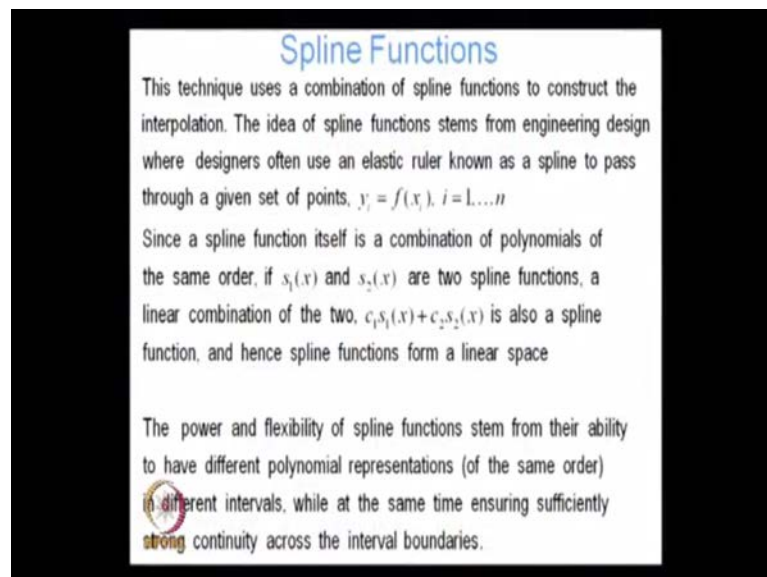


Numerical Methods in Civil Engineering
Prof. Arghya Deb
Department of Civil Engineering
Indian Institute of Technology, Kharagpur

Lecture - 36
Orthogonal Basis Functions for Solving PDE's

In lecture 36 of our series on numerical methods in civil engineering we will end up our discussion on spline functions, which we started last time and then move on to a discussion in orthogonal basis functions for solving partial differential equations.

(Refer Slide Time: 00:38)



Let us recall that spline functions are another set of basis functions, which can be used for constructing an interpolation. This technique uses a combination of spline functions of combination of functions, and the idea of spline functions we found stems from engineering design, were designers often used in elastic rule as a known as a spline to pass through a given set of points and people found that the spline was nothing but a series of cubic's defined over the intervals of interest.

If I have several grid points and I know the function values at those grid points. The final fit was obtained by considering cubic functions, cubic polynomials over each of those intervals and then ensuring continuity in the function values, as well as in the derivatives across the element boundaries not only the first derivative, but also the second derivative.

In case of cubic splines and these basis functions are independent. So, the different cubic polynomials, different basis functions in different intervals only difference with the type of basis functions at we were considering earlier. These basis functions have local support. So, they are defined over small intervals not over the entire domain.

And the spline functions are combination of these polynomials in the power and flexibility of spline functions stem from their ability to have different polynomial representations in different intervals while at the same. So that is why you can basically modify a complicated function with lot of variation using different functions in different intervals, you do not have to use a very high order. The other alternative is to use a very high order polynomial throughout the interval but that is no longer required. So, you use a relatively low order polynomial in case of cubic splines a cubic polynomial over these intervals and they are different over each interval.

(Refer Slide Time: 02:48)

Cubic splines


The cubic spline in $[a, b]$ has the following representation in terms of a cubic polynomial in $[x_{i-1}, x_i]$:

$$q_i(x) = ty_i + (1-t)y_{i-1} + h_i t(1-t)[(k_{i-1} - d_i)(1-t) - (k_i - d_i)t]$$

where $h_i = x_i - x_{i-1}$, $t = \frac{(x - x_{i-1})}{h_i} \forall x \in (x_{i-1}, x_i)$, $d_i = \frac{y_i - y_{i-1}}{h_i}$ and the k_i 's are obtained by solving a tridiagonal system of equations:

$$h_{i-1}k_{i-1} + 2(h_i + h_{i-1})k_i + h_i k_{i+1} = 3(h_i d_{i+1} + h_{i-1} d_i), i = 1, 2, \dots, m-1 (**)$$

The system is tridiagonal because equation i involves k_{i-1} , k_i and k_{i+1} only. The coefficients of the other k 's in the equation are zero.



And we also found that, the cubic spline has this representation. So, if I define the spline over the interval $x_{i-1} \leq x \leq x_i$ and denoted by $q_i(x)$, then that cubic spline has the following representation, where t is nothing but $\frac{x - x_{i-1}}{h_i}$. So, it is the parameter over that interval $x_{i-1} \leq x \leq x_i$ for all x belonging to that interval h_i is just the size of the interval d_i is the slope $\frac{y_i - y_{i-1}}{h_i}$ and the k_i 's the k_i 's in this equation. In this expression for the cubic polynomial are obtained by solving this tri diagonal system of equations.

And towards the end of the last class, I told you that this k_i 's are nothing but the second derivatives of this q_i and this system is to. So, what we find at the end of last class was that given this representation of q given this representation of the cubic polynomial. It satisfies continuity in the function values and continuity in the first derivatives by construction the way it is constructed. It always satisfies continuity at the ends of the interval both in the function values as well as in the derivatives but in order to ensure that the second derivative is also continuous across the intervals. The k_i 's have to satisfy equations of these sort and you can see that this system. So, there is $m - 1$ equation but there are $m + 1$ k_i 's. So, because of that we need two other constraint equations, which we are going to talk about later.

(Refer Slide Time: 04:44)

Continuity

Recall, $q_i(x) = ty_i + (1-t)y_{i+1} + ht(1-t)[(k_{i+1} - d_i)(1-t) - (k_i - d_i)t]$

In $[x_{i-1}, x_i]$ if $x = x_i, t = 1$. Therefore,
 $q_i(x_i) = 1 \cdot y_i + (0)y_{i+1} + h(1)(0)[(k_{i+1} - d_i)(0) - (k_i - d_i)1] = y_i$

In $[x_i, x_{i+1}]$ if $x = x_i, t = 0$. Therefore,
 $q_{i+1}(x_i) = 0 \cdot y_{i+1} + (1)y_i + h_{i+1}(0)1[(k_{i+1} - d_{i+1})(1) - (k_{i+1} - d_{i+1})0] = y_i$

Hence $q_i(x_i) = q_{i+1}(x_i) \Rightarrow$ continuity in function values

To prove continuity in the derivatives we use the result $\frac{dt}{dx} = \frac{1}{h_i}$

since $\frac{(x - x_{i-1})}{h_i} = t$

And from as I said that given the definition of y continuity in the function value is satisfied by construction. So, since in x_{i-1}, x_i , if x is equal to x_i , this means t is equal to 1. So, t goes from 0 to 1 throughout the interval. So, if I am looking at the hand point at x is equal to x_i at this point, when t is equal to 1. If I substitute t equal to 1 in this equation I can find that, this gives me $q_i(x_i)$ is equal to y_i . Similarly, if I am looking at the interval x_i, x_{i+1} the adjacent interval to that interval if x is equal to x_i t must be equal to 0, because it is at the starting point of the interval the left hand starting point.

So, at is equal to 0 if I substitute t is equal to 0 at that interval in this equation and evaluated at x_i instead of q_i . I will use q_{i+1} and evaluated at x_i , I am also going

to get y_i that means, what the function values $q_i(x_i)$ is equal to $q_{i+1}(x_i)$, that means, it is continuous at the interval of the function values of are continuous at the interval boundaries to prove continuity in the derivatives. We use the following result $\frac{d}{dx} = \frac{1}{h} \frac{d}{dt}$ and try to find the derivative of this expression. I try to find the derivative of that expression.

(Refer Slide Time: 06:23)

Continuity


Evaluating the derivative $q'_i(x) = \frac{dq_i(x)}{dx} = \frac{dq_i(x)}{dt} \frac{dt}{dx}$

$$= \frac{1}{h} [y_i - y_{i-1} + h_i(1-2t)(k_{i-1} - d_i)(1-t) - (k_i - d_i)t + h_i t(1-t)(-k_{i-1} + d_i - k_i + d_i)]$$

Therefore:

$$q'_i(x_{i-1}) = q'_i(t=0) = \frac{1}{h} [y_i - y_{i-1} + h_i(k_{i-1} - d_i)] = d_i + k_{i-1} - d_i = k_{i-1}$$

$$q'_i(x_i) = q'_i(t=1) = \frac{1}{h} [y_i - y_{i-1} + h_i(-1)(-k_i + d_i)] = d_i + k_i - d_i = k_i$$

 NPTEL

So, I find $q'_i(x)$, while x instead of now t is the independent variable. So, $\frac{d}{dx} = \frac{1}{h} \frac{d}{dt}$ I want to find but then I have used this intermediate parameter t . So, I use $\frac{d}{dx} = \frac{1}{h} \frac{d}{dt}$ and $\frac{dt}{dx} = \frac{1}{h}$. So, I have $\frac{1}{h} \frac{d}{dt}$ times $\frac{d}{dx}$, $\frac{d}{dt}$ of this expression. I have $\frac{d}{dt}$ of that expression. So, I get that and then if I want to evaluate $q'_i(x)$. So, I look at the interval x_{i-1} and I want to evaluate $q'_i(x)$ at x_{i-1} . Our $q'_i(x)$ means the derivative, if this function is belongs function cubic function with respect to this interval x_{i-1} .

(Refer Slide Time: 07:24)

Continuity


Evaluating the derivative $q'_i(x) = \frac{dq_i(x)}{dx} = \frac{dq_i(x)}{dt} \frac{dt}{dx}$

$$= \frac{1}{h_i} [y_i - y_{i-1} + h_i(1-2t)](k_{i-1} - d_i)(1-t) - (k_i - d_i)t$$

$$+ h_i t(1-t)[-k_{i-1} + d_i - k_i + d_i]$$

Therefore :

$$q'_i(x_{i-1}) = q'_i(t=0) = \frac{1}{h_i} [y_i - y_{i-1} + h_i(k_{i-1} - d_i)] = d_i + k_{i-1} - d_i = k_{i-1}$$

$$q'_i(x_i) = q'_i(t=1) = \frac{1}{h_i} [y_i - y_{i-1} + h_i(-1)(-k_i + d_i)] = d_i + k_i - d_i = k_i$$


And I am going to evaluate it at x_{i-1} . So, that means I evaluate it at t is equal to 0 because the interval is $x_{i-1} \leq x \leq x_i$ at x_{i-1} t is equal to 0 at x_i . So, I evaluate this at t is equal to 0 if I do that I get k_{i-1} . So, I just substitute t is equal to 0 in this expression then if I want then I want to evaluate q'_i at x_i .

So, I am using the same interval $x_{i-1} \leq x \leq x_i$ and I am evaluating the derivative at x_i that means I am evaluating the derivative at t is equal to 1, if I do that I substitute t equal to 1 in this expression I get is equal to k_i that equal to k_i .

(Refer Slide Time: 08:15)


Continuity

Since $q'_i(x_{i-1}) = k_{i-1}$ one obtains by replacing i by $i+1$ above,
 $q'_{i+1}(x_i) = k_i$ But we already have $q'_i(x_i) = k_i$.

Thus by construction q_i ensures that the first derivative of the spline function is continuous at the interval boundaries.

But in addition the second derivatives of the spline also have to be continuous across the interval boundaries i.e. $q''_i(x_i) = q''_{i+1}(x_i)$.

This is ensured by the linear system of tridiagonal equations (**) along with two additional conditions to determine all the unknown k_i 's.



Then, I use the fact that since $q_i = q_{i+1}$ at x_{i+1} is equal to k_{i+1} if I want to evaluate if I replace i by $i+1$ I can get $q_i = q_{i+1}$ at x_{i+1} just replacing i by $i+1$ in this expression x_i is equal to k_i . But, we have already found that $q_i = q_{i+1}$ at x_{i+1} is equal to k_i . So, that means for the interval $x_{i+1} - x_i$, if I evaluate the derivative at the right hand point, I get k_{i+1} . For the interval $x_i - x_{i-1}$, if I evaluate the derivative with at the left hand point, I get k_i that means, that the derivatives are equal at the boundaries and therefore, we have continuity in the derivative as well.

Thus by construction q_i is the construction, q_i has continuous function values and derivatives of the spline function at the interval boundaries but in addition the second derivatives of the spline also have to be continuous across the interval boundaries, that means, this condition has to be satisfied at the end of interval $x_{i+1} - x_i$. The second derivative must be equal to the second derivative at the beginning of the interval $x_i - x_{i-1}$, which is this condition. And then if I impose that condition on this equation.

If I use this equation, I put I impose that condition. That is the second derivatives are continuous at the interval boundaries on this equation. I get these equations here, these diagonal system and then I need to solve that tridiagonal system. But, as I said we need two additional equations but because there are fewer equations than the number of unknowns. So, we need to solve that system with constraints.

(Refer Slide Time: 10:22)

The slide contains the following text:

Constraints on second derivative

The most common constraints used require that the spline be a straight line outside $[a,b]$ i.e. $s''(x) = 0 \forall x \leq a$ or $x \geq b$.

If $q_i(x)$ is the cubic in the interval $[x_{i-1}, x_i]$ and $q_{i+1}(x)$ is the cubic in $[x_i, x_{i+1}]$ this requires $q_i''(x_i) = q_{i+1}''(x_i) = 0$

Spline is a straight line outside the interval

The graph shows a spline function $s(x)$ on a coordinate system with the x-axis. The interval $[a, b]$ is highlighted. The spline consists of several cubic segments. Blue arrows point to the segments for $x < a$ and $x > b$, which are straight lines, indicating that the second derivative is zero in these regions.

And the constraints we use require that the spline be a straight line outside the interval. If it is a straight line, that means its curvature got to be 0, curvature got to be 0 that means that the second derivative got to be 0. So, as double prime x is equal to 0 for x lesser than or equal to a and x lesser than or equal to b . So that means we are looking at the first interval and the last interval. So, if $q_1 x$ is the cubic in the first interval and $q_m x$ is the cubic in the last interval, this means that q_1 double prime at a must be equal to q_1 , q_m double prime at b because q_m refers to the last interval and both must be equal to 0 both must. you can see these are spline's straight line outside that interval. What happens?

(Refer Slide Time: 11:21)

Error due to spline approximation


This leads to the equations:

$$2k_0 + k_1 = 3d_1$$

$$k_{m-1} + 2k_m = 3d_m$$

If a cubic spline is used to approximate a function $f(x)$ whose second derivatives are not zero at $[a, b]$ then a good fit is still obtained near the centre of the interval

Near the center of the interval the error $= o(h^3)$ while the error near the boundaries of the interval are larger.



So, these conditions give me, these two additional equations you can see that, the first equation involves k_0 and k_1 , because it refers to the first interval the last equation involves k_{m-1} k_m , because it refers to the last interval and these two are the additional constraints. Now, I have $m+1$ equation for my $m+1$ constraint. I can solve them, I get my k values and once I know my k values, I can split my I can fit my spline throughout the interval.

So, it is not expensive because the system as we have seen earlier is a tridiagonal system solving a tridiagonal system is not that hard. Now, we have said that we are going to use a cubic spline to exactly fit the function values but suppose in that interval but suppose my actual function does not have 0 curvature, then my spline has got 0 curvature, then

what happens if my actual function does not have 0 curvature, then in that case there is some loss of accuracy the fit is not as good. So, the good fit is still obtained at the center of the interval but towards the end of the interval the errors are somewhat larger. So, near the center of the interval the error is of the order of h to the power 4. So, you can see the error is really, it is the order of accuracy is really high. So, h to the power 4 if I as you reduce the size the error becomes goes down like $(\)$ where the error near the boundaries are somewhat larger, if the real function does not have 0 curvature at the ends of the interval.

So, with that I want to draw close to my discussion of spline functions. So, these are very useful functions, because they have this. They give me very good accuracy recall, if I have a polynomial with a lot of with a maxima and minima in order. If I have a function with a lot of maxima and minima in order to have a polynomial maxima and minima in a certain interval lots of stationery points within an interval. If I have to use a polynomial to fit that function, it has to be a very high order polynomial and as we have seen with a high order polynomial, if we have equidistant grid we are going to get erratic behavior ill-conditioning and we. So, poor fit at the ends of the interval.

So, alternative to do that, we found that were one alternative was to use chebyshev interpolation, other alternative is to use splines, where you use a relatively lower order polynomial do not have to use a very high order polynomial use a relatively lower order polynomial fit it across that interval which assumes different forms within each subinterval same order but different form and then you can get a good fit even using a equidistant grid.

(Refer Slide Time: 14:37)

Basis functions for linear pdes

The notion of a linearly independent basis for a function space is widely used: it is the foundation of techniques such as the Galerkin method, the collocation method and weighted residual methods such as the Finite Element method for the solution of ordinary and partial differential equations

Suppose we have a linear pde denoted by the action of a linear operator L on the variable u : Lu

Also suppose that $u \in D$ where D is a subset of R^k where R^k is the k 'th dimensional Euclidean space

In D , $Lu = f$. On ∂D , the boundary of D , suppose that u satisfies the following relationship defined by the action of another linear operator \bar{L} on u : $\bar{L}u = g$ on ∂D

So, with that we are ready, we have talked enough about orthogonal basis functions. So, we want to use these basis functions for solving our partial differential equations and we can say, we will see that, this idea of orthogonal basis functions is the foundation of most of almost all widely used methods used for the numerical solution of partial differential equations including the finite element method. So, let us do that.

So, notion of linearly independent basis functions for a function space is widely used. It is the foundation of techniques such as the galerkin method, the collocation method the weight and weighted residual methods such as the finite element method for the solution of ordinary and partial differential equations. Suppose we have a linear partial differential equation denoted by the action of a linear operator L which is have encountered earlier on the variable u . So, $L u$ is also, suppose that u belongs to the domain D , where D is a subset of R^k , R^k is the k 'th dimensional Euclidean space, so two dimensional Euclidean space or 3 dimensional Euclidean space.

In D $L u$ is equal to f . So, this linear operator operating on u is equal to f . a given function f suppose and on the boundary of D so on. ∂D which is the boundary of D let us suppose, that u satisfies another relationship again defined by another linear operator in this time, in this case \bar{L} . So, $\bar{L} u$ is equal to g on ∂D . So, within the domain D $L u$ is equal to f on the boundaries of that domain $\bar{L} u$ is equal to g .

(Refer Slide Time: 16:34)

The general problem

Examples may include any of the canonical pds encountered earlier
e.g. Laplace's equation in a 2D domain with a fully constrained
boundary: $\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} = f(x, y)$ on $D \in \mathbb{R}^2$
 $u(x, y) = 0$ on ∂D

In this case $L = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} = \nabla^2$ the Laplacian operator in 2D space
while \bar{L} is the identity operator and g is equal to zero.

The general linear problem (A): $Lu = f$ in D , $\bar{L}u = g$ on ∂D can be
simplified somewhat if we can solve the two independent problems:
 $Lu_1 = f$ in D , $\bar{L}u_1 = 0$ on ∂D (B) $Lu_2 = 0$ in D , $\bar{L}u_2 = g$ on ∂D (C)
then the solution of (A) can easily be obtained as $u = u_1 + u_2$

NPTEL

So, examples can include any of the canonical partial differential equations, we encountered earlier for example, Laplace's equation in a 2 D domain. So, $\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} = f(x, y)$ on D , which is the subset of the 2 dimensional Euclidean space and u is equal to 0 on ∂D .

In this case, L obviously is $\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}$ plus $\frac{\partial^2}{\partial y^2}$ laplacian operator in 2 D space, while L bar is the identity operator, because L bar u is equal to u . So, L bar is the identity operator and g in these cases equal to 0. So, the general linear problem A, if we define the general linear problem A to be $Lu = f$ in D and L bar u is equal to g on ∂D can be simplified somewhat if we can solve two independent problems what are the 2 independent problems 2 independent problems are $Lu_1 = f$ in D and L bar u_1 is equal to 0 on D . Now, instead of solving this problem we solve. So, the instead of solving this problem, we solve the homogeneous problem, First the homogeneous boundary condition.

So, $Lu_1 = f$ in D but L bar u_1 is equal to 0 on ∂D , same problem with homogeneous boundary condition, that the first part, the second problem is $Lu_2 = 0$ in D . So, within the domain $Lu_2 = 0$. The boundaries L bar $u_2 = g$. So, it is the complimentary problem. So, this is the problem b and it is complementary problem c, if we solve B and C then we can always obtain a solution for A as u is equal

to $u_1 + u_2$ as the sum of these two solutions, why? Because this operator L is a linear operator.

(Refer Slide Time: 18:40)

Two independent problems

This is because taking advantage of the linearity of the operators:
 $L(u_1 + u_2) = Lu_1 + Lu_2 = f$ in D . $\bar{L}(u_1 + u_2) = \bar{L}u_1 + \bar{L}u_2 = g$ in ∂D

Recall that one of the analytical techniques for solving 2nd order linear pde's encountered earlier was the method of eigenfunctions. In this technique the eigenfunction of the linear operator was found by solving the eigenvalue problem $Lu = -\lambda u$ subject to homogeneous boundary conditions

We found that if the operator L were self-adjoint, then the eigenfunctions formed an orthogonal basis for the solution space of $Lu = f$ subject to general boundary conditions. Thus any solution could be expressed as a linear combination of the eigenfunctions

NPTEL

So, $L u_1 + L u_2$ is equal to $L u_1 + L u_2$ which is going to be f in D , because $L u_2$ is equal to 0 in t $L u_1$ is equal to f in D . So, $L u_1 + L u_2$ is going to be f in D and $\bar{L} u_1 + \bar{L} u_2$ again taking advantage of linearity it is going to be $\bar{L} u_1 + \bar{L} u_2$ this is equal to 0, that is equal to g . So, this whole thing $u_1 + u_2$ satisfies my original problem. So, if I can solve the problems B on and C then I always construct solutions to my original problem A, I adding those two solutions together taking advantage of the linearity of the operator.

Recall that one of the analytical techniques we looked at for solving second order linear partial differential equations was the method of Eigen functions. In this method we found the, we solve the Eigen value problem. So, initially we solved this problem $L u$ is equal to minus lambda u subject to homogeneous boundary conditions and we found that, the solution if this operator was self-adjoint, if this operator was self-adjoint then the Eigen functions formed an orthogonal basis for my solution space of this function. So, it formed an orthogonal basis for the solution space. So, any solution could be constructed by taking a linear combination of my Eigen functions that we have seen in great detail earlier we have used that technique for solving the wave equation and the diffusion equation and so on.

(Refer Slide Time: 20:27)

Using linearly independent bases

Often the operators L and \bar{L} are too complicated or the domain is too cumbersome to solve the eigenvalue problem analytically. In such a situation it is not possible to obtain a solution for (A) in terms of the eigen functions

However in that case given an appropriate set of linearly independent basis functions $\{\psi_j\} = \{\psi_1, \psi_2, \dots, \psi_n\}$ we attempt to construct approximate numerical solutions \tilde{u} taking advantage of the fact that any \tilde{u} belonging to the n dimensional function space spanned by $\{\psi_j\}$ can be expressed as a linear combination of the basis functions $\psi_j, j=1,2,\dots,n$

$$\tilde{u} = c_1 u_1 + c_2 u_2 + \dots + c_n u_n$$

There are a number of methods which can be used to construct the solution in the above manner. The methods differ in the choice of the n dimensional function space spanned by $\{\psi_j\}$

However the operators L and \bar{L} are often too complicated. They never if they are not as simple as my Laplacian, if they are complicated or if my problem domain geometry is really horrendous, it is very complicated. Then it is not possible to solve this problem analogically to get the Eigen functions. So, then my analytical approach is break stop, I can no longer solve my Eigen functions and I can no longer construct my solution using those Eigen functions. Then what do I do?

Well, in such a situation it is not possible to obtain a solution for in terms of Eigen functions. However, in that case given an appropriate set of linearly independent basis functions we attempt to construct approximate numerical solutions \tilde{u} . Taking advantage of the fact that any \tilde{u} belonging to the n dimensional function space spanned by ψ . These basis functions can be represented as a linear combination of the basis functions. Now, there are number of methods, which can be used to construct the solutions in this manner. These methods differ first on the choice of the basis functions, first on the choice no not just the basis, it depends on the choice of the space, choice of the function space, n dimensional function space spanned by ψ .

(Refer Slide Time: 21:57)

Choice of function space

A particular method may require the function space to be the space of functions with continuous first derivatives (C^1) while another may require it to be the space of all continuous functions (C^0). In addition the methods differ in the way the coefficients $c_1, c_2, c_3, \dots, c_n$ are evaluated.

Since the problem (A) can be easily solved if (B) and (C) can be solved, approximate solutions for (B) are considered. (If we can solve (B) we can solve (C) as well). To solve (B) we use n dimensional subspace H^n such that \tilde{u} obtained as above also satisfy the condition $\bar{L}\tilde{u} = 0 \quad \forall \tilde{u} \in H^n$

H^n may, for instance, comprise polynomials of order 0 to n multiplied by some appropriate function in order to satisfy the boundary conditions. The members of H^n are denoted by $\{\psi_j\}, j = 1, \dots, n$

NPTEL

Particular method may require the function space to be the space of functions with continuous first derivatives. Another method might require the function space to be a space of continuous functions only. It only requires continuity in the function values not in the derivatives. In addition, the methods may differ in the way the coefficients are evaluated. The coefficient $c_0, c_1, c_2, c_3, \dots, c_n$ the way I form my coefficients.

So, it depends on the function space on which function space. I choose to construct my approximate solution. So, once I know my functions space probably the basis functions are known. So, then I depends on the basis functions and then finally, depends on the coefficients. I depend on the coefficients since the problem A can be easily solved, if B and C can be solved approximates.

We will consider approximate solutions to the problem B to this problem. We will consider approximate solutions to the problem B. So, if we can solve B, we can easily solve C as well. So, we will only consider solutions of B. The same methods can be used to solve C and once we have solved B and C we can construct solutions to A to solve B. We can use the n dimensional function space H^n such that, \tilde{u} obtained as above also satisfies.

So, \tilde{u} obtained as above I mean \tilde{u} obtained like this. So, that is a typo. So, it is $c_1 \psi_1, c_2 \psi_2$ and $c_n \psi_n$. So, if I construct \tilde{u} like this, I construct it. But, \tilde{u}

\tilde{u} also has to satisfy this condition. So, \tilde{u} belongs to the function space is constructed by taking a linear combination of the basis functions spanning.

The function space H_n which I am denoting as ψ_0, ψ_1 through ψ_n . But, \tilde{u} in addition it satisfies the boundary condition for my problem B which is $L\tilde{u} = 0$ for all \tilde{u} belonging to H_n . So, H_n may for instance comprised polynomials of order 0 to n multiplied by some appropriate function in order to satisfy the boundary conditions. The members of H_n are which we have already seen are denoted by ψ_j j is equal to 1 to n .

(Refer Slide Time: 24:43)

Least Squares Minimization

To solve $L\tilde{u} \approx f$ with $\tilde{u} = c_1\psi_1 + c_2\psi_2 + \dots + c_n\psi_n \in H^n$, we have to satisfy: $c_1L\psi_1 + c_2L\psi_2 + \dots + c_nL\psi_n \approx f$

The criterion used to enforce the condition that f is indeed approximately equal to $\sum_{i=1}^n c_iL\psi_i$ determines the solution method

If Least Squares Minimization is used, this condition is enforced by requiring that $\left\| f - \sum_{i=1}^n c_iL\psi_i \right\|$ be a minimum

If the L_2 norm is chosen for the least squares minimization

$\left\| \sum_{i=1}^n c_iL\psi_i \right\|^2 = (f - \sum_{i=1}^n c_iL\psi_i, f - \sum_{i=1}^n c_iL\psi_i)$ must be a minimum

NPTEL

To solve the $L\tilde{u}$ as approximately equal to f with \tilde{u} is equal to $c_1\psi_1, c_2\psi_2$ through $c_n\psi_n$, we have to satisfy this equation $c_1L\psi_1 + c_2L\psi_2 + \dots + c_nL\psi_n$ is approximately equal to f . The criterion is very important, the criterion used to enforce the condition, that f is indeed approximately equal to $\sum c_iL\psi_i$ determines the nature of the solution method as we will see least squares approximation is different from galerkin, why because the criteria used to enforce this condition is different.

So, the criteria defines the method, the criteria used to enforce this condition, that $L\tilde{u}$ is indeed approximately equal to f determines the approximate solution method, if least squares minimization is used. This condition is required, is enforced by requiring norm of f minus $\sum_{i=1}^n c_iL\psi_i$ be a minimum only then it is the best solution it is the minimum.

If the L_2 norm is chosen for the least squares minimization that means, this square which is in the L_2 norm. This is equal to the inner product norm square is equal to the inner product. So, this is equal to $f - \sum_{i=1}^n c_i \psi_i$ must be a minimum.

(Refer Slide Time: 26:29)

Least squares minimization

Recall from the discussion of linearly independent polynomials that in order to minimize the approximation error in the L_2 norm,


$$f - \sum_{i=1}^n c_i \psi_i \text{ has to be orthogonal to each and every } \psi_i, i=1 \dots n$$

or $(f - \sum_{i=1}^n c_i \psi_i, \psi_j) = 0 \quad \forall \psi_j, j=1, 2, \dots, n \quad (*)$

This requires that $(f, \psi_j) = (\sum_{i=1}^n c_i \psi_i, \psi_j) = \sum_{i=1}^n (\psi_i, \psi_j) c_i$

Denoting $c = (c_1, c_2, \dots, c_n)^T$ $f = \{(L\psi_1, f), (L\psi_2, f), \dots, (L\psi_n, f)\}$

$$A = \begin{bmatrix} (L\psi_1, L\psi_1) & (L\psi_1, L\psi_2) & \dots & (L\psi_1, L\psi_n) \\ (L\psi_2, L\psi_1) & (L\psi_2, L\psi_2) & \dots & (L\psi_2, L\psi_n) \\ \dots & \dots & \dots & \dots \\ (L\psi_n, L\psi_1) & (L\psi_n, L\psi_2) & \dots & (L\psi_n, L\psi_n) \end{bmatrix}$$



And we have seen from our discussion of linearly independent polynomials, that in order to minimize the approximation error in the L_2 norm. This has to be the residual, the residual $f - \sum_{i=1}^n c_i \psi_i$ has got to be orthogonal to each ψ_i . Because I am taking the linear combination of the ψ_i 's to construct my approximate solution.

My approximate solution is equal to $c_1 \psi_1 + c_2 \psi_2 + \dots + c_n \psi_n$. So, $f - \sum_{i=1}^n c_i \psi_i$ must be equal to these building blocks, $\psi_1, \psi_2, \dots, \psi_n$. My approximate solution is actually $c_1 \psi_1 + c_2 \psi_2 + \dots + c_n \psi_n$ and so on and so forth, but this is my approximately equal to linear combination of these and we have seen that in the least squares method the residual must be equal to these quantity must be orthogonal to these quantities $\psi_1, \psi_2, \dots, \psi_n$.

It must be orthogonal to the building blocks of my of what is approximately equal to f ? The quantity, which is approximately equal to f is that is clear. So, earlier we were looking at we were not looking at differential equations. So, there was no L , there we are just trying to fit a function but now we are solving a partial differential equation. Now,

there is operator L . So, the difference must be orthogonal to $L\psi_1, L\psi_2, L\psi_3$ and $L\psi_n$.

So, this must be orthogonal to that. For all ψ_j, j is equal to 1 through n . And this requires if I just expand this out expand this inner product out that means, $f, L\psi_j$ must be equal to $\sum c_i L\psi_j, L\psi_i, \psi_i, \psi_j \sum c_i L\psi_i, L\psi_j$ which again if I pull out the constant I get that. So, denoting these c_i 's as the vector c vector $f, L\psi_1, f, L\psi_2$ with the scalar components of f being $L\psi_1$ inner product $f, L\psi_2$ inner product f and so on. So, I get a vector here, I denote that as a vector and here I get a matrix whose components are these dot products.

So, the first component is $L\psi_1$ inner not a dot product, it is inner product. So, $L\psi_1, L\psi_1$ second component is $L\psi_1, L\psi_2$ third components are $L\psi_1, L\psi_3$ and so on. So, then I get a system which is equal to A, c is equal to f, A, c is equal to f where i this is my A . So, if I know my basis functions, I can evaluate the components of A , because this is nothing but $L\psi_1, L\psi_1$ inner product of $L\psi_1$ with itself. This is $L\psi_1$ inner product $L\psi_2$. So, I know the components of A , I know the right hand side, because my function f is known my $L\psi_1, L\psi_2, L\psi_3$ are known. So, my hand side is also known. So, then I can solve for my c 's and I get my solution.

(Refer Slide Time: 30:12)

Collocation Method

we finally get the matrix vector equation:

$$Ac = f$$

Solution of the above system yields c_1, c_2, \dots, c_n and thus $\tilde{u} = \sum_{i=1}^n c_i \psi_i$

the approximate solution

If instead of evaluating the inner products $(L\psi_j, L\psi_j)$ and $(L\psi_j, f)$ as integrals over the problem domain, we evaluate the inner product at a discrete set of say ' m ' points in the domain, we get what is known as the collocation method.

In that case $A_j = \sum_{k=1}^m L\psi_j(x_k) L\psi_k(x_k), f_j = \sum_{k=1}^m f(x_k) L\psi_j(x_k)$

NPTTEL

If I only get the matrix vector equation ac is equal to f solving the above system a, c_1, c_2 through c_n and once, I get c_1 and c_2 through c_n and I get \tilde{u} is equal to $\sum c_i$

psi i. So, that is my least squares method, then if instead of evaluating these inner products. So, these are inner products that means. It involves evaluating an integral it is continuous assuming. That the functions are continuous and I am evaluating that inner product over my domain of interest. So, if instead of evaluating that integral, that is treating it as a continuous basis function. This psi i's as continuous basis functions.

If I treat it as a discrete problem and I start evaluating the inner products at discrete points suppose m points in the domain, we have what is known as the collocation method. So, in that case my A_{jI} , I am going to evaluate as the sum and that sum is going to involve these sort of L operating on psi j evaluated at x_k . So, I am again, I am evaluating my basis functions at discrete points at x_1, x_2, x_3 to x_m . So, $L \psi_j$ evaluated at x_k times $L \psi_i$ evaluated at x_k and then I sum it over k is equal to 1 to m, I have think like that, I have made a mistake here, there is no sum here.

So, A_{ji} is equal to $L \psi_j L \psi_i$ at x_k there is no sum here, there is no sum. So, each of those components are evaluated there or is there can we see, no there is a sum I apologize again, there is a sum ,because this involves I am just evaluating that integral but I am evaluating that integral at a discrete set of points So, there is a sum I am sorry, for the confusion.

So, the only difference is that instead of evaluating that inner product as an integral. I am evaluating it as a sum. So, I am evaluating these basis functions at each of my grid points and then summing them up to get. So, to get A_{jI} , I am evaluating psi j at k is equal to 1 psi i at k x_1 then $L \psi_j$ at x_1 $L \psi_i$ at x_1 then I am adding to it $L \psi_j$ at x_2 times $L \psi_i$ at x_2 and so on. So, it is the sum I am sorry for the confusion and then f j to evaluate the f j i similarly, I convert it into a sum.

So, again i evaluate $L \psi_j$ at x_1 times f evaluated at x_1 add to that $L \psi_j$ evaluated at x_2 times f evaluated at x_2 and. So, on and. So, forth and I get my f j the contribution to f of sort of taking the projection with psi j. So, this allows me to evaluate these evaluate my coefficient matrix as well as my hand side in a discrete fashion without performing the integration.

This gives me, what is known as the collocation method, because as we will see in case in the collocation method typically, these psi j's are delta functions. So, basically they are the delta functions. So that means, that each of these basis functions are 1 suppose psi

ψ_1 is 1 at x_1 but 0 everywhere else ψ_2 is 1 at x_2 but 0 everywhere else and so on. So, if these are delta functions, then in this summation only. So, $L \psi_i$, it becomes a lot simpler, if once they are delta functions is that clear. So, the number of contributions they come much smaller in that summation. And actually, if they are delta functions then we are going to get whole thing becomes uncoupled. So, my coefficient matrix is actually going to become a diagonal matrix see.

(Refer Slide Time: 35:11)

The Galerkin method

Unlike the least squares minimization technique and the collocation method which follows therefrom, the Galerkin method determines the coefficients using a different criterion

In the Galerkin method the residual function $f - \sum_{i=1}^n c_i L \psi_i$ is required to be orthogonal to each and every member of H^n

This imposes the criteria $(f - \sum_{i=1}^n c_i L \psi_i, \psi_j) = 0 \forall \psi_j \in H^n$.

$j = 1, 2, \dots, n$ (**)

Comparison of (**) with (*) reveals the difference between the Galerkin and the least squares method. In the least squares method the residual is required to be orthogonal to each and every linearly independent component of the best approximation to f i.e. to each and every $L \psi_i$.

So, then we let us talk about the galerkin method, which is slightly different from the least squares method, unlike the least squares minimization technique and the collocation method which follows there from which we have seen earlier, where the collocation method is just the discrete version of the least squares method. It is just the discrete version of the least squares method. The galerkin method determines the coefficients using different criteria.

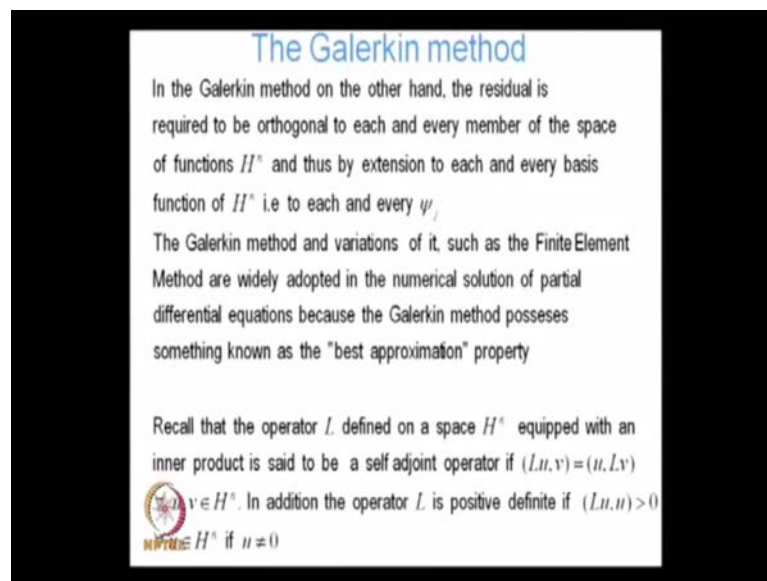
In the galerkin method, the residual function which is $f - \sum_{i=1}^n c_i L \psi_i$ remember that, we are constructing the best approximation to f using the basis functions ψ_i . So, $L \psi_i$ linear combination of that is approximately equal to f is required to be orthogonal to each and every member of H^n . This is different, because the least squares method what did we see, this had to be orthogonal, this residual was orthogonal to each of the $L \psi_i$. So, it is orthogonal to the linear operator operating on each of the ψ_i , $L \psi_1$, $L \psi_2$, $L \psi_3$ and $L \psi_n$. So, residual is orthogonal to L

ψ_i 's but in this case, the residual has to be orthogonal to the basis functions themselves. So, it is orthogonal to each and every member of H_n this imposes the restriction that this imposes the criterion that $f - \sum_{i=1}^n c_i L \psi_i$ is equal to 0 for all ψ_j belonging to 0 to n .

So, if I compare this with let us see with that, you can see the crucial differences are orthogonal to $L \psi_j$, that one in the galerkin method it is orthogonal to ψ_j . In the least squares method, the residual is required to be orthogonal to each and every linearly independent component of the best approximation to f . It is and the best approximation to f is considered to be this.

The residual must be orthogonal to each and every linearly independent component of the best approximation to f linearly component independent component of best approximation to f are $L \psi_1$, $L \psi_2$, and $L \psi_3$. So, this is by the definition of the least squares method f must be orthogonal to each and every linearly independent component of the best approximation to f , that is why we have this criteria, while in the galerkin method this residual is required to be orthogonal to my basis functions for that function space. So, that is a very important point of difference. So, that is the basic difference between the galerkin method and least squares minimization.

(Refer Slide Time: 38:26)



In the galerkin method on the other hand, the residual is required to be orthogonal to each and every member of the space of functions H_n and thus by extension to each and

every basis function of H^n , it is required to be orthogonal to each and every ψ_j . The galerkin method and variations of it such as the finite element methods are widely adopted in the numerical solution of partial differential equations why because the galerkin method possess something known as the best approximation property and by extension since the finite element method is also a galerkin method there are variations but let us assume that. So, it is a galerkin method it also possess the best approximation property.

Recall that the operator L defined on a space H^n equipped with the inner product is said this. We have discussed when we talking about partial differential equations operator L is self adjoint if $L u \cdot v$ is equal to $u \cdot L v$ for all u, v belonging to H^n in addition. The operator L is positive definite if $L u \cdot u$ is greater than 0 for all $u \in A$, u belonging to H^n if u is not equal to 0. So, that it is positive definite that is true.


(Refer Slide Time: 40:00)

Best approximation property

Assuming L is self adjoint as well as positive definite, a new norm and associated inner product can be defined on the function space H^n as follows: $(u, v) = (u, Lv)$, $(u, u) = (u, Lu) = \|u\|_L^2 \quad \forall u, v \in H^n$

This inner product as distinct from the inner product associated with the L_2 norm is defined with respect to the operator L .

If L is positive definite and u^* is the solution of (B) i.e. $Lu^* = f$ on D and $\bar{L}u^* = 0$ on ∂D , then the Galerkin method gives the best possible approximation to u^* in the function space H^n measured in the (\cdot, \cdot) norm

 NPTEL

Assuming L is self –adjoint as well as positive definite we define a new norm new norm associated with the operator L and what is that new norm the norm of $u \cdot v$ is we an associated inner product the norm depends on the inner product. So, the inner product $u \cdot v$ is equal to $u \cdot L v$ it is no longer equal to my original inner product which I defined earlier $u \cdot v$. Now, it is the inner product is with respect to this linear operator. So, this is a new inner product I define and using this inner product I get this norm. So, $u \cdot u$ using this new definition of the inner product is $u \cdot L u$ and this norm is equal to

the norm square is equal to the inner product. So, this norm square is equal to that because the norm square we said is equal to the inner product, so in this new definition of the norm. So, every a function space has a certain inner product a function space with an inner product and the norm is always related to the inner product the norm arises from that inner product.

So, in this case the inner product is defined by that and this gives raise to this norm u . So, norm of u is a member of that function space. If I am interested in the magnitude of u in the norm of u , how am I going to evaluate the magnitude of the norm of u ? I am going to take the inner product of u with itself and now my inner product is different. It is no longer $u \cdot u$ it is $u \cdot L u$ and whatever I get there is the square of the norm of u is the square of the norm of u . So, there is a one to one relationship between the norm and the inner product norm vector space in a norm function space, the norm is related to the inner product in this way.

So, the inner product is distinct from the inner product associated with the L^2 norm inner product and it is defined with respect to the operator L . So, what is the best approximation property is this? If my operator L is positive. Definite meaning that it satisfies this property, satisfies that property. If my operator L is positive definite and u^* is the solution of my problem my problem B which was $L u^*$ is equal to f on D $L \bar{u}^*$ is equal to 0 on ∂D and u^* is the solution is the true solution of the problem. Then the galerkin method always gives the best possible approximation to u^* in the function space measured in this norm.

Best approximation as soon as we say it is a best approximation, we have to show in what norm it is the best approximation. How do you say it is the best approximation? We say it is the best approximation we if your solution obtained in the galerkin method. That differs from the best solution we calculate the difference between the solution obtained using the galerkin's method and the true solution in some norm which norm is that, this norm which we have defined that gives me the smallest possible norm.

So, it is closest to the true solution in this norm. It is closest to the true solution in this norm. So that is the property. So, if we have a norm defined like this and we get the solution of a problem using galerkin's method. That solution to the problem obtained using galerkin's method differs from the exact solution but the difference is minimum in

that norm. So, in that if you obtained the solution by some other method for instance by the least squares method and you calculate the difference in this norm that difference will be larger than the solution we have got obtained using galerkin's method that difference will be larger than the solution, you obtained using galerkin, this is the property, this is the best approximation property of the galerkin method, which passes on the finite element method and that is why the one reason why the finite element method is so widely adopted.

(Refer Slide Time: 45:06)

Best approximation property

From the solution of the error minimization problem, the best possible solution u in H^n in the (\cdot, \cdot) norm must satisfy the requirement

$$\langle u - u^*, v \rangle = 0 \text{ for each and every } v \in H^n$$

However $\langle v, u - u^* \rangle = (v, L(u - u^*)) = (v, Lu) - (v, Lu^*)$

$$= (v, Lu) - (v, f) = (v, Lu - f)$$

Thus requiring $\langle v, u - u^* \rangle = 0$ is equivalent to requiring $(v, Lu - f) = 0$

But from (**) $(v, Lu - f) = 0$ is the Galerkin condition. Hence finding the best possible solution $u \in H^n$ in the (\cdot, \cdot) norm is equivalent to

finding the solution using the Galerkin method.

NPTEL

From the solution of the error minimization problem, the best possible solution u in H^n must belong to H^n . It is the best possible solution that can be constructed from the basis functions used in H^n must satisfy the requirement $u - u^*$ comma v is equal to 0 for each and every v belong. That is we know solution of the error minimization problem, we know that the residual inner product v must be equal to 0 for each and every v belonging to H^n .

However v , if I evaluate that, $u - u^*$ comma v I take advantage of symmetry write it like that and that can be written as v L $u - u^*$, because this inner product means v comma $L u - u^*$ my usual inner product my usual inner product and that is equal to v comma $L u - v$ comma $L u^*$ again taking advantage of the linearity of the operator. So, I get v comma $L u - v$ comma f , because $L u^*$ is the exact solution u^* is the exact solution $L u^*$ has got to be equal to f . So, v comma $L u$

minus v comma f which I can write as v comma $L u$ minus f thus requiring v comma u minus u^* is equal to 0 is equal equivalent to requiring v comma $L u$ minus f is equal to 0 but v comma $L u$ minus f is equal to 0 is nothing but the galerkin condition which we have seen v comma $L u$ minus f is equal to 0. That was my galerkin condition. That was my galerkin condition if ψ is v and I think of ψ as v and this is f minus $L u$ that is my galerkin condition.

So, to minimize the error if I minimize the error, if I minimize the error, then I satisfy galerkin's condition to minimize the error I have to satisfy that requirement that I know from earlier to minimize the error. I have to satisfy that requirement and satisfying that requirement is equivalent to satisfying the galerkin condition hence finding the best possible solution u belonging to h_n in this norm is equivalent to finding the solution using the galerkin's method. So, instead of finding the best possible solution to u and this norm, if I solve the equation using galerkin's method find the best solution using galerkin's criterion by basically find reduce the make ensure that approximation satisfies this criterion. The galerkin's criterion then I am going to also get my best approximation property.

(Refer Slide Time: 48:28)

Minimization of a functional

It can be shown that the best approximation property of the Galerkin solution also ensures that it minimizes the functional $(u, Au) - 2(f, u)$ if this functional can be written as $(u - u^*, u - u^*) - (u^*, u^*)$:

$$\begin{aligned} (u - u^*, u - u^*) &= (u - u^*, Au - Au^*) \\ &= (u, Au) - (u, Au^*) - (u^*, Au) + (u^*, Au^*) \\ &= (u, Au) - (u, f) - (Au^*, u) + (u^*, Au^*) \quad (\text{due to symmetry}) \\ &= (u, Au) - (u, f) - (f, u) + (u^*, Au^*) = (u, Au) - 2(f, u) + (u^*, u^*) \end{aligned}$$

This establishes equivalence. Thus if $u = u^*$, $(u, Au) - 2(f, u)$ is minimized among all functions u for which the functional $(u, Au) - 2(f, u)$

exists
NPTEL

It can be shown that the best approximation property of the galerkin's criteria. It is not only minimizes, it not only gives me satisfies that condition it also minimizes a certain functional which if I define that functional like this. It is also minimizes, that functional

what is the advantage of why do we want to emphasize this? The fact, that the galerkin's solution minimizes that functional well we are going to see that later on. Actually it can be shown that, this functional can be written like this $u - u^*$ inner product of $u - u^*$ minus inner product of $u^* - u^*$, why well let us see how let us see.

$u - u^*$ inner product $u - u^*$, I can write it as $u - u^*$ $A u - A u^*$ by definition of the inner product. This I can write as $u, A u - u, A u^*$ minus $u^*, A u - u^*, A u^*$ taking advantage of linearity, this becomes equal to $u, A u - u, A u^*$ because $A u^* - u^*$ remembers the exact solution.

So, $A u^*$ is equal to f u, f and again I have interchanged u due taking advantage of symmetry. We can write as $A u$ no sorry, I have not interchanged. I have taken advantage of the fact, that my operators self adjoint. So, $A u^*, u - A u^*, u^*$ is equal to $A u^*, u$, because the operator A is the self adjoint operator.

This I can write as $u, A u - u, A u^*$ minus $A u^*, u - A u^*, u^*$. I can again replace by f minus $f, u - f, u^*$ $A u^*$. So, this is equal to $u, A u$ and then again taking advantage of symmetry, I can write f, u as u, f . So, minus $2 f, u - u^*$ inner product $u^*, A u^*$. I can write as inner product of u^*, u^* is that how I define my inner product.

So, you can see that inner product of $u - u^*$ $u - u^*$ minus inner product of $u^* - u^*$ is actually equal to $u, A u - 2 f, u$ if u is equal to u^* , that means if u is equal to the true solution, then this thing becomes 0. So, this difference is minimized $u, A u - 2 f, u$ is minimized among all functions u for which is the functional $u, A u - 2 f, u$ exists, because then it becomes 0.

(Refer Slide Time: 51:54)

Equivalence with variational methods

Since Galerkin's method gives the best approximation to u^* in the (\cdot, \cdot) norm, it also minimizes the above functional in H^n .

In many problems of mechanics, variational principles exist which lead to derivation of the governing equations of a problem by minimizing a functional, typically the energy functional associated with that problem.

The Galerkin method for self adjoint operators L is thus a way to minimize the associated energy functional, if the energy functional can be expressed in the above form, and thus can be regarded as a variational method.

NPTEL

Since, galerkin's method gives the best approximation to u^* in that norm. It also minimizes the above functional in H^n since galerkin's method.

(Refer Slide Time: 52:06)

Minimization of a functional

It can be shown that the best approximation property of the Galerkin solution also ensures that it minimizes the functional $(u, Au) - 2(f, u)$ if this functional can be written as $(u - u^*, u - u^*) - (u^*, u^*)$:

$$\begin{aligned} (u - u^*, u - u^*) &= (u - u^*, Au - Au^*) \\ &= (u, Au) - (u, Au^*) - (u^*, Au) + (u^*, Au^*) \\ &= (u, Au) - (u, f) - (Au^*, u) + (u^*, Au^*) \quad (\text{due to symmetry}) \\ &= (u, Au) - (u, f) - (f, u) + (u^*, Au^*) = (u, Au) - 2(f, u) + (u^*, u^*) \end{aligned}$$

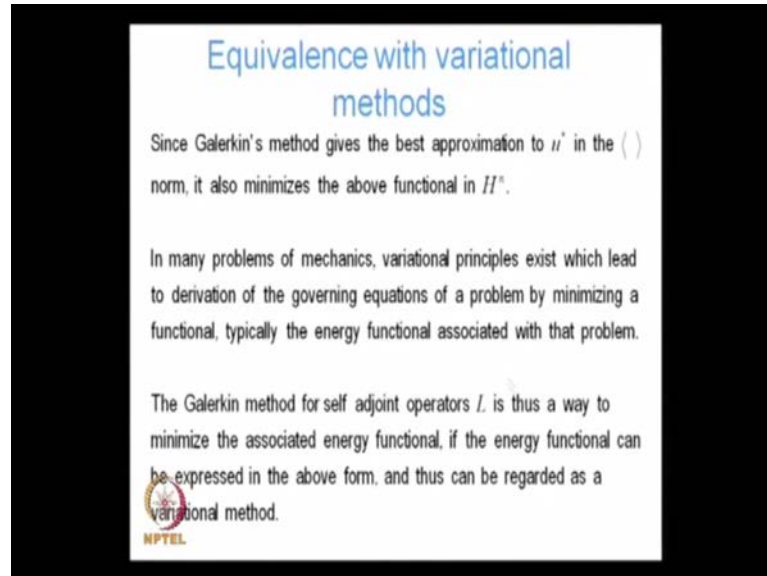
This establishes equivalence. Thus if $u = u^*$, $(u, Au) - 2(f, u)$ is minimized among all functions u for which the functional $(u, Au) - 2(f, u)$

NPTEL

We have seen that galerkin's method gives me the best approximation to u^* since galerkin's method. So, if I calculate u using galerkin's method. I am assured that, this difference is going to be a minimum, because galerkin's method gives me the best approximation to u^* . So, this norm is going to be minimum, this norm is going to be minimum, that means that also gives me, it minimizes this functional. It minimizes the

galerkin's method minimizes this functional. Why is that important? Well we are just going to see.

(Refer Slide Time: 52:45)



In many problems of mechanics variation principles exists which lead to derivation of the governing equations of a problem by minimizing a functional typically, the energy functional associated with their problem. So, I am able to write an expression for the energy and by minimize by the variation principles which by minimizing that energy allow me to get the equations of motion.

So, we write an expression for the work. The principle of virtual work for instance principle of virtual work. So, all that depends on this I do not want to get much mechanics but there you can write an expression for the energy minimizing that you can get the equations of motion. So, the galerkin method for self adjoint operators L is thus a way to minimize the associated energy functional, because we have seen that by when we solve the problem using the galerkin's method, when we find the solution using galerkin's method, we are also minimizing that potential, that functional like this. So, when we are solving the problem using galerkin's method we are minimizing that potential. So, if this potential of this functional I am always talking potential, but if this functional is the energy potential it is the energy potential energy associated with that problem. I am also minimizing the energy.

So, galerkin's method for self-adjoint operators, L is thus a way to minimize the associated energy functional, if the energy functional can be expressed in the above form and thus can be regarded as a variation method. The galerkin method what self –adjoint operators can therefore, be regarded as a variation method, because it leads to the same result. Is that clear? I think we will stop there, and we will talk about weighted residual methods and specialize them to finite element methods in the next class.