

Neutron shielding of low aspect ratio torii modeled by Monte Carlo methods and Machine Learning

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RENAISSANCE
FUSION

Overall Aim of Renaissance Fusion: Build a compact stellarator with Liquid Metal first wall

Blanket functions :

1. Heat removal

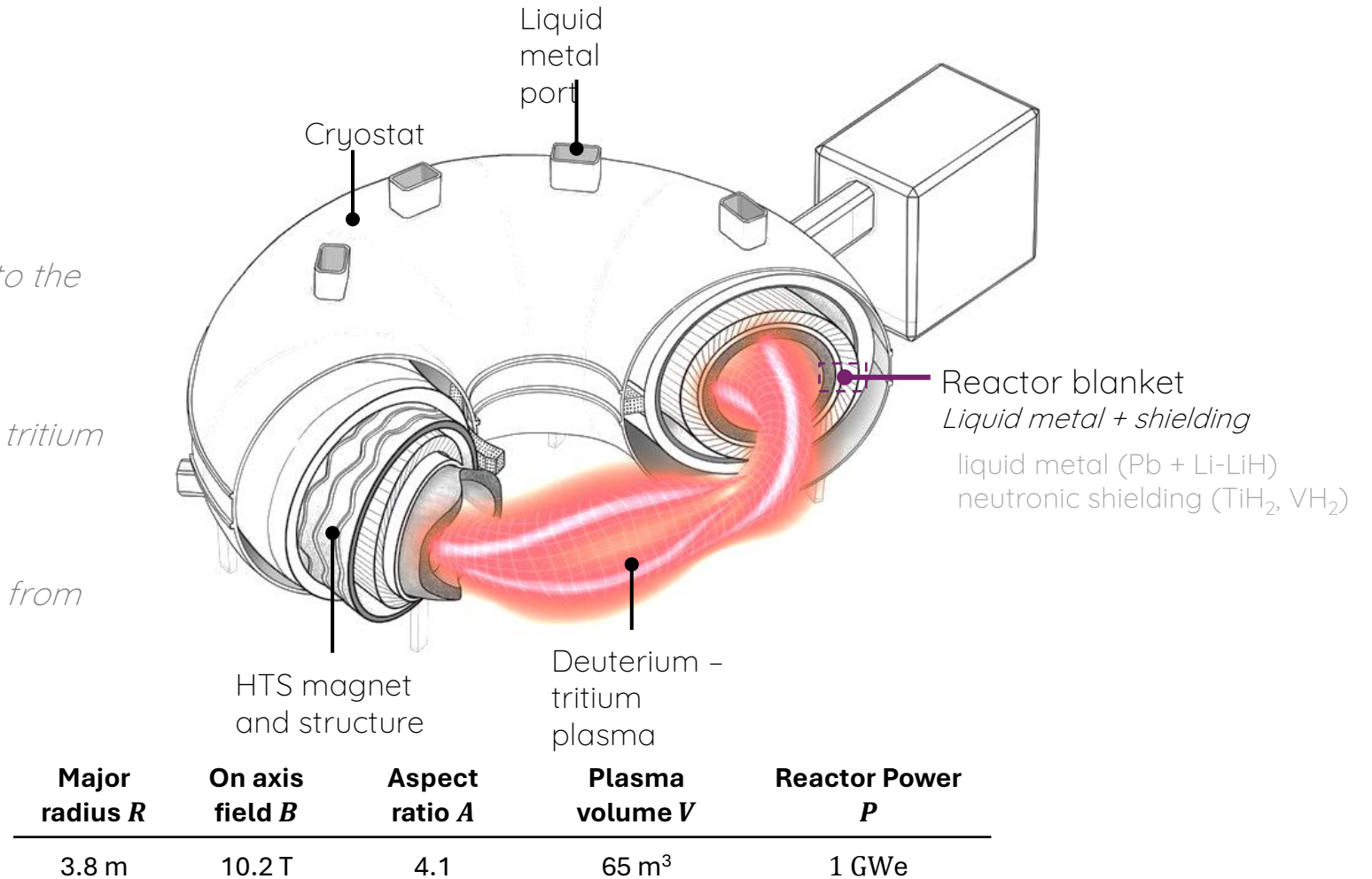
Extract heat from the plasma and transfer to the power conversion system

2. Tritium breeding

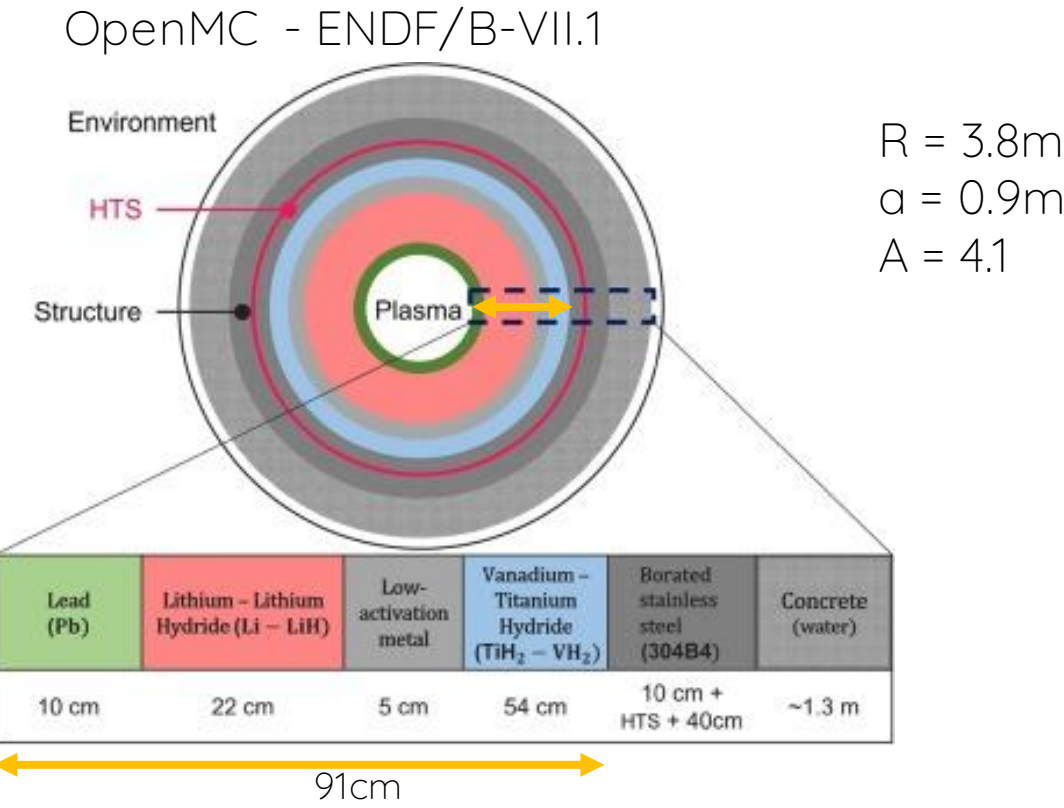
Produce tritium to fuel the fusion reaction – tritium breeding ratio (TBR)

3. Radiation shielding

Protect structures, coils, and environment from radiation damages



1D neutronic model provided initial results but relied on simplistic cylindrical geometry



Limitations:

- Parametric manual search/optimization (long)
- 1D geometry is an initial guess but we need a more robust and generalizable tool

	Functions and requirements	Targets	Designed
Heat extraction	Heat removal	-	> 92 % nuclear heat on LM layers
	Energy multiplication	≥ 1.0	1.1

Tritium breeding ratio	≥ 1.15	1.6
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40 years with 80% availability			
Neutron shielding	Total fluence on HTS coils	< 10 ¹⁹ n/cm ²	0.9 10 ¹⁹ n/cm ²
	LM vessel DPA	< 200 DPA	~100 DPA
	Magnet structure DPA	< 200 DPA	< 1 DPA

↑
Primary confinement vessel

* Prost, V., Ogier-Collin, S., Volpe, F. A. - 2024 - Compact fusion blanket using plasma facing liquid Li-LiH walls and Pb pebbles



Developed a torus shape neutronic module to be included in stellarator systems code

Neutronic model

Input:

- Reactor major radius
- Reactor minor radius
- Fusion power
- Blanket material thicknesses

FIXED

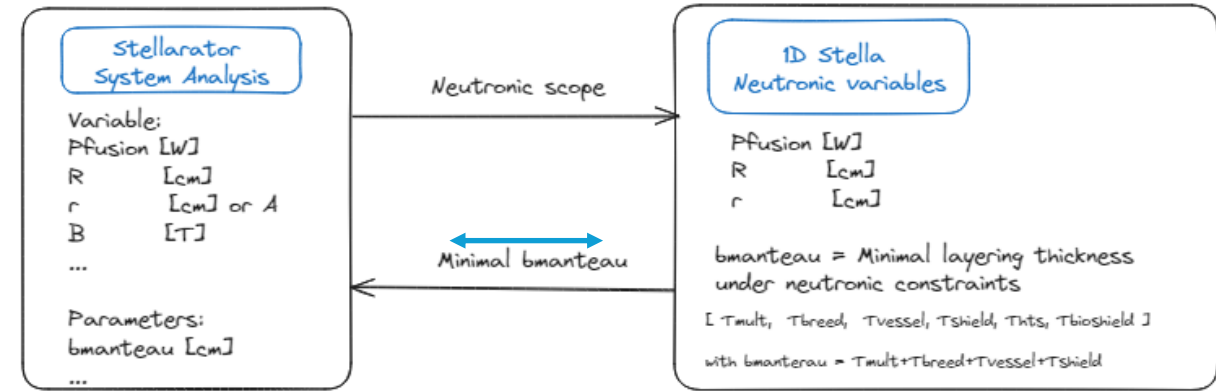
THICKNESS TO MINIMIZE

Output:

- Tritium breeding ratio
- Energy multiplication
- Power deposited in LM layer
- Neutron flux
- Radiation damage

CONSTRAINED
TARGET
PERFORMANCE

Neutronic module in the System Analysis



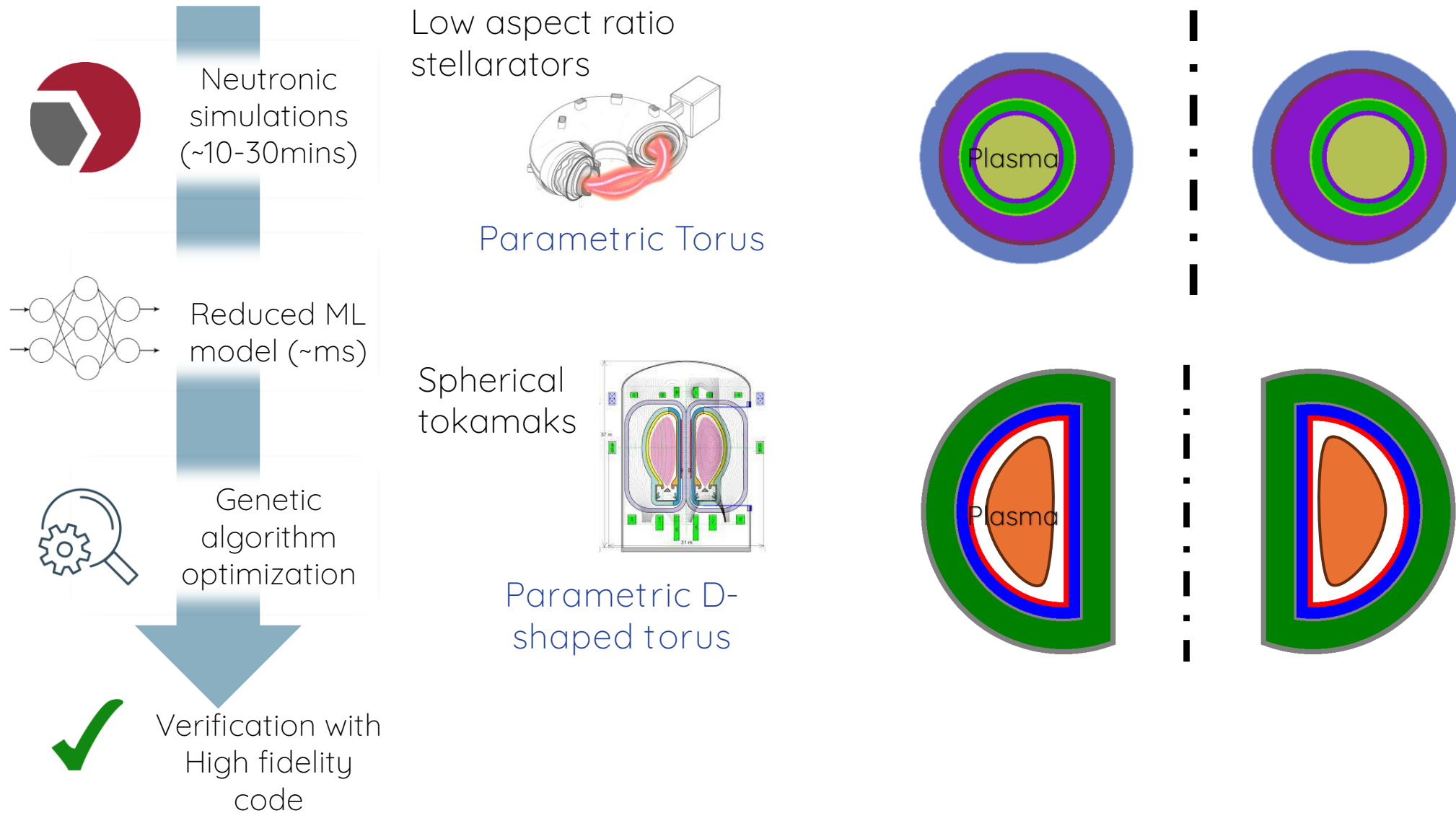
Performance:

- Accurate evaluation of the material configuration
- Fast evaluation of the reactor performance

Solution:

- Surrogate model for the high-fidelity neutronic model
- Optimization loop

Reduced ML model optimisation scheme



Input data for ML – generation of 20 000 configurations

Parameters variations:

Parameters	Min	Max	Discretisation
Reactor [cm]			
Minor Radius	50	200	10
Major Radius	300	600	10
Eccentricity	0	15	0.5
Blanket [cm]			
Lead	1	20	0.5
LiLiH	5	45	0.5
SiC	5	5	0.5
VH2	10	60	0.5
Steel (Boronated)	10	10	0.5
REBCO buffers	0.0441	0.0441	0.0441
Steel (Boronated)	40	40	0.5

VARIED

VARIED

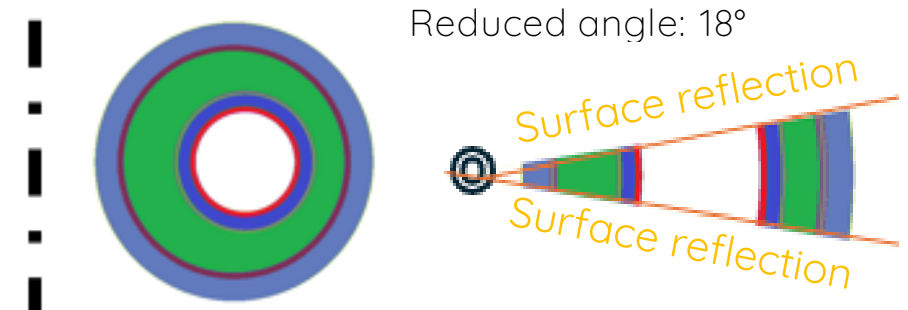
VARIED

Acceleration of the simulations

- Variance Reduction with Pre-build feature MAGIC*

```
wws.update_magic(ww_tally, value='rel_err', threshold=0.7)
```

- Reduced angle: profiting of the symmetries with



Generation:

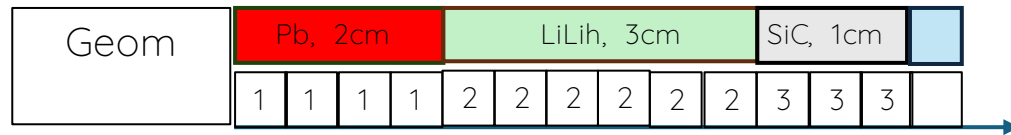
- Tallies output with tagged UUID result file
- Decrease 1 run time from days => tens of minutes => few minutes
- About 2 full weeks to generate the input data for ML

*<https://inis.iaea.org/records/231pm-zzy35>

ML model accurately predicts neutronic simulations

Configuration data :

R | r | ecc | layers (material, thickness)



Formalized in a 700 elements vector for layer configuration (discretization at 0.5 cm) with material coding

Results data :

TBR | Energy mult | Heat removal | Fluence on coils | DPA on coils structure | DPA LM vessel

Machine learning Model:

Optimization : Adam at learning rate 2E-3					
layer	Activation	Constraints	Units	Batch Normalization	Dropout (Rate)
Input	-	-	703	-	-
Dense	ReLU	L1, L2	256	Yes	0.3
Dense	ReLU	L1, L2	128	Yes	0.3
Dense	ReLU	L1, L2	64	Yes	0.3
Dense	ReLU	L1, L2	32	Yes	0.3
Output	ReLU	L1, L2	6	-	-

- Train and Test sets: 80%, 20%
- Training time: 30 minutes with 16 cpus

Quantity	Diff {Pf _{us} =1.8GW, R=3.8m, r=0.9m}
TBR	4.4%
Energy Mult	0.9%
Energy removal [%]	0.7%
Fluence on Coil [cm ² /n]	26.8%
DPA on coil [dpa/n]	30.9%
DPA on Liquid metal [dpa/n]	46.0%

- Comparison with “Reference case”:
- The uncertainties are under control regarding the constraints’ precision and model accuracy



Genetic Algorithm for a minimal blanket – Get results in 15 min

Set the input reactor parameter for a minimal blanket

Reactor parameter			
Pfusion, Major radius, Minor radius, Eccentricity			
Blanket [cm]			
Parameters	Min	Max	Discretisation
Lead	1	20	0.5
LiLiH	5	45	0.5
SiC	5	5	0.5
VH2	10	60	0.5
Steel (Boronated)	10	10	0.5
REBCO buffers	0.0441	0.0441	0.0441
Steel (Boronated)	40	40	0.5

Implementation : α -Fair allocation* principle

Suppose $x = x(n)$ chosen to

Maximise
$$\sum_r \omega_r \frac{x_r^{1-\alpha}}{1-\alpha}$$

Subject to
$$\sum_r A_{jr} n_r x_r \leq C_j ; j \in J$$

$$x_r \geq 0 ; r \in R$$

Set the input Genetic Algorithm parameters

Category	Parameters
Genetic Algorithm	Population Size: 2000, Generations: 15, ...
Optimization Weights	TBR: 1.0, Energy Multiplication: 1.0, Heat Removal: 1.0, Fluence HTS: 1.0, DPA HTS: 1.0, Thickness: 1.0
Target Values	TBR: 1.15, Energy Multiplication: 1.0, Heat Removal: 95.0, Fluence HTS: 1.0e+19, DPA LMS: 200.0, DPA HTS: 200.0
Additional Parameters	Thickness Penalty Weight: 1.0, Adaptive Penalty: Min Weight: 0.1, Max Weight: 1000.0

Performance:

About 15 minutes per 16 CPUs.

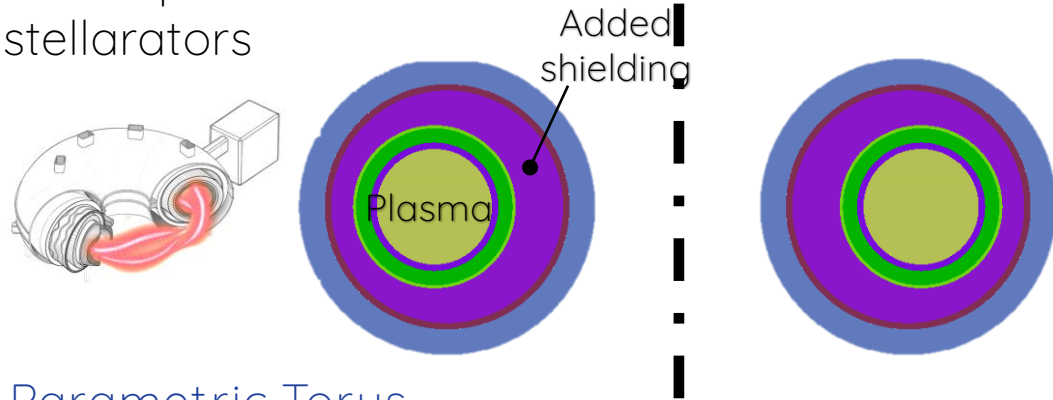
Verification

High Fidelity code

*A weighted α - fair allocation , Mo and Walrand 2000

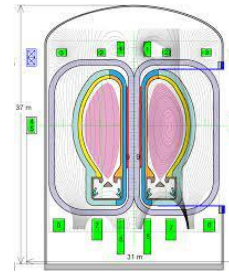
Surrogate models for 3D stellarator and tokamak predict neutronic simulations within tens of percent

Low aspect ratio stellarators

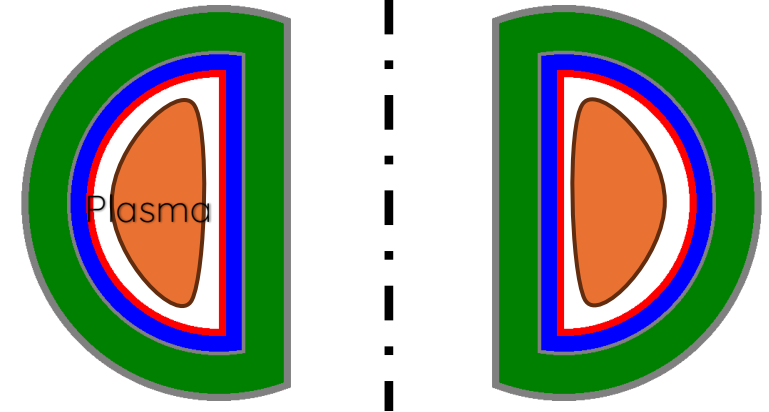


Parametric Torus with eccentricity

Spherical tokamaks



Parametric D-shaped torus*

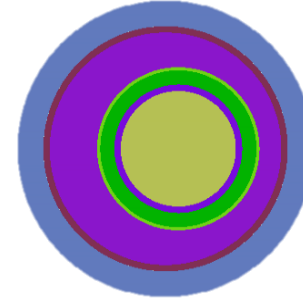
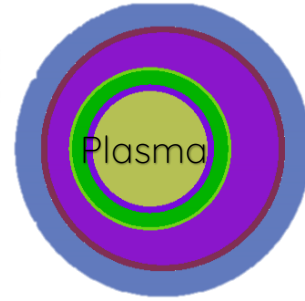
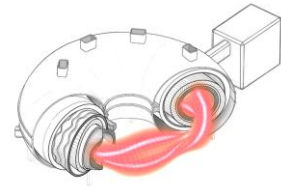


Quantity	3D High Fidelity	3D Surrogate	Differences
TBR	1.64	1.66	1.5%
Energy multiplication	1.20	1.20	0.2%
Heat removal	94.5	96.7	2.4%
Fluence HTS [cm ² /n]	4.73E-11	5.31E-11	12.2%
DPA HTS [DPA/n]	1.65E-32	2.27E-32	37.6%
DPA LM [DPA/n]	5.09E-28	2.13E-28	-58.1%

Quantity	3D High Fidelity	3D Surrogate	Differences
TBR	1.52	1.66	-8.4%
Energy Multiplication	1.21	1.19	1.4%
Heat Removal	93.7	95.2	-1.7%
Fluence HTS (cm ² /s/n)	7.20E-11	1.18E-10	-39.2%
DPA HTS (dpa/n)	1.55E-32	2.44E-32	-36.6%
DPA LM (dpa/n)	2.22E-28	2.52E-28	-12.2%

Optimization Module align with the Reference case

Low aspect ratio
stellarators

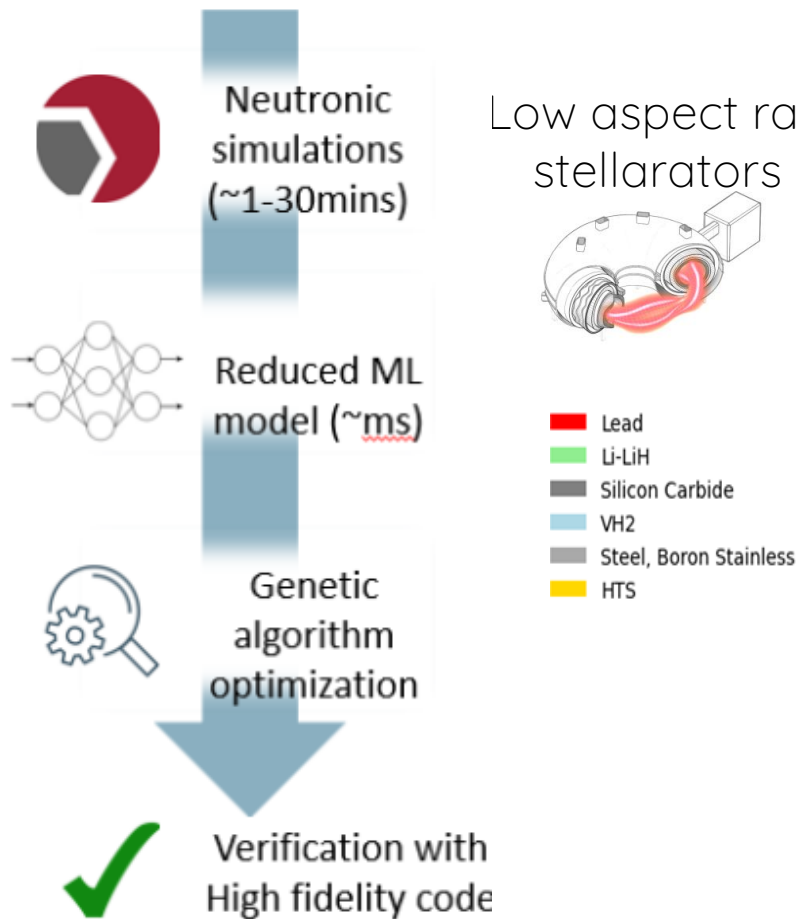


Parametric Torus
with eccentricity

Thickness [cm]	Reference*	3D Surrogate	Status
Lead	10	11	Optimized
LiLiH	22	22	Optimized
SiC	5	5	Fixed
VH2	54	53	Optimized
Steel	10	10	Fixed
HTS	0.04	0.04	Fixed
Total	101	101	

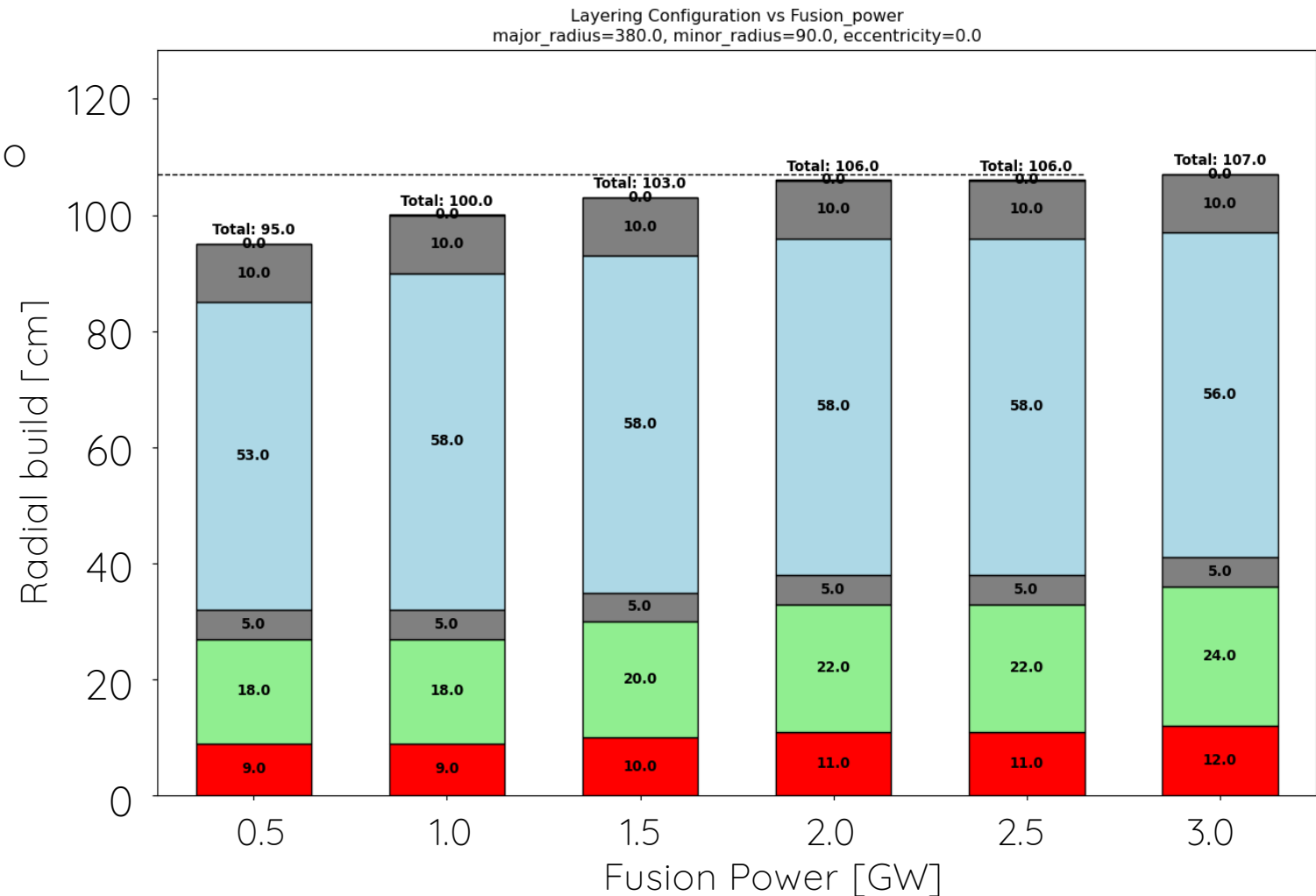
Reduced ML model optimization scheme highlights benefits for high power reactors (1 GWe vs 100 MWe)

X2 in fusion power \rightarrow ~5/6 cm increase thickness



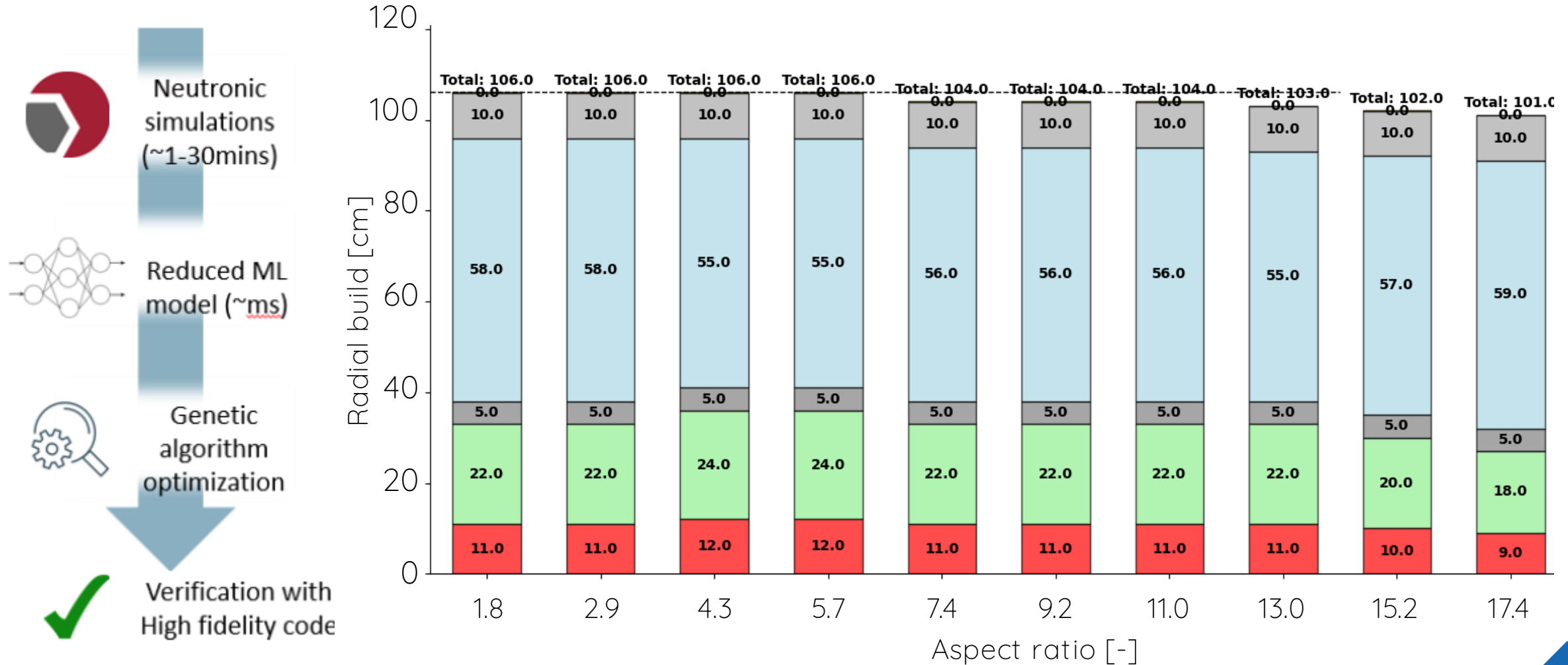
Legend for material layers (cm):

- Lead (Red)
- Li-LiH (Green)
- Silicon Carbide (Dark Grey)
- VH2 (Light Blue)
- Steel, Boron Stainless (Medium Grey)
- HTS (Yellow)



Model optimization scheme shows limited impact of reactor's aspect ratio

Neutron flux scales with $\sim A^{-1/3}$
With constant volume (100 m³) and power (2 GW)



Take aways

- Machine learning model developed for rapid neutronics performance prediction
- Genetic algorithm used to optimize blanket configuration
- Key findings:
 - Efficient optimization of blanket thickness and composition
 - Slight increase in blanket thickness needed for higher fusion power
 - Limited impact of reactor aspect ratio on neutronics performance
- Methodology enables rapid, optimized design for compact fusion reactors
- Studies (scan over aspect ratio and run power) within hours range instead of multiple days with manual search
- Potential for extension to other reactor design aspects