

**Dynamical Systems and Control**  
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**Lecture – 50**  
**Optimal Control - I**

Dear students. Welcome to the lecture on optimal control I. In our previous lectures, we have seen various aspects of control systems namely the control ability, observability, stability aspects.

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$\dot{x} = Ax + Bu$   
 $x(t_0) = x_0 \quad x(T) = x_1$   
 $u(t) = B^{-1}(t) \phi^T(t, t_0) W^{-1} [\phi(t_0, T) x_1 - x_0] \quad (1)$   
 $\phi(t_0, t)$  = state transition matrix  
 $W$  = Controllability Gramian matrix  
 $u(t)$  is another control which steers  $x(t)$  from  $x_0$  to  $x_1$  in  $[t_0, T]$   
 $J = \int_{t_0}^T \|u(t)\|^2 dt \leq \int_{t_0}^T \|v(t)\|^2 dt$   
 $J = \int_{t_0}^T \|v(t)\|^2 dt = \min_v J = \min_v \int_{t_0}^T \|v(t)\|^2 dt$   
 Optimal Control problem  
 $\dot{x} = f(x(t), v(t))$   
 such that the cost functional  
 $J = \int_{t_0}^T F(x(t), v(t)) dt$   
 is minimized, or optimized under suitable boundary conditions.

So mainly we have seen linear control system of the form  $dx/dt = Ax + Bu$  with initial condition  $x(t_0) = x_0$ ,  $x(T) = x_1$ . So in this case if the system is controllable, then we will be able to find a control  $u$  of  $t$  given by this expression  $B^{-1}(t) \phi^T(t, t_0) W^{-1} [\phi(t_0, T) x_1 - x_0]$ . So if the system is controllable, then this control  $u$  of  $t$  will be able to steer the system or steer the solution  $x$  of  $t$  from the initial condition  $x_0$  to the final condition  $x_1$  at time  $T$ .

If here the  $W$ , notation  $W$ , it is nothing but the controllability Gramian matrix which was described in the previous lectures. And if  $W$  is non-singular, the system is controllable, that is how we will be able to find this control like this. Apart from this particular control, there may be several other control functions which can perform the same type of work that is taking the system from the initial condition to the final condition.

So there may be several such controls and there may be several solutions for this control system. So if let us say  $V$  of  $t$  is another control which steers the system, steers  $x$  of  $t$  from  $x_0$  to the  $x_1$  in the interval  $t_0$  to  $T$ , then we have also proved that  $\int_{t_0}^T \text{norm of } u^2 dt$ , it is less than or equal to  $\int_{t_0}^T \text{norm of } V^2 dt$ . So in the sense that if you take any control which is steering that solution from  $x_0$  to  $x_1$ , the control given in this particular expression has the lowest value for this integral.

So if you call this  $J$  to be this expression, so  $J$ , the minimum of  $J$  which is equal to  $\int_{t_0}^T \text{norm of } V^2 dt$ , over all functions  $V$  all possible control functions  $V$ , if you find this minimum value, that will be equal to this  $J$  value, expression this thing. Or in another words we can say that the control given in this expression minimizes the functional  $J$  which is given in this expression.

The functional  $J$  is  $\int_{t_0}^T \text{norm of } V^2 dt$ . The minimum value of this functional is given by the control  $u$  of  $t$ . So now this is one particular case of an optimal control problem. So in general, the optimal control problem is given by, we consider a control system  $\dot{x} = f(x, u, t)$ . Let us say nonlinear control system is given by this expression which, such that the cost function between some 2 times of the expression  $x$  of  $t$   $u$  of  $t dt$  is minimized.

So the optimal control problem is as follows. We have a control system  $\dot{x} = f(x, u, t)$  such that the cost functional  $J$  is minimized or optimized, minimized or maximized according to the statement of the problem under suitable boundary conditions. So in this lecture, we will see how to derive conditions or necessary conditions for finding the optimal control for a system, a linear system in this expression.

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Calculus of variations deals with finding the optimum (maximum or minimum) value of a functional.

The increment of the functional  $J$ , denoted by  $\Delta J$ , is defined as

$$\Delta J \triangleq J(x(t) + \delta x(t)) - J(x(t))$$

The diagram shows a coordinate system with a vertical axis and a horizontal axis. The horizontal axis has two points marked:  $t_0$  and  $T$ . Two curves are drawn above the axis, both starting at  $t_0$  and ending at  $T$ . The upper curve is labeled  $x(t) + \delta(x(t))$  and the lower curve is labeled  $x(t)$ . A bracket above the curves spans from  $t_0$  to  $T$  and is labeled  $J = \int_{t_0}^T F(x(t), \dot{x}(t)) dt$ .

So first let us see the preliminary results which will lead to the necessary conditions. So it is based on the calculus of variation. Let  $J$  be a functional which is to be maximized or minimized and  $\Delta J$  is the notation for the increment of the functional. So  $J$  as we have given, it may be of the form integral from the interval of a function  $x$  of  $t$  and  $x$  dot of  $t dt$ . So expression of this form if you consider, then we can find the increment  $\Delta J$  given by this expression  $\Delta J$  of  $x$  of  $t + \delta x$  which is the variational in the function  $x$  of  $t - J$  of  $x$ .

So, for example, if we consider the time  $t_0$  to  $T$  is this and  $x$  of  $t$  is a function between  $t_0$  to  $T$ , then the variation, by adding some variation, we will get a new function. So we call it as  $x$  of  $t + \delta x$  of  $t$ . So if we calculate  $J$  at the function  $x$  of  $t$ , it will be of this expression and we calculate  $J$  at the incremental function  $x$  of  $t + \delta x$ . We have to substitute in the place of  $x$  the expression  $x + \delta x$  and then subtract this 2, we will get the increment of this thing.

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**Example:** The increment of the functional

$$J = \int_{t_0}^T [x^2(t) + 3x(t)] dt$$

is given by  $\Delta J \triangleq J(x(t) + \delta x(t)) - J(x(t))$ ,

$$\begin{aligned} &= \int_{t_0}^T [x(t) + \delta x(t)]^2 + 3x(t) + \delta x(t) dt - \int_{t_0}^T [x^2(t) + 3x(t)] dt. \\ &= \int_{t_0}^T [2x(t)\delta x(t) + (3\delta x(t))^2 + 3\delta x(t)] dt. \\ &\approx \int_{t_0}^T [2x(t) + 3]\delta x(t) dt. \end{aligned}$$

For example, if we consider an expression J as a function of x here, it is integral t0 to Tx square of t+3xt, then how to find the increment of this functional. It is given by this expression directly substituting x=del x in the place of x and subtracting J of x directly, we will get the expression. So the last line we are omitting the second variation that is del x whole square, term is omitted and remaining term gives the first variation, this is called first variation of the functional J here, okay.

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### Variation of a Functional:

Consider the increment of a functional

$$\Delta J \triangleq J(x(t) + \delta x(t)) - J(x(t))$$

Expanding  $J(x(t) + \delta x(t))$  in a Taylor series, we get

$$\begin{aligned} \Delta J &= J(x(t)) + \frac{\partial J}{\partial x} \delta x(t) + \frac{1}{2!} \frac{\partial^2 J}{\partial x^2} (\delta x(t))^2 + \dots - J(x(t)) \\ &= \delta J + \delta^2 J + \dots \end{aligned}$$

where,

$$\delta J = \frac{\partial J}{\partial x} \delta x(t) \quad \text{and} \quad \delta^2 J = \frac{1}{2!} \frac{\partial^2 J}{\partial x^2} (\delta x(t))^2$$

are called the first and second variation of the functional J, respectively.

So here, again we calculate the increment of the functional del J=J of x+del x-J of x and expanding it in the Taylor series, xfJ of x+del x will give J of x + the first variation, del J/del x\*the delta x of t+1/2 factorial and the second variation, etc., -J of xt. So that gives the increment

and  $J$  gets cancelled, we will get  $\delta J + \delta^2 J$ . This is the notation for the second variation.  $\delta J$  is the notation for the first variation and that was shown in the previous example.

This is the first variation and now, in the previous case, the Taylor series expansion will stop up to the square term. There will not be any cube terms, etc. because it is a polynomial of degree 2 here. But in general, for any general function, we will get all the terms and then we can calculate first variation, second variation and etc.

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**Optimum of a Functional:** A functional  $J$  is said to have a relative optimum at  $x^*$  if there is a positive  $\epsilon$  such that for all functions  $x$  in a domain  $\Omega$  which satisfy  $|x - x^*| < \epsilon$ , the increment of  $J$  has the same sign.

In other words, if

$$\Delta J = J(x) - J(x^*) \geq 0,$$

then  $J(x^*)$  is a relative minimum. On the other hand if

$$\Delta J = J(x) - J(x^*) \leq 0,$$

then  $J(x^*)$  is relative maximum. If the above relations are satisfied for arbitrary large  $\epsilon$  then  $J(x^*)$  is a global absolute optimum.

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So using this first and second variation, we can get the optimal value of the functional using the following theorem. So here we define the  $J$  is said to have a relative optimum at a function  $x^*$  if there exists a positive epsilon such that for all functions  $x$  in the domain  $\Omega$ , the neighbourhood of the function  $x^*$  which satisfy this. So we take the collection of all functions which are near the function  $x^*$  in the epsilon neighbourhood and then the increment has the sign, positive sign always, then it is called relative minimum.

The function  $x^*$  is called the relative minimum if the increment  $\delta J$  is greater than or equal to 0. And if the increment  $\delta J$  is less than or equal to 0, then the function  $x^*$  is called the relative maximum. And instead of the neighbourhood, the epsilon neighbourhood, if it is, the condition is satisfying for all values of epsilon, then we say that it is the global optimum, global minimum or global maximum depending on the increment nature.

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**Theorem 1:** For  $x^*(t)$  to be a candidate for an optimum, the first variation of  $J$  must be zero at  $x^*$ , i.e.,  $\delta J(x^*(t), \delta x(t)) = 0$  for all admissible values of  $\delta x(t)$ . This is a necessary condition. As a sufficient condition for minimum, the second variation  $\delta^2 J > 0$ .

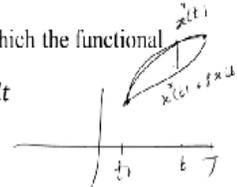
**Fixed-End Time and Fixed-End State System:**

The problem is to find the optimal function  $x^*(t)$ , for which the functional

$$J(x(t)) = \int_{t_0}^T F(x(t), \dot{x}(t), t) dt$$

has a relative optimum, given that

$$\begin{aligned} x(t_0) &= x_0; x(T) = x_f \\ \delta x(t_0) &= \delta x(T) = 0, \end{aligned}$$



So then we can, the standard theorem on the optimum function is as follows. The function  $x^*t$  is said to be an optimum function or it is a candidate for optimum function because this theorem, first statement is only the necessary condition. So it will be a candidate for optimum function if the first variation of  $J$  is equal to 0. So it is a necessary condition. Then we can confirm whether it is maximum or minimum by the second variation if  $\delta^2 J < 0$ , then it is the maximum value and if  $\delta^2 J > 0$ , it is minimum value.

So even though it is similar to the theorem for functions, here the similar result holds good for the functional  $J$  also, okay. Now We will come to the result on how to find the optimum function for the functional  $J$ . So let us say  $J$  of  $x$  is given by this expression integral  $t_0$  to  $T$   $F$  of  $x$ ,  $\dot{x}$ ,  $t$ ,  $dt$  with the initial condition  $x$  of  $t_0$  is  $x_0$  and  $x$  of  $T$  is  $x_f$ , okay. So the function has these 2 fixed boundary conditions, that is from  $t_0$  to  $T$ .

These 2 are fixed, initial and final conditions are fixed here. Now because these 2 are fixed, the variation at the end point is 0 because if you add a delta, this is our  $x$  function and if you add a delta  $x$  function. So there is a variation at other points of  $t$ . If take general  $t$ , there is a variation between  $x$  and  $\delta x$  but there is no variation at the end point. So the variation at  $t_0$  and variation at  $T$ , both are 0.

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Let us first define the increment as

$$\begin{aligned}\Delta J &\triangleq J(x^*(t) + \delta x(t), \dot{x}^*(t) + \delta \dot{x}(t), t) \\ &\quad - J(x^*(t), \dot{x}^*(t), t) \\ &= \int_{t_0}^T F(x^*(t) + \delta x(t), \dot{x}^*(t) + \delta \dot{x}(t), t) dt \\ &\quad - \int_{t_0}^T F(x^*(t), \dot{x}^*(t), t) dt\end{aligned}$$

Expanding in a Taylor series about the point  $x^*(t)$  and  $\dot{x}^*(t)$ ,

So now the increment  $\delta J$  is given by  $J$  of  $x^* + \delta x$ .

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$$\begin{aligned}\Delta J &= \int_{t_0}^T \left[ \frac{\partial F(x^*(t), \dot{x}^*(t), t)}{\partial x} \delta x(t) + \frac{\partial F(x^*(t), \dot{x}^*(t), t)}{\partial \dot{x}} \delta \dot{x} \right. \\ &\quad \left. + \frac{1}{2!} \left\{ \frac{\partial^2 F(\dots)}{\partial x^2} (\delta x(t))^2 + \frac{\partial^2 F(\dots)}{\partial \dot{x}^2} (\delta \dot{x}(t))^2 + 2 \frac{\partial^2 F(\dots)}{\partial x \partial \dot{x}} \delta x(t) \delta \dot{x}(t) \right\} \right] dt \\ \delta J(x^*(t), \delta x(t)) &= \int_{t_0}^T \left[ \frac{\partial F(x^*(t), \dot{x}^*(t), t)}{\partial x} \delta x(t) + \frac{\partial F(x^*(t), \dot{x}^*(t), t)}{\partial \dot{x}} \delta \dot{x}(t) \right] dt\end{aligned}$$

So we calculate the variation between, so let us say this is our required optimum solution. For example, if we take it as the optimum solution, then the increment is given by  $x^* + \delta x$ . Now calculating  $J$  value at this end, these 2 functions. So the increment is  $J$  calculated at  $x^* + \delta x$  minus  $J$  calculated at the function  $x^*$ . So that is given by integral  $t_0$  to  $T$  of, we substitute the  $x^* + \delta x$  in the suitable places, minus integral  $t_0$  to  $T$  of  $x^*$  and  $\dot{x}^* dt$ .

Now we use the Taylor series expansion for the function  $F$ , term similar to the second,  $F$  of  $x^* + \delta x$  is the first term of the Taylor series which will get cancelled. So the remaining terms will

appear like this. So the increment J is given by  $\frac{\partial F}{\partial x} \delta x + \frac{\partial F}{\partial \dot{x}} \delta \dot{x} + \dots$ , the second derivative terms are given by this expression,  $\delta^2 x$ . So the first variation is given by only the first derivative terms here. So it is  $\frac{\partial F}{\partial x} \delta x + \frac{\partial F}{\partial \dot{x}} \delta \dot{x}$ . And we omit all the second derivative terms here.

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Now

$$\int_{t_0}^T \left( \frac{\partial F}{\partial \dot{x}} \right) \delta \dot{x}(t) dt = \int_{t_0}^T \left( \frac{\partial F}{\partial \dot{x}} \right) \frac{d}{dt} (\delta x(t)) dt$$

$$= \left[ \left( \frac{\partial F}{\partial \dot{x}} \right) \delta x(t) \right]_{t_0}^T - \int_{t_0}^T \delta x(t) \frac{d}{dt} \left( \frac{\partial F}{\partial \dot{x}} \right) dt.$$

Hence

$$\delta J(x^*(t), \delta x(t)) = \int_{t_0}^T \left[ \left( \frac{\partial F}{\partial x} \right) - \frac{d}{dt} \left( \frac{\partial F}{\partial \dot{x}} \right) \right] \delta x(t) dt.$$

$\Rightarrow \frac{\partial F}{\partial x} - \frac{d}{dt} \left( \frac{\partial F}{\partial \dot{x}} \right) = 0$

*Handwritten notes on the slide:*  
 $\delta x(t_0) = 0$   
 $\delta x(T) = 0$   
 and  $\delta x(t)$  is arbitrary



Because of the theorem statement, the first variation if we equate it to 0, it is the necessary condition for the optimum function condition. So now if you calculate this term, second term,  $\frac{\partial F}{\partial \dot{x}} \delta \dot{x}$ , we take that term,  $\frac{\partial F}{\partial \dot{x}} \delta \dot{x}$  is written as  $\frac{\partial F}{\partial \dot{x}} \frac{d}{dt} \delta x$ , this expression. Now we integrate by parts, this term. We get  $\frac{\partial F}{\partial \dot{x}} \delta x$  evaluated at  $t_0$  to  $T$ , the end points,  $-\int_{t_0}^T \delta x$  of  $\frac{d}{dt}$  of the first function,  $\frac{\partial F}{\partial \dot{x}}$ .

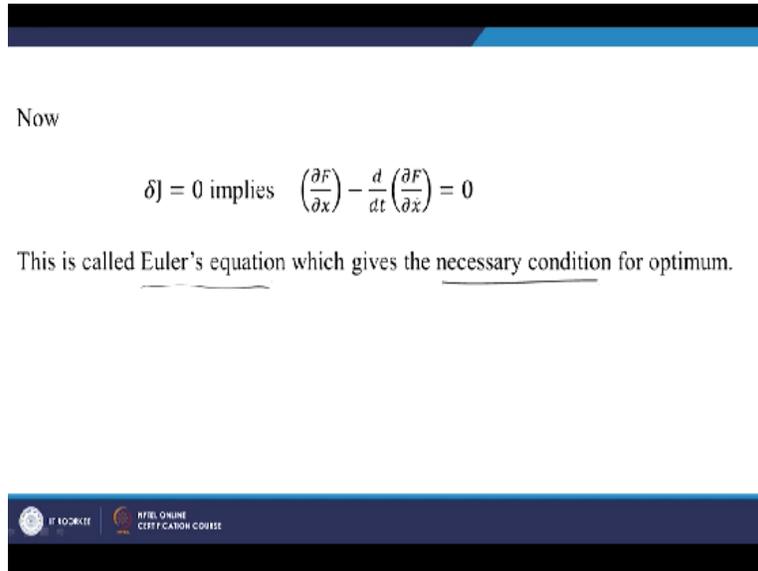
Hence we get the expression of this form. The first variation in J,  $\delta J$ , is given by integral  $t_0$  to  $T$  of from the previous slide, this  $\delta J$  is given by  $\frac{\partial F}{\partial x} \delta x$ , dt is one term and this term, second term is replaced by this expression. So ultimately we get  $\delta J = \int_{t_0}^T \left[ \frac{\partial F}{\partial x} - \frac{d}{dt} \left( \frac{\partial F}{\partial \dot{x}} \right) \right] \delta x dt$ . And this term is 0 because there is no variation. If you substitute  $t_0$  at  $T$ , we know that  $\delta x(t_0) = 0$  and  $\delta x(T) = 0$  because there is no variation at the 2 end points as shown here the  $\delta x$  at  $t_0$  is 0 and  $\delta x$  at  $T$  is 0, so here this term will become 0.

Now this implies the variation  $\delta x$  is also arbitrary. From this picture, we can see that  $x^*$  is a



fixed, it is the function, required function. Then we can add any  $\delta x$  function with this, so that we get infinitely many such, this type of functions. So the variation  $\delta x$  is arbitrary. We get this expression  $\delta J = \int \left( \frac{\partial F}{\partial x} - \frac{d}{dt} \frac{\partial F}{\partial \dot{x}} \right) \delta x dt = 0$ ,  $\delta x$  is arbitrary.

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Now

$$\delta J = 0 \text{ implies } \left( \frac{\partial F}{\partial x} \right) - \frac{d}{dt} \left( \frac{\partial F}{\partial \dot{x}} \right) = 0$$

This is called Euler's equation which gives the necessary condition for optimum.

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So this equation is called the Euler's equation for the minimization or maximization of the functional  $J$  here. So here there is no guarantee that this equation will give minimum or maximum because it is only the necessary condition. And if you check the second variation whether it is positive or negative at this solution of this equation, then we can conclude whether the solution is actually minimum or maximum or none of this. Euler's equation gives a necessary condition for the optimum function.

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**Extrema of Functional with Conditions:**

Let

$$J(x_1(t), x_2(t), t) = J = \int_{t_0}^T F(x_1(t), x_2(t), \dot{x}_1(t), \dot{x}_2(t), t) dt$$

Subject to the condition (system equation)

$$g(x_1(t), x_2(t), \dot{x}_1(t), \dot{x}_2(t)) = 0$$

With fixed end point conditions

$$\begin{aligned} x_1(t_0) &= x_{10}; & x_2(t_0) &= x_{20} \\ \dot{x}_1(T) &= x_{11}; & \dot{x}_2(T) &= x_{21} \end{aligned}$$



So now we quickly generalize the previous procedure for 2 variables. So J is a function of x1, x2 given by this expression integral t0 to TF of x1, x2, x1 dot, x2 dot\*dt subject to the condition g of x1, x2, x1 dot, x2 dot=0 with the boundary conditions x1 of t0 and x2 of t0. Similarly, x1 dot at T and x2 dot at T, these values are given, the fixed values are given. So now we can, because it is, previously it was 1 variable, now it is 2 variable.

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**Lagrangian:** We form an augmented functional

$$J_a = \int_{t_0}^T L(x_1(t), x_2(t), \dot{x}_1(t), \dot{x}_2(t), \lambda(t), t) dt$$

Subject to the condition (system equation)

$$g(x_1(t), x_2(t), \dot{x}_1(t), \dot{x}_2(t)) = 0$$

$$g = \begin{bmatrix} g_1(x_1, x_2, \dot{x}_1, \dot{x}_2) \\ g_2(x_1, x_2, \dot{x}_1, \dot{x}_2) \end{bmatrix}$$

Where  $\lambda(t)$  is the Lagrange multiplier, and the Lagrangian L is defined as

$$L(x_1(t), x_2(t), \dot{x}_1(t), \dot{x}_2(t), \lambda(t), t) = F(x_1(t), x_2(t), \dot{x}_1(t), \dot{x}_2(t), t) + (\lambda(t))' g(x_1(t), x_2(t), \dot{x}_1(t), \dot{x}_2(t))$$

$$\lambda(t) = \begin{bmatrix} \lambda_1(t) \\ \lambda_2(t) \end{bmatrix}$$



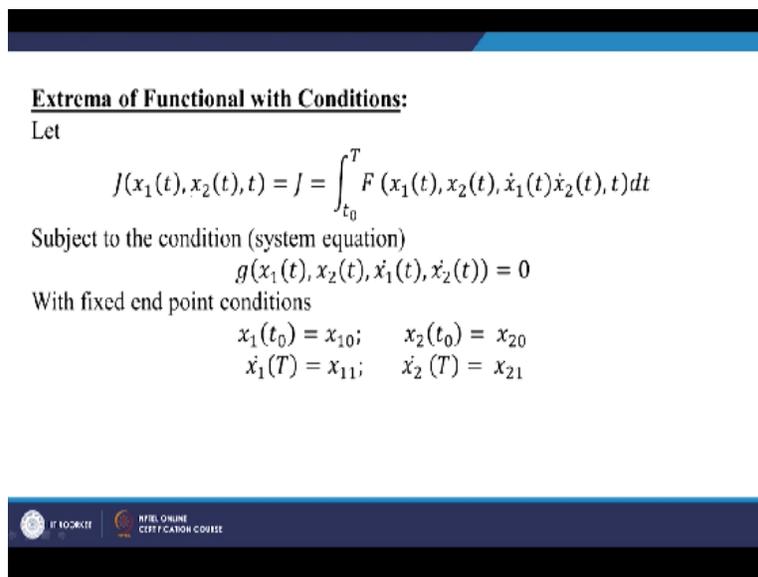
The procedure is exactly the same except that we have to write the Taylor series for the 2 variable and omit the second order terms and take the first variation=0. And the difference between the previous one and here is, there is a constraint. The minimization or maximization of J subject to the condition g of x1, x2, x1 dot, x2 dot=0. So this can be done in the usual way of

the Lagrange multiplier method because this is a constraint.

So we define the Lagrange function  $L$  of  $x_1, x_2, \dot{x}_1, \dot{x}_2, \lambda$ , which is the Lagrange multiplier, =the function  $F + \lambda$ \*the function  $g$ . Here  $g$  is a vector function because there are 2 variables. It may contain 2 function  $g_1, g_2$ .  $g_1$  of  $x_1, x_2, \dot{x}_1, \dot{x}_2$ . Similarly,  $g_2$  also contain, so  $g$  is a vector function. And therefore,  $\lambda$  is also having 2 components,  $\lambda_1, \lambda_2$  and the transpose is given.

So we get a scalar functional here,  $L$  is  $F$ , which is a scalar function,  $+\lambda$  dashed\* $g$ , that is also a scalar function, and now we can proceed with this  $J$ . Minimizing  $J$  will give the minimum value of the  $J$  itself, okay.

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**Extrema of Functional with Conditions:**  
Let

$$J(x_1(t), x_2(t), t) = J = \int_{t_0}^T F(x_1(t), x_2(t), \dot{x}_1(t), \dot{x}_2(t), t) dt$$

Subject to the condition (system equation)

$$g(x_1(t), x_2(t), \dot{x}_1(t), \dot{x}_2(t)) = 0$$

With fixed end point conditions

$$\begin{aligned} x_1(t_0) &= x_{10}; & x_2(t_0) &= x_{20} \\ \dot{x}_1(T) &= x_{11}; & \dot{x}_2(T) &= x_{21} \end{aligned}$$

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Assume optimal values and then consider the variation and increment as

$$\begin{aligned}x_i(t) &= x_i^*(t) + \delta x_i(t), \\ \dot{x}_i(t) &= \dot{x}_i^*(t) + \delta \dot{x}_i(t); i = 1, 2.\end{aligned}$$

$$\Delta J_a = J_a(x_1^* + \delta x_1, x_2^* + \delta x_2, \dot{x}_1^* + \delta \dot{x}_1, \dot{x}_2^* + \delta \dot{x}_2, t) - J_a(x_1^*, x_2^*, \dot{x}_1^*, \dot{x}_2^*, t)$$

$$\delta J_a = \int_{t_0}^T \left[ \left( \frac{\partial L}{\partial x_1} \right) \delta x_1(t) + \left( \frac{\partial L}{\partial \dot{x}_1} \right) \delta \dot{x}_1(t) + \left( \frac{\partial L}{\partial x_2} \right) \delta x_2(t) + \left( \frac{\partial L}{\partial \dot{x}_2} \right) \delta \dot{x}_2(t) \right] dt$$

So to generalize the previous procedure, we take the incremental function, that is  $x_1^*$  is the required function and then if you add a variational function  $\delta x_1$  along with that, we get the function variation of  $x^*$ . Substituting the variation and then subtracting with the original function  $J_a$  and taking only the first order terms in this way, we get the equation exactly similar to the previous one.

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Let us choose the multiplier  $\lambda^*(t)$  which is arbitrarily introduced and is at our disposal, in such a way that the coefficient of the dependent variation  $\delta x_1(t)$  vanish. That is

$$\begin{aligned}\left( \frac{\partial L}{\partial x_1} \right) - \frac{d}{dt} \left( \frac{\partial L}{\partial \dot{x}_1} \right) &= 0 \\ \left( \frac{\partial L}{\partial x_2} \right) - \frac{d}{dt} \left( \frac{\partial L}{\partial \dot{x}_2} \right) &= 0\end{aligned}$$

Also, note that

$$\left( \frac{\partial L}{\partial \lambda} \right) = g = 0.$$

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Assume optimal values and then consider the variation and increment as

$$\begin{aligned}x_i(t) &= x_i^*(t) + \delta x_i(t), \\ \dot{x}_i(t) &= \dot{x}_i^*(t) + \delta \dot{x}_i(t); i = 1, 2.\end{aligned}$$

$$\Delta J_a = J_a(x_1^* + \delta x_1, x_2^* + \delta x_2, \dot{x}_1^* + \delta \dot{x}_1, \dot{x}_2^* + \delta \dot{x}_2, t) - J_a(x_1^*, x_2^*, \dot{x}_1^*, \dot{x}_2^*, t)$$

$$\delta J_a = \int_{t_0}^T \left[ \left( \frac{\partial L}{\partial x_1} \right) \delta x_1(t) + \left( \frac{\partial L}{\partial \dot{x}_1} \right) \delta \dot{x}_1(t) + \left( \frac{\partial L}{\partial x_2} \right) \delta x_2(t) + \left( \frac{\partial L}{\partial \dot{x}_2} \right) \delta \dot{x}_2(t) \right] dt$$

And replacing the terms containing dot,  $\frac{\partial L}{\partial \dot{x}_1} \delta \dot{x}_1$ , so if you use the integration by part method as done before, we get exactly similar equation. Instead of one equation, we will get 2 equations, 2 Euler's equation and the constraint function  $g$ .  $g$  means the vector  $g_1, g_2=0$  is given here.

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Now, we generalize the preceding procedure for an  $n^{\text{th}}$  order system.

Consider the extremization of a functional.

$$J = \int_{t_0}^T F(x(t), \dot{x}(t), t) dt$$

$$x = \begin{pmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{pmatrix}, \quad \dot{x} = \begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \vdots \\ \dot{x}_n \end{pmatrix}$$

Where,  $x(t)$  is an  $n^{\text{th}}$  order state vector, subject to the plant equation (condition)

$$g_i(x(t), \dot{x}(t), t) = 0; \quad i = 1, 2, \dots, m$$

and boundary conditions,  $x(0)$  and  $x(T)$  we form an augmented functional

$$J = \int_{t_0}^T \mathcal{L}(x(t), \dot{x}(t), \lambda(t), t) dt$$

where the Lagrangian  $\mathcal{L}$  is given by

$$\mathcal{L}(x(t), \dot{x}(t), \lambda(t), t) = F(x(t), \dot{x}(t), t) + (\lambda(t))' g_i(x(t), \dot{x}(t), t)$$

$$\lambda = [\lambda_1, \lambda_2, \dots, \lambda_m]'$$

So the same thing is expand, it is extended for the general one. If your  $x$  is a vector,  $x_1$  of  $t$ ,  $x_2$  of  $t$ , etc.,  $x_n$  of  $t$  and its derivative is given and  $g_i$ , so  $g$  is  $g_1, g_2, g_m$ , okay. There are  $m$  constraints and  $n$  variables are given. So the procedure is exactly similar. And here, the lambda will be simply lambda 1, lambda 2, lambda m dashed which are functions of  $t$ . So we proceed in the similar manner as we did earlier.

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and the Lagrange multiplier  $\lambda(t) = [\lambda_1(t), \lambda_2(t), \dots, \lambda_m(t)]'$ . We now apply the Euler-Lagrange equation on  $J_a$  to yield

$$\frac{\partial L}{\partial x} - \frac{d}{dt} \left( \frac{\partial L}{\partial \dot{x}} \right) = 0$$

and

$$\left( \frac{\partial L}{\partial \lambda} \right) - \frac{d}{dt} \left( \frac{\partial L}{\partial \dot{\lambda}} \right) = 0$$

$$\Rightarrow g_i(x(t), \dot{x}(t), t) = 0 \quad i = 1, 2, \dots, m$$


And we get the Euler's equation for the  $n$  Euler's equation will be obtained and the  $m$  constraints are already given in the thing. And the initial conditions and final conditions are taken as in the previous case. Here we have given. so initial and final condition for 2,  $x_1$  and  $x_2$  are given. Similarly, we can take the fixed initial and final condition for  $n$  such functional. So now we will use this procedure to solve the optimal control problems as follows.

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$\dot{x} = 2x + 3u \quad \dots (1)$

Minimize  $J = \int_1^5 (5x^2 + u^2) dt \quad \dots (2)$

Boundary conditions  $x(1) = 0, x(5) = 4 \quad \dots (3)$

$F(x, u, t) = 5x^2 + u^2$

$g(x, u) = 2x + 3u - \dot{x} = 0$

Then  $L(x, \dot{x}, u) = F + \lambda g$   
 $= 5x^2 + u^2 + \lambda(2x + 3u - \dot{x})$

The Euler's eq.  $\frac{\partial L}{\partial x} - \frac{d}{dt} \left( \frac{\partial L}{\partial \dot{x}} \right)$



So for example if you consider the equation  $\dot{x} = 2x + 3u$  and we want to minimize the functional say 1 to 5 of  $5x^2 + u^2$ , these are functions of the  $dt$ , okay. We want to minimize this expression under the condition say  $x$  of 1, these are the boundary conditions  $x$  of 1

is 0 and  $x(5)=4$ . So the equation is given. The constraint equation is given, the first one and the functional to be minimized is given and the boundary conditions are given here.

So we can construct the Euler-Lagrange equation as given here for the 1 variable case. So we have to construct  $L$ .  $L$  of  $x$  and  $\dot{x}$  is given by  $F$  function,  $+\lambda * g$  function. So this too we will construct here. So here, the function  $F$  of  $x$  and  $\dot{x}$  is given by  $5x^2$  and  $u^2$ . So this function and  $g$  of  $x, u; x$  and  $\dot{x}$  is given by  $2x+3u-x\dot{x}$ . Is not it? Because  $g$  of  $x, u$  should be equal to 0 that is given from the equation 1.

Then the Lagrangian is given by, the Lagrangian is a function of  $x, \dot{x}$  and  $u$  that is given by  $F+\lambda * g$ . So if you take this one, we get  $5x^2+u^2+\lambda * g$ ,  $g$  function is given by  $2x+3u-x\dot{x}$ . So the Euler's equation is, Euler-Lagrange equation is  $\frac{\delta L}{\delta x} - \frac{d}{dt} \frac{\delta L}{\delta \dot{x}}$ . See here, we note that this problem  $J$  of  $x_1, x_2$  is given by  $\int F(x_1, x_2, \dot{x}_1, \dot{x}_2)$ . That is to be minimized.

So now we can take in this problem  $x$  and  $u$  are there. In our statement of the problem  $J$  is  $5x^2+u^2$ . So we can take this  $x_2$  function,  $x_1$  as  $x$  in the problem and  $x_2$  as the  $u$ , the control  $u$  and  $g$  of  $x_1, x_2, \dot{x}_1, \dot{x}_2$ . So  $x_1$  is replaced by  $x$  here.  $x_2$  is replaced by  $u$ . And  $\dot{x}_1$  is replaced by  $\dot{x}$  and  $\dot{x}_2$  is not available in the equation. So we can simply write the expression like this. So  $g$  of  $x, u$ . We are writing in the place of  $x_1, x_2$ , we have  $x$  and  $u$  and this expression is given.  $x$  and  $\dot{x}$  also.

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$\dot{x} = 2x + 3u \quad \dots (1)$   
 Minimize:  $J = \int_1^5 (5x^2 + u^2) dt \quad \dots (2)$   
 Boundary conditions:  $x(1) = 0, x(5) = 4 \quad \dots (3)$   
 $F(x(t), u(t)) = 5x^2 + u^2$   
 $g(x, \dot{x}, u) = 2x + 3u - \dot{x} = 0$   
 Then  $L(x, \dot{x}, u, \lambda) = F + \lambda g$   
 $= 5x^2 + u^2 + \lambda(2x + 3u - \dot{x})$   
 The Euler's eq.  $\left. \begin{aligned} \frac{\partial L}{\partial x} - \frac{d}{dt} \left( \frac{\partial L}{\partial \dot{x}} \right) &= 0 \\ \text{and } \frac{\partial L}{\partial u} - \frac{d}{dt} \left( \frac{\partial L}{\partial \dot{u}} \right) &= 0 \\ \frac{\partial L}{\partial \lambda} - g &= 0 \end{aligned} \right\}$   
 $\Rightarrow \begin{cases} 10x + 2\lambda = 0 \\ -\frac{d}{dt}(-\lambda) = 0 \\ \Rightarrow -10\dot{x} - 2\dot{\lambda} = \dot{\lambda} \quad \dots (1) \\ 2u + 3\lambda = 0 \\ \Rightarrow u = -\frac{3}{2}\lambda \quad \dots (2) \end{cases}$   
 $g = 0 \Rightarrow \dot{x} = 2x + 3u \quad \dots (3)$   
 Solve:  
 $\begin{cases} \dot{x} = 2x + 3u = 2x - \frac{9}{2}\lambda \\ \dot{\lambda} = -10x - 2\lambda \\ x(1) = 0, x(5) = 4 \\ \begin{pmatrix} x \\ \lambda \end{pmatrix} = \begin{pmatrix} 2 & -\frac{9}{2} \\ 10 & 2 \end{pmatrix} \begin{pmatrix} x \\ \lambda \end{pmatrix} \end{cases}$

So we have this expression and we can write the Euler's equation like this with the initial and boundary condition given by 3. And  $\frac{\partial L}{\partial x^2}$ ; in the place of  $x^2$ , you have  $u$  here,  $-\frac{d}{dt}$  of  $\frac{\partial L}{\partial u \dot{}}$ . So these are the equation to be solved and we get  $\frac{\partial L}{\partial \lambda}$  that is equal to  $g$  which is also equal to 0. So these equation to be solved. Now directly if we differentiate  $\frac{\partial L}{\partial x}$ , etc., we will get the equations in this form.

So this implies  $\frac{\partial L}{\partial x}$  from here directly if we differentiate, we will get  $10x + 2\lambda$ , okay,  $-\frac{d}{dt}$  of  $\frac{\partial L}{\partial x \dot{}}$ . There is an  $x \dot{}$  here, so it is  $-\lambda \dot{}$ ,  $= 0$ . So from the first equation, we get this. This implies,  $= \lambda \dot{}$ , the derivative  $\frac{d}{dt}$  of  $\lambda$ . And then  $\frac{\partial L}{\partial u}$ , if we differentiate with respect to  $u$  in the second equation, we get  $2u$  and  $-\frac{\partial L}{\partial u}$  that is  $+3\lambda$ , so that is equal to 0. So this equation implies that  $u = -\frac{3}{2}\lambda$ .

So we get this as the first equation and this as second equation. The third equation is already given  $g = 0$  that is the given constraint. That implies  $x \dot{=} 2x + 3u$ . So this is the third equation. So combining all these equation, we get; so now we have to solve the equation  $x \dot{=} 2x + 3u$  from the third equation. The first equation is  $\lambda \dot{=} -\frac{3}{2}\lambda$ . If you substitute  $u$  in this expression, we will get  $2x, \frac{3}{2}\lambda$ , so we will get  $9/2\lambda$ .

So we have made use of all the equation. This is the expression with the boundary condition  $x$  of  $1=0$  and  $x$  of  $5=4$ . So this is the system of equation. We get  $x \lambda$ . if you write in the matrix



form, this equation will give  $2 - 9/2$  and  $\lambda \dot{\lambda}$  is  $10$  and  $2 \times \lambda$ . So we get the matrix equation in this form. By finding the exponential of this matrix, we can find the solution of this problem under the boundary condition.

Here  $x_1$  of  $0=0$  and  $x_5=4$ . So with this we come to the conclusion of this lecture. We have demonstrated how to find the optimal control for a linear system with the fixed boundary conditions. But this procedure is not restricted to only linear system because the equation given in the procedure which we have explained earlier, the constraint is given by  $g_i$  of  $x$ ,  $\dot{x}=0$  which can be a nonlinear system also.

But in this particular example, we have taken the linear system because the solution of the linear system can be obtained analytically and the result can be obtained analytically. Otherwise, the procedure can be applied for nonlinear system also. Thank you.