

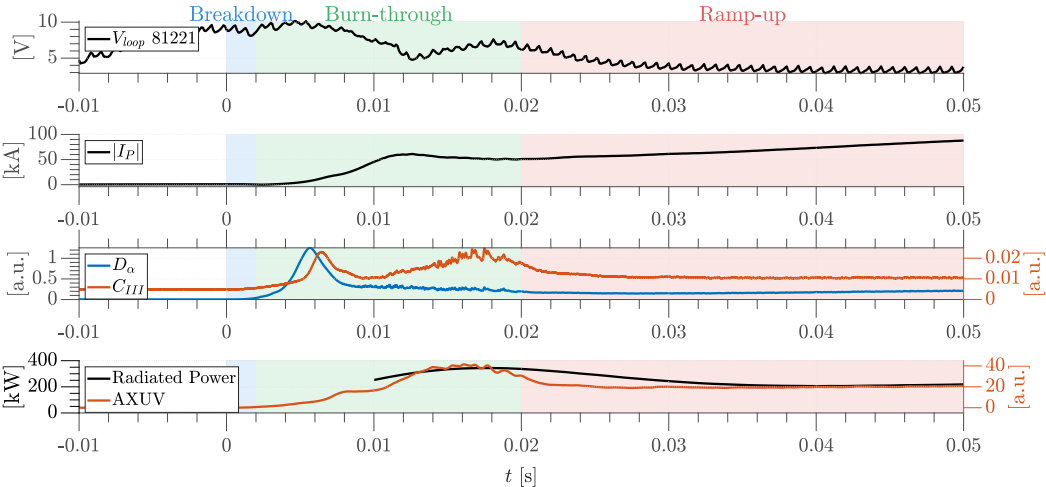
Sensitivity analysis of STREAM burn-through simulations on TCV: identifying the dominant input parameters

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What is the start-up?



Runaway electrons in the burn-through

- REs: low electron density and/or a strong electric field
- REs are hard to control, can limit ohmic heating, and may damage the vessel
- ITER: $E_{\max} = 0.3 \text{ V m}^{-1}$, $p_{\text{prefill}}^{\max} = 2 \text{ mPa}$ (de Vries & Gribov, Nucl. Fusion, 59, 2019)

STREAM

- SStart-up Runaway Electron Analysis Model (Hoppe *et al.*, J. Plasma Phys., 88, 2022)
- 0D burn-through code.
 - Volume-averaged outputs
 - Fluid model
 - Self consistent runaway electron evolution

STREAM — equations

- Energy balance:

- $\frac{dW_e}{dt} = j_\Omega E_{||} - P_{\text{inelastic losses}} - \sum_i Q_{ei} - \frac{W_e}{\tau_e}$

- $\frac{dW_i}{dt} = \sum_k Q_{ik} - P_{\text{losses}} - \frac{W_i}{\tau_i}$

- Particle balance: accounts for all species

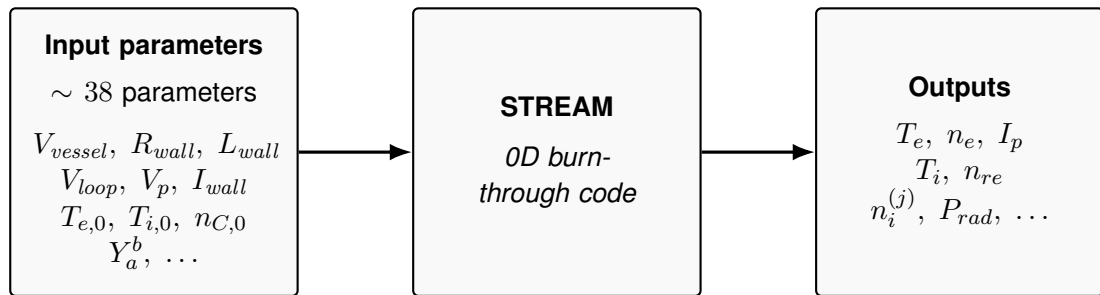
- Circuit:

- $2\pi R_0 E_{||} + L_p \frac{dI_p}{dt} + M_{vp} \frac{dI_{wall}}{dt} = V_{loop}$

- $R_{wall} I_{wall} + L_{wall} \frac{dI_{wall}}{dt} + M_{vp} \frac{dI_p}{dt} = V_{loop}$

- Runaway electron evolution: $\frac{dn_{re}}{dt} = \gamma_{Dreicer} + \Gamma_{ava} n_{re} - \frac{n_{re}}{\tau_{re}}$

STREAM — schematics

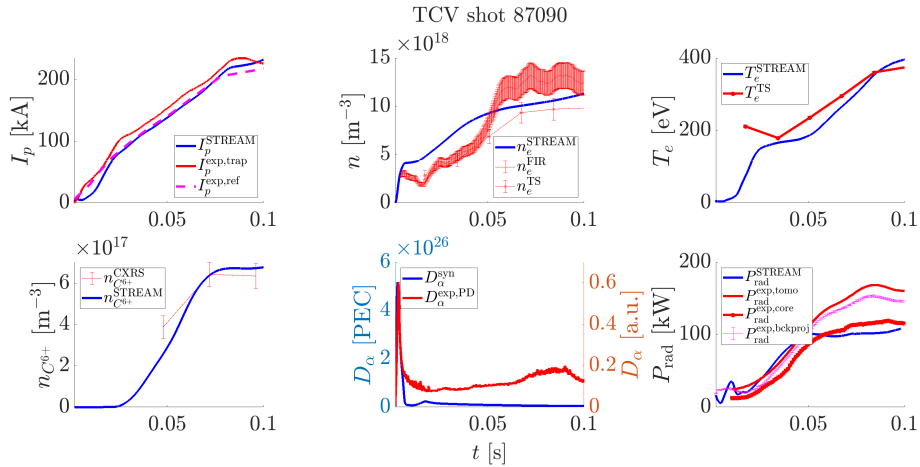


STREAM — Input parameters

- Physical features of TCV: V_{vessel} , R_{wall} , L_{wall} , ...
- Discharge parameters: V_{loop} , V_p , I_{wall} , ...
- Uncontrolled parameters: Y_a^b , $T_{e,0}$, $T_{i,0}$, $n_{C,0}$, ...

STREAM — Outputs

• Joint REM and WPTE RT03 Analysis meeting



Sensitivity analysis — the question

Which input parameters most influence burn-through dynamics and runaway-electron generation?

Sensitivity workflow

- 1 sample perturbed STREAM inputs,
- 2 compare each run with a reference run,
- 3 reduce all output variation to one score ϖ ,
- 4 rank inputs by the induced variation of ϖ .

Uncertain inputs

STREAM: $K \approx 38$ inputs. For each input,

$$x_k \in [\mu_k - \sigma_k, \mu_k + \sigma_k].$$

μ_k : the average

σ_k : the uncertainty.

Step 1 — score the variation to the reference

Each run produces time traces. For one monitored quantity Y , compare it with the reference trace, point by point:

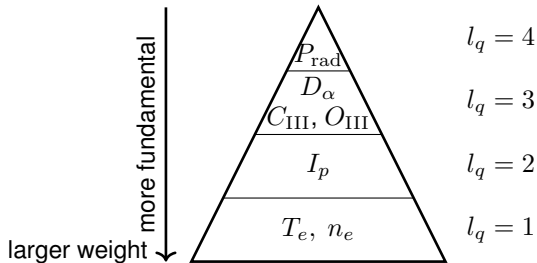
Raw variation

$$\text{RMSE}(Y, Y^{ref}) = \sqrt{\frac{1}{M} \sum_{m=1}^M (Y_m - Y_m^{ref})^2}$$

Dimensionless variation

$$\text{NRMSE}(Y, Y^{ref}) = \frac{\text{RMSE}(Y, Y^{ref})}{\text{RMS}(Y^{ref})}$$

Step 2 — weight the outputs by importance



Weights:

$$w_q = \frac{1}{l_q}.$$

One discrepancy score per run:

$$\varpi = \frac{\sum_q w_q \text{NRMSE}(Y_q, Y_q^{\text{ref}})}{\sum_q w_q}.$$

Large $\varpi \implies$ strong deviation on fundamental outputs.

Step 3a — the idea: companion runs that share one input

For each input we want *one number*: how strongly does it control the match score ϖ ? (*small ϖ = good match, large = poor match*).

	Run	
	$T_{e,0}$ [eV]	$T_{i,0}$ [eV]
run 1	1.0	0.4
run 2	1.5	0.6
run 3	2.8	0.3

one row = one full run $\rightarrow \varpi_b$

	Companion	
	$T_{e,0}$ [eV]	$T_{i,0}$ [eV]
run 1	1.0	0.5
run 2	1.5	0.3
run 3	2.8	0.7

same $T_{e,0}$, new $T_{i,0} \rightarrow \varpi_b^{(k)}$

A run and its companion share **only** $T_{e,0}$.

Step 3b — the sample matrices

One companion is noisy, so repeat it B times. Each row e_b of $E \in \mathbb{R}^{B \times K}$ is one configuration; **one STREAM run per row**. For parameter k : keep the blue column, redraw the rest $(\curvearrowright) \Rightarrow E^{(k)}$.

$$\underbrace{\begin{bmatrix} e_{1,1} & \cdots & e_{1,k} & \cdots & e_{1,K} \\ \vdots & & \vdots & & \vdots \\ e_{B,1} & \cdots & e_{B,k} & \cdots & e_{B,K} \end{bmatrix}}_E \rightarrow \begin{matrix} \varpi_1 \\ \vdots \\ \varpi_B \end{matrix}$$

$$\underbrace{\begin{bmatrix} \tilde{e}_{1,1} & \cdots & e_{1,k} & \cdots & \tilde{e}_{1,K} \\ \vdots & & \vdots & & \vdots \\ \tilde{e}_{B,1} & \cdots & e_{B,k} & \cdots & \tilde{e}_{B,K} \end{bmatrix}}_{E^{(k)}} \rightarrow \begin{matrix} \varpi_1^{(k)} \\ \vdots \\ \varpi_B^{(k)} \end{matrix}$$

Blue column kept, rest redrawn: keeps interactions. $B(K+1)$ runs total.

Step 3c — the measure of importance

$$I_k = \sqrt{\langle \varpi \varpi^{(k)} \rangle - \langle \varpi \rangle^2} \quad (k = T_{e,0} \text{ here})$$

Measures of Importance — Homma & Saltelli, *J. Nucl. Sci. Technol.* **32** (1995)

- paired scores move together $\Rightarrow$ large $I_k \Rightarrow$ input k matters,
- unrelated scores $\Rightarrow I_k \approx 0 \Rightarrow$ input k is negligible,
- a reliable I_k needs many simulations $\Rightarrow$ large B .

Results — two discharges analysed

Shot 84108 — burn-through

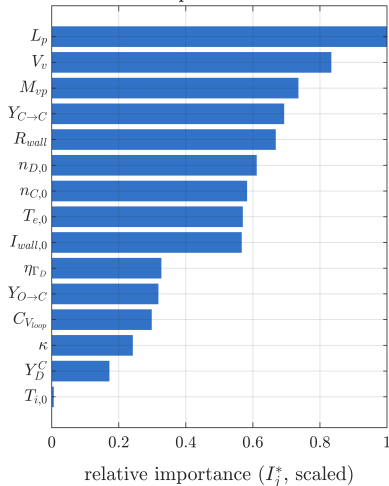
- no runaways
- 23 inputs
- 8 outputs

Shot 87090 — runaways

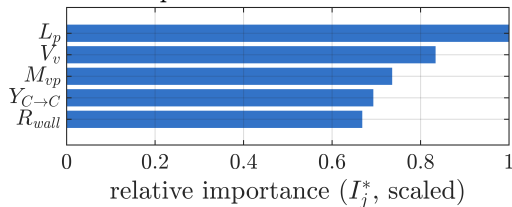
- no gas fuelling → runaways
- 5 inputs
- extra output: n_{RE}

Burn-through shot — only a handful of inputs matter

Parameter importance — shot 84108

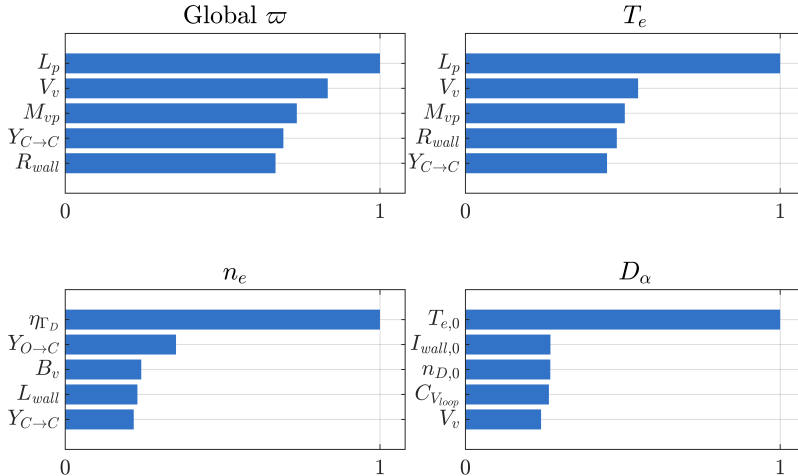


Top 5 drivers — shot 84108



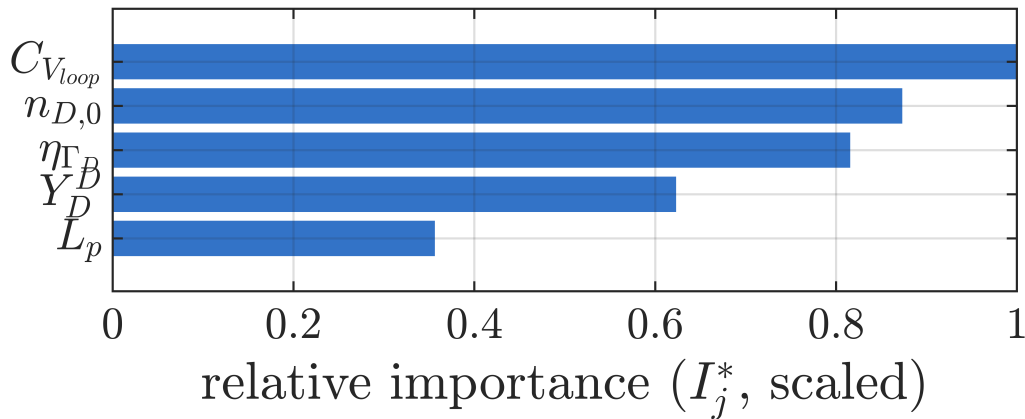
Burn-through shot — comparison

Top 5 parameters — shot 84108



Runaway — what drives n_{RE}

Drivers of n_{RE} — shot 87090



Results — takeaways

■ Burn-through discharge:

- High dimensionality $\rightarrow$ lower dimensionality
- Stiff: L_p , V_v , M_{vp}
- Sloppy: $T_{i,0}$

■ Runaway discharge:

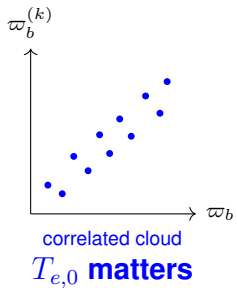
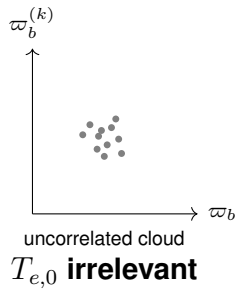
- The 5-input study should be extended.
- V_{loop} is the leading driver, followed by $n_{D,0}$

Closing

Questions?

Appendix — reading the pairs: correlated or not

Each point is a (run, companion) pair, $\varpi_b^{(k)}$ vs ϖ_b (example: $T_{e,0}$ frozen):



$$I_k = \sqrt{\langle \varpi \varpi^{(k)} \rangle - \langle \varpi \rangle^2}$$
 large for a tilted (correlated) cloud, near zero for a round one.

Appendix — why B must be large I

The example $B = 3$ only illustrates the matrix construction; it is far too small for a reliable estimate. Following Saltelli et al. (2000, pp. 171–173):

Let $\boldsymbol{\theta} = (\theta_1, \dots, \theta_K)$ be the uncertain inputs and $\varpi(\boldsymbol{\theta})$ the scalar discrepancy score of one run. For input k ,

$$I_k^2 = \text{Var}(\varpi) - \mathbb{E}[\text{Var}(\varpi \mid \theta_k)] = U_k - (\mathbb{E}(\varpi))^2,$$

$$U_k = \int (\mathbb{E}(\varpi \mid \theta_k))^2 p_k(\theta_k) d\theta_k,$$

where p_k is the marginal distribution of θ_k .

For $b = 1, \dots, B$, let $\boldsymbol{\theta}^{(b)}$ be the b -th base sample and $\boldsymbol{\theta}^{(b,k)}$ the resampled configuration (θ_k fixed, the rest redrawn independently), with

$$\varpi_b = \varpi(\boldsymbol{\theta}^{(b)}), \quad \varpi_b^{(k)} = \varpi(\boldsymbol{\theta}^{(b,k)}).$$

Appendix — why B must be large II

U_k has no closed form and full Monte Carlo is impractical, so Saltelli et al. (1993) estimate

$$\hat{U}_k = \frac{1}{B} \sum_{b=1}^B \varpi_b \varpi_b^{(k)}, \quad \mathbb{E}[\varpi] = \langle \varpi \rangle = \frac{1}{B} \sum_{b=1}^B \varpi_b,$$

$$\hat{I}_k^2 = \hat{U}_k - \langle \varpi \rangle^2 = \frac{1}{B} \sum_{b=1}^B \varpi_b \varpi_b^{(k)} - \left(\frac{1}{B} \sum_{b=1}^B \varpi_b \right)^2.$$

Appendix — why B must be large III

Convergence (law of large numbers). If the base samples are i.i.d. and the resampled configurations are drawn independently, then the products $\varpi_b \varpi_b^{(k)}$ are i.i.d., so

$$\frac{1}{B} \sum_{b=1}^B \varpi_b \varpi_b^{(k)} \xrightarrow{B \rightarrow \infty} \mathbb{E}[\varpi \varpi^{(k)}] = U_k,$$

$$\frac{1}{B} \sum_{b=1}^B \varpi_b \xrightarrow{B \rightarrow \infty} \mathbb{E}(\varpi).$$

Hence

$$\hat{I}_k^2 \xrightarrow{B \rightarrow \infty} U_k - (\mathbb{E}(\varpi))^2 = I_k^2.$$

Appendix — why B must be large IV

Increasing B improves the statistical stability of the estimator. In practice, B is increased until the $\hat{I}_k$ no longer change significantly when additional samples are added.