Optimization of Nuclear Fuel Cycle using Simultaneous Perturbation Stochastic Approximation

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Abstract: Sustainability is a multi-faceted objective for any energy production technology covering economic, environmental and socio-political aspects, and elements of the nuclear fuel cycle have impacts across all facets. The increasing use of nuclear power puts stringent demands on nuclear fuel cycle activities and on understanding the behavior of materials used in nuclear reactors. Optimized in-pile fuel performance is required to ensure the reliability and economic efficiency in nuclear fuel utilization. A novel optimization method based on the Simultaneous Perturbation Stochastic Approximation (SPSA) is proposed to maximize the system's control performance. Rather than traditional controller parameter tuning method, this method optimizes the control system by directly using measurements of control performance. Neural network based predictive control solves the nonlinear tracking problems. Simulation comparison tests were done on nonlinear plants thereby effectiveness of the novel based predictive control is improved.

Keywords: Nuclear Fuel Cycle, SPSA Optimization, Neural Networks, Simulation.

1. INTRODUCTION

Nuclear fuel management (Turinsky and Parks, 1999; Turinsky, 2005) involves the following decisions: the quantity and attributes of the fresh fuel assemblies, the partially burnt fuel assemblies that will be reinserted, the locations of both the fresh and partially burnt fuel assemblies within the core, i.e., core loading pattern (LP), and for a boiling water reactors the control rod program/core flow (CRP/CF) strategy [9].These decisions need to be made for each reload cycle.

The objective of nuclear fuel management is to minimize the nuclear fuel cycle cost while satisfying the cycle energy requirement. This must be done such that all safety and operational constraints are satisfied with sufficient margin. Many fuel-shuffling methods have been studied to satisfy these objectives, that is, to obtain the optimal loading patterns. Some of these methods are as follows: linear programming, dynamic programming, variational OCT, perturbation theory, direct search, heuristic search. Discroll et al., 1990)[1]. None of these optimization approaches ensure the global optimum solution because of the limitations of their search algorithms; they can only find near-optimum solutions (Kim et al., 1997)[4].

One of the most promising long term solutions is to switch to alternative, non-polluting, primary energy sources. S.Jiang, (2008) have used several NNs in order to predict core parameters for PWRs.[3] They have employed a rule based system and the simulated annealing technique, respectively to optimize LPs. Ziver et al. (2004) used several NNs to predict reactor parameters for an Advanced Gas-Cooled Reactor[11].

Erdogan and Geckinli (2003) used NNs to predict channel power distributions and k_{eff}.[2] The method proposed involves the application of simultaneous perturbation stochastic approximation (SPSA) in modeling the weight update process of an NN. The FBs (Fuel Bundles) k_{∞} values in a quarter core symmetry are used as the NN input data, and k_{eff} (in the BOC and EOC cases) as the NN outputs. The distributed control problem can be redefined as finding the set of NN weight parameters $w_i(T)$ for each A_i, $i \in N$ that minimizes the approximated cost function $\hat{C}$, where $\hat{C}$ is a function of $w_i(T)$.

2. NUCLEAR FUEL CYCLE

Nuclear reactor fuel consists of Uranium oxide or blend of mixed Uranium and Plutonium oxides. Energy in Nuclear reactions yields “Nuclear Fission products and minor actinides”. Hence fuel is subjected to treatment of :

a) Partition the materials that are to be recycled from other radioactive elements, making up the waste.

b) Condition that waste in to a form that are inert, and safe.

Nuclear energy development was based on the expectation that recycling of the fissionable materials in the used fuel from today's light water reactors into advanced (fast) reactors would be implemented in order to extend the nuclear fuel resources. More recently, arguments have been made for deployment of fast reactors in order to reduce the amount of higher actinides, hence the longevity of radioactivity.

The cost of the fast reactors, together with concerns about the proliferation of the technology of extraction of plutonium from used LWR fuel as well as the large investments in construction of reprocessing facilities have been the basis for arguments to defer the introduction of recycling technologies in many countries including US. The fuel cycle options of the 2010 MIT fuel cycle[5] study are re-examined in light of the expected slower rate of growth in nuclear energy today, using the CAFCA (Code for Advanced Fuel Cycle Analysis). The stochastic optimization tool, was used to identify non-inferior solutions.

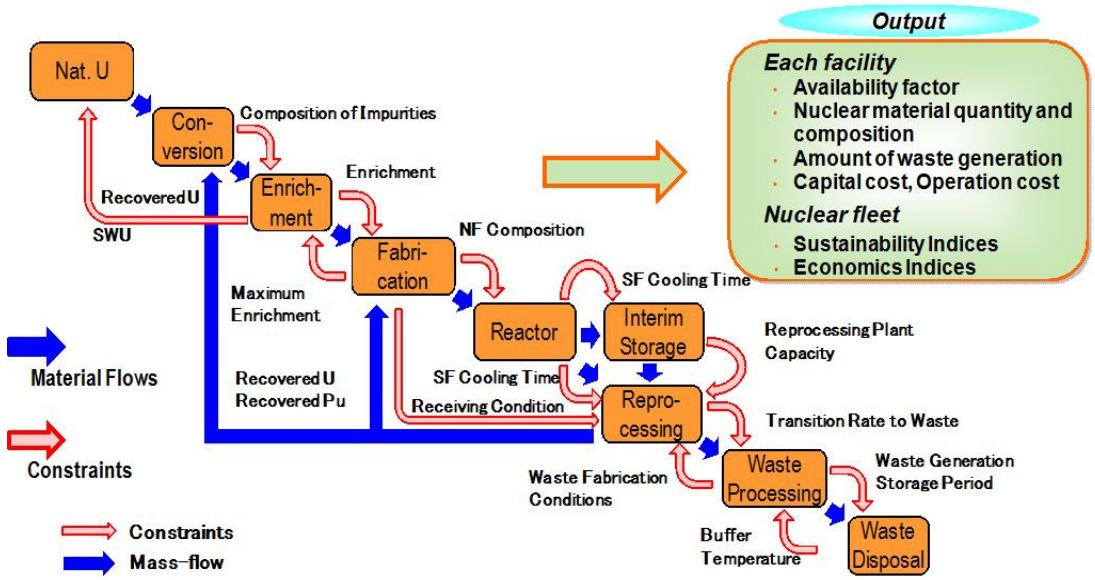


Fig.1. Nuclear Fuel cycle

Input parameters are categorized into three groups:

(a) **Strategy Parameters:** Nuclear capacity variants, reprocessing-recycling strategies, reactor type mixtures and load factors for each type of reactor.

(b) **Fuel Parameters:** Average discharge burn up, average initial enrichment, average tail assay on an annual basis and aggregated for each reactor type.

(c) **Control Parameters:** Share of MOX fuel in reactor fuel, lead and lag times for different processes and the number of spent fuel reprocessing cycles.

Outputs are:
Natural uranium, conversion and enrichment service requirements.
Fresh fuel requirements and spent fuel arising.
Total plutonium arising and separated plutonium utilization.
Reprocessing and MOX fuel requirements.

Reactivity requirements

In order to start the reactor from a cold zero power (CZP) state to a hot full power (HFP) state, the core must have sufficient reactivity to compensate for the temperature and other defects. The temperature defect is the reactivity decrease due to the negative temperature coefficients, and there

are coolant temperature-based defects and fuel temperature-based defects. The temperature defect from the CZP state to the hot zero power (HZP) state comes mostly from the coolant temperature rise because the fuel temperature coefficient is much smaller than the moderator temperature coefficient. In a PWR, the magnitude of the CZP-to-HZP temperature defect varies from time to time during the cycle quite significantly since the moderator temperature coefficient changes substantially due to the change in soluble boron density. On the other hand, the HZP to HFP temperature defect is mostly due to the fuel temperature contribution since the fuel temperature increases significantly at power.

Xenon is built up at power as a fission product and reduces core reactivity. This is called the xenon defect. More xenon is built up after the shutdown because more xenon is produced by the decay of iodine than it is lost by absorption or decay during the reactor operation. The xenon worth peaks about 6 hours after the reactor shutdown.[8] Thus for immediate startup after the reactor shutdown, the additional xenon should be compensated by the fuel reactivity. This is called xenon override. In addition to the temperature and xenon defects, there is a defect due to neutron leakage, which is unavoidable in a finite physical system. The last reactivity component to be compensated for is fuel depletion. Since the reactivity of the fuel diminishes in general as the fuel burns out and also the reactor must be operating at the end of cycle, the fuel depletion effect should be included in the initial reactivity. The amount of reactivity loss due to fuel depletion is dependent on the cycle length and the types of the fuel used.

Table 1. Reactivity requirements for HFP fuel cycle

Reactivity Component	Magnitude, %
CZP to HZP temperature defect	2 - 5
HZP to HFP defect	1 - 2
Xenon defect	2.5 - 3
Xenon override	~ 1
Neutron leakage	2.5 - 3.5
Fuel depletion	5 - 8
Total	14 - 22.5

Simultaneous Perturbation Stochastic Approximation:

The problem of online tuning the model on the basis of measures with available sensors should be faced. Two distinct approximate blocks are defined with mathematical structures (with SPSA) and unknown parameters(using ANN).

The simultaneous perturbation approximation has all elements of θ ^ (K) randomly perturbed together to obtain two measurements of y (·), but each component g_{ki} θ^ (k) is formed from a ratio involving the individual components in the perturbation vector and the difference in the two corresponding measurements. For two sided simultaneous perturbation, we have

$$g_{ki}\,\theta\hat{}\,(k) = \frac{y(\theta\hat{}\,k + c_k\Delta_k) - y(\theta\hat{}\,k - c_k\Delta_k)}{2c_k\Delta_{ki}} \quad (1)$$

where the distribution of the user-specified p-dimensional random perturbation vector is $\Delta k = (\Delta k1, \Delta k2,\ldots,\Delta kp)^T$ & c_k denotes a small positive number. SPSA is central to the approach by providing a means for making small simultaneous changes to all the signal timings in a network and using the information gathered in this way to update the system-wide timing strategy. By avoiding conventional "one-signal-at-a-time" changes to the signal timing strategies, the time it would take to produce an overall optimal strategy for the system is reduced from years or decades. SPSA works by varying all of the aim point coordinates simultaneously and running a simulation in the process of producing the gradient approximation for the optimization process. This procedure is repeated as the iteration for the optimization proceeds. This method contrasts significantly with conventional methods where one would vary only one of the coordinates for one of the aim points prior to running a simulation, repeating that process as each coordinate for each aim point was changed at a specified nominal set of aim points to construct a gradient approximation at the given nominal point. The process is repeated as the nominal aim points are varied over the course of the optimization. By simultaneously changing the aim points, one is able to reduce by a factor of p the number of simulations needed, possibly reducing the run times from days to minutes or hours.

Artificial Neural networks assisted SPSA:

Artificial Neural networks have been found to be an attractive tool for dynamic process modeling and model based control in situations where empirical model becomes impractical. Specifically it should be able to optimize the input space of ANN model representing process variables, (fuel concentration, reactor temperature etc...) such that the model output is maximized or minimized. SPSA methodologies need only the measurements of objective function, and not the gradient measurement. Uncertainties need to be classified :

(a) **Process inherent Uncertainty**: Due to random variation in process parameters such as flow rate, temperature and pressure in the fuel cycle.

(b) **Model inherent Uncertainty**: Kinetic Constants, heat-mass transfer coefficients, physical properties.

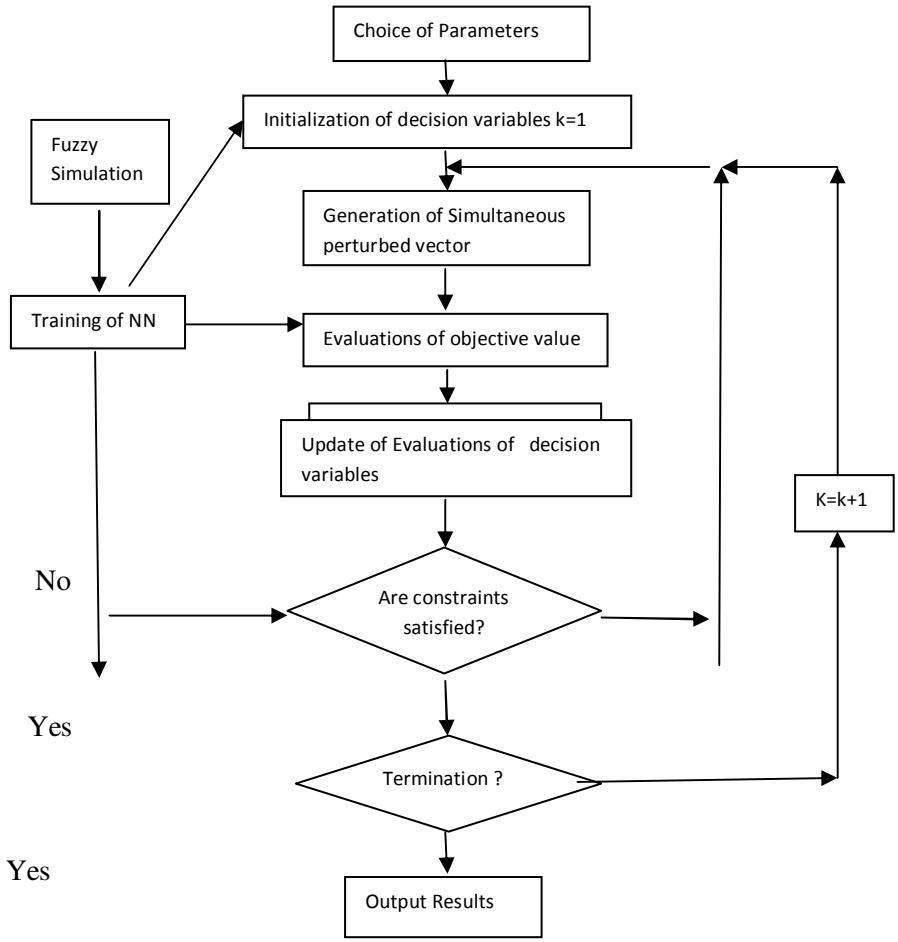


Fig.2. SPSA Assisted ANN in Nuclear Fuel Cycle

The purpose of training NN in the proposed algorithm is to improve the efficiency of the algorithm. During the iterations of SPSA, the values of objective functions and constraint functions are used. These values are obtained by NN. In order to solve the model, we first produce training input-output data for the uncertain functions

$$U_1 : x \rightarrow E\,[\sin(x+\xi) + 2\sin(x+\xi) + 3\sin(x+\xi)] \rightarrow \quad (2)$$

$$U_2 : x \rightarrow E\,[\,|\xi x + \xi x + \xi x|\,] \quad \rightarrow \quad (3)$$

where x is a decision vector; ξ is a fuzzy vector,

Choose nonnegative parameters a, c, A, α and β which are predetermined confidence levels

Then we train an NN (3 input neurons, 5 hidden neurons, 2 output neurons) to approximate these uncertain functions. Then the trained NN is embedded into SPSA.

3. SIMULATION RESULTS

Fuel cycle reload optimization problems are restricted to following constraints:

(a) Maximization of cycle energy production (maximizing K_{eff} at the EOC burnup)

(b) Radial power peaking minimization throughout the cycle.

(c) Discharge burn up maximization.

(d)Again EOC k_{eff} maximization but with alternative fuel loading and reduced target cycle length.

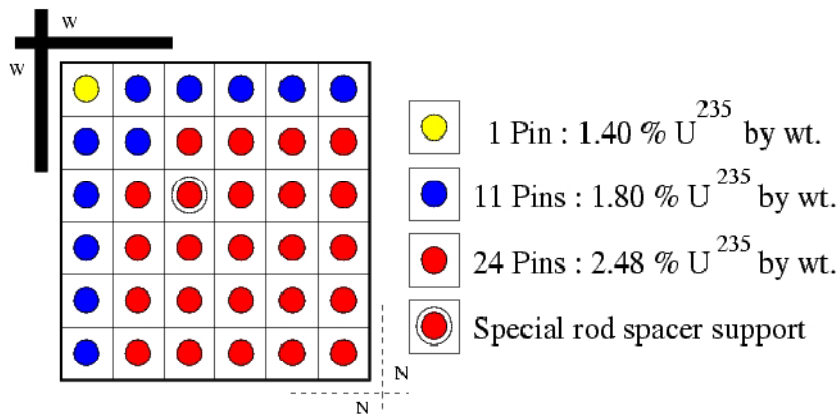


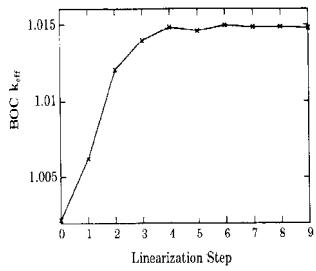
Fig .3. Fuel Assembly

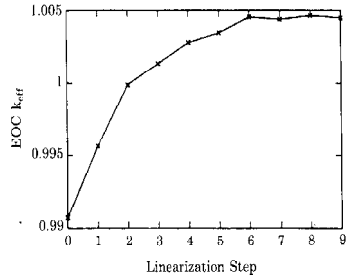
The fuel assembly consists of 36 fuel pins in 6x6 matrix or 49 pins in 7x7 matrix. Each 6x6 FA has 3 enrichments viz 2.66%, 2.1% and 1.66% while each 7x7 FA has and one fuel pin of natural uranium. Uncertainties in the imported fuel supply led to development of indigenous mixed oxide fuel (MOX) for these reactors. The objective function was recast in the form of minimization problem as

$$f = -10^5\left(\frac{k'}{k^{ref}} - 1\right), \quad \text{->} \qquad (4)$$

Where k' and k^{ref} represents the k_{eff} values at the target of EOC burn up of the perturbed and reference reloading fuel patterns. As shown in Fig.4 BOC k_{eff} is constrained to 1.0150, implying

that the minimum required number of burnable poisons for reactivity control was loaded. Also the optimum EOC k_{eff} values (Fig.5) were within 0.02% of the mean optimum k_{eff} values and the results are well within the Generalized Perturbed Theory.





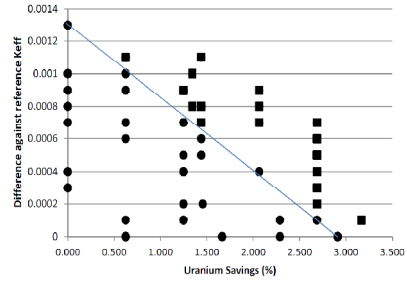


Fig 4. BOC K_{eff} **Fig 5. EOC K_{eff}** **Fig 6.Uranium Vs K_{eff}**

4. CONCLUSION

Nuclear cycle core fuel management, cannot produce beforehand the design for the next fuel reload, and has to wait for the shut-down period to carry out his calculations. This is due to the fact that the exact parameters of the shut-down configuration will change the desired solution totally. The solution for the problem you actually got may be found by taking one known solution, and then modifying it - this is called reshuffling - by switching cases in the grid of the reactor core geometry, until you get a solution that is both admissible and good for solving your own problem. The SPSA algorithm has proven to be an effective stochastic optimization method. Its primary virtues are ease of implementation and lack of need for loss function gradient, theoretical and experimental support for relative efficiency, robustness to noise in the loss measurements, and empirical evidence of ability to find a global minimum when multiple (local and global) minima exist. SPSA is primarily limited to continuous-variable problems and, relative to other methods, is most effective when the loss function measurements include added noise. Neural networks can capture complex dynamics of the system yielding satisfactory predictions. ANN software is to obtain fast estimation tool which allows large explorations of core safety parameters. This software is very useful in reactor core designing and in-core fuel management or loading pattern optimization. This research work has extended the application of hybrid computational intelligence techniques to a large-scale real-world application using an simultaneous approximated algorithm. For such applications, the concept of effective continuous learning is of utmost importance given the undesirability of having to retune the control parameters from time to time.

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