

# Report - Assignment #2: $\Phi_{g,2}$

Bottom node:

want to compute:  $\frac{\bar{\sigma}_{g,2} - \bar{\sigma}_{g,1}}{\Delta z}$

$$\bar{\sigma}_{g,2} = \frac{D_{g,1} \cdot D_{g,2}}{\Delta z/2} \cdot \frac{\hat{\Phi}_{g,2} - \hat{\Phi}_{g,1}}{D_{g,1} + D_{g,2}} \quad \text{from equation (A14)}$$

But  $\bar{\sigma}_{g,1}$  requires special attention (since there's no node below it):

Assume Dirichlet boundary condition:

$$\left\{ \begin{array}{l} \bar{\sigma}_{g,1} = -D_{g,1} \cdot \frac{\hat{\Phi}_{g,1} - \hat{\Phi}_{g,1}}{\Delta z/2} \\ \bar{\sigma}_{g,1} = -\frac{\hat{\Phi}_{g,1}}{2} \end{array} \right. \Rightarrow \left\{ \begin{array}{l} \hat{\Phi}_{g,1} = \frac{\hat{\Phi}_{g,1}}{1 + \frac{\Delta z}{4D_{g,1}}} \\ \bar{\sigma}_{g,1} = -\frac{1}{2} \cdot \frac{\hat{\Phi}_{g,1}}{1 + \frac{\Delta z}{4D_{g,1}}} \end{array} \right.$$

So that:

$$\frac{\bar{\sigma}_{g,2} - \bar{\sigma}_{g,1}}{\Delta z} = -\frac{2}{\Delta z^2} \cdot \frac{D_{g,1} \cdot D_{g,2}}{D_{g,1} + D_{g,2}} (\hat{\Phi}_{g,2} - \hat{\Phi}_{g,1}) + \frac{1}{2\Delta z} \cdot \frac{1}{1 + \frac{\Delta z}{4D_{g,1}}} \hat{\Phi}_{g,1}$$

$$= \left( + \frac{2}{\Delta z^2} \cdot \frac{D_{g,1} \cdot D_{g,2}}{D_{g,1} + D_{g,2}} + \frac{1}{2\Delta z} \cdot \frac{1}{1 + \frac{\Delta z}{4D_{g,1}}} \right) \hat{\Phi}_{g,1} +$$

$$+ \left( - \frac{2}{\Delta z^2} \cdot \frac{D_{g,1} \cdot D_{g,2}}{D_{g,1} + D_{g,2}} \right) \hat{\Phi}_{g,2}$$

$$\Rightarrow \left\{ \begin{array}{l} a_{g,1} = \frac{2}{\Delta z^2} \cdot \frac{D_{g,1} \cdot D_{g,2}}{D_{g,1} + D_{g,2}} + \frac{1}{2\Delta z} \cdot \frac{1}{1 + \frac{\Delta z}{4D_{g,1}}} \\ b_{g,1} = -\frac{2}{\Delta z^2} \cdot \frac{D_{g,1} \cdot D_{g,2}}{D_{g,1} + D_{g,2}} \\ c_{g,1} = 0 \end{array} \right. \rightarrow \text{Some that we got in the lecture!}$$

Now, for the top node:

want to compute:  $\frac{\bar{\sigma}_{g,N+1} - \bar{\sigma}_{g,N}}{\Delta z}$

$$\bar{\sigma}_{g,N+1} = \frac{D_{g,N} \cdot D_{g,N+1} \cdot \Delta z}{D_{g,N} + D_{g,N+1}} \cdot \frac{\hat{\Phi}_{g,N+1} - \hat{\Phi}_{g,N+1}}{\Delta z/2}$$

Boundary condition:

$$\left\{ \begin{array}{l} \bar{\sigma}_{g,N+1} = D_{g,N} \cdot \frac{\hat{\Phi}_{g,N+1} - \hat{\Phi}_{g,N}}{\Delta z/2} \\ \bar{\sigma}_{g,N+1} = + \frac{\hat{\Phi}_{g,N+1}}{2} \end{array} \right.$$

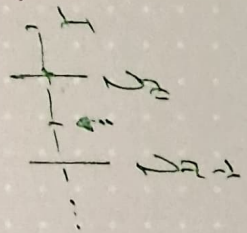
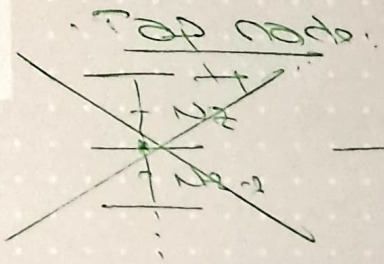
Check note in the next page.





Problem 1:

Proof:



$$\begin{aligned} \phi_{n+1} &= \phi_n + \Delta \phi_n \\ \phi_{n+1} &= \phi_n + \Delta \phi_n \end{aligned}$$

$$\phi_{n+1} = \phi_n + \Delta \phi_n$$

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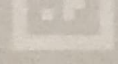
$$\phi_{n+1} = \phi_n + \Delta \phi_n$$

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$$\phi_{n+1} = \phi_n + \Delta \phi_n$$

$$\phi_{n+1} = \phi_n + \Delta \phi_n$$

$$\phi_{n+1} = \phi_n + \Delta \phi_n$$





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$$= \frac{1}{2\lambda_2} \cdot \frac{1}{1 + \frac{\lambda_2}{\lambda_1}} + \frac{\lambda_1 \lambda_2 + \lambda_2^2}{\lambda_1 \lambda_2 + \lambda_2^2} + \frac{\lambda_1 \lambda_2 + \lambda_2^2}{\lambda_1 \lambda_2 + \lambda_2^2} \cdot \frac{\lambda_1 \lambda_2 + \lambda_2^2}{\lambda_1 \lambda_2 + \lambda_2^2}$$

$$= \frac{1}{2\sqrt{2}} + \frac{1}{1 + \frac{\sqrt{2}}{2}} + \frac{2}{\sqrt{2}^2} \cdot \frac{2\sqrt{2} \cdot 2\sqrt{2}}{2\sqrt{2} + 2\sqrt{2}} = \frac{1}{2\sqrt{2}} + \frac{2}{2 + \sqrt{2}} + \frac{2}{2} \cdot \frac{4}{4} = \frac{1}{2\sqrt{2}} + \frac{2}{2 + \sqrt{2}} + 2$$

$$\frac{1}{x^2} \cdot \frac{D_1 u \cdot D_2 u}{D_1 u + D_2 u} = \frac{D_1 u \cdot D_2 u}{x^2 (D_1 u + D_2 u)}$$

$$= \int_0^1 \frac{1}{x^2} \cdot \frac{D_1(x) \cdot D_2(x)}{D_1(x) + D_2(x)} dx$$

0.12: 0

$$\textcircled{10} \quad x^2 = \frac{1}{2x^2} \cdot \frac{1}{1 + \frac{1}{x^2}} + \frac{2}{x^2} \cdot \frac{x^2 \cdot x^{2n-2}}{x^2 + x^{2n-2}}$$



Warrant's SLP technique:

notion of order as number of positive eigenvalues

$$A \cdot \Phi = \lambda \cdot \Phi \Rightarrow$$

$$\Rightarrow \left( \frac{\lambda - 1}{\lambda} \right) \Phi = \left( \frac{1}{\lambda} - 1 \right) \Phi \quad (\text{multiplying})$$

$$\Rightarrow \text{on both sides: } \lambda \Phi = \frac{1}{\lambda} \Phi$$

$$\Rightarrow \lambda^2 \Phi = \Phi$$

$$\Rightarrow \lambda^2 = 1$$

$$\Rightarrow \lambda = \pm 1$$

But,  $\lambda = 1$  doesn't exist ( $\neq$  pos. rank  $\Phi$  as  $\Rightarrow$  not invertible)

$$A \cdot \Phi = \lambda \Phi = \left( \frac{1}{\lambda} - 1 \right) \Phi \Rightarrow$$

$$\Rightarrow \left( \lambda^2 - 1 \right) \Phi = \left( \frac{1}{\lambda} - 1 \right) \Phi \Rightarrow$$

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$$\Rightarrow \left( \lambda^2 - 1 \right) \Phi = \left( \frac{1}{\lambda} - 1 \right) \Phi \Rightarrow$$

So, we have arrived at a "matrix" Warrant's SLP matrix:

$$\Phi(A) = \begin{bmatrix} \frac{1}{K(A)} & \left( \frac{1}{K(A)} - 1 \right) \end{bmatrix} \cdot \Phi(A-1)$$

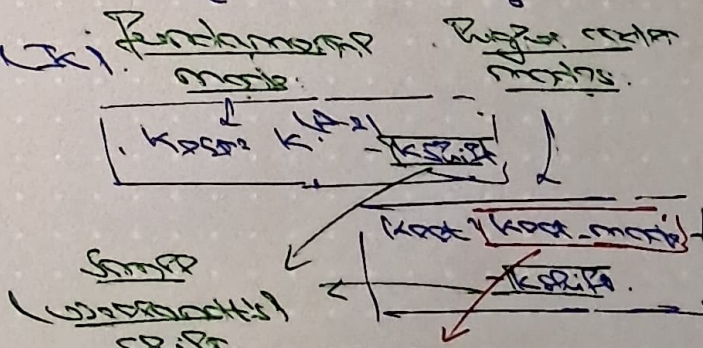
$$A \cdot \Phi = S$$

$$\begin{bmatrix} K(A) & I(A-1) & \Phi(A-1) & \Phi(A) \\ \Phi(A-1) & \Phi(A-1) & \Phi(A-1) & \Phi(A-1) \end{bmatrix}$$

$$\begin{bmatrix} \frac{1}{K(A)} & \frac{1}{K(A)} & \frac{1}{K(A)} \end{bmatrix}$$

Step 11: AIP. Order

Warrant's SLP  
comes in the definition of



Definition of the  
"Order" Rank  
Order matrix

TIF330  
Computational Continuum  
physics

Report: Assignment 2

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# 1 Step 11: Compare the different solution strategies

## 1.1 Plot the spatial distribution of the neutron flux, $\phi_{g,n}$ for all energy groups for the different methods

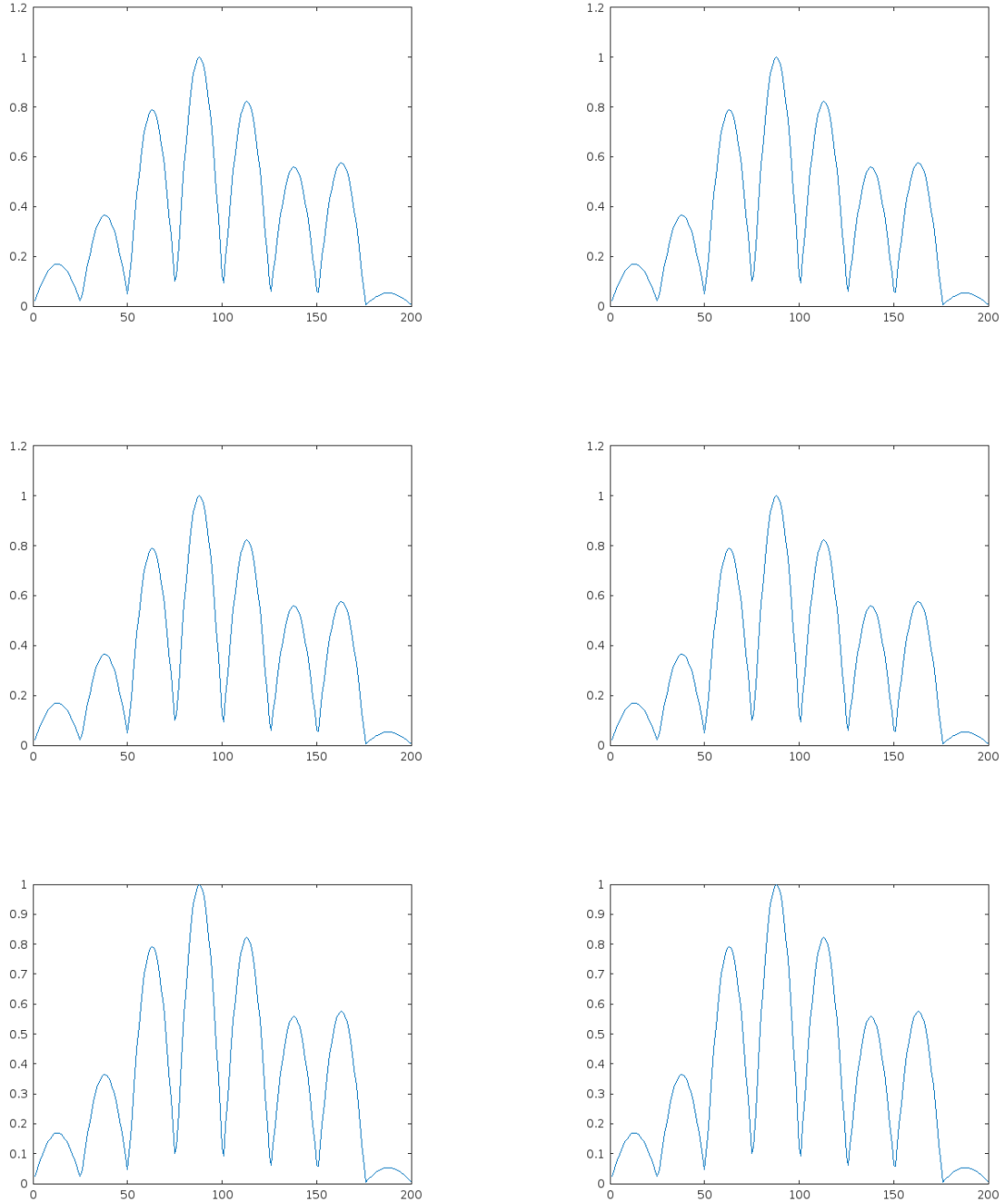


Figure 1: Spatial distribution of the neutron flux, for the 6 different implemented methods. In the order left to right, up to down, we have methods 1, 2, 3, 4, 5 and 6, respectively, exactly like they are defined in MATLAB Grader.

Notes - Input parameters: `solver_nk(0, 100*eps, 1E-5, flag1, flag2, ones(NZ, 1), ones(NZ,1))`. Also, note how `k_est_mode = 0`, which means our code searches for the dominant mode. On the other hand, `k_est_mode = c,  $\forall c \neq 0$`  looks for eigenvalues close to  $c$  (The plots presented are for `k_est_mode = 0`). As can be seen, there isn't any

noticeable difference: the results appear to be consistent across all the 6 implemented methods.

## 1.2 Compare the effective multiplication factor, $k_{eff}$ , computed by the different methods

```
keff =
```

```
struct with fields:
```

```
met1: 1.127918965406380
met2: 1.127918965406380
met3: 1.127918965406379
met4: 1.127918965406380
met5: 1.127918965406379
met6: 1.127918965406367
```

Once again, the results appear to be consistent. Only the last 2 digits sometimes vary ever so slightly between methods.

## 1.3 Compare the residuals between the different methods

Below, the residuals are presented, in the order: met1, met2, met3, met4, met5, met6.

```
met1: 1.457238798051035e-14
met2: 1.457106025822903e-14
met3: 1.461304304020238e-14
met4: 2.168183648046661e-14
met5: 9.215369235893368e-17
met6: 4.263464898658743e-13
```

This is the first metric that makes it blatantly apparent that method 5 is much more accurate than the rest. This method corresponds to: Power iteration method with acceleration (*Wielandt's* shift), with LUPQ decomposition.

## 1.4 Compare the number of iterations between the different methods

```
n_out =
```

```
struct with fields:
```

```
met1: 58
met2: 58
met3: 58
met4: 599
met5: 5
met6: 40
```

The first three methods show the same number of iterations. This makes perfect sense,

since they all correspond to the same power iteration method (without acceleration), but using different techniques to perform the matrix inversion of  $M$ . Furthermore, method 4 (Power iteration method without acceleration, using stationary method) appears to be the clear loser, with 599 iterations. This is likely due to an unfortunate decomposition of the  $M$  matrix, which results in a slow convergence. Method 5, on the other hand, is noticeably head and shoulders above the rest, whereas method 6 appears to be a little better than methods 1 to 3, but still not as good as 5.

## 1.5 Compare the CPU times between the different methods

```
t =

struct with fields:

    met1: 0.0292580000000000
    met2: 0.0779910000000000
    met3: 0.0335510000000000
    met4: 0.0536230000000000
    met5: 0.0064380000000000
    met6: 6.6359990000000000
```

The thing that stands out the most here is how method 5 is considerably faster than all the other methods. This is consistent with the fact that method 5 required less (5) iterations to converge. Additionally, `met6` also stands out as significantly slower than all the other techniques. This is due to the nature of the method: In this case, we treat the problem as if it were a non-linear problem and use MATLAB's `fsolve` function. This is clearly less efficient than simply solving the eigenvalue problem using any of the other five methods (as can be seen by the CPU times).

## 1.6 Method 5: $k_{\text{est\_mode}} = 0.8$ . Analysis of the results

The obtained results is presented below.

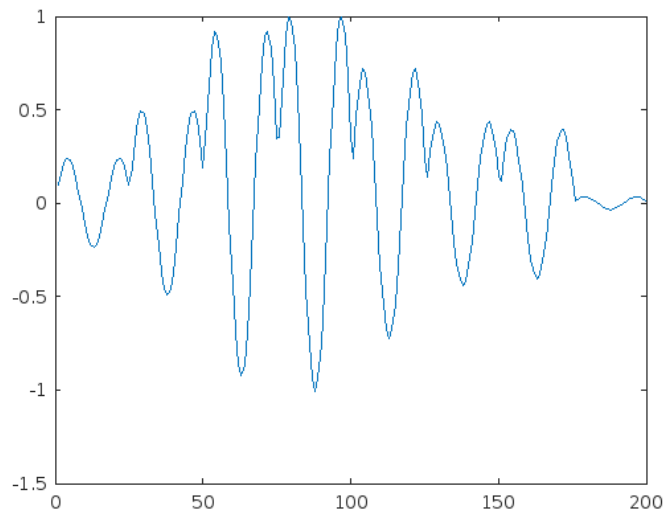


Figure 2: Spatial distribution of the neutron flux, for method 5, using  $k_{\text{est\_mode}} = 0.8$ .



And,  $k_{eff}$  value:

```
ans =  
0.7043
```

As can be clearly seen, this mode is distinctly different from the one in Figure 1. As explained previously, using `k_est_mode = c`,  $\forall c \neq 0$  makes it so our code looks for eigenvalues close to  $c$ . As such, `c = 0.8` results in convergence to  $k_{eff} = 0.7043$ , which corresponds to the eigenvalue the closest to 0.8. Quick tests show that the other closest eigenvalues would be: 0.9259 (`k_est_mode = 0.85`) and 0.5227 (`k_est_mode = 0.55`).