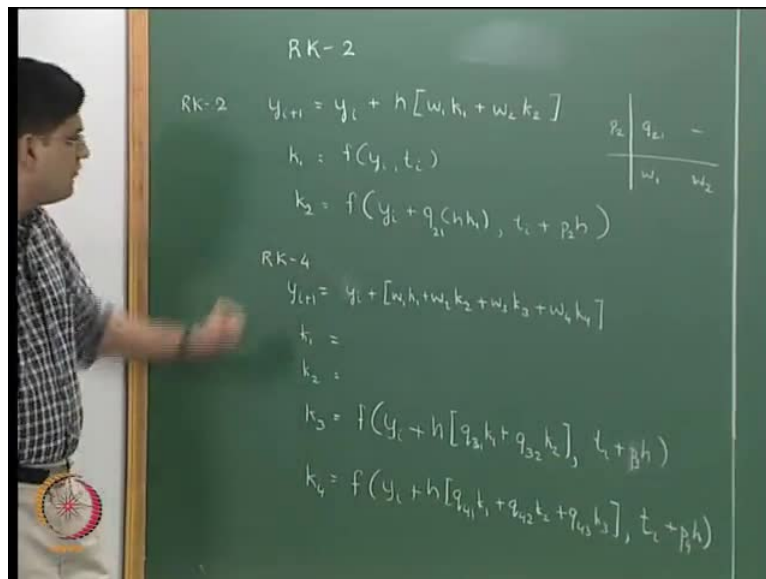


Computational Techniques
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Module No. # 07
Lecture No. # 05
Ordinary Differential Equations

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Hello and welcome to lecture 5 of module 7. We have been considering numerical methods for solving ordinary **ordinary** differential equations, the initial value problems in this particular module. So far we have covered the Runge-kutta family of method and specifically we have covered r k - 2 and r k - 4 methods. In the r k 2 method what **what** we do is, we write our y i plus 1 equal to y i plus h times slope, where slope is computed as some of two slopes k 1 and k 2.

So, I will write this as h times w 1 k 1 plus w 2 k 2 that is the r k - 2 method, where k 1 is going to be equal to **computed as** the function f computed at (y i, t i), and k 2 is computed at some point y i plus **q 2 multiplied** by h k 1, t i plus p 2 multiplied by h **what are sorry** q2 2 1 multiplied by h k 1; this 2 corresponds to this particular 2 the same index, and this 1 index corresponds to this index 1 over here.


So, this is an explicit $r_k - 2$ method that **that** we have over here. So, these weights w_1 , w_2 , q_2 and p_2 are related to each other based on certain rules, those rules were w_1 plus w_2 equal to 1; w_2 multiplied by q_2 equal to half; w_2 multiplied by p_2 equal to half. These were the three rules that we obtained; we have three equations for four unknowns, that means, one of those values we can choose **on our** on our own whichever value that we want, usually we tend to choose our value p_2 .

And based on that, we have looked at three different variants of $r_k - 2$ method, the midpoint method, the Heun's method and the Ralston's method. So, this was about $r_k - 2$, and the way we represent these weights is, what we will do is will just draw a table with two lines, and the weights w_1 and w_2 will go below this this particular line, and **the weights p at the** weight p_2 will come to the left of the vertical line and q 's we will write it in this particular row.

So, we will have this q_2 over here and we would not have anything in this particular **this particular** column of the first row. So, this is going to be the representation for $r_k - 2$. Now, the $r_k - 4$ method will have y_{i+1} computed as y_i plus $w_1 k_1$ plus $w_2 k_2$ plus $w_3 k_3$ plus $w_4 k_4$, where k_1 was as before; k_2 was also as before the same expressions. We may not have the same q_2 and p_2 values, the expression is the same; it is not the values that are the same.

k_3 is going to be equal to f of y_i plus h multiplied by **$q_2 k_1$ sorry** $q_3 k_1$ this time plus $q_2 k_2$, t_i plus p_3 multiplied by h ; and k_4 is f of y_i plus h multiplied by $q_4 k_1$ plus $q_2 k_2$ plus $q_3 k_3$. And now, we have our k_1 , k_2 , k_3 and k_4 for our $r_k - 4$ method. And in $r_k - 4$ method, the same kind of table will have w_1 w_2 w_3 and w_4 and then, instead of having just one row above this particular guy, we will have three rows above this guy- $p_2 q_2$, p_3 **q_2** q_3 and q_3 , and $p_4 q$ **3** 4 4 2 and 4 3 .


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Overview

- Runge-Kutta Family of Methods
 - Euler's methods
 - Explicit vs. Implicit Methods
 - Higher order Runge-Kutta methods
 - Error analysis and Stability
- Predictor-Corrector Methods
- Adam-Moulton's Family of Methods
- Adaptive Step Sizing
- Stiff ODE Solvers

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Runge-Kutta Methods (RK-2)

$$y_{i+1} = y_i + h[w_1k_1 + w_2k_2]$$
$$k_1 = f(y_i, t_i)$$
$$k_2 = f(y_i + q_{21}[hk_1], (t_i + p_2h))$$
$$w_1 + w_2 = 1$$
$$w_2p_2 = \frac{1}{2}$$
$$w_2q_{21} = \frac{1}{2}$$

0.5	0.5	-
	0	1

Mid-Point Method

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Runge-Kutta Methods (RK-2)

$$y_{i+1} = y_i + h[w_1k_1 + w_2k_2]$$
$$k_1 = f(y_i, t_i)$$
$$k_2 = f(y_i + q_{21}[hk_1], (t_i + p_2h))$$

$$w_1 + w_2 = 1$$
$$w_2p_2 = \frac{1}{2}$$
$$w_2q_{21} = \frac{1}{2}$$

0.75	0.75	-
1/3	2/3	

Ralston's Method



What I will do now is, I will go through some of the slides that I have already made, to show you some of the variants of the r k - 4 method, I will just go and review some of the things that we did in the last 5 minutes of the previous lecture and then, we will go on to the r k - 4 method. Let us start from essentially the over view of this particular module - in the r k family of method we have considered the r k - 2 and r k - 4 as higher order methods; r k 3 method is also there and usually its r k - 2, r k 3 and r k - 4 methods that are typically more popular with r k - 4 being the most popular, and the reason for that is better ah accuracy of r k - 4 method compared to the any of the earlier methods. And the r k - 2 method, I had just written down on the board and I had gone over these particular expressions in **in** the previous lecture and we write **this** the weights in this particular form, q 2 2 the weight we are not going to use and so for different values of weights, we will get the midpoint method, the Heun's method and the Ralston's method.

(Refer Slide Time: 06:57)

Runge-Kutta Methods (RK-n)

$$y_{i+1} = y_i + h \sum_{m=1}^n w_m k_m$$

$$k_1 = f(y_i, t_i)$$

$$k_m = f\left((y_i + h[q_{m1}k_1 + \dots + q_{m,m-1}k_{m-1}]), (t_i + p_m h) \right)$$

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Runge-Kutta Methods (RK-4)

p_2	q_{21}	-	-	-	0.5	0.5	-	-	-
p_3	q_{31}	q_{32}	-	-	0.5	0	0.5	-	-
p_4	q_{41}	q_{42}	q_{43}	-	1	0	0	1	-
	w_1	w_2	w_3	w_4	$\frac{1}{6}$	$\frac{2}{6}$	$\frac{2}{6}$	$\frac{1}{6}$	

"Classical"

Now, when we go to an r k n, we will have a general formulation of this type, where it is a weighted sum of k 1, k 2 up to k n, where k 1 is the slope computed at (y , t); k 2, k 3, k 4 and so on are the slopes computed at internal points. And we just on the green board, we just look at the expression that we get when n that is the number of internal points for computing the r k method was equal to 4 that is we have seen the r k - 4 variant on the green board of you a minute back. And the the table for r k - 4 method that we get will be constructed in this particular form.

So, we have the four weights w_1 , w_2 , w_3 and w_4 ; these are the weights for k_1 , k_2 , k_3 and k_4 to compute the slope S ; p_2 , p_3 and p_4 are the slopes in computing $t_i + h$ multiplied by p ; these are the p values, and q values are the weights that are **computed** are used in computing the intermediate y points using the $r k$ method.

For example, the classical $r k$ method was p_2 was equal to half; p_3 was equal to half and p_4 was equal to 1, and q_{21} was also equal to half **.in** And then, for computing k_3 **we had** we had used only k_2 ; we had not used k_1 at all. So, therefore, q_{31} was 0; q_{32} was half and p_3 was half. So, if you recollect what we did, was we computed the slope at the initial point, then we computed the slope at midpoint; midpoint means, the weights are going to be equal to half; we computed the slopes at midpoints using k_1 , then we computed the slope again at midpoint not using k_1 that is why we get the 0, but using k_2 , we computed the slope at the midpoint and that was called our k_3 . And then, using the slope at k_3 , we projected up to the end point so that is why this particular guy is equal to 1, because we are projecting up to end point, that means, we are projecting at $t_i + 1$ multiplied by h that is why this guy is 1; we did not use k_2 , k_1 or k_4 in this projection we only used k_3 in this projection.

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Runge-Kutta Methods (RK-4)

p_2	q_{21}	-	-	-
p_3	q_{31}	q_{32}	-	-
p_4	q_{41}	q_{42}	q_{43}	-
	w_1	w_2	w_3	w_4

0.5	0.5	-	-	-
0.5	$\frac{\sqrt{2}-1}{2}$	$\frac{2-\sqrt{2}}{2}$	-	-
1	0	$\frac{-1}{\sqrt{2}}$	$\frac{2+\sqrt{2}}{2}$	-
	$\frac{1}{6}$	$\frac{2-\sqrt{2}}{6}$	$\frac{2+\sqrt{2}}{6}$	$\frac{1}{6}$

RK-Gill

So, it was $y_i + h$ multiplied by k_3 and that is why we have this guy equal to 1; and the weights were 1 by 6; 2 by 6; 2 by 6 and 1 by 6. Remember that S , we computed as one sixth multiplied by k_1 plus 2 k_2 plus 2 k_3 plus k_4 ; so this is the classical Runge-

kutta fourth order method. Various different people have since device different methods for computing this for using this r k - 4 method. One of the more popular once explicit popular method is the Runge-kutta gills method. The reason why Runge-kutta gills method is popular, is the objective of the r k gill method is not just to minimize the truncation error, but it also tries to minimize the round off error.

(Refer Slide Time: 10:43)

The slide displays two coefficient matrices for Runge-Kutta methods. The first is the standard RK4 matrix, and the second is the RK-Fehlberg matrix.

	q_{21}	q_{31}	q_{41}	
p_2	-	-	-	
p_3	q_{32}	-	-	
p_4	q_{42}	q_{43}	-	
	w_1	w_2	w_3	w_4

$\frac{1}{4}$	$\frac{1}{4}$	-	-	-
$\frac{3}{8}$	$\frac{3}{32}$	$\frac{9}{32}$	-	-
$\frac{12}{13}$	$\frac{1932}{2197}$	$-\frac{7200}{2197}$	$\frac{7296}{2197}$	-
	$\frac{25}{216}$	$\frac{1408}{2565}$	$\frac{2197}{4104}$	$-\frac{1}{5}$

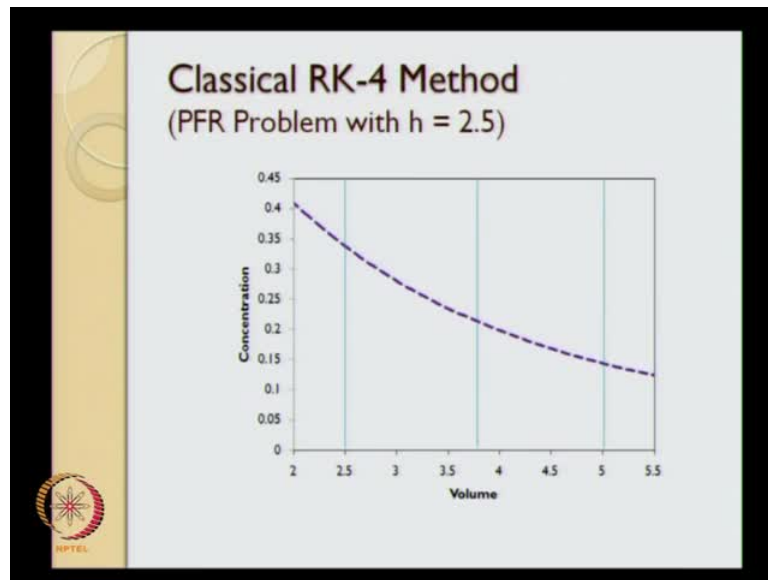
RK-Fehlberg

So, with an objective function of minimizing the round off errors, these are basically the weights that are obtained for the r k gill method; perhaps is one of the most popular r k - 4 methods when it comes to non-adaptive r k - 4 methods. And finally, we have the Runge-kutta Fehlberg method; the Runge-kutta Fehlberg method comes under the category of embedded r k methods, and the embedded r k methods I will cover very briefly in the next lecture when I am going to discuss about in the next lecture when I discuss about the adaptive step size methods. And so, these are weights that are obtained for the Runge-kutta Fehlberg method. This is probably the most popular of the r k methods when we are going to use adaptive step size methods using what is known as this ah the types of r k methods.

So, essentially what the weights that we get or of of this type, we have one fourth and one fourth weight for p and q, and these are the weights for computing k 3, and these are the weights for computing k 4, and once you get k 1 k 2 k 3 and k 4, these are the weights that you will use for w 1 w 2 w 3 and w 4. In fact you can actually indeed verify

that some $w_1 + w_2 + w_3 + w_4$ is always going to be equal to 1 in all of the RK-4 methods that we obtained. And this particular property that $w_1 + w_2 + w_3 + w_4 = 1$ is required for consistency and we will talk about that in about ten minutes from now .

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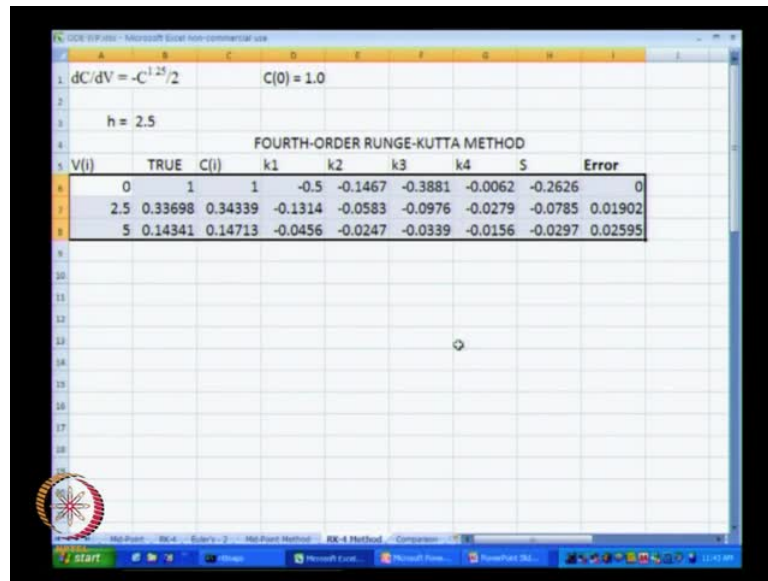
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The figure shows an Excel spreadsheet titled "FOURTH-ORDER RUNGE-KUTTA METHOD". The spreadsheet contains the following data:

Differential equation: $dC/dV = -C^{1.25}/2$
 Initial condition: $C(0) = 1.0$
 Step size: $h = 0.125$

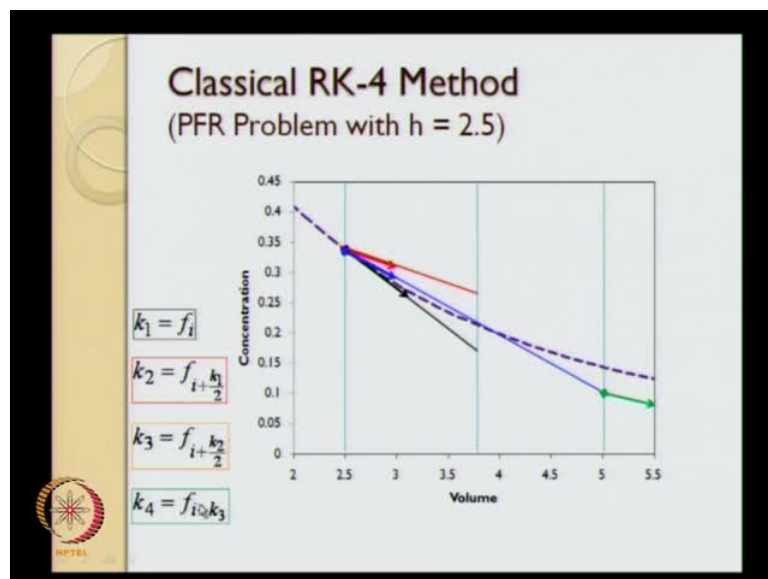
V(i)	TRUE	C(i)	k1	k2	k3	k4	S	Error
0	1	1	-0.5	-0.4805	-0.4813	-0.4627	-0.4811	0
0.125	0.93987	0.93987	-0.4627	-0.445	-0.4457	-0.4287	-0.4454	1.4E-08
0.25	0.88419	0.88419	-0.4287	-0.4125	-0.4131	-0.3976	-0.4129	2.7E-08
0.375	0.83257	0.83257	-0.3976	-0.3829	-0.3834	-0.3692	-0.3832	3.8E-08
0.5	0.78466	0.78466	-0.3693	-0.3557	-0.3562	-0.3432	-0.3561	4.9E-08
0.625	0.74016	0.74016	-0.3433	-0.3309	-0.3313	-0.3194	-0.3312	5.83E-08
0.75	0.69876	0.69876	-0.3194	-0.3081	-0.3085	-0.2976	-0.3083	6.70E-08
0.875	0.66022	0.66022	-0.2976	-0.2871	-0.2875	-0.2775	-0.2874	7.50E-08
1	0.6243	0.6243	-0.2775	-0.2679	-0.2682	-0.259	-0.2681	8.22E-08
1.125	0.59078	0.59078	-0.259	-0.2501	-0.2504	-0.2419	-0.2503	8.88E-08
1.25	0.55949	0.55949	-0.2419	-0.2338	-0.2341	-0.2262	-0.234	9.49E-08
1.375	0.53024	0.53024	-0.2262	-0.2187	-0.219	-0.2117	-0.2189	1.00E-07
1.5	0.50288	0.50288	-0.2117	-0.2048	-0.205	-0.1983	-0.205	1.05E-07
1.625	0.47726	0.47726	-0.1983	-0.1919	-0.1921	-0.1859	-0.1921	1.10E-07
1.75	0.45325	0.45325	-0.186	-0.18	-0.1802	-0.1745	-0.1801	1.14E-07
1.875	0.43074	0.43074	-0.1745	-0.169	-0.1691	-0.1638	-0.1691	1.18E-07

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So, now, to summarize what we get with the r k - 4 method what I have done is, I have used the solution using the r k - 4 method using the previous solver, that we had we had develop recall that we had developed this particular solver using the r k - 4 method and what I did was, I change h equal to 2.5, and for h equal to 2.5 these are the results that we obtained for v equal to 0 v equal to 1; V equal to 0, V equal to 2.5 and V equal to 5.

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And for v going from V equal to 2.5 to V equal to 5 what I have done is, I have just created an animation and I will just show that animation in the slide show, the dash line

that you see the purple thick dash that you see over here is the true solution; the three vertical lines that you see over here are t_i , $t_i + 1$ and the midpoint. I have showed the midpoint, because in computing the classical $r_k - 4$ method, we are going to use projections at the midpoint. So, we will start at this particular point and compute k_1 .

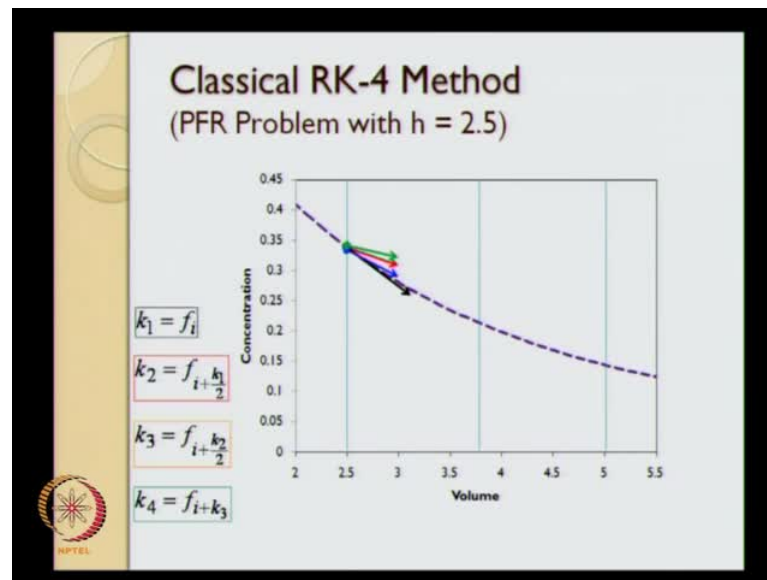
So, the k_1 is computed at the point shown by this black circle; so k_1 so the slope k_1 is just going to be equal to f of (y_i, t_i) . So, the slope at this particular point will be k_1 and that is shown by the black line over here and then, we project along this slope up to the midpoint to compute our k_2 . Keep in mind, the k_2 was computed at f of i plus half for time t , and i plus $k_1 h$ by 2 for y_i .

So, k_2 is going to be computed at this point; it is computed at (t_i, y_i) . So, the k_2 computed at this point these are actual slopes that are obtained from from excel. This is not a cartoon; these are indeed actual slopes that I have obtained from excel and I have animated the slope. So, this particular red line that you see over here is the slope k_2 , and using the slope k_2 , we are going to project to project over here in order to get our k_3 ; k_3 again is obtained at the midpoint. So, we take this particular arrow, this slope is unchanged and we will just bring it back to the point (t_i, y_i) and then, project it to the midpoint.

So, the t point (t_i, y_i) is projected at the midpoint and that we will get as k_3 , and the k_3 is f computed at y_i plus $k_2 h$ by 2 that is this particular point, and t_i plus h by 2, which is this vertical point over here. Now, k_3 will be computed at this point and the k_3 that is computed at this point is shown by the blue arrow over here.

So, this red arrow sorry the black arrow is k_1 ; this red arrow is k_2 ; this blue arrow is k_3 , and the blue arrow gets again moved back to the point (y_i, t_i) . And now, what we are going to do is, we are going to use k_3 to project at $t_i + 1$. So, we will project along this line all the way up to $t_i + 1$ and will compute the slope at that point $t_i + 1$.

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So, this is the point at which we will compute our fourth slope, which will be given by this green line. So, this is the slope computed at this particular guy k_4 computed at $i + 1$ for the time, and $i + h$ times k_3 for the concentration. So, this is the green slope representing k_4 and we now take this green slope back over here.

So, now, we have k_1 , k_2 , k_3 and k_4 ; I have discarded all those lines **for lines** for projections. So, 1 multiplied by k_1 plus 2 multiplied by **by** k_2 plus 2 multiplied by k_3 plus 1 multiplied by k_4 ; the entire thing divided by 6 is going to give us the final slope S and using that final slope, we will project up to **from** this point, we will end up reaching actually the point right over here. So, this is geometric interpretation of $r k - 4$ method using the actual values for **r k the** classical $r k - 4$ from the Microsoft excel.

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Heun's Method

- RK-2 variant gives:

$$k_1 = f(y_i, t_i)$$
$$k_2 = f\left(\underbrace{y_i + hk_1}_{\bar{y}_{i+1}}, \underbrace{t_i + h}_{t_{i+1}}\right)$$
$$\cancel{y_{i+1} = y_i + \frac{h}{2}[k_1 + k_2]}$$
$$y_{i+1} = y_i + \frac{h}{2}[f(y_i, t_i) + f(\bar{y}_{i+1}, t_{i+1})]$$

The graph shows Concentration on the y-axis (0 to 0.45) and Volume on the x-axis (2 to 5.5). A solid black line represents the exact solution, and a dashed purple line represents the numerical solution. A red arrow points from the \bar{y}_{i+1} term in the formula to the dashed purple line.

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Overview

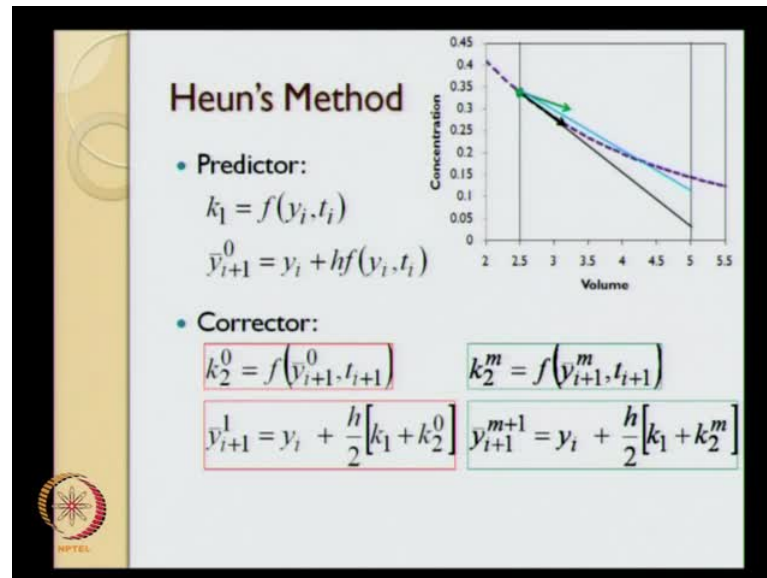
- Runge-Kutta Family of Methods
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We will do the same thing for Heun's method also. If we go on to some of the earlier slide, I will just go on to the **the** overview slide; we have covered the Heun's method under the context of higher order Runge-kutta method. Now, what I will do is I will go on to the predictor-corrector methods and **I will give you a motivation for using the Heun's** using the Heun's method, I will motivate the predictor-corrector methods.

So, **the Heun's method variant**, the r k - 2 variant of Heun's method is, k_1 is the slope computed at this point and we project all the way up to **y_i all the way up to $t_i + 1$** . So,

for the k_2 will be the slope computed at $y_i + h \times k_1$ and $t_i + 1$. So, $t_i + h$ is $t_i + 1$; $y_i + h \times k_1$ is what we will call as \bar{y} . So, the k_2 variant is y_{i+1} equal to $y_i + h \times \frac{k_1 + k_2}{2}$. Now, what we can say about k_1 , is that k_1 predicts, what value we will reach with y_{i+1} ; so this \bar{y}_{i+1} is the predicted value y_{i+1} .

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So, what we are going to say in the predictor-corrector form is, instead of calling this as y_{i+1} equal to $y_i + h \times \frac{k_1 + k_2}{2}$, we will call this as y_{i+1} equal to $y_i + h \times \frac{f(y_i, t_i) + f(\bar{y}_{i+1}, t_{i+1})}{2}$, where \bar{y} is the predicted value, $y_i + h \times k_1$ so this is the predictor-corrector variant.

Now, let us put the Heun's method in the predictor-corrector form. So, k_1 is the slope computed over here; \bar{y}_i y_{i+1}^0 is the predicted point at this particular location. And now, we write in the corrector equations, the corrector equation is k_2^0 is going to be nothing but f at y_{i+1}^0 , t_{i+1} , and the new value \bar{y}_{i+1} computed using the first iteration is going to be $y_i + h \times \frac{k_1 + k_2^0}{2}$. So, if we stop at this location what we are going to get is, we are going to have these two slopes - this black slope and this red slope and the new slope is going to be just an average of the slope using the Heun's method.

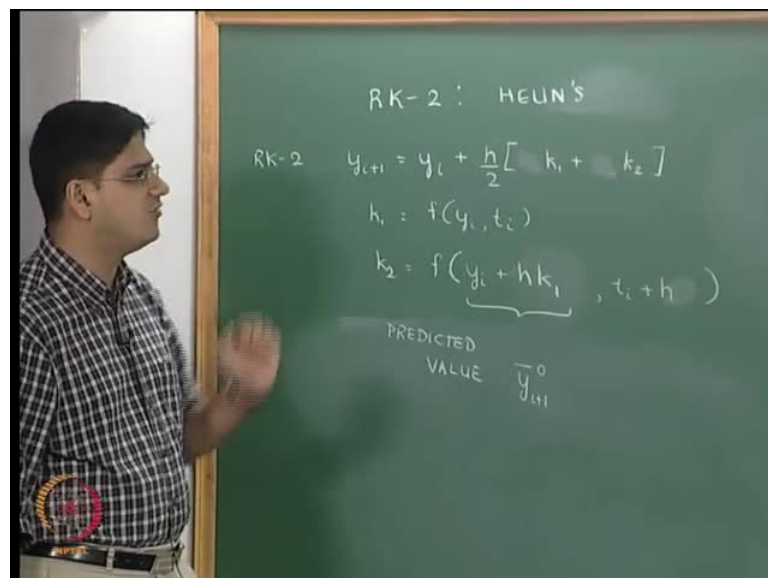
If we stop at this point, we will get a predictor-corrector form of Heun's method, which is exactly the same as the k_2 method, but there is no need to stop at this point. This is

going to be the average of the two slopes; the average of the red line over here and the black line over here is shown by this particular thin line. Now, this thin line with we can use to project once again to get y_{i+1} ; this y_{i+1} in the same manner we can get y_{i+2} , which is essentially going to be this point. Keep in mind k_2 is just going to be nothing but this particular slope, which is midpoint of though of the previous slopes. And now, we compute the slope at this point, we projected back that the slope computed at this point discard the red lines, which represent the the corrector forms for the first iteration.

So, now, we have the corrector form for the second iteration; now, we have this black line and this blue line and we can get the average of the black and blue line and we can keep repeating this again and again multiple number of times in order to get the Heun's method the predictor-corrector form.

So, what I have done is, I have shown you the Heun's method in the predictor-corrector forms using animation using Microsoft excel results. Now, what I will do is, I will go on to the green board and I will again re-derive the Heun's method using the predictor-corrector form.

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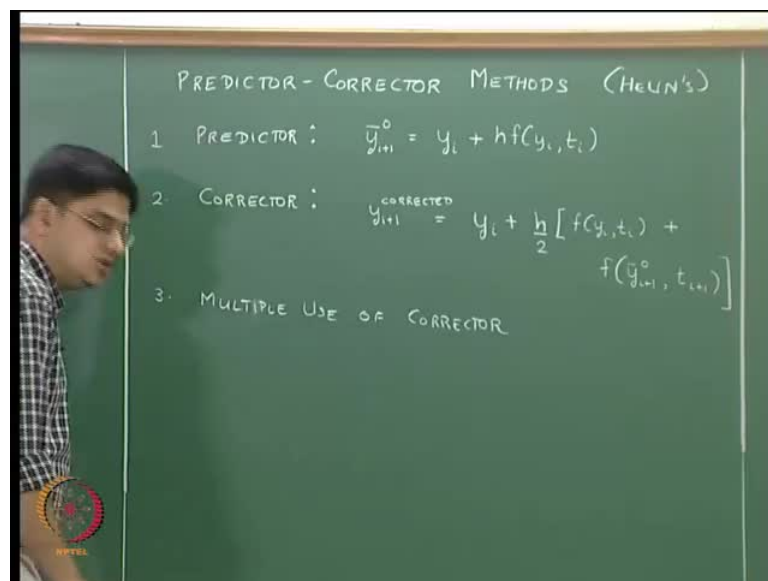


So, now, let us on the on the green board, let us see the r k - 2 variant of Heun's method and then, the predictor predictor-corrector variant of Heun's method. The general r k - 2 method had already written written down on the board. For Heun's method, the weights

w_1 and w_2 are $1/2$ and $1/2$; so I will replace them by those numbers. So, I will replace w_1 and w_2 by half each and I will take half outside the bracket; so will get this as $h/2 \cdot k_1$ that was nothing but f computed at (y_i, t_i) and k_2 is f computed at $y_i + h$ multiplied by $h/2$ that was what Heun's method was. Our q_2 and our p_2 , were both equal to 1. So, I will write it in that particular form; so it is h multiplied by k_1 and $t_i + h$ over here; so this is going to be our k_2 . Now, what we do is, we call this particular guy, **we call this as a predicted value will call this** predicted value y_{i+1}^0 , and this predicted value we will correct it using Heun's method recursively.

So that is what we are we are going to do with **with** this. Now, here if we were to use this k_2 variant, this is where we stop and we do not proceed ahead **any further** this becomes the k_2 variant, which is equivalent to the Heun's method predictor-corrector with the corrector used once only.

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RK-2 : HEUN'S

$$y_{i+1} = y_i + \frac{h}{2} [k_1 + k_2]$$
$$k_1 = f(y_i, t_i)$$
$$k_2 = f(\underbrace{y_i + hk_1}_{\text{PREDICTED VALUE } \bar{y}_{i+1}^0}, t_i + h)$$

Now, the predictor-corrector form of Heun's method, where we use the predictor-corrector multiple time is what I am going to write now. So, the Heun's method with the predictor-corrector form, again **we will** we will write down the same expressions, pretty much will derive the same expressions in the same form. First thing to do is to derive the predicted value. So, first item in our agenda is to choose the predictor, which uses the value k_1 only. So, our predicted value \bar{y}_{i+1}^0 is going to be equal to $y_i + h$ multiplied by f of (y_i, t_i) .

So, if we look at what our \bar{y}_{i+1}^0 was, if we go back to this particular part and see what our \bar{y}_{i+1}^0 was, \bar{y}_{i+1}^0 was nothing but $y_i + h$ times k_1 ; k_1 was nothing but f of (y_i, t_i) that is the predictor that so that is the same equation that I have written in a slightly different form over here.

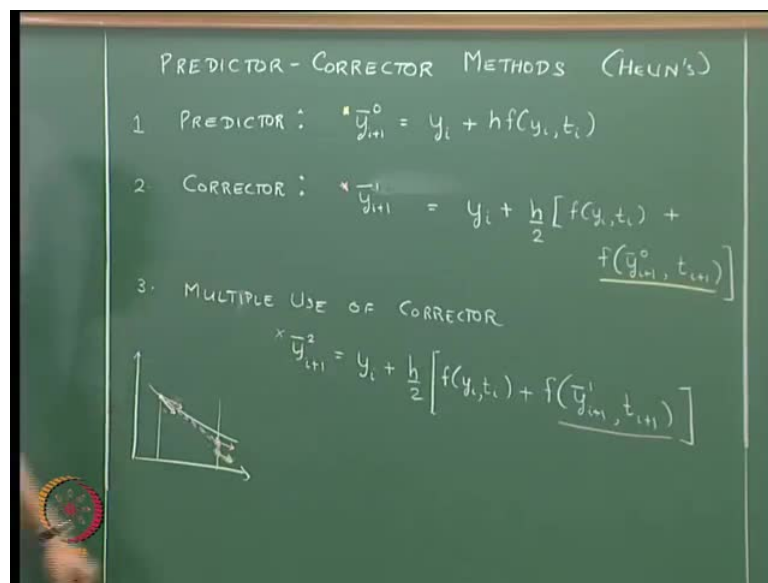
Now, let us look at the corrector form of the equation. Corrector is nothing but a trapezoidal rule that we use. Two lectures earlier, I believe in lecture 3, we had shown that the Heun's method is kind of like using a trapezoidal rule, if we had the function f as function just of the time t ; likewise, the corrector form is going to be the implementation of trapezoidal rule. In the corrector form what we do is y_{i+1} corrected, we will write this equal to $y_i + h$ by 2 multiplied by $k_1 + k_2$.

We have this as k in in computing The Heun's method using $r k - 2$ we have y_{i+1} equal to $y_i + h$ by 2 multiplied by $k_1 + k_2$ what is k_1 ? k_1 is nothing but the slope

computed at y_i, t_i . What is k_2 ? k_2 is nothing but slope computed at y_{i+1}^0 and $t_i + 1$. So, I will write that down over here; so h by 2 multiplied by f of (y_i, t_i) plus f at $y_{i+1}^0, t_i + 1$.

Now, if we stop at this point, the result that we get from the Heun's predictor-corrector method is the same as the result that we will get from the $rk-2$ method, but we are not going to stop at this point, but we will **going to** use the corrector multiple number of times. So, the third item is the multiple use of corrector.

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So, what do you mean by multiple use of corrector? Instead of calling this as just y_{i+1} corrected, I will just erase this corrected part; I will put a bar over here and write this as y_{i+1}^1 . So, the multiple uses of corrector would be y_{i+1}^2 is going to be equal to $y_i + h$ by 2 multiplied by f of (y_i, t_i) plus f of $(y_{i+1}^1, t_i + 1)$. So, if we compare it with the first use of corrector, if we compare the second use of corrector, instead of computing y_{i+1}^1 , we are now computing y_{i+1}^2 .

This guy remains the same; this particular guy does not change what it means? It means, it is the slope that is computed at the initial point. So, this means it is a slope computed over here. **y_{i+1}^0 is going to be** y_{i+1}^0 is going to be the point that is projected using this particular slope. So, **y_i** y_{i+1}^0 is going to be the yellow line; **that** so y_{i+1}^0 is the point by the yellow x , and f of y_{i+1}^0 is going to be the yellow arrow over here.

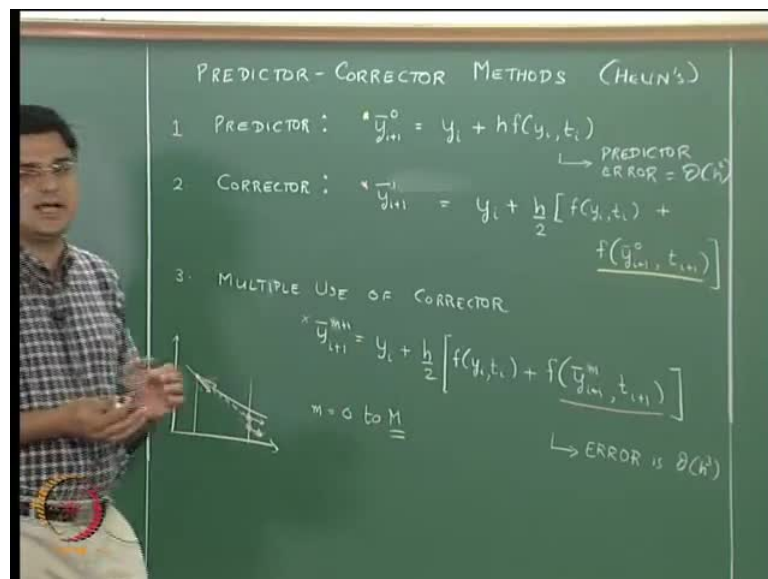
So, now, what **what** we do with **with** this particular guy is that we project again using the average slope of \bar{y}_1 and y_i . So that means, we are going to use this yellow slope and this white slope and then, **we will get this is a** average slope is going to lie midway between these two arrows and that is going to be this particular dotted line.

So, our x over here or the star over here is going to be this particular guy over there. And the slope computed at that point is I am going to show this with a red arrow, and that red arrow is going to be the slope computed over here and that red arrow is this **this** particular guy and then, I will get I will draw this red arrow over here.

I will now discard this yellow arrows; I do not really need these yellow arrows any more so I will just discard this yellow arrows get an average slope of this white and this red arrow and that **white** average slope I am going to predict once again to the end and this is our purple x ; our purple x is over here.

Now I can use So, this is the second time I have used the corrector; I will use the corrector third time, fourth time and so on and so forth. I will use it recursively in order to get better and better guesses. So, the recursive use of this corrector means that this guy has to be replaced by appropriate quantity.

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So, we will replace this with $m + 1$ equal to $y_i + h$ by $2 f y_i t_i$ plus f of y_i bar m , instead of $(1, t_i)$, where y_0 is obtained from this particular equation and this equation is

used for m equal to 0 to some M . So, we use this predictor-corrector equation a capital M number of times, lets we predecide what this M is going to be.

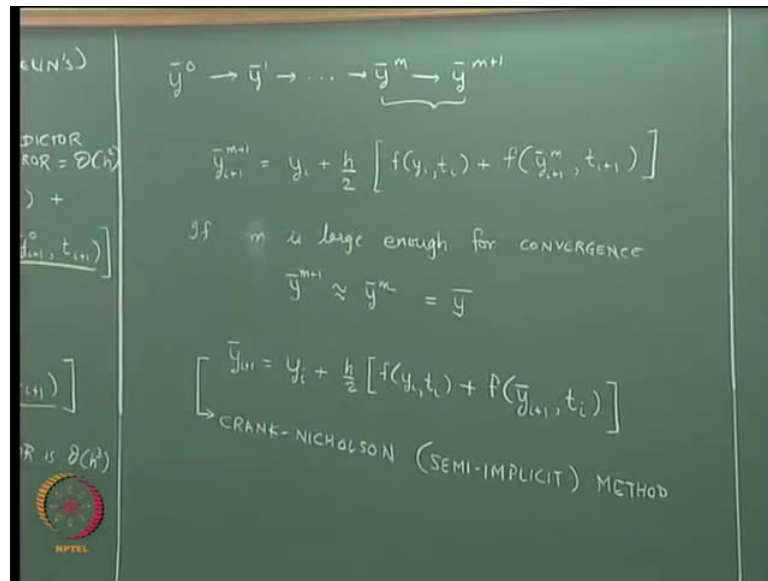
So, let us say that we are going to use the corrector equation five times. So, we will use the predictor equation once; we will use y_0 in order to compute \bar{y}_1 ; \bar{y}_1 we will use to compute \bar{y}_2 ; \bar{y}_2 to \bar{y}_3 ; \bar{y}_3 to \bar{y}_4 ; and \bar{y}_4 to compute \bar{y}_5 , when we reach \bar{y}_5 that is what we say that the solution is the solution that we need for d_{i+1} and entire process is repeated all over again at the next step.

So that is the idea behind predictor-corrector methods. We will take up predictor-corrector methods once again in the last lecture of this module when we are when I very briefly I am going to cover some of the more advanced methods and why this idea of predictor-corrector method actually is fairly popular and some of these methods, specifically in the Adam-Moulton family of methods, those are also the predictor-corrector methods.

So, in summary what we have covered so far is, we have covered r_k methods; we have covered the error analysis of r_k methods and we have covered the predictor-corrector methods. The error analysis of the predictor-corrector methods is fairly straight forward; this is nothing but an Euler's explicit method. As a result, the error for the predictor equation is that its order of h^2 , whereas the corrector equation is kind of like using the trapezoidal method and because it is kind of like using the trapezoidal method, the error in corrector equation is of the order of h^3 . So, this error is of the order of h^3 ; this error is of the order of h^2 .

Now, why is this particular method actually useful? The reason why predictor-corrector methods are useful is because they are still explicit methods; they are not implicit method. But if this Heun's method was repeated large enough number of times, in that case what will happen is that if there is convergence, then Heun's method will converge to a totally an implicit method. Why that is so? is What I mean by that is every time what we do is when we use this particular equation y_{i+1} , \bar{y}_{i+1} is changing compared to \bar{y}_i .

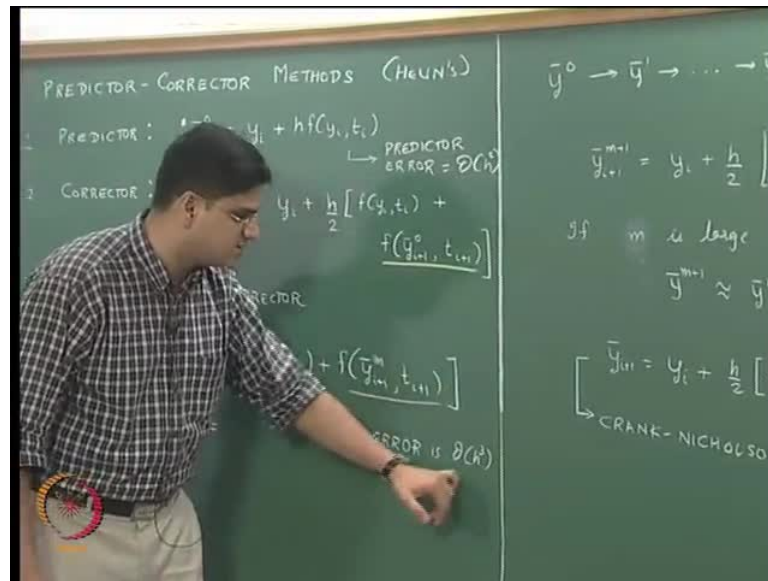
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So, if we go from y bar 0 to y bar 1 and so on up to say y bar m and we go to y bar m plus 1, if the error between y bar m and y bar m plus 1 is very small **if that error is very small**, then **if** we are going to substitute that in this particular equation. The equation that we are going to get is y bar m plus 1 is going to be equal to y i plus h by 2 multiplied by f of $(y$ i , t i) plus f of y bar m i plus 1, t i plus 1.

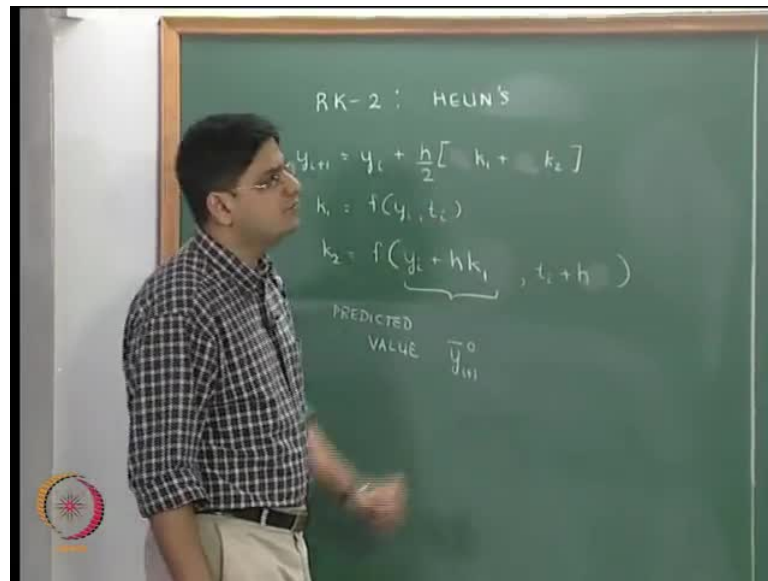
If m is large enough, we repeat this multiple number of times till we get convergence. If m **if m** is large enough for convergence, then what **what what we are going** we are saying is y bar m plus 1 is approximately equal to y bar m and let us just represent this as y m or let just represent as y bar without any superscript over here. So, if we write **if we write** y bar m plus 1 equal to y bar, and y bar m also equal to y bar we will get our y bar computed at time i plus 1 equal to y i plus h by 2 multiplied by f of $(y$ i , t i) plus f of $(y$ i plus 1 bar, t i); keep in mind that this bar just represents a dummy type of variable.

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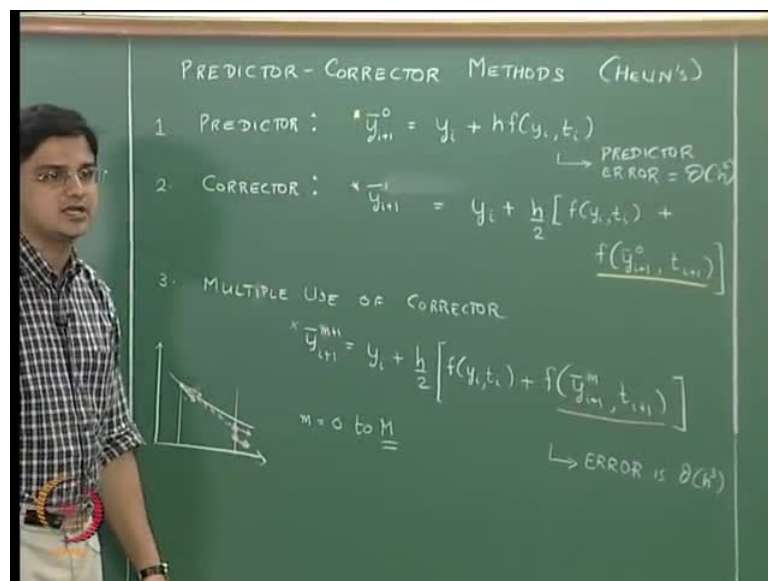


Now, if you see this particular equation, this equation is if you recollect something that we did in lecture two of this particular module, this is nothing but Crank-Nicholson method. And this completes the promise that I made in the in lecture in lecture 2 itself, why Crank-Nicholson method is going to be preferred over implicit Euler method. The reason why Crank-Nicholson method is going to be preferred over implicit Euler method is because implicit Euler method we derive were we saw was of the order of h^2 accurate and we have just derived that. Because of this corrector equation, a method of the type of Crank-Nicholson method is h^3 accurate. So, to recollect what we have done in the last half an hour - we started with rk-2 method, specifically we started with the Heun's variant of the of the rk-2 method. From the rk-2 method we said that by repeatedly calculating this guy k^2 , what we are going to do is, we are going to convert that rk-2 method into a predictor-corrector Heun's method.

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In the Heun's method, we use this predictor equation that means we use k_1 as a predictor equation and then, use the k_2 equation repeatedly in order to improve or in order to correct the value of \bar{y} . If you go from \bar{y}_0 to \bar{y}_1 and so on up to \bar{y}_M . So, this what we do in order to use the predictor-corrector Heun's method.

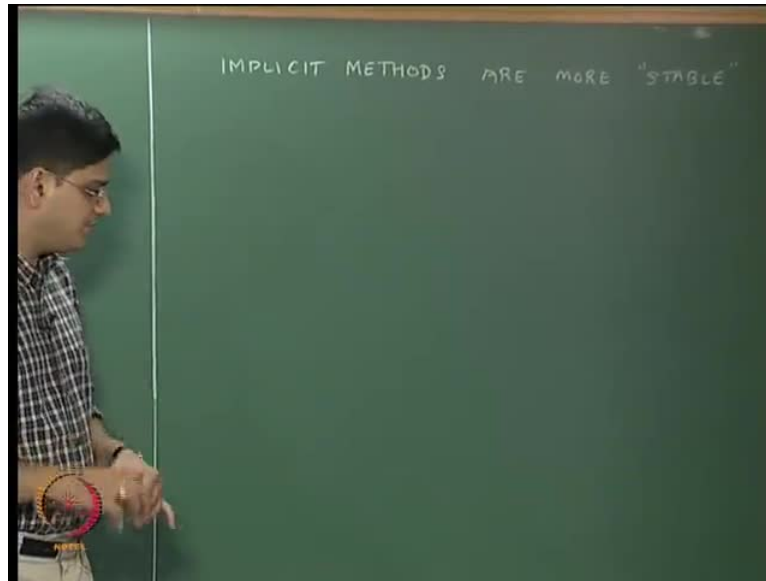
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The image shows a chalkboard with handwritten mathematical notes. At the top, a sequence of values is shown: $\bar{y}^0 \rightarrow \bar{y}^1 \rightarrow \dots \rightarrow \bar{y}^m \rightarrow \bar{y}^{m+1}$. Below this, the equation for \bar{y}_{i+1}^{m+1} is written: $\bar{y}_{i+1}^{m+1} = y_i + \frac{h}{2} [f(y_i, t_i) + f(\bar{y}_{i+1}^m, t_{i+1})]$. A note says "if m is large enough for CONVERGENCE" followed by $\bar{y}^{m+1} \approx \bar{y}^m = \bar{y}$. At the bottom, the equation $\bar{y}_{i+1} = y_i + \frac{h}{2} [f(y_i, t_i) + f(\bar{y}_{i+1}, t_{i+1})]$ is shown, with an arrow pointing to it from the text "CRANK-NICHOLSON (SEMI-IMPPLICIT) METHOD". There is a small logo in the bottom left corner of the chalkboard image.

Now, instead of stopping at capital M number of iterations, if we keep doing the iterations, until \bar{y}^{m+1} converges to \bar{y}^m , then what we have solved over here is, we have essentially solved a non-linear equation of this type. We have solved this equation using the fixed-point iteration method - the method of successive evaluations.

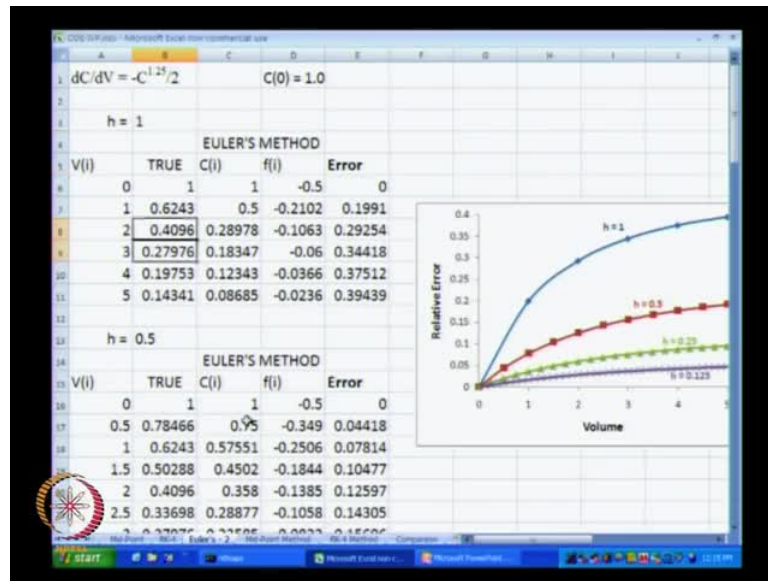
So, if we actually do that, we will get Crank-Nicholson method. If we stop at a finite number of iterations, we will get the predictor-corrector method; if we stop only in the first step, not do any iterations of the corrector, we will get the rk-2 Heun's method. So that is basically what I wanted to cover with respect to rk-2 methods and with respect to the predictor-corrector methods.

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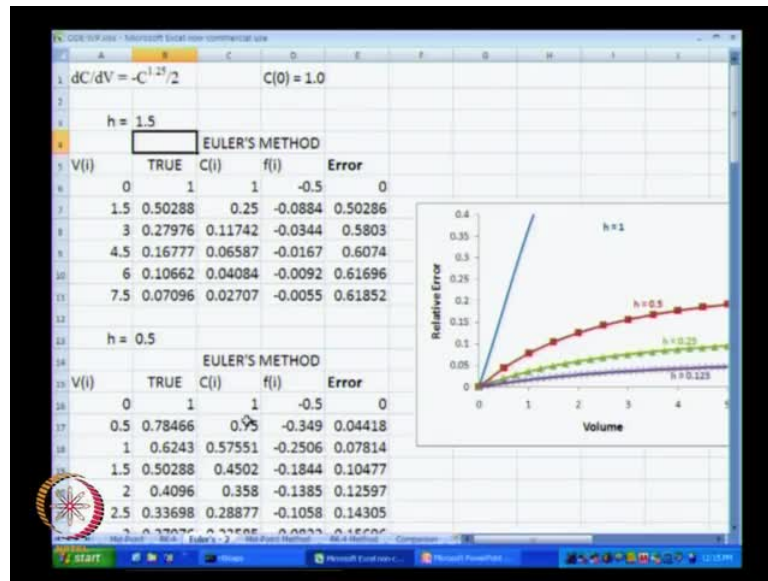
The next question and a very important question comes up is why do you want to look at the implicit methods **at the at the first** in the first case itself? Because the the $r k - 2$ method we saw had an accuracy of h cubed; predictor-corrector had an accuracy of h cube; Crank-Nicholson method has as accuracy of h cube, but clearly the amount of effort that is required in order to solve this particular algebraic equation problem is significantly higher than the amount of effort that is required to solve **the r k** the $r k - 2$ method. So, the question comes is why implicit method and the answer to that question is because implicit methods are more stable. The question is what do we mean by a stability?

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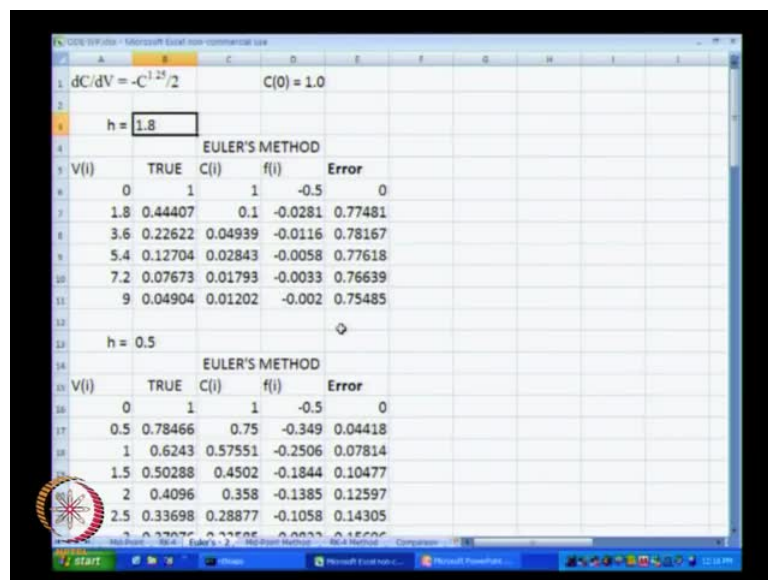
So, let us again go back to the Microsoft excel and try to see what we actually mean by stability. Now, let us consider what we mean by stability and what I have done over here is from the same excel sheet that we have we have been looking at in the in the past few lectures, I have opened up the same Euler's explicit method sheet. So, this is where we computed the ah we where we used Euler's explicit method in order to compute the solution for V equal to 5, given that concentration C 0 equal to 1. What we had seen is, as we decrease the value of our step size h, we get more and more accurate results; likewise, as we increase the value of our step size, we are going to get less and less accurate results.

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So, from h equal to 1, let me increase this to h equal to 1.5, what happens when we increase this to h equal to 1.5? What I will do is I will just take this figure a little bit away so that they do not distract us from our discussion.

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So, what happens when we go from h equal to 1 to h equal to 1.5 is that the error that we get increases, but nothing more has happened, besides error increasing. Let us go to h equal to 1.8 and again, we find that the error has increased even further.

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The screenshot shows an Excel spreadsheet with the following content:

Equation: $dC/dV = -C^2/2$, Initial condition: $C(0) = 1.0$

Step size: $h = 2$

EULER'S METHOD

V(i)	TRUE C(i)	C(i)	f(i)	Error
0	1	1	-0.5	0
2	0.4096	0	0	1
4	0.19753	0	0	1
6	0.10662	0	0	1
8	0.0625	0	0	1
10	0.03902	0	0	1

Step size: $h = 0.5$

EULER'S METHOD

V(i)	TRUE C(i)	C(i)	f(i)	Error
0	1	1	-0.5	0
0.5	0.78466	0.75	-0.349	0.04418
1	0.6243	0.57551	-0.2506	0.07814
1.5	0.50288	0.4502	-0.1844	0.10477
2	0.4096	0.358	-0.1385	0.12597
2.5	0.33698	0.28877	-0.1058	0.14305

Let us now go to h equal to 2; now, when we see h equal to 2, there is some funny business that is happening. Let If we look at the predictions of the Euler's method with h equal to 2, the initial concentration was equal to 1, but the concentration immediately at volume V equal to 2 has dropped to 0, and beyond that, this method cannot continue because C itself is 0; when C is 0, f that is computed is 0; if f that is computed is 0, then C i plus 1 equal to C plus h multiplied by f is going to be equal to C i itself. So, C i plus 1 equal to C i equal to 0. So, immediately within one step C i **c I** has gone to a value equal to 0.

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The screenshot shows an Excel spreadsheet with the following content:

Equation: $dC/dV = -C^2/2$, Initial condition: $C(0) = 1.0$

Step size: $h = 2.1$

EULER'S METHOD

V(i)	TRUE C(i)	C(i)	f(i)	Error
0	1	1	-0.5	0
2.1	0.39362	-0.05	#NUM!	1.12703
4.2	0.18489	#NUM!	#NUM!	#NUM!
6.3	0.09795	#NUM!	#NUM!	#NUM!
8.4	0.05662	#NUM!	#NUM!	#NUM!
10.5	0.03497	#NUM!	#NUM!	#NUM!

Step size: $h = 0.5$

EULER'S METHOD

V(i)	TRUE C(i)	C(i)	f(i)	Error
0	1	1	-0.5	0
0.5	0.78466	0.75	-0.349	0.04418
1	0.6243	0.57551	-0.2506	0.07814
1.5	0.50288	0.4502	-0.1844	0.10477
2	0.4096	0.358	-0.1385	0.12597
2.5	0.33698	0.28877	-0.1058	0.14305

So, now, that is a little bit of a problem over here. This problem arises, because at h equal to 2, we have limit of stability of this particular method what that means is lets go from h equal to 2 to h equal to 2. 1.

And if we go to h equal to 2 to h equal to 2.1, this is what we observe. What we observe is quite clearly that the concentration goes to a negative value and beyond that our method cannot **cannot** proceed. The reason why the method cannot proceed is because the concentration to the power 1. 2 5, it is a fractional power. As a result of the fractional power, **because** we get negative concentration; we are not able to proceed further.

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V(i)	TRUE C(i)	f(i)	Error	dC	dV
0	1	-0.5	0	-0.5	0.5
0.5	0.7788	-0.375	0.03698	-0.375	0.5
1	0.60653	-0.2813	0.07259	-0.2813	0.5
1.5	0.47237	-0.2109	0.10689	-0.2109	0.5
2	0.36788	-0.1582	0.13992	-0.1582	0.5
2.5	0.2865	-0.1187	0.17173	-0.1187	0.5
3	0.22313	-0.089	0.20236	-0.089	0.5
3.5	0.17377	-0.0667	0.23185	-0.0667	0.5
4	0.13534	-0.0501	0.26026	-0.0501	0.5
4.5	0.1054	-0.0375	0.28762	-0.0375	0.5
5	0.08208	-0.0282	0.31396	-0.0282	0.5

So, now, what I will do is, I will change this problem a little bit from dC/dV equal to 1.25 to dC/dV equal to minus C to the power 1 divided by 2. And what **what** we will do is, we will go back to h equal to 0. 5, and let us see what happens now. Let us consider the case, where we have f to the power 1, instead of f to the power 1. 2 5, everything else remains the same; I have only changed this particular expression over here.

So, now, I will drag it and drop it over here and the true values are also going to change. **True values is are going to be...** For the first order reaction, **the** basically the true values are going to be e to the power minus t by 2 or e into minus 2 t . So, with **with** this particular change **we** what we have is dC/dV ; dC/dV is going to be equal to minus 0. 5 into C .

So, what we can do is, dC we can write this as dC divided by C is going to be equal to minus 0.5 into dV and when we integrate this, we are going to get \ln of C equal to minus 0.5 into v integrating from 0 to v and from $C_A 0$ to C_A .

So, we will have \ln of C_A / C_{A0} divided by C_{A0} , where C_{A0} was equal to 1 . So, \ln of C by C is going to be equal to minus $0.5 V$ or C is going to be e to the power minus 0.5 and this is what we have written over here, concentration is equal to e to the power minus 0.5 multiplied by V or minus V divided by 2 so that is the true value that we get. The numerical value using Euler's explicit method for h equal to 0.5 or as shown over here and we can extend further.

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The screenshot shows an Excel spreadsheet with the following data:

Equation: $dC/dV = -C^{1/2}$, Initial condition: $C(0) = 1.0$

Step size $h = 1$:

V(i)	TRUE C(i)	f(i)	Error	
0	1	-0.5	0	
1	0.60653	0.5	-0.25	0.17564
2	0.36788	0.25	-0.125	0.32043
3	0.22313	0.125	-0.0625	0.43979
4	0.13534	0.0625	-0.0313	0.53818
5	0.08208	0.03125	-0.0156	0.6193

Step size $h = 0.5$:

V(i)	TRUE C(i)	f(i)	Error	
0	1	-0.5	0	
0.5	0.78466	0.75	-0.349	0.04418
1	0.6243	0.57551	-0.2506	0.07814
1.5	0.50288	0.4502	-0.1844	0.10477
2	0.4096	0.358	-0.1385	0.12597
2.5	0.33698	0.28877	-0.1058	0.14305

And we can extend it up to V equal to 5 and we will get the concentration of the species coming out from the PFR using the Euler's explicit method. Now, let us increase our h to 1 and see what happens. When our h has increased to 1 , the overall errors have also increased. So, the errors have increased, indeed when **we have** we go from h equal to 0.5 to h equal to 1 , but the solution is still available for us to see.

(Refer Slide Time: 49:27)

The screenshot shows an Excel spreadsheet with the following data:

Equation: $dC/dV = -C^{1/2}$, $C(0) = 1.0$

Step size: $h = 2$

EULER'S METHOD

V(i)	TRUE C(i)	f(i)	Error
0	1	1	-0.5
2	0.36788	0	0
4	0.13534	0	0
6	0.04979	0	0
8	0.01832	0	0
10	0.00674	0	0

Step size: $h = 0.5$

EULER'S METHOD

V(i)	TRUE C(i)	f(i)	Error
0	1	1	-0.5
0.5	0.78466	0.75	-0.349
1	0.6243	0.57551	-0.2506
1.5	0.50288	0.4502	-0.1844
2	0.4096	0.358	-0.1385
2.5	0.33698	0.28877	-0.1058

Now, for if we go from h equal to 1 to h equal to 2 what happens is what we had seen earlier; immediately the concentration has become 0 and from that point onwards, we cannot proceed.

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The screenshot shows an Excel spreadsheet with the following data:

Equation: $dC/dV = -C^{1/2}$, $C(0) = 1.0$

Step size: $h = 2.1$

EULER'S METHOD

V(i)	TRUE C(i)	f(i)	Error
0	1	1	-0.5
2.1	0.34994	-0.05	0.025
4.2	0.12246	0.0025	-0.0013
6.3	0.04285	-0.0001	6.3E-05
8.4	0.015	6.3E-06	-3E-06
10.5	0.00525	-3E-07	1.6E-07

Step size: $h = 0.5$

EULER'S METHOD

V(i)	TRUE C(i)	f(i)	Error
0	1	1	-0.5
0.5	0.78466	0.75	-0.349
1	0.6243	0.57551	-0.2506
1.5	0.50288	0.4502	-0.1844
2	0.4096	0.358	-0.1385
2.5	0.33698	0.28877	-0.1058

Now, what do we do, if h happens to be h equal to 2.1? And this is what we see when h equal to 2.1 is that the concentration has become 1, has become negative and then, it is oscillating and finally, settling down at the steady state value.

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Excel spreadsheet showing Euler's Method results for the differential equation $dC/dV = -C^2/2$ with initial condition $C(0) = 1.0$.

Step size $h = 4$:

V(i)	TRUE	C(i)	f(i)	Error	dC	dV
0	1	1	-0.5	0	$-0.5 \cdot C$	
4	0.13534	-1	0.5	8.38906		$-0.5 \cdot dV$
8	0.01832	1	-0.5	53.5982		
12	0.00248	-1	0.5	404.429		
16	0.00034	1	-0.5	2979.96		
20	4.5E-05	-1	0.5	22027.5		

Step size $h = 0.5$:

V(i)	TRUE	C(i)	f(i)	Error
0	1	1	-0.5	0
0.5	0.78466	0.75	-0.349	0.04418
1	0.6243	0.57551	-0.2506	0.07814
1.5	0.50288	0.4502	-0.1844	0.10477
2	0.4096	0.358	-0.1385	0.12597
2.5	0.33698	0.28877	-0.1058	0.14305

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Excel spreadsheet showing Euler's Method results for the differential equation $dC/dV = -C^2/2$ with initial condition $C(0) = 1.0$.

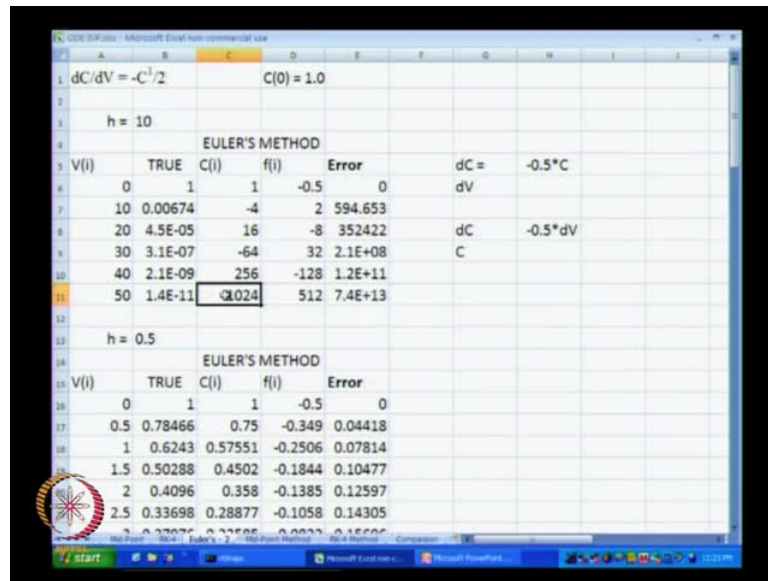
Step size $h = 5$:

V(i)	TRUE	C(i)	f(i)	Error	dC	dV
0	1	1	-0.5	0	$-0.5 \cdot C$	
5	0.08208	-1.5	0.75	19.2737		$-0.5 \cdot dV$
10	0.00674	2.25	-1.125	332.93		
15	0.00055	-3.375	1.6875	6103.14		
20	4.5E-05	5.0625	-2.5313	111508		
25	3.7E-06	-7.5938	3.79688	2037687		

Step size $h = 0.5$:

V(i)	TRUE	C(i)	f(i)	Error
0	1	1	-0.5	0
0.5	0.78466	0.75	-0.349	0.04418
1	0.6243	0.57551	-0.2506	0.07814
1.5	0.50288	0.4502	-0.1844	0.10477
2	0.4096	0.358	-0.1385	0.12597
2.5	0.33698	0.28877	-0.1058	0.14305

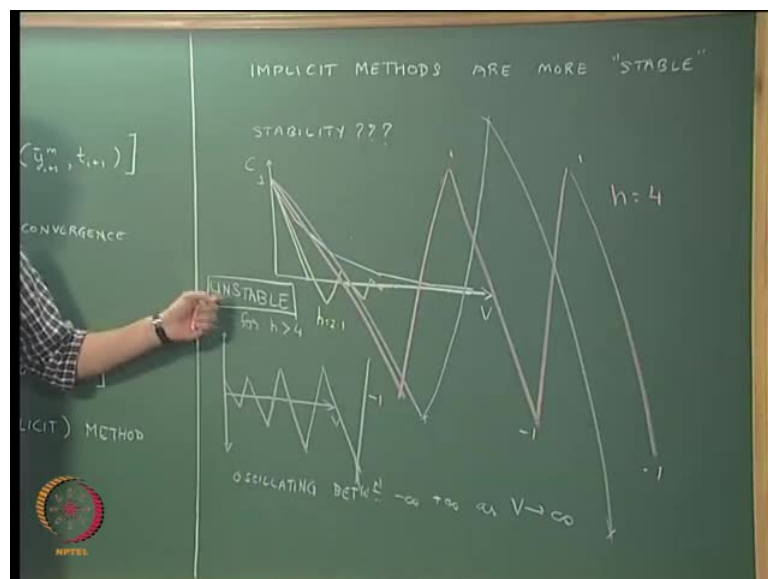
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Now, let us say if h equal to 4 what happens. We get the value oscillating at 1, minus 1, 1, minus 1, 1 minus 1 and so on. Now, if h is increased to 5, there is an interesting thing that happens. It is 1, minus 1.5, 2, minus 3, 5, minus 7. Now, when I increase h to 10 see what is happening is, see 1, minus 4, 16, minus 64, 256, 1024.

So, what essentially is happening over here is as we are increasing h beyond a certain point, the solution from Euler's method is going unstable. So, I will go to the green board and I will plot out what actually happened in the Euler's explicit method.

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So, what I have said over here is implicit methods are more stable; we are investigating what it means by stability. So, **what happened** what we saw over here is **we were** if we were to plot the concentration C against the volume, the **the** numerical method for getting concentration C against the volume, if we were to use say h equal to 1, we will perhaps get the results something like this.

If we were to use h equal to 2, we will get perhaps the result going something like this; **when we used** when we used value h equal to 2.1, the results that we got were something of this sort; **this is with when h** again this **this** is a cartoon. So, this not exactly drawn with scale; this is just to show you what **what** we get.

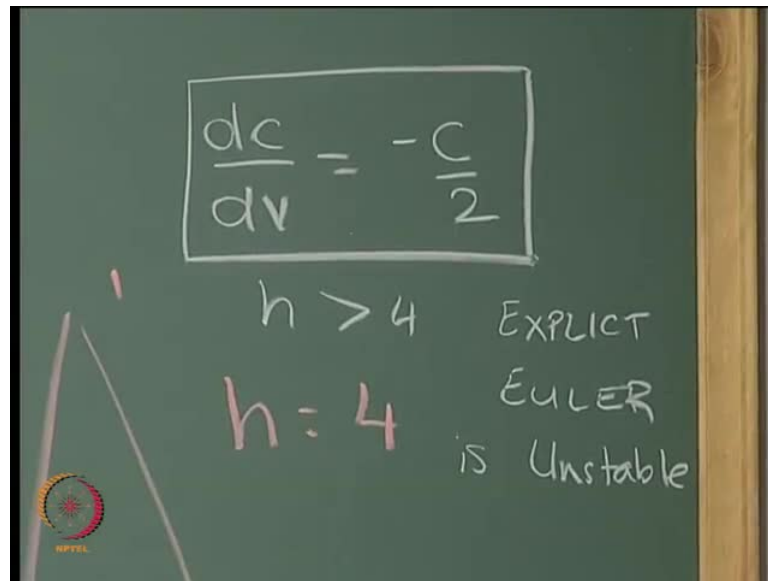
(Refer Slide Time: 52:28) Now, when h was equal to 4, the type of results that we got when h was equal to 4. So, this we started out at 1; this value was minus 1; this value again was 1; this value was minus 1; this was 1 and this value was minus 1 again.

So, this is the curve that we got when h was equal to 4. Now, what do we get when h **increased** is increased to beyond 4? What we get when h is increased to beyond 4 is this particular value goes beyond minus 1, the next value goes beyond 1, the value after that goes even below minus 1 so on and so forth.

So, if we were to shrink this plot, **we were** if we were to shrink the **the** ordinate for this particular system and we were to plot this for h greater than 4, **we will start at minus 1** **sorry** we will start at plus 1; go to a value below minus 1 and if we repeat it for large enough volume what we will get is, we will get the overall result oscillating between minus infinity and plus infinity as h tends to infinity. This is known as an unstable solution.

So, I am going to end the lecture **over here in this in the lecture** 5 of this module. **I am going to end over here.**

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$$\frac{dc}{dv} = -\frac{c}{2}$$

$h > 4$ EXPLICIT

$h = 4$ EULER
is Unstable

In the next lecture, I am going to consider the stability issues; specifically I will talk about the equation. So, the equation that we had dC by dV was equal to minus C by 2 . For this particular condition, we saw that when h becomes greater than 4 , at that time the explicit Euler's method becomes unstable. And we will do some theoretical analysis of this particular condition to find out under what conditions do the explicit Euler's method becomes unstable, under what conditions do the implicit Euler method methods become unstable. And what we will show is that implicit methods are globally stable; there is no limit on h for which this remains unstable. What we will also show is that for the condition for which explicit Euler's method becomes stable is going to be, when h is greater than 2 divided by the coefficient of this term. When that h is greater than 2 divided by 1 by 2 that is where the explicit Euler's method is going to be unstable, that is something that we are going to start off in the next lecture in this particular module.

Thank you.