

## **CH5230: System Identification**

### **One step and multi-step**

### **ahead prediction 2**

So let's take a moving average process. All right. So I have a moving average process and given now  $v$  evolves in particular way. So we are jumping from the world of random variables to the world of random signals. You should observe that now given that this is an MA1 process. And I want to

construct a one-step ahead prediction. What is the one-step ahead prediction? Given all the information up to  $k$  I want to estimate, what happens at  $k$  plus 1? I want to guess what happens at  $k$  plus 1? That is one-step ahead prediction. So given that  $v_k$ , sorry, evolves this way. What would be the one-step ahead prediction? Well,  $\hat{v}$  of  $k$  plus 1 given  $k$ . Given  $k$  meaning not just that  $k$  given information up to  $k$ . Is conditional expectation itself. What do you mean information here? How do you understand my information?

(Refer Slide Time: 01:13)

One-step and multi-step ahead predictions

### Example 1: Prediction for MA(1) process

Consider an MA(1) process:  $v[k] = e[k] + c_1 e[k - 1]$

- ▶ The one-step ahead predictor is

$$\hat{v}[k + 1|k] = E(v[k + 1]|k) = c_1 e[k|k] \quad (3)$$

- ▶ The quantity  $e[k|k]$  is not known, but has to be estimated using the observations
- ▶ How does one obtain  $e[k|k]$ ?

$$e[k] = v[k] - c_1 e[k - 1] = v[k] - c_1 v[k - 1] + c_1^2 e[k - 2] = v[k] + \sum_{n=1}^{\infty} (-c_1)^n v[k - n]$$

For the infinite sum on the RHS to converge,  $|c_1| < 1$ .

Arun K. Tangirala, IIT Madras      System Identification      March 17, 2017      10

Simply observations of  $v$ , there is no mystery about anything. All of this is pretty straightforward when I say information, I'm given observations of  $v$ . I am given  $v$  values up to  $k$ . Of course, it's a single realisation, but yes, I'm given up to  $k$ . So which means I'm given  $v_k$ ,  $v_k$  minus 1,  $v_k$  minus 2, each of this is a random variable. We study the result between, for univariate case that is  $y$  is univariate  $x$  is single random variable. Now,  $v_k$  plus 1 you can think of as  $y$ . If you apply the previous result what would be  $x$ ? With respect to whatever we are study until now, I can say  $v_k$  plus 1 is  $y$ , I want to predict  $v_k$  plus 1. What is  $x$ ? Simply  $v_k$ . We just know said we are giving the information up to  $k$ . So why are you again going back to only  $k$ ? All the random variables  $x$  is now not a single random variable.  $x$  is now going to be from minus infinity, whatever observations of  $v$  up to  $k$ , which means  $v_k$ ,  $v_k$  minus 1,  $v_k$  minus 2, up to  $v_8$  minus infinity. But the result still holds. So we don't apply that conditional expectation and say that the best prediction Of  $v$  at  $k$  plus 1 in the minimum meansquare errors sense will not keep saying that  $e_k$  is conditional expectation of  $v_k$  plus 1 given  $k$ .

Now, you apply that to the given model, right. So you have  $v_k$  equals  $e_k$  plus  $c_1 e_k$  minus 1. So when I take the conditional expectation of the right hand side, because I want to construct this optimal prediction. I have expectation of  $e_k$  plus  $c_1 e_k$  minus 1 given  $k$ , information up to  $k$ . What would this, sorry. What should we hear? Is that a confusion? Some of you are very silent today. It's a conditional expectation of  $v_k$  plus 1. What is  $v_k$  plus 1 as per the model? That's all. So  $e_k$  plus 1 plus  $c_1 e_k$ . Now what can you say about these two terms here. I have expectation of  $e_k$  plus 1 given  $k$ . What is that? That zero, very good. Because there is nothing in  $k$  or  $k$  minus 1 or anything in the past, which will improve the prediction of  $e_k$  plus 1 beyond its average. What about a second term? Now there was a question about this term about this expression here, after the end of the class yesterday,  $y$  is not expectation of  $e_k$  given  $k$  0. First of all do you believe it should be 0? What do you think? Do you think it should be 0? Nithya, what do you think? What do you think sir?

[04:54 inaudible]

Sorry.

We know information about [04:58 inaudible].

The information is it in the form of  $e_k$  or  $v_k$ ? It's a good point. Do we have  $v_k$  or  $e_k$ ?

$V_k$ .

$V_k$ . So we do have the information but in an indirect fashion, correct. So that's the key there that I do have the information about  $e_k$  now. Whereas in the first term I don't have anything in the past  $e_{k-1}$ , whereas expectation of  $e_k$  given  $k$  is, forget about  $v_{k-1}$ ,  $v_{k-2}$ , because that won't have any effects of  $e_k$ ,  $v_k$  will have something about  $e_k$ , because after all as for the model  $v_k$  contains partly the  $e_k$ . So which means expectation of  $e_k$  given  $k$ , what is it now, is it a prediction? We use some. We introduce some terminology earlier, right? What is it? It's a filtered; it's a filtered version of  $e_k$ . Now we are looking at filtering. We are not looking at prediction. Prediction always involves at least one-step in future. So the second component is a filtered version. So from  $v_k$  somehow I have to apply. Like your coffee filter or whatever. I put it through a filter only  $e_k$  should come out. See the simple example that I give is  $e_k$  is like a shockwave, like an earthquake,  $e_k$  earthquake you can remember.

Now, I can't predict an earthquake. How many of earthquakes have occurred in history until now, still my prediction of earthquake is kind of mean whatever average. Now if I want to assess how intense that earthquake was. That is filtering given the effect of the earthquake. After the earthquake has occurred, I want to estimate or at the time the earthquake is occurring, I can guess, but I can't predict, correct. So what you are observing is  $v_k$ . You're shaking of the building or whatever structure that you are looking at that is your  $v_k$ . That is what you are observing. You are not observing the earthquake. You are observing the effect of the earthquake that is  $v_k$ . Based on that you can assess how intense  $e_k$  would be. But you couldn't predict the earthquake. That is how white noise is, right. So you can't say since I couldn't predict whatever I'm observing my prediction of earth, my estimate of earthquake is 0. That doesn't make sense. The effect of earthquake is visible right in front of you.  $V$  is for visible. You can think of it that way. So, expectation of  $e_k$  given  $k$  is exactly that.

It cannot be 0. Now, how do they recover this that's extremely important? Another way to recover this is go back to the generating equation. What do we mean by recovering? I want estimate  $e_k$  given  $v_k$ 's. So what you do is you rewrite  $e_k$  in terms of  $v_k$ 's. You see that all I have done is recursive substitution for  $e_k$ 's. So what does it this equation tell me, if I want to recover  $e_k$  accurately what do I need? I need observations all the way up to minus infinity not just  $v_k$  alone. Okay. I thought I could just use  $v_k$ , but it turns out to correctly recover  $e_k$  I need all the observations in the past. Now that sounds a bit awkward, because the observations in the past actually did not have any information about  $e_k$  as such however, if you look at the equation  $e_k$  says it is  $v_{k-1} - c_1 e_{k-1}$ . What is  $c_1 e_{k-1}$ ? It is the best prediction of  $v_k$ , if you are standing at  $k-1$ , if you are given information up to  $k-1$ . So you can think of it this way you can say  $e_k$ , instead of asking in this way you say  $e_k$  is nothing but  $v_{k-1}$  minus whatever prediction you would have made of  $v_k$ . Standing at  $k-1$ , whatever you would have predicted of  $v_k$ , correct. This is the trick that is used. Otherwise how will you ever make a prediction at all for this? Apart from that the most important thing that you should observe is, now  $e_k$  has been obtained, is a non-linear function of your model parameters  $c_1$ . Do you see that?  $e_k$  is a non-linear function of the model parameters  $c_1$ . Which means my  $\hat{v}_{k+1}$  given  $k$  is going to be a non-linear function of the parameters. And that's always the case with moving average. So  $\hat{v}_k$  of  $k$

plus 1 is  $c_1$  times an estimate of  $e_k$  obtained from information up to  $k$ , but that estimate in turn requires the model itself. And in the net effect is that the predictor isn't non-linear function of the parameters  $c_1$ . And that is why estimating MA models is not so easy. Compared to autoregressive models, which will give you linear predictors. Now another point that you should observe is if you go back to this  $e_k$  here, expression for  $e_k$ . If I want an estimate of  $e_k$  and it tells me that there is an infinite summation here that is involved. I know  $e_k$  is stationary which means its amplitude should be bounded. That's the foremost thing. Now, what you are actually implying here is this submission should converge. When will it converge? When  $|c_1| < 1$ . Now that's a new restriction I'm seeing on moving average model, right. Earlier we never restricted. We never imposed any restrictions on moving average model at all. We simply said that moving average models are stationary as long as the coefficients are bounded. AR models on the other hand have not necessarily stationary unless the poles are within the unit circle. But now we are saying that there is an additional restriction on the moving average model, which is that it should be invertible. So what you're essentially doing is, in order to complete the prediction here. We are saying there is an  $e$  that is generating  $v$ . There is an  $e$  that is generating  $v$ . And now in order to predict  $v$ , I need to recover  $e$ . So therefore I need some other filter which will take in all the information of  $v_k$ . The  $v_k$ ,  $v_{k-1}$  everything and it'll produce this  $e_k$ . So it is as if you are doing an inversion here. You're the forward problem is  $e_k$  generating  $v_k$ . The inverse problem is given  $v$  recovery  $e_k$ . This inverse now in some sense should be stable. If this inverse is not stable, my predictions of  $e_k$  will go haywire.  $e_k$  as such as white noise, but my estimates of  $e_k$  are going to go haywire. Therefore moving average models are in general any time series model, if you want to use it in prediction, the inverse of the model should be stable. In some sense you can say here  $h$  of  $q$  inverse. For this MA1 is  $1 + c_1 q$  inverse. What is the inverse although there is a lot of formalization that is required I'm cutting short all that formalization and I'm straight away writing the inverse. You should not think it is so obvious that the inverse is simply  $1 / (1 + c_1 q)$  inverse. Because what is this rule of inverse? The rule of inverse is to connect  $v$  to  $e$ . And that requires some formalization to prove that the inverse is  $1 / (1 + c_1 q)$  inverse. Anyway, so cutting short that formalization simply  $h$  inverse is the inverse of  $h$ . What are we saying now? To obtain a stable estimate of  $e$ , it is like any other random process now,  $v$  is some random process generating  $e$ , correct. And what kind of a transfer function is this? This is MA. This is?

AR.

AR. We know already if AR transfer functions have to produce stationary signals. Then the pole should be within the unit circle. Which means we are saying that the poles of  $h$  inverse should be within the unit circle, which means the zeroes of  $h$  should be within the unit circle? And we say any noise model is invertible, if the zeros are within the unit circle. Any noise model is stationary. If the poles are within the unit circle, which means now we have an additional requirement that the noise model should not only be stationary but also invertible. Inversion is becoming necessary because of one prime reason, what is that? Because I do not know the signal input that is generating  $v$ . If I know the input I don't have to worry at all, right. I can straightaway use this equation. I can straightaway use  $e_k$ , I don't even have to say  $e_k$  given  $k$ , I would know  $e_k$ . It is this white noise that is not known to me that is endogenous to  $v$  that I have to estimate is forcing me to seek this inverse model. And that is why we have an additional requirement. On the G there is no requirement. By the way, why are we studying predictions of random processes, because that's more challenging, if you go back to the expression that we had here. If I were to predict  $y$  using  $u$ , I think I'll be given  $G$ , I'll be given  $H$  and I'm given  $u$ . And the measurements up to  $k-1$  or up to  $k$  depending on what I have. What is a big

challenge in this? The big challenge is not in the first term, because the first time is deterministic. It is the second term that is going to present challenges and that's why we're discussing that. Okay.  
(Refer Slide Time: 15:39)

## Predictions

One of the primary uses of a model is **prediction**. We first learn how to build a predictor given an LTI model,

$$y[k] = G(q^{-1})u[k] + v[k] = G(q^{-1})u[k] + H(q^{-1})e[k] \quad (1)$$

- ▶ Clearly, prediction requires knowledge of the past/present in addition to the model
- ▶ The “quality” (accuracy, precision) of the prediction clearly depends on the quality of the model, prediction horizon (how far ahead we wish to predict) and uncertainty levels (variance of  $v[k]$ )
- ▶ One of the foremost uses of a prediction expression is in the construction of a **prediction error**, which can be then used in estimating the model

So now let's formalize this very quickly. Whatever we have observed for AR models it's pretty straightforward. AR models say there is nothing to worry about as long as your model is stationary. See the AR model also there is an inverse involved, but we have already said that AR model is stationary. You have already required that. If it is stationary, it's going to be invertible as well. That means the predictions will be stable. So look at this, I have an AR1 process and I have this prediction written up very easy, because the AR model is purely in terms of observations, it makes it. It's a pretty sweet predictor. No, it's like very, it's like a laddu. Do you have  $v_k$  equals minus  $d_1 v_{k-1}$  plus  $e_k$ . All you have to do is apply the conditional expectation. The first term is given to me. The second term what is a prediction? Zero. So the predictor is simply minus  $d_1 v_k$ . I don't have to recover anything  $v_k$  is given to me. And since  $d_1$  is going to guarantee that I'll get stable predictions. There is no issue at all. So that is AR models are preferred. That is why you have a different routine for AR model estimation, because you will minimize, you will write quotes or algorithms that minimize the prediction error. And if we use Least Squares Algorithm the predictor is linear in unknowns. Here we are assuming model is given in making a prediction, but in the estimation problem, model estimation problem. I'm given data and I'm supposed to estimate  $d_1$ . So this is always the case with AR models, if the predictor if you can imagine if it was AR2 then you would have minus  $d_1 v_{k-1}$ . Sorry, minus  $d_1 v_k$  minus  $d_2 v_{k-1}$ .

(Refer Slide Time: 17:32)

## Example 2: Prediction of an AR(1) process

Consider now an AR(1) process:  $v[k] = -d_1 v[k-1] + e[k]$

- ▶ The one-step ahead prediction of  $v[k]$  is then,

$$\hat{v}[k+1|k] = E(v[k+1]|k) = -d_1 v[k] + E(e[k+1]|k) = -d_1 v[k]$$

- ▶ Notice that the **predictor is linear in the parameter!**
  - ▶ This is **always the case with auto-regressive models.**
  - ▶ Minimization of squared prediction errors with linear predictors provide unique solutions
  - ▶ Thus, AR models hold an edge over MA models in identification.

Okay. So let's very quickly formalize this, before we conclude the class. So  $v_k$  in general for a linear random process we know  $h[0]$  is 1, this is a standard linear random process. Let us write this  $v_k$  in two parts. Very simple now we want to graduate from AR1 and MA1 to a general ARMA process or a general linear random process. Why are we doing this? Because when I want to construct the one step ahead prediction, let us say I am given the formation up to  $k-1$  and I want to predict  $k$ , I can straightaway see that the first term here won't participate, because expectation of  $e_k$  given information up to  $k-1$  is going to be 0. So I have separated out the unpredictable component of  $v_k$ , whatever is predictable is the summation. But of course, I have to apply an inverse noise model to recovery  $e$ , correct. That we have already seen.

(Refer Slide Time: 18:33)

## General expression for prediction

Consider the causal impulse response model for  $v[k]$

$$v[k] = \sum_{n=0}^{\infty} h[n] e[k-n] \quad \text{with} \quad h[0] = 1, \quad H(q^{-1}) = \sum_{n=0}^{\infty} h[n] q^{-n} \quad (4)$$

- ▶ Then, for one-step ahead prediction, we re-write the previous expression,

$$v[k] = e[k] + \sum_{n=1}^{\infty} h[n] e[k-n]$$

so that the second term on the RHS is (theoretically) known at  $k-1$

- ▶ The best prediction of the first term is zero given any amount of past

So let's write this now the second term is the prediction  $\hat{v}$  of  $k$  given  $k-1$ , I have switched over from  $\hat{v}$  of  $k+1$  given  $k$  to  $\hat{v}$  of  $k$  given  $k-1$  that doesn't matter. It is a dummy variable here,  $k$  is just a dummy variable. So the prediction of  $k$  given  $k-1$  is simply the second term and notice that the second term is nothing, I can rewrite the summation by adding and

subtracting  $e_k$ . All I have done is into this term, this submission begins from 1, correct. By adding  $e_k$  and I know that already  $h$  of 0 is 1. I recognize what is this first term here. The first term is simply  $h$  of  $q$  inverse  $e_k$ , correct. So I can write  $\hat{v}$  of  $k$  given  $k$  minus 1 as  $h$  of  $q$  inverse minus 1 operating on  $e_k$ . Is it clear? Now what is the  $e_k$ ? Do I know  $e_k$ ? I don't know  $e_k$ . But  $e_k$ 's  $h$  inverse  $v$ . Look at this blog diagram.

(Refer Slide Time: 19:43)

One-step and multi-step ahead predictions

## One-step ahead prediction

The best one-step ahead prediction is

$$\hat{v}[k|k-1] = \sum_{n=1}^{\infty} h[n]e[k-n] = \sum_{n=0}^{\infty} h[n]q^{-n}e[k-n] - e[k]$$

$$= (H(q^{-1}) - 1)e[k]$$

- ▶ The quantities  $e[k-1], e[k-2], \dots$  are unknown, but their effects are "felt" in  $v[k-1], v[k-2], \dots$
- ▶ It is a good practice to re-write the predictions in terms of known quantities.

Arun K. Tangirala, IIT Madras
System Identification
March 17, 2017
14

Ultimately my prediction or prediction expression should be in terms of known quantities. I do not know  $e_k$ . So somehow I have to rewrite this in terms of  $v_k$ 's that is a goal. So I'm going to replace  $e_k$  with  $h$  inverse  $v$ . As I said there is a lot of formalization let's not worry about it. So  $e_k$  is  $h$  inverse  $v$ , when a substitute for  $e_k$  as  $h$  inverse  $v$ , what do I get? How is  $h$  inverse defined?  $H$  inverse is defined such that when  $h$  operates on  $h$  inverse or  $h$  inverse operates on  $h$  you will get 1, like your matrix inverse. So  $h$  of  $q$  what we have is  $\hat{v}$  of  $k$  given  $k$  minus 1, is  $h$  of  $q$  inverse minus 1, operating on  $e_k$ , which is  $h$  inverse  $v_k$ . So what is  $h$  operating on  $h$  inverse? That is 1. So I have here 1 minus  $h$  inverse  $q$  operating on  $v_k$ . Now this is more like it because now on the right hand side I have known quantities  $v_k$ . However doesn't it sound weird that I'm predicting at  $k$  and on the right hand side I have  $v_k$ , it looks a bit awkward. What I'm intending to do is I'm intending to predict  $v_k$ . But all you're saying on the right hand side there is  $v_k$  already. But truly is  $v_k$  required on the right hand side, what do you think?

(Refer Slide Time: 21:23)

## One-step ahead prediction

... contd.

The following result is useful in the context.

$$e[k] = \sum_{n=0}^{\infty} \tilde{h}[n]v[k-n]$$

then  $\{\tilde{h}[n]\}$  are the IR coefficients of  $H^{-1}(z)$ , implying we may be able to write

$$e[k] = H^{-1}(q)v[k]$$

$$\text{Thus, } \hat{v}[k|k-1] = (1 - H^{-1}(q))v[k] \quad (5)$$

- The RHS of the expression may look a bit awkward, but by recalling that the leading coefficient of the noise model is unity.

Remember the first coefficient of H is one. What will be the first quotient of h inverse? When I do a long division one, which means when it expanded h inverse in the polynomial form, infinitely long polynomial are finitely one. The first quotient is going to be one, which means that's going to be cancelled out. What about the remaining terms? They'll begin with q inverse, q inverse square and so on. So which means truly although I have written symbolically that vk is required here. Strictly speaking, I do not need vk. So when I expand this term, I will have only vk minus 1, vk minus 2 and so on. So you can straightaway see for moving average. Let's apply this formula here. If h is 1 plus c1 or let us say, I have AR it's easier to verify. What is the transfer function of AR, AR1, 1 over 1 plus d1 q inverse. What will be h inverse? One plus d1 q inverse, therefore when I work this out for AR1, I am left with minus d1 q inverse, which means I am left with minus d1 vk minus 1, which is what we derive. So we're going to put this result together and derive the one-step ahead prediction. The one-step ahead prediction, therefore of y, the first time is deterministic. I don't have to worry about it. I'm given everything. G of q inverse uk. It's the second term that we have worked upon and we have gotten this result, 1 minus H inverse vk, but I mean given vk, now in SysID? In time series I am given vk, in SysID do I know v? Yes or no?

(Refer Slide Time: 23:07)

## One-step ahead predictor

... contd.

Substituting (5) in the prediction for  $y[k]$ , we have

$$\hat{y}[k|k-1] = G(q^{-1})u[k] + (1 - H^{-1}(q))v[k] \quad (6)$$

The quantity  $v[k]$  is unknown, but can be recovered from  $y[k]$  as,

$$v[k] = y[k] - G(q^{-1})u[k] \quad (7)$$



What do I know? I know input and output only I don't know  $v$ . What is  $v$ ?  $y$  minus  $G$   $u$ . So I'm going to substitute that. Once I do that I get this beautiful result for one-step ahead predictor.

(Refer Slide Time: 23:23)

One-step and multi-step ahead predictions

## One-step ahead predictor ... contd.

Combining (6) and (7) we have,

**One-step ahead predictor**

The one-step ahead prediction and the prediction error of the LTI deterministic-plus-stochastic system:

$$y[k] = G(q^{-1})u[k] + v[k] = G(q^{-1})u[k] + H(q^{-1})e[k]$$

is given by

$$\hat{y}[k|k-1] = H^{-1}(q)G(q^{-1})u[k] + (1 - H^{-1}(q))y[k] \quad (8a)$$

$$\varepsilon[k|k-1] = y[k] - \hat{y}[k|k-1] = H^{-1}(q)(y[k] - G(q^{-1})u[k]) \quad (8b)$$

Arun K. Tangirala, IIT Madras
System Identification
March 17, 2017
17

So I'm going to substitute 7 in 6. Because what is a goal? I want to write a predictor in terms of known quantities. What are the knowns? The model and the observations,  $v_k$  is not known to me. So I am going to replace  $v_k$  with  $y - G$  and  $u$ , because they are known to me. Once I do that I get this result. So in place of  $v_k$ , I'm going to replace with this expression here in equation 7. And once they complete that I get this expression for  $\hat{y}$  in equation 8a. So I have  $\hat{y}[k|k-1]$  as  $H^{-1}(q)G$  plus  $(1 - H^{-1}(q))y$ . Again here it may seem awkward that I need  $y$  but I don't need  $y$  to predict  $y$  because I already know  $(1 - H^{-1}(q))y$ . Again here it may seem awkward that I need  $y_k$ , but I don't need  $y_k$  to predict  $y_k$ , because I already know  $(1 - H^{-1}(q))y$  will not have the first coefficient. On the right hand side I will have  $G$   $u$  and all the past wise. So let me close by saying here. If I were to apply this result. So what this result tells me is, if I am given  $G$  and  $H$  I can straightaway write a predictor, which is what I promised yesterday that we will have an expression for one-step ahead prediction for a generic parametric model. So here I have  $\hat{y}[k|k-1]$ . What is  $G$  for FIR? FIR for  $G$  is  $B$ . And what is  $H$ ? One. Correct. So when  $H$  is 1  $H^{-1}$  is also 1, which means the second term doesn't participate and in an FIR the prediction is simply  $B$  of  $q^{-1}$   $u_k$  that means only inputs are involved in prediction of  $y$ , naturally because the FIR model expresses  $y$  purely as inputs.

(Refer Slide Time: 25:17)

## Predictors for parametric models

Using the general expression for one-step ahead predictions, we can develop the predictors (and the errors) for different parametric models

FIR	$\hat{y}[k k-1] = B(q^{-1})u[k]$ since $(H(q^{-1}) = 1)$
ARX	$\hat{y}[k k-1] = B(q^{-1})u[k] + (1 - A(q^{-1}))y[k]$
ARMAX	$\hat{y}[k k-1] = \frac{B(q^{-1})}{C(q^{-1})}u[k] + \left(1 - \frac{A(q^{-1})}{C(q^{-1})}\right)y[k]$
OE	$\hat{y}[k k-1] = G(q^{-1})u[k]$

- ▶ The FIR model is both a non-parametric as well as a parametric model
- ▶ Both the OE and FIR model predictions do not involve any output measurements

Likewise for output error model also H is 1. But the difference is in the output error model I use G. Whereas in FIR model I only use the numerator part of the B, because that's how the FIR is. Whereas for ARX and ARMAX and so on. All the past measurements will come in. So what we'll do is when we meet next class we'll complete this discussion on infinite-step ahead prediction. We are talking about one-step ahead prediction. We'll talk about L-step ahead prediction and infinite-step ahead prediction and we'll notice a very beautiful result, which will tell us again something new about this model structures that we have studied. By the way we have studied IDpoly in MATLAB if you recall. Now you understand what those ABCDF and so on. Okay. So when we come back next week we'll complete this discussion. Thank you.