ECOLE POLYTECHNIQUE DE BRUXELLES

State of the art on the Application of artificial intelligence techniques to in-core fuel management for nuclear reactors

PROJ-H-403

Project in physics engineering : *Tractebel Engie*

Contents

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1 Introduction

The design and improvement of the loading pattern scheme in a PWR system relative to the refueling planning of a plant is a very complicated process. Two aspects of the engineering sciences have to be explored in the design of such a loading pattern. First the technical aspect relative to the RAMS studies (Reliability, Availability, Maintainability, and Safety) of the reactor, that is maintaining safety margins for controlling and shutting down the reactor. Second the economical aspects where at any point the power demand has to be reached as well as avoiding wastes. Luckily, through the 70' until now many optimizing methods have been developed in the area with the rise of many optimization algorithms. Two main techniques have now been used for a while : genetic algorithms which are quite powerful to give good answers to multi-variables optimization problems, and simulated annealing for finding a global optimum of a function. Two of those are meta-heuristic probabilistic methods and will be powerful tools in the conception of a loading pattern design.

Machine learning is not a new field, *symbolic* machine learning has been worked on since the seventies and has given its load of results. However we witnessed since the beginning of the 2000 a boom around *non-symbolic* machine learning systems, that is systems acting like a "Black box", where it is not possible to figure out its inner workings after training. The latter systems showed amazing results in fields such as image recognition, language recognition and generative text as well as some encouraging properties in combinatory problems and a variety of families of optimization problems (or near-optimal). That is why this first look into non-symbolic machine learning in loading pattern optimization is justified. [1]

As the task at hand is to find a place in the loading pattern design process where the addition of ML (Machine-Learning) code can improve the workflow of the engineer, it is clear that the process as it is done now have to be exposed :

The first step of design is building a first refueling plan based on various time constraints, knowing how long it takes for refueling, the workers availability, possible maintenances, meeting **Elia** energy demand and the period of the year, for example. When the schedule is mostly done, the engineer has to design a loading pattern respecting those parameters, where the **natural life** of the reactor with possible stretch-out up to 60 days are possible (at lower power output). To do so, tools are available to the engineer at Tractebel : database search algorithms are used to give a head start on the design, as well as genetic search algorithm using shuffling methods. However it is up to the engineer to tweak and rework what the tools gave. The search space in which the acceptable fuel configurations lays is so large (ant multi-dimensional) that the complete and ready design -even with the previously mentioned tools- requires a lot of manual work from the engineer [2]. That is why non-symbolic machine learning to help this process is envisioned and looked after by Engie-Tractebel.

The goal of this project is thus to understand and explore what are the "Artificial Intelligence" methods available, what are the ones adapted to this problem and establish three strategies and how to implement them. A prototype is build on one of the proposed strategies.

2 Problem definition : In-core fuel management optimization

2.1 PWR operation, in-core physics

Nuclear reactor physics is a large field, however even if the main physics and models would be described by nuclear physics, neutronics (mainly neutron transport theory), in practice we can get a workaround based on expressions of the reactor by defining a few measurable parameters characterizing the reactor. Let us expose the usual configuration of a PWR reactor and the basic physics inside, then the main parameters used in the industry to discuss the reactor properties.

2.2 Problem definition and scope

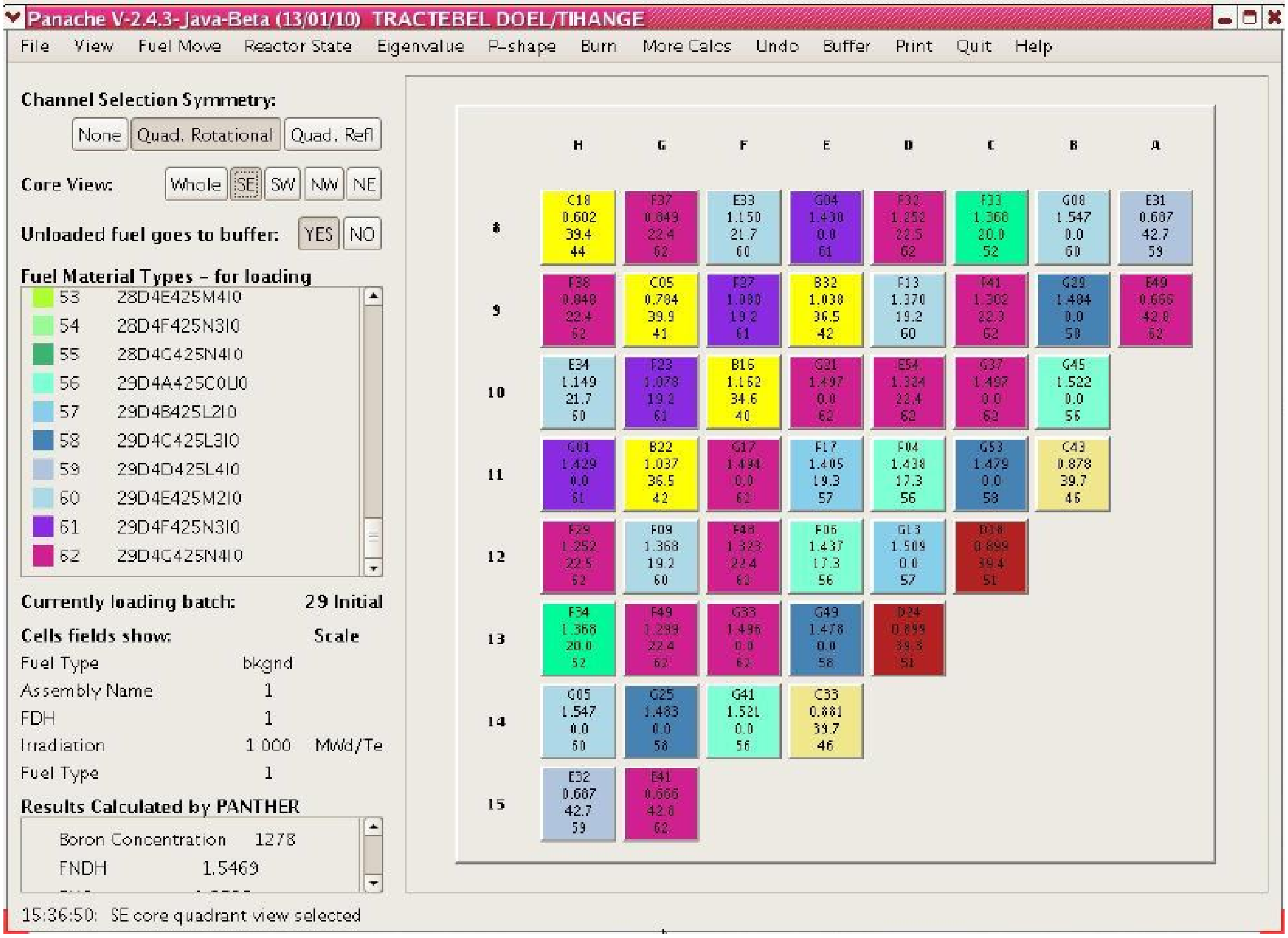
What is asked is to elaborate a list of artificial intelligence strategies allowing engineers to find faster a first almost-optimized loading pattern based on the optimization of the safety constraints, economical constraints and physical requirements. Let's evaluate a few of the variables (this is not an exhaustive list, just a reminder and variables that had been insisted on for in-core fuel management) :

- k_∞ **:** The multiplication factor of the reactor, that is the ratio of the fresh neutron population per fission cycle. Defined by the four-factor equation : $k_\infty = \eta\epsilon pf$. This grandeur allows us to evaluate if the chain-reaction can be sustained by the fuel.
- **FDH :** Nuclear Enthalpy Rise Hot Channel Factor ($F^N_{\Delta H}$, this parameter is essential in PWR control as it gives a good insurance the core is far (or close) from a DNB scenario, in practice at Engie it has to be below 1.4 when using the assembling tools. [3]
- **Neutron poisons :** During operation, the part of ^{235}U atoms that undergo fission will create various fission products with different neutron absorption cross-sections, yield and decay rates. The huge absorption cross-section of ^{135}Xe in the thermal energy range makes it a great source of anti-reactivity and has to be taken into account. We distinguish two type of poisons, the ones creating **slagging**, which determines the natural life of the loading pattern (essential when planning a cycle). And nuclear **poisoning**, which diminishes global k_{eff}. Often we use neutron poisons to reduce the reactivity of fresh assemblies with ^{155}Gd and ^{157}Gd the two Gadolinium isotopes. It is thus used as a burnable absorber [4].
- **Natural life :** Expected time (in MWd/tU) for the core to burn at full power until neutron poisons brings down the reactivity. After that time one can stretch up the fuel consumption for around thirty days at lower power to match the refueling schedule.
- **MTC :** The moderator temperature coefficient, defined as the change in reactivity per degree change in the moderator temperature, mostly a function of the moderator-to-fuel ratio [5], when designing most safety guidelines order that *"The MTC should be non-positive over the entire fuel cycle when the reactor is at a significant power level."* (for LWR or PWR)
- **Fluence :** We define the neutron fluence as the time integral of the neutron flux density. Not a quantifiable parameter for the reactor, but has to be taken into account in the LP design. It is expressed as number of particles $/cm^2$. It is important as it can be used as a measure of fuel burnup. It is also important to protect the structure of the reactor as it is a measure of the potency of the neutron flux of neutron embrittlement [6].
- **Burnup and burnup gradient :** The burnup is defined as the measure of how much energy is being extracted from the fuel, and is used as a measure of fuel depletion [7]. Essential to monitor has it is an essential part in the power distribution problem, power tilts (asymmetrical power distribution in the core), which imposes symmetry in the placing of assemblies in the LP-design.

From the internal documentation at Engie, we define In-core fuel management as : *calculating core reactivity, power distribution and isotropic inventory in order to meet these technical and economical requirements during subsequent cycles* [8].

We define on the other hand the loading pattern design as : *find a suitable configuration of fresh and irradiated FA (= fuel assemblies) in order to meet the needs put forward by in-core fuel management.*

The tools used in house are **PANTHER**, **PANACHE**, **AUTUNITE** (Engie-developped) and **LPO** (Loading pattern optimizer). PANTHER is the 3D diffusion code for transient and steady-state core calculation. LPO gives an initial LP for the engineer to optimize further with the graphical interface of PANACHE, which presents itself as follow :



AUTUNITE searches the database if there is in the past design patterns that matches (or closely match) the constraint at the moment and propose a first LP based on the plan-required natural life and available fuel stocks in pools. The search query being faster than the LPO process.

The work is usually done by visualizing one quarter of the core, the reactor demanding a 8-axis symmetry this representation is sufficient. The user shuffles the cells until the design is satisfactory. A color scheme represents each cell reactivity and is given a name for identification in the fuel inventory. Furthermore is given all useful metrics for the whole core in the box on the left.

3 Machine learning tools in fuel management

The *Introduction to loading pattern design* gives a good idea of what type of input/output we are looking for. It is quite clear that the considering of all parameters would be out of scope for this project. Let's define :

3.1 Problem characterization

[2], we see that the pseudo-code has to work as following :

```
INPUT :
    Stock assemblies
        Each assembly caracterized :
            Burnup
            k_inf
            gadolinium content
            enrichment
            past position

OUTPUT :
    Number of fresh assembly required
    Loading pattern
    (Risk and flexibility analysis)
    Gain evaluation
```

The first approach (prototyping the propositions of the next paragraph) should only focus on the most important parameters of a loading pattern, that is the FDH, total reactivity and burnup tu match the given loading plan. For PWR the most critical security issue is the *Departure From Nucleate Boiling* [3] (DNB), that is when a local vapor layer forms around the core. When it happens, good heat transfer is not sufficient anymore and an huge amount of heat is accumulated at the core.

3.2 Literature review, state of the field

Theoretical work has been done on the subject of using *non-symbolic* methods for in-core fuel management, but very little implementation has been achieved [1]. The most reoccurring methods that appear in the literature are *Particle Swarm Optimization*, *fussy techniques*, *tabu search* and *cellular automata*, however those are still explicitly logic-based genetic-style algorithms, a new approach would be to directly train some neural networks or ants based pheromone mimetism.

3.3 IA and fuel management, a strategic approach

3.4 Machine-learning algorithms

- **CNN (Convolutional neural network)**
  From libraries such as *TensorFlow* or *OpenNN*, it is fairly easy to build a convolutional neural network. The main difficulty of this approach is to build a sensible database which has an effective conversion table to the weighting functions of the nodes of the net [9]. One idea, which could be beneficial but hard to put in place would be to gather data on how the engineers themselves work on the tools. This is hard to do for two reasons, first as it is not really ethical to record what the worker does at all time, it is required to plan short sessions in advance where the work is recorded and the worker made completely aware. Secondly following that strategy more work has to be done on the data-structure on which it has to be recorded, and if this approach would be sufficient to have a database large enough to train the algorithm.

  Another approach would be to use LPO to create starting LP, then from further random shuffling and the large database available on autunite try to train the algorithm to get from generation to generation as close as the available database (and thus, training the algorithm for a long list of generated fictitious plans). The strength of this approach is that all the data is available. However we need to implement a generative planning system which is not an easy task, but can be done with traditional logic-based symbolic algorithm.

- **Ant based biomimetism**
  In [2] is exposed another approach to genetic algorithm from the way ants find the most effective path in *Traveling salesman* type of problem. The setback is that if this approach taken the system has to be implemented from scratch as this approach is problem-bound. It could however be an original direction. The strategy would be close to the second CNN one to train the "colony" of ants to find the most effective path to one of the configuration in the searchspace. See the complete description still in [2].

- **Particle Swarm Optimization**
  This method pops up often in the literature. This would be a sensible choice as it has been implemented for a lot of combinatory problems in the past, but no in in-core fuel management problems [1]. This has to be explored further.

3.5 Strategies

The following essential question is how can we use the previous algorithms to help the engineers. In all strategies, we use the same main idea :

1. **Heuristically improved swapping** : The idea is to implement a slight improvement to LPO after the fact. Panache will be the tool used to evaluate the quality of the LP. The NN will start with fully randomized symmetrical swapping. At each move, the quality function will give feedback on of it was a good decision or not.

2. **Post-LPO filtering** : LPO gives 500 possible LP, implementation of ML pattern recognition if well trained could be useful to very quickly make a hierarchy in all of them, from most probable solution to worse solution.

3. **Autunite pattern comparison** :

4 Proof of work prototype

4.1 Conception

4.2 Results

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