

# Assessment of strategy robustness under disruption of objective in dynamic fuel cycle studies

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## Abstract

*The future of nuclear power depends on the interests and decisions. To take the relevant deep uncertainty into account, a new methodology of robustness analysis of fuel cycle strategies has been developed. The method has been applied to the French cycle, considering the future deployment of fast reactor as the pre-selected objective and an uncertain change, called disruption, towards a new objective: the minimization of transuranic inventories without fast reactor. The status of plutonium is contradictory in two cases. Two approaches of identifying robust strategies were tested, which correspond respectively to the static and adaptive robustness assessment. One identifies static strategies in a pre-disruption scenario, which achieve acceptable outcomes for both objectives. The other takes a trajectory pursuing the pre-selected objective and, in case of disruption, adapts it for the new objective. The comparison of two approaches indicates the temporality of adaptation relative to immediate actions under the uncertain disruption.*

*Keywords: Nuclear fuel cycle, Robustness, Disruption of objective, Status of plutonium, Temporality of adaptation*

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## I. INTRODUCTION

Deployment of Sodium-cooled Fast Reactors (SFRs) of GEN IV used to be one of the referential perspectives of nuclear power development in France [1][2]. Some studies of nuclear fuel cycle show that the integration of SFRs can reduce the pressure on the interim storages of spent fuels (SFs) [3] as well as the consumption of natural uranium resources [1][4], and it is possible to stabilise the plutonium inventories in the cycle [5]. If SFRs are deployed, plutonium (Pu) inventories in the interim storages of SFs will be strategic resources because plutonium is one of the main element of SFR fuels in European design [6]. However, given the cancellation of ASTRID project [7], the SFR deployment in France seems to be uncertain. If the planning of SFR deployment is given up, plutonium inventories can be considered as potential nuclear wastes due to the high toxicity during long time. In particular, the minimization of all transuranic inventories (TRU) in the fuel cycle is emphasised in this case. Concerning the status of plutonium, these two states of future are contradictory. Owing to the deep uncertainty of future and objectives, the relevant strategy specific to the nuclear power development cannot be simply decided.

Optimisation methods of dynamic fuel cycle simulations in nuclear scenario studies can identify optimal strategies with respect to given objectives which are not changed over time. Given a single objective of stabilization of TRU inventories, [8] identify appropriate parameters of the fuel cycle using UOX and MOXEUS fuels in Pressurised Water Reactors (PWRs). Another study analyses the strategies of SFR deployment quantity in different phases, which can minimise both the consumption of natural uranium resources and the nuclear waste packages [9]. But these methods of optimisation cannot provide sufficient information of strategies or related consequences if the objective is deeply uncertain, especially when the possible choices are contradictory. In this situation, the robustness assessment of alternative strategies is more important than the optimisation.

This work develops a method of robustness assessment on possible strategies subject to such uncertainty. The concept of robustness is commonly employed in sociological studies and policy-making; but in practice, lots of metrics introduced in robustness assessment study are sometimes different or even inconsistent [10], and there is no standard mathematical definition. In this work, we will present our definition of robustness adapted for nuclear fuel cycle analysis. This paper is divided in four parts. Firstly, based on the example of objectives mentioned above, definition of disruption and the two approaches relevant respectively to static robustness and adaptive robustness are introduced. In the second step, a pre-disruption scenario is presented, in which the robust static strategy is identified. The static robustness of possible strategies is analyzed. In consideration of the information updating upon the uncertainty, adaptive strategies for the change of objective are studied, which is related to the adaptive robustness. Finally, in addition to concluding the strategy robustness and the temporality of adaptation in this example, we discuss the validity of our method as well as the relevant implicit assumptions.

## II. METHOD OF ROBUSTNESS ASSESSMENT

In dynamic fuel cycle simulations of nuclear scenario studies, trajectories of nuclear system are simulated under a set of assumptions. A trajectory denotes a single evolution of the nuclear system, with parameters and operation states explicitly set at each step of time. In the simulation, a trajectory is one deterministic run, with material evolutions well defined in all facilities simulated. A strategy is usually represented by a group of variables, which are some specifically controllable parameters. For example, nuclear industry can evaluate and then decide the burn-up of UOX fuel in current PWRs. Specified by these controllable parameters, a strategy leads to a trajectory when

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other parameters are well defined (and it is the case in our work, because the uncertain factor in this work is assumed to be the objective in the scenario, and all parameters of the fuel cycle can be well decided if a strategy is given). It seems that a trajectory is equivalent to a strategy, but they are conceptually different: a trajectory describes the evolution, whereas a strategy formalises a trajectory into variables and links the outputs to the objective in scenario studies. Involving the performance related to a given objective, a strategy can be assessed, but it does not make sense to evaluate a trajectory.

### i. Simulation of the French fleet by CLASS

The dynamic fuel cycle simulation is performed by the simulator CLASS, which employs artificial neuron networks to build simulation models [11]. For example, the equivalence model predicts the fissile content of fresh fuel for a given burn-up according to the isotopic composition of resources; the irradiation model simulates the evolution of material in the reactor. To carry out a fuel cycle simulation, facilities such as fabrication plant, reactor and cooling pool are simulated; the material flows among facilities are also taken into account. Take the French fleet of PWR UOX and PWR mono-MOX as example, which is simulated in this study. For a required burn-up of UOX fuel depletion, UOX fresh fuel is fabricated in the UOX fabrication plant for given time of fabrication. The fresh UOX fuel is then transported (instantly) to the PWR UOX. After the depletion, UOX SFs are put in the pool for a given time span of cooling. The UOX SFs is then available for reprocessing and MOX fabrication if it is demanded. To highlight the availability, the storage of SFs after necessary cooling is simulated separately from the pool. The MOX fuel follows the same steps in the cycle, except that the MOX SFs are not reprocessed because the Pu is mono-recycled in this example. Descriptions in detail of physics model building and facility simulation by CLASS can be found in [11].

Based on the French fleet, PWRs are normalized into 2 macro-reactors in this work. In other words, instead of 58 individual reactors, only 2 are simulated: one is a PWR UOX that contributes to 90% of the fleet total power, being 169.2 GWth at nominal state; the other is a PWR MOX with 18.8 GWth. The loading factors, burn-ups and heavy metal mass of 2 reactors are normalized according to the information of 58 reactors, summarized in [8].

### ii. Objectives, criteria and disruption

To illustrate the assessment method, the French fleet of PWR UOX and PWR mono-MOX aforementioned is considered. The objective of SFR deployment for 100% of fleet in 2090 is pre-selected. One of the most important constraints of deploying SFRs is the availability of plutonium inventory. To quantify the capacity of substituting the nuclear fleet of PWRs with SFRs at a given time, the ratio of substitution, denoted as  $R_{Subs}$ , is defined:

$$R_{Subs}(t) = \frac{P_{deployable,SFR}(Pu_{in}(t))}{P_{tot,elec}(t)} \quad (1)$$

where  $P_{deployable,SFR}$  denotes the deployable electric capacity by break-even SFRs only depending on the in-cycle inventory of plutonium  $Pu_{in}$ ;  $P_{tot,elec}$  denotes the total electric capacity of the nuclear fleet. In the definition,  $P_{deployable,SFR}$  only depends on the in-cycle Pu inventory, which means that SFR is not simulated. In this work, the specific thermal power of a SFR is supposed to be 48 MW/tHM as the model built in [12]; the core-average Pu content in the initial heavy metal of fresh fuel is supposed to be 17%, approximative to the design in [6]. It means that the content fluctuation due to isotopic effects and other operation requirements are neglected (for

instance, the fresh fuel richer in  $^{239}\text{Pu} + ^{241}\text{Pu}$  will require smaller content of Pu than the one richer in other Pu isotopes for the same burn-up). Besides, the dependency on the inventory of in-cycle plutonium  $Pu_{in}$  means that the plutonium in the cooling pools and even in the operating PWRs are required to achieve such ratio of substitution. Time of Pu recycling for SFRs, including two years of fuel fabrication and five years of SF cooling, is also taken into account, which means that the quantity of  $Pu_{in}$  allows to deploy SFRs with a capacity indicated by  $R_{Subs}$  in a closed cycle. Since the nuclear reactors are defined with thermal power in CLASS [11], the yield of a PWR and an SFR are supposed to be 34% and 40% respectively.

Value of  $R_{Subs}$  indicates that at the given time  $t$ , a fraction  $R_{Subs}$  of this PWR-fleet with  $P_{tot,elec}$  can be replaced by SFRs according to the material availability. Theoretically, SFR deployment for 100% of fleet requires a strategy leading to  $R_{Subs}(t = 2090) = 1$ . However, because of those assumptions on the estimation of  $P_{deployable,SFR}$  without simulation of SFR, a margin on the  $R_{Subs}$  should be taken to achieve the objective of SFR deployment, and thus a criterion of  $R_{Subs}(t = 2090) > 1$  is required. Moreover, the future of SFR deployment will not evolve to a phase-out state. For the first step, we suppose that the capacity of the nuclear fleet will finally evolve to a level between 50% and 150% of the current one. The objective pre-selected in this study, called "objective A" in the following, and the relevant criterion  $C_A$  can be summarized as:

- Obj. A: SFR deployment for 100% of fleet in 2090 with a capacity evolving finally to [50%, 150%] of the current one (64 GWe/188 GWth currently).
- Criterion  $C_A$ :  $R_{Subs}(t = 2090) > 1$  and maximization of  $R_{Subs}(t = 2090)$

One may consider that the criterion  $C_A$  is not sufficient to choose the strategies achieving objective A. The deployment of such new reactors is complicated, involving the development of SF reprocessing and fresh fuel fabrication plants, the requirement of new technology and nuclear safety, the engineering complexity, etc. In this work, these practical constraints are neglected, so that we can focus on the single factor of material availability.

It is possible that the objective pre-selected today will be changed before 2090. The change can be triggered by an accident, by economic and political interests of stakeholders, or by other factors that are not well previewed. Neither the probability nor the time of change is well estimated. The change of objective in such deep uncertainty is called the disruption of objective. If the pre-selected objective of SFRs deployment is given up, one may consider primarily the minimization of potential nuclear wastes in total cycle. We take the TRU inventory in the total cycle, noted as  $TRU_{tot}$ , as the output of interest for the new objective. In case of the disruption, new strategies are explored in order to minimize the TRU. Different from the context of objective A, a phase-out strategy is possible. Thus, the new objective and the relevant criterion  $C_B$  linked to the disruption can be summarized as:

- Obj. B: Minimisation of nuclear wastes without deployment of SFR; phase-out strategy is acceptable.
- Criterion  $C_B$ : Minimization of  $TRU_{tot}(t = 2090)$

Two foregoing objectives correspond to different states of future, indicating different criteria and strategy spaces. Nonetheless, it does not mean that the TRU cannot be minimized if the objective A is pursued; neither does it mean that the minimization of TRU inventory is the sole choice if SFR deployment is abandoned. Other objectives and criteria can also be suggested. For example, the minimization of nuclear wastes normalized by the electricity produced by reactors, or the minimization of natural uranium consumption can be considered after disruption. The objectives and the related criterion aforementioned are selected to simplify the analysis, and at the same time, to keep the contradiction between them.

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### iii. Pre-disruption precaution, post-disruption adaptation and the robustness of strategy

In the context of deep uncertainty, a robust strategy is often considered to be insensitive to violated assumptions and to have acceptable performance within a wide range of future states [13]. In our study, the possible violation of assumption is associated with the disruption of objective. To study the robustness of possible strategies under deep uncertainty in this work, two approaches are suggested, which are respectively related to static robustness and adaptive robustness described in [14]. One approach starts from the principle of precaution before disruption: the strategy is decided in a precautionary manner that assures an acceptable level of performance for any possible objective finally determined. Strategy studied in this approach is considered static, which means that parameters of system at each time step are decided at the beginning, and the decision of evolution of these parameters is not changed in case of the disruption. Since the disruption is deeply uncertain, the analysis of static strategy allows to estimate preliminarily the consequences on different states of future. The static robustness is assessed for static strategy. Technically, it is equivalent to study strategy performance in a multi-objective problem, in which the optima of problem are regarded as robust static strategies. Due to the contradiction of possible objectives, robust static strategies in the Pareto front trade some performance on one objective to another. In this work, a criterion  $C_{B|A}$  is defined to give a single optimum, called robust static optimum:

- Criterion  $C_{B|A}$ : Minimization of  $TRU_{tot}(t = 2090)$  under the condition of  $R_{Subs}(t = 2090) > 1$

By definition, the robust static optimum achieves the lowest  $TRU_{tot}(t = 2090)$  among all static strategies which keep theoretically the Pu availability for complete SFR deployment by 2090.

The other approach is based on the post-disruption adaptation: a strategy dedicated to the pre-selected objective (the A in our example) is firstly implemented; once the disruption takes place, the related trajectory will be adapted with readjustments for the new objective. Based on the given prior trajectory, the new adaptive strategy that minimizes  $TRU_{tot}(t = 2090)$  is called the adaptive optimum (under the disruption from objective A to B). Since only one trajectory is adapted in this work, the notation of "based on the given prior trajectory" is omitted in the rest of paper. If several trajectories are adapted, the link between the adaptation scenario and the prior trajectory should be highlighted. Adaptive robustness is assessed for adaptive strategies. In this work, an adaptive strategy is considered robust and called robust adaptive strategy if it has better performance (thus lower  $TRU_{tot}(t = 2090)$ ) than the robust static optimum. According to the assessment criterion, the adaptive optimum can be robust or non-robust over the time of adaptation, which indicates the temporality of adaptive robustness: if the adaptive strategy is implemented before the time limit, the prior trajectory can be readjusted to accumulate TRU inventories as low as the pre-disruption strategy with sufficient precaution; otherwise, there is regret in comparison to this optimal strategy decided before disruption. The temporality may impact the decision-making vis-à-vis the deep uncertainty of disruption.

To simplify the notations, the time "t=2090" is omitted when the outputs of interest  $R_{Subs}(t = 2090)$  and  $TRU_{tot}(t = 2090)$  are mentioned. Nevertheless, the year 2090 is so important that the subsequent analysis depend directly on it.

## III. PRE-DISRUPTION SCENARIO

### i. Design of experiment of the pre-disruption scenario

First of all, the pre-disruption scenario is studied: the objective A aiming at deploying SFRs in 100% of fleet by 2090 is pre-selected, while the stakeholders may remain a doubt on the disruption

towards the objective B, the minimization of TRU in total cycle without SFR deployment in the future. Subject to the deadlock between two contradictory objectives without a definitive decision, strategies are explored by varying the parameters of the fuel cycle, which requires the simulation of a large quantity of trajectories. Two outputs of interest,  $R_{Subs}$  and  $TRU_{tot}$ , are calculated for these trajectories.

The simulation of fuel cycle starts from the current French fleet, in which the PWRs are normalized to two macro-reactors, a PWR UOX and a PWR mono-MOX. To explore possible strategies, a transition is considered, starting from the time  $T_{start}$  (between 2030 and 2050). The transition will last for more than 10 years (duration denoted as  $D$ ) and end before 2090. In  $T_{start}$ , the burn-ups of UOX and MOX fuels (denoted respectively as  $BU_{UOX}$  and  $BU_{MOX}$ ), the cooling time of UOX SF (denoted as  $TC_{UOX}$ ) and the UOX SF reprocessing management for MOX fuel fabrication (denoted as  $MPu$ ) will be redetermined. The UOX SF reprocessing management for MOX fuel fabrication is either LiFo, "Last in First out", or FiFo, "First in First out". During the transition, the total thermal power as well as the MOX fraction of fleet changes linearly towards their final value (denoted as  $P_{tot,f}$  and  $FrMOX_f$ ); after the transition, they will keep constants until the end (year 2090). Under these hypotheses, possible strategies and the related trajectories are characterized by eight variables. The ranges of variation of these eight variables are presented in table 1. These strategies explored in the pre-disruption scenario are the so-called static strategies, since they are decided at the beginning of scenario, and the performance is evaluated at the end of scenario without adaptation.

Table 1: Initial values and variation ranges of variables of the pre-disruption scenario

Var.	$T_{start}$	$D$	$P_{tot,f}$	$FrMOX_f$	$BU_{UOX}$	$BU_{MOX}$	$TC_{UOX}$	$MPu$
<b>Init.</b>	-	-	188	10%	45.3	45	5	LiFo
<b>Min.</b>	2030	10	94	0%	30	30	3	1/LiFo
<b>Max.</b>	2050	$2090 - T_{start}$	272	30%	60	60	10	2/FiFo
<b>Unit</b>	-	year	GWth	-	GWd/t	GWd/t	year	-

Depending on the interest of stakeholders, some of these eight parameters are controllable, while others are not. In our study, we suppose that all of them are controllable so that the strategy space can be reasonably large for exploration. Their ranges of variation are not completely arbitrary: some of them are based on industrial and economic constraints (the ranges of  $FrMOX_f$ ,  $BU_{UOX}$ ,  $BU_{MOX}$ ,  $TC_{UOX}$  and  $MPu$ ), while others are associated with the assumptions of the future nuclear power development in France. The range of  $T_{start}$  supposes that the transition will start after the commissioning of the first European Pressurised Reactor (EPR) in France (around 2030 as supposed), and some old reactors will be shut down. The range of  $D$  cannot be too short because a period of adjustment is necessary for the change of electricity supply by nuclear power and the change of MOX fraction (related to licenses for MOX, fabrication capacity, etc.). Because the deployment of SFR is regarded as the pre-selected objective, the future installed capacity of fleet cannot be too low; the range of  $P_{tot,f}$  supposes therefore a wide range of possibility. Nonetheless, the control of total power of fleet for a given objective seems unreasonable, since it is related to the commissioning and shut-down of reactors; under the technical and the economic constraints, the controllability of total capacity of fleet by stakeholders is not obvious. One may also reckon that the evolution of total capacity should match the electricity demand and it is not controlled in the same way as other fuel cycle parameters. Anyway, the discussion on the nature of  $P_{tot,f}$ , to be controllable or not, is out of the scope of study. For the development of method, all groups of stakeholders who may "virtually control" the total capacity of fleet in order to achieve a given

objective, are included in this work.

## ii. Preliminary study of the nuclear system by Principal Component Analysis

According to the space of strategy aforementioned, 6400 strategies are selected by Latin Hypercube Sampling (LHS) [15] and the related trajectories are simulated. 3177 are valid without the Pu shortage for MOX fabrication before 2090. The problem of Pu shortage is well studied in [16], and in our work those invalid trajectories are not of interest. For each valid trajectory characterized by eight input variables, the outputs  $R_{Subs}$  and  $TRU_{tot}$  in 2090 are calculated. To study the impacts of input variables on a given output in a valid space a-posteriori defined, principal component analysis (PCA) is performed.

PCA identifies an orthonormal transformation of original variables to create new ones, called principal components (PCs), such that: the first created variable maximizes the variance among all possible linear combinations of original variables; the second one maximizes the variance among all possible linear combinations uncorrelated to the first one; the iterative steps are successively performed, subject to the condition that the new created variable is uncorrelated to all previously created ones. Mathematically, the eigenvalue-eigenvector pairs of the covariance/correlation matrix of original variables are respectively the variances of PCs and the corresponding linear combinations. In summary, the relation between an  $n$ -dimension vector of original variables  $\mathbf{X}$  and the vector of principal components  $\mathbf{Y}$  is  $\mathbf{Y} = \mathbf{A}^t \mathbf{X}$  or  $\mathbf{X} = \mathbf{A} \mathbf{Y}$ , where the columns of the  $n \times n$  orthonormal matrix  $\mathbf{A}$  are composed of the normalized eigenvectors of the covariance/correlation matrix of  $\mathbf{X}$ .

PCA is often used to reduce the dimensionality of variables, identifying a smaller number of variables (PCs) which account for the major variability of original variables; in this work, it is used to highlight the importance of an input variable on a given output. The output variable is considered to be a component of the original variable, so that the original variable vector is under the form of  $\mathbf{X} = (T_{start}, D, \dots, MPu, X_{out})$  where  $X_{out}$  denotes the output of interest  $R_{Subs}$  or  $TRU_{tot}$ . The square of correlation coefficient between  $X_{out}$  and the  $j$ -th PC  $Y_j$  is calculated, denoted as  $\rho^2(X_{out}, Y_j)$ . Letting  $\alpha_{ij}$  be the  $(i, j)$ -th element of matrix  $\mathbf{A}$  aforementioned, a brief proof is given in [17] that

$$\rho^2(X_{out}, Y_j) = \frac{\alpha_{out,j}^2 V(Y_j)}{V(X_{out})} \quad (2)$$

where  $V$  denotes the variance, and the index  $out$  of  $\alpha_{out,j}$  denotes the row with respect to the position of  $X_{out}$  in the variable vector. Given the orthonormality of  $\mathbf{A}$  revealing that

$$V(X_{out}) = \sum_j \alpha_{out,j}^2 V(Y_j) \quad (3)$$

$\rho^2(X_{out}, Y_j)$  can be interpreted as the fraction of the variance of  $X_{out}$  explained by  $Y_j$ . In other words, if  $Y_j$  is highly correlated with  $X_{out}$ , the majority of variation of  $X_{out}$  can be explained by  $Y_j$ , and thus  $X_{out}$  can be sensitive to  $Y_j$ . In this case, because the coefficients of linear combination can indicate the weights of original variables on  $Y_j$ , they indicate the impacts of corresponding original variables on  $X_{out}$  as well.

One should distinguish the variability of original variables from the one of output  $X_{out}$ . The variability of all original variables include the ones of inputs sampled in a large exploration space, whereas the output of interest is a function of these input variables. Even though PCs are originally defined and used to represent the original variables with variability as large as possible (indicated by the corresponding eigenvalues of covariance/correlation matrix), we focus principally on the

variance of  $X_{out}$  explained by PCs (indicated by  $\rho^2(X_{out}, Y_j)$ ) which allows to analyze the influence of the input on the output  $X_{out}$ .

In practice, the analysis with the output  $R_{Subs}$  and the one with  $TRU_{tot}$  are separate. Valid observations of 9-dimension vector (8 inputs + 1 output) are considered. PCs of the dataset are identified after being centred and scaled in the software R [18]. After that, the squares of correlation coefficients  $\rho^2(R_{Subs}, Y_j)$  (resp.  $\rho^2(TRU_{tot}, Y_j)$ ) are calculated, indicating the fractional variation of  $R_{Subs}$  (resp.  $TRU_{tot}$ ) explained by PCs. Once the most correlated PC is found, the coefficients that transform original variables to this PC are investigated; due to the high correlation between the PC and  $R_{Subs}$  (resp.  $TRU_{tot}$ ), the coefficients of original variables indicate their importance on  $R_{Subs}$  (resp.  $TRU_{tot}$ ).

The correlation between a given PC and the output of interest in two analyses are shown in table 2. The PCs are ordered by the corresponding eigenvalues of the correlation matrix of original variable data: the PC  $Y_1$  has the largest variance and thus it explains most of the variability of original variables among all PCs, whereas the PC  $Y_9$  has the smallest variance. The variability of PCs are also presented by the ranges of axis in figure 1a and 1b.

Table 2: Correlation squares between the given output  $X_{out}$  and PCs in the corresponding PCA

$\rho^2(X_{out}, Y_j)$	$Y_1$	$Y_2$	$Y_3$	$Y_4$	$Y_5$	$Y_6$	$Y_7$	$Y_8$	$Y_9$
$X_{out} = R_{Subs}$	.88	.02	.04	.00	.00	.00	.03	.01	.02
$X_{out} = TRU_{tot}$	.95	.01	.02	.00	.00	.00	.00	.00	.02

Regarding  $R_{Subs}$ ,  $Y_1$  can explain about 88% of the variance of  $R_{Subs}$ . It means that as a linear combination of original variables,  $Y_1$  has a strong impact on the output  $R_{Subs}$ , which can be observed in the scatter plot of  $Y_1$  and  $R_{Subs}$  in figure 1a. Table 3 shows the coefficients of original variables with respect to  $Y_1$ . Besides  $R_{Subs}$  itself, the coefficient of  $P_{tot,f}$ , which means that  $P_{tot,f}$  also has a large weight in the component  $Y_1$ . Given the high fraction of  $R_{Subs}$  variance explained by  $Y_1$ , it indicates the strong impact of  $P_{tot,f}$  on  $R_{Subs}$ . The coefficients of  $FrMOX_f$  and  $BU_{UOX}$  seem non-negligible. Other input variables contribute to the variability of other PCs on which  $R_{Subs}$  has little dependence, as shown by scatter plots in figure 1a, and thus they have little effect on the variation of  $R_{Subs}$ .

One may argue that the weak correlation between a PC and  $R_{Subs}$  does not imply that they are weakly related, such as the special pattern of  $Y_9$  over  $R_{Subs}$  in figure 1a; and thus we cannot conclude that other inputs, possibly with high weights in the PC  $Y_9$ , have negligible influence on  $R_{Subs}$ . To answer this question, we should first note that the variation of  $Y_9$  is actually much smaller than other PCs. We can also verify the composition of  $Y_9$ , indicated by the coefficients of original variables in  $Y_9$  as presented in table 3. Similar to the weights in  $Y_1$ , the coefficients of  $P_{tot,f}$  and  $R_{Subs}$  are also large in  $Y_9$ ; the coefficients of  $FrMOX_f$  and  $BU_{UOX}$  seem non-negligible as well. Actually,  $Y_9$  is the last PC and explains the least of variability of original variable vector; Johnson and Wichern commented that [19] this last PC indicate an unnoticed linear dependency. As shown by the axis of PC,  $Y_9$  can be approximately regarded as constant due to its limited variation in comparison to other PCs. The coefficients of original variables in  $Y_9$  reveal therefore the linear dependency between  $P_{tot,f}$  and  $R_{Subs}$ . Again, the importance of  $P_{tot,f}$  on  $R_{Subs}$  is emphasized.

The same analysis is carried out with the output  $TRU_{tot}$  (the PCs deduced from the analysis with  $TRU_{tot}$  are different from the ones with  $R_{Subs}$ , because the analyses are separate). The PC  $Y_1$  shown in table 2 of PCA with  $TRU_{tot}$  can nearly explain the total variance of  $TRU_{tot}$ . The composition of  $Y_1$  presented in table 3 shows important weights of  $P_{tot,f}$  and  $FrMOX_f$  in addition to  $TRU_{tot}$ . As a result,  $TRU_{tot}$  is sensitive to  $P_{tot,f}$  and  $FrMOX_f$ . Other variables have non-measurable impacts



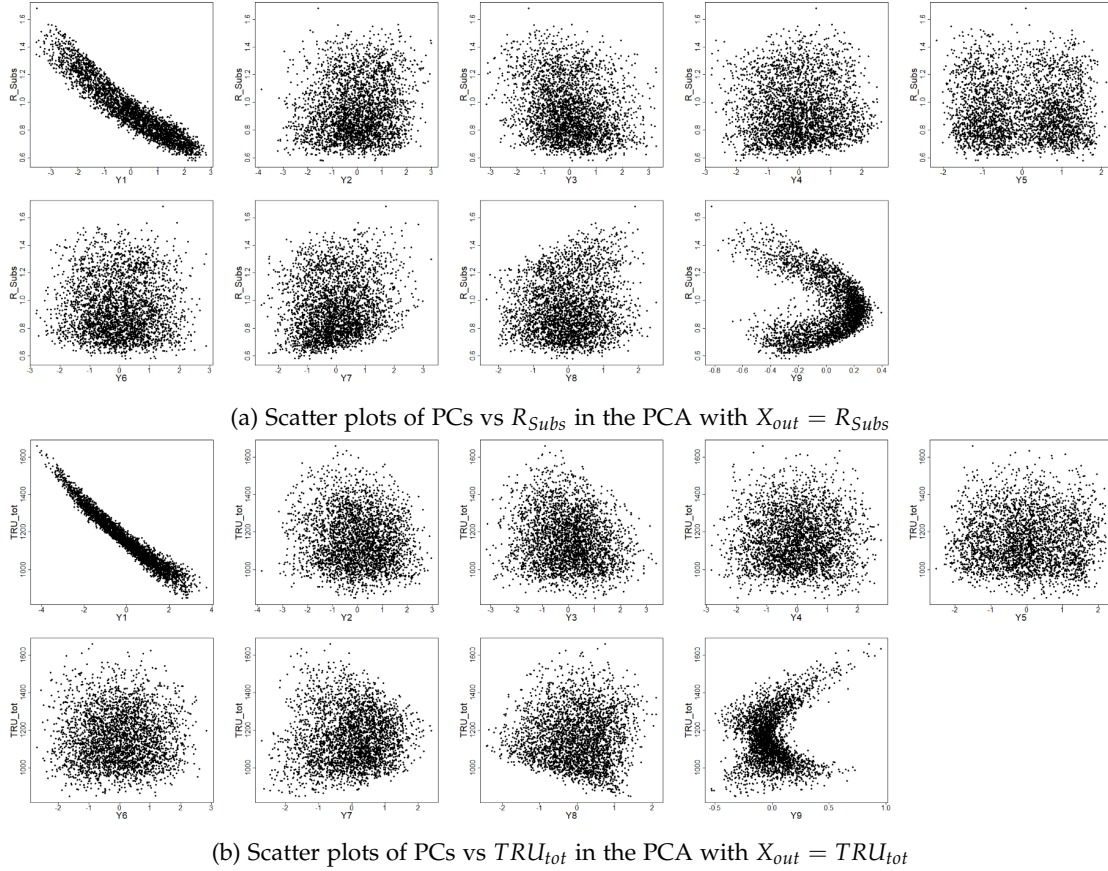


Figure 1: Scatter plots of PCs vs  $X_{out}$  in two PCA

on  $TRU_{tot}$ . The coefficients in  $Y_9$ , the PC with little variation, also indicate a strong dependence of  $TRU_{tot}$  on  $P_{tot,f}$ , and that it is possibly influenced by  $FrMOX_f$  and  $BU_{UOX}$ .

In conclusion, PCA and the correlation squares between the output and PCs help identify important input variables with regard to given outputs of interest in a simple but quantitative manner, and thus help understand the behaviour of system: the input variable  $P_{tot,f}$  dominates the behaviour of two outputs of interest  $R_{Subst}$  and  $TRU_{tot}$ ;  $FrMOX_f$  has measurable impact on  $TRU_{tot}$ ;  $FrMOX_f$  and  $BU_{UOX}$  may have some effect on  $R_{Subst}$  as well. Other parameters have non-measurable effects on two outputs of interest. This result should not be over-interpreted, because the importance of an input variable depends not only on the system and output of interest, but also on the assumptions of the design of experiment, such as the variation range. The non-measurable impact of an input on the output does not prove the independence between them; it only indicates that the contribution of this input within the given variation range is much smaller than the most impacting one.

### iii. Static robustness and robust static optimum

Result of two outputs of valid strategies without Pu shortage for MOX fabrication is shown in figure 2, coloured by the value of  $P_{tot,f}$ . Among them, the lowest  $TRU_{tot}$  achieved in 2090 is about 848 tons, and the maximal  $R_{Subst}$  is 1.68. The dispersion of points in figure 2 shows the

Table 3: Coefficients of original variables in the component  $Y_1$  and  $Y_9$  in two PCA

Coef. of	$T_{start}$	$D$	$P_{tot,f}$	$FrMOX_f$	$BU_{UOX}$	$BU_{MOX}$	$TC_{UOX}$	$MPu$	$X_{out}$
in $Y_1$ , $X_{out} = R_{Subs}$	-.02	-.05	<b>.68</b>	-.24	.17	.04	.03	.00	<b>-.67</b>
in $Y_9$ , $X_{out} = R_{Subs}$	.00	.01	<b>-.69</b>	-.19	-.17	-.01	-.01	-.02	<b>-.68</b>
in $Y_1$ , $X_{out} = TRU_{tot}$	.07	.08	<b>-.60</b>	<b>.41</b>	.09	.06	-.05	-.01	<b>-.67</b>
in $Y_9$ , $X_{out} = TRU_{tot}$	.02	.01	<b>-.59</b>	.25	.25	.03	.00	.00	<b>.73</b>

complexity of the relation between two outputs of interest for a valid strategy. Actually, within a small variation of  $P_{tot,f}$  (which means that the final level of nuclear capacity in France is well decided), two outputs show a strong correlation, plotted with the same colour. That is because the TRU in total cycle is principally composed of the in-cycle Pu inventory, which is proportional to  $R_{Subs}$  if  $P_{tot,f}$  is constant; when  $P_{tot,f}$  varies, the slope of the linearity changes as well, according to the definition of  $R_{Subs}$ . Trajectories with low  $TRU_{tot}$  and high  $R_{Subs}$  result from low  $P_{tot,f}$ , whereas a high level of power will finally yield high inventory of TRU and a relatively low material availability for future substitution of PWRs with SFRs.

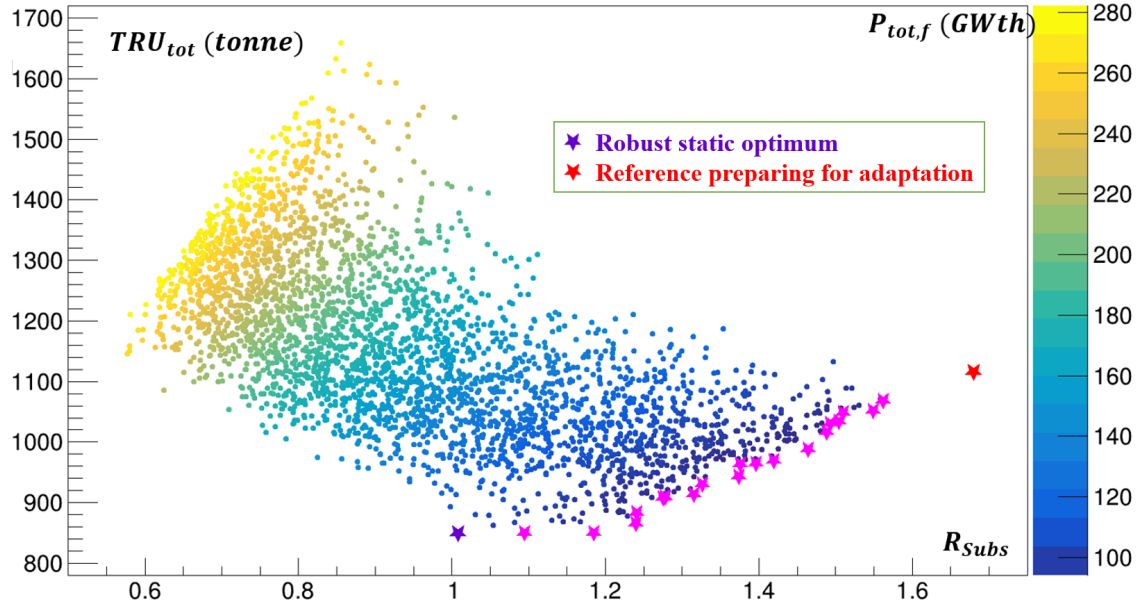


Figure 2:  $TRU_{tot}$  versus  $R_{Subs}$  of valid trajectories in pre-disruption scenario, coloured by  $P_{tot,f}$

The complexity of the relation between two outputs of interest indicates the contradiction of two objectives and the existence of the Pareto front, shown as stars in figure 2 (in consideration of objective A, their  $R_{Subs}$  should be larger than 1). They are robust static strategies if two objectives are considered at once, and present the competition between the risk of failing objective A and the regret on the TRU inventory production regarding the disruption towards objective B. According to the criterion  $C_{B|A}$ , the robust static optimum is shown as purple star in figure 2. The value of its inputs and outputs of interest are summarized in table 4. Particularly, it is also the global optimum for TRU minimization in the pre-disruption scenario, which means that the optimal strategy dedicated to TRU minimisation in the pre-disruption scenario can theoretically achieve

objective A.

The robust static optimum identified by the criterion  $C_{B|A}$  in the pre-disruption scenario leads to  $TRU_{tot}(t = 2090)$  as low as 848 tons, but to a margin less than 1% for objective A ( $R_{Subs} = 1.01$ ). Although the objective finally adopted in 2090 is unknown, this precautionary strategy sets a bound of optimal performance for TRU minimization among valid static strategies that achieves theoretically objective A.

Table 4: Variables and outputs in 2090 of the robust static optimum and the reference strategy in pre-disruption scenario

Traject./Strategy	$T_{start}$	$D$	$P_{tot,f}$	$FrMOX_f$	$BU_{UOX}$	$BU_{MOX}$	$TC_{UOX}$	$MPu$	$R_{Subs}$	$TRU_{tot}$
<b>Rob. stat. op.</b>	2031.0	14.2	109.4	13.6%	52.5	56.2	8.2	FiFo	1.01	848
<b>Ref.</b>	2032.7	56.3	94.6	1.9%	32.4	41.9	3.6	LiFo	1.68	1116
(Unit)	-	year	GWth	-	GWd/t	GWd/t	year	-	-	tonne

#### IV. POST-DISRUPTION: SCENARIO OF ADAPTATION

The strategy represented as a red star in figure 2, called reference strategy in the subsequent analysis, maximizes  $R_{Subs}$  among all possible static strategies. In conventional scenario study without consideration of disruption, the reference strategy can be chosen for the pre-selected objective A according to the criterion  $C_A$ . Its inputs and outputs are shown in table 4. The reference strategy leads to 68% of margin of Pu availability for objective A ( $R_{Subs} = 1.68$ ), and more than 1100 tons of TRU is accumulated in the cycle by 2090.  $FrMOX_f$  in this strategy is low so that Pu can be accumulated effectively, and the total thermal power evolves to a relatively low level so that  $R_{Subs}$  can be maximised.

In the analysis of adaptive robustness, readjustment by new adaptive strategies for the new objective B is allowed in case of disruption. Since the reference strategy is optimal for objective A before disruption, the related trajectory is adapted in this work. In other words, the reference strategy is supposed to be implemented specifically for the objective A before any disruption of objective; in case of the disruption towards objective B, new strategies is explored in order to minimize the TRU inventories.

The minimization of TRU in this adaptation scenario problem is based on a given prior choice of strategy before disruption (the reference strategy in this work); the global minimum that minimizes TRU over any possible trajectory before disruption is not studied. A-priori, if a trajectory of a static strategy presents fewer than 1000 tons of TRU by 2090, it is highly possible that a TRU-reduction adaptive strategy that adapts it will lead to lower TRU inventories than that the trajectory of reference strategy is adapted. Nevertheless, for the first step of applying the assessment method, two prior choices studied that respect the objective(s) before disruption should have "large difference" (from the viewpoint of the consequences of interest, e.g. indicated by  $R_{Subs}$  and  $TRU_{tot}$ ), in order to highlight the difference of consequence. The reference strategy and the robust static optimum are two extreme cases of preference in the pre-disruption scenario. The assessment of adaptive robustness depending on these two strategies may give a relatively wide range of information on the difference between a precautionary strategy (represented by the robust static optimum) and post-disruption adaptation (represented by the readjustment on the trajectory of reference strategy). Hence, the trajectory of reference strategy will be adapted in the following adaptation scenario study, and the results will be compared with the ones of robust static optimum.

### i. Design of experiment of post-disruption adaptation

In the scenario of post-disruption adaptation, the reference strategy is supposed to be implemented before disruption, and adaptation is allowed in case of disruption. To analyse the temporality of adaptive robustness, the adaptation time  $T_{ad}$  is sampled, which must be later than the disruption. To simplify, year 2040, 2050, 2060 and 2070 are considered for  $T_{ad}$ .

According to the objective B after disruption, the planning of SFR deployment is abandoned, and the minimization of TRU inventories is required. The new context different from the one with objective A implies different strategy space from the one of pre-disruption scenario. A new transition of adaptation is supposed after  $T_{ad}$ , and the duration as short as 1 year is considered acceptable. It means that an abrupt change of the fuel cycle is possible in order to adapt for objective B. Similar to the pre-disruption scenario, burn-ups  $BU_{UOX}$  and  $BU_{MOX}$ , UOX SF cooling time  $TC_{UOX}$  and UOX SF management for MOX fuel fabrication  $MPu$  will change after  $T_{ad}$ ; total capacity and MOX fraction of the fleet will change linearly during the transition. To minimise TRU in a PWR UOX and mono-MOX fleet, the final total capacity  $P_{tot,f}$  is supposed to be at a level between 0 and the one just before adaptation  $P_{tot}(t = T_{ad})$ . It means that a phase-out strategy is possible for objective B. It is also supposed that the full MOX in PWRs can be realized ( $FrMOX_f$  can be 100%). The new ranges of input variables in the adaptation scenario are summarized in table 5.

Table 5: Variation ranges of variables in the adaptation scenario

Var.	$T_{ad}$	$D$	$P_{tot,f}$	$FrMOX_f$	$BU_{UOX}$	$BU_{MOX}$	$TC_{UOX}$	$MPu$
<b>Min.</b>	2040	1	0	0%	30	30	3	1/LiFo
<b>Max.</b>	2070	2090- $T_{ad}$	$P_{tot}(t = T_{ad})$	100%	60	60	10	2/FiFo
<b>Unit</b>	-	year	GWth	-	GWd/t	GWd/t	year	-

### ii. Assessment of adaptive robustness over adaptation time

For each  $T_{ad}$  considered, 2000 adaptive strategies are sampled by LHS of the corresponding design of experiment (hence, 8000 trajectories have been simulated for this part of study). Some trajectories have Pu shortages for MOX fabrication and they are considered invalid. Figure 3a shows the approximative percentage of valid strategies in the total sampling with different  $T_{ad}$ . It shows that earlier is the adaptation, fewer strategies are valid. It can be explained by the fact that the reference trajectory accumulates progressively a large inventory of Pu in the interim storage of UOX SF due to decreasing MOX fraction. Earlier is  $T_{ad}$ , earlier this accumulation is stopped and lower is the Pu inventory presented in the storage. Furthermore, an earlier  $T_{ad}$  is equivalent to a longer scenario of adaptation, because the output of interest  $TRU_{tot}$  in the adaptation scenario is also evaluated in 2090. For a given nuclear fuel cycle characterised by the same parameters (total capacity, MOX fraction, burn-ups of fuels, etc) and a given stock of Pu, the risk of Pu shortage for MOX fabrication is evidently higher with a longer time horizon of scenario.

However, the percentage of valid adaptive strategies does not indicate well the information about adaptive robustness. We recall that an adaptive strategy is considered robust if it leads to smaller  $TRU_{tot}(t = 2090)$  than the one of the robust static optimum identified in pre-disruption scenario, being 848 tons in this study. As shown by approximative distributions of  $TRU_{tot}(t = 2090)$  of valid trajectories with different  $T_{ad}$  in figure 3b, a larger part of valid trajectories is adaptively robust when  $T_{ad}$  is earlier.

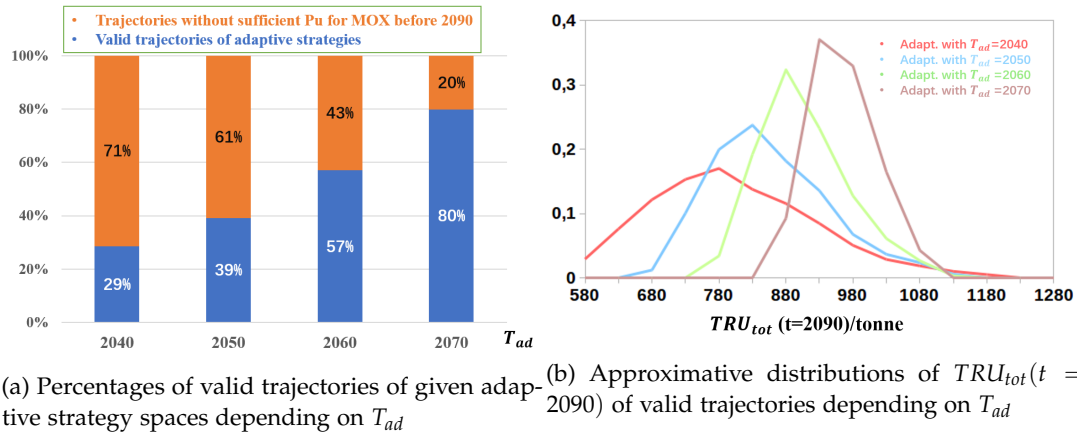


Figure 3: Global analysis of post-disruption scenario of adaptation

The evolution of TRU inventory resulting from valid adaptive strategies is presented in figure 4. Without any adaptation, the evolution of  $TRU_{tot}$  of the (static) reference strategy is presented by the bold curve in red, and the one of the robust static optimum is presented by the bold curve in purple. The grey thin curves present the results of all valid static strategies in the pre-disruption scenario. The zone of light red curves shows the  $TRU_{tot}$  evolution of valid adaptive strategies when  $T_{ad} = 2040$ ; by definition, the corresponding adaptive optimum is presented by the bold curve in brown. Similarly, the thin curves in light blue, light green and light magenta present the  $TRU_{tot}$  evolution of adaptive strategies with respect to  $T_{ad}$  of year 2050, 2060 and 2070; the adaptive optima are respectively the bold curve in deep blue, the curve in deep green and the one in deep magenta.

When  $T_{ad}$  is early, such as in 2040,  $TRU_{tot}(t = T_{ad})$  is much lower than 848 tons as the "threshold", so that the margin to be robust for those adaptive strategies is relatively large. If the adaptation is late, like in 2060, the margin becomes small (or even negative if  $T_{ad} = 2070$ , which means that the  $TRU_{tot}$  should strictly decrease with adaptation in order to be robust). Figure 4 also shows that the  $TRU_{tot}$  of reference trajectory will go over 848 tons around year 2063 if no adaptive strategy is implemented. Otherwise, some adaptive strategies before 2060 will lead to lower  $TRU_{tot}(t = 2090)$  than 848 tonnes by 2090. Therefore, some adaptive strategies upon the reference trajectory can be robust if the objective is disrupted and the readjustments are taken before 2060. However, none of the adaptations in our scenario is robust if  $T_{ad} = 2070$ : the adaptive optimum presented by the bold curve in magenta is always above the robust static optimum.

Value of inputs and the output  $TRU_{tot}(t = 2090)$  of adaptive optima over different adaptation time  $T_{ad}$  are presented in table 6. The respective evolution of  $TRU_{tot}$  are presented by the bold curves in brown, deep blue, deep green and magenta in figure 4. All adaptive optima show an abrupt transition towards a fleet with very high MOX fraction and low installed capacity of fleet. It is coherent with the variable analysis that  $P_{tot,f}$  and  $FrMOX_f$  are the most impacting factors on TRU inventory in total cycle (even though it is not exactly the same design of experiment). Low level of nuclear capacity limits the net production of TRU; high MOX fraction allows to incinerate lots of Pu in UOX SF interim storage; and moreover, a short transition amplifies these effects.

Another remark can be observed from the evolutions of  $TRU_{tot}$  of adaptive optima in figure 4: the later is  $T_{ad}$ , the more negative is the slope of the TRU evolution of the adaptive optimum. Again, the accumulation of Pu in UOX SFs in the reference trajectory and different time length

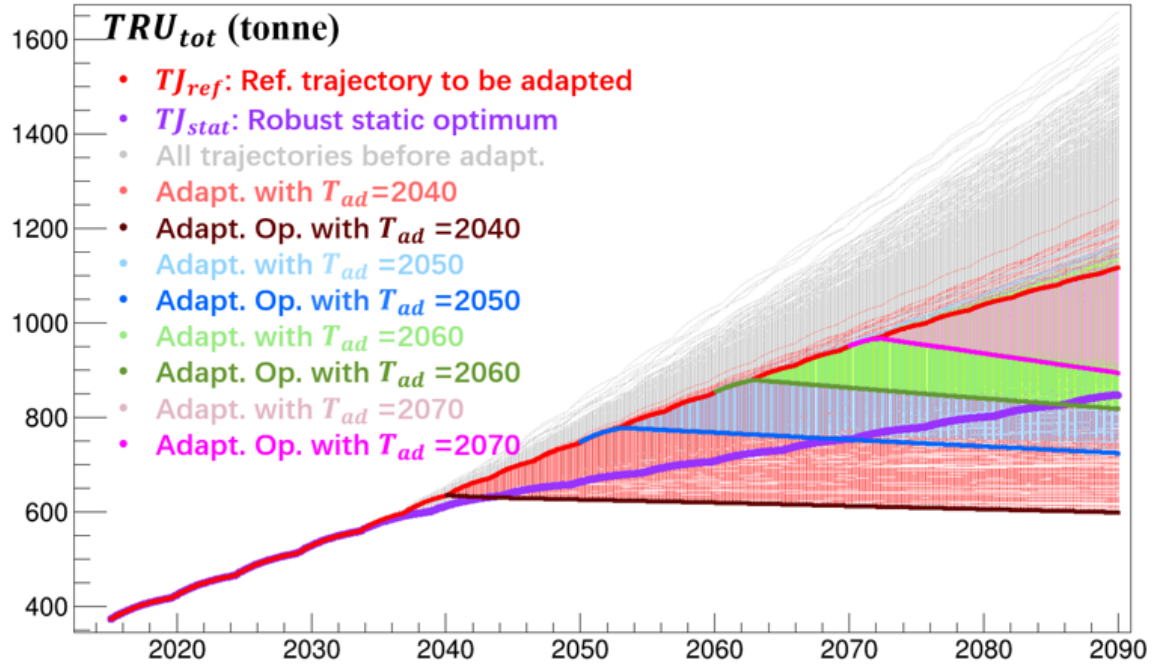


Figure 4: Evolutions of  $TRU_{tot}$  of valid adaptations from the referential trajectory

Table 6: Variables and the outputs  $TRU_{tot}(t = 2090)$  of adaptive optima over different  $T_{ad}$  in the adaptation scenario

$T_{ad}$ of the Op.	$D$	$P_{tot,f}$	$FrMOX_f$	$BU_{UOX}$	$BU_{MOX}$	$TC_{UOX}$	$MPu$	$TRU_{tot}$
2040	1.4	8.0	83.2%	54.8	49.0	7.4	LiFo	599
2050	2.5	20.2	80.0%	46.1	44.7	7.7	FiFo	724
2060	3.3	26.9	90.2%	39.5	37.7	3.5	FiFo	818
2070	2.9	37.3	98.3%	41.1	58.8	4.1	LiFo	894
(Unit)	year	GWth	-	GWd/t	GWd/t	year	-	tonne

of adaptation scenario due to  $T_{ad}$  should be emphasized: the accumulation of Pu in the storage of UOX SF in the reference trajectory allows to feed higher and higher MOX fraction if needed; later  $T_{ad}$  yields a larger Pu inventory in UOX SFs as well as a shorter time length of adaptation scenario, so that such a higher incineration rate of Pu by MOX can be realized. Nevertheless, such post-disruption incineration is always less efficient than the previous accumulation. Adaptive robustness can be no longer achieved if readjustment is too late.

Last but not least, the year 2090 as observation time should be highlighted for the assessment of robustness. If the adaptive optimum with  $T_{ad} = 2070$  is extrapolated, we may expect that its  $TRU_{tot}(t = end)$  can be lower than the one of the robust static optimum after a certain time (so that it can be adaptively robust). However, the threshold of being adaptively robust should be modified (as the time horizon of scenario should be also extended in this case). Moreover, the validity with regard to Pu shortage after 2090 of these two trajectories are not a-priori assured. Analysis with other time of interest requires actually a new study and new simulations. Hence, the

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analysis of robustness in this work depends on the assumptions and constraints of this scenario study, including the method of robustness evaluation, time horizon of scenarios studied, etc. It is dangerous to extrapolate any result on the domain out of the scope of study.

## V. CONCLUSION AND DISCUSSION

### i. Conclusion on the example

In this work we develop a method of strategy robustness assessment vis-à-vis the deep uncertainty of disruption of objectives based on the nuclear fuel cycle in France. The pre-selected objective is to substitute the PWR-based French fleet with SFRs by 2090, and the one linked to disruption is to minimize TRU inventories in the total cycle without SFR deployment in the future. The disruption of objective before 2090 is so uncertain that the choice of strategy for nuclear development is problematic. Starting from the principle of immediate precaution which assures acceptable outcomes for possible objectives, a conservative strategy, which considers two objectives at once, is identified. By applying this strategy, 848 tonnes of TRU will be accumulated in 2090 in total cycle, and less than 1% of margin of material availability will be kept to achieve the pre-selected plan of SFR deployment. Since it leads to the lowest TRU inventory among all possible static strategies with  $R_{Subs} > 1$ , it is identified as the robust static optimum in the pre-disruption scenario. Another approach suggests post-disruption adaptation, according to the updating information on the uncertainty of objective. In this approach, an optimal strategy dedicated to the pre-selected objective about SFR deployment is implemented before disruption. If without adaptation, it leads to 68% of margin on the Pu availability for SFR deployment by 2090. In case of the disruption, adaptive strategies are explored based on this trajectory. It is shown that some adaptive strategies before 2060 lead to lower TRU inventories in the cycle by 2090 than the TRU inventory of robust static optimum. However, if it is not adapted until 2070, all valid adaptive strategies lead to higher TRU inventories by 2090 than the robust static optimum. Hence, subject to the uncertain disruption of objective analysed in this work, the time limit for adaptive robustness related to the reference trajectory is around the year 2060. Whether to make immediate decision in a conservative manner as the robust static optimum, or to pursue the objective currently determined with a preparation plan for the future adaptation, depends on the estimation of disruption and the relevant temporality. Is year 2060 the time when stakeholders can determine their objective for year 2090? It is an open question for different audiences regarding the information updating in the future.

### ii. Conclusion on the method of robustness assessment

This work develops a method of strategy robustness analysis applied in dynamic nuclear fuel cycle study. In the analysis of static robustness, the robust static strategy is identified in the pre-disruption scenario, which can theoretically achieve the pre-selected objective, and it is optimised for another objective linked to the disruption. It is called "static" because the results of relevant trajectory are evaluated without adaptation. In terms of adaptive robustness, the outcomes of adaptive strategies is analyzed based on the trajectory initially pursuing the pre-selected objective. As the disruption is deeply uncertain, robust adaptive strategies are analyzed over different adaptation time. The time limit for adaptive robustness is deduced by comparing two approaches. Robust strategies suggested by two approaches can animate the discussion among stakeholders over their estimation of disruption.

As it is shown in [10], a single strict mathematical definition of robustness and relevant metrics does not exist, and therefore the results of robustness assessment can be strongly dependent on

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the specific definition of robustness, the assumptions of scenario study, the context of problem and the interests of stakeholders. The criteria of robustness are adapted for the scenario study of nuclear fuel cycle in this work; it is also possible to apply other definitions to different problems. Nonetheless, the comparison of analyses with diverse robustness methods is out of our study category.

Moreover, the results of robustness assessment in this work is directly linked to the reference strategy and the robust static optimum identified in the pre-disruption scenario. These two strategies are studied in this work because they are two extreme cases in the Pareto front, which helps develop the methodology and highlight the impact of uncertain disruption. But depending on the evaluation upon the disruption and the interest of stakeholders, other strategies, e.g. other strategies on the Pareto front in figure 2, can be chosen as reference strategy or robust static optimum, which indicate different hypotheses of scenario study. In this case, other trajectories can be adapted and the threshold deduced from the robust static optimum with regard to adaptive robustness may vary. The relevant results are a-priori different from the ones in this work. Again, the results of robustness assessment in this work are not absolute for decision-making; instead, with different assumptions, the method help stakeholders discuss and manage their strategies involving disruption of objectives.

Besides the specific assumptions made in this scenario study, one may have different interpretations of static and adaptive robustness. The robust static optimum in this work can be simply regarded as a role of threshold, which indicates the most conservative performance among all possible strategies subject to the deep uncertainty of disruption. In this respect, the adaptive robustness indicates the possibility of post-disruption adaptations with better performance than any historical choice made before disruption. It can be also interpreted as the optimal strategy under the assumption of staticity, which means that the post-disruption adaptation is not allowed, possibly due to technological and economic concerns. Staticity or autorization of adaptation depends on the evaluation of future industrial and political decisions, which are different assumptions of scenario study. From this angle, these two relevant approaches can be interpreted as the robustness assessment associated with different assumptions of staticity.

### iii. Perspectives

As it is mentioned, the nature of total capacity of fleet seems different from other input variables of strategy. The change of total capacity of fleet may involve many stakeholders, and it is not obvious that it can be decided as easily as others. To be more conservative, several similar analysis with different assumptions of total capacity evolution should be carried out.

This kind of problem can be generalized to other variables as well, because the difficulty of modifying the parameters of fleet depends on the agreement and the interests of stakeholders. Some loss of performance is possibly more acceptable than a huge modification of a special parameter of fleet. This kind of study involves the preference on the gain of performance as well as the inertia or the difficulty of modification, which in practice, constrains the exploration space of strategy in the adaptation scenario. For instance, we can suppose that the constraints of modifying operation parameters for adaptation in reality are much stricter than the ones assumed in this work:

- $Ct(P)$ : Nuclear industry does not accept the phase-out strategy; the lowest acceptable level of total capacity is the half of  $P_{tot}(t = T_{ad})$ . The constraint becomes  $P_{tot,f} \geq \frac{1}{2}P_{tot}(t = T_{ad})$
- $Ct(D)$ : Due to the demand of stability of electricity supply, the new transition should be more than 10 years. The constraint becomes  $D \geq 10$ .



- $Ct(PMOX)$ : Even though the full MOX core is considered possible after disruption, the reprocessing and fabrication capacity is not infinite. Since the MOX fuel demand is proportional to the capacity contributed by MOX (for the first degree of approximation), one may suppose that the final capacity contributed by MOX cannot exceed the double of current level (it is a choice depending on industrial and sociological estimation; here it serves as an example). The constraint may be  $P_{tot,f} \times FrMOX_f \leq 188 \times 10\% \times 2 = 37.6$  GWth.
- $Ct(TC)$ : Due to the high requirement for nuclear safety, it is possible that all UOX SF should be cooled at least 5 years in the future. The constraint may become  $TC_{UOX} \geq 5$ .

$Ct$  denotes the different constraints from the adaptation scenario in our work. To see the impacts of these constraints on the adaptation, we can accumulate them in the order of  $Ct(P)$ ,  $Ct(D)$ ,  $Ct(PMOX)$  and  $Ct(TC)$  and check the lowest  $TRU_{tot}(t = 2090)$  achieved in our sampling. Without launching new calculations and without losing generality, we take the valid trajectories in the adaptation scenario with  $T_{ad} = 2070$  as example. By accumulating constraints in the order aforementioned, the lowest  $TRU_{tot}$  achieved by adapting the reference trajectory are presented in table 7.

Table 7: Effects of accumulation of stricter constraints than the original study of adaptation in a given order on the lowest achievable  $TRU_{tot}$ , when  $T_{ad} = 2070$

Cumul. Ct	-	Ct(P)	Ct(D)	Ct(PMOX)	Ct(TC)
Min. $TRU_{tot}$ (in ton)	894	914	920	1028	1030

Since new constraints are stricter than the ones in our work, the lowest  $TRU_{tot}$  achieved becomes higher than 894 tons that is identified with original constraints. The richness and the degree of freedom of strategies characterized by the strategy space, as discussed in [13], affect evidently the space of result and therefore the conclusion of a scenario study. However, the sensitivity of output (in this example it is the lowest  $TRU_{tot}$ ) on different constraints is still not obvious. The preference of stakeholders, the role of constraints and the normalization of gain should be investigated in order to answer these questions. But on one hand, each sub-scenario of this analysis may require large quantity of calculations (problems of optimisation); on the other hand, the determination of constraints involve further research in the field of economy and sociology, which are completely out of the scope of this work.

Another problem related to constraints may be involving some new variables and technology that are not considered in the pre-disruption scenario. In this work, reactors and fuels of the French fleet are still PWR UOX and PWR MOX after the disruption. In consideration of TRU minimization, is it possible to employ Pu multi-recycling fuels in PWRs such as MIX or CORAIL [7]? The gain of performance by employing new technology can be studied in the future.

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