Plasma scenario design with 0D optimization and transport solution

J.C. Rivas[1], J. Seo[1]

[1] *Department of Nuclear Engineering, Seoul National University, Seoul, Republic of Korea*

Introduction.

For the optimization of plasma scenario parameters in systems studies, 0D models[1] are often used, because the resulting computational model is 'cheap' in terms of computational resources. The drawback is that 0D models lack accuracy and can be too simplistic regarding for example the description of the main plasma phenomena determining the performance of a design[2]. Transport solvers, on the other hand, can provide a higher resolution and completeness in the results, but they are costly in terms of computational resources, and therefore its use in optimization activities is not practical. In this contribution, a 0D plasma code is used for optimization of figures of merit deemed of interest, by changing some input parameters, and constraining the solution with physics and technological limits. The obtained solution is then used as a guess solution for a transport solver, which provides a more reliable solution based on the 0D optimization.

Setup. A 0D plasma core equilibrium code has been developed, largely based on models described in previous works[1,3]. The code also can calculate the target power density based on a model from the Aries AT physics basis[3].

This 0D plasma code is used as objective function by a genetic algorithm[4] optimizer code to search for a solution that minimizes a penalty function which is calculated from the values of constraints and figures of merit.

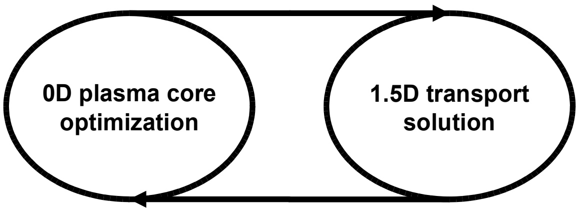

Figure 1.

Once a solution is produced by the 0D optimizer, the transport solver will take its input parameters and try to reproduce it from more detailed models. The result will be evaluated as a possible solution, and the divergences between both 1.5D and 0D solutions will be fed back to the 0D code through a hyperparameter fitting algorithm.

Typically, parameters with high uncertainty will be fitted to the 1.5D solution values. For example, the parabolic profile used in the 0D code will be fitted to the 1.5D temperature radial profile solution.

This way, the next optimization, provided that it lies close to the first one, should show a higher similarity with the 1.5D solution. In the way to convergence, which won't be necessarily achieved, better 1.5D solutions can be found.

The way the **genetic algorithm optimization** works is as follows:

1. An initial population is generated by varying randomly the **design vector** inside the allowed range for each component.
2. The **objective function** is calculated for each individual. From the result, a penalty value is assigned to the individual to determine its "fitness". The penalty function depends on the objective variable value and on the constraints vector value.
3. For the next iteration, a new population is built from the previous one. The process starts with the selection of the "fittest" individuals, that will produce the next "**generation**".
4. Next, a "**crossover**", or exchange of parameters among the selected individuals is performed to produce new individuals.
5. Finally, a "**mutation**", or random variation of parameters in individuals is done to further increase the diversity of the population.
6. The iteration process will continue until the algorithm is not producing significant improvement in new generations.

Typical dependencies for the terms used in the algorithm description are listed below:

- Constraints vector(P_{fus},n_{lim},β_{lim},q_{95}, Q, B_t, <NWL>)
- Design vector(n,T,R,A,k_u,d_u,k_l,d_l,P_{ext},HH98,n_{ped},T_{ped},I_{pl},B_t,X_W,X_{Ar},X_{He},f_T,f_{3He})
- Objective function: plasma 0D equilibrium calculation
- Objective variable: Major radius (R) (minimize)
- Penalty function: R + f(constraint vector)

For the 1.5D solution, ASTRA [6] transport solver is used, CHEASE [7] for the equilibrium reconstruction, and NUBEAM [8] for the heating and current drive calculation. GLF23 [9] and NCLASS [10] models are used for the core heat transport coefficient, and EPED1-NN [11] for the pedestal determination.

The 1.5D transport solution is obtained after the convergence by iterative calculation of the multiple codes. Only the energy transport and the current density (or magnetic flux) diffusion are solved, whereas the density profile is fixed with the initial one provided by the 0D code since there are uncertainties to solve the particle transport such as the particle source profile and the pedestal decoupling between the density and temperature.

KDEMO plasma design point optimization: an example

		K-DEMO REPORT [3]		INITIAL CALCULATION		PRELIMINARY SOLUTION		EURODEMO1 [5]
		0D Systems Code	TSC 1.5D time-dependent	0D	1.5D	0D	1.5D	
PLASMA DESIGN POINT	I_p [MA]	12.30	12.30	12.30	15.61	22.28	16.21	19.60
	f_{bs}	0.67	0.68	0.34	0.42	0.28	0.52	0.35
	B_{tor} [T]	7.40	7.40	7.40	7.40	4.60	4.60	5.70
	n/n_{Gr}	1.15	1.19	1.14	1.00	1.20	1.18	1.20
	W_{th} [MJ]	677.00	746.00	550.60	760.88	1,880.99	1,257.90	-
	β_{Nth}	2.53	2.88	2.12	2.81	3.19	3.88	2.60
	H 98(y,2)	1.30	1.30	1.00	1.36	1.25	1.62	1.10
	P_{alpha} [MW]	298.00	308.00	274.64	337.18	587.77	314.28	407.40
	P_{aux} [MW]	119.00	120.00	146.60	146.45	101.80	99.09	50.00
	P_{rad} [MW]	112.40	98.00	104.61	121.86	108.10	55.89	306.00
	Z_{eff}	2.04	1.48	1.99	1.99	1.17	1.17	2.60
	n_{He}/n_e	0.06	0.08	0.08	0.05	0.06	0.06	0.10
	R_0/a [m]	6.8/2.1				9.20/3.07		9.10/2.93
	κ_{95}/δ_{95}	2.0/0.625				1.94/0.37		1.59/0.33
	A[m^2]/Vol[m^3]	~690/~1184				1807/2845		-
ENGINEERING FIGURES OF MERIT	Psep/R [MW/m]	44.79	48.53	46.56	53.20	63.20	38.86	17.00
	<NWL> [MW/m^2]	1.73	1.79	1.59	1.95	1.30	0.70	1.05
	n_G <T>τ [keV s $10^{19}/m^3$]	90.06	93.41	65.00	108.16	190.62	77.89	125.11
	Bmax [T]	16.00				10.51		12.30
	Q	12.52	12.83	9.37	11.51	28.87	15.86	40.74

Table 1. The combined optimization system is applied to find a new K-DEMO option design plasma, starting from the Option II[3].

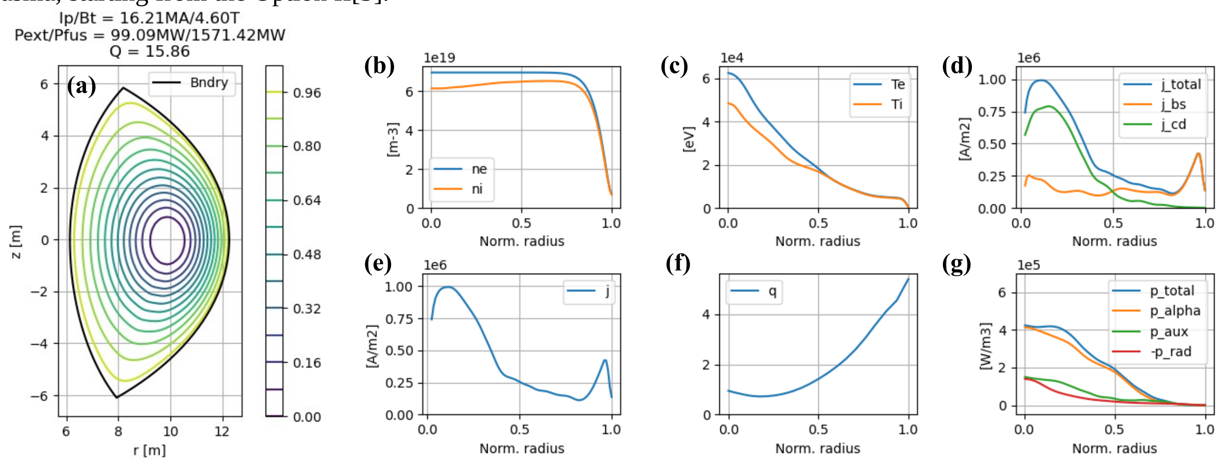

Figure 2. Plasma equilibrium and profiles obtained by 1.5D transport solver

Discussion. The initial calculation was performed to benchmark the presently used codes with the results in the K-DEMO report [3]. There are some divergences due to the different models used in the codes.

The preliminary solution seems more conservative from an engineering point of view than the reference K-DEMO design. When comparing the divertor load figure of merit with EURODEMO1, it must be noted that EURODEMO1 is a single null design.

From the physics point of view, the solution is also conservative but underperforms the EURODEMO1 solution for similar geometry, which points to the need of improving the physics models in both the 0D and the 1.5D codes.

Otherwise, the solution seems to be in a similar line to the EURODEMO1 design which is a conservative design from the physics and engineering point of view and therefore with a potentially higher technological readiness.

The higher Q factor favors a higher plant performance than in K-DEMO option II. A lower maximum toroidal field than K-DEMO II favors a lower building cost per megawatt. However, the lower neutron wall loading even favoring a higher availability, will limit the achievable blanket performance.

The 1.5D transport solution shows a lower level of the fusion power and Q factor with the 0D solution, which is due to using different models for each physics element[6-11]. Figure 2 shows the 2D plasma equilibrium, the density and temperature profiles, and the heating and current drive profiles. It shows fully non-inductive current drive with $f_{BS} \approx 0.52$, and alpha-heating dominant reactor-relevant condition.

Conclusions and future work

We developed an algorithm that combines the optimization of a 0D tokamak plasma equilibrium and the refinement of the solution with a 1.5D transport code. The optimization uses a genetic algorithm combined with a penalty function to implement constraints. The 1.5D solution is used to change a set of hyperparameters in the 0D plasma code, and further iterate until a satisfactory solution is achieved. There is work ongoing to further develop this concept and apply it to produce new solutions.

Acknowledgements

This work was supported by the National Research Foundation of Korea(NRF) funded by the Ministry of Science & ICT (Brain Pool Program: NRF-2020H1D3A1A02081518), and by R&D Program of "Development of integrated tokamak simulation technology (CN2101-1)" through the Korea Institute of Fusion Energy(KFE) funded by the Government funds, Republic of Korea.

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