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# Nuclear fuel lattice performance analysis by data mining techniques

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ABSTRACT

In this paper a data mining analysis for BWR nuclear fuel lattice performance is shown. In a typical three-dimensional simulation of the reactor operation simulator gives the core performance for a fuel lattice configuration measured by thermal limits, shutdown margin and produced energy. Based on these results we can determine the number of fulfilled parameters of a fuel lattice configuration. It is interesting to establish a relationship between the fuel lattice properties and the number of fulfilled core parameters in steady state reactor operation. So, with this purpose data mining techniques were used. Results indicate that these techniques are able to predict with enough accuracy (greater than 75%) if a given fuel lattice configuration will have a either "good" or "bad" performance according to reactor core simulation. In this way, they could be coupled with an optimization process to discard fuel lattice configurations with poor performance and, in this way accelerates the optimization process. Data mining techniques apply some filter methods to discard those variables with lower influence in the number of core fulfilled parameter. From this situation, it was also possible to identify a set of variables to be used in new optimization codes with different objective functions than those normally used.



## 1. Introduction

In-core fuel management for BWRs is an activity that requires solving at least four combinatorial optimization problems. Firstly, a fuel lattice design is made according to the energy requirements of a Nuclear Power Plant. Secondly, a fresh fuel bundle is designed using the optimized fuel lattices. In the next problem, once fresh fuel bundles are designed, the most burned fuel bundles at the end of the cycle length are discharged from the core and then, they are replaced by the fresh fuel bundles. New and old fuel bundles are shuffled into the core to make a new fuel reload scheme (fuel load design). Finally, control rod patterns (CRP) for that new fuel reload, are designed. If CRPs cannot be designed, it must be necessary to change either the fuel reload or the fuel lattice design, and repeat all the optimization steps. Each optimization problem is very expensive in both time and computational effort. So the whole process may take several days.

Efforts made at the National Institute of Nuclear Research in Mexico to solve the complete process mentioned above, includes the design of the fuel lattice considering both the Local Power Peaking Factor (LPPF) and the neutron infinite multiplicative factor ($k_{inf}$). A fuel lattice design needs around three hours to be optimized with heuristic algorithms. In that optimization process, LPPF is minimized while $k_{inf}$ is kept in a proposed reactivity interval. Both the average uranium enrichment and the gadolinia concentrations are fixed at the beginning of the optimization process. CASMO-4 (Rhodes and Edenius, 2004) code is used to calculate both the LPPF and the $k_{inf}$ parameters at 0.0 GWD/T of fuel lattice exposure. However, if both the LPPF and the $k_{inf}$ along the fuel lattice life are computed by CASMO-4 in order to be used in the objective function, the optimization process could delay 2 or 3 days approximately. This is the main reason to use fuel lattice parameters at the beginning of the fuel lattice life. Here, the problem is to verify the fuel lattice behavior at high exposures. This is verified by a reactor core simulation (using SIMULATE-3 code (Studsviks Scandpower, 2005) with the designed fuel lattices allocated into a fresh fuel batch and loaded into the reactor core.

Now, efforts to estimate the fuel lattice three-dimensional (3D) performance without SIMULATE-3 executions are being made. In Ortiz-Servin et al. (2014), an Artificial Neural Network (ANN) (Haykin, 2008) was trained to predict when a fuel lattice design could operate into the core in a safe way for both fixed fuel reload and CRPs. In Appendix 1, a brief description of the ANN is given.

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In Ortiz-Servin et al. (2014), the authors considered a fuel lattice configuration as a set of six fuel lattices belonging to two fresh fuel batches. They trained an ANN to assess if a given fuel lattice design is "promising" or not. If it was "promising", then that design was evaluated with the reactor code and energy requirements were verified. In that paper, it was seen that the cycle length could be increased and uranium enrichment could be decreased with respect to a reference fuel cycle. ANN to predict the parameter CPF (number of core parameters fulfilled) was presented. Parameters included in CPF are: (1) fraction to linear power density (FLPD), (2) fraction to critical power rate (FLCPR), (3) fraction to average linear power (MAPRAT), through of the cycle length; (4) cold shutdown margin (SDM) at the beginning of the cycle, and (5) deviation of the effective multiplicative factor ($k_{eff}$) from the target $k_{eff}$ throughout of the cycle length. CPF measures the number of fulfilled parameters. If CPF = 0, it means that fuel lattice will not fulfill any of safety parameters; in the opposite, if CPF = 5 this implies that fuel lattice fulfills all the safety parameters described. A good fuel lattice combination is that with CPF = 5. Fuel lattices combination with CPF < 5 will have poor performance in reactor operation.

It is very well known that ANN acts like "black boxes". We do not have information about how they learn to classify in a correct way. In order to understand this point, think in the neutron flux distribution into the reactor core. It depends on neutrons energy, materials, temperature, etc. There is an explicit way to relate input and output variables through of Neutrons Transport Theory. But, in ANN is not possible to represent an explicit relation between input and output patterns. Certain data mining techniques (Shu-Hsien et al., 2012) may allow to extract more information about the relation between inputs and outputs, which helps to improve understanding of the problem at hand.

The aim of this paper is to show how some data mining based models or classifiers can be used to improve the classification of the fuel lattice designs in terms of CPF values. Data mining is described in Shu-Hsien et al. (2012) as the process of extracting new, useful, comprehensible knowledge from data. In other words, the fundamental task of data mining is to find intelligible models, starting from the data.

Application of data mining techniques for a classification task requires, essentially, addressing all or some the following steps:

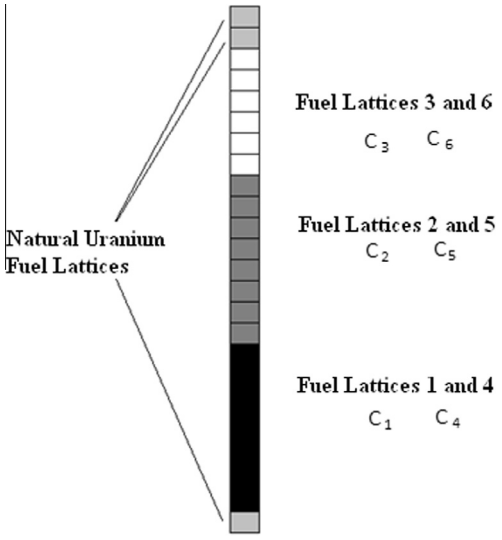


**Fig. 1.** Fuel bundle axial composition.

- Identification of the problem.
- Data preparation:
  - Construction of a data set of the problem: Data set (observations, measurements, etc.) are accompanied by labels indicating the class or categories of the observations.
  - Definition of the training data set.
  - Data pre-processing.
- Training step: Data mining technique builds a model (classifier) using the training data set.
- Testing step (evaluation): Estimate the classifier accuracy. The classifier is evaluated (verified) with respect to the previously unseen examples. For this, we use a testing data set.

In our particular case, we address the following steps:

- Data sets construction: The data set contains BWR fuel lattice features as variables, and the corresponding CPF value as label. The original data set is splitted in two: Data-TR (training data set) and Data-TS (testing data set).
- We will use several data mining techniques (C4.5 (J48), RepTree and Random Forest) provided in the WEKA Package (the Waikato Environment for Knowledge Analysis) (Hall et al., 2009). These techniques obtain models based on decision trees. Decision trees are comprehensible and interpretable models, and they allow a better understanding of the relationships between the categories and variables.

**Table 1**
List of design variables of the fuel lattice.

| Variable name | Description |
|---|---|
| $C_x$_GD | Total number of gadolinia rods |
| $C_x$_sGD | Total number of rods without gadolinia |
| $C_x$_gd9 | Number of rods with $U$% = 3.60 and gadolinia concentration of 2% |
| $C_x$_gd10 | Number of rods with $U$% = 3.60 and gadolinia concentration of 4% |
| $C_x$_gd11 | Number of rods with $U$% = 3.60 and gadolinia concentration of 5% |
| $C_x$_gd12 | Number of rods with $U$% = 3.60 and gadolinia concentration of 6% |
| $C_x$_gd13 | Number of rods with $U$% = 3.95 and gadolinia concentration of 2% |
| $C_x$_gd14 | Number of rods with $U$% = 3.95 and gadolinia concentration of 4% |
| $C_x$_gd15 | Number of rods with $U$% = 3.95 and gadolinia concentration of 5% |
| $C_x$_gd16 | Number of rods with $U$% = 3.95 and gadolinia concentration of 6% |
| $C_x$_gd17 | Number of rods with $U$% = 4.40 and gadolinia concentration of 2% |
| $C_x$_gd18 | Number of rods with $U$% = 4.40 and gadolinia concentration of 4% |
| $C_x$_gd19 | Number of rods with $U$% = 4.40 and gadolinia concentration of 5% |
| $C_x$_gd20 | Number of rods with $U$% = 4.40 and gadolinia concentration of 6% |
| $C_x$_gd21 | Number of rods with $U$% = 3.95 and gadolinia concentration of 7% |
| $C_x$_gd22 | Number of rods with $U$% = 4.40 and gadolinia concentration of 7% |
| $C_x$_gd-gd | Number of gadolinia rods with gadolinia rods around it |
| $C_x$_gd-h20 | Number of gadolinia rods next to water channels |
| $C_x$_ud1 | Number of rods with $U$% = 2.0% not in peripheral fuel lattice |
| $C_x$_ud2 | Number of rods with $U$% = 2.4% not in peripheral fuel lattice |
| $C_x$_ud3 | Number of rods with $U$% = 2.8% not in peripheral fuel lattice |
| $C_x$_ud4 | Number of rods with $U$% = 3.2% not in peripheral fuel lattice |