Design Optimization of Tokamak Fusion Reactor through Deep Reinforcement Learning

Fusion Reactor design optimization with single-step reinforcement learning

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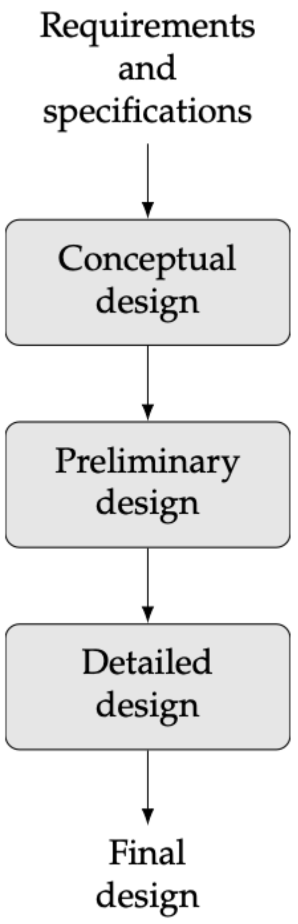
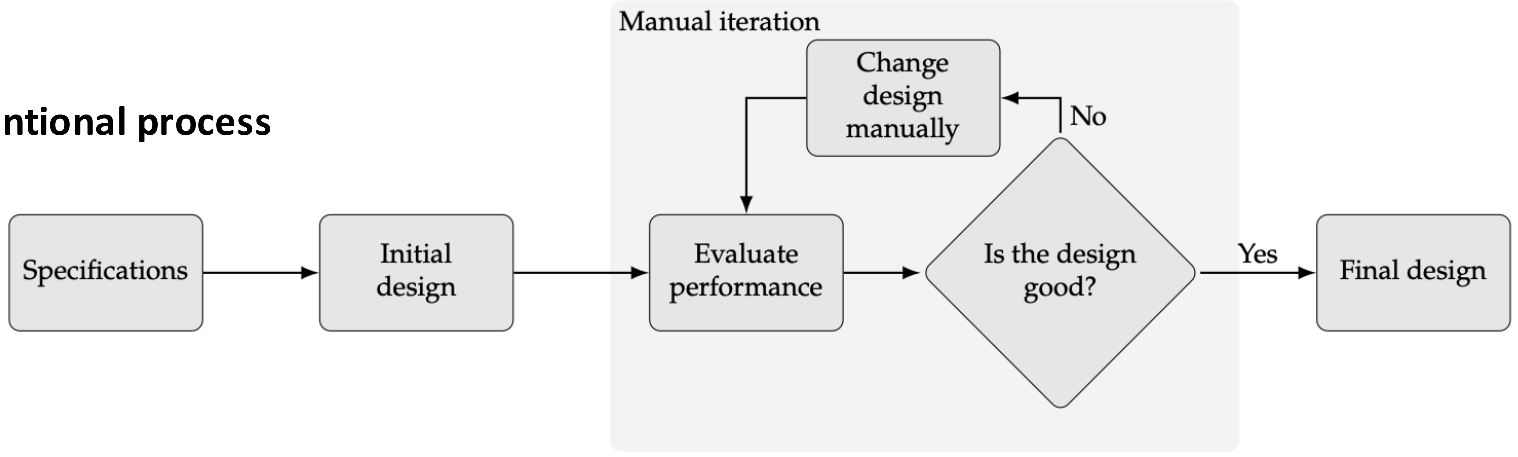
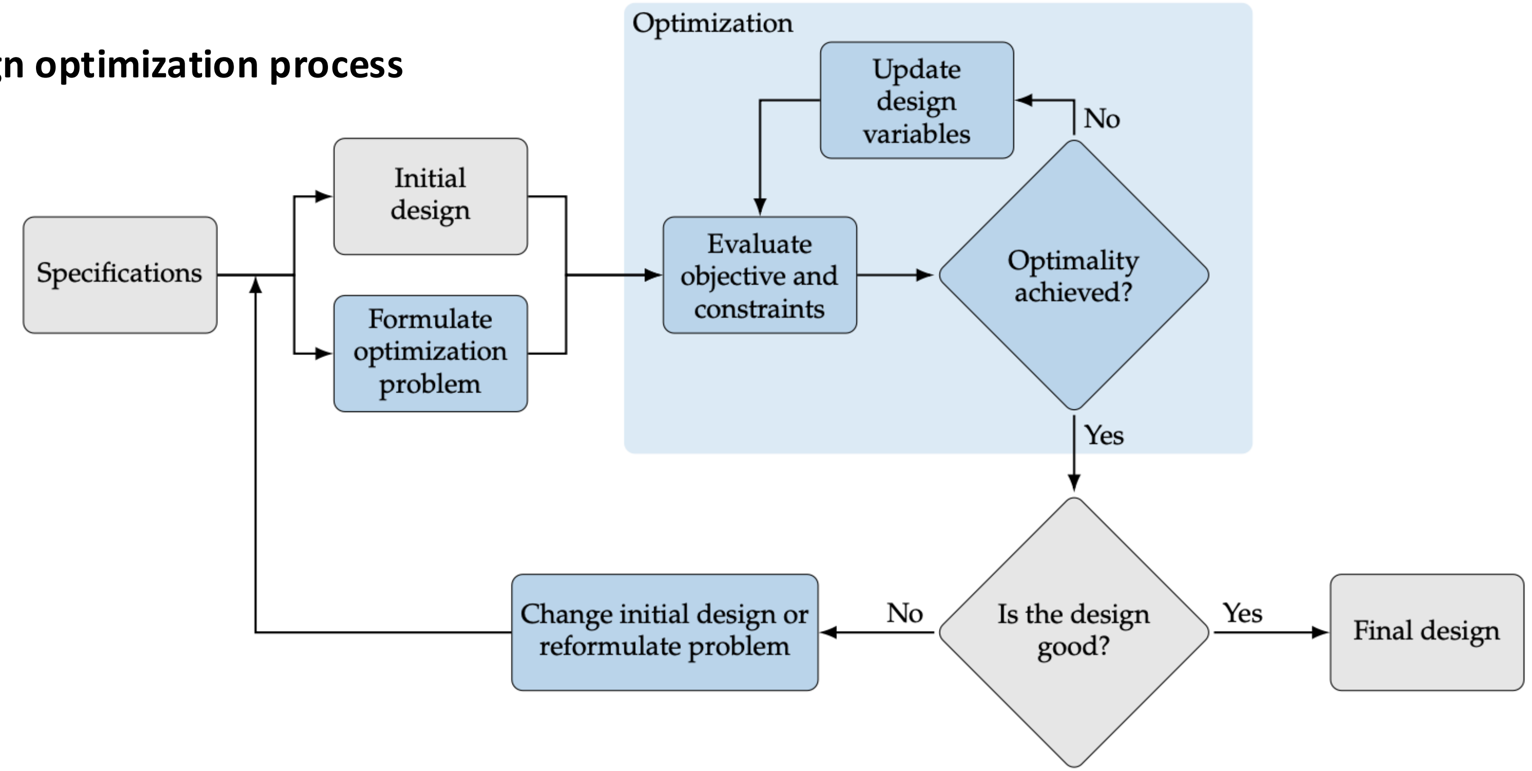
Conceptual design phase



Conventional process



Design optimization process

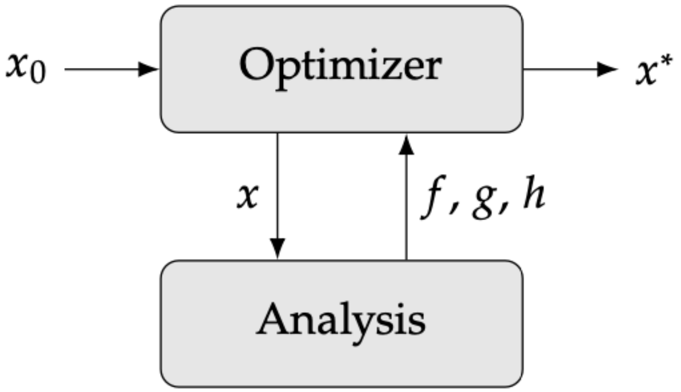


Design Optimization

Design variables

- Input parameter
- Must not depend on each other
- X = [x1,x2,x3,x4,…]
- The optimizer must be free to choose the elements of x independently.
- Each x should be bound for physical constraints

$$
\begin{array}{rlr}
\text{minimize} & f(x) & \\
\text{by varying} & \underline{x}_i \le x_i \le \overline{x}_i & i = 1, \ldots, n_x \\
\text{subject to} & g_j(x) \le 0 & j = 1, \ldots, n_g \\
 & h_l(x) = 0 & l = 1, \ldots, n_h \,.
\end{array}
$$



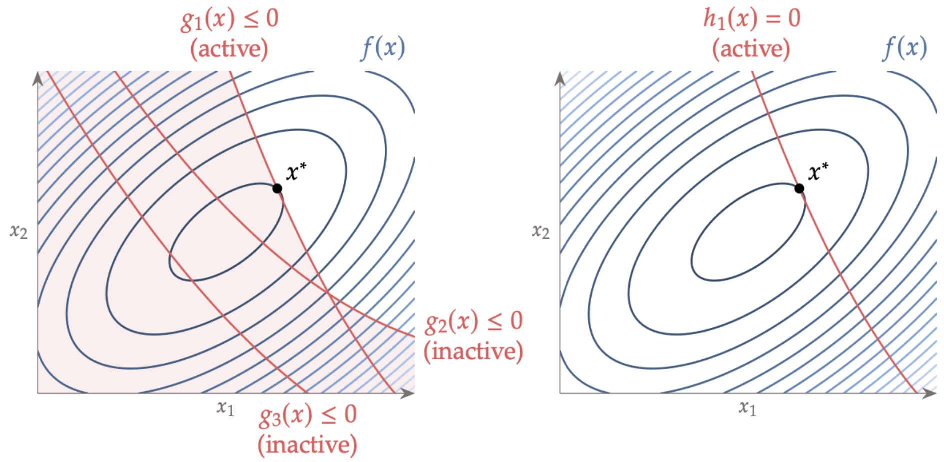
Design Optimization - Objectives

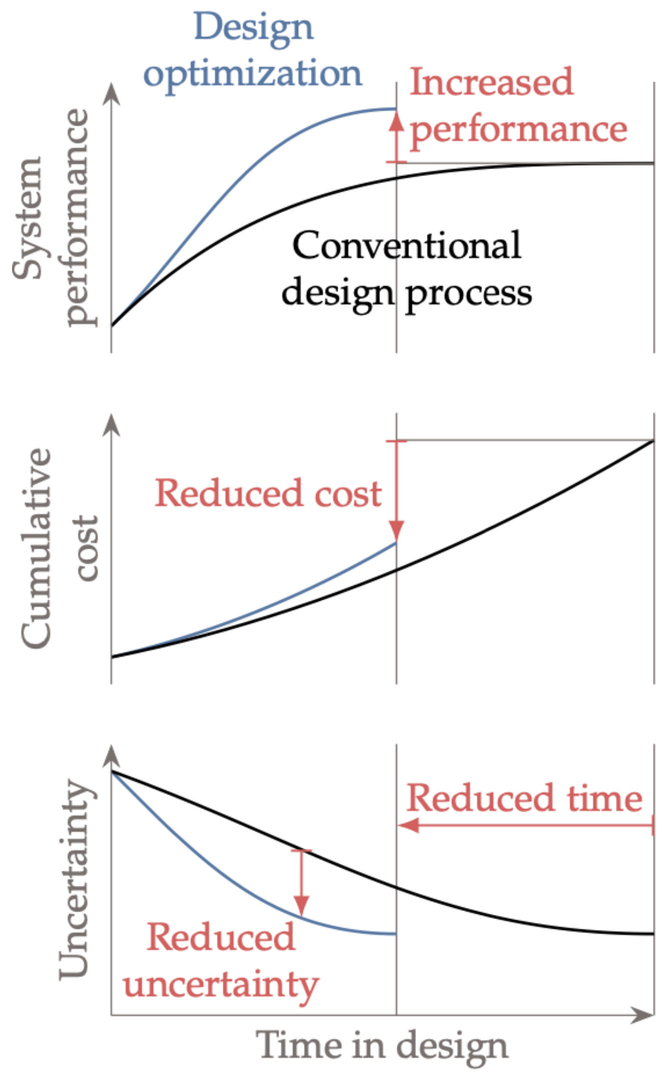
Objectives (targets) of design optimization

- System performance
- Cost
- Uncertainty
- Physical consistency

What we need

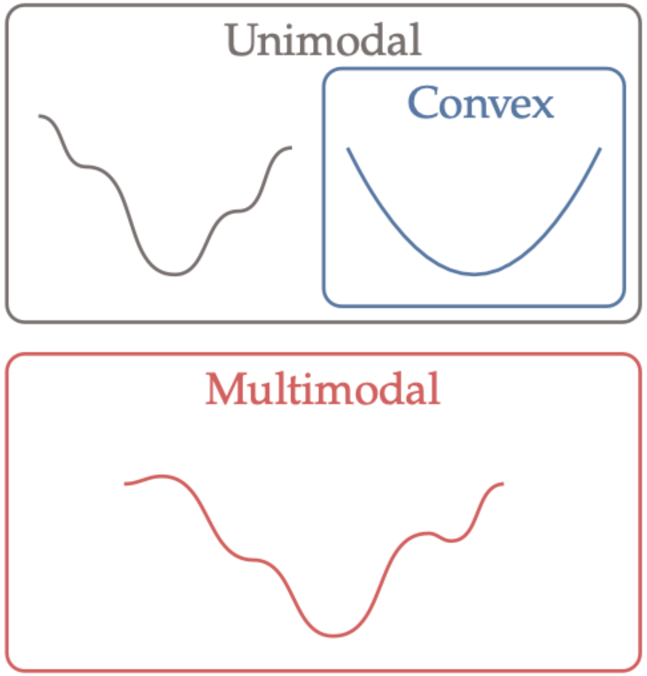
- Objective function: A quantity that determines if one design is better or not
- Constraints: Restrict design variables to be set on a feasible region
  - ✓ Equality constraint
  - ✓ Inequality constraint



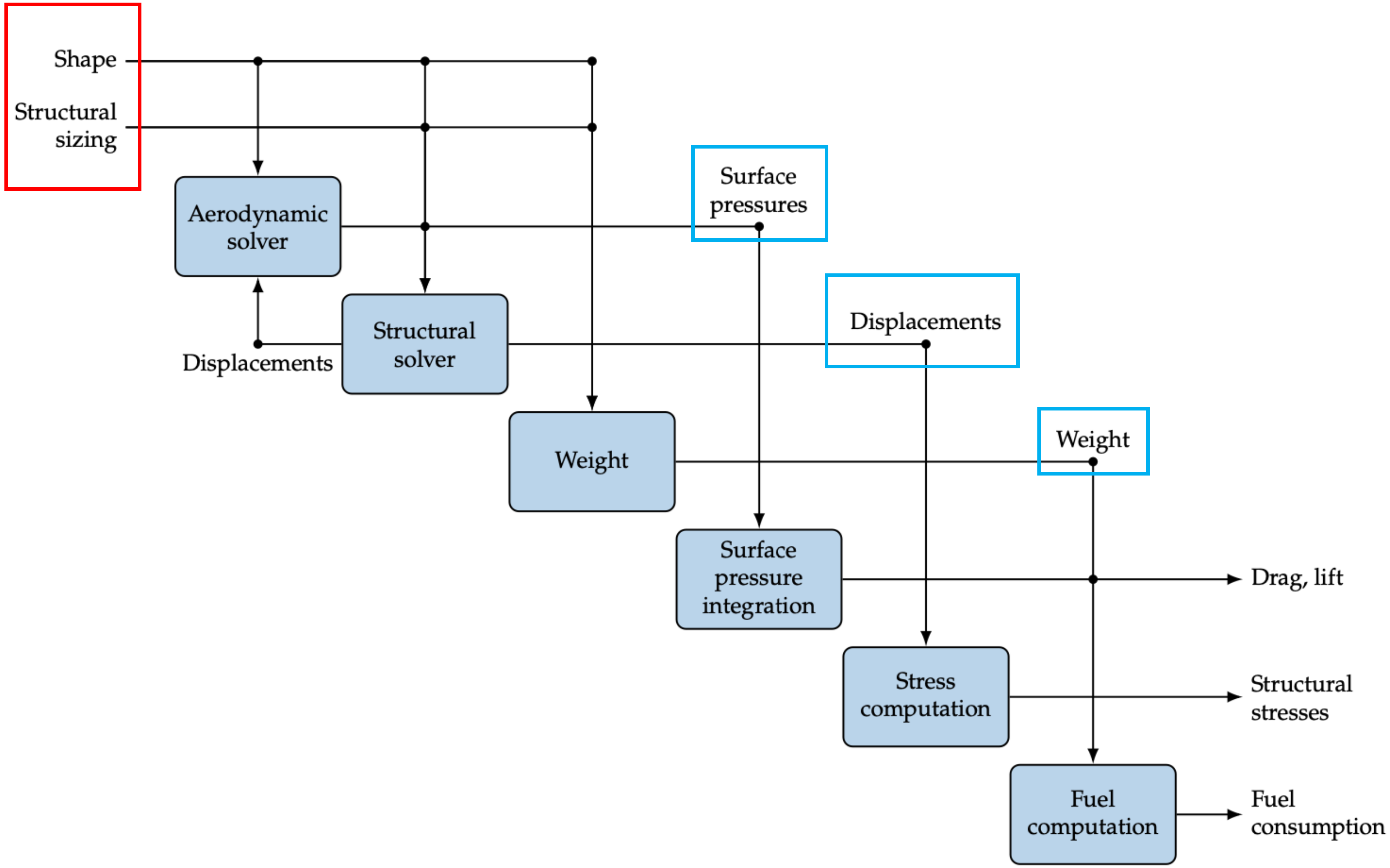


Design Optimization - Issues

Multi-modality



Multidisciplinary Design Optimization



Design Optimization - How to approach

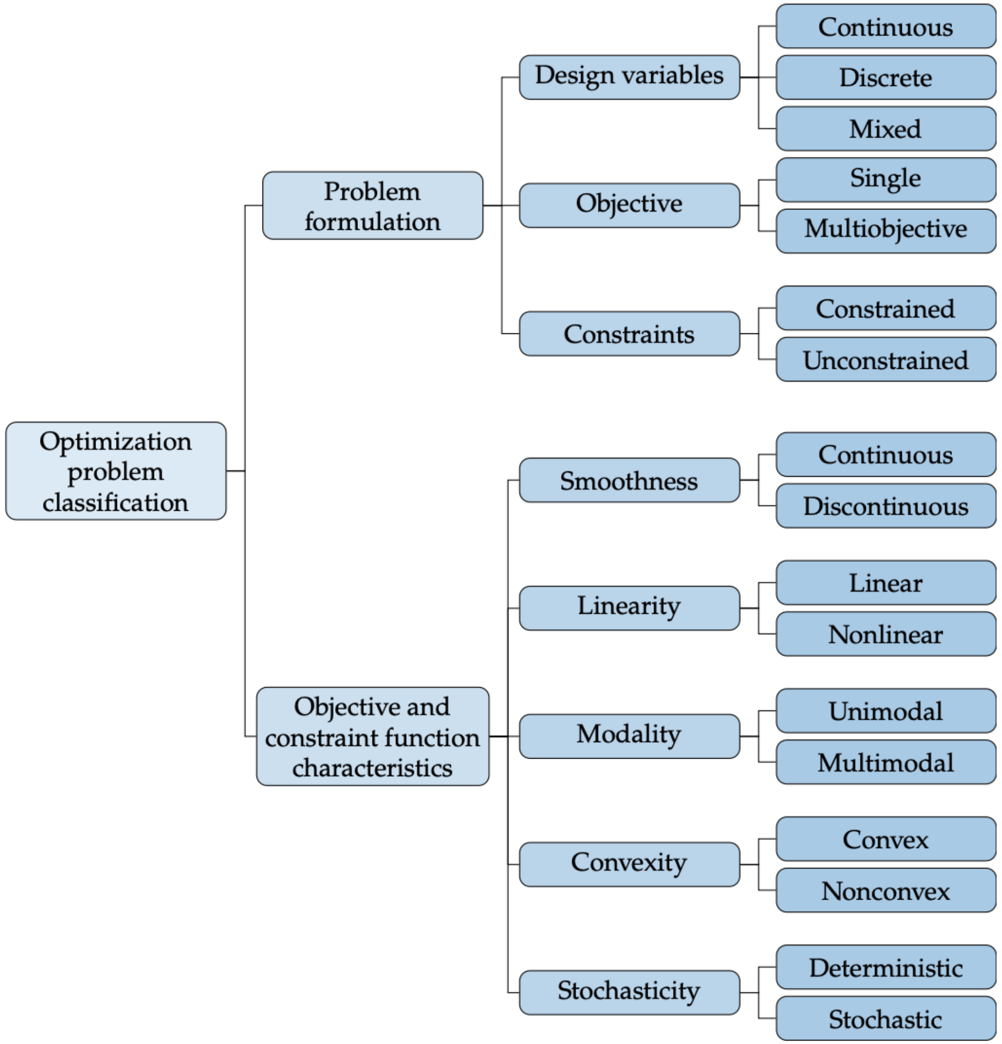


Fig 1.22 from Engineering Design Optimization

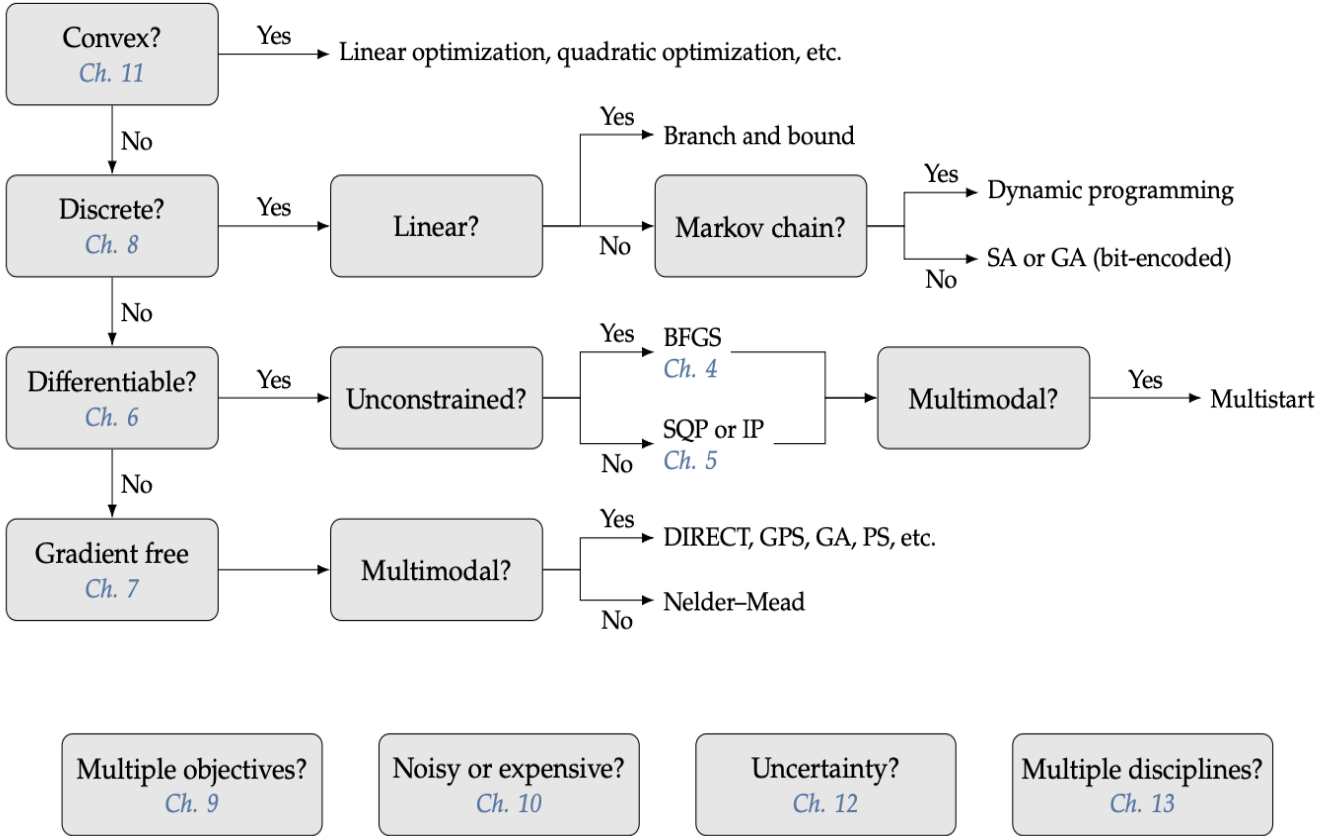


Fig 1.24 from Engineering Design Optimization

Design Optimization - How to approach

Single-step reinforcement learning for design optimization

- Surrogate models based on ML / Genetic algorithm: High computational cost
- Discrete design parameters vs Continuous design parameters: RL can handle both variables
- RL training process => directly finding the optimal solutions

ALGORITHM 1: Proximal policy optimization.

1 Initialize policy model parameters θ_0, value model parameters ϕ_0;
2 **For** each episode, $i = 1, \ldots, N$ **do**;
3 Based on current policy $\pi_{\theta,i}$ for T time steps, collecting trajectories $\{\tau\} = \{s_t, a_t, r_t\}$;
4 Estimate advantage values $\hat{A}_t = \sum_{t'>t} \gamma^{t'-t} r_{t'} - V_\phi(s_t)$;
5 $\sum_{t'>t} \gamma^{t'>t} r_{t'}$ is the rollout policy;
6 V_ϕ is given by the value network;
7 $\gamma \in (0, 1)$ is the discount factor, which represents the influence of future states on the current state;
8 Update θ by a gradient method (e.g., Adam) with respect to J_θ:

$$J_\theta = \sum_{t=1}^{T} \min\left[\frac{\pi_\theta(a_t/s_t)}{\pi_{\text{old}}(a_t/s_t)}\hat{A}_t, clip\left(\frac{\pi_\theta(a_t/s_t)}{\pi_{\text{old}}(a_t/s_t)}, 1-\varepsilon, 1+\varepsilon\right)\hat{A}_t\right],$$

where ε is a hyperparameter, $\varepsilon = 0.2$;
9 Update ϕ by a gradient method (e.g., Adam) with respect to L_ϕ:

$$L_\phi = -\sum_{t=1}^{T}\left(\sum_{t'>t} \gamma^{t'-t} r_{t'} - V_\phi(s_t)\right)^2.$$

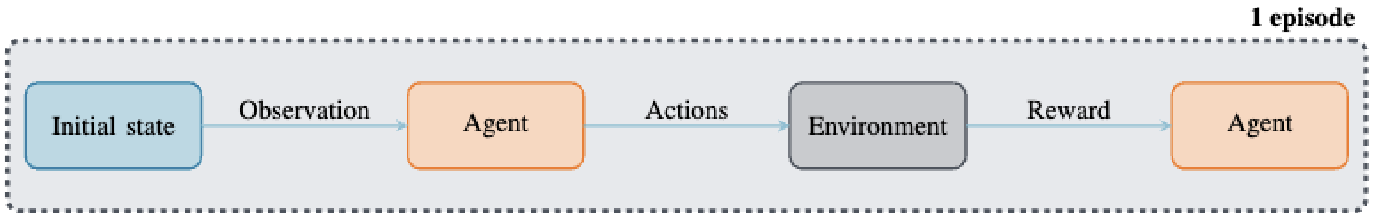
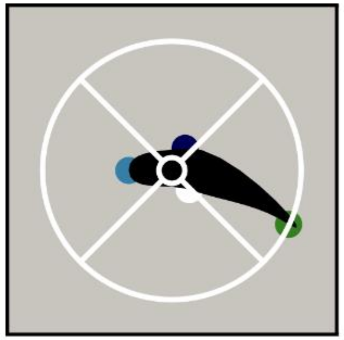


Figure 4: **Degenerate reinforcement learning framework used in this paper**. One episode consists of a single control from the agent: the same initial observation is provided to the agent at the start, which in return provides an action to the environment. The environment returns a reward value to the agent, and the episode is terminated.

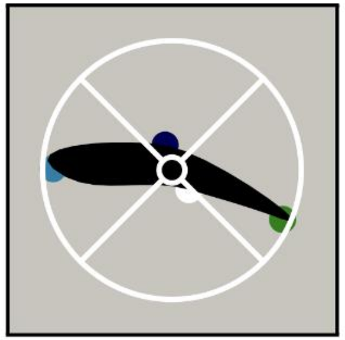
Related Works

Paper: Direct Shape Optimization through Deep Reinforcement Learning

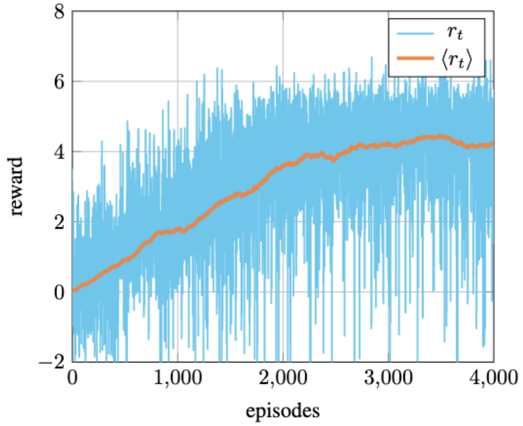
(a) Best shape with 4 points, 1 free point (3 d.o.f.s)



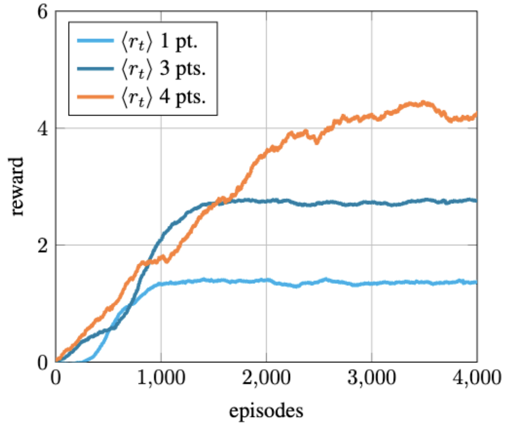
(b) Best shape with 4 points, 3 free points (9 d.o.f.s)



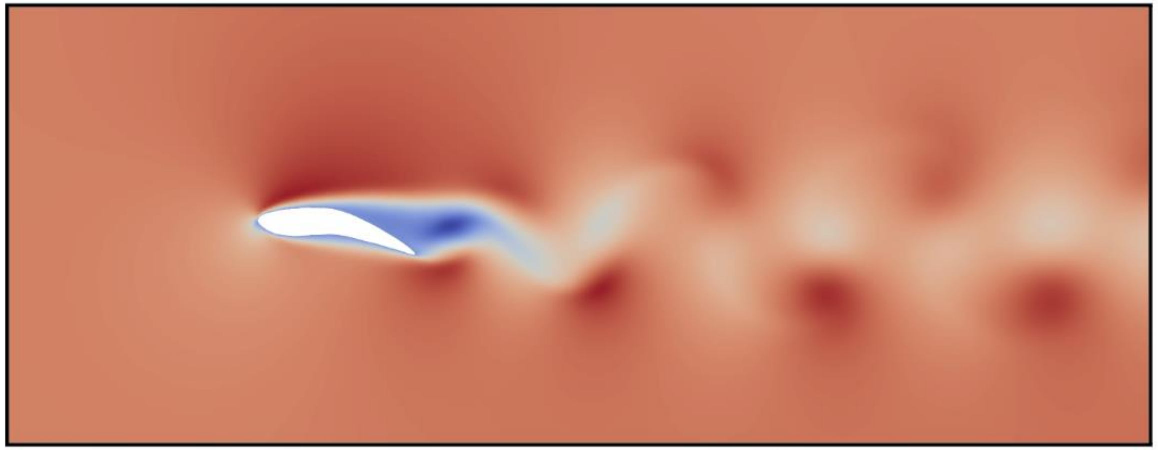
(c) Best shape with 4 points, 4 free points (12 d.o.f.s)



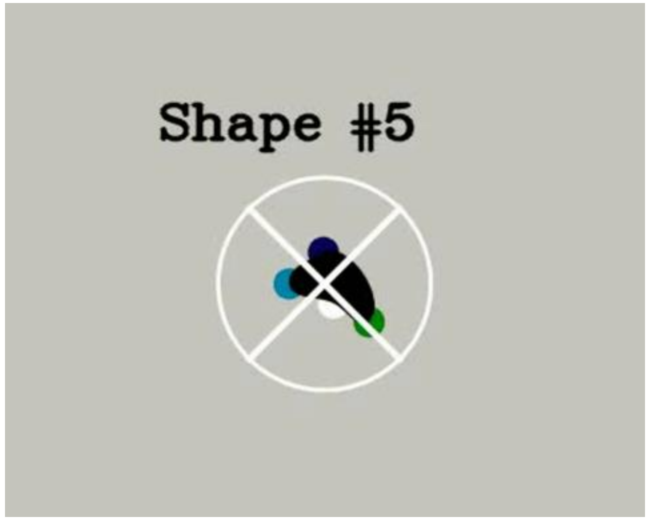
(a) Instantaneous and moving-average reward history using 4 free points



(b) Moving-average reward history using 1, 3 and 4 free points



(d) Computed v_x velocity field at $Re \sim 600$ around shape 5c (the domain is cropped).

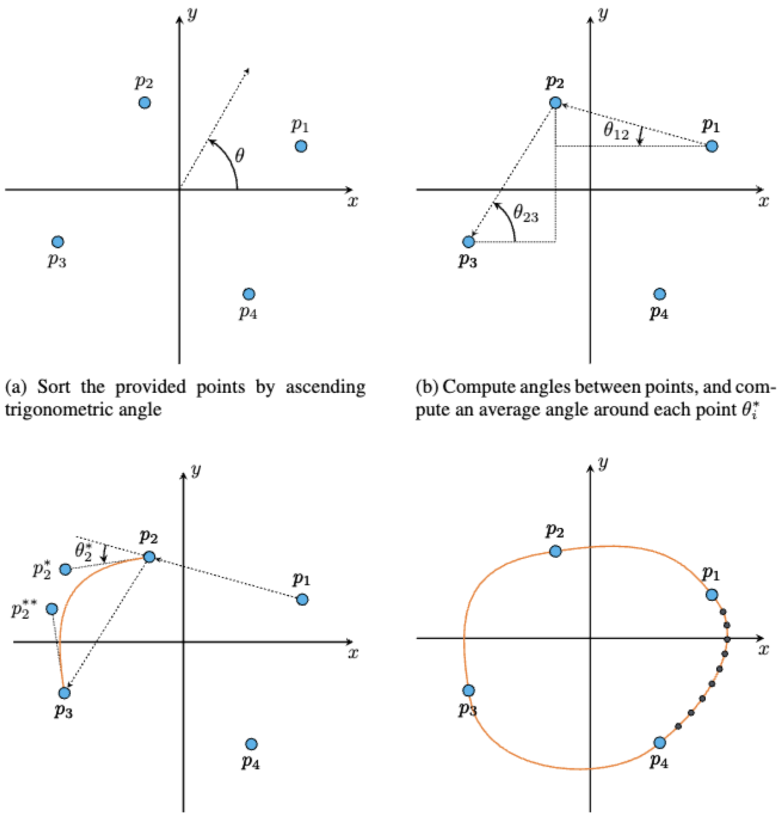


Related Works

Paper: Direct Shape Optimization through Deep Reinforcement Learning

$$
\begin{cases}
r = r_{\max} \max\left(|p|, r_{\min}\right), \\
\theta = \dfrac{\pi}{n}\left(i + \dfrac{q}{2}\right), \\
x = r\cos\left(\theta\right), \\
y = r\sin\left(\theta\right), \\
e = \dfrac{1}{2}\left(1 + s\right).
\end{cases}
$$

Design variables: 4 points



(a) Sort the provided points by ascending trigonometric angle

(b) Compute angles between points, and compute an average angle around each point θ_i^*

(c) Compute control points coordinates from averaged angles and generate cubic Bézier curve

(d) Sample all Bézier lines and export for mesh immersion

Interpolation for Airfoil Design Configuration

C Shape generation using Bézier curves

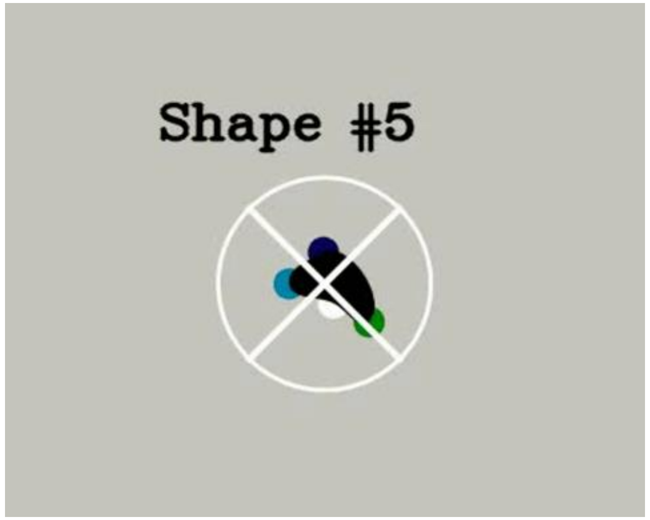
This section describes the process followed to generate shapes from a set of n_s points provided by the agent. Once the points are collected, an ascending trigonometric angle sort is performed (see figure 11a), and the angles between consecutive points are computed. An average angle is then computed around each point (see figure 11b) using:

$$\theta_i^* = \alpha\theta_{i-1,i} + (1-\alpha)\theta_{i,i+1},$$

with $\alpha \in [0,1]$. The averaging parameter α allows to alter the sharpness of the curve locally, maximum smoothness being obtained for $\alpha = 0.5$. Then, each pair of points is joined using a cubic Bézier curve, defined by four points: the first and last points, p_i and p_{i+1}, are part of the curve, while the second and third ones, p_i^* and p_i^{**}, are control points that define the tangent of the curve at p_i and p_{i+1}. The tangents at p_i and p_{i+1} are respectively controlled by θ_i^* and θ_{i+1}^* (see figure 11c). A final sampling of the successive Bézier curves leads to a boundary description of the shape (figure 11d). Using this method, a wide variety of shapes can be attained.

Related Works

Paper: Direct Shape Optimization through Deep Reinforcement Learning



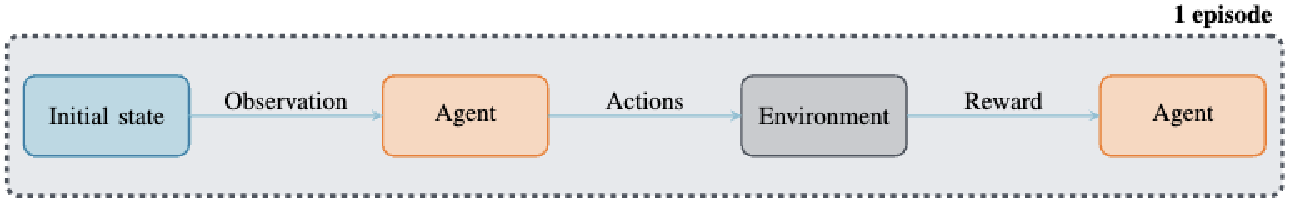


Figure 4: **Degenerate reinforcement learning framework used in this paper**. One episode consists of a single control from the agent: the same initial observation is provided to the agent at the start, which in return provides an action to the environment. The environment returns a reward value to the agent, and the episode is terminated.

- Determine 4-points
- Interpolation for designing airfoil
- Compute the design performance (drag / lift coefficient)

$$C_d = \frac{f_d}{\frac{1}{2}\rho v_{in}^2 s} \qquad C_l = \frac{f_l}{\frac{1}{2}\rho v_{in}^2 s}$$

$$f_d = \int \sigma\, n e_x dS \qquad f_l = \int \sigma\, n e_y dS$$

- Evaluate the reward w.r.t design objectives

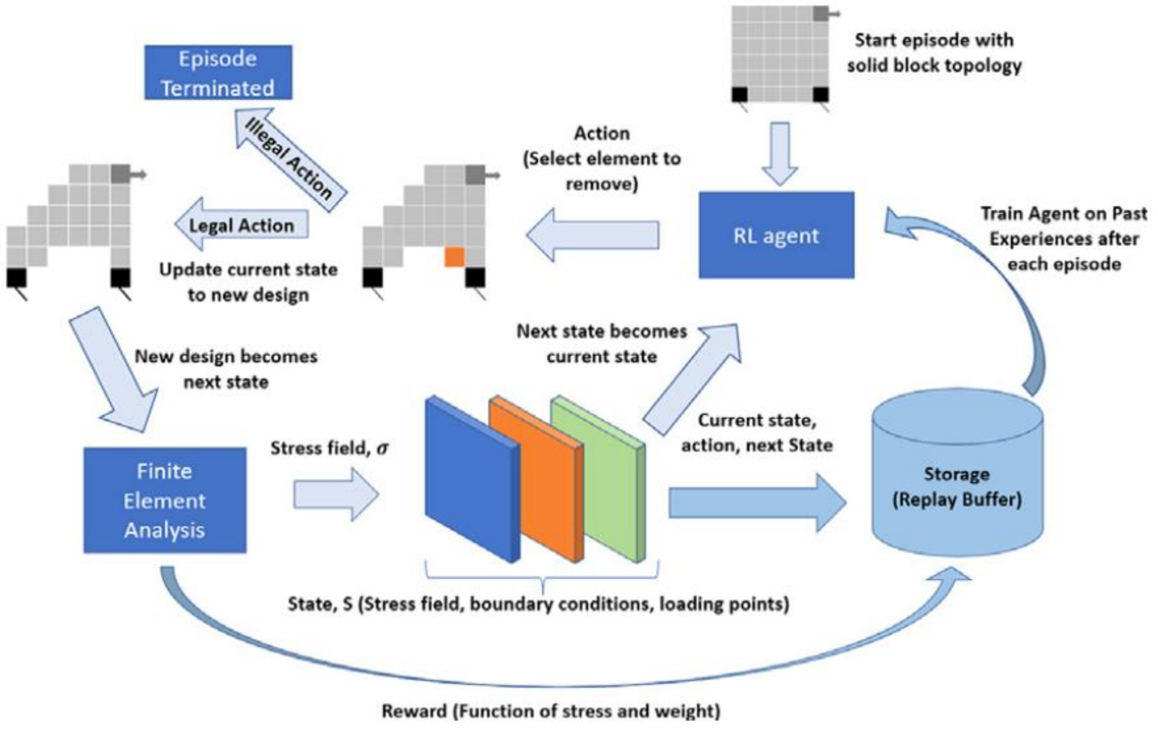
$$r_t = < \frac{C_l}{|C_d|} > - < \frac{C_l}{|C_d|} >_{cyl}$$

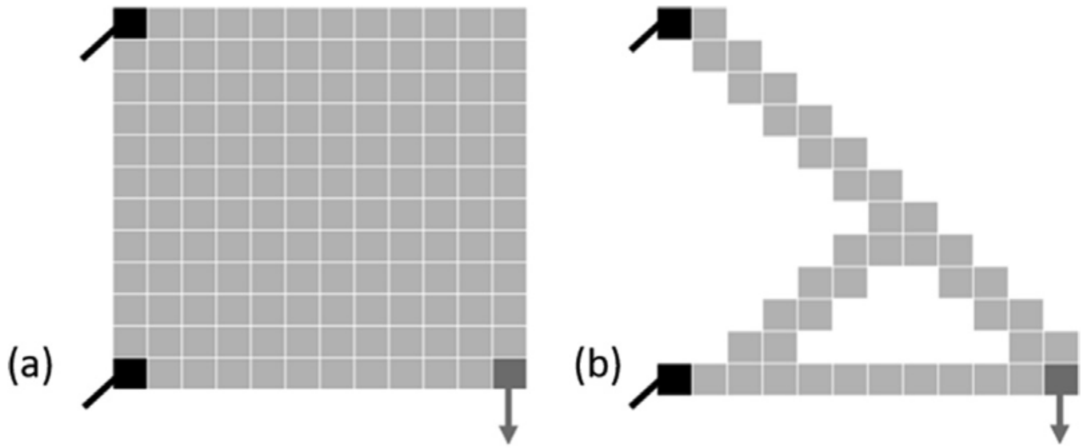
- Optimize the policy through Single-step PPO algorithm

Related Works

Paper: DRL for engineering design through topology optimization of elementally discretized design domains

- Topology optimization through DRL for 2D material design
- Pixel -> discrete actions
- Input: 2D pixels => output: change of pixel flips





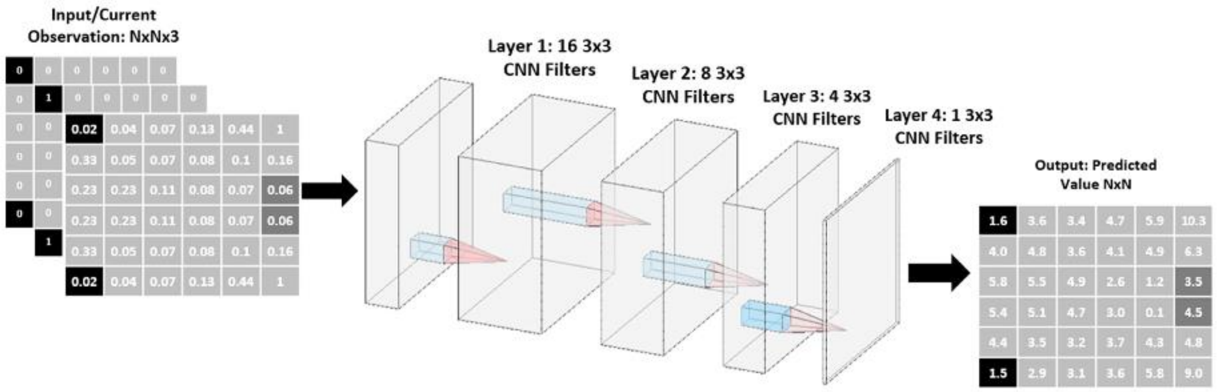
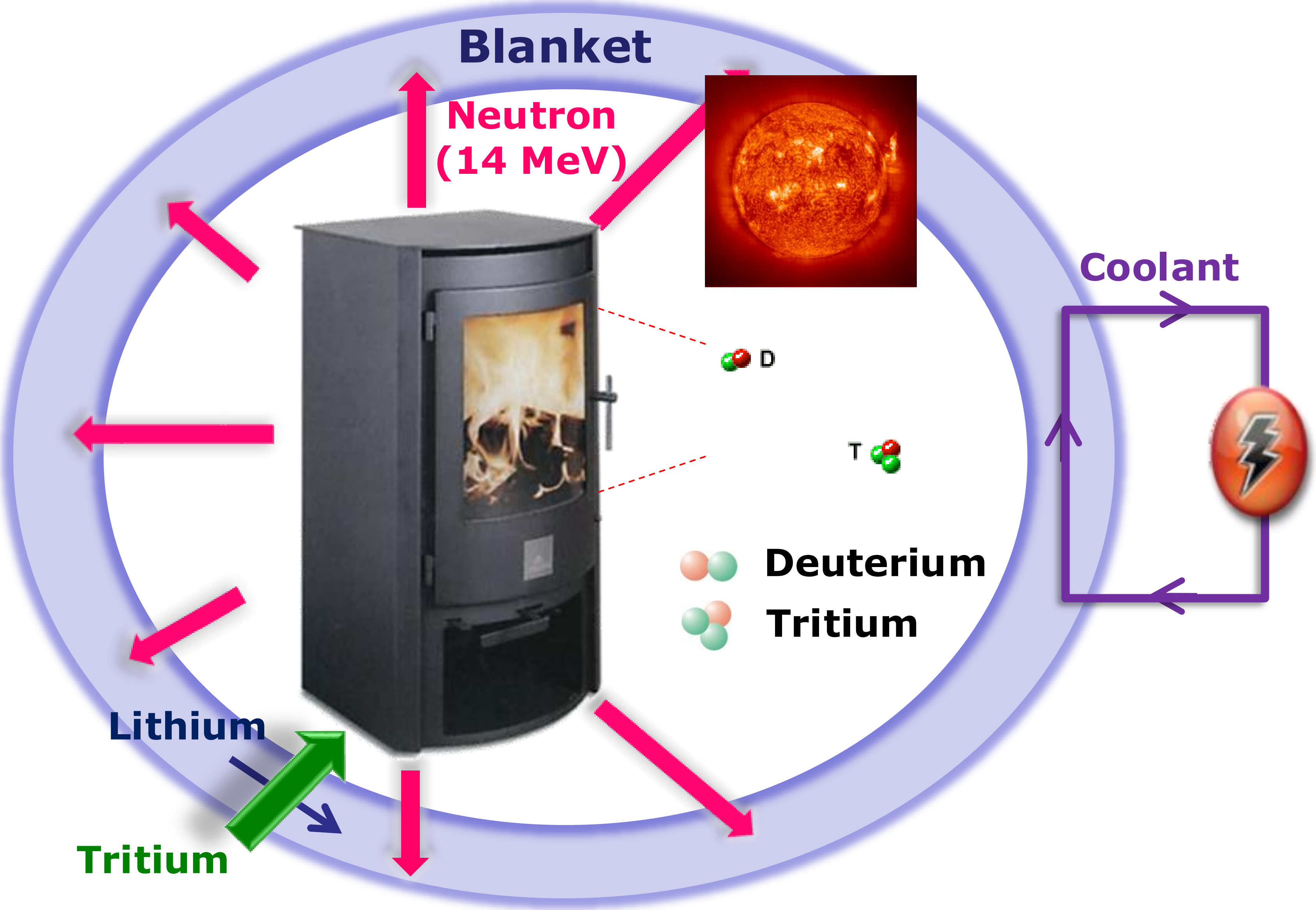


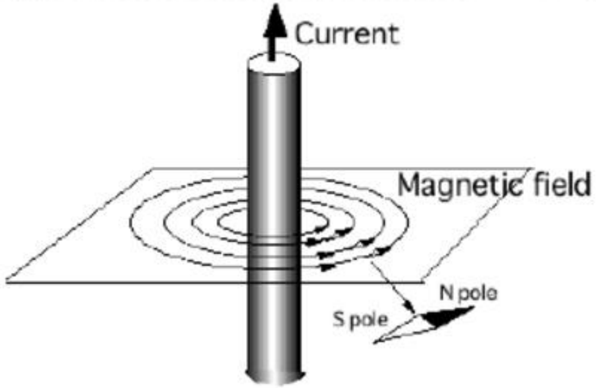
Fig. 6. Deep convolutional neural network architecture.

Fusion Power Plant (FPP) System

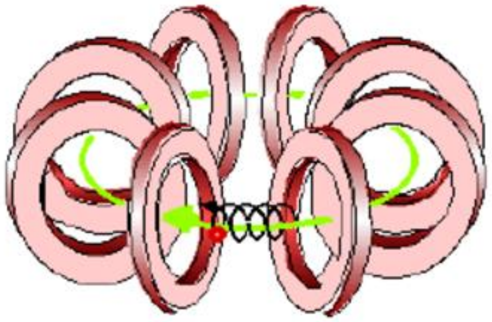


Designing a Nuclear Fusion Reactor

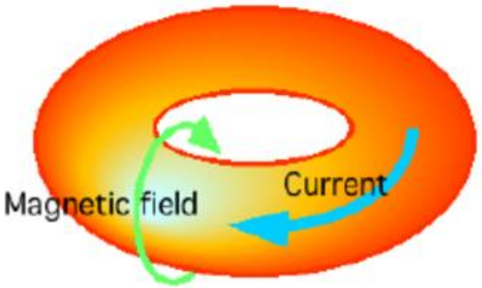
a) Magnetic field around the current



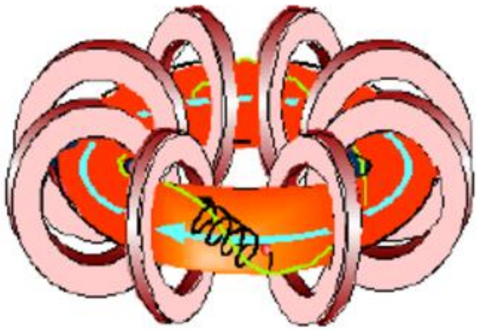
b) Magnetic field by cylindrical curcular coils

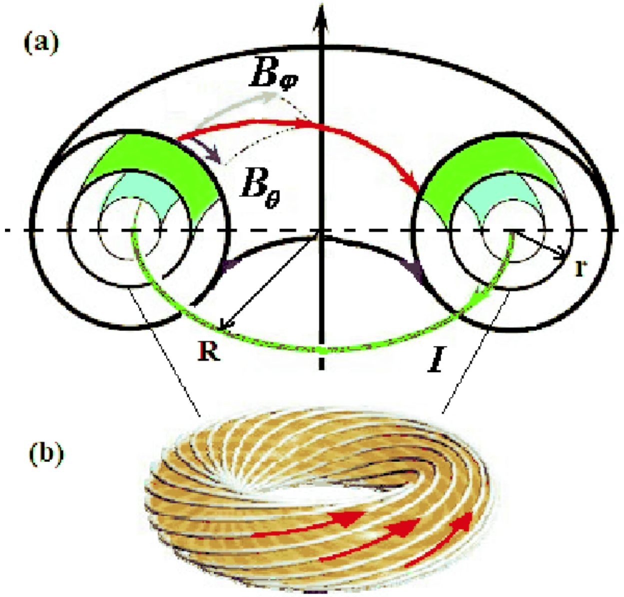


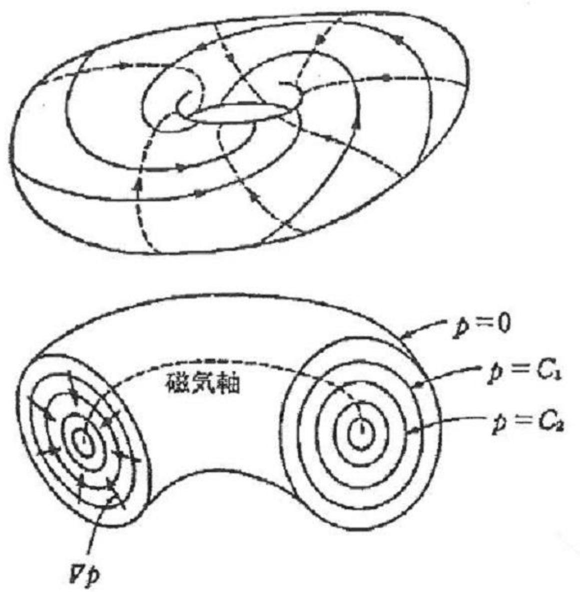
c) Magnetic field by toroidal current

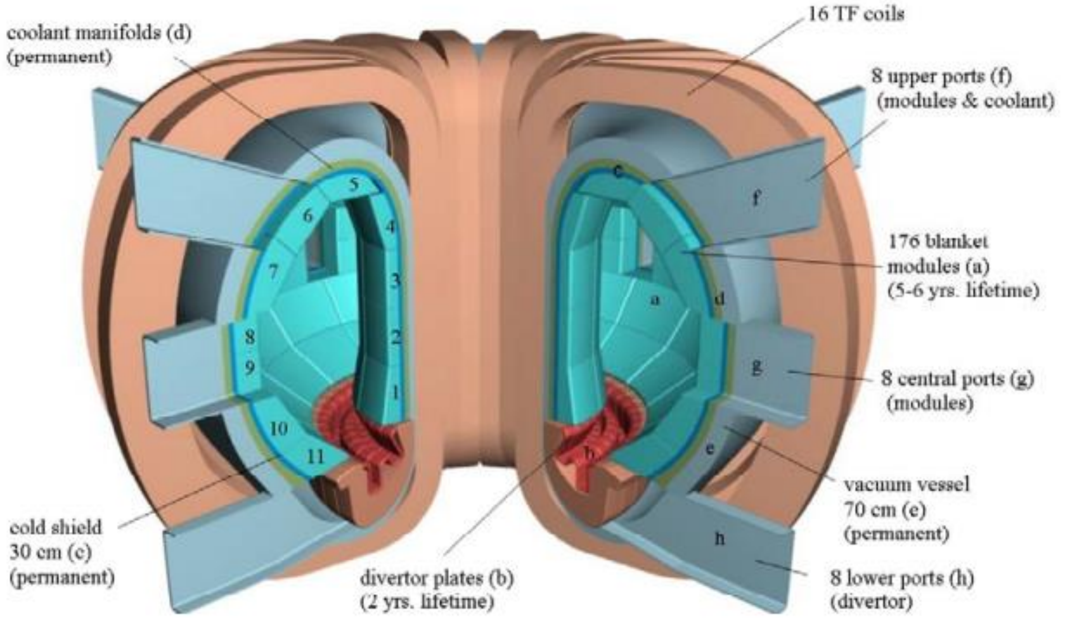


d) Twisted field line by b)and c)



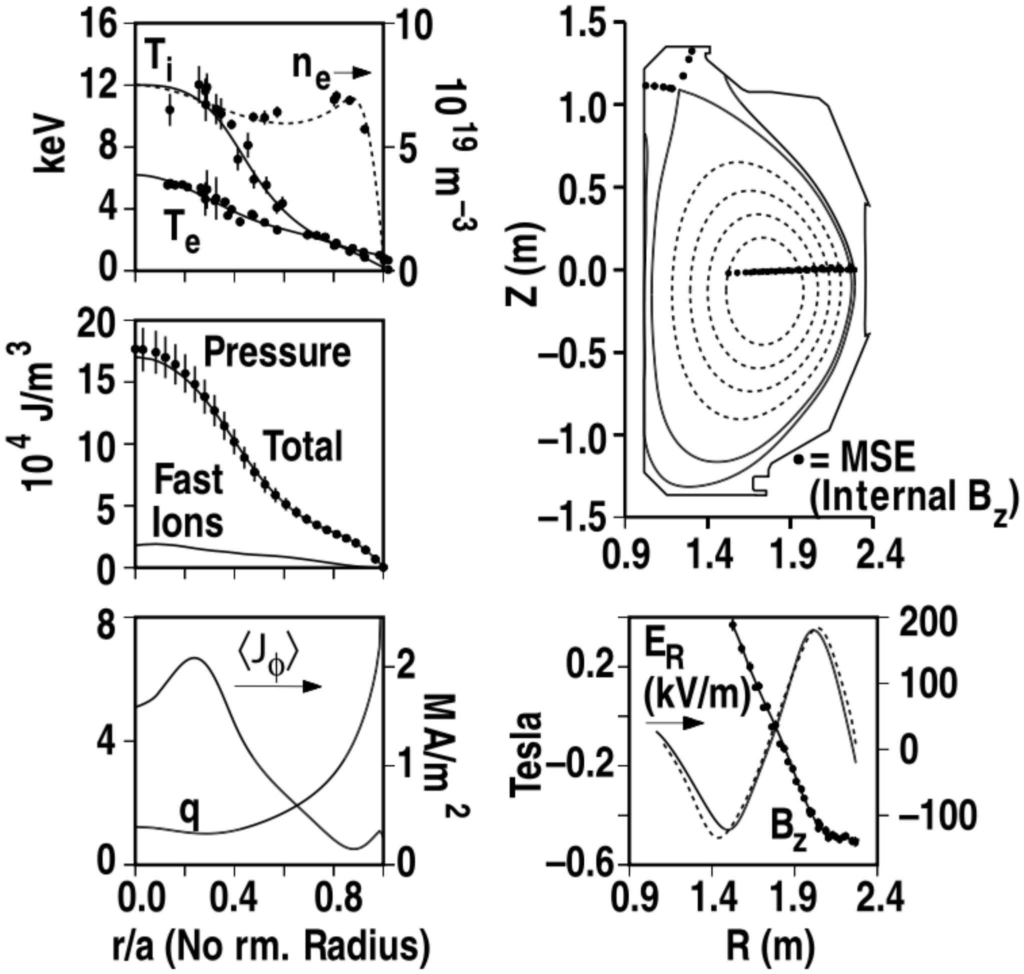






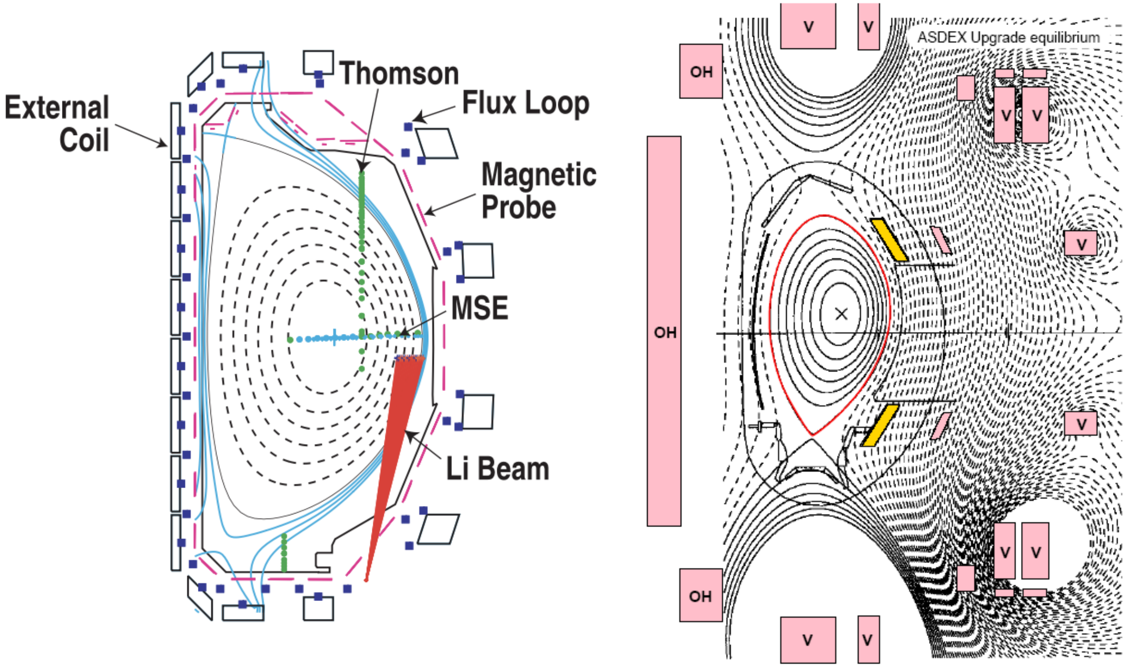
Designing a Nuclear Fusion Reactor

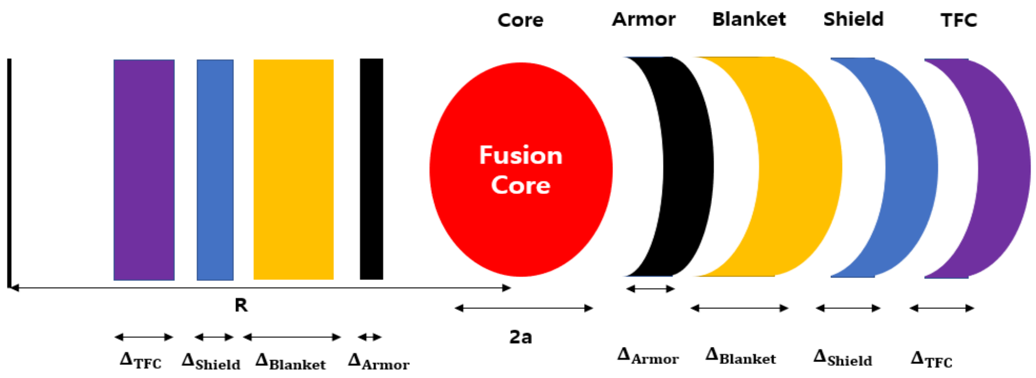
Objectives for designing a nuclear fusion reactor



Plasma operation condition

Poloidal plane of a Tokamak system





Reactor wall configuration

Basic concept of our research

Overall framework

Fusion reactor design simulator

INPUT VARIABLES
- Aspect ratio $\boldsymbol{A}$ (R/a)
- Elongation $\boldsymbol{\kappa}$
- Maximum Magnetic field $\boldsymbol{B_0}$
- Blanket thickness $\boldsymbol{b}$
- Electrical power output $\boldsymbol{P_E}$
- Neutron wall loading $\boldsymbol{P_W}$
- Plasma temperature $\boldsymbol{T}$
- H-mode enhancement factor $\boldsymbol{H}$

Based on J.P.Freidberg

CODE

OUTPUT VARIABLES
- Major/minor radius $\boldsymbol{R}, \boldsymbol{a}$
- Plasma density $\boldsymbol{n}$
- Plasma pressure $\boldsymbol{p}$
- Plasma beta $\boldsymbol{\beta}$
- Plasma current $\boldsymbol{I_p}$
- Energy confinement time $\boldsymbol{\tau_E}$

LIMITATIONS
- Greenwald density limit
- Troyon beta limit
- Kink safety factor limit
- (Bootstrap fraction)
- Lawson criterion

Single-step RL

Design optimization process through deep reinforcement learning

Design objectives and constraints

- Small reactor size : cost reduction
- TBR > 1 : Fuel-efficient
- High Q (Ignition condition)
- Avoidance of the operation limits
  - Density limits
  - Beta limits
  - Safety-factor > 2
  - Neo-classicial bootstrap current > Operational requirement of bootstrap current

Reward = R(cost-params) + R(beta) + R(safety-factor) + R(density) + R(TBR) + R(bootstrap) + R(Q-factor)

Reward contains design objectives (constraints from plasma physics and nuclear engineering) and performances (Q-factor + TBR)

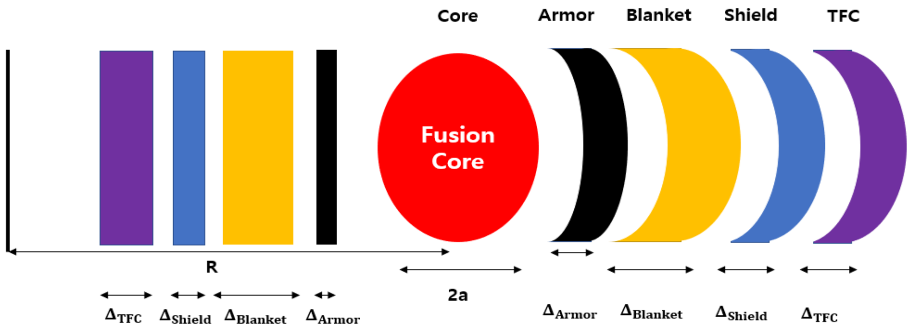
How to apply

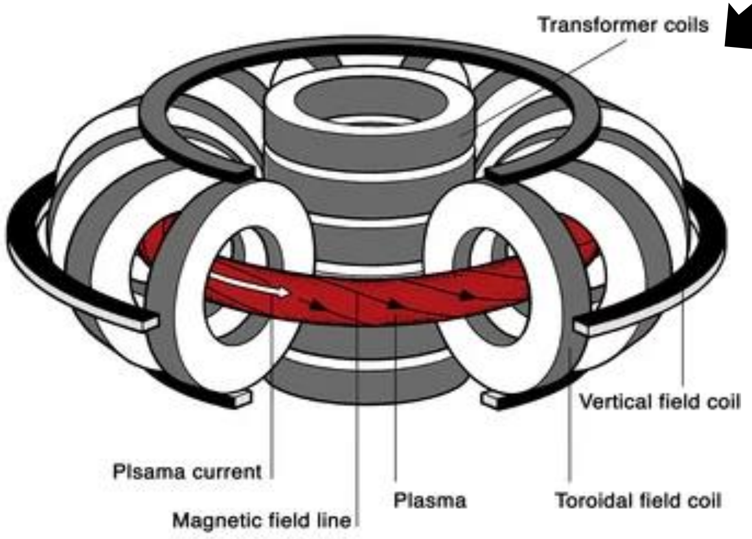
- Definition of the custom rewards that represent the objectives (Cost + TBR + Operation limits + Q-factor)
- Training the policy network to learn the optimal policy to determine the best control parameters

Step 1: Development of a Fusion Reactor Design Simulator

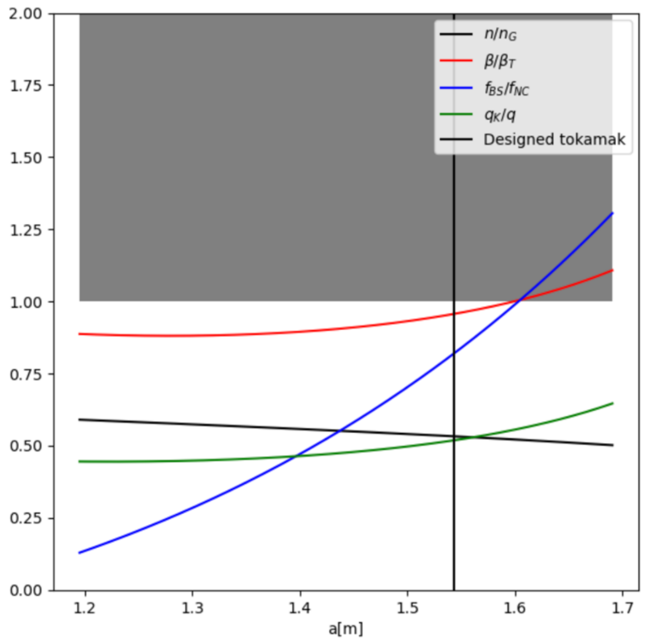
INPUT VARIABLES
- Aspect ratio $\boldsymbol{A}$ (R/a)
- Elongation $\boldsymbol{\kappa}$
- Maximum Magnetic field $\boldsymbol{B_0}$
- Blanket thickness $\boldsymbol{b}$
- Electrical power output $\boldsymbol{P_E}$
- Neutron wall loading $\boldsymbol{P_W}$
- Plasma temperature $\boldsymbol{T}$
- H-mode enhancement factor $\boldsymbol{H}$

Structural design parameters determined through physical constraints





Design of the tokamak determined



Example of the simulation result

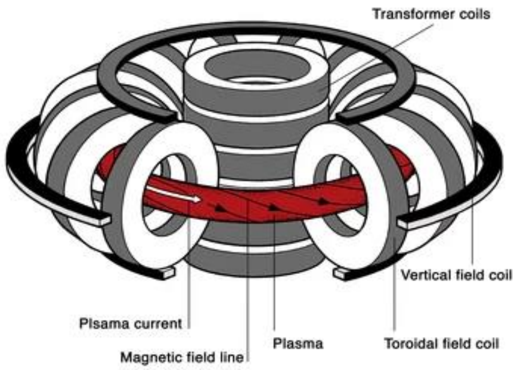
```
================ Geometric info ================
| Major radius R : 4.630 m
| Minor radius a : 1.543 m
| Armour : 0.100 m
| Blanket : 1.276 m
| Shield : 0.100 m
| TF coil : 0.522 m
| total thickness : 3.541 m
============== Physical parameters ==============
| Magnetic field : 16.000 T
| Elongation : 1.700
| Aspect ratio : 3.000
| Thermal efficiency : 0.400
| Electric power : 1000.000 MW
| TBR : 1.362
| beta : 6.034
| tau : 1.159 s
| Ip : 15.345 MA
| q : 3.855
| f_bs : 0.534
| Q-parallel : 513.03 MW-T/m
| T_avg : 20.00 keV
| n_avg : 1.09x10^20 #/m^3
| p_avg : 8.39 atm
=============== Operation limit ================
| Greenwald density : 2.051, operation density : 1.092 | O
| q-kink : 2.000, operation q : 3.855 | O
| Troyon beta : 6.307, operation beta : 6.034 | O
| Neoclassical f_bs : 0.651, operation f_bs : 0.534 | O
| Lawson nTau : 1.812 , operation n*Tau: 1.266 | X
| Cost params : 0.757
================================================
```

Step 2: Implementation of a RL based Design Optimization Code

INPUT VARIABLES
Aspect ratio $\boldsymbol{A}$ (R/a)
Elongation $\boldsymbol{\kappa}$
Maximum Magnetic field $\boldsymbol{B_0}$
Blanket thickness $\boldsymbol{b}$
Electrical power output $\boldsymbol{P_E}$
Neutron wall loading $\boldsymbol{P_W}$
Plasma temperature $\boldsymbol{T}$
H-mode enhancement factor $\boldsymbol{H}$

Input parameters (Action)

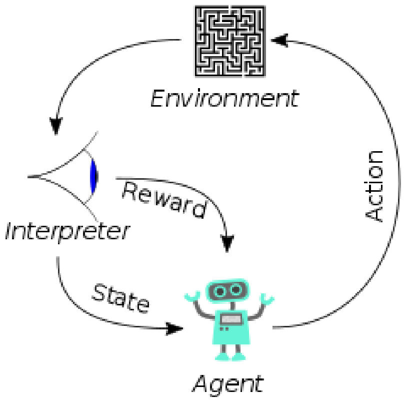
Designed reactor



Simulation result (Next state)

- Small reactor size : cost reduction
- TBR > 1 : Fuel-efficient
- High Q (Ignition condition)
- Avoidance of the operation limits
  - Density limits
  - Beta limits
  - Safety-factor > 2
  - Neo-classicial bootstrap current > Operational requirement

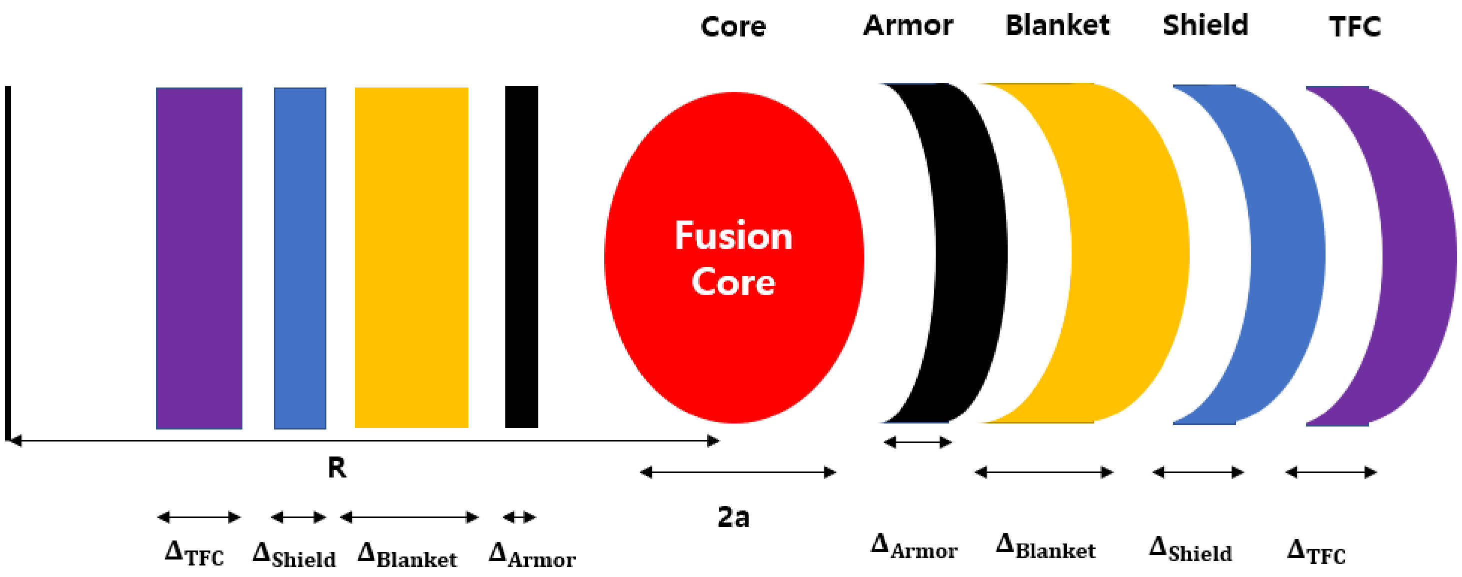
Reward = R(cost-params) + R(beta) + R(safety-factor) + R(density) + R(TBR) + R(bootstrap) + R(Q-factor)



Deep Reinforcement Learning
Decision making = Optimal design parameters estimation

Reactor structure and configuration

Default structure design and configuration – fixed during the optimization



Tokamak structural design parameter	
R (Major radius)	4.473 m
a (Minor radius)	1.597 m
Δ_{Armor}	0.1 cm
$\Delta_{Blanket}$	1.276 m
Δ_{Shield}	0.1 m
Δ_{TFC}	0.512 m
κ	1.7
ϵ	2.8

- **Main concepts for our fusion reactor**
  - Liquid type blanket: Coolant + Tritium breeding + relatively simple design
  - Avoidance of the operation limits + High Q-factor + TBR > 1 + Low volume for reducing cost
  - D-T fusion + ECRH & LHCD heating + H-mode plasma

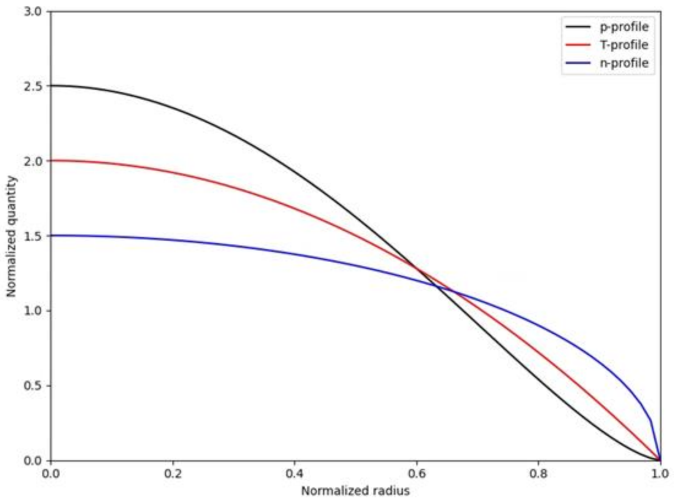
Core Design

Plasma core profile: n, T, P

- **Profile effects on high Q subignited Tokamak Fusion Plasmas**
  - The Q-value clearly expresses its dependence on the radial profile of T,N,P
  - Same configuration for radial profiles of T,N,P referred from Friedberg et al.
  - Parabolic profiles with numerical coefficient

$$T = \bar{T}(1+\nu_T)(1-\rho^2)^{\nu_T} = 2\bar{T}(1-\rho^2),$$
$$p = \bar{p}(1+\nu_p)(1-\rho^2)^{\nu_p} = 2.5\bar{p}(1-\rho^2)^{3/2},$$
$$n = \bar{n}(1+\nu_n)(1-\rho^2)^{\nu_n} = 1.5\bar{n}(1-\rho^2)^{1/2}.$$

$\nu_T = 1$
$\nu_p = 3/2$
$\nu_n = 1/2$



- **Effect of elongation**
  - Plasma current and elongation
    - Vertical elongation of the plasma cross-section brings the increased plasma current
    - Due to the increase of plasma current, the energy confinement time can also increase

Both of these advantages have been demonstrated experimentally up to elongations of k = 2.35: Set initial K = 1.7

$$I_p \sim \frac{\kappa^2+1}{2}$$

  - Beta and elongation
    - Vertically elongated and D-shape cross-section allow much high beta values than circular ones
    - Troyon beta limit: High elongation plasma allow the beta value higher

$$\beta_m \le \beta_n \frac{I_p}{aB}$$

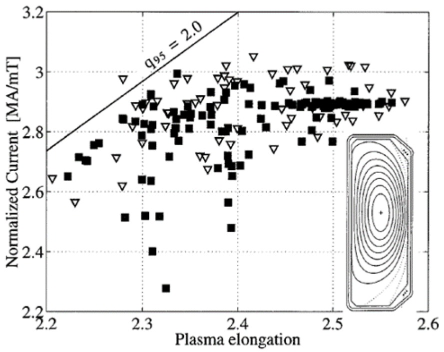


Fig 1. From F.Hofmann, Physical Review Letters, Volume 81, 14, 1998

Blanket Design

Breeder design and material

- Materials : liquid-type
  - Lithium leads (Li17Pb83)
  - Versatile: Coolant + Tritium breeding
  - Lead : Neutron multiplier
  - Corrosion: middle
  - Chemical stability: less than other liquid materials
  - Inboard shield thickness reduction / but the thickness of the blanket may increase
  - Structures for additional coolant system would not be necessary

- Structures
  - Structure type of TBM: CLAM designed by EU
  - Breeder Inlet / Outlet: 300 / 480
  - Breeder Maximum temperature: 543 + 273 K -> High enough
  - Breeder coolant pressure drop : less than 0.8 MPa
  - TBR : 0.43 -> using lead as a multiplier

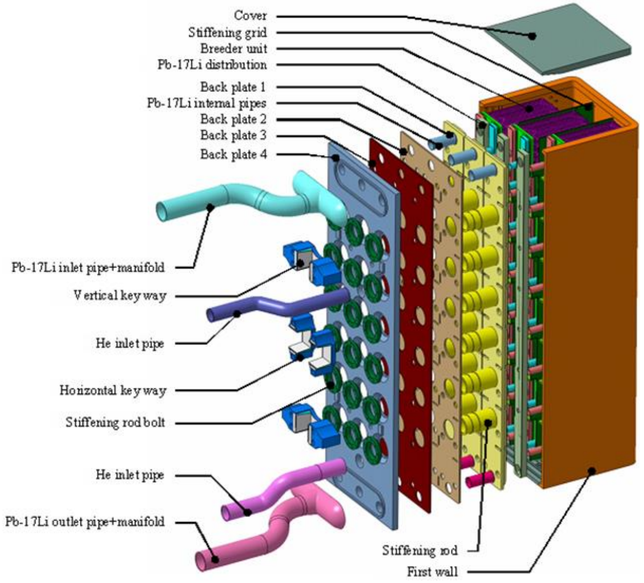
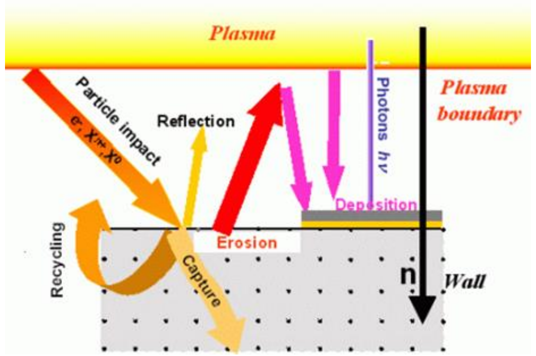


TABLE I. Physical properties of eutectic LiPb compared with other possible breeding materials.

Liquid Breeder	Li	$Li_{17}Pb_{83}$	Flibe	$Li_{20}Pb_{80}$
Melting Point (°C)	180	235	459	320
Density (g/cm^3) 873K	0.48	8.98	2.0	6.0
Li Density (g/cm^3) 873K	0.48	0.061	0.28	0.09
Breeding property	Good	Fairly good	Neutron multipler required	Neutron multipler required
Chemical stability	Active	Middle	Almost stable	Almost stable
Corrosion	Severe	Middle	HF exist severe	?
Tritium release form	HT, T_2	HT, T_2	HT,T_2 TF	HT, T_2
Tritium solubility (atom frac$Pa^{-0.5}$ T=873K)	Very high 7.49×10^{-3}	Very low 1.93×10^{-8}	Very low HT/T_2 1.77×10^{-11} TF 1.77×10^{-11}	Middle 2×10^{-7}-1×10^{-5}
Tritium diffusivity order (m^2/s) (873K)	Relatively high 10^{-9}	Relatively high 10^{-9}	Relatively high 10^{-9}	Relatively high 10^{-9}
Thermal conductivity	Li>$Li_{20}Sn_{80}$> **$Li_{17}Pb_{83}$** > Flibe			
Dynamic viscosity	Flibe>$Li_{20}Sn_{80}$~**$Li_{17}Pb_{83}$** >Li			

Table 2. From A.Fraile, Molecular dynamics simulations of lead and lithium in liquid phase

Armor and Shielding



Armor design and material

- Material: Tungsten
  - Thickness : 10 cm
  - Good resistance for physical, chemical sputtering
  - Tungsten exhibit pronounced surface morphology changes under He plasma exposure
  - High radiational loss can be occurred due to high atomic number and induce instabilities
  - Tungsten surface energy limit : 0.5MJ/m^2

Shielding design and material

- Material: Graphite
  - Thickness : 10cm
  - Neutron reflector and moderator for shielding the materials (TF coil)
  - Located between the blanket and TF coils
  - Good neutron-moderating properties and availability in large quantities
  - Neutron reflection outside the blanket : enhancing TBR

Table 2
Typical densities of carbon and graphite products.

Material	Bulk density, g/cm^3
Pyrolytic carbon	1.2–2.2
Single crystals (theoretical density)	2.26
Nuclear graphite-moderator and reflector	1.5–1.7
Porous electrocarbons and graphites	0.6–1.3
Carbon felt	0.08–0.17

Table 3
Vaporization data for carbon [20].

Temperature, K	Pressure, atm
2000	1.31×10^{-10}
2500	1.05×10^{-6}
3000	5.38×10^{-4}
3500	5.30×10^{-2}
3800	1.0

Table 2 and 3. From D.E.Baker, Graphite as a neutron moderator and reflector materials

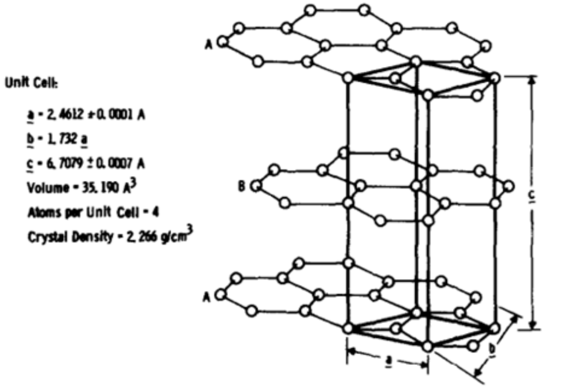
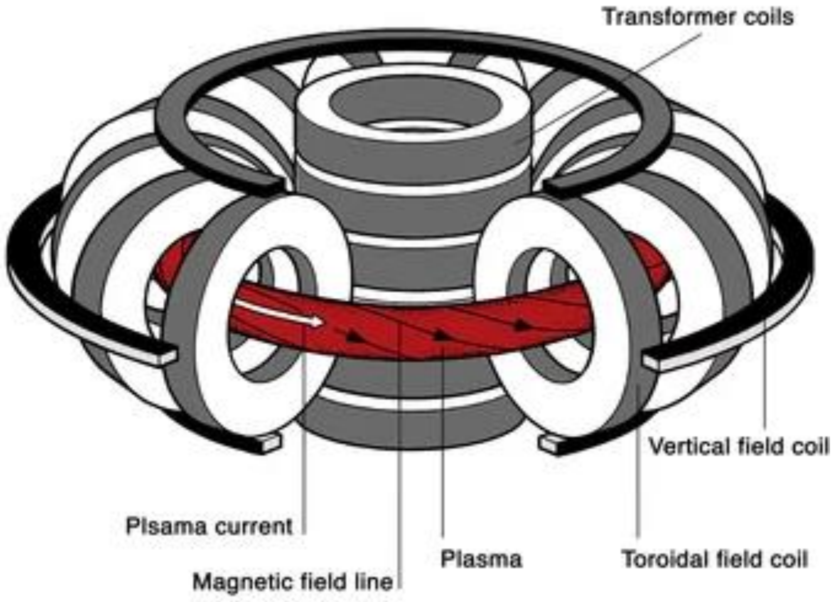


Fig 2. From D.E.Baker, Graphite as a neutron moderator and reflector materials

TF coils and PF coils



TF coil thickness

$$c = R_0 \left\{ 2(1-\varepsilon_B) - \left[(1-\varepsilon_B)^2 - \boxed{\alpha_M}\right]^{1/2} - \left[(1-\varepsilon_B)^2 - \boxed{\alpha_J}\right]^{1/2} \right\}$$

Tensile Strength

Current Density

Common steel Ref. c = 0.97 [m]
Maximum Tensile Strength : 600 [MPa]
Maximum current density : 20 [MA/m^2]

2800 Maraging Steel Ref. c = 0.66 [m]
Maximum Tensile Strength : ~ 2700 [MPa]

HTS coil Ref. c = 0.44 [m]
Maximum current density : ~ 200 [MA/m^2]

TF, PF coils
CAN BE MADE THINNER !

Heating and Current Drive Sources

Heating and Current Drive – ECRH and ICRH

- ECRH
  - Functions
    - Plasma startup
    - Heating for access to H-mode
    - q profile control
    - CD for steady-state
  - Requirement
    - Frequency : ~200GHz
    - Power : determined by tokamak design
    - Gamma : 0.15

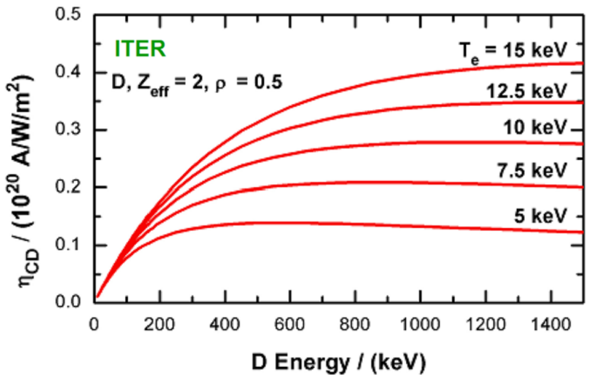
$$\eta_{CD} = \frac{R_0 \bar{n} I_{CD}}{P_{CD}} \approx \frac{1.2}{n_{\parallel}^2},$$

$$n_{\parallel} \approx \frac{\omega_{pe}}{\Omega_e} + \left(1 + \frac{\omega_{pe}^2}{\Omega_e^2}\right)^{1/2} \left(1 - \frac{\omega_{LH}^2}{\omega^2}\right)^{1/2}$$

- LHCD
  - Functions
    - Current is driven by lower hybrid waves in our cases
    - High efficiency
  - Requirement
    - Considered coupling of the edge plasma and generator power : 0.4
      - P > 4MW -> no experiment has ever coupled ICRF power into an H-mode
      - Efficiency of LH klystrons : ~ 50%
    - Power : determined by tokamak design
    - Gamma : 0.3 - 0.4

$$\eta_{CD} = \frac{I_{NBCD} n_e R}{P_{dep}}$$

major radius R
deposition power of the beam P_{dep}



ITER: 2 MA current drive! (33 MW heating power)

	Wall-plug to coupled power efficiency CONVERSION (Technology)	Wall-plug to coupled power efficiency COUPLING (Physics)	CD efficiency (DEMO-like plasmas) PHYSICS
NNBI	Low (20-30%)	high	high
ICRH	Medium (40-50%)	low-medium	medium
LHCD	Medium (40-50%)	medium	high
ECRH	Low-Medium (20-40%)	high	low-medium

Finding the optimal engineering parameters

Design optimization with single-step reinforcement learning

❑ <u>Single-step reinforcement learning and design optimization</u>

- Policy gradient method to find out the best design choice of the tokamak
- Control parameters: H, armor thickness, T, betan, elongation, aspect ratio, B-field, RF recirculated efficiency, electric power
- Conventional optimization method: hard to find out the optimal configuration (Multi-objective + High dimensional space)

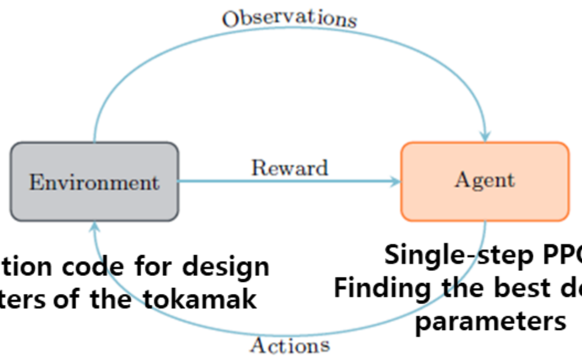


Figure 4: **Degenerate reinforcement learning framework used in this paper.** One episode consists of a single control from the agent: the same initial observation is provided to the agent at the start, which in return provides an action to the environment. The environment returns a reward value to the agent, and the episode is terminated.

By customizing the reward function, we can optimize our tokamak design with respect to any design strategy!

Reward = R(cost-params) + R(beta) + R(safety-factor) + R(density) + R(TBR) + R(bootstrap) + R(Q-factor)

❑ <u>How to apply</u>

- Definition of the custom rewards that represent the objectives (Cost + TBR + Operation limits + Q-factor)
- Training the policy network to learn the optimal policy to determine the best control parameters

Finding the optimal engineering parameters

Reward engineering for satisfying stabilities + maximum performance

- **Stability**
  - Kink instability
  - Troyon beta limit
  - Greenwald density limit

$$R_t = a \times sigmoid\left(\frac{x}{x_{limit}} - 1\right) + R_{fail} \times \theta(1 - \frac{x}{x_{limit}})$$

- **Design Performance**
  - High beta
  - Low cost (proportional to volume)
  - Bootstrap current ratio

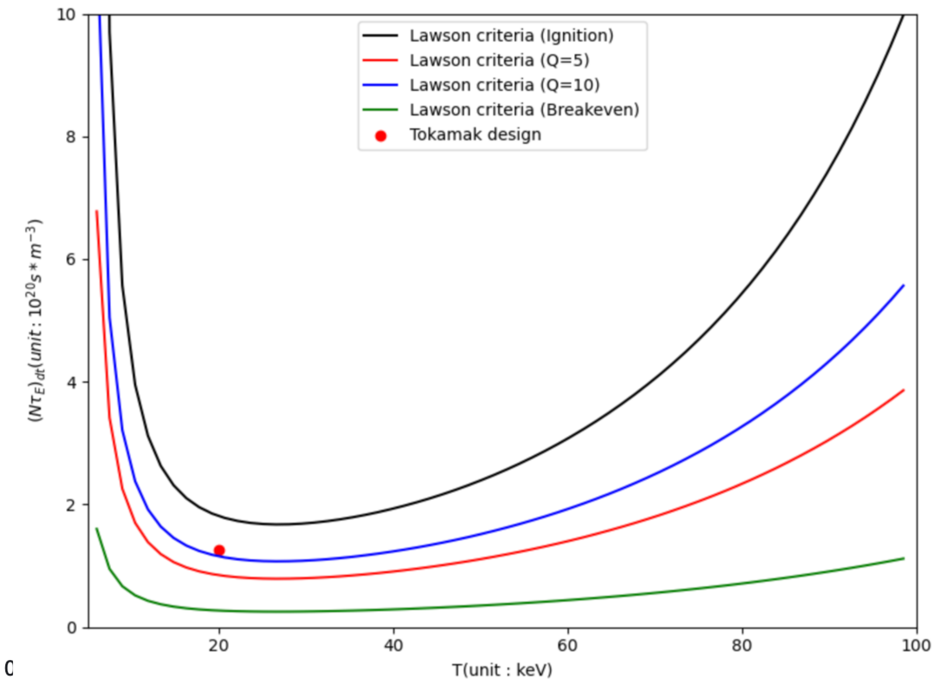
$$R_t = a \times sigmoid\left(\frac{x}{x_{scale}} - 1\right)$$

Design Optimization Results

Comparison between the reference (Friedberg) and the optimized reactor

```
================ Geometric info ================
| Major radius R : 5.346 m
| Minor radius a : 1.337 m
| Armour : 0.000 m
| Blanket : 0.899 m
| Shield : 0.100 m
| TF coil : 0.954 m
| total thickness : 3.289 m
============== Physical parameters ==============
| Magnetic field : 13.000 T
| Elongation : 1.700
| Aspect ratio : 4.000
| Thermal efficiency : 0.400
| Electric power : 1000.000 MW
| TBR : 1.153
| beta : 3.595
| tau : 0.917 s
| Ip : 14.005 MA
| q : 3.398
| f_bs : 0.612
| Q-parallel : 550.25 MW-T/m
| T_avg : 14.00 keV
| n_avg : 1.43x10^20 #/m^3
| p_avg : 7.67 atm
=============== Operation limit ================
| Greenwald density : 2.495, operation density : 1.426 | O
| q-kink : 2.000, operation q : 3.398 | O
| Troyon beta : 4.007, operation beta : 3.595 | O
| Neoclassical f_bs : 0.464, operation f_bs : 0.612 | X
| Lawson nTau : 2.507 , operation n*Tau: 1.308 | X
| Cost params : 0.756
================================================
```

```
================ Geometric info ================
| Major radius R : 4.630 m
| Minor radius a : 1.543 m
| Armour : 0.100 m
| Blanket : 1.276 m
| Shield : 0.100 m
| TF coil : 0.522 m
| total thickness : 3.541 m
============== Physical parameters ==============
| Magnetic field : 16.000 T
| Elongation : 1.700
| Aspect ratio : 3.000
| Thermal efficiency : 0.400
| Electric power : 1000.000 MW
| TBR : 1.362
| beta : 6.034
| tau : 1.159 s
| Ip : 15.345 MA
| q : 3.855
| f_bs : 0.534
| Q-parallel : 513.03 MW-T/m
| T_avg : 20.00 keV
| n_avg : 1.09x10^20 #/m^3
| p_avg : 8.39 atm
=============== Operation limit ================
| Greenwald density : 2.051, operation density : 1.092 | O
| q-kink : 2.000, operation q : 3.855 | O
| Troyon beta : 6.307, operation beta : 6.034 | O
| Neoclassical f_bs : 0.651, operation f_bs : 0.534 | O
| Lawson nTau : 1.812 , operation n*Tau: 1.266 | X
| Cost params : 0.757
================================================
```



Design Optimization Results

Comparison between the reference (Friedberg) and the optimized reactor