SIMULACIÓN CON CÓDIGOS NUMÉRICOS +3D

NUCLEAR FUEL CYCLE OPTIMIZATION UNDER UNCERTAINTY

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Nuclear fuel cycle simulators are extensively used by researchers and policy makers for the study and evaluation of complex electronuclear strategies. Given the large number of parameters involved in this kind of analyses, recently the simulators have been upgraded for performing optimization and thus reducing the user interaction. Under this approach, the objectives of the scenario are firstly defined, and the tool retrieves the best scenario given a relaxed set of initial conditions.

However, nuclear fuel cycle studies are surrounded by uncertainties, and they can have a major impact in the scenario. Typically, a scenario consists of a delicate balance between different quantities which can be broken in the presence of perturbations leading to undesirable effects. For example, if there is not enough material for fuel fabrication the energy demand will not be satisfied. Under these ideas, this work aims to present a novel methodology for coupling optimization and uncertainty analyses.

The methodology implemented in TR_EVOL fuel cycle simulator and based on the DEMO metaheuristic multioptimization algorithm, has been applied to an advanced European transition scenario. In order to reduce and stabilize the TRU inventories while keeping the economic cost low, an initial LWR fleet is replaced by ADS and FR reactors. The scenario has been firstly optimized in a traditional way without uncertainties, and then with uncertainties in the total energy production and the reprocessing capacity. The comparison of both results shows that the Pareto front obtained as a consequence of the incompatibility between both objectives, is notably reduced in the presence of uncertainties.

INTRODUCTION

Nuclear fuel cycle simulators have been proven to be crucial tools for researchers and policy makers due to the complexity of electronuclear fuel cycle scenarios. The usual approach to use them is first to define the scenario by means of a set of descriptive parameters and changes along the scenario period. Then these parameters are introduced as input in the codes and the results are provided (natural uranium consumption, nuclear waste generation, levelized cost of electricity, etc.), allowing the users to analyse them and obtain conclusions (OECD/NEA, 2013). However, in the decision making problem, the approach is the contrary: given a desired outcome, the codes should find the set of input parameters that fulfil it. In the latest years, this inverse problem has been implemented as an optimization problem, and an improvement in the codes has been necessary to perform the analyses in an automatized way without the interaction of the user (Freynet et al., 2016).

Additionally, uncertainty analyses in this kind of studies are gaining importance since they might have a significant impact in the robustness of the scenario. For instance, the lack of a material due to the uncertainty in its generation may have fatal consequences such as that the electricity demand cannot be satisfied. This is of special importance in optimization analyses, given that the optimized scenario is already pushed to the limit and there is no guarantee that it remains viable when uncertainties are considered.

This works presents and discusses a methodology for exploring multiobjective optimization problems while considering uncertainties in input parameters. In multiobjective problems, instead of a single solution, in general there are a collection of optimal solutions where usually improving one objective leads to worsening the others. More precisely, a dominant solution can be defined as that one improving at least one objective without degrading the others and the set of all dominant solutions forms the so-called Pareto front which conform the desired collection of solutions.

The TR_EVOL code used in this work (Álvarez-Velarde and González-Romero, 2010; Merino Rodríguez et al., 2016) has been upgraded with an evolutionary algorithm able to solve this kind of problems. This methodology has been applied to an advanced fuel cycle scenario formed by different reactor fleets, as described in the next section, having the objective of finding the most sustainable variation. The optimization procedure has been studied for the scenario with and without uncertainties to check the consequences of disregarding them.

SCENARIO DESCRIPTION

The scenario chosen for this work is based on the one present in the EU CP-ESFR project (Garzenne et al., 2011). This scenario is graphically depicted in Figure 1 and contains a Generation II fleet of pressurized light water reactors (PWR) burning two types of fuels, UO_2 and mixed U-Pu oxides (MOX). There also exists a legacy of spent nuclear fuel (SNF). This fleet lasts from year 2010 until year 2040. From this year, this initial phase turns into the burner phase, that will last until year 2100. This phase is characterized by a gradual transition during 20 years from the PWR fleet to a new one consisting in Generation III European Pressurized Reactors (EPR), Generation IV sodium-cooled fast reactors (SFR) and accelerator-driven subcritical systems (ADS), and has the objective of burning as much transuranic elements (TRU, that is, the addition of minor actinides (MA) and plutonium) as possible. The final stabilization phase starting in year 2100 contains the same reactors than in the burning phase (with a different energy share) but it has the objective of reaching a sustainable level in the TRU inventories. It also includes a 20-year transition between phases.

The electricity production of this scenario is constant with a value of 800 TWhe/yr, as in the CP-ESFR scenario. In the second and third phases, the energy share will change between the three types of reactors in order to optimize the respective objectives. Also, the maximum reprocessing capacity is fixed at 2850 t_{HM}. These two variables have been specified here because they will be parametrized with an arbitrary variation of ±10%. They are the only input parameters to have uncertainties. Other information concerning the reactors and facilities can be found in bibliography (Skarbeli et al., 2020).

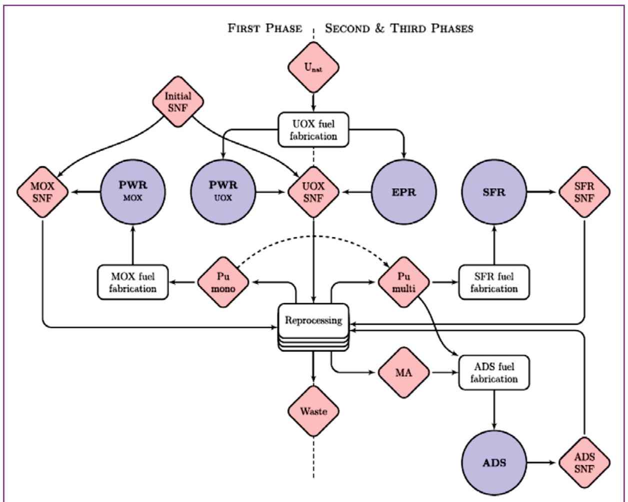

Figure 1. Main facilities in the scenario. Circles represent reactors, diamonds represent stocks of materials and boxes, rest of facilities.

The objective of the study is to obtain the most sustainable scenario, as stated in the previous section. In order to define that, two parameters have been considered: the TRU inventory mass and the cost of the fuel cycle, making this work a multiobjective analysis. On the one hand, the cost has been considered to have only two components, the capital cost and operation and maintenance cost, for simplicity. These components have been reported (Merino Rodríguez et al., 2014) to provide around 80% of the fuel cycle cost. On the other hand, the TRU inventory mass has been calculated as the total TRU mass present at all the stages of the cycle shown in Figure 1, excepting the reprocessing losses. In order to find the optimal scenario, some free parameters may change. These free parameters to be determined are the energy shares of PWR, EPR, SFR and ADS in the burning and stabilization phases.

Two additional boundary conditions or constraints have been considered in this work. Firstly, related to the robustness of the scenario, it has been assumed that no external TRU mass is required for the scenario to fulfil its objectives, meaning that it always has its own available TRU for fuel fabrication and the scenario does not break due to lack of resources. Secondly, related to the sustainability goal, the stabilization phase is mathematically described as the TRU mass inventory changes in the last 10 years of the scenario must be smaller than 1 t. In particular, this assumption has been divided into two, to avoid possible compensations: the changes in the separated amounts of Pu and MA must be smaller than 1 t in the last 10 years of the scenario.

METHODOLOGY

The TR_EVOL code has been improved with the implementation of a feature based on a Differential Evolution (DE) algorithm (Storn and Price, 1997, 1995) to solve optimization problems. This algorithm works by means of an iterative process in which candidate solutions are randomly selected (values of the free parameters, in this study, the energy shares of the different reactor fleets in the second and third stages) and then updated using stochastic operators. Each step includes an automatic selection of the best candidates (those that are closer to the chosen objectives) and the worst are disregarded. With this method, the search for the optimum scenario is done by steps, focusing on the region of the space that produce the best results.

The particular algorithm implemented in TR_EVOL has been the Differential Evolution for Multiobjective Optimization (DEMO) algorithm (Robic and Filipic, 2005). The DEMO algorithm is an extension of the DE method, with a special selection of the best solutions: the algorithm compares the solutions in search for the one providing the lowest penalty. In TR_EVOL this penalty is defined as the squared sum of the boundary conditions or constraints defined in the previous sections.

It has to be mentioned that the presence of uncertainties produces a probability density function of the solution parameters instead of a single value and that there is no guarantee that the solution without uncertainties will remain stable with the use of uncertainties. In order to account them, the Sample Average Approximation (Ruszczyński and Shapiro, 2003) has been employed. It consists in drawing several samples from the uncertainty parameters, and taking the average value of the obtained results for a given set of input parameters.

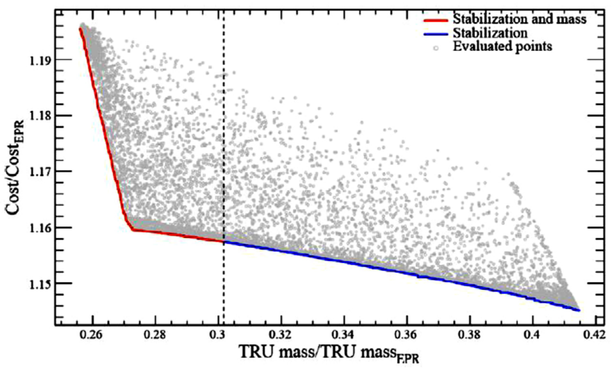

Figure 2. Solutions of the optimization problem without uncertainties, including the Pareto front.

RESULTS

Without uncertainties

The results of the optimization process in the case that no uncertainties are considered in the energy production and the reprocessing capacity are shown in Figure 2, where every grey dot corresponds to a feasible solution. In the axes, both objectives to minimize can be found (cost and TRU mass) relatively to an open cycle. The coloured curve in the figure shows the so-called Pareto front, where the dominant solutions are represented. Red/blue colour meaning will be explained later. First, the Pareto front shows that to reduce the TRU mass, the cost must increase, meaning that both objectives cannot be fulfilled at the same time. This is due to the fact that to reduce the relative TRU mass, new advanced and more expensive technologies (SFR, with a cost increase of 15% regarding the EPR and ADS, with a cost increase of 3.8 regarding the EPR, according to (Skarbeli et al., 2020)) must be commissioned.

Also, an L-shaped dependence can be found between the cost and the TRU mass in the Pareto front, with ~0.272 in the X axis as the point where the elbow is located. In order to analyse this result, the Pareto optimal solutions for the input parameters have been analysed. They are shown in Figure 3, where pairwise representations of the objectives and the free parameters are included. In this figure, subscript refers to the phase in which the parameter is being considered, for instance, ADS2 means the ADS fleet in the second, burning phase. Note that with this representation, the Pareto front shown in Figure 2 appears now in subfigure 5.1 in Figure 3. These subfigures allow obtaining, for any point in the Pareto front, all the data concerning the free parameters.

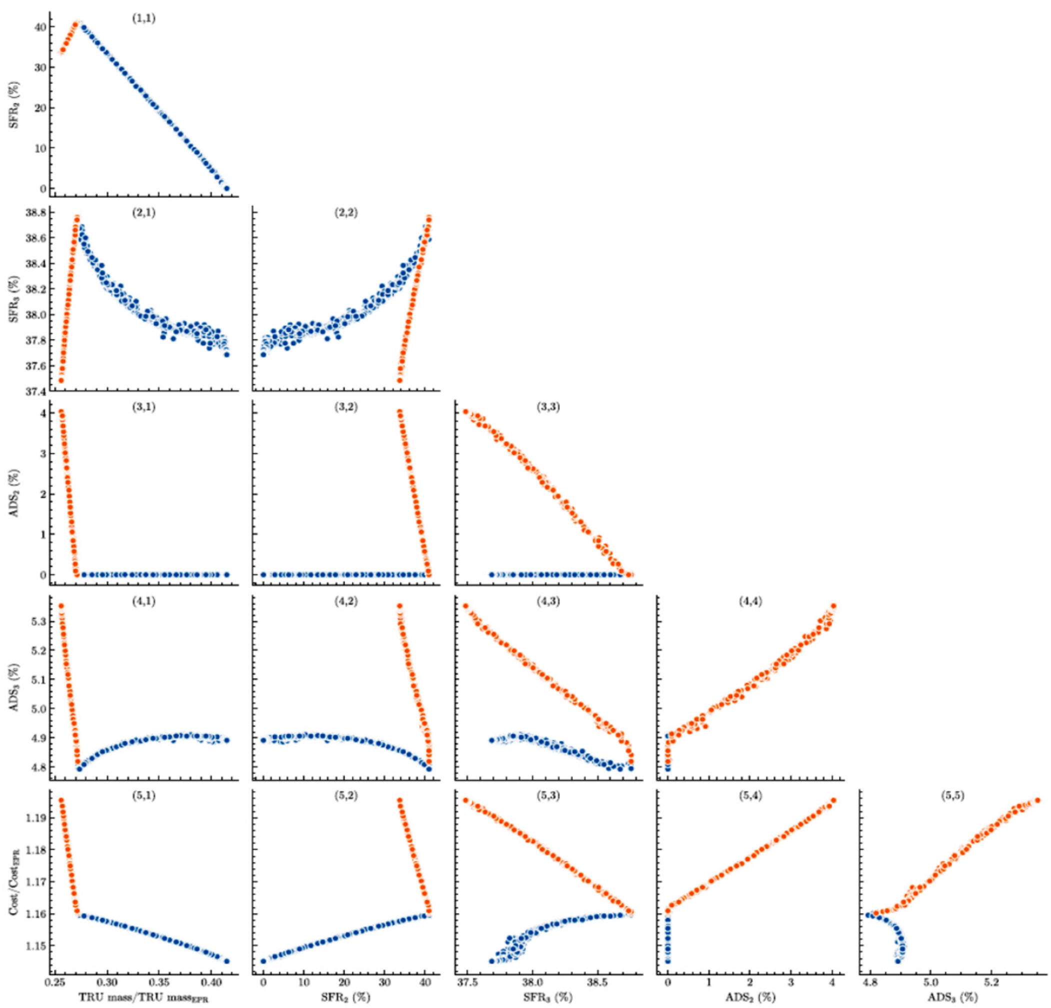

Figure 3. Pairwise representation of both optimization objective and the input optimization parameters.

All subfigures in Figure 3 show two different branches in the results, which have been coloured (as in Figure 2) in orange and blue. These two different branches are separated according to the relative value of the TRU mass: In orange, the points correspond to values of the relative TRU mass smaller than 0.272 while in blue, points have values of the relative TRU mass larger than 0.272. Considering subfigure 5.1, these two branches represent the values that minimize the cost (in blue) and that minimize the TRU mass (in orange). For instance, during the burning phase, subfigure 1.1 shows that during the burning phase the SFR energy share has to range between 34% and 42% for the minimization of the TRU inventories, while subfigure 3.1 shows that the ADS share has to be between 0 and 4%. On the other hand, the cheapest scenarios are found when no ADS are commissioned in the burning phase (subfigure 5.4) and the SFR share is low (subfigure 5.2). Besides, subfigure 5.4 also shows why the sharp increase in the TRU mass/TRU $mass_{EPR}$ around 0.272 in the Pareto front in Figure 2: The introduction of the ADS during the burning phase reduces the TRU mass but at a significantly higher cost.

With uncertainties

Once the uncertainties are included in the scenario calculations, the robustness of the solutions can be checked attending to the two constraints defined in the previous sections. Results show that none of the solutions found in the Pareto front of the scenario without uncertainties was stable, meaning that at least one of the constraints is violated. The Pareto front coloured line in Figure 2 shows this fact: in blue, the Pareto front points violate the stabilization constraint and in red, the solutions violate both stabilization and additional mass need (in this case, the TRU is minimized and the scenario is pushed to the limit, producing a scenario break due to lack of material), when uncertainties are considered. This evidences that dealing with uncertainties may lead to suboptimal solutions and that these may not be stable.

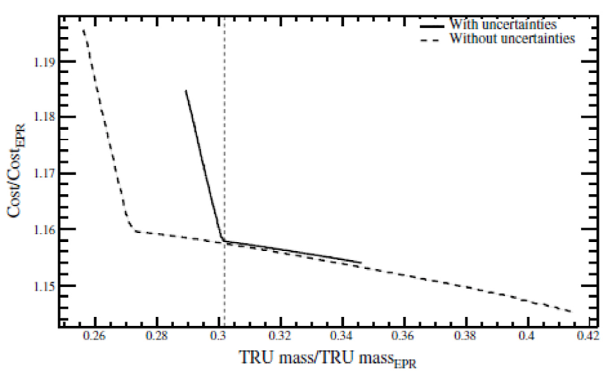

Figure 4. Pareto front of the optimization problem with and without uncertainties

Given that none of the solutions in the Pareto front obtained without uncertainties is viable when uncertainties are considered, the new solutions produce a new Pareto front, as shown in Figure 4. The figure shows how the uncertainties make the new Pareto front (continual line) be located inside the region of non-dominant but feasible solutions obtained in the case without uncertainties. The solutions for the cost parameter space (chosen as an example for clarity) are shown in Figure 5, where two different branches can again be found. The separation between the branches occurs at a relative TRU mass of 0.301 (subfigure A). Again, following the interpretation introduced in the previous section both branches can be identified with TRU minimization (orange) and cost minimization (blue). Also, the L-shaped lines can be found in the case with uncertainties because of the introduction of ADS in the burning phase.

Figure 4 shows that the effect of the uncertainties is to shrink the solutions space, since now the ranges of the relative cost and the relative TRU mass are smaller than in the case without uncertainties. Consequently, the energy share of the SFR+ADS fleet must be lower when compared to that case, which was expected given that the scenario is pushed to the limit and it has to remain feasible in the presence of uncertainties.

CONCLUSIONS

In the recent years, the nuclear fuel cycle tools have been improved to consider both uncertainties and optimization problems for decision making but, due to its complexity, only decoupled analyses were possible and hence the optimization problems suffered from lack of robustness. In this work, a methodology for performing optimization analyses in the presence of uncertainties has been developed and tested using an advanced nuclear fuel cycle scenario involving light water reactors and advanced designs. In particular, the parameters to optimize were the cost of energy and the TRU mass at the end of the scenario, having the energy share of the different fleets as free parameters. The uncertainties were present in the energy production of the whole scenario and the reprocessing capacity.

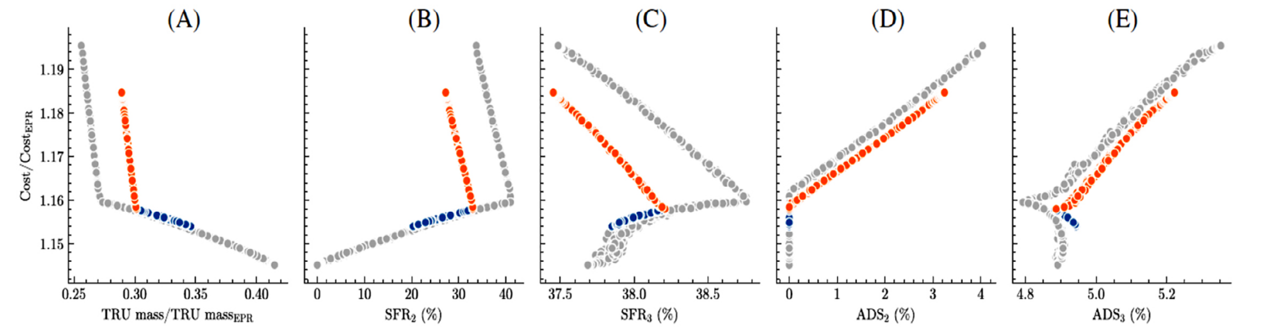

Figure 5. Scatter plots between cost and free parameters/TRU inventories for the uncertainty case (coloured). In grey, results for the case without uncertainties.

In the first analysis of the scenario without uncertainties, it was found that both objectives cannot be fulfilled at the same time. The Pareto front obtained that a TRU mass reduction of 60% to 75% could be achieved with a cost increase of 20% to 15%, respectively, compared to an open cycle scenario. These results were shown to be unstable, meaning that they could not be obtained in the presence of uncertainties.

The analysis of the optimization problem in the presence of uncertainties proved that the Pareto front is shrunk, as a consequence of constraint violations. The new Pareto front where the constraints are respected, that is, there is equilibrium at the end of the scenario and there is no need of external material, showed that a TRU reduction of 65% to 71% can be obtained with a cost increase of 18.5% to 16%, respectively, regarding the open cycle. These results show that uncertainties play a major role in optimization problems and therefore they must be included in the analyses.

ACKNOWLEDGEMENTS

This work was supported in part by the Spanish national company for radioactive waste management ENRESA, through the CIEMAT-ENRESA agreement on "*Transmutación de residuos radiactivos de alta actividad*" and the Spanish "*Programa Estatal de I + D + I Orientada a los Retos de la Sociedad*" project SYTRAD2 (ENE2017-89280-R).

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