

Computational lattice design

Numerical methods I

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Plan for today



- Lecture 1:
 - Conceptual overview of numerical methods for accelerator design and simulation codes.

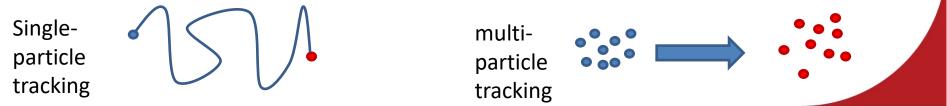
- Lecture 2:
 - Detailed look at the structure of tracking codes

- Lecture 3:
 - Practical tutorial to writing your own basic tracking code
 - If you don't have a laptop with you, or don't have some coding language (matlab, Python, C/C++...) then please pair up with someone.

What are computational methods used for?



- Tracking codes:
 - A generated particle distribution is tracked along a beam line with the distribution output at certain points to allow for analysis.
- Single-particle tracking is used for accurate modelling of trajectories.
 - Usually works with small step sizes or higher order integrators.
 - Computationally intensive, so only used for small number of particles.
 - Most commonly used for longitudinal dynamics where transverse effects are less important.
- Multi-particle tracking used for global exploration of phase space
 - Less computationally intensive, at cost of slight reduction in accuracy, allowing for more particles
 - Good for long-term or nonlinear effects (bunching, dynamic aperture studies...)

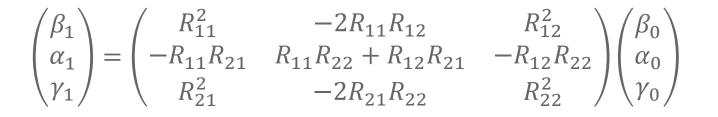


What are computational methods used for?



- Beam line design and optimisation:
 - For example, MAD, ELEGANT
 - Primarily focused on matching beam and/or lattice parameters.

$$\begin{pmatrix} x_1 \\ x_1' \end{pmatrix} = \begin{pmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{pmatrix} \begin{pmatrix} x_0 \\ x_0' \end{pmatrix}$$





What types of methods are used for accelerator codes?

- Tracking codes:
 - Numerical integrators:
 - There are many different options on integration that we will look into.
 - This is the main focus of today's lectures
- Lattice design and optimisation
 - Numerical optimisers
 - Again, many different options with pros/cons depending on application
 - Will touch on this, but won't go into too much depth



Why do we need computational methods in lattice design?

- In simple cases, we can solve Hill's Equation (X'' + K(s)X = 0), or use other techniques to solve or optimise analytically (e.g., transfer matrices)
 - E.g., thin-lens FODO can be completely solved analytically
 - However, this is arduous, and the complexity of the equations grows rapidly if we add more elements.
- In many cases, as we shall see, the equations cannot be solved analytically.
- We must either solve numerically, or use approximations (e.g., thin-lens)
 - Optimisation of lattice and beam parameters can be difficult even in simple cases
 - E.g., minimising the beam size in a thin-lens FODO cell
 - Nonlinear elements such as sextupoles must be solved numerically.



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• For a quadrupole, we know the magnetic field varies as:

$$B_y = x \frac{dB_y}{dx}$$

- Recall:
$$k = \frac{e}{p} \frac{dB_y}{dx}$$

• The force on a moving charged particle due to a magnetic field is:

$$F = ev \times B$$

$$\Rightarrow F_x = ev_z B_y = v_z e\left(x \frac{dB_y}{dx}\right) = kv_z px$$

• Writing this as a differential equation:

$$\frac{d^2x}{dt^2} = \frac{kv_zp}{\gamma m}x$$



• Next, we want to convert from time to z position:

$$z = v_z t$$

• So our differential equation changes as:

$$\frac{d^2x}{dt^2} = \frac{kv_zp}{\gamma m} x \Rightarrow v_z^2 \frac{d^2x}{dz^2} = \frac{kpv_z}{\gamma m} x$$

• Rearranging gives us:

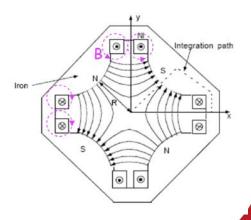
$$\frac{d^2x}{dz^2} = k\frac{p}{\gamma m v_z}x = kx$$

- Recall:
$$p = \beta \gamma mc = \gamma mv_z$$

• Therefore:

$$\frac{d^2x}{dz^2} = kx$$

- This is the Hill's equation for a quadrupole



$$\frac{d^2x}{dz^2} = kx$$

Iron N Integration path

• The general solution for this is:

$$x = \begin{cases} A \cos\left(\sqrt{kz}\right) + B \sin\left(\sqrt{kz}\right), & k < 0\\ A \cosh\left(\sqrt{kz}\right) + B \sinh\left(\sqrt{kz}\right), & k \ge 0 \end{cases}$$

Differentiating, we get:

$$x' = \begin{cases} -\sqrt{k}A\sin\left(\sqrt{k}z\right) + \sqrt{k}B\cos\left(\sqrt{k}z\right), & k < 0\\ \sqrt{k}A\sinh\left(\sqrt{k}z\right) + \sqrt{k}B\cosh\left(\sqrt{k}z\right), & k \ge 0 \end{cases}$$



• If we furthermore apply the initial conditions:

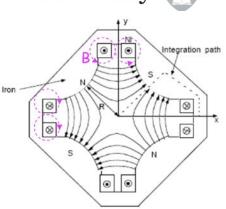
$$x(0) = x_0$$

 $x'(0) = x'_0$

• We get:

$$x = \begin{cases} x_0 \cos\left(\sqrt{k}z\right) + \frac{x'_0}{\sqrt{k}} \sin\left(\sqrt{k}z\right), & k < 0\\ x_0 \cosh\left(\sqrt{k}z\right) + \frac{x'_0}{\sqrt{k}} \sinh\left(\sqrt{k}z\right), & k \ge 0 \end{cases}$$

$$x' = \begin{cases} -x_0 \sqrt{k} \sin\left(\sqrt{k}z\right) + x'_0 \cos\left(\sqrt{k}z\right), & k < 0\\ x_0 \sqrt{k} \sinh\left(\sqrt{k}z\right) + x'_0 \cosh\left(\sqrt{k}z\right), & k \ge 0 \end{cases}$$







- And we can put this all together into a familiar transfer matrix form:
- Focusing quad (k < 0):

$$\begin{pmatrix} x_1 \\ x'_1 \end{pmatrix} = \begin{pmatrix} \cos\left(\sqrt{k}z\right) & \frac{\sin\left(\sqrt{k}z\right)}{\sqrt{k}} \\ -\sqrt{k}\sin\left(\sqrt{k}z\right) & \cos\left(\sqrt{k}z\right) \end{pmatrix} \begin{pmatrix} x_0 \\ x'_0 \end{pmatrix}$$

• Defocusing quad (k > 0):

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$$\underbrace{\begin{pmatrix} x_1 \\ x'_1 \end{pmatrix}}_{\text{integration path}} \begin{pmatrix} x_1 \\ x'_1 \end{pmatrix} = \begin{pmatrix} \cosh\left(\sqrt{kz}\right) & \frac{\sinh\left(\sqrt{kz}\right)}{\sqrt{k}} \\ \sqrt{k}\sinh\left(\sqrt{kz}\right) & \cosh\left(\sqrt{kz}\right) \end{pmatrix} \begin{pmatrix} x_0 \\ x'_0 \end{pmatrix}$$



• What about a sextupole? In this case, we can write the magnetic field due to a transverse offset as:

$$B_y = \frac{k_3 p}{e} x^2$$

• From the force and converting $t \rightarrow z$, we get the differential equation:

$$\frac{d^2x}{dz^2} = k_3 x^2$$

• To solve this, we will use a different approach and assume the solution is:

$$x = \sum_{n=0}^{\infty} a_n z^n$$



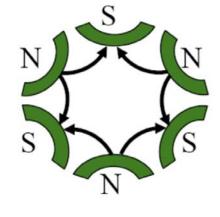


Example 2: trajectory through a sextupole

$$x = \sum_{n=0}^{\infty} a_n z^n \to \frac{d^2 x}{dz^2} = k_3 x^2$$

• Plugging our assumed solution into our equation, we get:

$$\sum_{n=2}^{\infty} (n-1)na_n z^{(n-2)} = k_3 \left(\sum_{n=0}^{\infty} a_n z^n\right)^2$$



- Writing out the first few terms on each side, we get: $2a_2 + 6a_3z + 12a_4z^2 + \dots = k_3a_0^2 + 2k_3a_0a_1z + k_3(2a_0a_2 + a_1^2)z^2 + \dots$
- Now we can solve coefficients by comparing like terms: $a_2 = \frac{k_3 a_0^2}{2}$; $a_3 = \frac{k_3 a_0 a_1}{3}$; $a_4 = \frac{k_3^2 a_0^3 + a_1^2}{12}$

Example 2: trajectory through a sextupole



• Applying the same initial conditions as before, we find that our solution is:

$$x = k_3 x_0^2 + 2k_3 x_0 x_0' z + \left(k_3^2 x_0^3 + k_3 x_0'^2\right) z^2 + \cdots$$

$$x' = 2k_3 x_0 x_0' + 2\left(k_3^2 x_0^3 + k_3 x_0'^2\right) z + \cdots$$

- Key points about this:
 - For sextupoles and other nonlinear elements, there is no closed form solution for the trajectory.
 - The trajectory has a nonlinear dependence on initial conditions and sextupole strength, making them difficult to model analytically.
 - By assuming a series expansion solution, we can solve similar problems like this to any order.
 - But need to note this will always be an approximation.

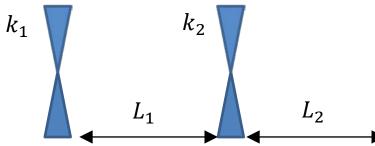
Lattice design & optimisation: numerical optimisers



- As mentioned at the beginning of the lecture, lattice design and optimisation is focused on matching beam and lattice parameters.
 - Require numerical optimisers to do this, but what type?
- Global optimisers
 - Good at finding globally optimal region of parameter space
 - Generally poor (or slow) at converging to the globally optimal solution.
- Local optimisers
 - Will rapidly converge to an optimal solution
 - Prone to getting stuck in a local minimum
- Quite common to use a global optimiser then a local one to find solutions



- As with integration, optimisation problems can get very complicated very quickly!
 - E.g., Consider a beam line of 2 quads and 2 drift lengths, where we want to define the quad strengths and drift lengths in order to match the initial and final beam parameters:
 - Unknowns: L_1 , L_2 , k_1 , k_2
 - Knowns: Initial and final β_x , β_y , α_x , α_y
- This seems like quite an easy problem until you look at the equations to solve...





$$\beta_{i}^{2} = \left(\left(\cos(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}}t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) \left(\cos(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}}t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) \right) + \left(\frac{\sin(\sqrt{k_{i}}t_{i})}{\sqrt{k_{i}}} + t_{i} \cos(\sqrt{k_{i}}t_{i}) \right) \left(\cos(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}}t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) \right) + \left(\frac{\sin(\sqrt{k_{i}}t_{i})}{\sqrt{k_{i}}} + t_{i} \cos(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) \right) + \left(\frac{\sin(\sqrt{k_{i}}t_{i})}{\sqrt{k_{i}}} + t_{i} \cos(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} \sin(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k_{i}}t_{i}) \right) - \sqrt{k_{i}} t_{i} \sin(\sqrt{k$$

 $\sqrt{k_2 \cdot q} \sqrt{k_1}$

 β_y^0

- Not analytically solvable
- Parameter space riddled with local minima
- Even numerical optimisers struggle with this



My preferred approach to solving difficult optimisation problems

- 1. Simplify the problem to a thin-lens approximation
 - This reduces the constraints to polynomials, so we know there will only be a finite number of solutions (at most)
- 2. Solve this simplified problem numerically
 - Numerical optimisers will spit out a list of solutions
 - If there are no solutions, it's likely that there are no solutions in the thick-lens case (though not certain...)
- 3. Discard unphysical solutions from your list and select the "best" solution
 - Discard cases with negative lengths or complex values
 - "best" solution is usually obvious, such as smallest length, or lowest magnet strengths etc.
- 4. Use your "best" solution as the starting point for the thick-lens problem
 - Much more likely to find the best solution without being stuck in local minima.