KU LEUVEN



Sensitivity Analysis and Error Propagation for Plasma Edge Codes Status and Challenges

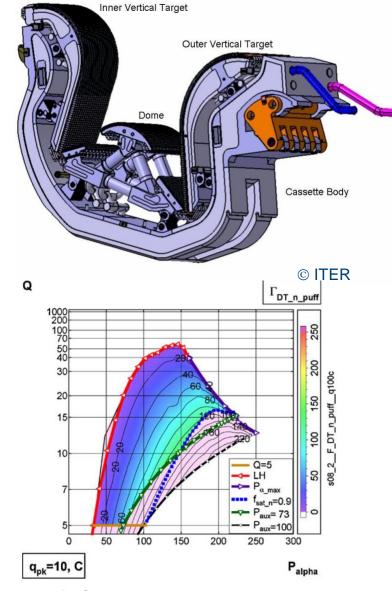
W. Dekeyser, M. Blommaert, S. Carli, M. Baelmans

KU Leuven, Department of Mechanical Engineering



Role of plasma edge modeling

- Design of divertors and power exhaust scenarios for next generation machines still an open question
 - Limit power load to PFCs to acceptable levels
 - Manage particle exhaust
 - Ensure compatibility with burning plasma conditions in the core
- Numerical codes (e.g. SOLPS-ITER) essential to consistently model the complex plasma edge
 - (Multi-)fluid plasma kinetic neutral models
 - Highly nonlinear, anisotropic, strongly coupled PDEs
 - Coupling with PWI models, MHD equilibrium,...
 - Coupled Finite Volume / Monte Carlo codes

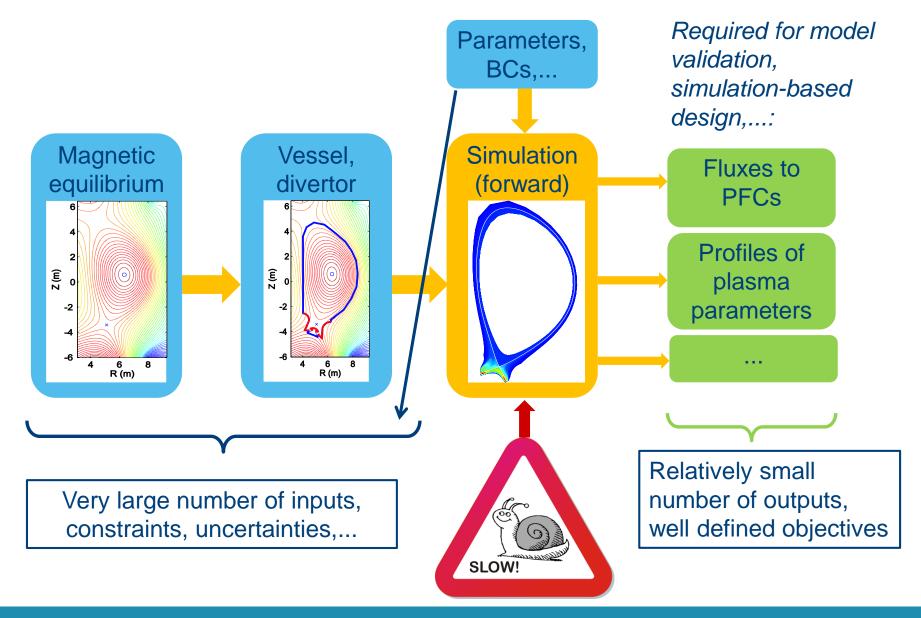


[A.S. Kukushkin et al., Fusion Eng.

Des. **96** (2011) 2865.]

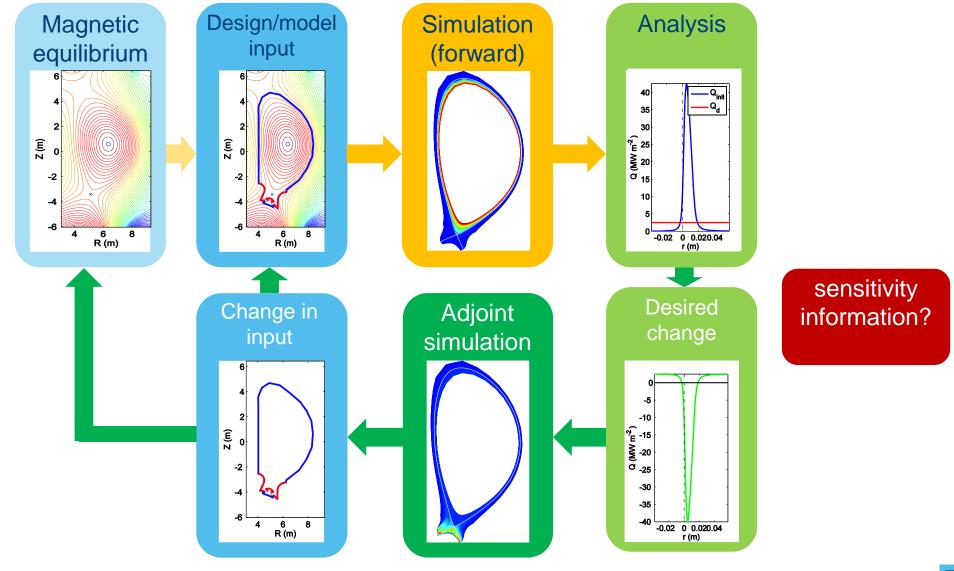


Plasma edge codes as analysis tools





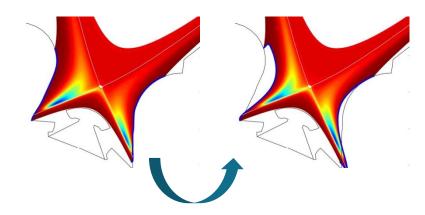
Plasma edge codes as optimization tools



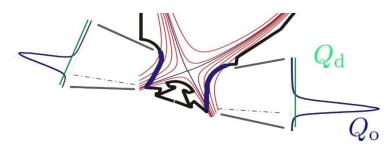


Applications of optimization tools

[W. Dekeyser et al., Nucl. Fusion 54 (2014) 073022, and M. Blommaert et al., Nucl. Fusion 55 (2015) 013001.]

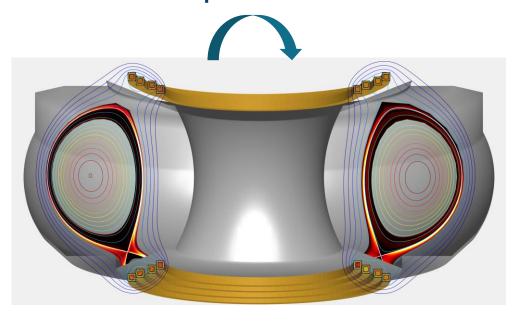


Divertor Shape optimization



$$J(\Omega, \mathbf{q}) = \frac{1}{2} \int_{\mathbf{t}} (\mathbf{Q}_{o} - \mathbf{Q}_{d})^{2} d\sigma$$

Magnetic divertor optimization



Using adjoint techniques, entire optimization problem solved at a cost of only a few forward simulations!



Model calibration through optimization

[M. Baelmans et al., PPCF 56 (2014) 114009.]

Cost function: match to "experimental data"

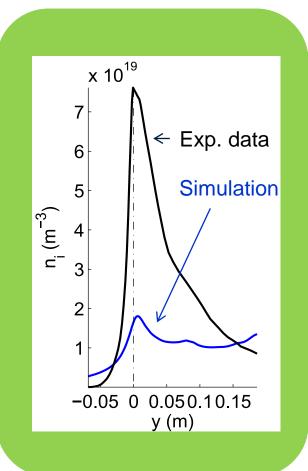
$$\min_{\phi, \mathbf{q}} J(\phi, \mathbf{q}) = \sum_{l=\text{OM}, \dots} \frac{1}{\Omega_l} \int_{\Omega_l} \left(\frac{\alpha_{l,n}}{2} \frac{(n - n^{\text{exp}})^2}{n_l^2} + \frac{\alpha_{l,T}}{2} \frac{(T - T^{\text{exp}})^2}{T_l^2} \right) d\Omega$$

s.t.
$$\mathcal{B}(\phi, \mathbf{q}) = 0$$

- ϕ transport coefficients and plasma edge model constants (the *control* variables)
- **q** state variables: plasma density, temperature,...

 $\mathcal{B}(\phi, \mathbf{q})$ plasma edge model: set of PDEs and boundary conditions

- Efficient solution through adjoint sensitivity analysis
- **Challenges:** accounting for multiple diagnostics? Prior information about uncertainties (Bayesian setting)? ...





Potential of sensitivity analysis for edge plasma model validation

- Efficient solution of UQ problems through optimization
- Identification of dominant uncertainties, guide for parameter space reduction
- Efficient parametrization of input and output PDFs, efficient propagation of uncertainty though the codes
- Construction of surrogate models

...but: several challenges to be addressed to enable application to realistic problems!

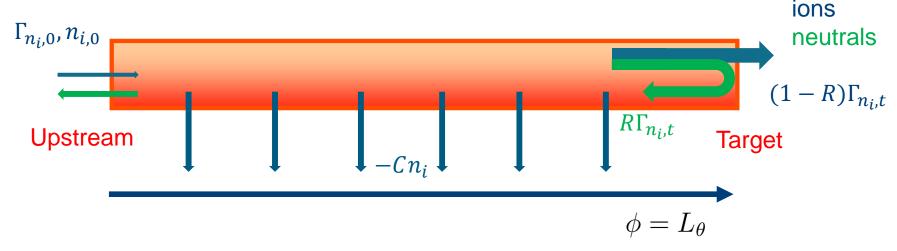


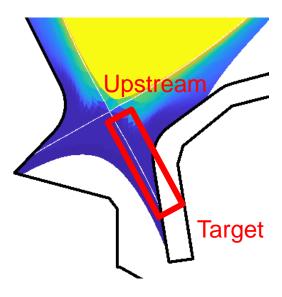
Outline

- Motivation
- Sensitivities in the presence of MC noise
- Partially adjoint techniques for simulation chains
- Practical implementation in big codes
- Summary and outlook



Optimization for fluid-kinetic models





- Sources from kinetic neutrals, but 'only flying left and right'
 - → Can be solved with Monte Carlo or finite volume method
- Some essential features of SOL models are present
 - Fluid-kinetic coupling, Monte Carlo noise, nonlinear source terms, ...
- Optimization of "divertor fluxes":

$$\min_{\phi, \mathbf{q}} J(\phi, \mathbf{q}) = \frac{\lambda}{2} (\Gamma - \Gamma_{\mathrm{d}})^2 |_{\mathrm{t}} + \frac{\lambda_0}{2} (\phi - L_0)^2$$

s.t.
$$\mathcal{B}(\phi, \mathbf{q}) = S - A(\phi, \mathbf{q}) = 0$$

plasma continuity and parallel momentum, state variables $\mathbf{q} = \{n_{i}, u_{||}\}^{T}$



Finite Difference (FD) sensitivities

Reduced cost function/state solver as 'black box'

$$\min_{\phi} \hat{J}(\phi) \equiv J(\phi, \mathbf{q}(\phi))$$

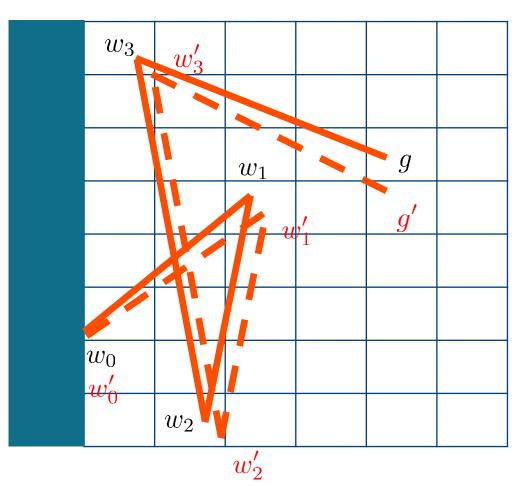
Sensitivity

$$\frac{\mathrm{d}\hat{J}}{\mathrm{d}\phi}\delta\phi \approx \frac{J(\phi + \delta\phi, \mathbf{q}(\phi + \delta\phi)) - J(\phi - \delta\phi, \mathbf{q}(\phi - \delta\phi))}{2}$$

- Cost scales with number of design variables
- Correlated random numbers to reduce variance

$$Var(X_1 - X_2) = Var(X_1) + Var(X_2) - 2Cov(X_1, X_2)$$

Some decorrelation hard/impossible to avoid in practice





The adjoint approach to sensitivity calculation

Constrained optimization problem

$$\min_{\phi \in \phi_{\mathrm{ad}}, \mathbf{q}} J(\phi, \mathbf{q})$$
 subject to $\mathcal{B}(\phi, \mathbf{q}) = 0$ $(= S - A(\phi, \mathbf{q}))$

Reduced cost functional

$$\min_{\phi \in \phi_{\text{ad}}} \hat{J}(\phi) \equiv J(\phi, \mathbf{q}(\phi))$$

Chain rule for sensitivity computation

$$\hat{J}_{\phi}\delta\phi = J_{\phi}\delta\phi + J_{\mathbf{q}}\delta\mathbf{q}
= J_{\phi}\delta\phi - J_{\mathbf{q}}\mathcal{B}_{\mathbf{q}}^{-1}\mathcal{B}_{\phi}\delta\phi
= J_{\phi}\delta\phi - (\mathcal{B}_{\mathbf{q}}^{-T}J_{\mathbf{q}}^{T})^{T}\mathcal{B}_{\phi}\delta\phi
= J_{\phi}\delta\phi + (\mathbf{q}^{*})^{T}\mathcal{B}_{\phi}\delta\phi$$

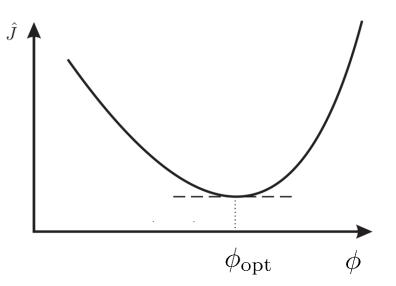
$$\mathcal{B}_{\phi}\delta\phi + \mathcal{B}_{\mathbf{q}}\delta\mathbf{q} = 0$$

$$\mathcal{B}_{\mathbf{q}}^{T}\mathbf{q}^{*} = -J_{\mathbf{q}}^{T}$$

Optimality conditions

Lagrangian

$$L(\phi, \mathbf{q}, \mathbf{q}^*) = J(\phi, \mathbf{q}) + \langle \mathbf{q}^*, \mathcal{B}(\phi, \mathbf{q}) \rangle$$



First order optimality conditions:

$$\begin{array}{lll} 0 & = & \nabla_{\mathbf{q}^*}L & = & \mathcal{B}(\phi,\mathbf{q}) & & \textit{State equations} \\ 0 & = & \nabla_{\mathbf{q}}L & = & \nabla_{\mathbf{q}}J + \mathcal{B}_{\mathbf{q}}^*\mathbf{q}^* & & \textit{Adjoint equations} \\ 0 & = & \nabla_{\phi}L & = & \nabla_{\phi}J + \mathcal{B}_{\phi}^*\mathbf{q}^* & & \textit{Design equations} \end{array}$$

- → Again a **coupled FV-MC system**!
- → How can we achieve low variance on the sensitivities?



The discrete adjoint approach

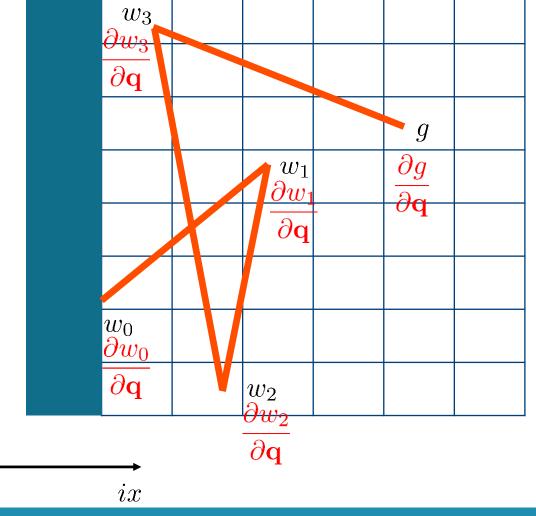
iy

Forward simulation

Contribution of particle to source in cell ix, iy

$$S_{ix,iy} = g_{ix,iy} \Pi_{i=0}^3 w_i$$

Accumulated weight factor will be a function of plasma properties in *all* the cells crossed by the particle



Adjoint simulation

Contribution of particle to source in cell ix, iy

$$\left(\frac{\partial S_{ix,iy}}{\partial \mathbf{q}}\right)^{T} q_{ix,iy}^{*}$$

$$= q_{ix,iy}^{*} \left(\frac{\partial g_{ix,iy}}{\partial \mathbf{q}}\right)^{T} \Pi_{i=0}^{3} w_{i}$$

$$+ q_{ix,iy}^{*} g_{ix,iy} \Pi_{i=0}^{3} w_{i} \sum \frac{\left(\frac{\partial w_{i}}{\partial \mathbf{q}}\right)^{T}}{w_{i}}$$

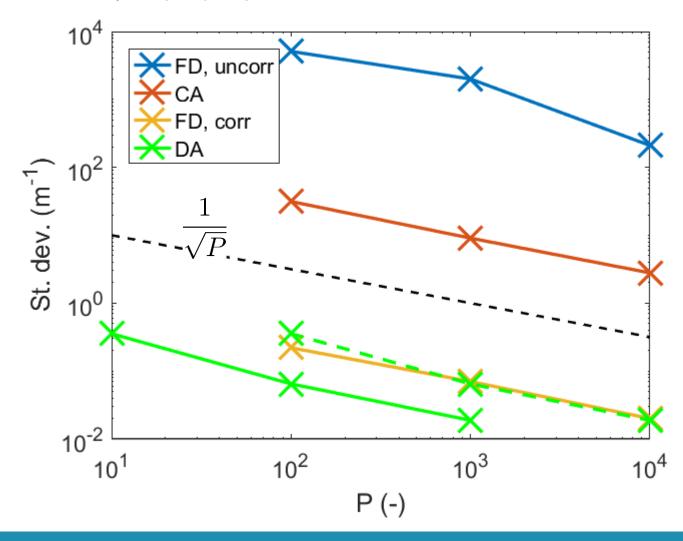
Adjoint particle contributes to source in *all* of the cells it crossed

- → more complex simulation
- → but *exact* correlation!

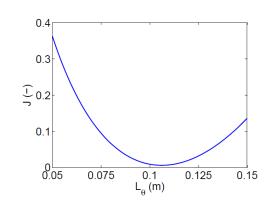


(Relative) standard deviation on sensitivity

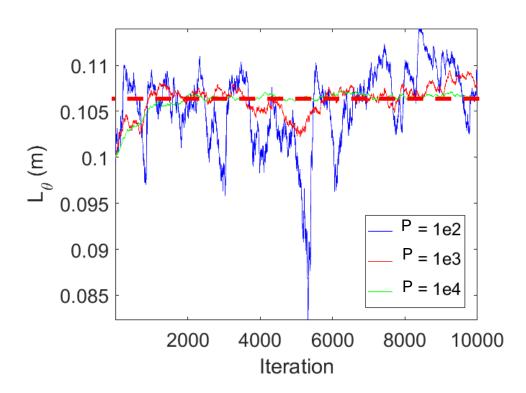
[W. Dekeyser et al., Contrib. Plasma Phys. 58 (2018) 718.]



Performance of the optimization algorithm

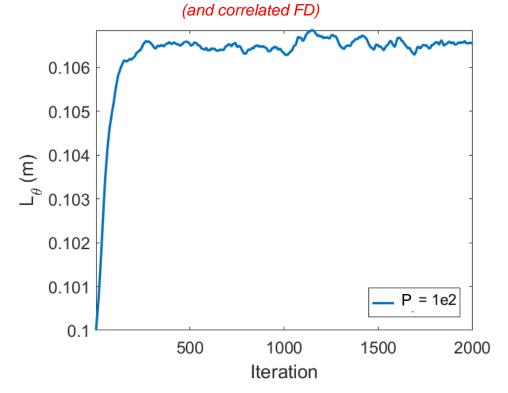


Continuous adjoint



Convergence 'on average'; reliable?

Discrete adjoint



Low noise, smooth convergence!

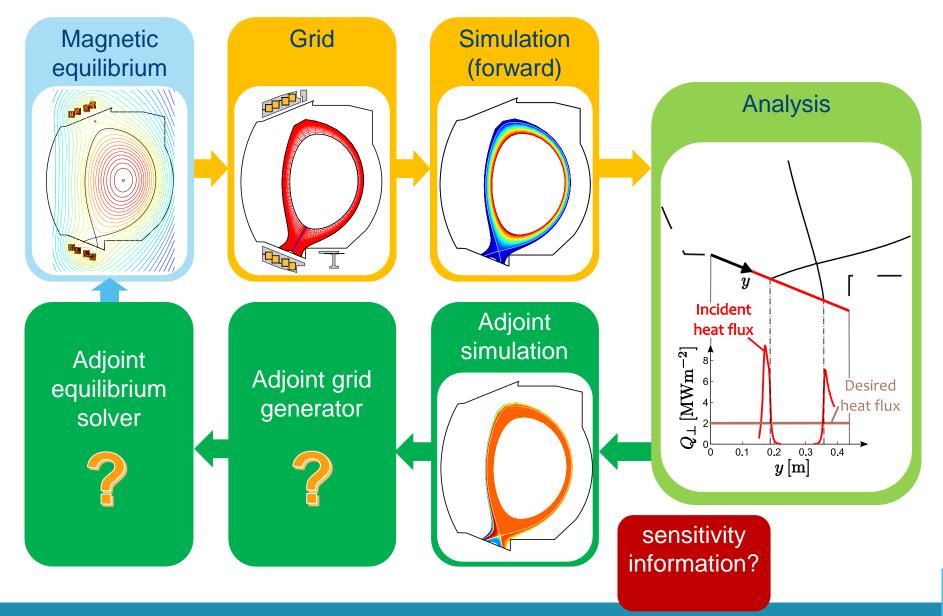


Outline

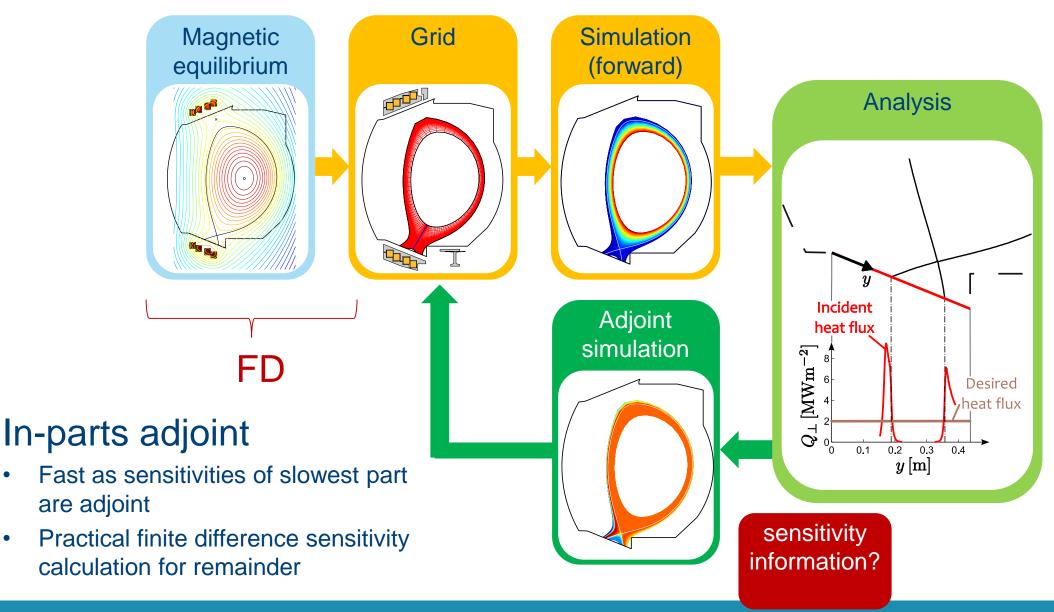
- Motivation
- Sensitivities in the presence of MC noise
- Partially adjoint techniques for simulation chains
- Practical implementation in big codes
- Summary and outlook



Propagating sensitivities through simulation chains

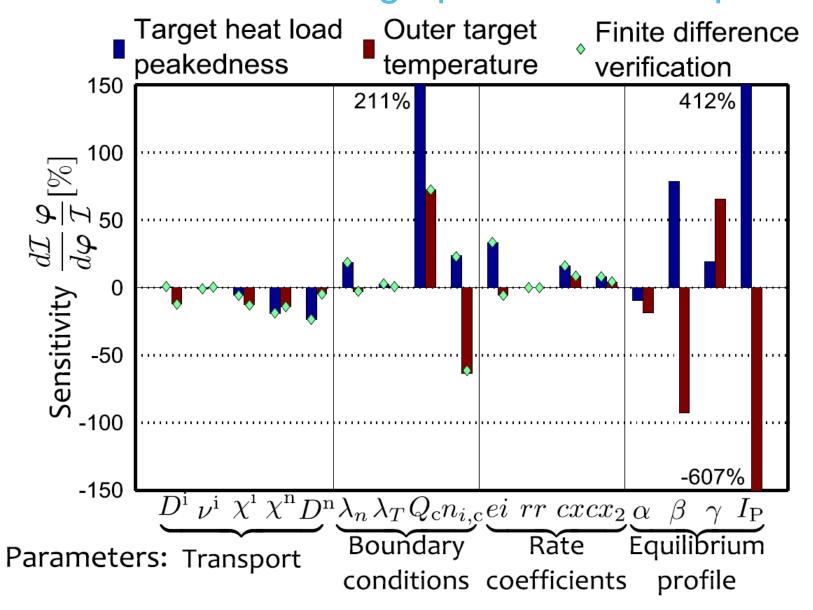


Propagating sensitivities through simulation chains

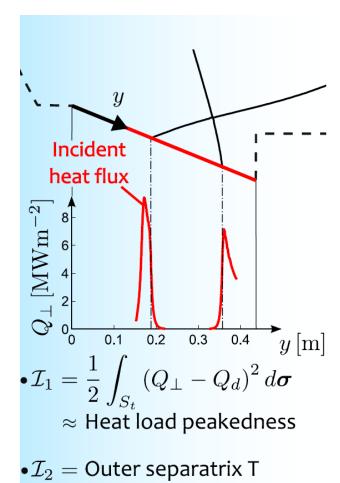


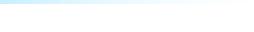


Sensitivities w.r.t. edge plasma model parameters



[M. Blommaert et al., NME 12 (2017) 1049.]







Outline

- Motivation
- Sensitivities in the presence of MC noise
- Partially adjoint techniques for simulation chains
- Practical implementation in big codes
- Summary and outlook



Implementation in full edge codes

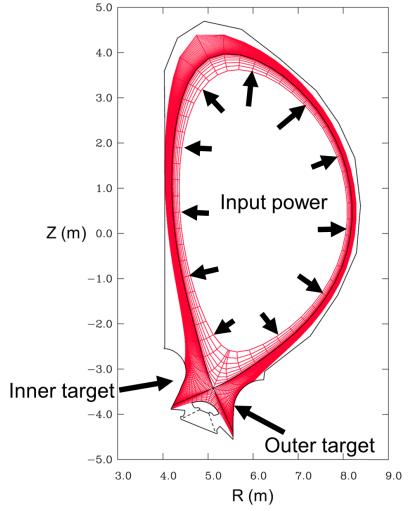
Challenges

- Dealing with "legacy code"
- Developer and user friendliness
- Maintainability
- Current research tracks for SOLPS-ITER
 - Use of AD tools ("Automatic/Algorithmic Differentiation"): TAPENADE (INRIA)
 - Link to discrete adjoint approach, very robust w.r.t. statistical noise
 - Practical combination of adjoint and finite differences (*in-parts adjoint* technique)



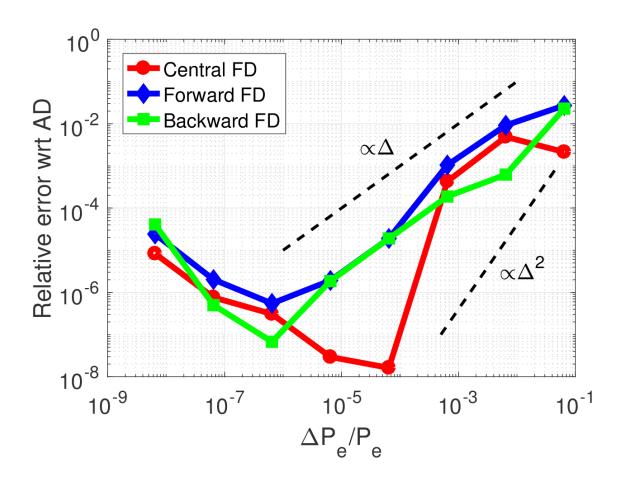
Proof-of-principle: forward AD in B2.5

- Case setup
 - D only, fluid neutrals
 - Input power P_{SOL} = 31 MW, split equally between ions and electrons
 - Low recycling conditions, χ_e , χ_i = 6.0 m² s⁻¹
- Quantities of interest (@ targets):
 - \circ Max. electron temperature $T_{e,max}$
 - $_{\circ}$ Max. heat load $q_{max}^{\prime\prime}$
- Varied model parameters:
 - o Input power (P_e, P_i)
 - \circ Radial heat diffusion coefficients (χ_e , χ_i)





Verification of AD sensitivities



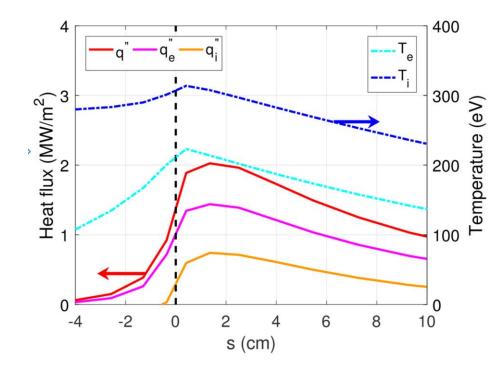
| | Relative error AD-central FD | |
|-------------|------------------------------|--------------------------|
| | $T_{ m e,max}$ | $q_{max}^{\prime\prime}$ |
| $P_{\rm e}$ | ~10 ⁻⁸ | ~10 ⁻⁷ |
| P_{i} | ~10 ⁻⁷ | ~10 ⁻⁷ |
| χ_{e} | ~10 ⁻⁹ | ~10 ⁻⁶ |
| χ_{i} | ~10 ⁻⁹ | ~10 ⁻⁶ |



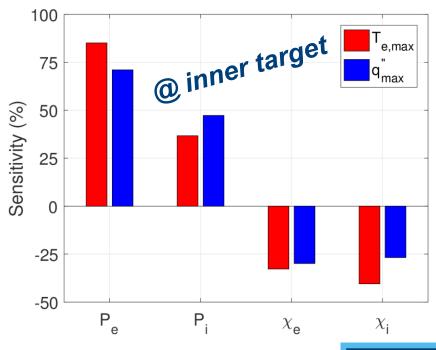
Sensitivity of target profiles

[S. Carli et al., NME 18 (2019) 6.]

- P_e strongly linked to T_e , ions need collisions
- q" mainly driven by e contribution
- $\chi \rightarrow$ spreading of plasma power



Normalized sensitivities e.g. $S = \frac{\partial T_{e,max}}{\partial P_e}\Big|_{OP} \cdot \frac{P_e}{T_{e,max}}$





Outline

- Motivation
- Sensitivities in the presence of MC noise
- Partially adjoint techniques for simulation chains
- Practical implementation in big codes
- Summary and outlook



Summary and outlook

- Several challenges to compute accurate sensitivities of plasma edge code have been addressed:
 - Handling of statistical noise
 - Complex simulation chains
 - Dealing with big codes
- Sensitivities may be essential to enable UQ studies for plasma edge models
 - Solving UQ problems through optimization
 - Identifying dominant uncertainties over a parameter range (parameter space reduction)
 - Efficient parametrization of input and output PDFs
 - Construction of surrogate models
 - 0 ...





Thank you for your attention!