

Surrogate Modelling of the Tritium Breeding Ratio

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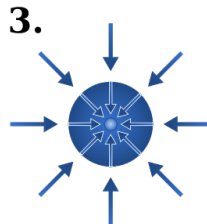
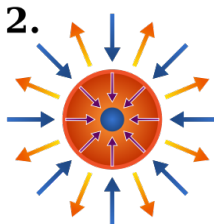
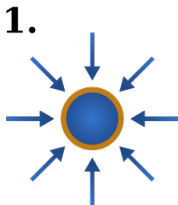
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Nuclear fusion – the energy of the future!

- Must produce and contain an extremely hot and dense plasma
 - Magnetic Confinement Fusion (MCF): toroidal circulation
 - Inertial Confinement Fusion (ICF): spherical compression
- Modern designs require enriched Hydrogen fuel of two varieties:
 - Deuterium (^2H) – abundant in naturally-sourced water
 - Tritium (^3H) – extremely rare, but can be produced *in-reactor*



Tritium breeding blankets convert neutron radiation from the fusion plasma into a steady supply of tritium fuel.



However, the tritium breeding ratio (TBR) depends on numerous geometric and material parameters.

TBR evaluation *Paramak* achieves very accurate results by OpenMC Monte Carlo neutronics simulation, but is computationally expensive.

Our Challenge:

Produce a fast TBR function which strongly approximates Paramak, making use of the latest in surrogate modelling techniques.

We designed the Approximate TBR Evaluator (ATE) package to generate training and test datasets from Paramak.

UCL's Hypatia cluster provided the multithreading power for us to produce one million TBR samples, representing 27 days of runtime.

These runs included full evaluations on the 18 continuous and discrete parameters of Paramak, and "slice" evaluations with all discrete parameters frozen.

	Parameter name	Domain
Blanket	Breeder fraction [†]	[0, 1]
	Breeder ⁶ Li enrichment fraction	[0, 1]
	Breeder material	{Li ₂ TiO ₃ , Li ₄ SiO ₄ }
	Breeder packing fraction	[0, 1]
	Coolant fraction [†]	[0, 1]
	Coolant material	{D ₂ O, H ₂ O, He}
	Multiplier fraction [†]	[0, 1]
	Multiplier material	{Be, Be ₁₂ Ti}
	Multiplier packing fraction	[0, 1]
	Structural fraction [†]	[0, 1]
First wall	Structural material	{SiC, eurofer}
	Thickness	[0, 500]
	Armour fraction [‡]	[0, 1]
	Coolant fraction [‡]	[0, 1]
	Coolant material	{D ₂ O, H ₂ O, He}
	Structural fraction [‡]	[0, 1]
	Structural material	{SiC, eurofer}
	Thickness	[0, 20]

Conventional regression task – search for a cheap surrogate $\hat{f}(x)$ that minimizes dissimilarity with an expensive function $f(x)$:

- Regression performance (capability to approximate)
 - Absolute: mean absolute error, σ of error
 - Relative: R^2 , R_{adj}^2 .
- Computational complexity: wall training & prediction time / sample.

2 approaches for surrogate training:

- 1 Decoupled – trains models from previously sampled $\mathcal{T} = \{(x, f(x))\}$.
- 2 Adaptive – repeats sampling & model training, increases sampling density in low-performance regions.









Adaptive sampling takes advantage of surrogate information content *during training* to reduce sample quantity.

We developed a technique which is novel in the literature:

- Construct surrogate quality distribution by nearest-neighbour interpolation.
- Draw candidate samples by quality using MCMC.
- Include samples with high crowding distance.
- Repeat!

