



Optimization of transformer ratio and beam loading in plasma wakefield accelerator with a structure-exploiting algorithm

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Optimization tools to improve beam quality

For the linear collider application of PWFA, we aim for a stable and efficient acceleration of the trailing bunch with good qualities.

Beam distribution $f(x, y, z, p_x, p_y, p_z, t)$

• Minimize relative energy spread

 $\frac{\sigma_p}{\overline{p}}, \sigma_p = \sqrt{\langle p^2 \rangle - \langle p \rangle^2}$

Maximize energy transfer efficiency and transformer ratio

$$\eta = \frac{\Delta W_{tr}}{\Delta W_{dr}}, \Delta W = \int d\vec{x} E_z(\vec{x}) \rho_b(\vec{x}) \qquad T = \frac{\max |E_z||_{\text{Trailing}}}{\max |E_z||_{\text{Drive}}}$$

• Minimize normalized emittance

$$\epsilon_{nx} = \sqrt{\langle x^2 \rangle \langle p_x^2 \rangle - \langle x p_x \rangle^2} \qquad \epsilon_{ny} = \sqrt{\langle y^2 \rangle \langle p_y^2 \rangle - \langle y p_y \rangle^2}$$

• Mitigate instability (Hosing)



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Wakefield in linear regime is fully predictable

In linear regime, the wakefield is predictable by a convolution of the field of each particles

1D linear thoery

$$E_{z} = -4\pi \int_{x}^{\zeta} d\zeta' \rho_{b} \left(\zeta'\right) \cos k_{p} \left(\zeta - \zeta'\right)$$



Optimal trailing beam profile:

$$\rho_b(\zeta) = -\frac{k_p E_0}{4\pi} \left[\left(k_p \cos k_p \xi_0 \right) \xi + \left(\sin k_p \xi_0 - k_p \zeta_0 \cos k_p \zeta_0 \right) \right]$$

Optimal drive beam profile:

$$\rho(\zeta) = -\frac{E_0}{4\pi\alpha} \left[\left(\alpha^2 + k_p^2 \right) e^{-\alpha\zeta} + k_p^2 (\alpha\zeta - 1) \right], \alpha \to \infty$$

P. Chen, et. al.. Physical Review Letters, 56:1252–1255, 1986. T. Katsouleas et. al, Particle Accelerators, 22:81–99, 1987

The multi-sheath model predict an accurate wakefield at rear of the bubble in the nonlinear blowout regime for symmetric beams

In the 3D blowout (nonlinear) regime, the wakefield is predicted by a modeling of the bubble sheath

Multisheath model

$$A'(r_b) \frac{d^2 r_b}{d\xi^2} + B'(r_b) r_b \left(\frac{dr_b}{d\xi}\right)^2 + C'(r_b) r_b = \frac{\lambda(\xi)}{r_b}.$$
$$E_z(\xi) = \frac{d}{d\xi} \psi_0(\xi) = D'(r_b) r_b \frac{dr_b}{d\xi},$$



W. Lu, et. al. Physics of Plasmas, 13(5):056709, 2006 M. Tzoufras, et. al. Physics of Plasmas, 16(5):056705, 2009. T. N. Dalichaouch et al., Physics of Plasmas, 28, 063103, (2021)



Optimization from simulation is required and faces great challenges

At present no theory describes all degrees of nonlinearity for a wide range of plasma and beam parameters

One simulation can be computationally expensive

Some parameters might be coupled, multivariate optimization needs more runs of PIC code

Constraint optimization

- Goals
 - The algorithm needs to be efficient
 - Fast PIC code (or surrogate models)

Platform for Optimization of Particle Accelerators (POPAS)

- Platform for Optimization of Particle Accelerators at Scale (POPAS)
 - Integrated platform for coordinating the evaluation and numerical optimization of accelerator simulations on super computers.
- PIC code : QuickPIC , QPAD, OSIRIS
- Method

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- Randomly select initial parameters, or initialize with theoretical model, then optimize with model-exploiting second-order trust-region algorithm
- Get great acceleration if objective is a known function of some output variable



$$\min_{x} f(F(x))$$

s.t. $lb \le x \le ub$
 $F_i(x) = c_i + g_i^T (x - x_0) + \frac{1}{2} (x - x_0)^T H_i (x - x_0)$



Optimize transformer ratio by flattening Ez field

$$\eta = \frac{\Delta W_{tr}}{\Delta W_{dr}}, \Delta W = \int d\vec{x} E_z(\vec{x}) \rho_b(\vec{x})$$
$$T = \frac{\max |E_z||_{\text{Trailing}}}{\max |E_z||_{\text{Drive}}} \qquad \frac{\sigma_p}{\overline{p}}, \sigma_p = \sqrt{\langle p^2 \rangle - \langle p \rangle^2}$$

Initialize longitudinally piecewise-linear beam Output Ez lineout at the center Two constraints : bound or fixing the total charge



 $\begin{array}{l} \underset{\Lambda_1,\ldots,\Lambda_p}{\text{minimize}}\\ \text{subject to:} \end{array}$

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$$f(\mathbf{\Lambda}) = \sum_{k=1}^{q} \left([\mathbf{E}_{z}]_{k} (\mathbf{\Lambda}) - \overline{\mathbf{E}}_{z}(\mathbf{\Lambda}) \right)^{2}$$
$$\sum_{i=1}^{p-1} 0.5 * (\Lambda_{i+1} + \Lambda_{i}) \Delta \xi_{i} = Q,$$
$$\mathbf{\Lambda}_{l} \leq \mathbf{\Lambda} \leq \mathbf{\Lambda}_{u}$$

Change piecewise-linear density in bins $\Box > \Lambda_i = (n_{b0} * \sigma_r^2/n_p) f_{z_i}$



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POUNDER Algorithm estimates a more accurate gradient and Hessian from the expression of optimization objective

$$-\nabla f(\mathbf{\Lambda}) = -2\sum_{k} \left[\left([\mathbf{E}_{z}]_{k} (\mathbf{\Lambda}) - \frac{1}{q} \sum_{j} [\mathbf{E}_{z}]_{j} (\mathbf{\Lambda}) \right) \left(\nabla [\mathbf{E}_{z}]_{k} (\mathbf{\Lambda}) - \frac{1}{q} \sum_{j} \nabla [\mathbf{E}_{z}]_{j} (\mathbf{\Lambda}) \right) \right]$$
$$\nabla^{2} f(\mathbf{\Lambda}) = 2\sum_{i} \left[\left([\mathbf{E}_{z}]_{i} (\mathbf{\Lambda}) - \frac{1}{q} \sum_{j} [\mathbf{E}_{z}]_{j} (\mathbf{\Lambda}) \right) \left(\nabla^{2} [\mathbf{E}_{z}]_{i} (\mathbf{\Lambda}) - \frac{1}{q} \sum_{j} \nabla^{2} [\mathbf{E}_{z}]_{j} (\mathbf{\Lambda}) \right) \right]$$
$$+ \left([\mathbf{E}_{z}]_{i} (\mathbf{\Lambda}) - \frac{1}{q} \sum_{j} [\mathbf{E}_{z}]_{j} (\mathbf{\Lambda}) \right) \left(\nabla [\mathbf{E}_{z}]_{i} (\mathbf{\Lambda}) - \frac{1}{q} \sum_{j} \nabla [\mathbf{E}_{z}]_{j} (\mathbf{\Lambda}) \right)^{T} \right]$$

Model each $[\boldsymbol{E}_z]_k$ via a quadratic $q_i(\Lambda) = c_i + g_i^T(\Lambda - \Lambda_0) + \frac{1}{2}(\Lambda - \Lambda_0)^T H_i(\Lambda - \Lambda_0)$. We can get $\nabla [\boldsymbol{E}_z]_k$ and $\nabla^2 [\boldsymbol{E}_z]_k$ by evaluating the neighborhood of Λ_0 .

The result can also be improved by causality

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The algorithm find a profile agrees with multi-sheath model with small improvement for the trailing beam

Multisheath model

$$A'(r_b) \frac{d^2 r_b}{d\xi^2} + B'(r_b) r_b \left(\frac{dr_b}{d\xi}\right)^2 + C'(r_b) r_b = \frac{\lambda(\xi)}{r_b}$$

$$\psi(r,\xi) = \psi_0(\xi) - \frac{r^2}{4}$$

= $\frac{r_b^2(\xi)}{4} (1 + \beta') - \frac{r^2}{4}$
 $E_z(\xi) = \frac{d}{d\xi} \psi_0(\xi) = D'(r_b) r_b \frac{dr_b}{d\xi},$

The current profile can be reverse engineered by

$$\lambda(\xi) = C'\tilde{r}_b^2 + \left(\frac{B'}{D'^2} - \frac{A'F'}{D'^3\tilde{r}_b^2}\right)f(\xi)^2 + \left(\frac{A'}{D'}\right)\frac{df(\xi)}{d\xi}$$



The optimized beam current shows a precursor at front of the drive beam which cannot be predicted by nonlinear theory

In linear regime, the optimal longitudinal profile is a delta function followed by a linear ramp

$$\rho(\zeta) = -\frac{E_0}{4\pi\alpha} \left[\left(\alpha^2 + k_p^2 \right) e^{-\alpha\zeta} + k_p^2 (\alpha\zeta - 1) \right], \alpha \to \infty$$

In nonlinear regime, Lu et. al. proposed a linear ramp by assuming an adiabatic response $\frac{d^2r_b}{d\xi^2} \ll 1, \frac{dr_b}{d\xi} \ll 1$

$$r_b \frac{d^2 r_b}{d\xi^2} + 2\left(\frac{dr_b}{d\xi}\right)^2 + 1 = \frac{4\lambda(\xi)}{r_b^2}$$
$$\psi(0,\xi) \approx \frac{r_b^2(\xi)}{4}, \ \Lambda(\xi) = \frac{\xi}{L_0}\Lambda_0, \ \psi(0,\xi) \approx \frac{\xi}{L_0}\Lambda_0$$
$$E_z(\xi) = \frac{d\psi}{d\xi} \approx \frac{\Lambda_0}{L_0}$$

P. Chen, et al. Phys. Rev. Lett., 56, 12, 1986 W. Lu, et al. Proc.PAC09, page 3028, 2009. W. Lu, et. al. Physics of Plasmas, 13(5):056709, 2006 T. N. Dalichaouch et al., Physics of Plasmas, 28, 063103, (2021)



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Optimized beam profile fixing the total charge



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Charge is fixed as Q = 5nC

$$E_{+} \approx \frac{1}{2} r_{m} \approx \sqrt{\Lambda_{0}} \qquad E_{+}/E_{-} \approx \sqrt{\Lambda_{0}} / \left(\frac{\Lambda_{0}}{L_{0}}\right) = \frac{L_{0}}{\sqrt{\Lambda_{0}}}$$

Use non-uniform bins to resolve the beam profile

Get "perfectly" flattened Ez field under current simulation resolution with objective down to 10^{-5}

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The optimized profile has a higher transformer ratio compared with triangular and Gaussian shape



A finite bin size of current profile will give a precursor and oscillation at front and end of the beam





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Long range simulation with QPAD shows high efficiency and low energy spread growth

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Summary

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- We utilize an optimization tool developed at ANL, to efficiently find optimized drive beam profile and witness beam profile in PWFA
- The algorithm converges quickly, and find witness beams shapes similar to those calculated by a recent multi-sheath model for the nonlinear wakefield
- It can also obtain optimized drive beam profiles that give high transformer ratios with constraint of fixing the total charge
- Some thoughts
 - Modeling of sheath at front of the beam
 - Long range acceleration optimization (surrogate models)

Thanks for your attention!