Resilience of Nuclear Fuel Cycle Scenarios

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DE LA RECHERCHE À L'INDUSTRIE

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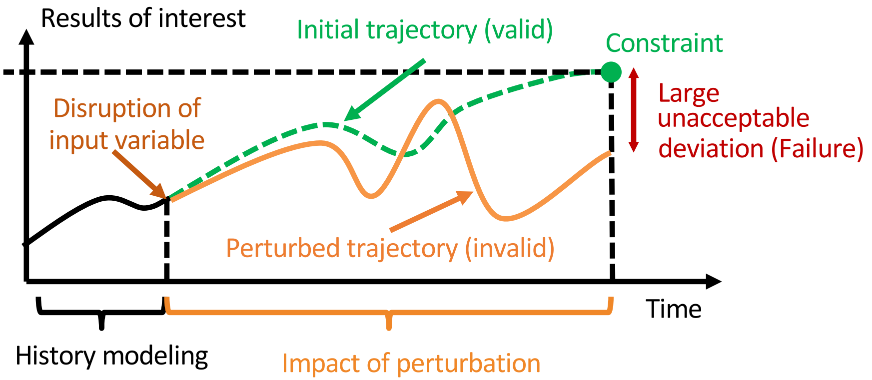
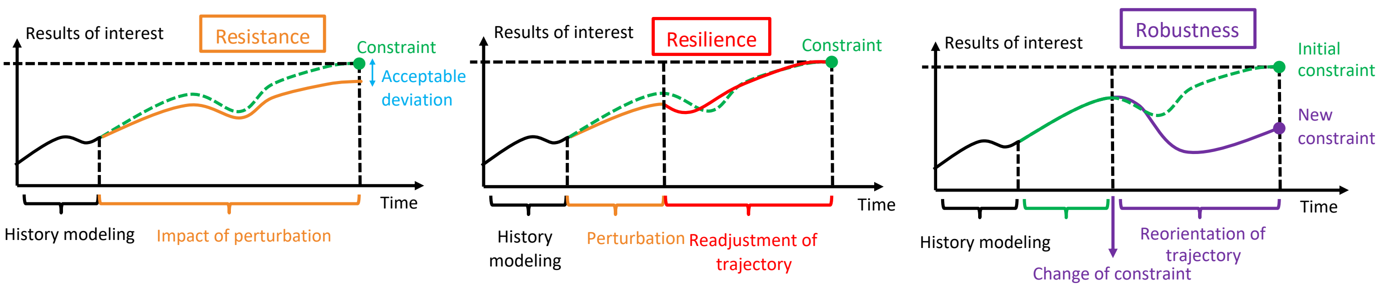
- Uncertainty degrades the results!



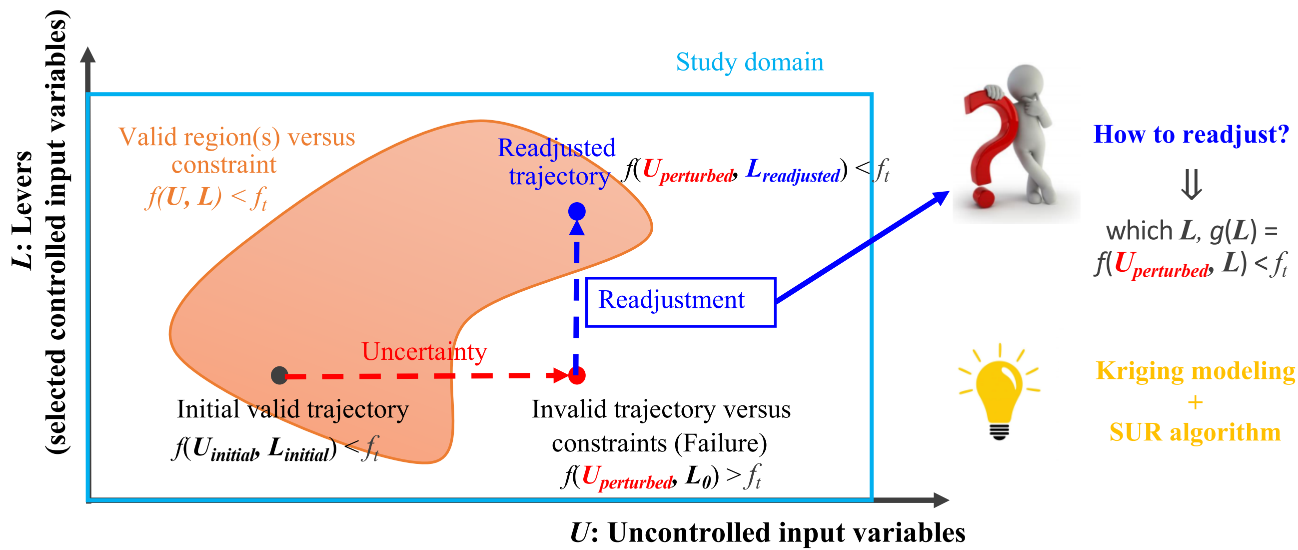
- Questions
  - Can one readjust failed scenario trajectories?
  - If yes, how to readjust?
  - How to produce the scenario trajectories that can be readjusted after disruption?

DIFFERENT ADAPTATION STRATEGIES FOR UNCERTAINTIES

- **Resistant –** A resistant trajectory can identify one or more trajectories that remain valid versus initial constraints after disruption on one of input variables
- **Resilient –** A resilient trajectory can identify one or more trajectories that remain valid versus initial constraints by **readjusting the controlled input variables** after disruption on uncontrolled input variables
- **Robust –** A robust trajectory can identify one or more trajectories that remain valid after **a disruptive change on the constraints** by adapting input variables after the disruption.



- The general idea of resilience is to readjust some selected controlled input variables, i.e. **levers**, to counterbalance the impact of perturbation caused by uncertainties so as to avoid the failure of trajectories.

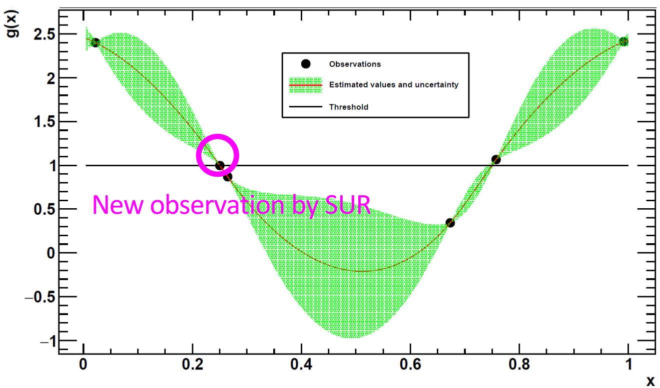


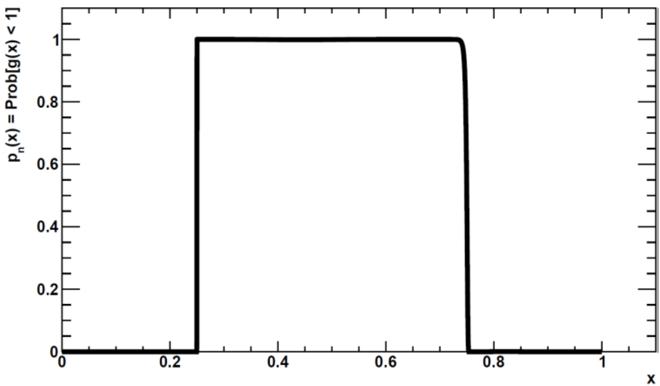
Remarks: *$f(U, L)$ observable; f_t target value*

KRIGING SURROGATE MODEL AND SUR ALGORITHM[1, 2]

- Example: which x, $g(x) < g_t = 1$
- Interpolation by Kriging modeling
  - Predictor: $g_n(x)$
  - Statistic information: $s_n^2(x)$ = *standard deviation* $(g_n(x))^2$

  Excursion probability: $p_n(x) = Prob[g(x) < 1]$
- SUR (Stepwise Uncertainty Reduction) algorithm provides "efficient" observations (around contour line) to construct excursion probability estimator.





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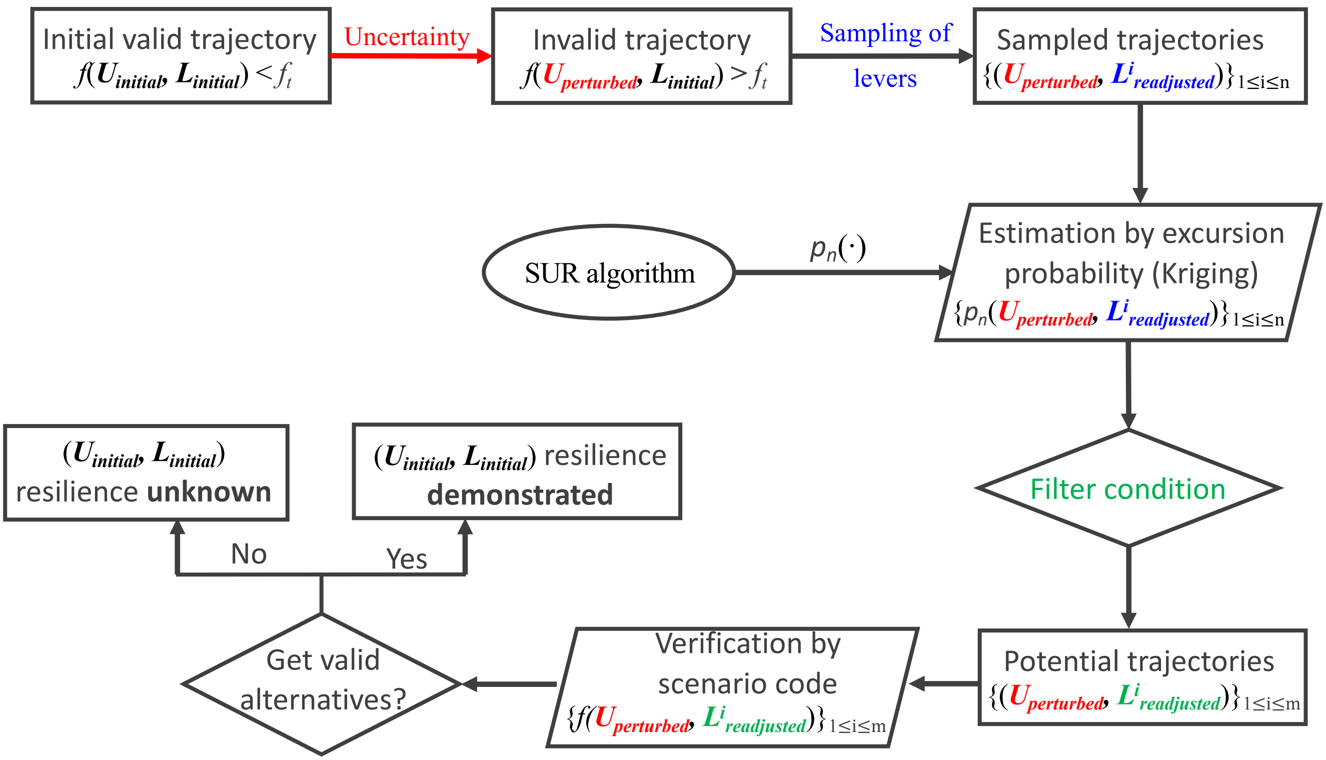
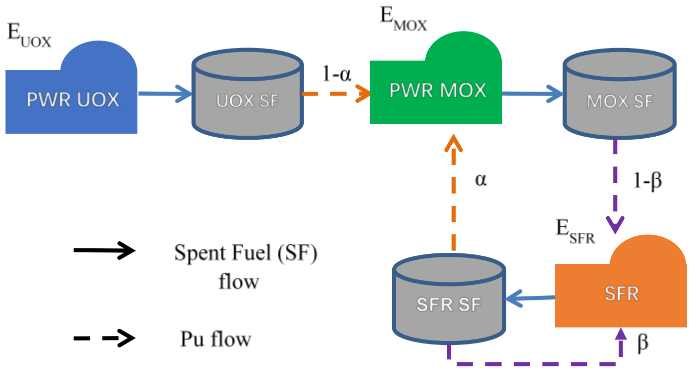
RESILIENCE EVALUATION SCHEMA





Assumption

- PWR UOX / PWR MOX / SFR fleet
- Constant total electrical production

Controlled variables (levers)

- Reprocessing strategy (2 variables): ***α*** and ***β*** (ratio of SFR spent fuel over the SFR and UOX (or MOX) spent fuel mix in Pu extraction to feed the fabrication of new PWR MOX (or SFR) fuel)

Uncontrolled parameters (uncertainty)

- UOX burnup

Constraints

- Pu equilibrium in spent fuel:
  I(Equilibrium), sum of the absolute values of the asymptotic slopes of the Pu inventory in the different spent fuel inventories
  I(Equilibrium)<1 kg/(TWe·h)
- Feasibility:
  No Pu shortage in reprocessing
  I(Feasibility) ∈{Yes, No}

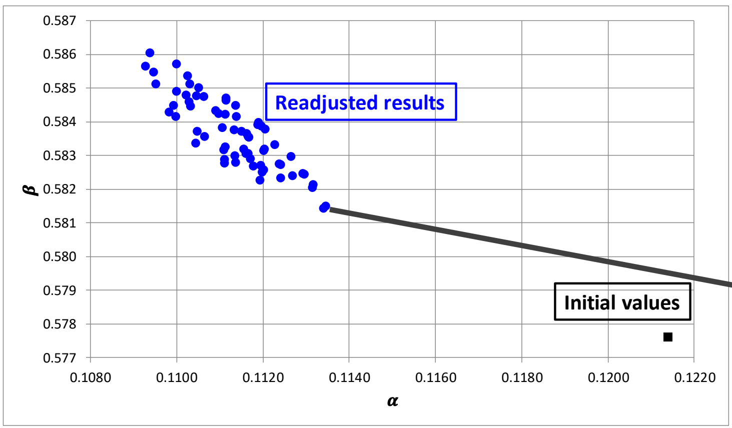
Application with single trajectory

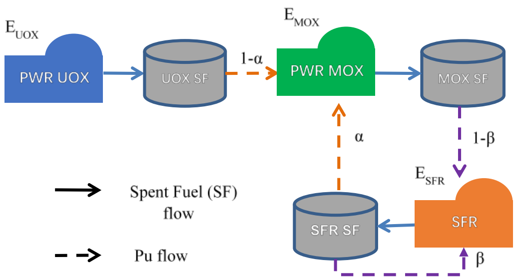
- **Failure of initial valid trajectory by uncertainty** (E_{MOX} = 0.1227 and E_{SFR} = 0.4949 fixed)

Parameters	α	β	BU_{UOX} (GW·d/tHM)	$I(Feasibility)$	$I(Equilibrium)$ (kg Pu/(TWe·h))
Valid traj.	0.1214	0.5776	45	Yes	0.67
Invalid traj.	0.1214	0.5776	41	Yes	1.57 (> 1, Failure)

- **Application results of resilience evaluation method**

66 valid alternatives trajectories



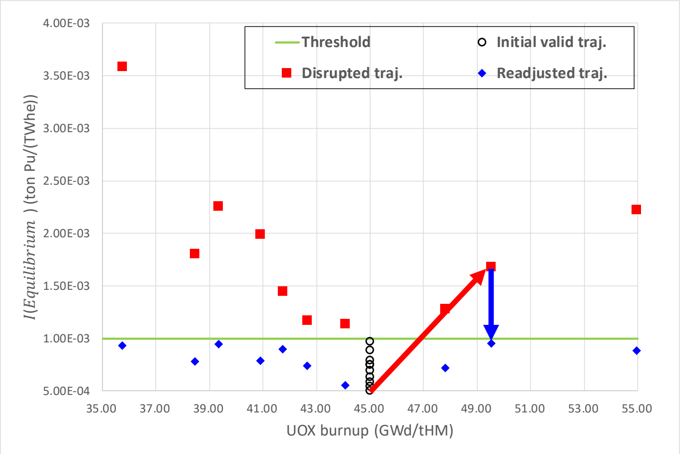


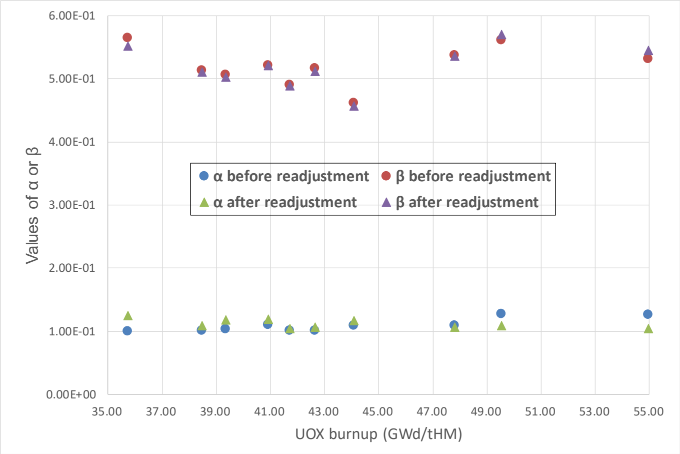
$(\alpha, \beta, \mathrm{BU}_{UOX})$ = $(0.1134, 0.5814, 41.0GW{\cdot}d/tHM)$
$\rightarrow$
$I(Feasibility)$ = Yes
$I(Equilibrium)$=0.84$kg\ Pu/(TWe{\cdot}h)$ (**OK**)

- The initial trajectory is resilient
- There are many different ways to readjust levers

Application with several trajectories

- 10 invalid trajectories with different UOX burnups (35 GWd/tHM ~ 55 GWd/tHM)
- Resilience evaluation method is applied to every invalid trajectory
  - 10 invalid trajectories are successfully readjusted
  - The readjusted values of α and β are not far away from their corresponding initial ones





CONCLUSIONS AND PERSPECTIVES

- Conclusions
  - A definition of resilience for nuclear fuel cycle scenario is given
  - A resilience evaluation method for scenario is developed based on Kriging modeling and SUR algorithm
  - A new SUR algorithm adapted for multi-constraint case is developed (W. Zhou, Global 2019 in Seattle, September 22-26)

- Perspectives
  - Use methods to reduce dimension of problem and visualize high dimensional data
  - Apply the developed resilience definition and methods to French nuclear fuel cycle scenarios

THANK YOU FOR YOUR ATTENTION

Backup

DE LA RECHERCHE À L'INDUSTRIE

- **Why** – evaluate the potential evolutions of nuclear fleet and provide decision supports
  - Identify strengths and weaknesses of a nuclear fuel cycle system
  - Analyze different fuel cycle strategies and help to choose an adaptive one
- **For whom** – decision-makers of nuclear energy (e.g. industry and government)
- **What** – tool to characterize the nuclear fleet and fuel cycle (e.g. performance and cost)
- **How** – evaluate the mass flows and inventories by physical modeling

CONTEXT – GLOSSARY OF SCENARIOS (*) (1/2)

- **Input variable** – Input simulation parameter whose value can vary within a given interval. A variable can be
  - **controlled**, whose values can be chosen with a level of satisfaction according to the requirements of decision-makers, or
  - **uncontrolled**, which includes uncertainties and whose values change according to the circumstances without this being the result of a desired choice of decision-makers.

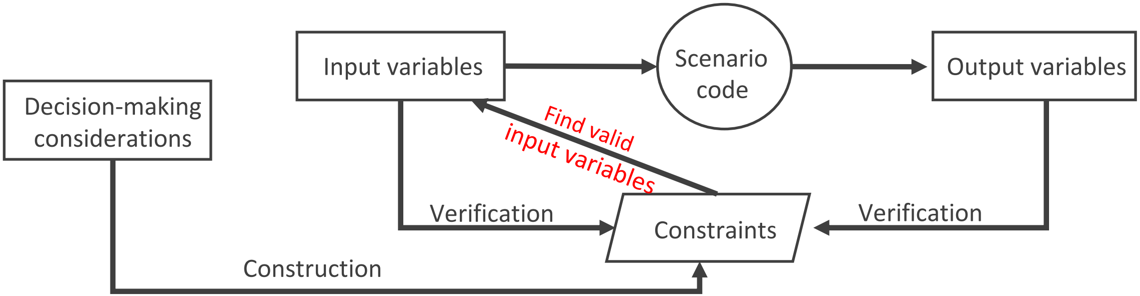
- **Trajectory** – A perfectly identified, concrete and determined evolution history of a nuclear fuel cycle system with a specific value set of scenario input variables.

- **Output variable** – Quantity calculated by the simulation code (mass of plutonium, electrical production per year ...)

(*) Collaboration with CNRS nuclear fuel cycle scenario group

- **Constraint** – Condition that a input or output variable must check for the trajectory to be valid (e.g. Pu stabilization). It integrates considerations of decision-makers and usually expressed by equality or inequality.

- **Scenario problem** – A study problem to propose some possible prospective valid trajectories of nuclear industry according to considerations of decision-makers



- **Disruption** – Sudden and unplanned change in input variables or constraints

(*) Collaboration with CNRS nuclear fuel cycle scenario group

CONTEXT – UNCERTAINTIES IN SCENARIOS (1/2)

- **Uncertainty of model error**
  - Result of abstraction and simplification of current problems studied
  - Possible sources: physical models, equivalence model, simplification of modeled objects (e.g. fabrication plant)

- **Uncertainty of nuclear data**
  - Uncertainty related to physical measurements
  - Described by matrices of covariance

- **Uncertainty of historical scenario parameters**
  - Need of history modeling to get a good starting simulation point
  - Difficult to completely obtain historical scenario parameters (difficulty of measurement, lack of information, etc.)

CONTEXT – UNCERTAINTIES IN SCENARIOS (2/2)

- **Uncertainty of prospective scenario parameters**
  - Prospective scenario parameters characterize a potential fuel cycle system, obtained through trends or prospective technical studies
  - Due to the lack of knowledge about the future, they may be very different from the actual parameters of the future, hence the uncertainty

- **Uncertainty of scenario assumptions**
  - Resulting from industrial decisions, scenario assumptions define the scenario structure (choice of fuel management strategy, introduction of new technologies, etc.)

- **Uncertainty of economic, social and political context**
  - Economic, social and political context determines the development direction of the nuclear energy industry.

CALCULATION STEPS OF SUR ALGORITHM[1, 2]

- Example: which x, $g(x) < g_t = 1$
- Calculation schema

  1. Initial design of experiments
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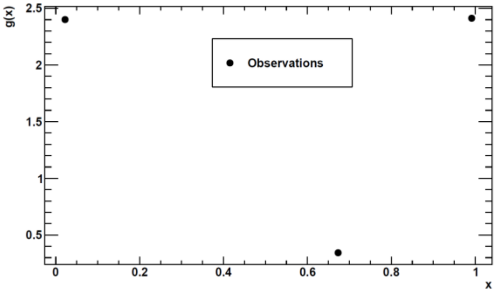

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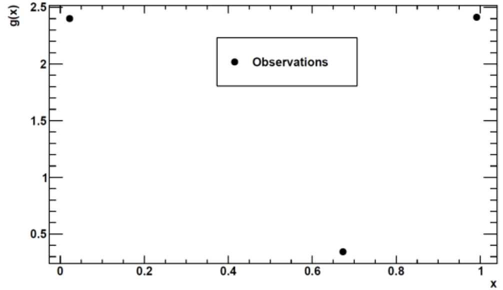

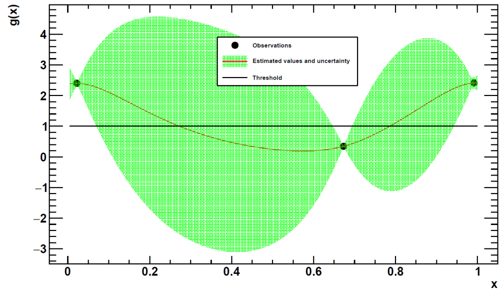

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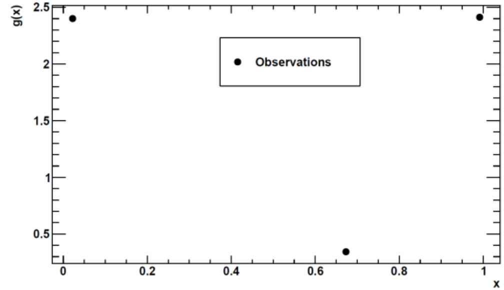

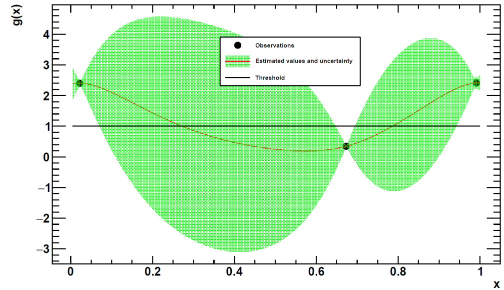

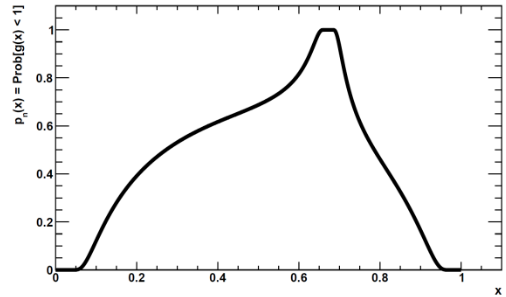

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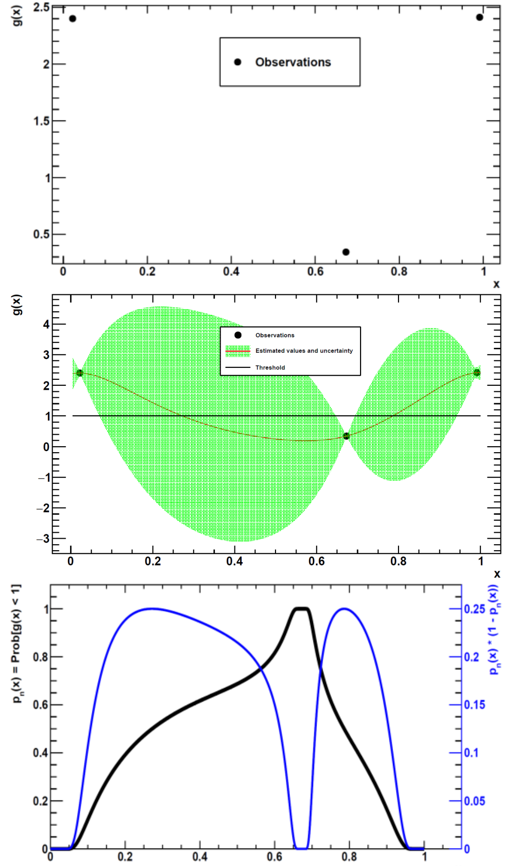
$$min[\int_\Omega p_{n+1}(x)(1 - p_{n+1}(x))dx]$$



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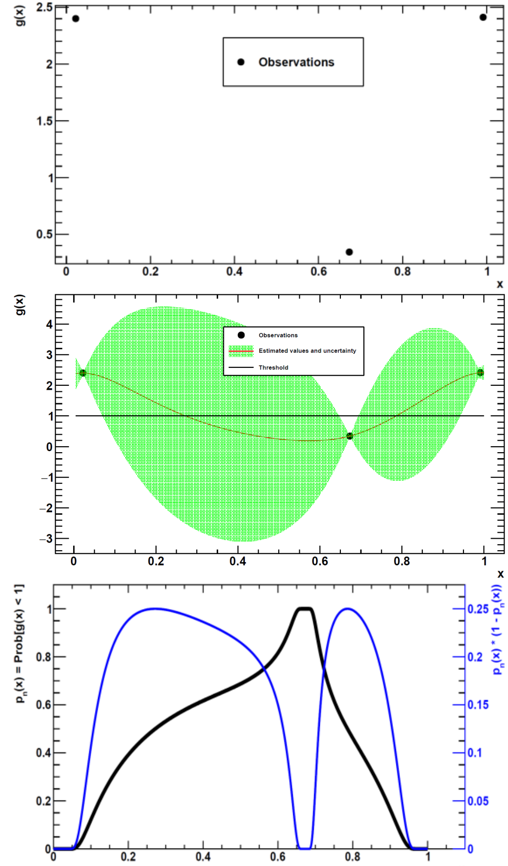

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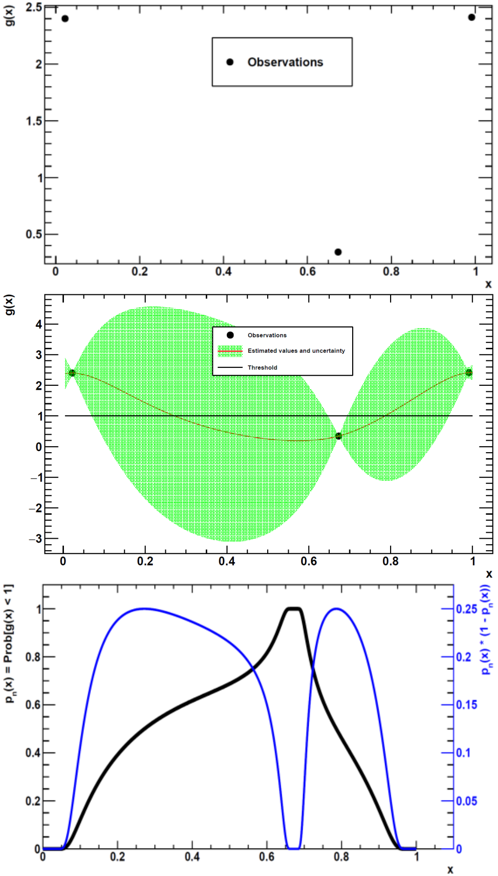

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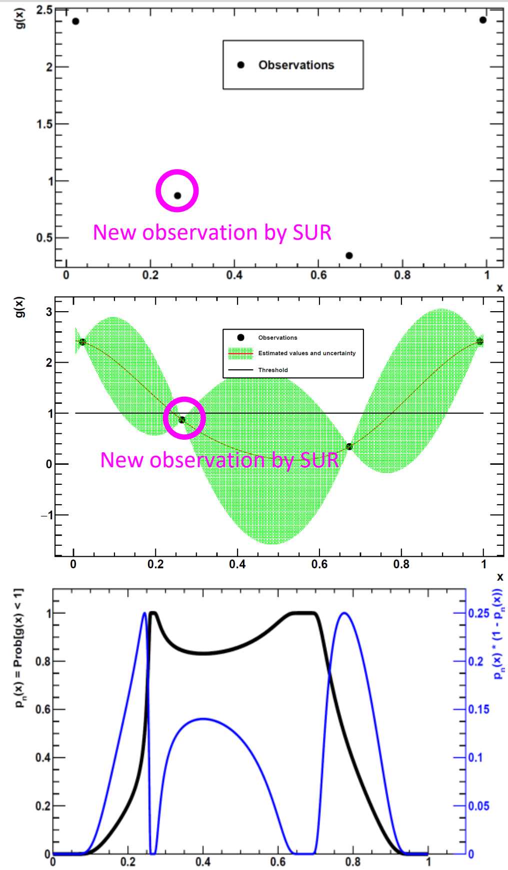

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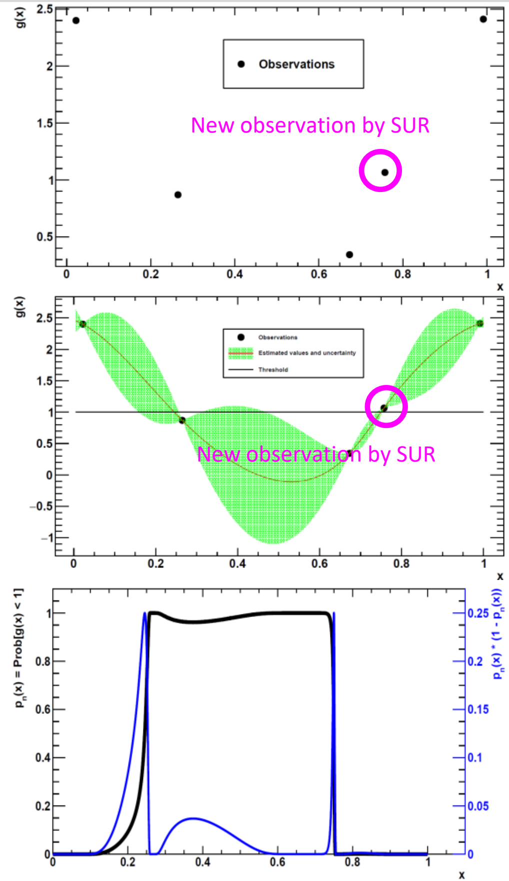

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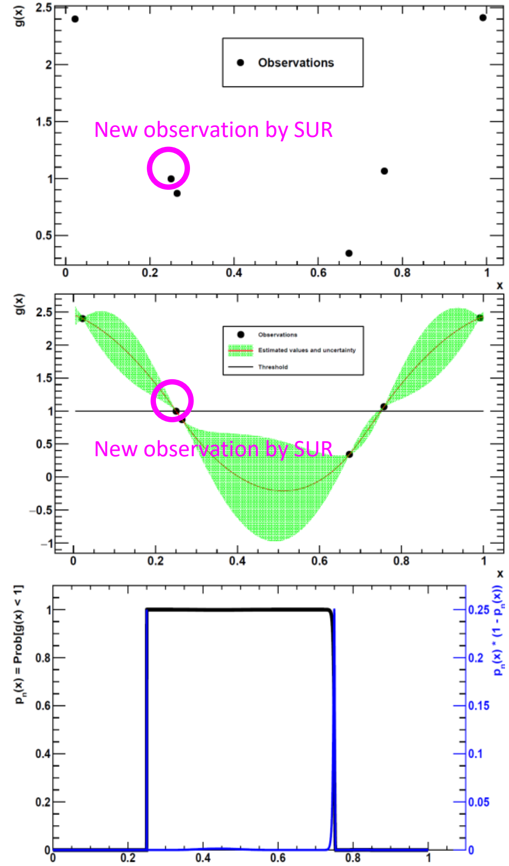

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