$$T_1 = \frac{\tau}{\ln\left(\frac{K_h \mp A_p}{K_h \pm A_p}\right)}$$

$$\theta = \mp T_1 \cdot \ln\left(\frac{K_h \mp A_p}{K_h}\right)$$

Symmetrical relay experimental.

NPTL

Let you give one simple example, suppose some T is a function of θ by τ , let us say. Then, how can I find the standard deviations; now σ_T will be equal to σ_θ upon σ_τ square plus σ_θ square plus σ_τ square root. This is how we can find the effects of the parameters θ , and T on the estimation value of capital T . So, this is how the standard deviations are found, suppose θ is deviated by some value, τ is deviated by some value, then how much accuracy we have in the estimation of T can be obtained from σ_T or the standard deviation of T .

So, using this, now we shall try to find the estimation errors associated with a first order plus dead time model parameters. What is one first order plus dead time transfer function model parameter, **FO OP** FOPDT model can be given in the form of $G(s)$ is equal to $K e^{-\theta s}$ upon $T_1 s \pm 1$. This is what we have already discussed earlier now, to estimate the parameters associated with this transfer function model. We have got some explicit expressions for T_1 , and θ ; and K can be found by some other technique or can be **can be** found from the measurement of the area of the output signal divided by the area of the input signal.

Now, we have got expression for T_1 as T_1 is given by plus **sorry** T_1 is given by minus plus τ divided by \ln of K_h minus plus A_p divided by K_h plus minus A_p . So, this expression has already been derived in our earlier lecture, similarly the expression for θ is given as minus plus T_1 times \ln of K_h minus plus A_p divided by K_h . When

you get, these type of expressions when we use symmetrical relay test - symmetrical relay experiment is conducted. Then the analysis of the limit cycle waveform results in explicit expressions of these forms T_1 , and θ .

Now as I am telling due to the measurement noise, it is possible to get inaccurate values for τ and A_p ; these are the three measurements, we are making. Now, assuming that K is also affected by the measurements of the ratio of output signal to the ratio of the input signal. So, let me find the standard deviation of T_1 with respect to that of the τ or variations in τ and A_p .

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$$T_1 = \frac{\tau}{\ln \left(\frac{K h \mp A_p}{K h \pm A_p} \right)} = \frac{\tau}{\ln x} \quad \text{where } x = \frac{K h \mp A_p}{K h \pm A_p}$$

$$\frac{\partial T_1}{\partial \tau} = \frac{1}{\ln x} = \frac{T_1}{\tau} \quad \text{--- (1)}$$

$$\frac{\partial T_1}{\partial A_p} = \left(\frac{\partial T_1}{\partial x} \right) \left(\frac{\partial x}{\partial A_p} \right)$$

$$\frac{\partial T_1}{\partial x} = \tau \cdot \frac{(-1)}{(\ln x)^2} \times \frac{1}{x} \quad ; \quad \frac{\partial x}{\partial A_p} = \frac{\partial}{\partial A_p} \left(\frac{K h \mp A_p}{K h \pm A_p} \right)$$

$$= \tau \times (-1) \left(\frac{T_1}{\tau} \right)^2 \times \frac{K h \pm A_p}{K h \mp A_p}$$

So, let me start with the basic expression T_1 is given as minus plus τ divided by \ln of $K h$ minus plus A_p divided by $K h$ plus minus A_p . Let us write this in the form of minus plus τ divided by $\ln x$, where x is equal to $K h$ minus plus A_p divided by $K h$ plus minus A_p ; why I have written in this form. So, that I will be able to find the partial derivatives, conveniently. Now, how much will be the partial derivative of T_1 with respect to the τ , this will be equal to minus plus 1 upon $\ln x$ - and $\ln x$ is how much, that is $\ln x$ from here can be obtained as or 1 upon $\ln x$ **1 upon $\ln x$** will be equal to T_1 divided by minus plus τ .

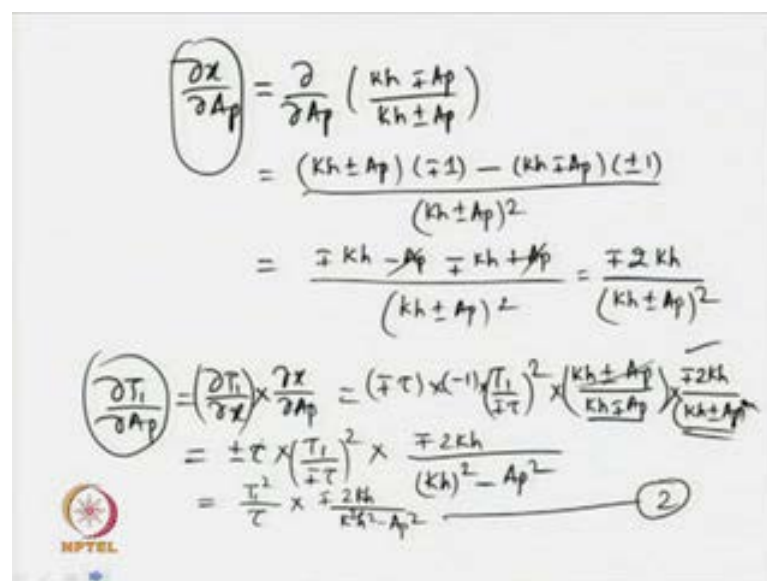
So, substitution of that will give us is equal to minus plus 1 minus plus times, your 1 upon this is equal to T_1 by minus plus τ . So, minus plus will cancel out giving us T_1 upon τ . So, this is what I get one partial derivative of the variable T_1 with respect to

the measurement tau. Similarly, we can find $\frac{\partial T_1}{\partial A_p}$ with respect to A_p ; now here, you need to find this in the form of $\frac{\partial T_1}{\partial x}$ upon $\frac{\partial x}{\partial A_p}$, because T_1 is a function of x now. T_1 is equal to $\frac{-\tau}{1+x}$. So, I have to use this identity $\frac{\partial T_1}{\partial A_p}$ is equal to $\frac{\partial T_1}{\partial x}$ times $\frac{\partial x}{\partial A_p}$. So, $\frac{\partial x}{\partial A_p}$ can cancel out giving us $\frac{\partial T_1}{\partial A_p}$.

So, I need to find two partial derivatives to find the partial derivative of T_1 with respect to A_p . So, how much is $\frac{\partial T_1}{\partial x}$. So, $\frac{\partial T_1}{\partial x}$ will be equal to $-\tau$ times, the differentiation of $\frac{1}{1+x}$ formula is to be used which gives us $-\tau$ divided by $(1+x)^2$ times $\frac{1}{1+x}$. And next will find $\frac{\partial x}{\partial A_p}$ will be equal to $\frac{\partial x}{\partial A_p}$ times $\frac{1}{x}$, this will be $\frac{1}{x}$ upon $\frac{\partial A_p}{\partial x}$ of x . So, what is x ? x is $\frac{K_h - A_p}{K_h + A_p}$. So, this is not difficult, once you know the way partial differentiations are down, then it is very easy to find the partial differentiation.

Now, we know that $\frac{1}{1+x}$, $\frac{1}{1+x}$ from here, $\frac{1}{1+x}$ is nothing but T_1 upon $-\tau$. So, I will make use of this. So, when you substitute this, then you get $-\tau$ times $-\tau$, then you will have for this T_1 divided by $-\tau$ square into $\frac{1}{1+x}$. So, $\frac{1}{1+x}$ means, you will get $K_h + A_p$ in the numerator, and $K_h - A_p$ in the denominator, because x is this much. So, $\frac{1}{1+x}$ will be the inversion of x . So, we will get this term.

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$$\begin{aligned} \left(\frac{\partial x}{\partial A_p} \right) &= \frac{\partial}{\partial A_p} \left(\frac{K_h - A_p}{K_h + A_p} \right) \\ &= \frac{(K_h + A_p)(-1) - (K_h - A_p)(1)}{(K_h + A_p)^2} \\ &= \frac{-K_h - A_p - K_h + A_p}{(K_h + A_p)^2} = \frac{-2K_h}{(K_h + A_p)^2} \\ \left(\frac{\partial T_1}{\partial A_p} \right) &= \left(\frac{\partial T_1}{\partial x} \right) \times \frac{\partial x}{\partial A_p} = (-\tau) \times \left(\frac{1}{1+x} \right)^2 \times \left(\frac{K_h + A_p}{K_h - A_p} \right) \times \frac{-2K_h}{(K_h + A_p)^2} \\ &= -\tau \times \left(\frac{1}{1+x} \right)^2 \times \frac{-2K_h}{(K_h)^2 - A_p^2} \\ &= \frac{\tau^2}{1+x} \times \frac{2K_h}{K_h^2 - A_p^2} \quad \text{--- (2)} \end{aligned}$$

Now, let me find $\frac{\partial x}{\partial A_p}$ which is given by $\frac{\partial x}{\partial A_p}$ will be equal to $\frac{\partial}{\partial A_p}$ of $K h \pm A_p$ times. What is x now; x is $K h \pm A_p$. So, $K h \pm A_p$ divided by $K h \pm A_p$. So, it will give now $K h \pm A_p$ times differentiation of this. So, that will give you ± 1 minus you will keep $K h \pm A_p$ here, times differentiation of this will give now ± 1 divided by $K h \pm A_p$ square. So, this is how, you find the partial derivative of x with respect to A_p . So, often simplification now, the numerator will give you $\pm K h$, then, it will be $\pm A_p$ and here. So, minus of minus **minus** times plus minus 1 will be $\pm K h$, then $\pm A_p$ times. So, it will give $\pm A_p$. So, this is how we get the numerator, where A_p **A_p** will cancel out, and ultimately giving us an expression of the form $\pm 2 K h$ divided by $K h \pm A_p$ square. Now, finally how much will be the partial differentiation of T_1 with respect to A_p . So, please substitute those expressions now $\frac{\partial T_1}{\partial x}$ times $\frac{\partial x}{\partial A_p}$. So, the first part we have obtained as $\pm \tau \pm \tau$, and then let me see $\pm \tau$ then ± 1 times T_1 by $\pm \tau$. So, ± 1 times T_1 by $\pm \tau$ square into $K h \pm A_p$. So, into $K h \pm A_p$ by $K h \pm A_p$.

So, all these terms are for the partial differentiation of T_1 with respect to x . Now, when it is multiplied with the partial differentiation of x with respect to A_p , I get $\pm 2 K h$ divided by $K h \pm A_p$ square at the end, **A_p square at the end**. Now, $K h \pm A_p$ in the numerator, and here the power will go out. So, leaving us an expression of the form \pm will come. So, \pm it does not matter, so $\pm \tau$ times T_1 upon $\pm \tau$ square into $\pm 2 K h$ due to this term divided by... If you multiplied now, this and this where the power has gone, $K h \pm A_p$ times $K h \pm A_p$ will result in $K h$ square minus A_p square. Please see the sign \pm will give minus, \pm multiplication will give minus. So, ultimately it will be like $a \pm b$ times $a \pm b$ giving us a square minus b square.

So, finally, what I get - the final expression for this one will be equal to... This is the final expression, no more simplification is required or further simplification is possible, because τ square will come in the numerator denominator cancelling this τ . So, I can get outright, your T_1 square. So, T_1 square divided by τ times $\pm 2 K h$ by $K h$ square minus A_p square. So, this is what? We have got for the partial differentiation of T_1 with respect to A_p .

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Handwritten derivation showing the partial differentiation of T_1 with respect to K .

Top equation: $\frac{\partial T_1}{\partial K} = \frac{\partial T_1}{\partial x} \cdot \frac{\partial x}{\partial K}$ (Note: $\tau = \text{half period}$)

Second equation: $T_1 = \frac{1}{\left(\frac{\tau}{2}\right)^2} \times \frac{\pm 2A_p h}{(Kh)^2 - A_p^2}$ (Note: $\tau = 10$, $\tau = 10.05$, $\tau = 10.1$)

Third equation: $\sigma_{T_1}^2 = \left(\frac{\partial T_1}{\partial \tau}\right)^2 \sigma_{\tau}^2 + \left(\frac{\partial T_1}{\partial A_p}\right)^2 \sigma_{A_p}^2 + \left(\frac{\partial T_1}{\partial K}\right)^2 \sigma_K^2$

Final equation: $\sigma_{T_1} = \sqrt{\left(\frac{T_1}{\tau}\right)^2 \sigma_{\tau}^2 + \left(\frac{2KhT_1^2}{\tau(Kh^2 - A_p^2)}\right)^2 \sigma_{A_p}^2 + \left(\frac{2A_p h T_1^2}{\tau(Kh^2 - A_p^2)}\right)^2 \sigma_K^2}$

So, similarly the partial differentiation of T_1 with respect to θ **sorry**, we do not have θ here in the expression T_1 . So, the T_1 expression has got three variables of three measurements τ , K , and A_p . Therefore, I need to find the partial differentiation of T_1 with respect to K , because K is now assume to be measured. So, $\frac{\partial T_1}{\partial K}$ will similarly result can be written as $\frac{\partial T_1}{\partial x} \times \frac{\partial x}{\partial K}$, giving us the terms minus plus T_1 upon plus minus τ square times minus plus $2A_p h$ now, divided by K square h square or you can outright write in the form of $K h$ square minus A_p square **sorry** $K h$ square minus A_p square. So, this **this** is our third expression.

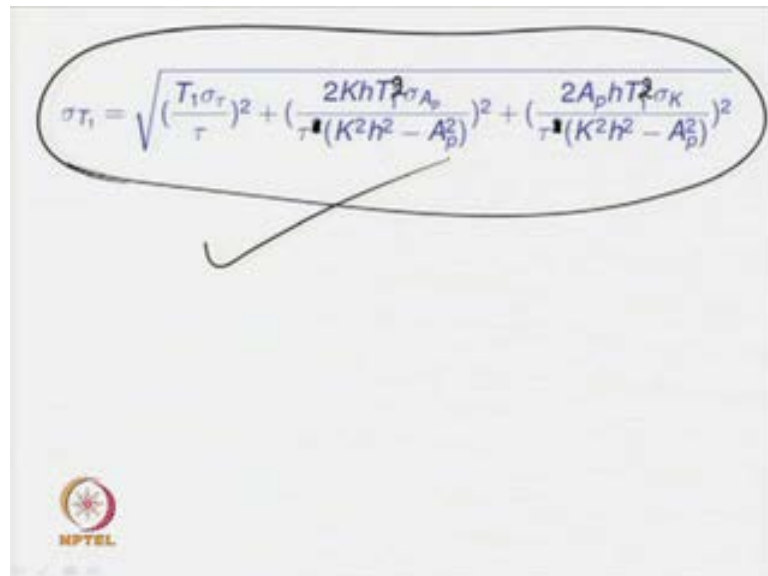
Now the finally, this standard deviation of T_1 is given by the expression $\frac{\partial T_1}{\partial \tau}$ upon σ_{τ} square plus $\frac{\partial T_1}{\partial A_p}$ upon σ_{A_p} square plus $\frac{\partial T_1}{\partial K}$ upon σ_K square root. So, this is how the standard deviation of the variable or the estimated parameter T_1 is given in terms of the measurement τ , A_p , and K . Now, you simply need to make use of the three expressions, we have found for partial differentiation of T_1 with respect to τ , A_p , and K over here to finally, get it in the form of T_1 upon τ square sigma τ square plus for this one will have $2 K h T_1$ square divided by τ times K square h square minus A_p square; **square** times sigma A_p square plus for this one already when you take the square, how do you get this one.

So, you have already got terms like $2 A_p h T_1$ square divided by τK square h square minus A_p square **square** sigma K square root. So, this is the final expression for the

standard deviation of T_1 , in terms of the standard deviation of τ , A_p , and k . So, assuming that the measurements what deviation means what basically, when I am measuring the half period, τ means what? This is the half period, when we have got a limit cycle of the form this one, τ means this is the half period. So, when you make measurement due to the presence of measurement noise, there will be measurement error. We may not be able to accurately measure τ . So, suppose instead of measuring the correct value τ is equal to 10 by measure τ by 10.05 or 10.1; then we have got the measurement error.

This will lead to the standard deviation in τ , and that results in the standard deviation deviating from the actual value or the accurate value. So, how much inaccuracy there is in the estimation of the parametric model T_1 , can be quantified using this expression. So, this is how the estimation errors are quantified using the statistical measure standard deviation.

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$$\sigma_{T_1} = \sqrt{\left(\frac{T_1 \sigma_\tau}{\tau}\right)^2 + \left(\frac{2KhT_1^2 \sigma_{A_p}}{\tau(K^2h^2 - A_p^2)}\right)^2 + \left(\frac{2A_phT_1^2 \sigma_K}{\tau(K^2h^2 - A_p^2)}\right)^2}$$

Similarly, let us go to the other parameters. So, this is the final expression that we have got, where this will be T_1 square, and this will be τ . I have made some mistake here. So, now it is correct, then this is what already we have derived.

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$$\theta = \mp T_1 \cdot \ln\left(\frac{K_h \mp A_p}{K_h}\right) = \mp T_1 \cdot \ln x$$

where $x = \frac{K_h \mp A_p}{K_h}$

$$\frac{\partial \theta}{\partial T_1} = \mp \cdot \ln x = \frac{\theta}{\mp T_1} \quad \text{--- (1)}$$

$$\frac{\partial \theta}{\partial A_p} = \left(\frac{\partial \theta}{\partial x}\right) \cdot \frac{\partial x}{\partial A_p} = \mp T_1 \cdot \frac{1}{x} \times \frac{\partial}{\partial A_p} \left(\frac{K_h \mp A_p}{K_h}\right)$$

$$= \mp T_1 \times \frac{K_h}{K_h \mp A_p} \times \frac{K_h(\mp 1) - (K_h \mp A_p) \times 0}{K_h^2}$$

$$= \frac{T_1}{K_h \mp A_p} \quad \text{--- (2)}$$

Similarly, allow me to derive the expressions for there of the other parameter associated with the first order plus dead time model. So, theta is given by minus plus T 1 times lon of K h minus plus A p divided by K h. Then, how can I get the partial differentiation now, for that take this as minus plus T 1 minus plus T 1 times lon x. Again, where x is given by now K h minus plus A p divided by K h. Then, to find the what are the parameters associated in this explicit expression for the time delay associated with the first order plus dead time model, we have got T 1, we have got K, and we have got A p. These are the three variables, there are going to affect the estimation error.

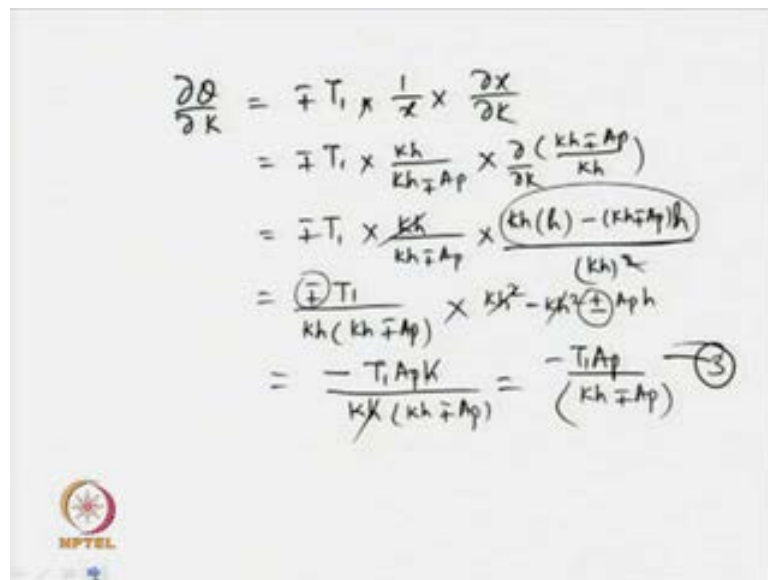
So, I need to find del theta upon del T 1. So, del theta upon del T 1 will be how much? This will be equal to minus plus lon x. So, this will be minus plus lon x, because you are differentiating with respect to T 1. So, lon x is how much theta by minus plus T 1. So, that way I can write this by theta by minus plus T 1. So, we got one partial differentiation of theta with respect to T 1, now another partial differentiation of theta with respect to the variable del A p can be obtained in the form of again del theta upon del x times del x upon del A p. So, please use this to find the partial differentiation.

Now del theta upon del x will be minus plus T 1 time; differentiation of lon x is x **sorry**, differentiation of lon x is 1 upon x only. So, giving us 1 upon x, this is for the first term. What about the second one - del x upon del A p will result in del x upon del A p will be del upon del A p times K h minus plus A p divided by K h. So, it will be minus plus T 1

times inverse of x will give you $K h$ divided by $K h$ minus plus $A p$. Now, the differentiation of this one will give you $K h$ times differentiation of this with respect to $A p$ will result **result** in minus plus 1 minus $K h$ minus plus $A p$ times differentiation of $K h$ will be 0. So, the second term is ultimately zero divided by $K h$ square.

So, when you simplify this $K h$ square power will go out minus plus minus plus multiplied that will give you plus. So, I will be left with, and expression of the form T_1 $K h$ in the numerator, and divided by T **sorry**, this **this** $K h$ again will cancel out. We have got $K h$ here. So, $K h$ will go out. So, in the numerator I will be left with T_1 only. So finally, $\frac{\partial \theta}{\partial A p}$ will be T_1 upon $K h$ minus plus $A p$. Now, let us try to find the partial differentiation of θ with respect to K similarly.

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$$\begin{aligned}
 \frac{\partial \theta}{\partial K} &= \mp T_1 \times \frac{1}{x} \times \frac{\partial x}{\partial K} \\
 &= \mp T_1 \times \frac{K h}{K h \mp A p} \times \frac{\partial \left(\frac{K h \mp A p}{K h} \right)}{\partial K} \\
 &= \mp T_1 \times \frac{K h}{K h \mp A p} \times \frac{(K h (h) - (K h \mp A p) h)}{(K h)^2} \\
 &= \frac{\mp T_1}{K h (K h \mp A p)} \times \frac{K h^2 - K h^2 \pm A p h}{(K h)^2} \\
 &= \frac{-T_1 A p K}{K K (K h \mp A p)} = \frac{-T_1 A p}{(K h \mp A p)} \quad \text{--- (3)}
 \end{aligned}$$

So, in this case $\frac{\partial \theta}{\partial K}$ will be equal to again minus plus T_1 time 1 upon x , like the earlier case it will be 1 upon x into $\frac{\partial x}{\partial K}$ is equal to minus plus T_1 into $K h$ by $K h$ minus plus $A p$ **minus plus A p** into $\frac{\partial}{\partial K}$ of $K h$ minus plus $A p$ divided by $K h$ upon $\frac{\partial}{\partial K}$. So, now, the differentiation is to be found with respect to K . So, simplification will give now, $K h$ upon $K h$ minus plus $A p$ - this differentiation how to find, we can find this like the earlier case $K h$ time differentiation with respect to K . So, it will leave as h **minus** then minus $K h$ minus plus $A p$ times, differentiation of $K h$ with respect to K , it will leave as h divided by $K h$ square.

So, I will cancel this giving us minus plus T 1 divided by K h times K h minus plus A p into the numerator of the last expression. So, how much it will be K h square minus K h square minus is there, therefore we will be left with plus minus A p h. So, you have got A p h finally, and due to this minus plus multiplication of minus plus with plus minus you will get minus here, leaving us in the numerator minus T 1 A p h divided by K h K h minus plus A p. So, further simplification can be obtained leaving us minus T 1 A p divided by K h minus plus A p. So this is how, the third partial differentiation is obtained for a finding the standard deviation of theta with respect to the measure quantities.

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$$\sigma_\theta = \sqrt{\left(\frac{\partial \theta}{\partial T_1}\right)^2 \cdot \tau_{T_1}^2 + \left(\frac{\partial \theta}{\partial A_p}\right)^2 \cdot \tau_{A_p}^2 + \left(\frac{\partial \theta}{\partial K}\right)^2 \cdot \tau_K^2}$$

τ_{T_1} and τ_{θ} for the FOPDT $G(s) = \frac{K e^{-\theta s}}{T_1 s + 1}$

τ, A_p, K θ, T_1

Quantify the estimation error in terms of the standard deviations.

$$\sigma_\theta = \sqrt{\left(\frac{\theta \sigma_{T_1}}{T_1}\right)^2 + \left(\frac{T_1 \sigma_{A_p}}{K h \mp A_p}\right)^2 + \left(\frac{A_p T_1 \sigma_K}{K(K h \mp A_p)}\right)^2}$$

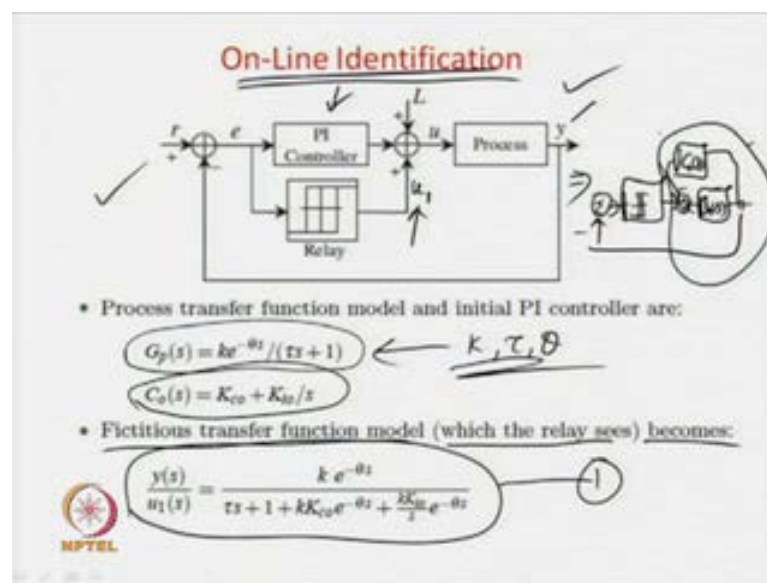
Now, I will write the final expression. So, sigma theta will be del theta upon del tau square plus sorry, no tau is there, T 1 is there; del T 1 square time sigma T 1 square plus del theta upon del A p square times sigma A p square plus del theta upon del K square sigma K square root. So, when you substitute the partial differentiations found earlier, we get the final expression as sigma theta is equal to square root of theta sigma T 1 upon T 1 square plus T 1 sigma A p divided by K h minus plus A p square plus A p T 1 sigma K upon K times K h minus plus A p square. Thus the standard deviations are found.

So, what benefit, we get from finding the standard deviations, basically we have been able to find sigma T 1, and sigma theta for the first order plus dead time model given by G(s) is equal to K e to the power minus theta s upon T 1 plus minus 1. So, the when there are measurement errors errors in the measurement of half period tau, the peak amplitude

A p, and the steady state gain K. Then the estimated parameters will be subjected to standard deviations of σ_{T1} , and σ_{θ} . This is how, it is possible to quantify the, **quantify the** measurement errors or quantify the estimation error, I would like to say estimation error in terms of the standard deviations.

So this is how, one can quantify the estimation errors associated with the measurement errors particularly or with respect to the measurement errors - the errors in estimation of K θ , and T 1 and particularly θ , and T 1 can be evaluated.

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Next, will go to the on-line identification technique, because the lecture is on review of the time domain based identification techniques. So, in the on-line identification scheme, we have used frequency domain analysis earlier, but not necessarily one has to go for frequency domain analysis, although for ease in analysis of the relay control system. The describing **describing** function based frequency domain analysis has been used earlier. In today's lecture, we will see how time domain based analysis can be extended for on-line identification of processes. Now, the on-line identification scheme with the help of a relay with hysteresis **relay with hysteresis** will be described very briefly. So, this is an on-line identification scheme, because the controller remains in operation throughout the operation of the process within during identification of the process. Therefore, this scheme is known as the on-line identification scheme, and we have **have** lot of advantages compare to the offline identification scheme, we have described earlier.

Now, let the process dynamics be described by a transfer function of the form $G_p(s)$ is equal to $K e^{-\theta s} / (\tau s + 1)$. So, please do not confuse, now the τ here represents the time constant of the process, **time constant of the process**, not the measurement parameter. Similarly, the PI controller that is employed in this on-line scheme has the form $c_0(s)$ is equal to $K_c + K_i / s$. Why the subscript o is there, that is for initial value when you are conducting some relay test or experiment; and after relay test and experiment, then the c or the controller will be $c(s)$, I believe you have follow. So, at the time of relay test, the controller dynamics is given by K_c , and K_i parameters with the help of K_c and K_i parameters.

Now, if you draw the equivalent circuit **circuit** diagram of this block diagram, then what relay sees basically. So, the relay will be subjected to... This is a relay with hysteresis, then you will have the process $G(s)$ negative feedback, and you have got the controller $c_0(s)$ present here. So, the relay sees basically a **a** dynamics of this form. So, fictitious transfer function model, which the relay sees becomes $y(s)$ upon $u_1(s)$, where is $u_1(s)$ - $u_1(s)$ is here. Then the transfer function between y and u_1 can be expressed in the form of $K e^{-\theta s} / (\tau s + 1) + k K_c e^{-\theta s} / (\tau s + 1) + K_i / s$.

So, what benefit you are getting from this fictitious transfer function model, this helps in the identification of the system in time domain. In place of using the frequency domain, I can use the state space analysis for identification of on-line identification of the system. How the state space model of this fictitious transfer function model can be found.

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$$\frac{Y(s)}{U(s)} = \frac{k e^{-\theta s}}{\tau s + 1 + k k_c e^{-\theta s} + \frac{k k_i}{s} e^{-\theta s}}$$

$$\tau \dot{y}(t) + y(t) + k k_c y(t - \theta) + \int k k_i y(t - \theta) dt = k u(t - \theta)$$

Let $x(t) = y(t)$

$$\tau \dot{x}(t) + x(t) + k k_c x(t - \theta) + \int k k_i x(t - \theta) dt = k u(t - \theta)$$

$$\lambda = -\frac{1}{\tau}$$

$$\dot{x}(t) = \lambda x(t) + \lambda k k_c x(t - \theta) + \lambda k k_i \int x(t - \theta) dt - k \lambda u(t - \theta)$$

$$y(t) = x(t)$$

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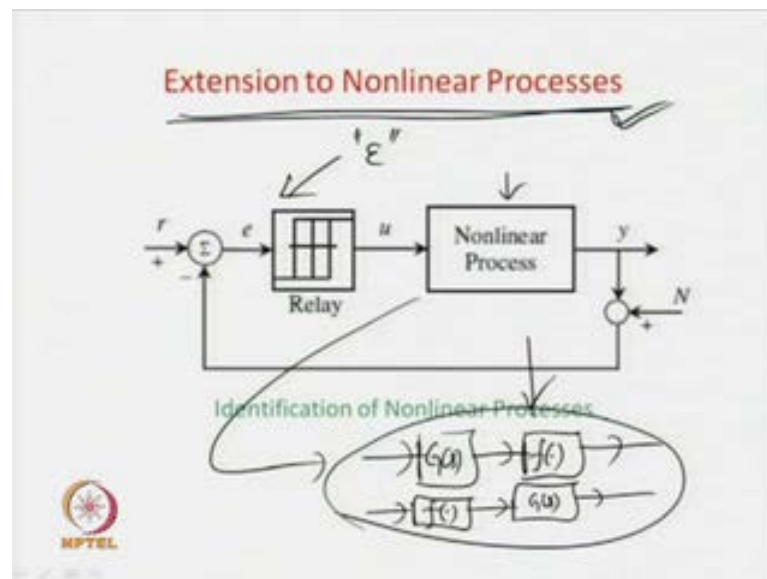
So, the state space model or state space equations can be obtained as given $y(s)$ upon $u(s)$ is $\frac{k e^{-\theta s}}{\tau s + 1 + k k_c e^{-\theta s} + \frac{k k_i}{s} e^{-\theta s}}$. Now multiply, and write the expression in the form of the differential equation giving us $\tau \dot{y}(t) + y(t) + k k_c y(t - \theta) + \int k k_i y(t - \theta) dt = k u(t - \theta)$. So, this is how, when you cross multiplied these terms, and take the inverse laplace transform.

We get the differential equation of this form. So, let $x(t)$ the state variable be $y(t)$ resulting in an expression of the form $\tau \dot{x}(t) + x(t) + k k_c x(t - \theta) + \int k k_i x(t - \theta) dt = k u(t - \theta)$. Implies $\dot{x}(t)$. So, let me take introduce one variable, suppose λ is equal to $-1/\tau$; in that case $\dot{x}(t)$ can outright be written in the form of $\lambda x(t)$, then these terms will go to the right half. So, that way you will have $\lambda k k_c x(t - \theta) + \lambda k k_i \int x(t - \theta) dt - k \lambda u(t - \theta)$. So, this is the state equation, we are getting from that fictitious transfer function model.

And the output equation is given by $y(t) = x(t)$. Now, using the state and output equations, and the limit cycle waveform, then now it is possible to find analytical expressions for the zero crossings, and for the peak amplitude, and how to find the

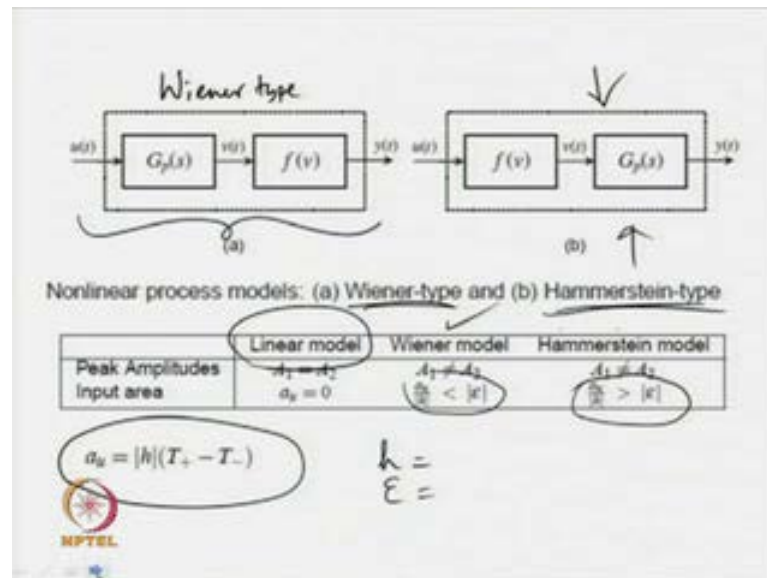
expressions for zero crossings, and peak amplitude have been described in our earlier lectures. Only, you need to make use of this state equation, and this output equation in place of the earlier state, and output equations. This is how from the measurement of the peak amplitude, and half period, and so on, it will be possible to estimate the parameters of this transfer function model; and the parameters of this transfer function models are K τ and θ . So, this is how I can make use of time domain analysis for on-line identification of systems.

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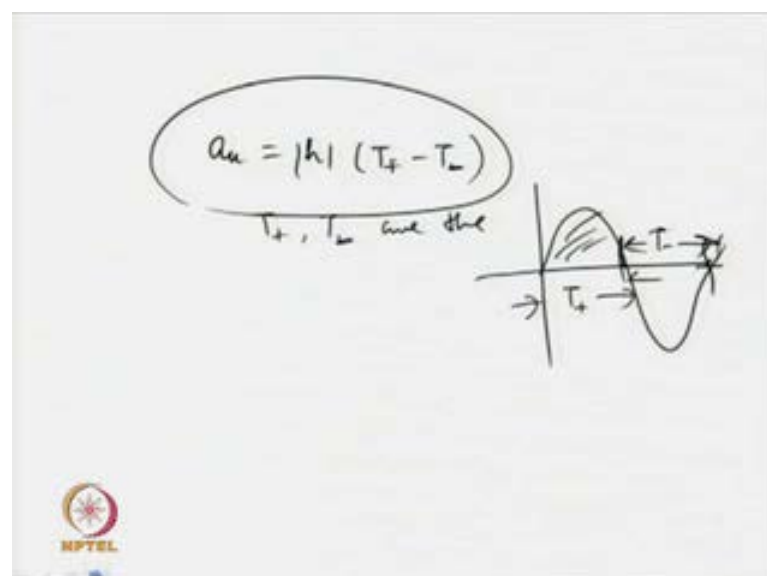
Next, we shall go to the extension of the time domain analysis to non-linear processes. So, how can we make use of the time domain analysis, state space based time domain analysis for a estimation of dynamics of non-linear processes. So far, we have discussed about or we have studied about the identification of linear processes. Now, the time domain analysis can also be used to identify non-linear dynamics. Now, the relay is having some hysteresis, you look at the relay. So, let the hysteresis of the relay be given by epsilon, then it is possible to conduct relay test like this, and the non-linear process dynamics can be represented by a linear dynamics given by $G(s)$ along with some non-linear function. The non-linear function can have static nonlinearity, can have dynamic nonlinearity or now the non-linear process dynamics can be given in two form - the nonlinearity can appear first, and then the process dynamics or dynamic model can be given later. So, these are the two ways, one can get the block diagram representation for the non-linear process or the models for the non-linear processes.

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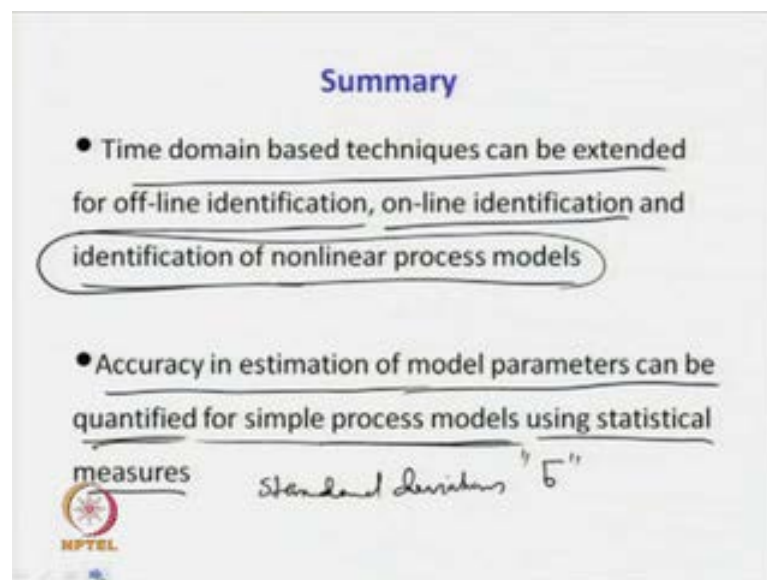
Now, how can you estimate, how can you find a certain that you will go for identification of linear system or non-linear system. Now, as I have already described when the non-linear system dynamics is given by this model, then we get some Wiener type model - this is called Wiener type non-linear process model, for non-linear dynamics associated with a system. And the second type of representation of non-linear dynamics in the form of block diagram is known as the Hammerstein type. Now, relay test is conducted with the relay having hysteresis, and one parameter a_u is measured; what is a_u ?

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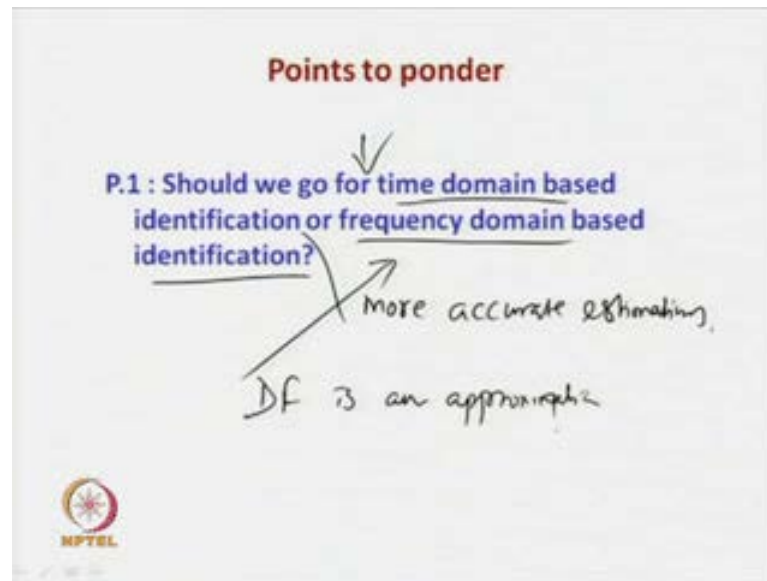
Now u is equal to a u is equal to h times T plus minus T minus. So, what are T plus and T minus - T plus and T minus are the width of the limit cycle output signal for positive output you get this as T plus, and for the negative output the the time from here to here. The next zero crossing is shown by T minus. So, using this information when u is equal to 0, then you can go for identification of a linear process model. When u upon h what is h ? h is the relay setting, and ϵ is the hysteresis $hysteresis$ width with associated with the relay. So, when this is satisfied go for a identification of an Wiener type model, and when this is satisfied go for identification of an of a Hammerstein type model. So, this is how non-linear process, are identified.

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Now, let me summarize the lecture now, time domain based techniques can be extended for offline identification can be used for on-line identification, and also can be used for identification of non-linear process models. This is what to we have not studied in any lectures so far, earlier now further accuracy in estimation of model parameters can be quantified for simple process models. Like first order plus dead time transfer function model using some statistical measures, such as standard deviation. So, standard deviations or the sigma's.

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And lastly any point to ponder: should we go for time domain based identification or frequency domain based identification. So, we have studied two type of identifications during our last lectures, where we have seen that one can make use of time **time** domain based identifications, and frequency domain based identification. Out of the two although frequency domain based identification is quite easy or easier compared to the time domain based one, time domain based identification results in more accurate estimations.

More accurate estimations of the transfer function model parameters. Whereas, frequency domain based identification **identification** techniques are subjected to identification errors or estimation errors. And frequency domain based identifications using describing function are subjected to erroneous results, because the describing function itself is an approximation. That is all, in this lecture. Thanks.