

**Methodology for an Advanced Risk Assessment
of Crud Induced Power Shift using Coupled Multi-
Physics Simulations and a Monte Carlo Scenario
Analysis of the Potential Financial Benefits**

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ABSTRACT

Beginning in the 1970's, power uprates in nuclear power plants began to cause an operational problem called Crud Induced Power Shift (CIPS). Over decades, a method has been developed and refined that has allowed industry to effectively avoid CIPS. However, increasingly challenging economic environments have caused power plants to utilize more aggressive core designs. The problem of CIPS still looms over many reactors as a potential hazard requiring conservative measures. CIPS is due to complex physical and chemical interactions. Current industry methods use multiple single-physics simulations in their analyses. However, improved 3D multi-physics models of CIPS can provide a better understanding of the interaction of the contributing physical phenomena. This increased understanding could help define and control the available margin and tradeoffs of operating with risk of having CIPS occur.

The Virtual Environment for Reactor Applications (VERA) has been developed within the Consortium for the Advanced Simulation of Light-water reactors to study the fundamentally 3D multi-physics phenomena that cause CIPS. The objective of this dissertation is to develop a methodology of applying VERA in industry to accurately determine the CIPS effects on varying core designs while providing information on their potential economic characteristics. The development and application of a methodology for advanced CIPS risk analysis has been performed by benchmarking of VERA models to plant data, improvements in VERA including the development a necessary boron hideout dissolution model, the comparative analysis of multiple core designs with differing CIPS risk, and the quantification of potential economic tradeoffs between the analyzed core designs. Application of the advanced CIPS risk methodology indicates that the feedback between multiple physics is critical to analyzing the effect of CIPS. This CIPS analysis shows relatively small differences in axial offset deviation for core designs with higher risk of CIPS, which translates to significant potential cost savings between core designs in all market scenarios with low additional risk from CIPS. This research provides insight into how varying core designs with specific maximum total core boron mass experience the effects of CIPS, what the magnitudes of those effects are, and the corresponding economic impacts of each core design.

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ACRONYMS

AOA	axial offset anomaly
ARI	all rods in
ARO	all rods out
BOA	Boron-Induced Offset Anomaly
BOC	beginning of cycle
CASL	Consortium for Advanced Simulation of Light Water Reactors
CBW	control rod bank worth
CHF	critical heat flux
CILC	Crud-induced localized corrosion
CIPS	Crud-induced power shift
CFD	computational fluid dynamics
CNS2	Catawba Nuclear Station Unit 2
CRUD	corrosion-related unidentified deposits or Chalk River unidentified deposits
CTF	COBRA-TF sub-channel thermal-hydraulics code
DBW	differential boron worth
DNB	departure from nucleate boiling
DOE	US Department of Energy
DRWM	dynamic rod worth measurement
EFPD	effective full power days
EIA	Energy Information Agency
EPRI	Electric Power Research Institute
EOC	end-of-cycle
EU	enriched uranium
GBM	geometric Brownian motion
GWd/MTU	Gigawatt-day/metric ton uranium
HFP	hot full power
HZP	hot zero power
IFBA	integral fuel burnable absorber
INL	Idaho National Laboratory
ITC	isothermal temperature coefficient
M&S	modeling and simulation
MAMBA	MPO advanced model for boron analysis
MAMBA-1D	MPO advanced model for boron analysis – 1 dimensional version
MOC	method of characteristics
MPACT	Michigan parallel characteristics transport code
MTC	moderator temperature coefficient
NA	natural uranium
NRC	Nuclear Regulatory Commission
ORNL	Oak Ridge National Laboratory
PCI	pellet-cladding interaction
PCM	percent mille (10-5)
PWR	pressurized water reactor
RCS	reactor coolant system
RIA	reactivity insertion accident
SDM	shutdown margin

SWU	separative work unit
T/H	thermal-hydraulics
VERA	Virtual Environment for Reactor Applications
WABA	wet annular burnable absorber
ZPPT	Zero Power Physics Testing or Low Physics Power Testing

CHAPTER 1. INTRODUCTION

1.1 RESEARCH OBJECTIVES

The objective of this research is the development and application of an advanced Crud Induced Power Shift (CIPS) risk methodology that builds upon the current industry methods with advanced, coupled multi-physics modeling and simulation. This method allows multiple future core design candidates to be compared by having the potential effects of CIPS in the core quantified. The goal of using advanced, coupled multi-physics modeling is to reduce industry conservatism and lower fuel reload and overhead costs.

To achieve this, an additional boron hideout dissolution model has been developed to better model the feedback and effects of a CIPS occurrence in the fuel design. In order to perform a valid CIPS analysis, models have been developed and benchmarked against measured plant data for multiple cycles, and including the development of an efficient approach to begin analysis at intermediate operating cycles. This adds to the validation of the software called the Virtual Reactor for Reactor Applications (VERA) being developed by the Consortium for the Advanced Simulation of Light-water reactors (CASL) at Oak Ridge National Laboratory (ORNL). The results of the CIPS analysis have been compared to current industry standard methods in order to better understand the differences in the capabilities. Key core operating parameters have been analyzed and compared to current standard industry limits. Finally, the potential economic tradeoffs have been quantified by developing a stochastic scenario analysis model.

1.2 DISSERTATION ORGANIZATION

In Chapter 2 the background for the multiple facets of the research is presented. The motivation is described by looking at the current status of nuclear power in the U.S. Operation issues will be discussed and an overview CIPS and the underlying physics is given. An overview is then given on the significant factors considered in the economic analysis. An overview of the current industry methods and tools is then given. Finally the modeling and simulation tools used in this research are presented.

In Chapter 3 the methodologies for both the advanced CIPS risk analysis and the economic investigation are developed. Additionally, the theory for the boron hideout dissolution model and the stochastic economic model is presented.

In Chapter 4, the results of the benchmarking of the VERA models to multiple cycles of plant data are presented and discussed. Particularly the Zero Power Physics Testing (ZPPT) benchmarking is examined. Additionally, the “jump-in”

model developed and applied in support of the benchmarking is presented and discussed.

Chapter 5 begins by comparing and discussing multiple aspects between the current industry standard code, the Boron-Induced Offset Anomaly (BOA) risk assessment tool, and the suite of codes used in the CIPS comparison analysis, VERA. Then the results of the CIPS analysis comparing the three different core designs of varying CIPS risk is presented and discussed.

Chapter 6 describes the application of the Monte Carlo scenario analysis. The results of the economic analysis for each core design are compared and discussed.

In Chapter 7, a summary of the research is given with highlighted results. Conclusions from the research are drawn and recommendations for future work are given.

CHAPTER 2. BACKGROUND

2.1 STATE OF NUCLEAR POWER IN THE U.S.

In the last few years, many nations around the world have seen a significant decrease in their nuclear power production capabilities in what has been called the “nuclear phase-out.” (Anderson, 2015) The post-Fukushima era for nuclear power has been marked largely by negative public opinion and a harsh political climate.

In the United States, the climate around nuclear power generation is primarily driven by historically low U.S. natural gas prices through advances in fracking technology (Douglas, 2013). The effects of the Fukushima accident have been felt indirectly through increased costs imposed on nuclear power plants by modifications for additional conservative safety measures. Despite these hurdles, nuclear power in the U.S. is still recognized as an essential part of our nation’s energy portfolio for low-carbon generation and energy security (Dominion, 2012). Therefore, continued research and development of technologies that increase the safety, efficiency, and economic viability of the United States’ nuclear power fleet remains indispensable. CASL is a key DOE-funded initiative that aims at achieving this goal by developing advanced multi-physics modeling and simulation tools for the US nuclear industry.

2.1.1 NUCLEAR POWER GENERATING COSTS

The major challenge to the nuclear power industry is the competitiveness of the electricity market. Over the last 13 years the nuclear power industry has seen an increase in total generating costs of 26 percent (NEI, 2016). These costs of power generation are shown in Table 2-1 and are broken down by year into three categories: capital, operations and maintenance, and fuel costs. Individually these categories have seen an increase of 11% for operations costs, 103% for capital costs, and 21% for fuel costs.

These significant increases in costs for nuclear power plants emphasize the need for the development of technologies and methods to increase the efficiency and safety of power plants, such as that furthered through CASL. The goal of applying advanced modeling and simulation tools would be to positively impact fuel, capital, and operating costs by increasing energy generated by the fuel, impacting equipment needs, such as ultrasonic cleaning of fuel, and improving operating costs by reducing fuel failures.

2.1.2 OPERATIONAL ISSUES

Current nuclear reactors face a series of complex engineering problems due to uprates in power and lifetime extensions in an attempt to maximize the output of

Table 2-1 U.S. Nuclear Power Plant Costs. (2015\$) (NEI, 2016)

Year	Fuel	Capital	Operating	Total
	5.73	3.92	18.61	28.27
2003	5.60	4.94	18.87	29.40
2004	5.29	5.66	18.56	29.50
2005	5.02	5.81	18.97	29.80
2006	5.05	5.56	19.23	29.85
2007	5.13	6.12	19.09	30.35
2008	5.36	6.77	19.53	31.66
2009	5.94	8.92	20.52	35.38
2010	6.77	9.17	20.66	36.59
2011	7.10	10.07	21.91	39.08
2012	7.47	10.77	21.50	39.75
2013	7.74	8.21	20.95	36.91
2014	7.22	8.19	20.95	36.35
2015	6.91	7.97	20.62	35.50
2002-2015 Increase	21%	103%	11%	26%
2010-2015 Increase	2%	-13%	0%	-3%

the current reactor fleet. CASL is targeting some of these operational issues including:

- *Chalk River Unidentified Deposits (crud)* – Corrosion products from the reactor and steam generator tubing deposited onto the fuel elements. Originally the cause of the deposits was unknown and the composition of the deposits could not be identified. Now it is known that the local thickness of the crud on the fuel rods is related to the local rod power density. Thick crud deposits can limit safety by causing CIPS and Crud Induced Localized Corrosion (CILC).
- *CIPS* – Crud preferentially forms on the top half of the fuel rods in nuclear reactors. If there is a significant absorption of boron from the coolant into the crud it can cause a depression in power in the top half of the core, shifting more power to the bottom half. This can cause a decrease in safety and shutdown margin while limiting operational flexibility. Because of changes in axial power distribution, the plant may have to decrease its power output in order to keep enough shutdown margin required for the safety of the plant.
- *CILC* – The deposition of crud causes localized hot spots by decreasing the heat transfer at the fuel rod cladding surface. These hot spots increase chemical reactivity and tend to oxidize and corrode at an accelerated rate. If the CILC is dramatic enough it can cause a breach in cladding and a release of radioactive material into the coolant system. Better understanding of CIPS and CILC could allow reactors to reach higher power densities while maintaining appropriate margins of safety.
- *Departure from Nucleate Boiling (DNB)* – Nuclear reactors generate electricity through producing heat from nuclear reactions and transferring that heat to the reactor coolant through nucleate boiling. If too much heat is generated, then the boiling may depart from the nucleate regime and move to film boiling. Film boiling is much less efficient at transferring heat and can cause a local dry-out condition where there is no liquid touching the nuclear fuel rod. This dramatically increases the temperature of the fuel rod materials and accelerates corrosion which may lead to fuel rod failures. Having an accurate prediction of the Critical Heat Flux (CHF) that causes the departure from nucleate boiling could allow for higher power generation while insuring adequate safety margins.
- *Pellet-Cladding Interaction (PCI)* – Current nuclear power reactors in the U.S. use pellets made of uranium dioxide inserted into a metal tube, called cladding, for their fuel rods. When the fuel rods are manufactured, there is a small gap between the pellet and the cladding. When the reactor is operating thermal expansion from the heat generated inside the pellets and the neutron flux irradiation of the pellets cause them to change size and shape. As the power is varied the pellets can shrink or swell and eventually the pellet and the cladding touch and begin to

interact. If they do not swell or shrink at the same rate, then the cladding can fail.

These are the key issues that limit reactor operation and represent current inefficiencies in nuclear power production because they limit increases in generation. These issues are good candidate areas of research to increase efficiencies through the application of advanced modeling and simulation.

To manage these operational issues, conservative measures are used to insure these issues do not occur. These conservative measures are typically implemented by adding additional operational “margin.” There are many types of “margin” analyzed and monitored before, during, and after reactor operation. The International Atomic Energy Agency states that “...margin is usually understood as the difference in physical units between the regulatory acceptance criteria and the results provided by the calculation of the relevant plant parameter. (IAEA, 2003)” The limiting value and the actual value are often uncertain and are not precisely known. Therefore, margin is implemented by analyzing acceptable operating conditions within the limits (with the current technology) and then reducing operations by an amount appropriate to instill high confidence that the limits are not exceeded during operations. The uncertainty inherent in the standard modeling and simulation is factored in with additional margin corresponding with the amount of uncertainty in the methods. Margin is also built into operations due to the uncertainty of local conditions inside the reactor core because of limited measurement devices and methods in the reactor. The method of implementing, and amount of margin, has changed as the confidence of knowing the actual value for a given parameter has grown. The IAEA describes the relationship between computational ability and margin in the following way (IAEA, 2003):

In the past [margin has] been determined by conservative evaluation model calculations. During the recent years an increasing tendency in computational reactor safety analysis is to replace these conservative calculations by “best estimate” or “realistic” calculations. In case of best estimate calculations it is necessary to supplement an uncertainty analysis of the code results when determining [margin]. A prerequisite for this approach is, however, that qualified computer codes are available which are validated by pre- and post-test calculations of appropriate experiments, experiences from other plants and/or benchmark calculations on national and international levels.

The practice remains that conservative margin is added when information is limited and uncertain. High fidelity multi-physics simulations help provide additional information and decrease uncertainty so that operational margin may be regained and efficiency increased while maintaining safety.

In order to improve the understanding of conservatism, advanced modeling and simulation could be used to make predictions on the local and global reactor conditions and safety of the reactor at a resolution and fidelity that has not been seen before. This could allow for a better quantification of the operational limits and the built in margin. This knowledge could then be used to decrease unnecessary margin and increase efficiency while maintaining a certain level of confidence in safe operations.

The application of this research is to address one of these problems specifically – crud induced power shift.

2.2 CRUD INDUCED POWER SHIFT

The occurrence of CIPS is a highly complex, multi-physics phenomenon. The Electric Power Research Institute (EPRI) found that CIPS is usually manifested in an abnormal shift in the axial power distribution, commonly shifting the power from the top to the bottom of the core (EPRI, 2004). The measure of the axial power distribution commonly used is called Axial Offset (AO), which is defined by Equation 2-1. The unexpected anomalous behavior in AO was originally named Axial Offset Anomaly (AOA). Much research has been performed to identify the root causes of AOA. It is generally recognized that CIPS is a form of AOA caused by significant amounts of boron being held in the porous crud deposits creating local neutron flux suppression (Zou, 2013). Three key factors have been identified by the Electric Power Research Institute as the root causes of the CIPS phenomenon. Those factors are (EPRI, June 1997):

1. Sufficient levels of soluble boron in the coolant
2. Sufficient levels of corrosion products in the coolant
3. Sub-cooled nucleate boiling at the fuel rod surfaces

These key conditions that are believed to be necessary for CIPS are portrayed below in Figure 2-1 (EPRI, 2004).

Boron is present in the coolant because it is used as a neutronic shim to control reactivity in the core throughout the length of the cycle. The boron is added to the coolant in the form of boric acid (H_3BO_3). Another chemical, lithium hydroxide (LiOH), is also added to the coolant to control the acidity and reduce corrosion. Natural boron is isotopically composed of 80.1% ^{11}B and 19.9% ^{10}B . The ^{10}B is significant in the operation of a nuclear reactor due to its relatively large neutron absorption cross section. This ability to absorb neutrons makes boron excellent for reactivity control by controlling the fission reaction rate and power output. However, that same property makes boron problematic when the amount and location of boron in the core cannot be controlled. Figure 2-1 shows that crud may still deposit on the fuel rod surfaces if there are sufficient corrosion products in the coolant along with sub-cooled nucleate boiling. However, CIPS becomes a

Rootcause of CIPS

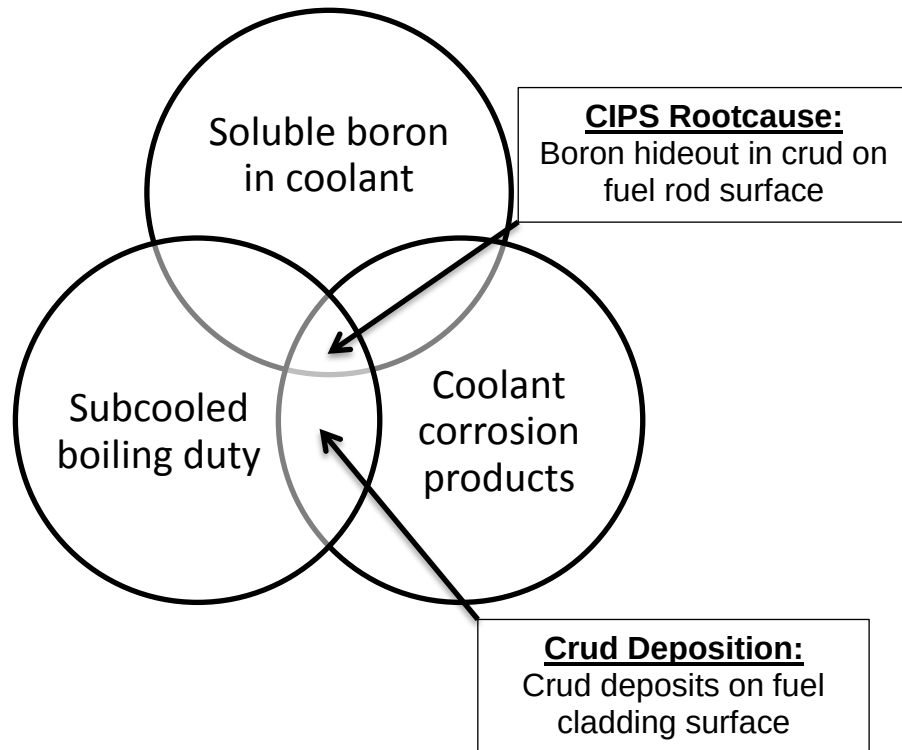


Figure 2-1 Factors Contributing to CIPS (EPRI, 2004)

concern only when there is sufficient soluble boron in the coolant that will deposit out in the porous crud layer. Complex chemical interactions must take place in the crud layer, forming boron containing chemical compounds, for this to happen. Evidence for multiple boron containing chemical compounds formed in the crud layer on nuclear fuel rods has been found (Byres & Deshon, 2004) (Sawicki, 2002) (EPRI, 2001). However, it is thought that boron hideout occurs mainly through the precipitation of lithium borate compounds including LiBO_2 , Li_2BO_7 , and $\text{Li}_2\text{B}_4\text{O}_7$ (EPRI, 2004) (EPRI, 2006) (Uchida, 2011). When the soluble boron deposits out in the crud layer, it becomes a fixed absorber that can significantly depress the local neutron population, and therefore lower fission rates and power production.

One measure of the impact of CIPS on power distribution is its influence on the axial offset in power. The axial offset (AO) is a measure of the axial symmetry of the core power and is defined by:

$$\text{AO} = \frac{\int_{H/2}^H \iint P(x,y,z) dx dy dz - \int_0^{H/2} \iint P(x,y,z) dx dy dz}{\int_{H/2}^H \iint P(x,y,z) dx dy dz + \int_0^{H/2} \iint P(x,y,z) dx dy dz} \times 100 \quad \text{Equation 2-1}$$

Where AO is expressed as a percent, P is the power distribution, H is the height of the active core, and x , y , and z are Cartesian directions with z being the axial direction of the core. This is used to calculate the predicted axial offset from design models. The actual AO is measured during reactor operations using ex-core neutron flux detectors. Historically, CIPS is suspected when the measured AO has more than a -3% deviation from the predicted AO. Measured AO deviations from the predicted AO of $\pm 3\%$ are considered to be within nominal measurement and design (EPRI, 2006). An example of CIPS can be seen represented in Figure 2-2. The predicted AO shown in Figure 2-2 for a normal, non-CIPS cycle typically begins slightly positive and then moves slightly negative for the remainder of the cycle. The slightly positive AO early on in the cycle is due to the higher concentrations of soluble boron used in the coolant. As the coolant gains heat while traveling up through the core, the density decreases. With high concentrations of soluble boron shim in the coolant early in the cycle, this causes an increase in reactivity due to decreasing concentration of neutron poison. The same decrease in coolant density causes the slightly negative AO in the later part of the cycle. However, with lower boron concentrations, the coolant's dominant effect is as a moderator. Therefore, as the coolant density decreases travelling up the core, the moderation and the fission rate decrease in the top of the core creating a negative AO.

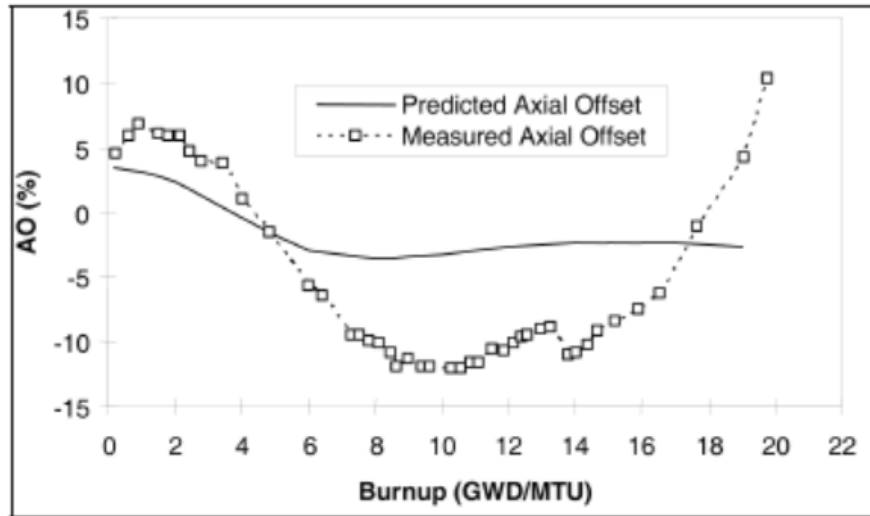


Figure 2-2 Example of Axial Offset Anomaly (EPRI, 2004)

There are other reasons that a plant can experience AOA that is not CIPS. Since AOA is a comparison between the measured and predicted axial offset, there may be multiple reasons these are not in agreement. Unanticipated physical phenomena, such as CIPS, can contribute as to disagreements between predicted and measured AO, but so can the assumptions and simplifications in the engineering models used to generate the predictions. This research will focus on CIPS and will not investigate other sources of AOA.

2.2.1 CIPS DEPENDENCE ON CRUD GROWTH AND BORON HIDEOUT

It has been found that subcooled nucleate boiling (SNB) enhances deposition of crud on the fuel rod cladding (EPRI, 1999). Deposition of crud on heated surfaces under SNB conditions is typically substantially higher than on surfaces under single phase forced convection (EPRI, 2003). The physical mechanisms involved in the deposition of corrosion products on a heated surface are described in Figure 2-3

The importance of heat flux was studied on the deposition of deposits of iron on heated rods. It was found that the two most important factors were: 1) the heat flux had an effect of increasing the deposit thickness proportional to the heat flux to the second power in the regions of SNB for uniform heat flux; 2) the total iron concentration increased the deposit proportional to the first power. This suggests that SNB is of great importance in deposition thickness. (Charlesworth, 1970)

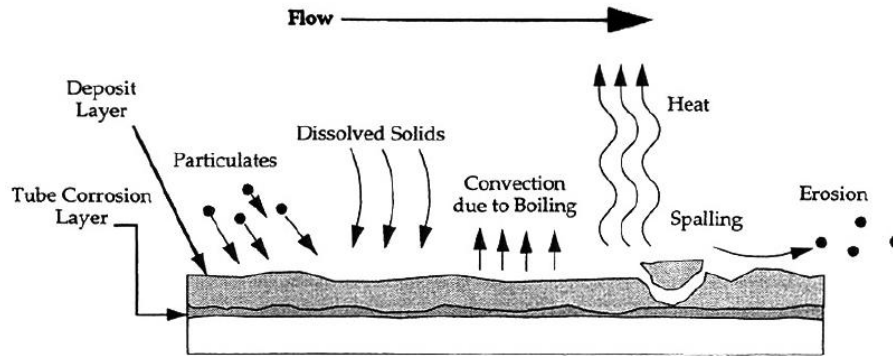


Figure 2-3 Diagram showing the Deposition and Release Mechanisms for Corrosion Products on the Surface of a Heated Tube (EPRI, 2003)

The effect of water temperature on the crud deposition and chemical characteristics has also been studied. It has been shown that in a simulated crud structure at water temperature gradients in the crud iron becomes less soluble at higher temperatures. This would suggest that iron would migrate to the interior of the crud layer and precipitate out if the temperatures are high enough. This is congruous with the crud that was analyzed from the Callaway plant cycle 9 that experienced CIPS. The chemical distribution analyzed in a crud sample is shown in Figure 2-4.

2.2.1.1 THE PRESENCE OF BORIC ACID

The favored mechanism of boron hideout is precipitation of boron containing chemicals through the concentration of chemical species in the crud layer due to boiling. The process of chemical concentration in the crud creates a complex feedback. One understood feedback mechanism is the change in saturation temperature of the coolant with increased concentration of boric acid. The increase in boric acid increases the saturation significantly (EPRI, 2005).

2.2.1.2 BORON HIDEOUT

The boron hideout without the presence of crud deposited on the fuel is unlikely. Multiple mechanisms of chemical species concentration in the crud are possible, but the most favored mechanism is by coolant transport via boiling to the crud/clad interface (EPRI, 2000). A presence and significant magnitude of the following three factors are required to produce CIPS: 1) SNB heat transfer 2) corrosion product deposits present in the boiling regions of the fuel rods 3) bulk coolant boron concentration in sufficient amounts.

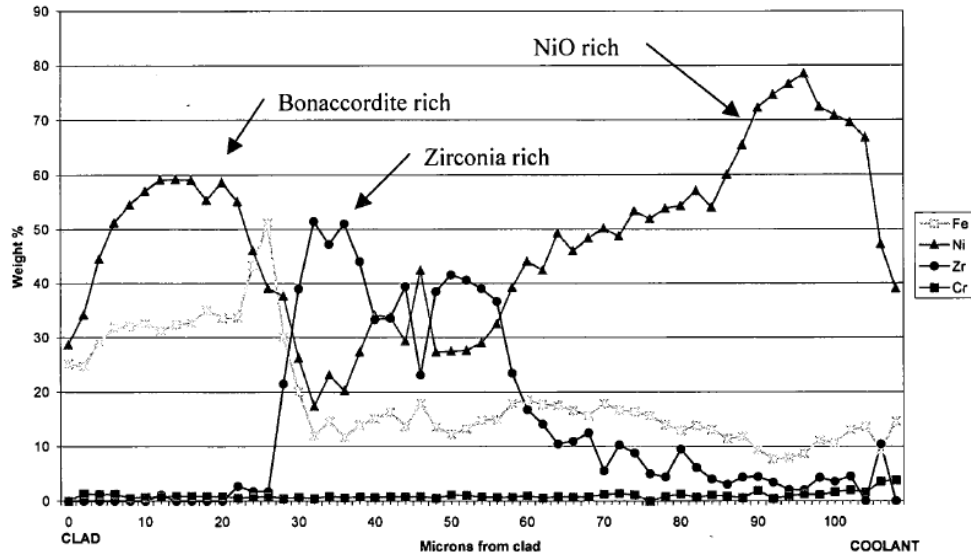


Figure 2-4 Elemental Analysis of a Corrosion Flake from Callaway Cycle 9 (EPRI, 2000)

There are multiple mechanisms for boron hideout. However, the main mechanism is the precipitation of lithium-boron species in the crud structure through the concentration of chemical species in the crud through coolant transfer in the boiling process. Many of these lithium-boron species have retrograde solubility so that an increase in temperature, as seen in the crud layer, would decrease the solubility and facilitate precipitation of solid boron species.

An observation in nuclear power plants that supports the boiling induced precipitation of lithium-boron species is the increase lithium concentrations during a down power. The boron concentration also increases, however detecting the contribution of boron increase from crud release is complicated by a number of factors including: the boron dissolution contribution would only be a few ppm (compared to the hundred's or 1000+ ppm present in the coolant normally), and a combination of control rod movement, coolant dilution, and coolant boration occurs during a power maneuver (EPRI, 2004).

Figure 2-5 shows that there is a strong return of lithium back into the bulk coolant during a down power maneuver to 30%. The down power decreases the core boiling and therefore concentration of chemicals in the crud layer and the solid precipitates in the crud begin to dissolve and diffuse back into the bulk coolant. This shows a significant lithium hideout that is strongly power dependent. It should be noted that the lithium return to the bulk coolant begins almost immediately when the power begins decreasing but it does not reach steady state during the time that the power is held constant at 30%. The power was held at 30% for 24 hours without the lithium concentration reaching a steady value.

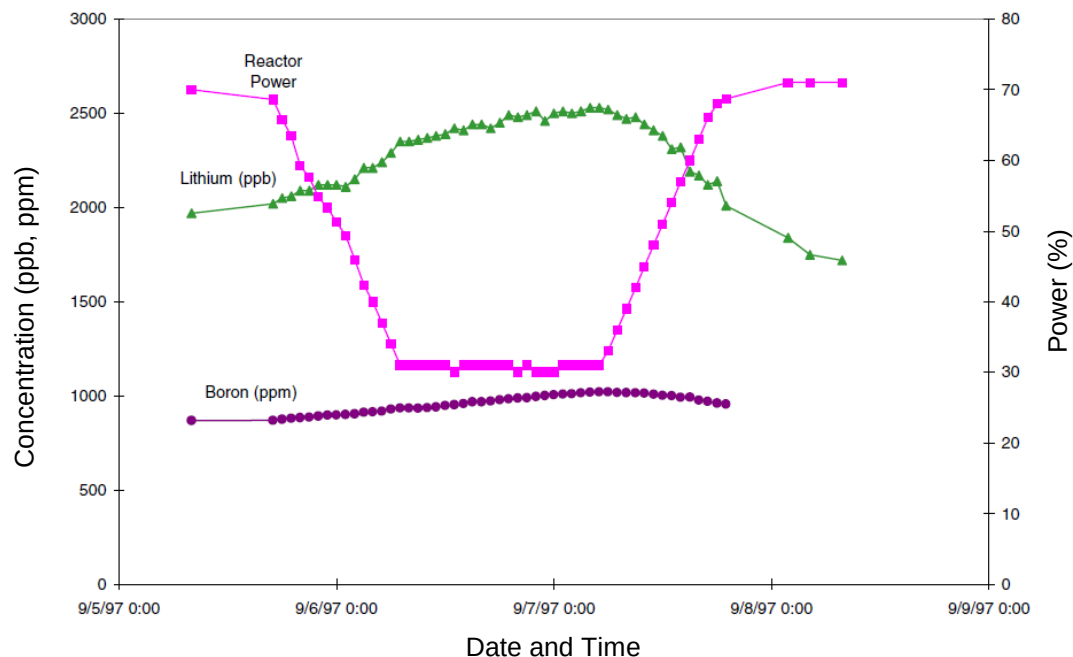


Figure 2-5 Boron and Lithium Concentrations during a Down Power to 30% at Callaway Nuclear Plant in 1997 during Cycle 9 (EPRI, 2001)

Additionally, the lithium concentration peaks and begins to decline again immediately after the power begins to increase. In fact, the bulk coolant lithium concentration decreases to a smaller concentration than the original amount before the power maneuver. This suggests that conditions that facilitate the lithium, and probably boron, hideout are not changed irreversibly by a power maneuver. It also suggests that the conditions that facilitate lithium hideout are stimulated since the lithium concentration decreases below pre-down power levels. This observation can be explained if the boiling induced chemical concentration and precipitation is the primary mechanism for hideout. A potential explanation of this effect is shown in the following 4 steps:

1. A lithium-borate species precipitates in the crud layer near the clad surface
2. The boron in the chemical absorbs a neutron and is transmuted into lithium that remains near the clad surface.
3. The original lithium and lithium from boron absorbing a neutron are released into the coolant by dissolution during a down power due to lack of chemical concentration from boiling effects. The released chemical species leave a porous crud structure behind.
4. The power increases again and boiling returns to the crud. Now the boiling will be enhanced from an increase in power because the neutron poisonous boron chemical species are gone and due to

increased contact with coolant in the porous crud channels. This generates above average boiling and mass transfer into the crud of chemical species in the coolant. This accelerates precipitation of chemical species into the pores of the crud layer.

An alternative mechanism of boron hideout has been proposed. This mechanism focuses on the physical adsorption of un-ionized boric acid to the chemical species present in the crud structure. This mechanism has been calculated to be sufficient to explain CIPS behaviors using adsorption data for iron based oxides (Frattoni, 2000). However, the reactors that have been prone to CIPS have crud that has a structure of mainly nickel based oxides. Data suggests that nickel oxide does not adsorb boric acid well and therefore this would not be a sufficient mechanism for the AO behavior seen. It has been shown by Chalk River Laboratories of Atomic Energy Canada and Oak Ridge National Laboratory that Zirconium Dioxide (ZrO_2) has the ability for adsorption of boric acid (EPRI, 2002) (Palmer, Machesky, Benezeth, Wesolowski, Anovitz, & Deshon, 2009). This is significant because the crud structure analyzed from Callaway Nuclear Plant had a significant mass of ZrO_2 present in it. This could be an additional mechanism for boron hideout.

Although the adsorption of boron and lithium may contribute, the dominant effect appears to be boiling induced concentration and precipitation of lithium-boron species. The data shown previously in Figure 2-5 shows that the primary mechanism responsible for boron and lithium hideout is positively correlated to power. It is assumed that this means that the primary hideout mechanism is also positively correlated with clad temperature as clad temperature increases as power increases. This assumption is in agreement with boiling induced precipitation being the primary mechanism responsible. If physical adsorption was responsible for being the primary mechanism for boron and lithium hideout the response to a down power should be the inverse of what was observed in Callaway. Figure 2-6 shows the Temkin isotherm for the adsorption of boron onto iron based oxides at high temperature and boric acid solution (EPRI, 2005). The slope of the adsorption with increasing temperature is negative.

This suggests that a decrease in temperature should increase boron adsorption and therefore hideout. Then it would be expected that a decrease in reactor power and clad temperature would not release boron and lithium into the coolant, but would instead adsorb more boron and lithium and decrease the coolant concentration. This is the opposite of what was observed in Callaway cycle 9. Therefore, the adsorption of boron containing chemical species on the crud structure surfaces is considered less significant than the precipitation of boron chemical species with retrograde solubility.

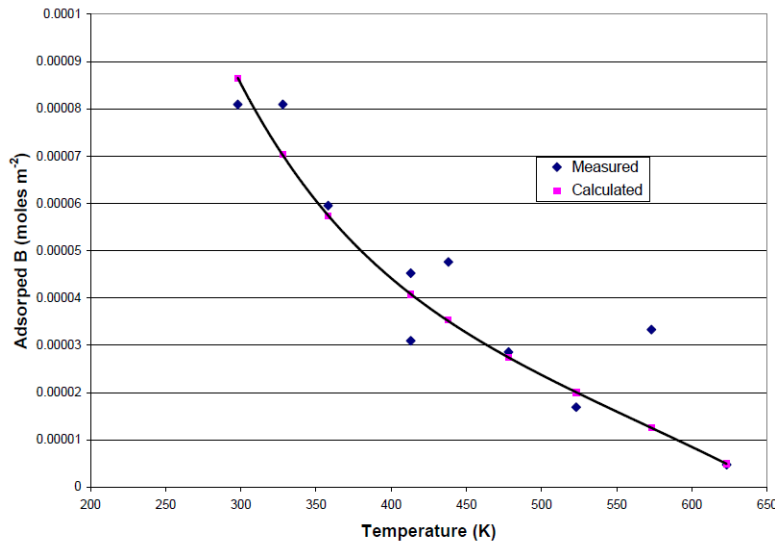


Figure 2-6 Data for Temkin Isotherm fit for the adsorption of boron at high temperatures using 2000 ppm boron solution (EPRI, 2005)

2.2.2 IMPORTANCE OF ADDRESSING CIPS

The first documented incidence of CIPS occurred at Obrigheim in the early 1970's (Reiss, 1976). The heavy corrosion product deposits on the fuel rods were attributed to insufficient hydrogen overpressure and lack of pH control in the first two cycles of operations. However, it is of interest that no LiOH was added to the reactor coolant. The properties of the deposits are characteristic of CIPS with thicker deposits at the top of the core. The axial offset decreased in the core as the boron in the coolant was burned out.

Since then, there have been many other power plants with cycles that have exhibited the characteristic behaviors associated with CIPS including: Calvert Cliffs Unit 1, Callaway cycle 4-6, Seabrook, Comanche Peak, Catawba, Watts Bar, and Wolf Creek. As of March 2014 there have been 49 plants that have had some instances of CIPS. (Feldman, 2014) The reason for the increased occurrence of AOA is suspected to be a combination of increased fuel thermal duty and higher peaking factors due to plant uprates.

CIPS can have significant operational and economic impacts on a power plant. The following are examples of significant negative impacts of AOA taken from the EPRI's Guidelines for AOA and from the VERA Value Proposition (Feldman, 2014) :

- A plant was forced to de-rate power production by ~ 25% to maintain safe shutdown margin for the final 1/3 of the cycle. The cost to replace the lost power production was estimated at ~\$30 million.

- CIPS has caused fuel failures in 4 plants that have degraded performance at an estimated cost of \$25 million.
- Additional regulatory scrutiny has been experienced by at least one plant due to the impact of CIPS on shutdown margin and the uncertainties involved in modelling AOA.
- Many plant staff workers have experienced increased radiation exposure due to activated corrosion products both in-core and ex-core.
- Multiple utilities purchase additional fuel assemblies when designing new cores to reduce peaking factors and steaming rates in order to avoid CIPS. These costs are estimated to be between \$0.5 million and \$2 million per plant cycle.
- Ultrasonic cleaning of fuel to reduce crud carryover between cycles is an added operational cost in time and equipment.

There are significant economic and safety incentives to more accurately predict CIPS behavior and magnitude. Further advancements of being able to predict reactor AO behavior as a monitored cycle progresses would enable mitigation and alleviation of the negative consequences associated with a CIPS occurrence.

2.3 CURRENT CIPS ANALYSIS METHODOLOGY

2.3.1 APPLICATION IN INDUSTRY

The nuclear industry currently addresses CIPS through a risk analysis methodology in their core reload design process. The analysis is only one of many (~30-40) analyses performed during the core reload design. However it is an important analysis since a core design may be considered to be unacceptable if the CIPS risk is considered too high.

A workflow for one pass of the CIPS analysis in the industry core reload design process can be seen in Figure 2-7 (Godfrey A. , 2012). The process utilizes industry standard codes. A brief explanation of the workflow process is as follows:

1. Candidate patterns for core loading are considered to optimize fuel costs, pin peaking, safety margin, and operational risks such as CIPS. Hundreds of full core or quarter core designs may be analyzed. A full cycle depletion is performed and 3D assembly power distributions are generated for the patterns that are passed on to CIPS analysis.
2. The 3D assembly power distributions are processed to be input to a sub-channel thermal-hydraulic (T/H) analysis. Additional externally-generated burnup dependent sub-channel inputs are incorporated into the T/H analysis. The T/H code calculates the subcooled-boiling for each channel at each state point from the given inputs. Additional inputs of best estimate

3. The results from the T/H calculations are processed into input for the CIPS analysis that utilizes the Boron-Induced Offset Anomaly (BOA) risk assessment tool. BOA uses inputs such as the assembly crud histories from previous cycles, boron concentration, lithium, corrosion source terms, and the sub-channel fluid conditions to calculate the crud thickness and deposition of boron for each state point in a cycle. BOA is developed and maintained by the EPRI and Westinghouse.
4. The BOA output is then compared to defined risk thresholds that consider max crud thickness and a pre-defined mass of core-wide boron (e.g. 0.3 lbs.). If BOA calculations show that the boron mass is above the pre-defined threshold then the core reload pattern is considered to have high CIPS risk and it is rejected.

```

graph TD
    Input1[Input] --> LP[Lattice Physics]
    Input2[Input] --> CP[Core Physics]
    Input3[Input] --> CTH[Core T/H]
    
    LP --> XS[(XS)]
    XS --> CP
    
    subgraph Core_Simulator [Core Simulator]
        CP
        CTH
    end
    
    PCD1[Previous Cycle Data] --> CP
    PCD1 --> CTH
    
    CP --> AP[(Assy Powers)]
    CTH --> PP[(Pin Powers)]
    
    AP --> PostProc[Post Proc]
    PostProc --> SCTH[Sub-Channel T/H]
    
    PP -.-> CILC[To CILC Analysis]
    
    SCTH --> Out1[/Output/]
    SCTH --> CRUD[CRUD]
    
    PCD2[Previous Cycle Data] --> CRUD
    AP --> CRUD
    
    CRUD --> Out2[/Output/]
    CRUD --> Ok{Ok?}
    
    Ok -- Yes --> Doc[Document & Verify]
    Ok -- No --> BM[/Boron Mass/]
    BM --> Out3[/Output/]
    BM --> CRUD
  
```

Core Simulator

- full cycle depletion
- loading pattern optimization

Criteria

Compare calculated Boron mass over entire cycle to a 'low risk' threshold = X lbm Boron

Figure 2-7 Sample Industry CIPS Analysis Workflow

The methods used in a current CIPS analysis are a series of single physics calculations that do not have feedback of the boron impacts until the end of the process. Additionally the radial mesh is 2x2 per assembly. This radially incorporates as many as 72 rods into a single mesh point. This CIPS risk analysis provides a quantitative prediction of risk based on the boron deposition, crud inventory, and mass evaporation. The pre-defined threshold for core-wide boron mass is set by benchmarking against a previous reference cycle. The reference cycle is assumed to have been close to having CIPS and used as a threshold so that the current design should have a risk of CIPS lower than that of the reference cycle. This method is therefore not predicting CIPS, but instead it attempts to insure that the future cycle with the new design will remain within the threshold set by previous operating experience of the reactor.

The current CIPS risk analysis performs well for avoiding CIPS. However, the amount of conservative operation, or margin, is not known and decreasing it could be a source of efficiency gains. Some operators may even be willing to operate with mild CIPS as long as it can be predicted and accounted for in the design process and safety analyses.

2.3.1.1 INDUSTRY SOFTWARE

The EPRI code BOA was developed (and is still under development) in collaboration with Westinghouse and industry experts to provide a risk assessment tool for CIPS in pressurized water reactor (PWR) core designs (EPRI, 2004). BOA was developed to consider three main components that contribute to CIPS: SNB, soluble boron, and circulating corrosion products. Since the soluble boron and circulating corrosion products are affected by conditions throughout the entire primary circuit, BOA was designed to be system-wide. The reactor coolant system (RCS) is modeled as an integrated system. By modeling the whole RCS, BOA is able to keep a mass balance of the circulating corrosion products. There are multiple mechanisms in the RCS that increase the circulating corrosion product inventory. These are known as corrosion product sources. There are also multiple mechanisms that decrease the circulating corrosion product inventory known as sinks.

The major sources in the circulation corrosion products are:

- Fresh corrosion products released from the inner pipe surfaces of the RCS, particularly the steam generator tubing.
- Corrosion products from crud carryover between cycles from once or twice burned fuel assemblies put back into the core.

The major sinks in the circulation corrosion products are:

- Scrubbing of corrosion products from the coolant by the letdown purification system
- Deposition of corrosion products on fuel rod surfaces in the crud layer
- Deposition on surfaces of pipes in the remainder of the RCS.

BOA takes all of these mechanisms into account at every time step in order to calculate the corrosion product mass balance. BOA also performs all of the heat transfer and steaming rate calculations. BOA relies upon an external T/H code to define the local T/H conditions. The core geometry must be carefully modeled and consistent between BOA and the external T/H code models

BOA models each fuel assembly as four channels, with each channel divided axially in the model and each axial plan must be equal height. BOA uses this information to establish the local coolant fluid conditions and the local heat flux. BOA calculates the steaming rate from the Dittus-Boelter and Thom heat transfer correlations. As the boiling builds crud on the fuel rod surfaces, BOA includes the thermal feedback into its future T/H calculations. The time dependent boiling calculated in BOA subsequently feeds back into the corrosion product mass balance as a sink. The boiling calculated in BOA is also used to calculate the solute concentration process in crud. This is critical for calculating the boron and lithium hideout.

The overall methodology requires that a minimum of two cycles previous to the cycle of interest be modeled. The cycles must be sequential and the AO behavior must be known. It is not required that AOA was experienced in the cycle. These two cycles are used to normalize the code due to the uncertainty of estimating the total corrosion product inventory available to be deposited in the core.

The normalization process by modeling two previous sequential cycles for estimating the corrosion product inventory for the cycle of interest for the CIPS risk analysis is as follows:

- Cycle N-1 – The purpose of this cycle is to estimate the carryover of crud mass on the used fuel assemblies to be used in the following cycle.
- Cycle N – This cycle uses the crud carried over from the previous cycle. The used fuel assemblies are shuffled and placed in their proper core location according to the historical loading design. BOA is executed and the new boron core loading is reviewed and analyzed. This cycle boron loading is compared to measured AO data. If CIPS was present, then BOA should have results with the appropriate level of core boron loading. If there was no CIPS experienced in the reactor operation, then the core boron level should be just below the threshold CIPS value. If the core boron values do not match the measured CIPS behavior then the steam generator corrosion product release rate and the crud mass on the used

fuel assemblies are adjusted to get the appropriate amount of core boron to correspond to the measured CIPS behavior.

- Cycle N+1 – This is the future cycle of interest for the CIPS risk analysis. Using the adjusted model parameters set in the previous two cycles the BOA analysis is performed for the future cycle to predict risk of experiencing CIPS.

This process was developed from data that came from multiple cycles of many different plants. It is intended to be a conservative method to screen for AOA risk for future cycle designs. From the process described above, EPRI has derived a set of threshold limits for the total core boron that is associated with a specific severity of AOA. These thresholds are shown for various core sizes in Table 2-2.

As indicated earlier, the onset of CIPS during reactor operation is considered as an AO differing from predicted by -3%. However, as an additional conservatism, a factor of two was built in to the “threshold” for CIPS, making it -1.5%. The “moderate” category of AOA is considered an AO difference of 5% from predicted. The “severe” category of AOA is considered an AO difference of 10% from predicted. All of the boron masses in Table 2-2 are based on the natural boron isotopic composition.

The limits set out in Table 2-2 above were derived from generating a fit to measured data from plants that did experience AOA. BOA was used to simulate the AOA cycles and the results were fit to the measured data to derive a linear relationship used for the limits. The fit for the 193 assembly cores can be seen in Figure 2-8 (EPRI, 2004).

Ultimately BOA uses a set of parameters that has been normalized to two previous cycles for a single plant in order to conservatively predict risk of a future cycle design experiencing AOA. BOA’s main criterion for risk is the maximum core boron mass deposition. The maximum core boron mass deposition is used to categorize the severity of AOA according to Table 2-2. While this process has served industry well for avoiding AOA, there are opportunities to improve on this process.

Table 2-2 BOA Core Boron Threshold for Various Size Cores (EPRI, 2004)

Core Size (# Assemblies)	121	157	177	193	217	241
Threshold for AOA (lbs)	0.19	0.24	0.28	0.30	0.34	0.37
Moderate AOA (lbs)	0.6	0.8	0.9	1.0	1.1	1.2
Severe AOA (lbs)	1.3	1.6	1.8	2.0	2.2	2.5

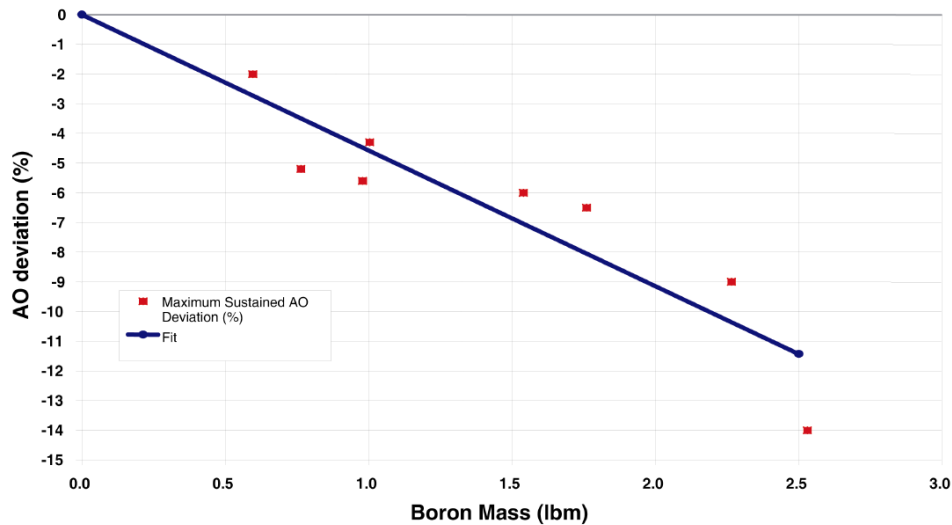


Figure 2-8 AO Difference as a Function of Boron Mass for 193 Assembly Cores

2.4 FUEL COSTS GENERAL OVERVIEW

A better physical understanding of CIPS through advanced modeling and simulation is certainly desirable; however, it remains theoretical and academic until it can be applied in industry by building on currently applied methodologies. The successful application of new technologies and methods in industry requires a strong set of motivations to overcome the status quo. The economic facet of these motivations is always a serious consideration. Therefore, this research seeks to provide information on the potential economic influences of using the advanced CIPS risk analysis. This will be performed by calculating the tradeoff of fuel cost savings and CIPS risk minimization. A discussion of the determination of cost of nuclear fuel is described below.

2.4.1 NUCLEAR FUEL CYCLE

In order to understand the economic influences providing motivation, a working knowledge of the nuclear fuel procurement process is necessary. The nuclear fuel cycle covers the life of nuclear fuel from being mined as ore to being used in a nuclear reactor to being disposed of or reprocessed. Figure 2-9 shows the major steps of the nuclear fuel cycle (World Nuclear Association, 2017).

The focus of the analysis will be on the nuclear fuel cycle from mining to electricity generation in the reactor. The nuclear fuel has costs associated with every step of the fuel cycle. From the perspective of the power plant operators there are four major costs when purchasing nuclear fuel:

1. The cost of the milled uranium that is in the form of uranium oxide, U_3O_8

2. The cost of converting the U_3O_8 to uranium hexafluoride (UF_6)
3. The cost of enriching the fuel from naturally 0.711% ^{235}U to the desired weight % ^{235}U (usually between 3-5%)
4. The cost of fabricating the fuel from the enriched uranium

The backend costs, such as waste storage or the mandatory 1 mil/kwh disposal fee are not included in this analysis. The exclusion of the backend costs should not significantly affect the results of the analysis. The following is a brief explanation of each step and the included costs.

2.4.1.1 MINING

These steps are combined into one step because they only have one cost – the cost of the raw U_3O_8 material. Uranium is naturally abundant in the earth's crust just like other metals. Uranium is about 40 times more common than silver and about 500 times more common than gold (Cameco, 2016). The uranium is mined from the earth in multiple minerals and then milled into a yellow oxide powder, U_3O_8 , called “yellowcake”. The uranium cost is determined by a financial futures market for this commodity. This market has both a spot price and a long term price set in contracts between purchasers and providers. The end cost of nuclear fuel is highly dependent on the cost of the uranium commodity. Figure 2-10 shows historical prices of uranium for both the spot price and the long term price (UxC Consulting Company, 2016).

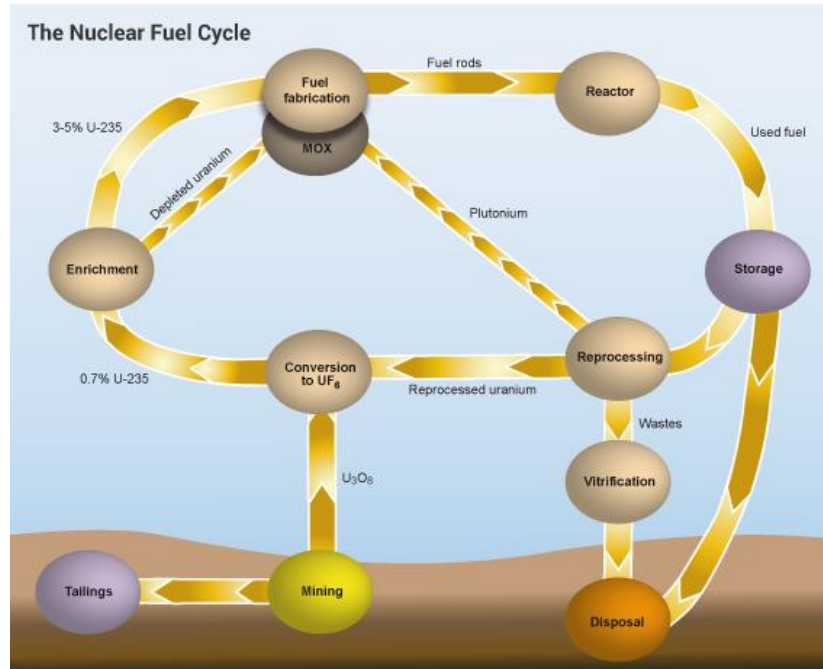


Figure 2-9 The Nuclear Fuel Cycle (World Nuclear Association, 2017)

Ux U3O8 Price - 2 Year History

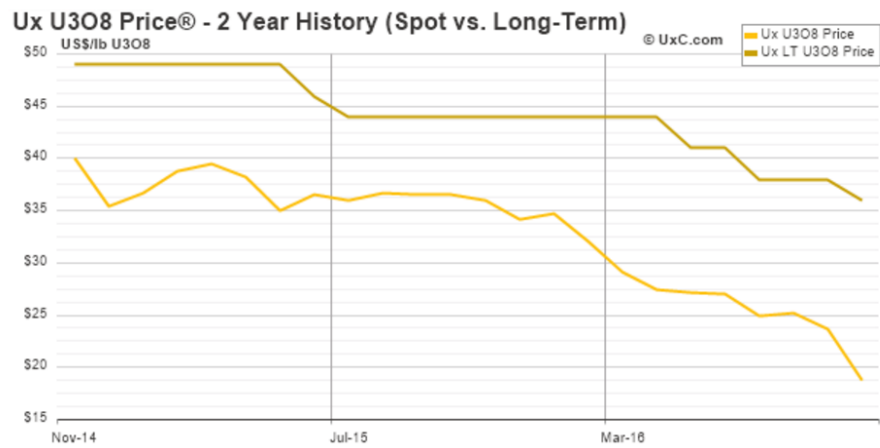


Figure 2-10 Two-Year Long Term and Spot Prices of Yellowcake Uranium (UxC Consulting Company, 2016)

2.4.1.2 CONVERSION

Once the U_3O_8 has been purchased it needs to be converted into UF_6 for the next step of manufacturing. The conversion process has a cost associated with it that also has a fluctuating financial market. The conversion of costs associated with natural uranium is being considered in this research. Figure 2-11 shows historical spot prices for the conversion process (UxC Consulting Company, 2016).

2.4.1.3 ENRICHMENT

Once the uranium has been converted into the gaseous UF_6 it undergoes enrichment of the ^{235}U content. The critical isotope of uranium for nuclear reactors is ^{235}U . Natural uranium is about 0.711% ^{235}U and 99.289% ^{238}U . The predominate approach for enrichment is using gas centrifuges. To produce uranium that is acceptable for use as fuel, a certain degree of enrichment must be reached. Light water reactors need uranium fuel at about 3-5% ^{235}U to operate. In order to reach the required enrichment, a certain amount of physical effort is needed to separate the ^{235}U from the ^{238}U . This effort is measured in a quantity known as a separative work unit (SWU). The amount of necessary SWU depends on the enrichment of the supplied feedstock (usually natural uranium), the amount of ^{235}U left in the waste stream, and the desired enrichment of the final product. The amount of SWU required determines the cost of the enrichment process. SWU trades in contracts similar to a financial market. The purchaser of an enriched uranium product usually gives an enrichment facility the feedstock of UF_6 and payment for the SWU and will get back enriched uranium to the specified enrichment. Figure 2-12 shows historical spot prices of SWU (UxC Consulting Company, 2016). The end price of nuclear fuel is largely dependent on the price of SWU since it can take over 8 SWU per kg of enriched uranium product produced.

2.4.1.4 FUEL FABRICATION

Once the power plant operator has uranium that is appropriately enriched it needs to be fabricated into UO_2 pellets and put into a cladding tube that is then fabricated into a fuel assembly. This cost varies with design and manufacturer. The approximate cost is \$200/kg of fuel (EPRI 2009). The fabrication cost includes the transportation of the fabricated fuel to the power plant site.

The market conditions for the price of U_3O_8 , conversion, and SWU are critical to any analysis of nuclear fuel costs. These major costs factors are considered in the model for the economic analysis described in detail in section 3.2.

Spot Ux NA & EU Conversion Prices

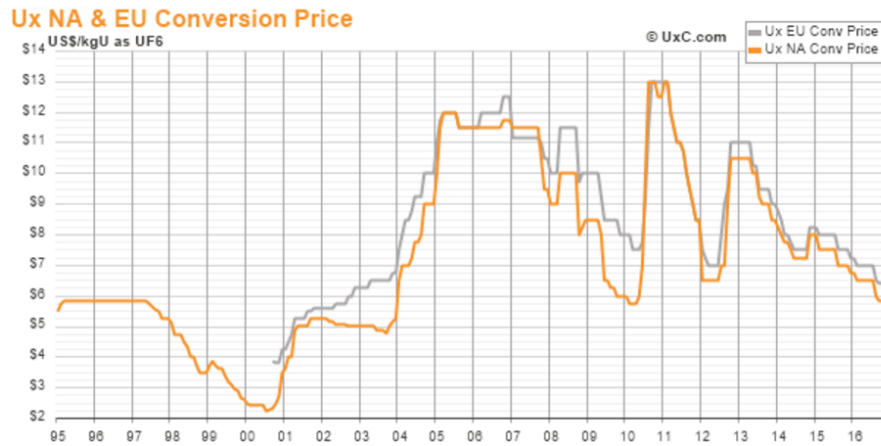


Figure 2-11 Spot Prices for the Conversion of Natural Uranium (NA) and Enriched Uranium (EU) to UF₆ (UxC Consulting Company, 2016)

Spot Ux SWU Price

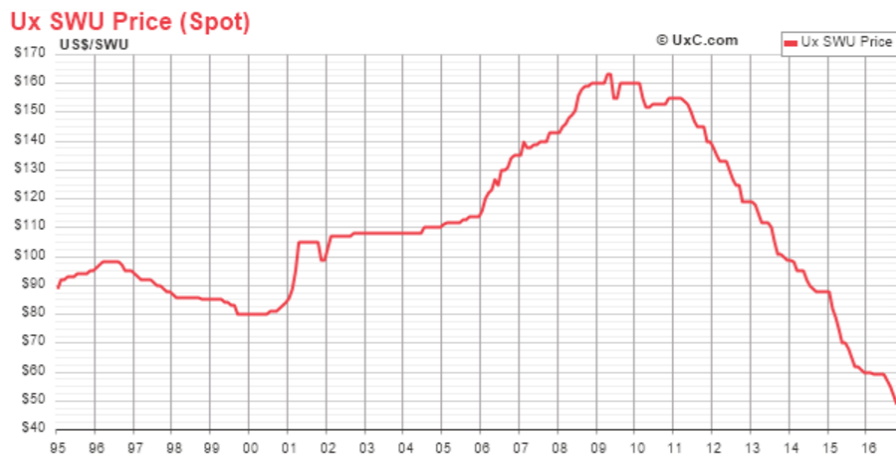


Figure 2-12 Spot Prices for SWU (UxC Consulting Company, 2016)

2.5 VIRTUAL ENVIRONMENT FOR REACTOR APPLICATIONS

Current industry standard modeling and simulation methods for reactor core analysis are limited in resolution and fidelity. They typically rely on loose offline coupling of separate physics codes with individual, and sometimes inconsistent, bounding analyses. The methods execute quickly and can be efficiently used by an experienced user with technical knowledge of the individual inputs for each physics package. Perhaps most significantly, the core simulation is performed in a serial, multiple stage process using the different physics codes where the feedback between single physics solution calculations is limited or non-existent. Despite these limitations, current methods used in industry have successfully supported the design and operations of nuclear power plants for decades all over the world.

The CASL program has been developing a new set of modeling and simulation tools to address some of the modeling and simulation limitations facing the nuclear industry today. CASL is developing a suite of codes called VERA. VERA is a high-fidelity modeling and simulation tool that leverages tightly coupled multi-physics packages for high resolution 3D reactor applications.

The main suite of coupled physics packages in VERA and consists of coupled neutronics, T/H, fuel performance, and chemistry. VERA can be applied with 2, 3, or all 4 physics packages enabled for a single simulation. Each multi-physics simulation is solved iteratively until convergence has been reached for all enabled physics packages. This allows for complex physical feedback mechanisms to be captured in the reactor simulations. The individual components of VERA are shown in Figure 2-13.

The CIPS analysis in this report utilizes VERA using the coupled neutronic, T/H, and chemistry physics packages. The non-CIPS cycle depletions are simulated using only the coupled neutronic and T/H physics packages. A general overview of the individual physics codes utilized as a multi-physics package in VERA for this analysis is given below.

2.5.1 NEUTRONIC CODE (MPACT)

MPACT is collaboratively being developed by the University of Michigan and ORNL to provide an advanced code within VERA that provides pin-resolved transport capabilities.

The critical component capabilities in MPACT include:

- 2D/1D synthesis method on a 3D coarse mesh finite difference method. The correction factor in the radial direction is obtained from 2D method of

characteristics (MOC) and the axial correction factor is obtained from 1D Simplified P_N

- Subgroup method and embedded self-shielding method for resonance treatment
- Depletion capability based on the ORIGEN exponential matrix method

Additional details on the methods used in MPACT as part of VERA is in the MPACT Theory Manual (University of Michigan, 2015).

The 2D/1D method is a numerical approach for whole-core transport. The method approximates the 3D Boltzmann equation more accurately than the 3D diffusion equation that is typically used. The 2D/1D synthesis method preserves exact transport physics in the radial directions and approximates the axial transport with diffusion physics. This allows higher fidelity physics while keeping computational costs manageable for practical reactor applications.

MPACT has many characteristics that make it suitable for applying in a CIPS analysis. CIPS occurs due to local neutronic effects that affect global core parameters. The 2D/1D method allows MPACT to resolve the local, highly heterogeneous radial neutronic effects due to boron deposition on the surface of a single fuel rod while capturing those effects on the global axial offset. The inclusion of ORIGEN in MPACT allows the accelerated, or decelerated, depletion of fuel due to the shift in power, and subsequent effect of fission product effects, to be captured throughout the entirety of the cycle. The ability of MPACT to capture and calculate these effects is critical to an accurate simulation of a CIPS occurrence.

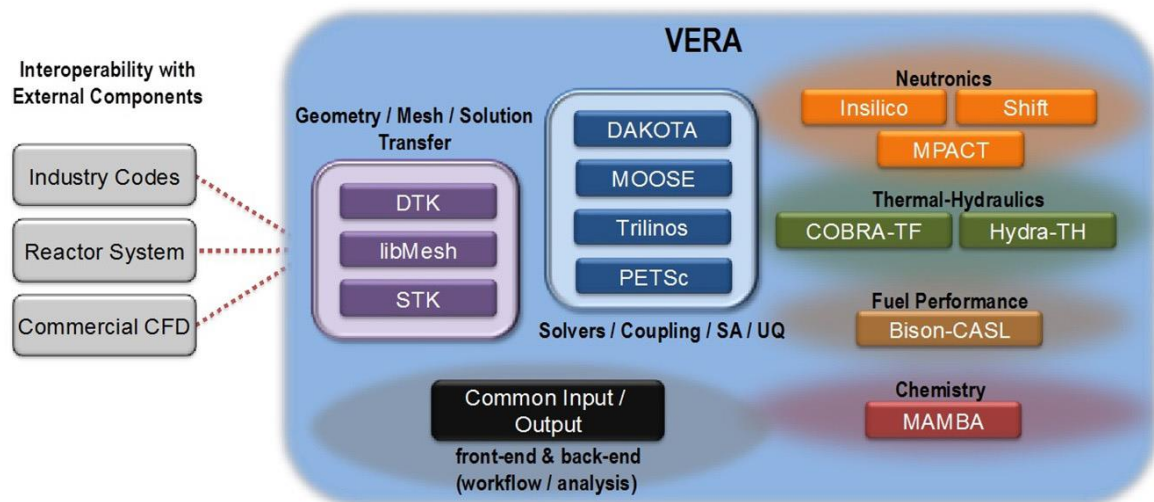


Figure 2-13 Components of VERA

2.5.2 THERMAL-HYDRAULIC CODE (CTF)

CTF is a code currently being developed collaboratively by North Carolina State University (and formerly the Pennsylvania State University) and ORNL as part of the CASL program (Avramova, 2009). CTF is an updated version of the COBRA-TF T/H code. VERA directly couples MPACT and CTF so that each code solution is iterated with feedback until both codes reach convergence.

CTF is a sub-channel T/H code that utilizes a two-fluid, three-field modeling approach. The fluids are liquid and vapor and the fields are liquid film, liquid drops, and vapor. Multiple flow-regime dependent closure models are used to capture multiple fluid flow and heat transfer mechanisms. These include:

1. Rod to fluid heat transfer
2. Wall and inter-phase drag
3. Inter-phase heat and mass transfer
4. Grid heat transfer enhancement effects
5. Grid-droplet breakup
6. Turbulent mixing and void drift

CTF solves a relatively high resolution mesh of pin-cells in order to capture local T/H (Salko & Avramova, 2012). CTF uses local power conditions supplied by MPACT and calculates the local heat transfer effects on the coolant. This information is passed back to MPACT and the power distribution is re-solved until convergence is reached by each code.

There are both benefits and drawbacks to using a sub-channel T/H code, such as CTF, for CIPS applications. CTF includes boiling and two phase heat transfer physics that is critical to accurate simulation of crud growth and CIPS onset. Ideally, the resolution would be similar to that of a computational fluid dynamics (CFD) code to capture surface-coolant interface effects (although this is more critical for CILC applications). However the computational requirements for using CFD for full core reactor analysis are prohibitively large. Therefore, CTF strikes a good balance of proper physics, low computational load, and sufficient resolution for CIPS simulation and analysis. In VERA, CTF is able to communicate with the neutronics solver, MPACT, so that these central physics are coupled to capture feedback effects during reactor operation. This is one of the key improvements of using VERA over current industry codes.

2.5.3 CHEMISTRY CODE (MAMBA-1D)

MAMBA-1D is a simplified version of the corrosion product chemistry code called MAMBA-3D. The primary difference between MAMBA-1D and MAMBA-3D is that MAMBA-1D does not explicitly model the azimuthal or axial heat and mass transfer in the crud layer. The heat, diffusion, and fluid flow transport is only solved in the radial direction in MAMBA-1D. This enables MAMBA-1D to have

significantly lower computational costs and is better suited to be coupled in VERA.

MAMBA-1D is coupled to CTF and simulates crud growth on the fuel rod surface with T/H and heat transfer data supplied by CTF. MAMBA-1D calculates crud growth, crud erosion, boron hideout, additional heat transfer resistance due to the updated crud data, and boiling mass transfer due to the heat transfer effects of the crud. This information is passed back to CTF and the T/H conditions are re-solved until convergence is reached.

MAMBA-1D requires global bulk coolant chemistry concentration information along with the local T/H information provided by CTF. A corrosion product mass balance model is being developed but is not yet available. As such, the global bulk coolant chemistry information for the CIPS analysis in this report is taken from a BOA output of the same cycle.

An additional model was developed and implemented into MAMBA-1D as part of this CIPS analysis investigation. As part of the approximations made when deriving MAMBA-1D from MAMBA-3D some of the chemical kinetic models were simplified. This resulted in MAMBA-1D not considering boron dissolution from the crud layer during a cycle. Industry experts gave feedback stating that the capability of a crud chemistry model to simulate boron dissolution during a CIPS occurrence is significant. Therefore, a 1D model of diffusion through porous media was developed and added for this CIPS analysis.

MAMBA-1D provides the final set of key physics to accurately simulate CIPS. The chemistry models in MAMBA-1D coupled to the T/H models in CTF give VERA the ability to calculate crud growth and boron precipitation/dissolution from the crud layer. The core wide behavior and effects from CIPS can then be captured when these chemistry and T/H models are coupled with the neutronic physics. The coupling in VERA between MPACT, CTF, and MAMBA is shown in Figure 2-14. This tight internal coupling between multiple physics allows VERA to capture feedback effects during reactor operation that are not currently captured in industry methods.

Efforts are underway to develop a more efficient version of MAMBA-3D and couple it with VERA for further accuracy improvements in CIPS modeling and prediction. However, MAMBA-3D coupled to VERA was not available to support the analysis performed for this research. Despite the opportunities for improvement, the current application of VERA in a CIPS analysis gives new insights a deeper understanding of the effects of CIPS using multiple coupled physics.

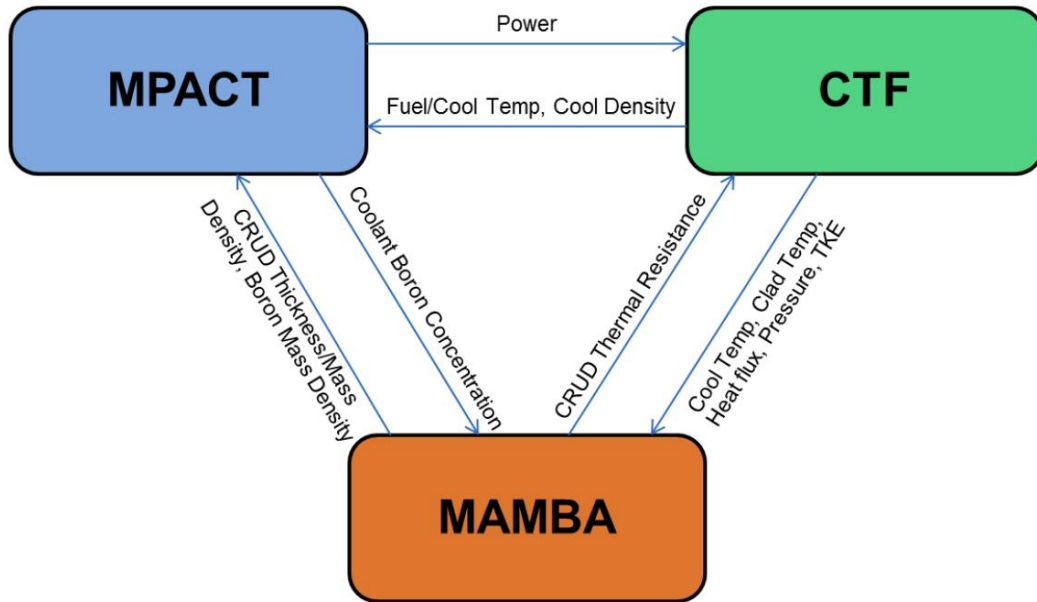


Figure 2-14 VERA Coupling for Multiple Physics in Core Simulator

2.5.4 SUMMARY

Overall, VERA is an advanced modeling and simulation tool that has applications in the nuclear power industry that can provide significant advancements and insight over current standard industry methods. The coupling of MPACT, CTF, and MAMBA-1D allows VERA to capture reactor core behaviors that manifest from the feedback of complex physical effects. It is important to understand the way that these local and global effects alter important operational parameters, such as axial offset and shutdown margin. VERA is able to analyze these parameters with respect to CIPS better than can currently be done with standard industry methods due to the abilities to perform simulations of crud and boron deposition on each fuel rod and to directly consider neutronics and thermal-hydraulics feedback from the boron deposition. The capability of VERA to simulate CIPS is applied in this report to build upon industry methods so that valuable insights may be gained in increasing fuel economics and better understanding risk of CIPS occurrence.

CHAPTER 3. DEVELOPMENT OF ADVANCED CIPS RISK ANALYSIS METHODOLOGY AND MODELS

The advanced CIPS risk analysis incorporates two complimentary analyses to inform on both the comparative risk of CIPS effects on the core designs and the potential economic tradeoff for that risk. The VERA simulations are performed first in order to determine the magnitude of additional AO effects due to increased maximum total core boron mass. The potential economic tradeoff is then calculated with a stochastic scenario analysis and combined with the CIPS AO effects to give a more complete picture of the involved factors of CIPS risk and economic effects. These analyses are explained below.

3.1 ADVANCED CIPS ANALYSIS METHODOLOGY

The CIPS analysis is performed using VERA with coupled physics for neutronics, T/H, and chemistry. The chemistry physics is simulated with an updated MAMBA-1D that contained the additional models described above including the boron dissolution model.

While MAMBA-1D has been applied to the analysis of CIPS for Watts Bar Unit 1 Cycle 7 (Collins, 2016) and Seabrook Cycle 5, the results obtained required a one-time tuning of MAMBA-1D parameters to obtain acceptable results. Therefore, while the overall CIPS behavior in terms of AO and measured axial power distributions was very good for the core designs, it is not possible to be confident that the MAMBA-1D results are predictive. Furthermore, given that it was not known if the three different core designs would require different tuning of the MAMBA-1D parameters, an alternative approach is needed. As described below in more detail, the approach was to normalize the MAMBA-1D calculated boron masses to the values computed with BOA for each core design. This would, in effect, result in a direct comparison of the industry methodology to the VERA-based methodology. In this approach MAMBA-1D is used to perform a representative distribution of boron on the fuel rods, but is not required to accurately predict the total boron mass deposited. A comparison of the impact of the boron deposition on AO or other parameters can then be performed and compared to acceptance parameters. In addition, since the industry already relies on the BOA calculations for their CIPS risk assessment, the simulations are more readily accepted by industry. It is anticipated that future version of MAMBA-3D with crud mass balance models incorporated would remove the need to normalize the crud mass to BOA.

3.1.1 MAMBA-1D: BORON DISSOLUTION MODEL

One of the assumptions in MAMBA-1D was that the boron deposited in the crud layer stayed in the crud layer once present. This is not what is expected to

happen in reality. The boron hideout mechanism has shown that during down powers the RCS boron concentration will rise without any introduction of external boron as shown in Figure 2-5. Due to this observation of plant data, it is expected that the boron and lithium species return into the solution when the chemical concentration mechanism from SNB is no longer present.

It is also expected that the boron returns to solution in the bulk coolant when the bulk coolant chemical concentration is so low that, even with the increase in concentration due to SNB in the crud layer, the liquid adjacent to the precipitate is no longer saturated or super-saturated. Therefore the precipitate will begin to dissolve back into solution and return back into the bulk coolant. This mechanism of boron returning to solution is also supported by nuclear power plant observations. The characteristic behavior of a reactor experiencing this boron dissolution due to low bulk coolant concentration is a shift of power back into the top of the core causing a positive AO. This is due to the boron poison disappearing from the upper spans of the fuel rods and since there is now increased reactivity due to lower burnup in the upper spans, the power shifts into the upper half of the core. The positive shift in AO has been captured by measured data from multiple plants. This is shown in Figure 3-1, Figure 3-2, and Figure 3-3.

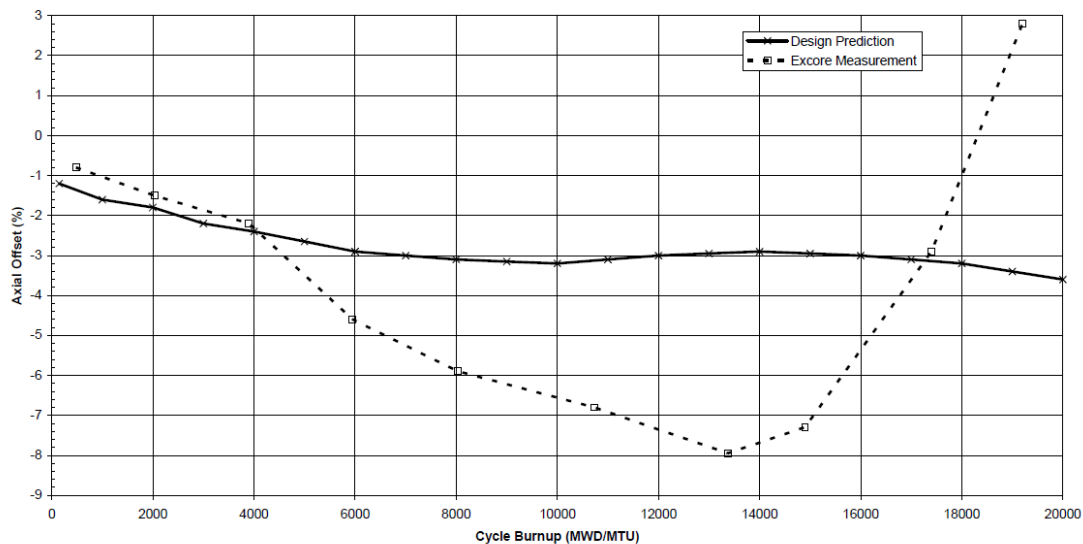


Figure 3-1 Typical Ex-core Axial Offset Response for Plant with AOA due to CIPS (EPRI, 1997)

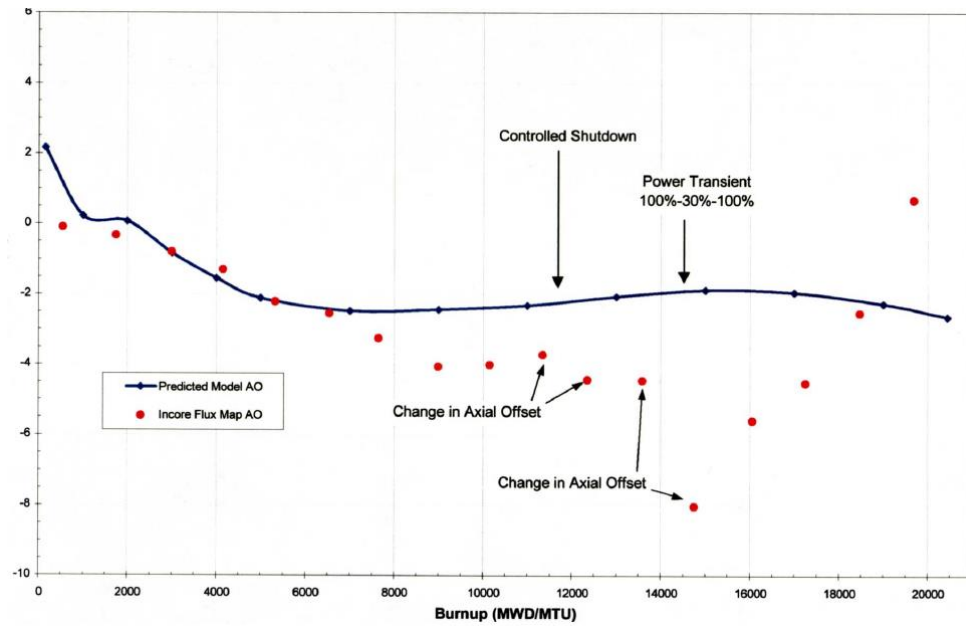


Figure 3-2 Axial Offset Behavior Following Power Maneuver and Controlled Shutdown Mid-Cycle (EPRI, 1997)

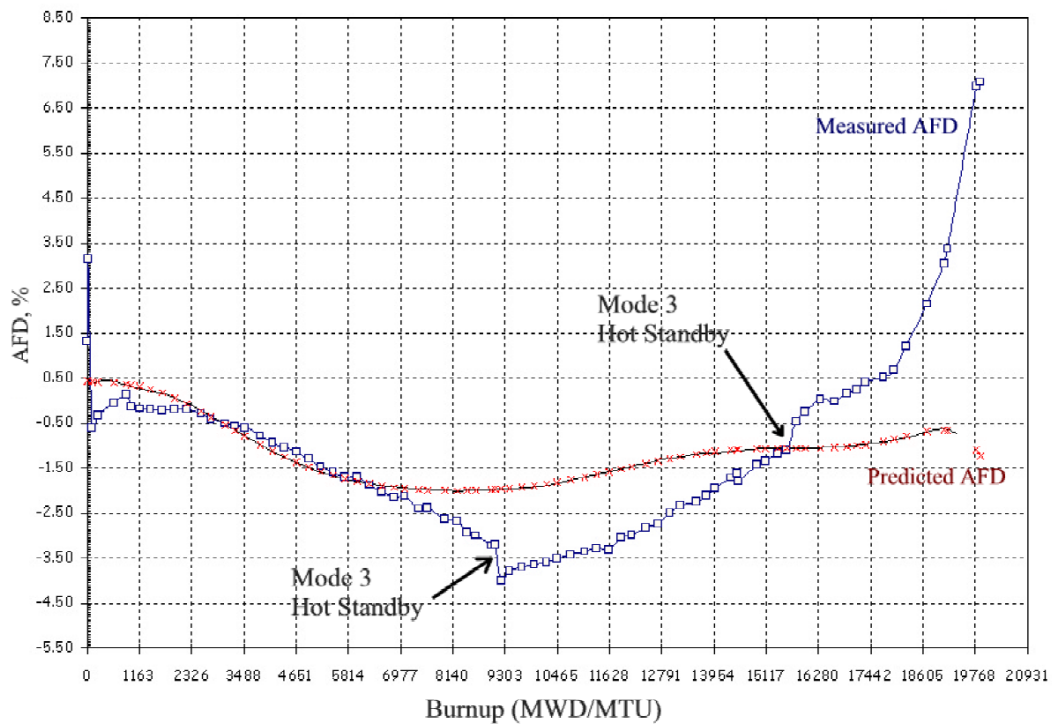


Figure 3-3 Measured vs. Predicted Axial Flux Difference Plot during Seabrook Cycle 7 (EPRI, 1997)

This positive shift in AO at the end of the cycle is unique compared to the boron dissolution due to power maneuvers because it is ubiquitous in all PWRs that use boron in the coolant as a neutronic shim. For most of the cycle the coolant boron concentration is decreased to nearly 0 ppm by the end of cycle to maximize the core cycle length and reactivity. While not all reactors experience a power maneuver during a CIPS occurrence. This is significant because the effects of boron leaving the crud due to low bulk concentration will be experienced by every PWR with boron precipitate present in the core. This makes it significant to capture these effects in order to accurately predict reactor AO behavior for the current cycle and the subsequent cycle due to changes in burnup carry over effects.

Prior to the implementation of the MAMBA-1D boron dissolution model the total core boron mass was monotonically increasing throughout the cycle. The boron precipitate would build up in the crud layer and without any dissolution model the total boron precipitate never decreased. An example of the total core boron mass buildup in the crud layer over time is shown in Figure 3-4. Notice that BOA's total core boron mass reaches a maximum at 350 Effective Full Power Days (EFPD) while VERA's total core boron mass never decreases. The behavior of the boron precipitate in the crud layer predicted by VERA is missing fundamental physics that has been observed in power plants in the return of boron and lithium from hideout mechanisms. A boron dissolution model was developed and implemented into MAMBA-1D to address this part of the physics.

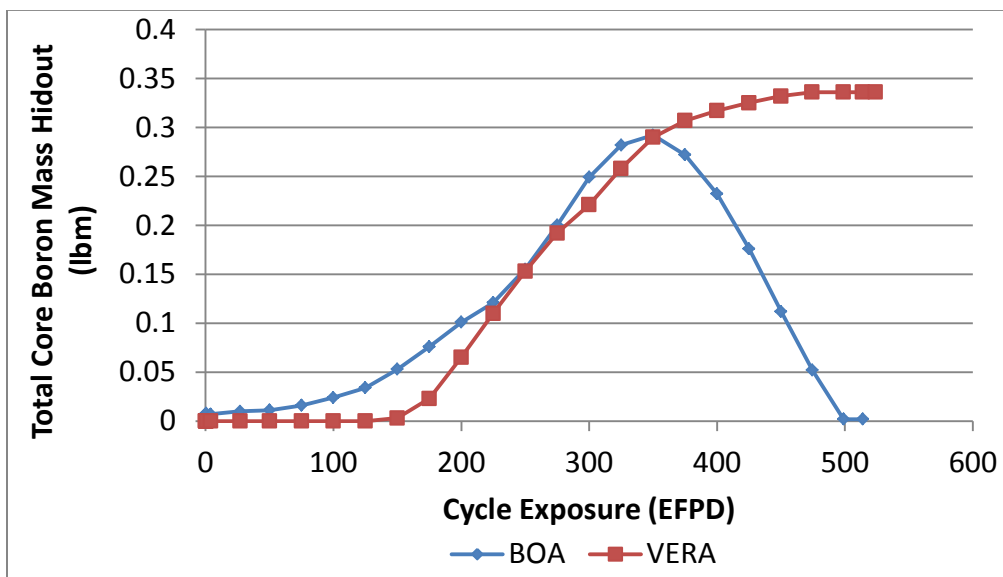


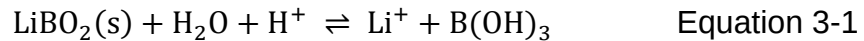
Figure 3-4 VERA Total Core Boron Mass before MAMBA-1D Dissolution Model

3.1.1.1 DEVELOPMENT OF THE BORON DISSOLUTION MODEL

A boron dissolution model was adapted and implemented into MAMBA-1D in order to accurately capture some of the global reactor behaviors during a CIPS occurrence. The model implemented in MAMBA-1D for boron dissolution is a 1-dimensional diffusion model through porous media. The model was adapted from models developed for diffusion on material in porous media (Grathwohl, 1998).

The dissolution model was developed with the following assumptions:

1. The boron concentration in the bulk coolant is constant for a given state point,
2. Steady state conditions apply for the dissolution flux through the crud layer,
3. The boron deposits are in the innermost part of the crud layer,
4. The solubility concentration of the boron precipitate is constant,
5. The boron dissolution is diffusion limited,
6. The boron precipitate is a lithium-borate compound and dissolves according to the chemical equation shown in Equation 3-1.



Assumptions 1 and 2 make the dissolution model a steady state model for a given time step. Assumption 3 assumes the location of the boron precipitation in the crud layer. This is supported by the findings of EPRI that boron is deposited in the inner dense crud layer (EPRI, 2010). This determines the distance of diffusion through the crud layer as the precipitate dissolves. Assumption 4 is a simplification of the dissolution kinetics. It is known that LiBO_2 has retrograde solubility. In fact, it is the retrograde solubility that makes lithium-borate species the most widely accepted boron and lithium hideout mechanism. However, this assumption can be eliminated and the boron dissolution model improved by including the temperature dependent solubility limit. Assumption 5 is the reason for making the boron dissolution model driven by diffusion. Assumption 6 allows the limiting diffusion coefficient to be found by analyzing the solutes.

These assumptions were made in an attempt to optimize VERA's ability to capture global reactor behavior from the physics of boron hideout while minimizing necessary computation resources and time.

3.1.1.2 THE FILM DIFFUSION MODEL

Diffusion is the process of mass transport down a concentration gradient due to the random motion of molecules. This random movement is known as Brownian motion. When molecules or atoms move randomly they preferentially move from

areas of high concentration to areas of low concentration. This results in increased entropy for the system. In diffusion the concentration gradient drives the mass flux. The flux per unit cross-sectional area can be expressed as is shown in Equation 3-2.

$$F = -D \frac{\partial C}{\partial x} \quad \text{Equation 3-2}$$

Where F is the mass flux, D is the diffusion coefficient, C is the time dependent solute concentration and x is distance. This is known as Fick's first law (Fick, 1855). The diffusion coefficient is a measure of how fast the molecules spread through their random motion. The diffusion coefficient is dependent on the physical characteristics of the media in which molecules are moving, the temperature, and the physical characteristics, such as volume and mass, of the diffusing molecules. Diffusion in liquids is one special case where the dynamic viscosity of the liquid media in which diffusion is occurring is the most influential characteristic. Since the dynamic viscosity of water is temperature dependent it is best to calculate the temperature of the region of interest. In VERA this is easily done since the temperature of the crud layer is already calculated for heat transfer. The region of interest for the boron dissolution model is inside the crud layer. The average temperature of the crud layer used in the boron dissolution model is defined in Equation 3-3.

$$T_{crud,avg} = \frac{T_{clad,surface} - T_{crud,surface}}{2} \quad \text{Equation 3-3}$$

Where $T_{crud,avg}$ is the average temperature in the crud layer, $T_{clad,surface}$ is the temperature at the clad-crud interface, and $T_{crud,surface}$ is the temperature at the crud-bulk coolant interface. Once the average crud temperature is calculated the dynamic viscosity of the water in that region is calculated as shown in Equation 3-4.

$$\eta = 2.414 * 10^{-5} * 10^{\left(\frac{247.8}{T_{crud,avg} - 140}\right)} \quad \text{Equation 3-4}$$

Where η is the dynamic viscosity and $T_{crud,avg}$ is the average temperature in the crud layer calculated above. Equation 3-4 is valid for water for the temperature range of 0°C to 370°C and is accurate to within 2.5% (Al-Shemmeri, 2012).

Now that the temperature dependent dynamic viscosity has been defined the aqueous diffusion coefficient can be expressed as seen in Equation 3-5 (Worch, 1993).

$$D_{aq} = \frac{3.595 \cdot 10^{-7} \cdot T_{crud,avg}}{\eta m_s^{0.53}} \quad \text{Equation 3-5}$$

Where D_{aq} is the aqueous diffusion coefficient, $T_{crud,avg}$ is the average temperature of the crud layer, η is the temperature depended dynamic viscosity of water, and m_s is the molecular weight of the diffusing substance. Note that the aqueous diffusion coefficient is inversely proportional to the molecular weight of the diffusing substance. The larger the weight of the molecule being diffused the lower the diffusion coefficient and the slower the diffusion process. In order to make the boron dissolution model diffusion limited, the largest mass of the solutes must be taken to calculate the limiting aqueous diffusion coefficient. According to Equation 3-1 the highest weight solute is $B(OH)_3$ with a molecular weight of 61.83 g/mol. This is used for m_s throughout the boron dissolution model.

Equation 3-5 is for diffusion in pure water. Since the boron precipitate is located in the inner layer of the crud, the effects of the crud layer must be taken into account. This is accomplished by defining an effective diffusion coefficient that is dependent on the physical characteristics of the crud layer. Equation 3-6 shows how the effective diffusion coefficient is calculated.

$$D_e = D_{aq} \frac{\varepsilon}{\tau_f} \quad \text{Equation 3-6}$$

Where D_e is the effective diffusion coefficient, D_{aq} is the diffusion coefficient in pure water, ε is the crud porosity, and τ_f is the tortuosity factor for the crud layer. For any porous media $D_e < D_{aq}$ since $\varepsilon < 1$ and $\tau_f > 1$.

Once the effective diffusion coefficient is calculated, the mass flux is calculated as shown in Equation 3-7.

$$F = -\frac{D_e}{\delta} \Delta C = -\frac{D_e}{\delta} (C_{sol} - C_{surf}) \quad \text{Equation 3-7}$$

Where F is the mass flux, D_e is the effective diffusion coefficient, δ is the diffusion layer thickness, C_{sol} is the solubility limit concentration of the boron precipitate, and C_{surf} is the concentration of $B(OH)_3$ at the crud-coolant interface.

In Equation 3-7, δ is the thickness of the “diffusion layer” or “stagnation layer.” This thickness is central to multiple different dissolution modeling strategies (Abdou, 1989) (Carstensen, 1997) (Costa, 2001). The diffusion layer concept is founded on the idea that there is a layer of fluid touching the dissolving solid that contains a high concentration of the solute. The boron dissolution model assumes that there is insignificant bulk fluid transport in the crud layer and therefore the thickness of the crud layer becomes the diffusion layer thickness.

The boundary conditions for the diffusion model are set assuming that the concentration of solute molecules at the interface of the precipitate is the solubility limit concentration. This term is C_{sol} in Equation 3-7. The other boundary is at the crud-coolant interface. Due to the large fluid transport at the surface of the crud layer, the concentration at this boundary condition is assumed to be the concentration of the bulk coolant. It is assumed that the mass flux being diffused into the coolant is insignificant compared to the coolant mass and therefore this boundary condition is constant for a given time step. The total mass dissolved is then calculated in Equation 3-8.

$$M_b = FA\Delta t \quad \text{Equation 3-8}$$

Where M_b is the mass of the dissolved boron, F is the mass flux, A is the area of the surface through which diffusion is occurring, and Δt is the length of time in the time step. Finally the mass of the boron precipitate is calculated by taking away the total dissolved mass as shown in Equation 3-9.

$$M_p = M_p - M_b \quad \text{Equation 3-9}$$

Where M_p is the mass of the boron precipitate, and M_b is the total dissolved mass from the boron precipitate. Equations 3-2 through 3-9 are solved for each rod axial surface on each fuel rod at each state point. A visual example of the axial meshing and the crud geometry is shown in Figure 3-5.

Following the development, the boron dissolution model was implemented into MAMBA-1D to support CIPS analysis using VERA. The new total core boron mass as a function of EFPD can be seen in Figure 3-6. In the CIPS analysis the maximum total core boron mass at 350 EFPD was matched to the maximum from BOA.

Figure 3-6 shows a significant improvement of VERA's ability to capture the decrease of the boron hideout precipitate at the end of the cycle. There is good agreement between the BOA total core boron mass curve and that of VERA after 350 EFPD. The CIPS analysis in VERA utilizing the updated models in MAMBA-1D is discussed more fully below in Chapter 5.

3.2 ECONOMIC ANALYSIS METHODOLOGY

3.2.1 MONTE CARLO SCENARIO MODELING

A Monte Carlo scenario analysis is performed to calculate the comparative economic tradeoffs for the core designs. The scenario analysis investigates the impacts of market conditions, through uranium, SWU, and conversion prices, on

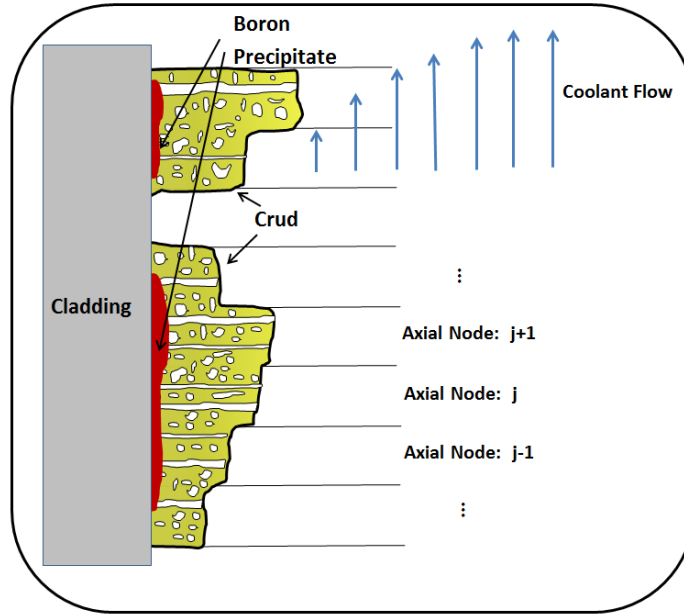


Figure 3-5 Geometry and Axial Meshing of the Crud used in the Boron Dissolution Model

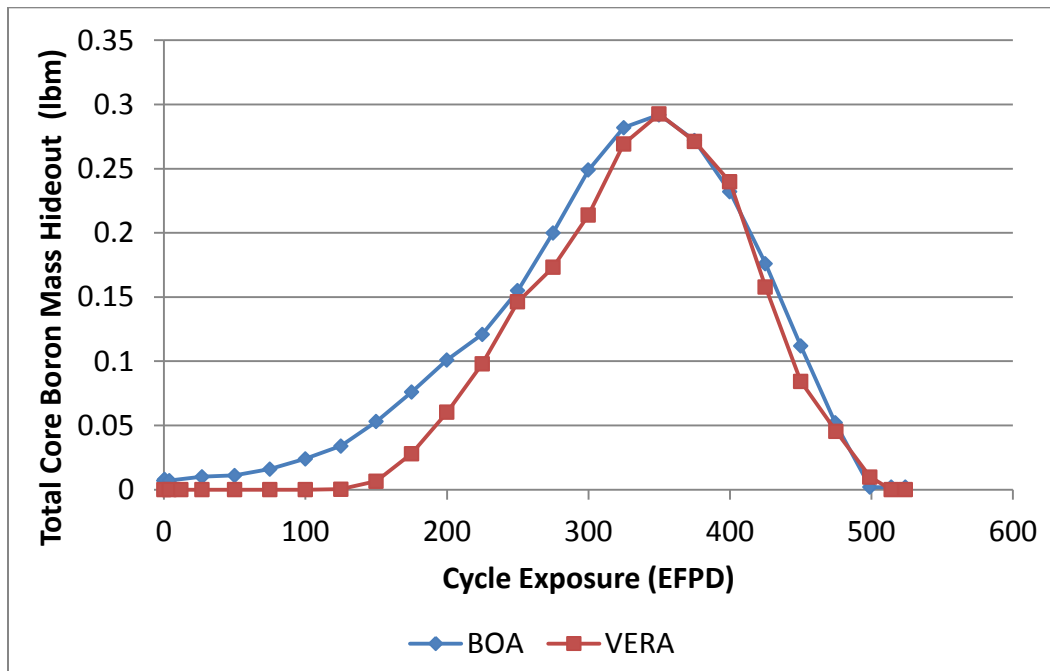


Figure 3-6 VERA Total Core Boron Mass after Implementing MAMBA-1D Boron Dissolution Model

the total fuel cost. The use of Monte Carlo scenario analysis allows for the potential fuel costs savings to be defined under different market conditions. This is important to provide information on whether or not the potential fuel cost savings are significant and worthwhile in uncertain market conditions.

Monte Carlo is a stochastic method of generating a distribution of outcomes for use in an analysis. The Monte Carlo method generates random variables that are used as inputs at different states of a simulation to calculate the outcomes. The Monte Carlo simulation is performed a large number of times each with randomly chosen input parameters. The large number of simulations generates a distribution of outcomes that can be used in analyzing the system that is simulated. The larger the number of simulations, also called histories, creates a more accurately represented distribution of the possible outcomes from the system. Monte Carlo analyses often contain hundreds of thousands or millions of histories.

The Monte Carlo simulations are used to simulate the market prices of the resources used in manufacturing nuclear fuel. The simulated market conditions will be calculated using geometric Brownian motion that is discussed below. The simulated resource prices include the uranium yellowcake, U_3O_8 , the separative work unit, SWU, and the price of conversion of the yellowcake to uranium hexafluoride for enrichment. Other variables in the system are assumed constant or derived from the simulated market prices. The generated market prices are then used in a scenario where the cost of fuel is calculated and optimized to those given conditions. The costs of each of the core designs will then be compared to calculate the potential cost savings in that scenario. A distribution of potential cost savings will then be generated from the large number of Monte Carlo simulations for the market conditions.

It is beneficial to be able to analyze future potential economic tradeoffs by simulating the future price the underlying markets that drive fuel costs. An extra layer of complexity is added since the decisions made in purchasing nuclear fuel are optimized depending on the relative costs of the U_3O_8 and SWU markets. Therefore the following process will be used:

1. Use the Monte Carlo simulation to generate a combination of future market conditions (U_3O_8 , Conversion, SWU) to create a scenario
2. The scenario is then analyzed by optimizing fuel costs for the simulated market conditions
3. Then the cost differences between different core designs are calculated
4. The analysis is repeated for a large number of histories
5. The distribution of potential fuel costs is calculated for total number of simulation histories and analyzed

By using this method we will be able to analyze the potential value of using VERA under possible future market scenarios. The analysis will also be able to show the effect of market movement on the total cost of the nuclear fuel.

3.2.2 MODELING GEOMETRIC BROWNIAN MOTION

For the economic analysis, it is important to be able to simulate the fluctuations in price of the underlying assets (i.e. uranium, SWU, and conversion). The scenario analysis depends on having asset prices that are randomly determined for each simulation. By using characteristics of the historical prices of each asset, geometric Brownian motion (GBM) can be used to simulate variations in price of each asset over time for a single scenario. Monte Carlo can then be used to introduce the random behavior of the price fluctuations between scenarios. The process of simulating market prices with GBM is often used and has been found to valid for established markets. (Marathe & Ryan, 2005)

Geometric Brownian motion is based on regular Brownian motion which is a stochastic process that is continuous in time (also called a Wiener process). In geometric Brownian motion the logarithm of the random quantity follows a Brownian motion with drift.

First there is need to describe Brownian motion and then build on it to define geometric Brownian motion and why it is advantageous. The following derivation of Geometric Brownian motion from standard Brownian motion is largely reproduced from the lecture notes of Karl Sigman from Columbia University (Sigman, 2013) and is used to detail the mathematical concepts implemented in the Monte Carlo scenario analysis.

3.2.2.1 STANDARD BROWNIAN MOTION

Standard Brownian motion is defined as a stochastic process $\mathbf{B} = \{B(t): t \geq 0\}$ that possesses continuous paths and:

1. $B(0) = 0$.
2. $\mathbf{B}$ has both stationary and independent increments.
3. $B(t_i) - B(t_{i-1})$ has a normal distribution with mean 0 and variance $t_i - t_{i-1}$, $0 \leq t_{i-1} < t_i$

Statement 3 can be shown as $B(t_i) - B(t_{i-1}) \sim N(0, t_i - t_{i-1})$ where N is a normal distribution.

When simulating multiple future scenarios the time should be represented as a vector of discrete times. Let time be portrayed as a vector of k discrete values such that $t_0 = 0 < t_1 < t_2 < \dots < t_k$ and let there is a corresponding stochastic process vector $(B(t_1), \dots, B(t_k))$. Using 2 and 3 from above we can solve for

$(B(t_1), \dots, B(t_k))$ by letting Z be a random variable that is a unit normal distribution, $Z \sim N(0,1)$, and constructing a vector of k independent and identically distributed random variables $Z_1, Z_2, \dots, Z_k$. Then we can construct independent increments using Equation 3-10.

$$B(t_i) - B(t_{i-1}) = \sqrt{t_i - t_{i-1}} Z_i, \quad i = 1, \dots, k \quad \text{Equation 3-10}$$

And since

$$B(t_{i-1} + t_i) = B(t_{i-1}) + (B(t_{i-1} + t_i) - B(t_{i-1})) \quad \text{Equation 3-11}$$

We can write

$$B(t_{i+1}) = B(t_i) + (B(t_{i+1}) - B(t_i)) = B(t_i) + \sqrt{t_i - t_{i-1}} Z_{i+1},$$

$$i \in \{0, \dots, k-1\} \quad \text{Equation 3-12}$$

By using this we can generate unit normals $Z_1, Z_2, \dots, Z_k$ sequentially and then recursively define:

$$B(t_1) = \sqrt{t_1} Z_1 \quad \text{Equation 3-13}$$

$$B(t_2) = B(t_1) + \sqrt{t_2 - t_1} Z_2 = \sqrt{t_1} Z_1 + \sqrt{t_2 - t_1} Z_2 \quad \text{Equation 3-14}$$

$\vdots$

$$B(t_k) = \sum_{i=1}^k \sqrt{t_i - t_{i-1}} Z_i \quad \text{Equation 3-15}$$

Therefore, in order to simulate standard Brownian motion it is only necessary to generate unit normals.

3.2.2.2 BROWNIAN MOTION WITH DRIFT

The next step in defining geometric Brownian motion is to add drift to the standard Brownian motion. Let $X(t) = \sigma B(t) + \mu t$ denote the Brownian motion with drift $\mu \in \mathbb{R}$ and variance term $\sigma > 0$. Then X will have continuous paths and be defined by:

1. $X(0) = 0$.
2. X has both stationary and independent increments.
3. $X(t_i) - X(t_{i-1})$ has a normal distribution with mean $\mu(t_i - t_{i-1})$ and variance $\sigma^2(t_i - t_{i-1})$, $0 \leq t_{i-1} < t_i$

$X(t_i) - X(t_{i-1})$ can then be constructed by generating a standard normal random variable Z and setting

$$X(t_i) - X(t_{i-1}) = \sigma\sqrt{t_i - t_{i-1}}Z_i + \mu(t_i - t_{i-1}), \quad i = 1, \dots, k \quad \text{Equation 3-16}$$

Similarly to above we can write

$$X(t_{i+1}) = X(t_i) + (X(t_{i+1}) - X(t_i)) = X(t_i) + \sigma\sqrt{t_i - t_{i-1}}Z_{i+1} + \mu(t_i - t_{i-1}), \\ i \in \{0, \dots, k-1\} \quad \text{Equation 3-17}$$

And again we can construct all of X by generating unit normals $Z_1, Z_2, \dots, Z_k$ sequentially and then recursively defining:

$$X(t_1) = \sigma\sqrt{t_1}Z_1 + \mu t_1 \quad \text{Equation 3-18}$$

$$X(t_2) = X(t_1) + \sigma\sqrt{t_2 - t_1}Z_2 + \mu(t_{i+1} - t_i) = \\ \sigma\sqrt{t_1}Z_1 + \mu t_1 + \sigma\sqrt{t_2 - t_1}Z_2 + \mu(t_2 - t_1) \quad \text{Equation 3-19}$$

$\vdots$

$$X(t_k) = \sum_{i=1}^k \sigma\sqrt{t_i - t_{i-1}}Z_i + \mu(t_{i+1} - t_i) \quad \text{Equation 3-20}$$

3.2.2.3 GEOMETRIC BROWNIAN MOTION

Now that we have defined standard Brownian motion with drift we can develop geometric Brownian motion which is given by:

$$S(t) = S(0)e^{X(t)}, \quad t \geq 0 \quad \text{Equation 3-21}$$

Where $X(t)$ is given above and is a standard Brownian motion with drift. $e^{X(t)}$ has a lognormal distribution since $X(t) \sim N(\mu, \sigma^2)$. Knowing this, let $Y = e^X = e^{\sigma Z + \mu}$ with $Z \sim N(0,1)$.

It holds that

$$S(t) = S(0) \frac{S(t_{i-1})}{S(0)} \frac{S(t_i)}{S(t_{i-1})} = S(0) e^{X(t_{i-1})} e^{X(t_i) - X(t_{i-1})}, \\ 0 \leq t_{i-1} < t_i \quad \text{Equation 3-22}$$

Since the increments are independent then the ratios of $\frac{S(t_{i-1})}{S(0)}$ and $\frac{S(t_i)}{S(t_{i-1})}$ are independent lognormals. Now $S(t_{i-1})$ and $S(t_i)$ can be simulated by generating two independent and identical distribution random variables $Z_1, Z_2 \sim N(0,1)$ and then setting

$$S(t_{i-1}) = S(0)e^{\sigma\sqrt{t_{i-1}}Z_1 + \mu(t_{i-1})} \quad \text{Equation 3-23}$$

$$S(t_i) = S(t_{i-1})e^{\sigma\sqrt{t_i-t_{i-1}}Z_2+\mu(t_i-t_{i-1})} = S(0)e^{\sigma\sqrt{t_{i-1}}Z_1+\mu(t_{i-1})}e^{\sigma\sqrt{t_i-t_{i-1}}Z_2+\mu(t_i-t_{i-1})} \quad \text{Equation 3-24}$$

Then we can define $Y_i = \frac{S(t_i)}{S(t_{i-1})}$, $i \in \{1, 2, \dots, k\}$ and write

$$S(t_1) = S(0) Y_1 \quad \text{Equation 3-25}$$

$$S(t_2) = S(t_1) Y_2 = S(0) Y_1 Y_2 \quad \text{Equation 3-26}$$

$$\vdots$$

$$S(t_k) = S(t_{k-1}) Y_k = S(0) \prod_{i=1}^k Y_i \quad \text{Equation 3-27}$$

By defining $S(0)$ as the current price of a market we can simulate market price at some time in the future $S(t)$.

3.2.3 CALCULATION OF THE FUEL COSTS

The geometric Brownian motion model can be applied to each individual market to simulate multiple market prices. Once the markets have been simulated the data needs to be used to calculate the cost of the nuclear fuel for the core designs. The cost of the nuclear fuel can be optimized depending on the cost of the underlying uranium and SWU prices. The overall nuclear fuel cost (in \$/kg) is calculated by the following equation (Cochran & Tsoulfanidis, 1999).

$$p_{Ftot} = \left[\frac{p_{U3O8}}{(1-l_c)(1-l_f)} + \frac{p_{conv}}{(1-l_f)} \right] \frac{F}{P} + \frac{p_{SWU}}{(1-l_f)} p_{fab} \quad \text{Equation 3-28}$$

The variables used in Equation 3-28 are defined in Table 3-1. The uranium, SWU and conversion prices are taken from the Monte Carlo scenario analysis as described in the previous section. The losses due to conversion, l_c , and fabrication, l_f , are assumed to be constant 0.5% and 1.0%, respectively. These values are used as upper bounding values since the actual losses in practice are lower than what is assumed. The fabrication costs, p_{fab} , are also assumed to be constant at \$200/kg (EPRI, 2009). The final term used in the price of the total fuel is the ratio of feed uranium mass to the mass of the enriched uranium product. This ratio can be optimized to minimize cost according to the prices of the three considered assets. The calculation of the optimized $\frac{F}{P}$ ratio is described below.

The mass of the feed product and the total amount of SWU required can be optimized for each core design depending on the underlying prices of the U_3O_8 and SWU. There is a tradeoff between the SWU and the U_3O_8 . It is possible to conserve the use of one while raising the use of the other. For example, if U_3O_8

Table 3-1 Variables for Calculation of Nuclear Fuel Costs

Variables	
P	Mass of the enriched uranium product
F	Mass of the feed natural uranium
W	Mass of waste product
x_f	Weight percent ^{235}U of the feed
x_p	Weight percent ^{235}U of the product
x_w	Weight percent ^{235}U of the waste
SWU	The total amount of separative work units required
SF	SWU factor
p_{U3O8}	Price of U_3O_8
p_{conv}	Price of uranium conversion
p_{SWU}	Price of SWU
p_{fab}	Price of fuel fabrication
p_{Ftot}	Total price of fuel
l_c	Losses during conversion of U_3O_8 to UF_6
l_f	Losses during the fabrication process

is very expensive then less of it can be used for the same end product by using more SWU in the making of the fuel, and vice versa.

Using conservation of mass we can define

$$F = P + W \quad \text{Equation 3-29}$$

And

$$x_f F = x_p P + x_w W \quad \text{Equation 3-30}$$

The enrichment of the feed product, x_f , is limited to that of the natural uranium used, which is 0.711% ^{235}U . The enrichment of the product, x_p , is defined by each individual core design. And the enrichment of the waste stream, x_w , is optimized to minimize the total cost of the fuel according to the price of SWU, conversion, and U_3O_8 . We can then define

$$F = P \frac{x_p + x_w}{x_f + x_w} \quad \text{Equation 3-31}$$

Which gives

$$\frac{F}{P} = \frac{x_p + x_w}{x_f + x_w} \quad \text{Equation 3-32}$$

The total number of SWU produced by an enrichment facility is given by (Benedict, Pigford, & Levi, 1981)

$$SWU = P * V(x_p) + W * V(x_w) - F * V(x_f) \quad \text{Equation 3-33}$$

Where the quantities $V(x_i)$ are known as “separation potentials” and are given by

$$V(x_i) = (2x_i - 1) * \ln\left(\frac{x_i}{(1-x_i)}\right) \quad \text{Equation 3-34}$$

Where x_i stands for x_p, x_f, x_w

From there a SWU factor can be defined as

$$SF = \frac{SWU}{P} = V(x_p) + \frac{W}{P} V(x_w) - \frac{F}{P} V(x_f) \quad \text{Equation 3-35}$$

Finally the total amount of SWU is calculated using

$$SWU = P * SF \quad \text{Equation 3-36}$$

In the scenario model the total fuel cost is minimized for a given set of asset prices through brute force computation by calculating the fuel cost for all possible waste stream enrichments (0% to 0.711%) in increments of 0.0001% and then selecting the minimum fuel cost. The optimized costs associated with each core design can then be compared in that scenario to calculate the potential economic tradeoffs of the core designs.

It should be noted that the fuel cost dependencies are investigated solely in relation to varying asset market scenarios and do not include cost considerations for financing, transportation, or spent fuel storage as these are assumed to be substantially similar or identical between the core designs analyzed in this research.

3.3 SUMMARY

There are two main features to this research: a CIPS risk analysis and an economic analysis using Monte Carlo scenario analysis. Each required models to be developed to complete the analyses and was developed above. A description of the model and the results for the CIPS risk analysis are given below in chapter 5 CHAPTER 5. Additionally a description of the model and results for the Monte Carlo scenario analysis is given in chapter 6.

CHAPTER 4. BENCHMARKING THE VERA MODELS WITH THE PLANT OPERATIONAL PARAMETERS

In this section, the Catawba Nuclear Station unit 2 (CNS2) is described and VERA is benchmarked against measured data for fuel Cycles 18-22. Benchmarking validation is important to quantify the predictive capability of these methods for baseline cores which are known not to have CIPS. The validated models are used to establish accurate isotopic distributions for the reload fuel used in the CIPS analysis for fuel cycle 22. CNS2 has fuel cycles that are often limited by risk of CIPS. Therefore CNS2 is a good candidate to use VERA to analyze CIPS for this reactor.

4.1 CATAWBA NUCLEAR STATION – UNIT 2

CNS2 is jointly co-owned by Duke Energy Carolinas, North Carolina Municipal Power Agency, North Carolina Electric Member Corporation, and Piedmont Municipal Power Agency. CNS2 is operated solely by Duke Energy and is located on the banks of Lake Wylie (shown in Figure 4-1) in York, South Carolina, 19 miles southwest of Charlotte, North Carolina.

CNS2 began commercial operation in August 19, 1986 and has been operating successfully for the last 30 years providing 1129 MW of clean electricity at capacity factors over 95% (Energy Information Agency, 2012) with the license set to expire in December 2043.



Figure 4-1 Catawba Nuclear Station located in York, South Carolina. (Duke Energy, 2013)

4.1.1 REACTOR AND FUEL DESCRIPTION

CNS2 is a Westinghouse pressurized water reactors (PWR) with a 4-loop cooling system. It is thermally rated for a power of 3,411 MW_{th}. The reactor consists of a pressure vessel that contains a stainless steel core barrel with 193 nuclear fuel assemblies of the Westinghouse 17x17 fuel design in a cylindrical arrangement inside. It operates at a nominal pressure and temperature of 2,250 psi and 557°F. During operation, heat is released through nuclear fission and the fuel assemblies are cooled by light water that is pumped through the pressure vessel at a rate of 136 million pounds per hour by four reactor coolant pumps. The water is borated with boric acid that is injected into the coolant as a chemical shim for reactivity control. The relative amount of boric acid in the RCS is reduced by dilution over the duration of the cycle as the fuel depletes. This boric acid dilution is known as the boron “letdown.” The boron letdown is monitored during the fuel cycle because it indirectly gives the core reactivity and is therefore useful for the validation of reactor core simulators. CNS2 fuel cycles (also called just cycles) are designed to operate for approximately 500 effective full power days (EFPD).

CNS2 utilizes the second generation of Westinghouse’s Robust Fuel Assembly (RFA-2) nuclear fuel assemblies. Each fuel assembly contains 264 fuel rods in a 17x17 lattice array with 25 non-fuel lattice positions. The non-fuel positions consist of guide tubes that provide channels for discrete burnable absorber inserts or movable control rods and one central instrument tube. Each of the 193 fuel assemblies is approximately 13 feet tall and is stabilized axially by spacer grids that also provide additional coolant mixing in operation.

There is a total of 50,952 fuel rods in the reactor core. Each fuel rod is made of sintered uranium dioxide fuel pellets stacked inside a zirconium metal alloy tube cladding. The enrichment of ²³⁵U in the fuel pellets ranges from 3-5%, which is constant for each assembly but may vary between assemblies. When fully loaded, the CNS2 reactor core holds approximately 90 metric tons of uranium.

Solid boron compounds, known as burnable absorbers, are used to control excess reactivity and control power peaking at the beginning of the fuel cycle. Modern burnable absorbers in CNS2 take two forms: Integral Fuel Burnable Absorber (IFBA) and Wet Annular Burnable Absorber (WABA). Unlike boric acid in the coolant that is diluted through intervention, both burnable absorbers are designed to improve fuel economy by being depleted of ¹⁰B (they are no longer strong neutron absorbers) by the end of the fuel cycle thereby limiting the residual reactivity penalty.

IFBA contains the boron neutron absorber in the form of an ultra-thin ZrB₂ coating on the fuel pellets that is built into the fuel rods. CNS2 currently utilizes IFBA in at least 32 fuel rods per assembly up to 128 fuel rods per assembly.

The WABA form of burnable absorber is a set of discrete rods that are inserted into the fuel assembly guide tubes. Each WABA rod is hollow in the center, where coolant flows, and contains the $B_4C-Al_2O_3$ neutron absorbing material in an annular ring that is clad on the inside and outside by a zirconium metal alloy. The WABA rods remain in the fuel assembly for the entirety of the fuel cycle but are then removed before the next fuel cycle.

Reactivity in the reactor is controlled throughout the cycle with not only the chemical boron shim but also with hybrid B_4C and Ag-I-Cd (AIC) control rods. The control rods are movable and provide instantaneous reactivity control and negative reactivity to ensure the shutdown of the reactor. 24 control rods are clustered into assemblies that fit inside the guide tubes a single fuel assembly. There are 53 rod cluster control assemblies (RCCAs) grouped into 9 separate “banks.” The RCCA banks can move independently of each other from the positions of fully withdrawn from the core to fully inserted. There are five RCCA banks that are reserved for shutdown. Of the other four banks, only bank D is maneuvered during nominal reactor operation. The control bank locations are shown in Figure 4-2, in quarter core symmetry.

Fuel Cycles 18-22 for CNS2, which are the cycles analyzed in this research, all utilizes a pattern of loading fuel assemblies into the core, known as a loading pattern. The loading pattern can be designed so that the reactor has certain characteristics during operation. The loading pattern that is used is one that tries to minimize leakage of neutrons from the outer periphery in the core to increase fuel utilization and to reduce neutron irradiation of the reactor pressure vessel.

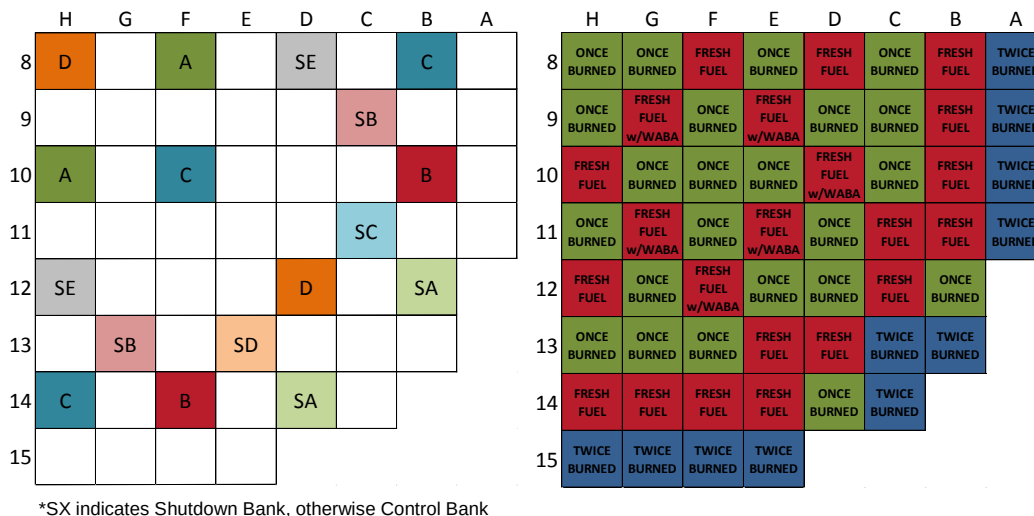


Figure 4-2 RCCA bank locations (left) and ultra-low leakage ring of fire loading pattern (right)

The ultra-low leakage core design used in CNS2, known as the “ring of fire”, is shown on the right in Figure 4-2. Although the ring of fire ultra-low leakage design has the aforementioned benefits, it creates high peaking factors on the interior of the core that must be managed with burnable absorbers. Because of these core design choices, CNS2 core designs are often limited by risk of CIPS making it a good candidate to use VERA to analyze CIPS for this reactor.

4.2 CATCHING UP TO CYCLE 22: THE “JUMP-IN”

METHOD

One of the challenges in the modeling and simulation of nuclear reactors is capturing the characteristics of the fuel in each reactor operation cycle. The initial conditions required for these simulations include detailed spatial distributions of isotopics and sub-pin level geometry along with core, cycle, and operational data. Since approximately 2/3 of the fuel is carried over between fuel cycles, the previous cycle’s operation has an effect on the subsequent cycle. The detailed isotopic distributions in the fuel are highly dependent on fuel history. This data must be obtained from simulations of previous cycles or approximated. It is possible to generate models and perform simulations from the beginning of the reactor life up to the cycle of interest to capture all of the carry over effects between cycles. However, when the cycle of interest is the twentieth cycle (or later) in the life of the reactor, it may require over a quarter of a million cpu-hours in computational resources and hundreds of person-hours. Therefore a method was developed and implemented to generate an accurate model of the current cycle without simulating all previous fuel cycles and requiring only a fraction of the potential computational and labor resources. This method is called a “jump-in.”

The VERA results for the cycles generated by the “jump-in” were benchmarked against measured data to strengthen the confidence in the VERA models used in the CIPS analysis. In previous work, VERA has been benchmarked with reactor cores by explicitly modeling all the prior cycles leading to a given cycle (Godfrey, et al., 2015). To save time and computational resources, the CIPS analysis used VERA models that had been validated for cycles 18-21 by performing a “jump-in” at cycle 18.

4.2.1 BACKGROUND FOR “JUMP-IN” MODEL

A “jump-in” is the process of modelling a reactor core by approximating the necessary, but unknown, 3D isotopic distributions for used fuel assemblies as inputs for a cycle for which none of the previous cycles have been modeled or simulated. The core designs analyzed in this research are three batch designs, so for any given cycle there are two cycles of past history which are required to

develop the proper isotopic vectors and spatial distributions for accurate simulation. In the case of the CIPS analysis for Cycle 22, accurate depleted fuel compositions from EOC 21 were required. In order to create the necessary EOC for Cycle 21, it was initially assumed that 4 previous cycles of simulated depletion would be necessary, making the Cycle 18 the “jump-in” cycle. Cycles 19-21 were simulated and compared to measured data for validation. The results of the validation are discussed below.

The “jump-in” process began by selecting an appropriate previous cycle to the one of interest and generating an approximate operational history for the fuel being reinserted into the jump-in cycle. Due to neutron reaction rates and kinetics involved in fuel depletion during power production, the inaccuracy of approximating the operational history of fuel assemblies decays as fuel cycle depletions are simulated to reflect historical operation. Finally, the cycle of interest can be simulated with adequate accuracy notwithstanding the “jump-in” process.

CNS2 utilizes a three-batch fuel management system, which means that three batches of fuel are loaded for a given cycle: the fresh fuel batch, the once burned fuel batch, and the twice burned fuel batch. Following is a summary of the fuel batch characteristics:

- The new fuel batch consists of un-irradiated uranium dioxide (UO_2) fuel that does not have any burnup history effects. No approximations are required to model this batch precisely in the “jump-in” cycle.
- The once burned fuel has been in the reactor for one full cycle before the “jump-in” cycle, thereby carrying history effects from power production and depletion resulting from its cycle of residency in the core. The average burnup of once burned fuel at BOC is approximately 24 GWd/MTU. This fuel must be approximated in the “jump-in” cycle to avoid explicit modeling of the previous cycles. Although this fuel has less burnup history effects than the twice burned fuel it bears more weight in the “jump-in” cycle due to its higher power sharing, and usually adjacent position to new fuel, in the low-leakage core loading patterns employed in modern reloads.
- The twice burned fuel has been in the reactor for two full cycles previous to the “jump-in” cycle. This fuel contains the most depletion history. The average burnup of the twice burned fuel at BOC is 45 GWd/MTU. The twice burned fuel is often placed in regions of lower power on the periphery and therefore plays a less significant role in the behavior of the cycle. The twice burned fuel must also be approximated for the “jump-in” cycle.

At the end of the cycle the twice burned fuel that was loaded has now been burned three times and is typically discharged from the reactor core and not reinserted in the subsequent cycle. Each batch is $\sim 1/3$ of the total fuel thereby creating a sustainable fuel cycle where about $1/3$ of the fuel is replaced each cycle. Therefore, all of the fuel has been replaced every 3 cycles. This allows for the approximated fuel batches to be cycled out of the subsequent core designs until there is no more approximated fuel in the cycle and all the fuel has been modeled and simulated from the beginning of its life. The goal of the “jump-in” approach is to start far enough back from the cycle of interest (Cycle 22) so that inaccuracies from the approximations are reduced to a negligible amount while establishing correct isotopic vectors and spatial distributions for nearly every fuel pellet in the core, totaling over 7.5 million regions in the fuel.

Typically, a batch of fuel is split into sub-batches. These are sets of fuel within the same batch that have differing fuel enrichments. This is done to optimize fuel management enabling optimum power shaping as well as increased fuel utilization. Typically there are 2 sub-batches of fuel in the same batch, but more have been used.

4.2.2 METHODOLOGY FOR “JUMP-IN” MODEL

In order to approximate the isotopics of the burned fuel in the “jump-in” cycle 18 single assembly simulations with radially reflective boundary conditions were depleted at the sub-batch average exposure at the BOC of cycle 18. This preserved the core average burnup at BOC. The approximated fuel assemblies were then loaded into cycle 18, along with the batch of fresh fuel. The cycles were depleted per historical operation of the cycles. At the end of each cycle, the now thrice-burned fuel is discharged and the remaining fuel is shuffled and loaded with fresh fuel into the subsequent cycle.

The workflow developed for the “jump-in” process is shown in Figure 4-3. The steps that were performed are as follows:

1. 3D single assembly depletions with reflective radial boundaries and vacuum (non-reentrant) axial boundaries were performed for each sub-batch of the once and twice burned fuels for cycle 18. The sub-batch average burnup was matched to BOC 18 exposures provided by Duke Energy. This is shown in the top left block in Figure 4-3.
2. The approximated fuel was loaded into the core, along with the new fuel, for cycle 18 and depleted according to historical plant data.
3. Cycles 19, 20, and 21 were depleted according to historical plant data by shuffling fuel from the previous cycle and loading the core with the new fuel. This is represented in Figure 4-3 by left column labeled “Jump-in 1st Iteration”.

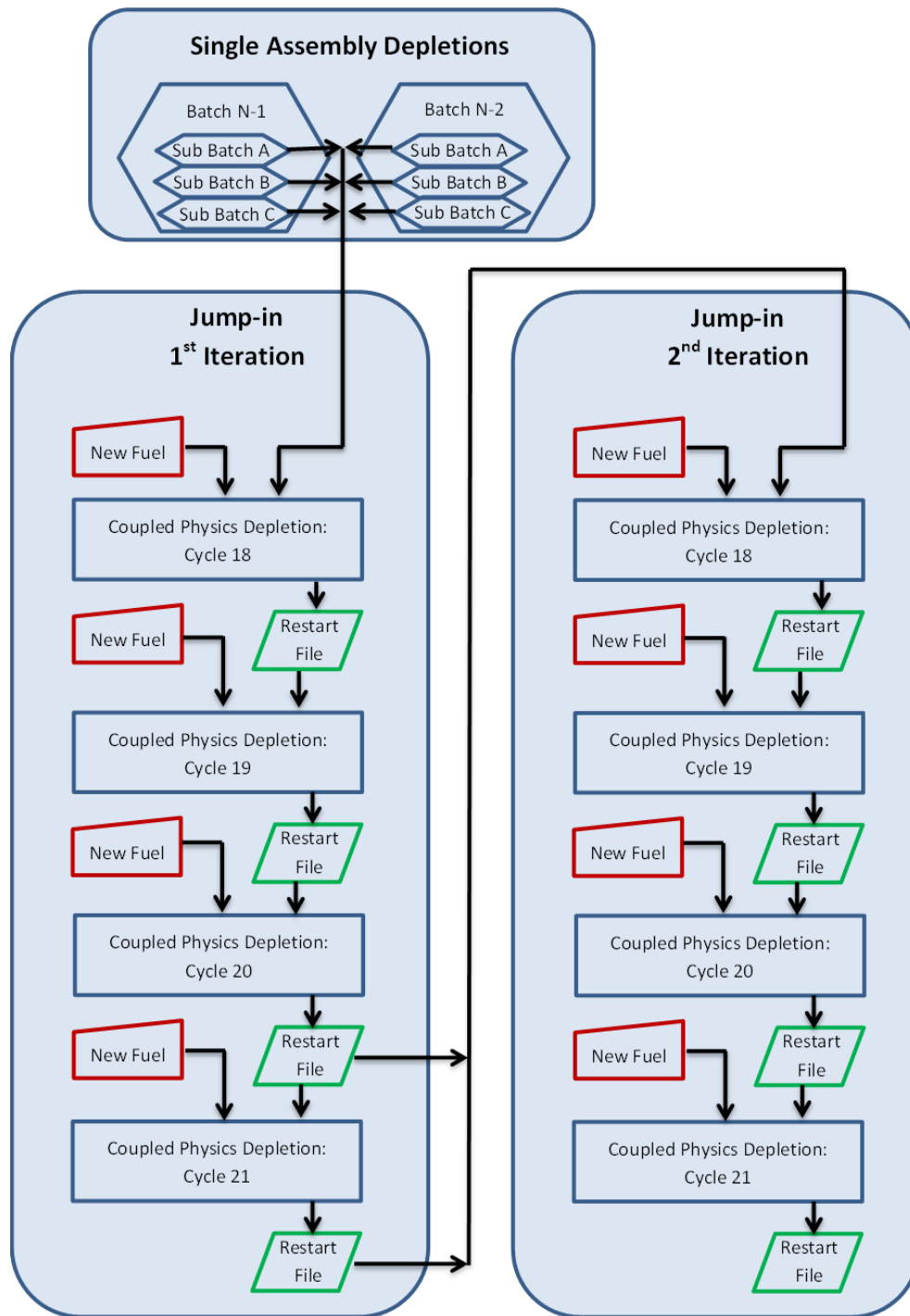


Figure 4-3 Workflow for the "Jump-In" Process Building up to the CIPS Analysis

The “1st iteration” column is one full application of the “jump-in” method. However, there are multiple ways to initialize the process. Another method of initialization that was investigated was to use fuel assemblies with full 3D isotopic distributions from the output of previously simulated fuel cycle. Initializing the process with assemblies output from a simulation allows the user to skip the single assembly depletions described in step 1. However, alternative approximations must be made since the output fuel assemblies do not match the batch average exposure or fuel enrichments as was done in the 1st iteration. In order to compare the two methods, a “2nd iteration” of the “jump-in” process was performed by utilizing outputs from Cycles 20 and 21 of the “1st iteration”. The steps taken for the “2nd iteration” are as follows:

4. At the end of cycle 21, fuel assemblies from the EOC 20 and 21 are matched approximately with the once and twice burned fuel in cycle 18 and used in place of the single assembly depletion approximated fuel. Cycle 18 is then simulated with a full depletion using the “new” approximated fuel that was pulled from the EOC 20 and EOC 21. This is shown in Figure 4-3 by the arrows connecting the “1st Iteration” column with the “2nd Iteration” column. The results of this simulation are compared to measured data for validation.
5. Cycles 19, 20, and 21 are re-simulated with full depletions in the same manner as step 3 using the updated cycle 18 feeding into the subsequent cycles. This is represented in Figure 4-3 by left column labeled “Jump-in 2nd Iteration”. The results of these simulations are compared to measured data for validation and benchmarking.

A comparison of the benchmarking results for Cycles 18-21 of both “jump-in” iterations was performed and is shown below.

4.2.3 RESULTS FOR “JUMP-IN” MODEL

An analysis of the results obtained for Cycles 18-21 and comparison to measured data shows large errors in cycle 18 that decrease as the cycle depletions progressed to cycle 21. This is due to the relatively large errors in the “jump-in” fuel approximations made in the single assembly depletion process.

The assumptions made during the single assembly 3D depletions used to initialize the “1st iteration” of the “jump-in” are:

Reflective radial boundary conditions – This is a significant assumption made in the depletion of the single 3D assemblies. Depending on the loading pattern, the adjacent neighbors to a fuel assembly during operation can have a significant impact on that assembly’s power and spectral history. Typically, fuel assemblies are loaded in a pattern where they are adjacent to assemblies of a different batch, meaning that they

have significantly different exposures, creating local radial heterogeneity in power. This is done to manage power peaking factors and keep a flatter radial power profile across the core. However, the radially reflective boundary condition assumes the assembly is surrounded by assemblies with duplicate characteristics. This assumption may cause the largest source of inaccuracies in the process of approximating fuel assembly isotopic distributions for the “jump-in” initialization. Vacuum (non-reentrant) axial boundary conditions – Nominal depletions contain additional core geometry above and below the fuel with a water reflector. Despite this added complexity used in quarter or full core depletions, a vacuum boundary condition axially is a good approximation.

- Constant soluble boron – As discussed previously, the soluble boron chemical shim undergoes a dilution during the cycle called the boron “letdown.” Due to the method with which the 3D single assemblies were depleted, a constant boron concentration was chosen that approximated the average boron concentration for a nominal fuel cycle.
- Depletion at 120% full power – For the first two cycles that a fuel assembly is in the core, the power peaking factor for the assembly is ranges from over 1.3 to about 0.9. This was approximated by depleting the single assemblies at 120% full power to the desired exposure.
- Some burnable absorbers – An average number of IFBA was used in the single assembly depletions. While the numbers of IFBA pins per assembly does range widely from 32 to 128, they are depleted within the first 100 EFPD of the first cycle of use. WABA inserts were not used because there are relatively few WABA inserts used in the Cycle 18 core design.

While these assumptions contain significant approximations, they allow for a method of initializing the “jump-in” that provides all of the necessary isotopic vectors and spatial distributions to be reasonably generated. These assumptions, however, are not present in the initialization of the “2nd iteration” of the “jump-in” due to taking assemblies that experienced depletions with nominal reactor conditions together with other assemblies in a quarter core model. The exposure effects for a representative fuel assembly from the single 3D assembly depletion and the fuel assembly from a quarter core depletion can be seen Figure 4-4.

Figure 4-4 shows the burnup distribution in plot A has a higher burnup at the top of the assembly than the bottom. This causes a strong negative axial offset when many of these assemblies are placed into a core model since the top of the fuel is more depleted in fissionable material. This was the fuel used in the first iteration of the “jump-in”. The axial burnup profile of plot B shows a more balanced profile that is expected to be seen in a nominally depleted assembly. This is the fuel used in the second iteration of the “jump-in” process.

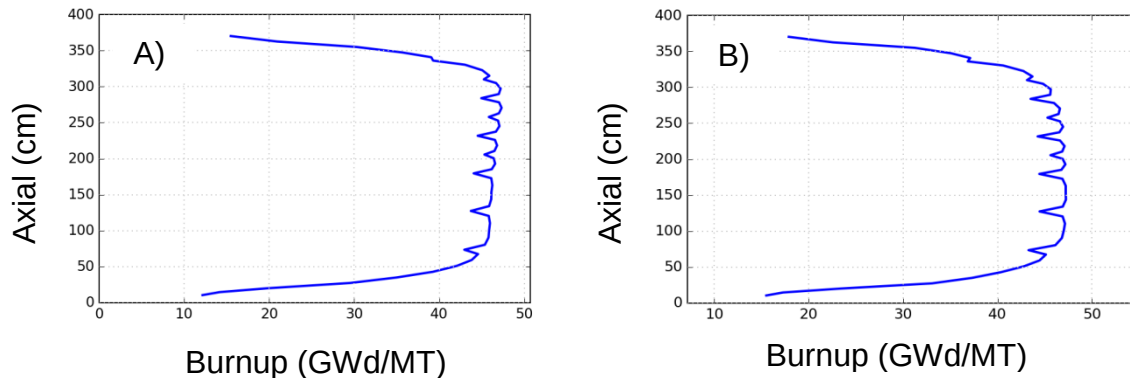


Figure 4-4 Axial Burnup for Assemblies Used for Jump-In Cycle – A) Single 3D Assembly with Approximated Conditions B) An Assembly depleted in an Actual Reactor core Configuration

The VERA results for the two iterations of the “jump-in” were benchmarked to measured data for the critical soluble boron concentration and AO throughout each cycle. An in-depth analysis of the second iteration of the “jump-in” is shown below in sections 4.3.6 and 4.3.7.

A comparison of the cycle summary statistics is shown in Table 4-1. As can be expected from the effects seen in Figure 4-4, the AO in cycle 18 for the first iteration of the “jump-in” has the largest discrepancy with measured data along with the largest standard deviation. As the cycle depletions in the first iteration of the “jump-in” continue the mean difference with measured data and the spread in the discrepancy decreases. This actively shows the negative effects from the approximated fuel history decaying away as the operating history of the reactor is simulated.

4.3 BENCHMARKING RESULTS

Cycles 18-21 of CNS2 were similar in design, and similarly well behaved operationally. All cycles used traditional IFBA/WABA burnable absorbers in varying amounts and same fuel design. The average fuel enrichment did increase from cycle 18 through 21. The benchmarking simulations were performed with VERA with coupled MPACT, and CTF. Since CIPS was not observed in these cycles, MAMBA-1D was not used.

4.3.1 ZERO POWER PHYSICS TESTING (ZPPT)

Zero Power Physics Tests (ZPPTs) are performed during the startup of the reactor before power is increased to normal power production levels to confirm

Table 4-1 Boron and Axial Offset Differences from Measured Data for 1st and 2nd Iterations of the “Jump-in”

		Axial Offset Difference		Critical Boron Difference	
		Mean	St. Dev.	Mean (ppm)	St. Dev. (ppm)
Jump-in 1st Iteration	Cycle 18	-3.1%	5.4%	16.3	7.2
	Cycle 19	0.6%	1.5%	9.9	10.0
	Cycle 20	-0.6%	0.9%	22.2	17.1
	Cycle 21	-0.6%	0.8%	4.0	17.6
Jump-in 2nd Iteration	Cycle 18	-1.7%	3.1%	10.9	13.9
	Cycle 19	-0.4%	0.3%	1.3	10.1
	Cycle 20	-0.5%	0.7%	18.3	8.1
	Cycle 21	-0.7%	0.9%	-5.1	13.0

that the fuel has been loaded correctly and simulated with sufficient accuracy to ensure adequate safety margins.

The standard ZPPT procedure includes testing the following key reactivity parameters:

1. Criticality
2. Control rod worths
3. Isothermal temperature coefficient
4. Differential soluble boron worth

The measurements are compared to the predicted values contained in the nuclear design report to ensure compliance with the acceptance criteria. The specifics of these acceptance criteria are discussed in their respective sections below.

The ZPPT calculations for each cycle were performed with VERA utilizing a single simulation containing 14 state points, to enable obtaining the following parameters to compare against the respective measured data:

A general example of the state point parameters used in the ZPPT simulation is shown in Table 4-2. The heading labeled k_{eff} is the core average eigenvalue, also known as k-effective. The core reactivity difference from critical is calculated by Equation 4-1.

$$\rho = \frac{k_{eff} - 1}{k_{eff}} \times 10^5 [pcm] \quad \text{Equation 4-1}$$

The following gives an explanation of the state points and the associate main parameters:

- State 1 is used as the base conditions for comparison. Note that the k_{eff} of the core is 1.000 meaning that the core is exactly critical. The power is at 0% for all state points. Temperature Y is the hot isothermal condition for the reactor, approximately 550°F. The soluble boron concentration is at the critical boron concentration X.
- States 2 and 3 vary the soluble boron concentration and keep all other conditions the same. The differences in k_{eff} are used to calculate the differential boron worth.
- States 4 and 5 vary the coolant/moderator and fuel temperature and keep the other conditions at their original conditions for critical. The differences in k_{eff} from these states are used to calculate the isothermal temperature coefficient.
- States 6 through 14 sequentially insert each individual control rod bank into the core all other bank completely removed. The worth of each bank is calculated from the magnitude of the inserted reactivity.

Table 4-2 Core Conditions by State Point used in ZPPT

State Point	Power	k_{eff}	Soluble Boron Concentration (ppm)	Temperature (°F)	Control Bank Positions
1	0%	1.000	1900	557	ARO
2	0%	1.002	1880	557	ARO
3	0%	0.999	1920	557	ARO
4	0%	1.001	1900	552	ARO
5	0%	0.999	1900	562	ARO
6	0%	0.997	1900	557	Bank A Fully Inserted
7	0%	0.995	1900	557	Bank B Fully Inserted
8	0%	0.992	1900	557	Bank C Fully Inserted
9	0%	0.996	1900	557	Bank D Fully Inserted
10	0%	0.999	1900	557	Bank SA Fully Inserted
11	0%	0.992	1900	557	Bank SB Fully Inserted
12	0%	0.998	1900	557	Bank SC Fully Inserted
13	0%	0.998	1900	557	Bank SD Fully Inserted
14	0%	0.996	1900	557	Bank SE Fully Inserted

The change in reactivity for a specific test is calculated as shown in Equation 4-2.

$$\Delta\rho_{test} = \left(\frac{1}{k_{test}} - \frac{1}{k_{base}} \right) \times 10^5 [pcm] \quad \text{Equation 4-2}$$

Where k_{test} is the k-effective calculated by VERA for the test state point and k_{base} is the k-effective calculated by VERA for the base case. The base case is the state point with conditions chosen to be used for comparison. For the ZPPT process performed, the base case is defined as critical with All Rods Out (ARO) at HZP with the critical boron concentration.

All the simulations supporting the calculations of the ZPPT parameters were performed with VERA in quarter-core symmetry without T/H feedback. Thermal expansion of the reactor internals is considered by calculating material expansion at 565°F.

4.3.2 BOC HZP CRITICAL BORON CONCENTRATION

At the beginning of the fuel cycles, criticality is initially attained at HZP conditions through the positioning of the regulating control bank and dilution of the boric acid in the RCS. Once criticality is attained the soluble boron concentration is recorded. This result is compared to the value predicted by the design code to verify compliance with the acceptance criterion, e.g. a ± 50 ppm maximum deviation between the measured and predicted critical boron concentration (Duke Energy, 2003).

The differences between VERA's calculated critical boron concentrations and the measured values from CNS2 are shown in Figure 4-5. The average difference is 12.8 ppm with a standard deviation of 13.3 ppm. This is very good agreement, well within the current acceptance criterion for BOC HZP critical boron concentration.

Cycle 20 has the largest error in the critical boron prediction, +31 ppm. The BOC HZP overestimation from VERA in core reactivity for cycle 20 is consistent with the HFP depletion. The source of this difference is unknown, but may be the result of a difference between the modeled and as-built fuel characteristics.

The computation time required for the ZPPT simulations is reasonable, making them practical on engineering computing clusters of 1000 cores. The average runtime for the 14 ZPPT simulations conducted was about 7.5 hours, or an average runtime per state point of 33 minutes on 960 cores. A breakdown of the data by cycle is shown Table 4-3.

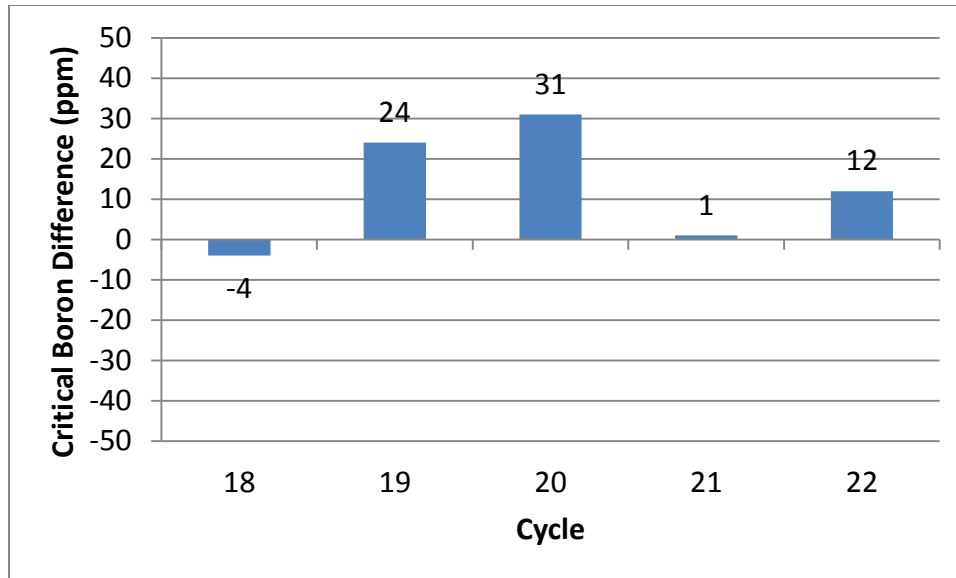


Figure 4-5 BOC HZP Critical Boron Concentrations for Catawba Cycles 18-22

Table 4-3 Computer Resources and Runtimes for ZPPT

Cycle	Hours	Cores	State Points
18	7.7	960	14
19	7.5	960	14
20	8.2	960	14
21	7.8	960	14
22	7.2	960	14
Total	38.4		70
Total cpu-hrs			36,816
hrs/state point			0.55

4.3.3 BOC HZP CONTROL BANK WORTHS

Control Bank Reactivity Worth (CBW) is measured for multiple reasons. One is to ensure that the uncertainty in the bank worths that was assumed in the safety analysis remains bounding. Another is to verify the fuel shuffle and core loading was performed properly.

There are multiple different types of CBW methodologies in the nuclear industry. The technique used in cycles 18-21 was the Dynamic Rod Worth Measurement (DRWM) technique. DRWM is a method that is based on 3-D, space-time kinetic simulations of rapid rod movements (Chao, 2000). The DRWM technique cannot be directly simulated by VERA currently because they would require transient neutronics and ex-core detector response models. Rather, the VERA simulations for calculating CBW were performed at steady-state critical conditions, which is consistent with current industry core design methods.

The CBW value calculated by VERA is the reactivity worth of fully inserting each individual bank from the ARO conditions at HZP. The relative CBW errors (VERA – measured) are presented Figure 4-6 below. Due to the “Jump-in” approach, cycle 18 results are not as well predicted. However, the values for the following cycles are in good agreement with plant data.

The acceptance criteria for the CBW predicted values is a difference from the measured data of less than 15% or 100 pcm, whichever is greater, for any single bank. The CBW errors shown in Figure 4-6 are all within 15% of the measured values. Cycle 18 has the highest divergence from measured data, up to 12.4%, due to the approximations made with the “jump-in” technique. The errors drop significantly after the jump in cycle to no more than 7.5%.

The error for the total rod worths for cycles 18 through 22 are shown below in Figure 4-7. The acceptance criteria for the total bank worths are that the measured and predicted values need to agree within 8%, and the total measured bank worths must be greater than or equal to 90% of the total predicted values.

Different from the bank worths, cycle 18 has the lowest error. This is likely due to the incidental cancellation of errors due to high and low CBW individual banks as shown in Figure 4-6. The remaining cycles all show an overall underestimation of the CRW from VERA compared to the measured values. The errors are all within the acceptance criterion, with the largest error being -4% in cycle 22.

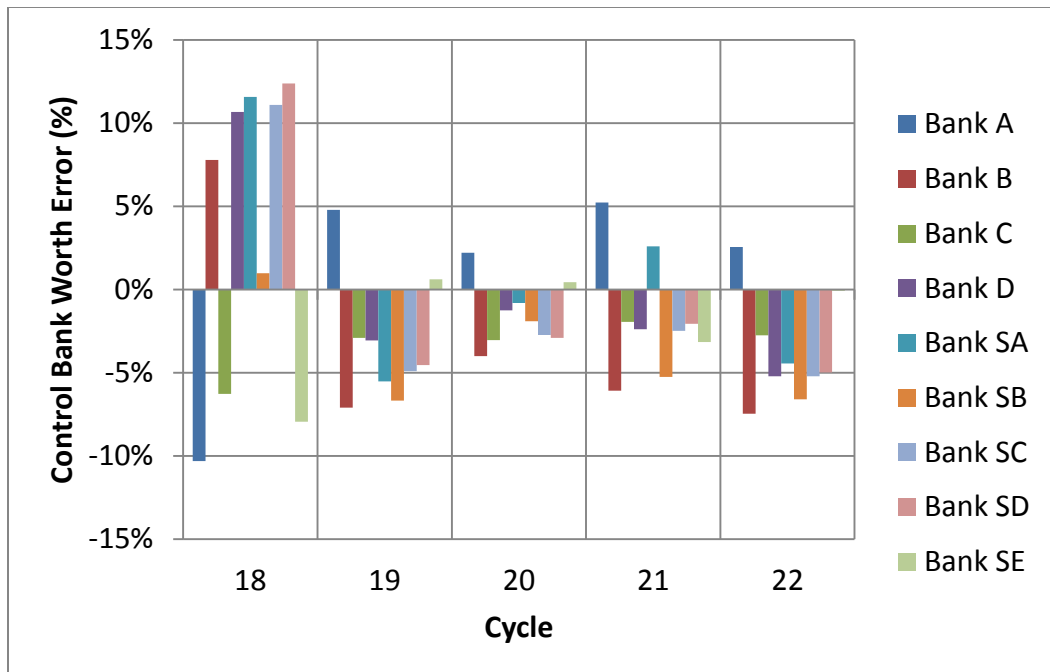


Figure 4-6 BOC HZP Individual Control Bank Worth Errors (VERA – Measured)

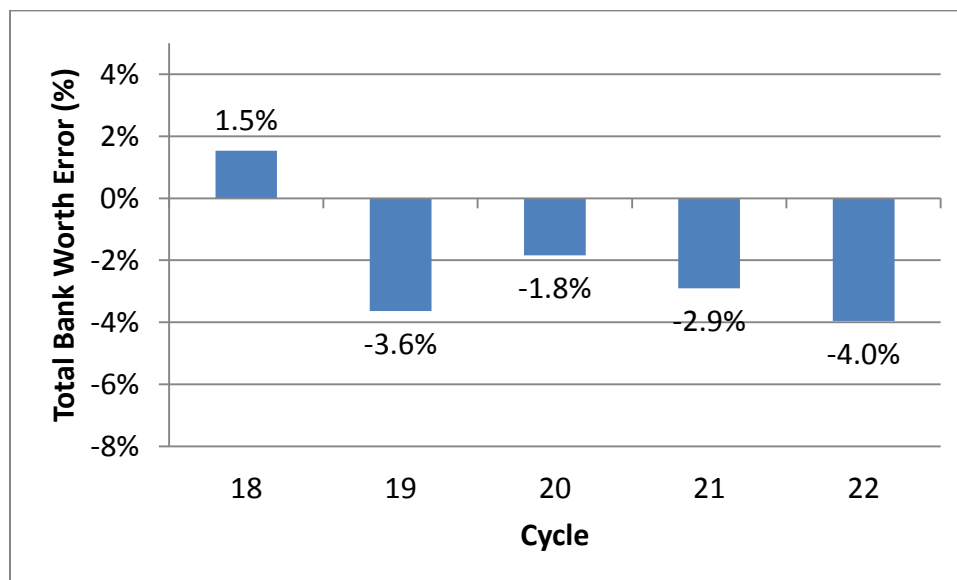


Figure 4-7 Total Control Bank Reactivity Worth Error (VERA – Measured)

4.3.4 BOC HZP ISOTHERMAL TEMPERATURE COEFFICIENT

The Isothermal Temperature Coefficient (ITC) is measured during the ZPPT process to verify that it meets plant specifications. The Moderator Temperature Coefficient (MTC) cannot be measured directly; therefore the MTC is inferred from the measured plant value of the ITC. The Doppler temperature coefficient for the fuel is predicted by computational methods in the core design and used with the ITC to calculate the MTC as shown in Equation 4-3 (American Nuclear Society, 1997).

$$MTC = ITC - DTC \quad \text{Equation 4-3}$$

The ITC is measured by varying the temperature of the moderator (and core internals, including fuel) and having the reactivity of the core measured by the reactivity computer while keeping the soluble boron concentration constant. The ITC is then calculated with Equation 4-4.

$$ITC = \frac{\Delta\rho}{\Delta T} = \frac{\frac{1}{k_1} - \frac{1}{k_2}}{T_2 - T_1} \times 10^5 \left[\frac{pcm}{^\circ F} \right] \quad \text{Equation 4-4}$$

Where $\Delta\rho$ is the change in reactivity and ΔT is the change in temperature for the measurement.

The acceptance criterion for the ITC of a plant is ± 2 pcm/ $^\circ F$. The difference in the ITC for each cycle between cycles 18 to 21 are shown in Figure 4-8. The average ITC difference is -1.02 pcm/ $^\circ F$ with a standard deviation of ± 0.23 pcm/ $^\circ F$. VERA consistently predicts an ITC that is more negative than the measurement.

4.3.5 BOC HZP DIFFERENTIAL SOLUBLE BORON WORTH

The Differential Boron Worth (DBW) is predicted by standard industry methods. The predicted values are calculated by determining the change in reactivity due to perturbations of the soluble boron concentration at fixed conditions for the other state variables. The DBW is calculated as shown in Equation 4-5.

$$DBW = \frac{\Delta\rho}{\Delta C_B} = \frac{\frac{1}{k_1} - \frac{1}{k_2}}{C_{B2} - C_{B1}} \times 10^5 \left[\frac{pcm}{ppmB} \right] \quad \text{Equation 4-5}$$

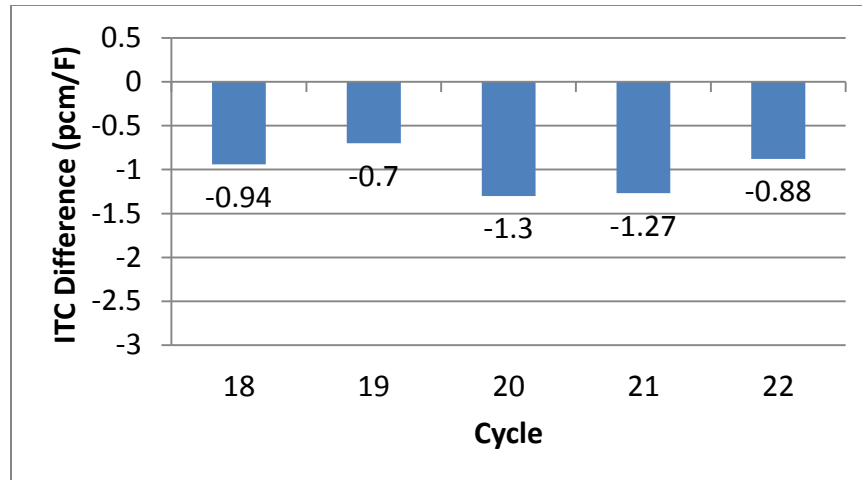


Figure 4-8 BOC HZP Isothermal Temperature Coefficient Differences (VERA – Measured)

The percent deviations in DBW calculated by VERA from those calculated by industry are shown in Table 4-4. The percent deviation of the DBW for all cycles is rather low. An acceptance criterion of agreement between the measured and predicted values of the DBW of $\pm 15\%$ has been used. The VERA results are well within this acceptance criteria.

4.3.6 HOT-FULL-POWER CRITICAL BORON LETDOWN

To achieve the desired cycle length, the reactor is designed with the necessary amount of excess reactivity at the beginning of the cycle. This excess reactivity is controlled throughout the cycle by burnable poisons in the fuel and soluble boron in the coolant. As the core reactivity decreases, the burnable poisons deplete and the soluble boron concentration is decreased, through boron dilution with non-borated water, to maintain criticality. The critical boron concentrations are measured throughout the cycle and are a valid source of benchmarking data for reactor physics codes validation.

Table 4-4 BOC HZP Differential Boron Worth Differences

Cycle	DBW % deviation
18	2.4%
19	2.1%
20	2.3%
21	2.1%
22	2.0%

The actual cycle operational history was followed as closely as possible in the VERA cycle depletion simulations. Very few power maneuvers occurred during cycles 18-21. This made it possible to assume much of the cycle depletions approximately a constant depletion at equilibrium full power conditions. The cycle depletion simulations were performed with an initial power escalation from BOC HZP to HFP conditions accomplished over a few EFPDs, and then continued at nominal HFP conditions with intervals of 25 EFPD for the duration of the cycle, approximately 500 EFPD, at equilibrium xenon conditions. A power coast down is performed towards the end-of-cycle (EOC) to match the plant operating history. The depletions were simulated with quarter-core rotational symmetry to reduce the computational requirements, and with the critical boron search turned on to calculate the soluble boron concentration required to keep the core critical $k_{eff} = 1$ for each state point.

The differences in the measured critical boron and the critical boron calculated by VERA are shown in Figure 4-9 for cycles 18-21. Data with known anomalies was removed. Cycle 22 had just started up and did not have any operating history data for the critical boron letdown.

The soluble boron differences are calculated as the VERA predicted minus the measured values. The average difference for all four cycles is 6.7 ± 14.6 ppm. If cycle 18 is excluded, the average difference decreases by 22% to 5.2 ± 14.7 ppm. Although the average difference is reduced when cycle 18 is eliminated, the spread of the data remains nearly constant. Additional statistics are broken down by cycle in Table 4-5.

Overall, the agreement is excellent. Note that the differences in the critical boron values typically increase from the BOC to EOC. This may be attributable to inaccuracies introduced by history effects, such as the neutronic impact of higher actinide buildup, and/or fuel temperature induced effects, and depletion of burnable absorbers.

4.3.7 AXIAL OFFSET

Another figure of merit that is measured throughout a cycle is the AO. The calculation for AO is defined in Equation 2-1. AO is monitored during a reactor cycle because it is one of the key indicators of CIPS. By measuring and monitoring the AO, any warning signs of CIPS can be detected and analyzed so that corrective steps may be taken if necessary.

During a normal cycle, the AO will behave predictably and consistently with its predicted value. A comparison between the AO values predicted by VERA and the measured AO is shown in Figure 4-10. Note that the AO difference plotted is the VERA AO minus the measured AO.

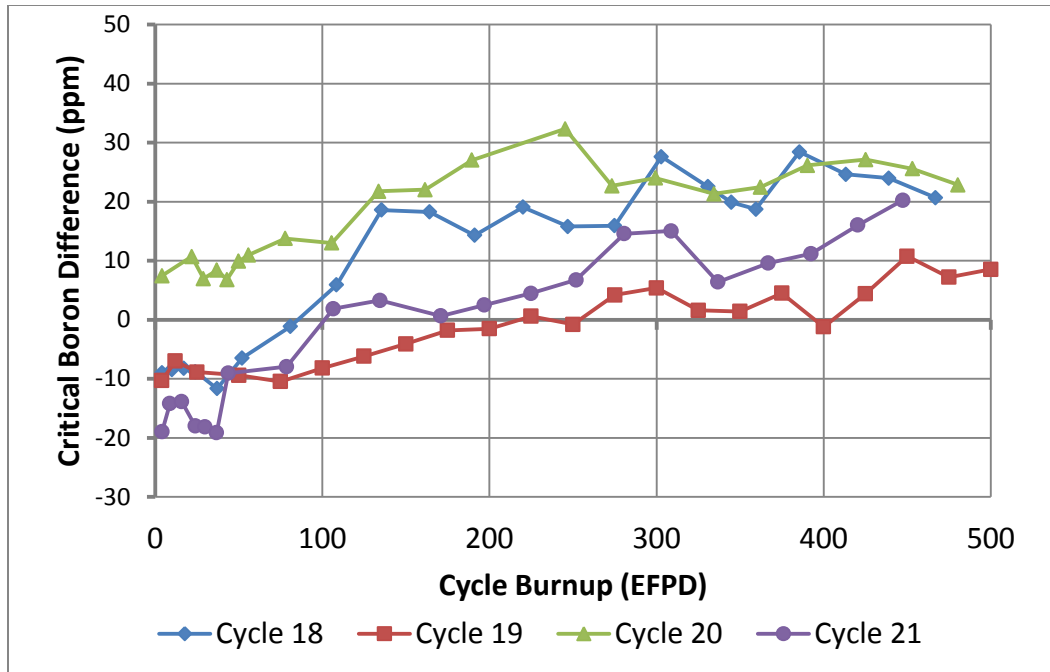


Figure 4-9 HFP Critical Boron Differences

Table 4-5 HFP Critical Boron Difference Statistics

Cycle	State Points	Mean (ppm)	Std. Dev. (ppm)
18	22	10.9	13.6
19	22	1.3	9.9
20	22	19.1	8.6
21	21	-5.1	12.7
Total	87	6.7	14.6
Total w/o "jump-in" cycle	65	5.2	14.7

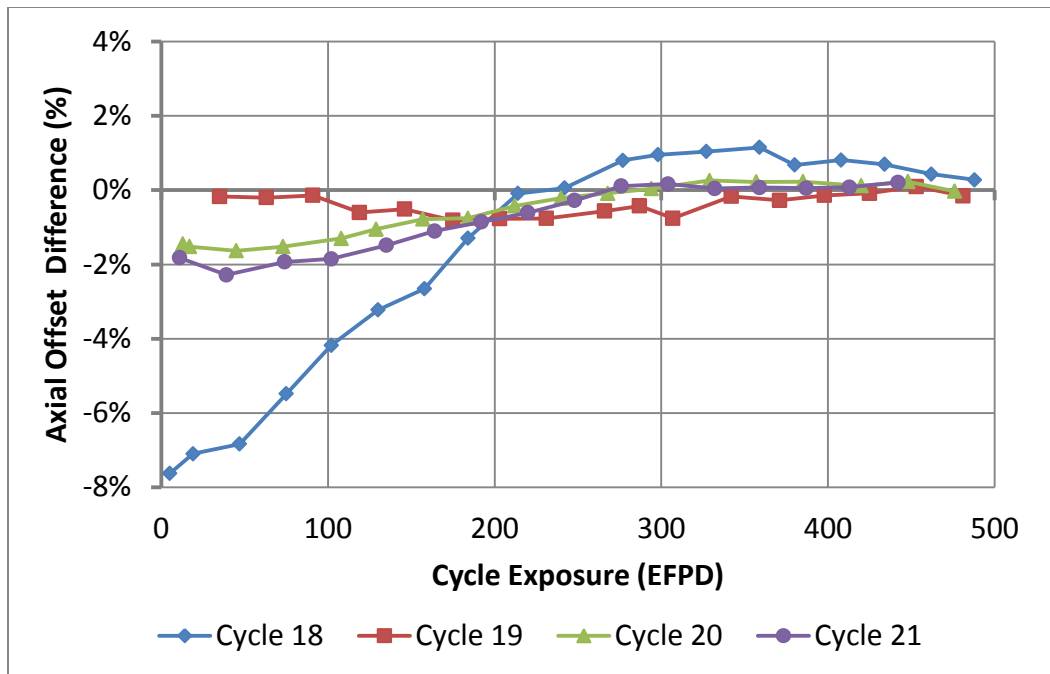


Figure 4-10 Axial Offset Differences

The cycle with the largest AO difference is cycle 18. This is expected due to the approximated burned fuel history from the “jump-in” process that created relatively large AO differences for the first 200 EFPD. From 200 through 500 EFPD the cycle 18 VERA AO prediction is within about 1% from the measured data revealing a remarkable agreement once the effect of the depletion history burns out. The predicted AO for the remainder of the cycles remains within about -2% of the measured data. It is interesting to note that cycles 20 and 21, where the effects of the “jump-in” process are less than the previous cycles, show similar trends in their difference with measured data. Both cycles 20 and 21 show the largest AO differences early in the cycle with VERA under predicting the AO compared to measured data. After 200 EFPD the incorrect prediction in AO for cycles 20 and 21 drops below 0.5% which suggests that the reason for the discrepancy may be due to an incorrect prediction or model which effects the first part of the cycle in particular. This could be related for instance to an incorrect prediction in the MTC, which is supported by the more negative ITC values predicted by VERA vs. the ZPPT measured values in particular for cycles 20 and 21 and which would be in line with the more negative AO prediction from VERA for the early part of these cycles. In addition, the presence of burnable absorbers in the burnable poisons and associated modeling assumptions could be compatible with the AO trend observed. While the type, number, and location of burnable absorbers is modeled in detail, the poison loading is assumed ideal and manufacturing tolerances are unknown and not considered. Additionally, the measurement techniques contain their own level of uncertainty in the ex-core detector responses and in the signal processing of that data. This too could contribute to uncertainties in the compared data.

Some statistics for the AO differences are broken down in Table 4-6. The average AO difference for all four cycles is $-0.85 \pm 1.76\%$ dropping to $-0.54 \pm 0.67\%$ when the “jump-in” cycle is removed from the analysis, due to the related inaccuracies, and only cycles 19-21 are compared, . This shows good prediction capabilities from VERA, in line with the plant’s goal of keeping the measured and predicted AO data within 1% or less, which is often achieved using industry tools.

It is interesting to note that if only the only data considered is that past 200 EFPD the average difference for all four cycles is $0.07 \pm 0.47\%$. This is a remarkable agreement and calls for a thorough investigation on the reasons for the lower degree of agreement in AO in the early part of the cycles.

The VERA depletions were performed on the Falcon supercomputer at Idaho National Laboratory (INL). The runtimes averaged 23.3 hours/cycle on 960 cores (40 nodes). The average runtime for each state point was 0.91 hours. The total computer resources employed for one round of these simulations were 223,992 cpu-hours. Since multiple rounds of simulations have been performed due to various code updates and other reasons, the total cpu-hours used for this

research are more than 500,000. The computer resources used by cycle are broken down Table 4-7.

Table 4-6 Axial Offset Difference Statistics

Cycle	State Points	Mean (ppm)	Std. Dev. (ppm)
18	19	-1.66%	3.04%
19	17	-0.38%	0.28%
20	18	-0.54%	0.69%
21	16	-0.72%	0.87%
Total	70	-0.85%	1.76%
Total w/o “jump-in” cycle	51	-0.54%	0.67%

Table 4-7 VERA Depletion Runtime Statistics

Cycle	Hours	Cores	State Points
18	23.1	960	27
19	25.0	960	26
20	20.4	960	24
21	26.0	960	27
22 Low Risk	21.5	960	26
22 Medium Risk	23.9	960	26
22 High Risk	22.7	960	26
22 Low Risk CIPS	24.8	960	25
22 Medium Risk CIPS	24.6	960	25
22 High Risk CIPS	21.3	960	25
Total	233.3		257
Total cpu-hrs			223,992
hrs/statepoint			0.91

CHAPTER 5. ADVANCED RISK ANALYSIS ON CIPS-LIMITED CORE DESIGNS

The analysis uses three core designs that were developed by Duke Energy's core design team as cycle 22 core design candidates. Jason Young at Duke Energy was the designer of these three designs for Catawba Unit 2. These three core designs varied in aggressiveness with differing fuel characteristics and requirements. The low risk core design was eventually chosen for cycle 22 while the other designs were discarded due to elevated CIPS risk as determined by BOA.

The goal of the CIPS analysis performed here is to assess the impact of CIPS for these cycles using VERA which, unlike the BOA analysis, relies on higher-resolution, coupled physics. Each of the three core designs were individually analyzed by BOA during the standard core design process at Duke Energy. BOA's analysis of the core designs resulted in varying levels of CIPS risk for each design, referred to as low risk, medium risk, and high risk. As discussed previously, the current industry CIPS risk methodology uses BOA to rank core design for risk per the maximum total core boron mass deposited. Typically, the limit of 0.3 lbm boron, based on experience, is used as the threshold for CIPS occurrence. The core chosen by Duke Energy for cycle 22 has a BOA maximum total core boron mass of 0.292 lbm. This results in a core with low CIPS risk and is not expected to experience CIPS during the cycle. The medium-risk core design has a BOA-calculated maximum total core boron mass of 0.352 lbm boron and the high-risk core design has a BOA maximum total core boron mass of 0.411 lbm boron, both exceeding the acceptance criteria. This standard method of choosing a core design has worked very well for avoiding CIPS in the nuclear industry for decades.

In contrast to the current industry approach, The CIPS risk assessment approach based on the use of VERA seeks to quantify the CIPS-induced AO deviation for the specific core designs, including those core designs at that would be considered to have an increased CIPS risk. The AO then can be directly evaluated to determine if it is acceptable, rather than relying on a comparison of the deposited boron mass with past experience.

The CIPS analysis using VERA was performed through the following simulations:

1. A simulation of the low risk design with no CIPS as a base model for comparison. This was performed in the same manner as the cycles 19-21 used for benchmarking.
2. A simulation of the low risk pattern using calibrated MAMBA-1D to match the total core boron mass to 0.292 lbm boron.

3. A simulation of the medium risk pattern using calibrated MAMBA-1D to match the total core boron mass of 0.352 lbm boron.
4. A simulation of the high risk pattern using calibrated MAMBA-1D to match the total core boron mass of 0.411 lbm boron.

Recall that the boron masses noted in items 2-3 above are taken from BOA simulations and are not predicted by VERA.

Each of the full cycle depletions were performed with no power maneuvers or corrective action that may have been taken if this was a real CIPS occurrence. The bulk coolant corrosion product concentration was taken from the output of BOA and used as an input for VERA.

The results from the VERA low risk core design CIPS analysis were then compared to the BOA results for the same core design. Since BOA does not use physics with feedback, this gives some insight into the effects calculated with the coupled feedback VERA utilizes. Full BOA results were only available for the low risk pattern. An analysis of the three separate VERA simulations for the low, medium, and high risk designs was then performed. This is visualized in Figure 5-1. The key metric of AO was compared and the difference quantified between the three core designs.

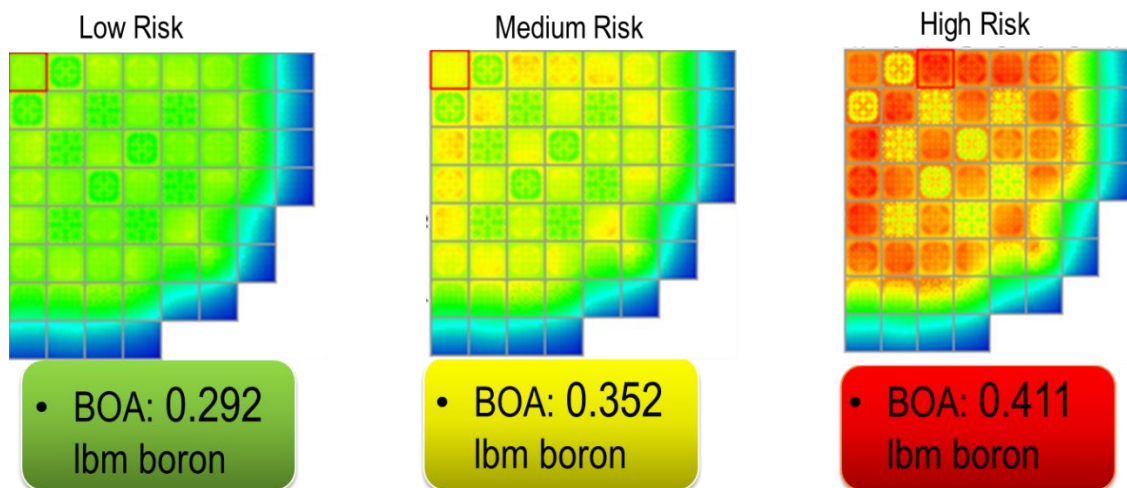


Figure 5-1 Qualitative Visualization for the Low, Medium, and High Risk Core Designs

5.1 COMPARISON OF VERA AND BOA RESULTS FOR LOW RISK DESIGN

Full BOA results were available for the low risk design since it was the actual design chosen for cycle 22. This allowed for a comparison of the two codes of the same core design.

The comparison of VERA and BOA was started by calibrating MAMBA-1D to match the maximum total core boron from BOA. This allowed the investigation of what VERA would predict the reactor effects would be using a multi-physics simulation if the reactor core experienced a buildup of maximum total core boron mass predicted by BOA. The maximum total core boron parameter was chosen because it is the critical parameter used to make decisions and distinguish the CIPS risk of a core design in BOA.

Three parameters are used in MAMBA-1D to calibrate the crud chemistry model. Those parameters are B_thresh, B_fract, Pore_fill. They are discussed here:

- B_thresh is the threshold concentration at which solid lithium tetraborate begins to precipitate in the crud layer. There are a number of physical mechanisms that are calculated in MAMBA-1D that model the boric acid concentration in the crud layer. Boiling models calculate the concentrating effect on the boric acid while diffusive forces create a lower boric acid concentration in the crud. This threshold concentration for boron precipitation is used as the threshold for the boron dissolution model as well.
- B_fract is the fraction of the crud thickness that the boron precipitate may occupy. It is input as a percentage of the total crud thickness of a surface node. As the crud thickness grows, so may the boron precipitate thickness but the total boron precipitate thickness is limited by this input.
- Pore_fill is the percentage of the pores in the crud layer structure that the boron precipitate may fill up. Only the empty pores of the crud structure can hold precipitated boron and this parameter sets a maximum percentage of the empty pore volume that may be filled.

All of the parameters used in the calibration relate to a physical constant in the model equations. These calibrating parameters are required in MAMBA-1D due to the simplifications made to make it capable of running a quarter-core depletion for a full cycle.

5.1.1 MATCHING BOA'S MAXIMUM TOTAL CORE BORON MASS

By calibrating MAMBA-1D, the VERA simulation was able to match the BOA maximum total core boron of 0.292 lbm. A comparison of the total core boron as a function of burnup for BOA and VERA is shown in Figure 5-2.

The primary endeavor was to match the maximum total core boron. Both BOA and VERA calculate that the total core boron maximum occurs at 350 EFPD for the low risk core design. BOA calculates more boron precipitate present in the core in the first half of the cycle than VERA. This is because BOA contains a crud carry-over model. The crud layer that built up on the once burned fuel last cycle was still on the fuel rods when it was shuffled into this cycle. Therefore the crud layer is already thick enough on the once burned fuel assemblies to begin boron deposition very quickly. VERA on the other hand, begins the cycle with completely clean fuel rods for every fuel assembly and must build up a crud layer on the rods before boron begins to precipitate into the crud. This explains why VERA has no boron precipitate present in the core until 150 EFPD where it begins to increase.

The BOA and VERA boron dissolution models agree quite well as the boron precipitate in the core begins to decrease after 350 EFPD. The parameters in

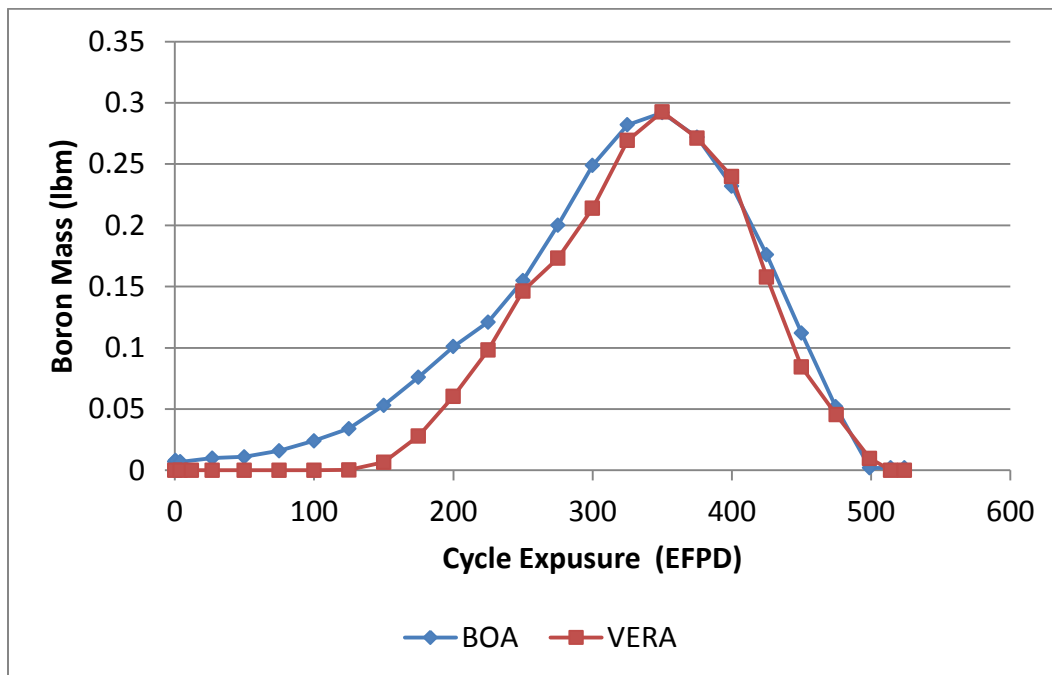


Figure 5-2 Total Core Boron Calculated by BOA and VERA for the Low Risk Core Design

MAMBA-1D used for calibration were set to match only the maximum total core boron and the dissolution model was not calibrated. As mentioned above, the boron dissolution model does use the B_thresh parameter used in the calibration of the maximum total core boron. Therefore, by changing the threshold at which boron precipitates and dissolves both the sides of the VERA total core boron curve would be affected.

5.1.2 COMPARISON OF SIMULATION RESOLUTION

One of the improvements offered by VERA is its higher resolution with the pin-by-pin neutron transport, which allows local phenomena in the fuel assemblies to be calculated and analyzed. BOA has a much coarser resolution, at the node level, where each node is one quarter of an assembly. A comparison of the radial power factors as calculated by VERA and BOA is shown in Figure 5-3.

Each $\frac{1}{4}$ assembly node can be seen in the BOA figure. It will be noted that both BOA and VERA calculate quite similar values over the same areas in the core. There is a strong correlation between the codes. However, VERA is able to distinguish much of the finer details in the fuel assemblies. This allows VERA to calculate much more local effects and discern local phenomena better than BOA. Ideally, this sub-pin resolution will enable VERA to be able to calculate extremely local phenomena such as crud induced localized corrosion.

An example of showing the resolution of boron deposition in the fuel assemblies is shown in Figure 5-4. VERA's sub-pin resolution allows for distinguishing the effects on phenomena of interest inside the assemblies. During a CIPS occurrence VERA shows strong heterogeneity inside fuel assemblies. This is due in large part to the local boiling history. BOA is able to capture a similar assembly wise distribution without the internal detail. Both BOA and VERA capture the in-out tilt that is seen in the boron distribution. Areas of materials that are neutronicly heterogeneous are even captured in the boron mass distribution as shown in assembly E11 displayed in Figure 5-4. This level of detail for boron mass distributions has never been seen when modeling CIPS. In fact, it has been assumed in industry that when visually inspecting fuel assemblies for crud deposition that the internal rods of the fuel assembly had a very similar crud thickness to what was observed on the outer rods. This analysis shows that there is strong heterogeneity present inside some assemblies.

5.1.3 AXIAL BORON MASS DISTRIBUTION

The axial boron mass distribution was also compared between BOA and VERA. The axial distribution of crud is shown in Figure 5-5. The VERA data was post-processed to do a nodal average in order to match the radial meshing used by BOA. This allows for a comparison of similarly meshed data.

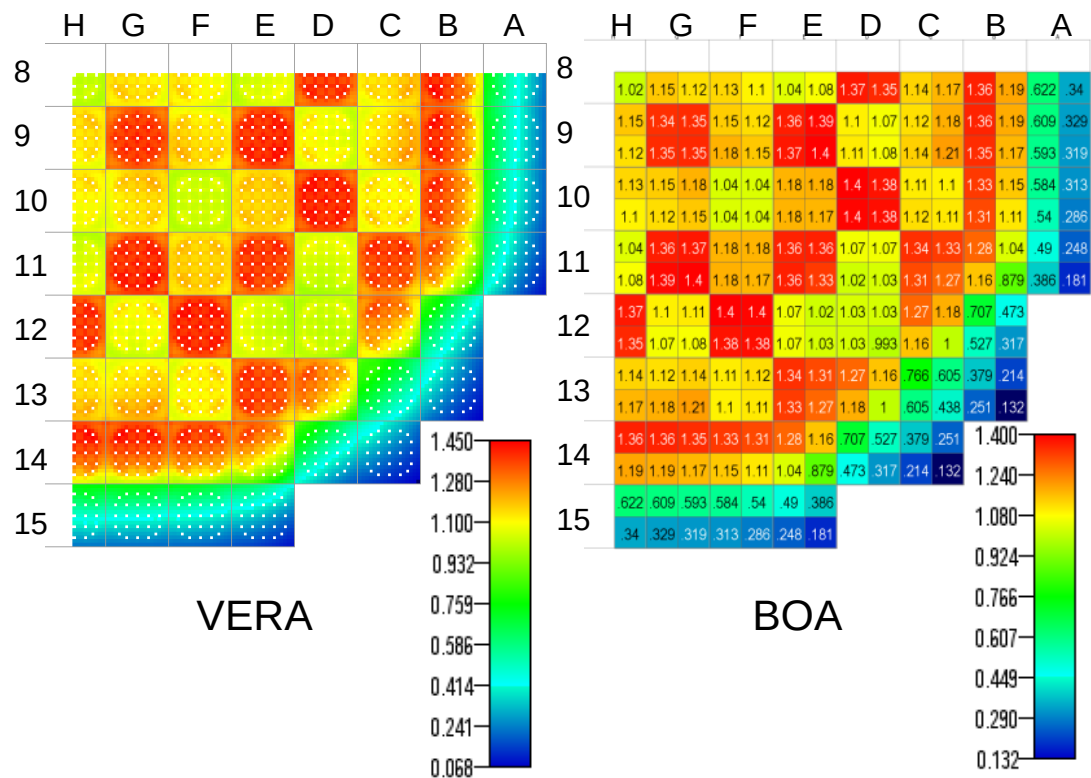


Figure 5-3 Comparison of VERA and BOA Resolution using Radial Pin Power Factor

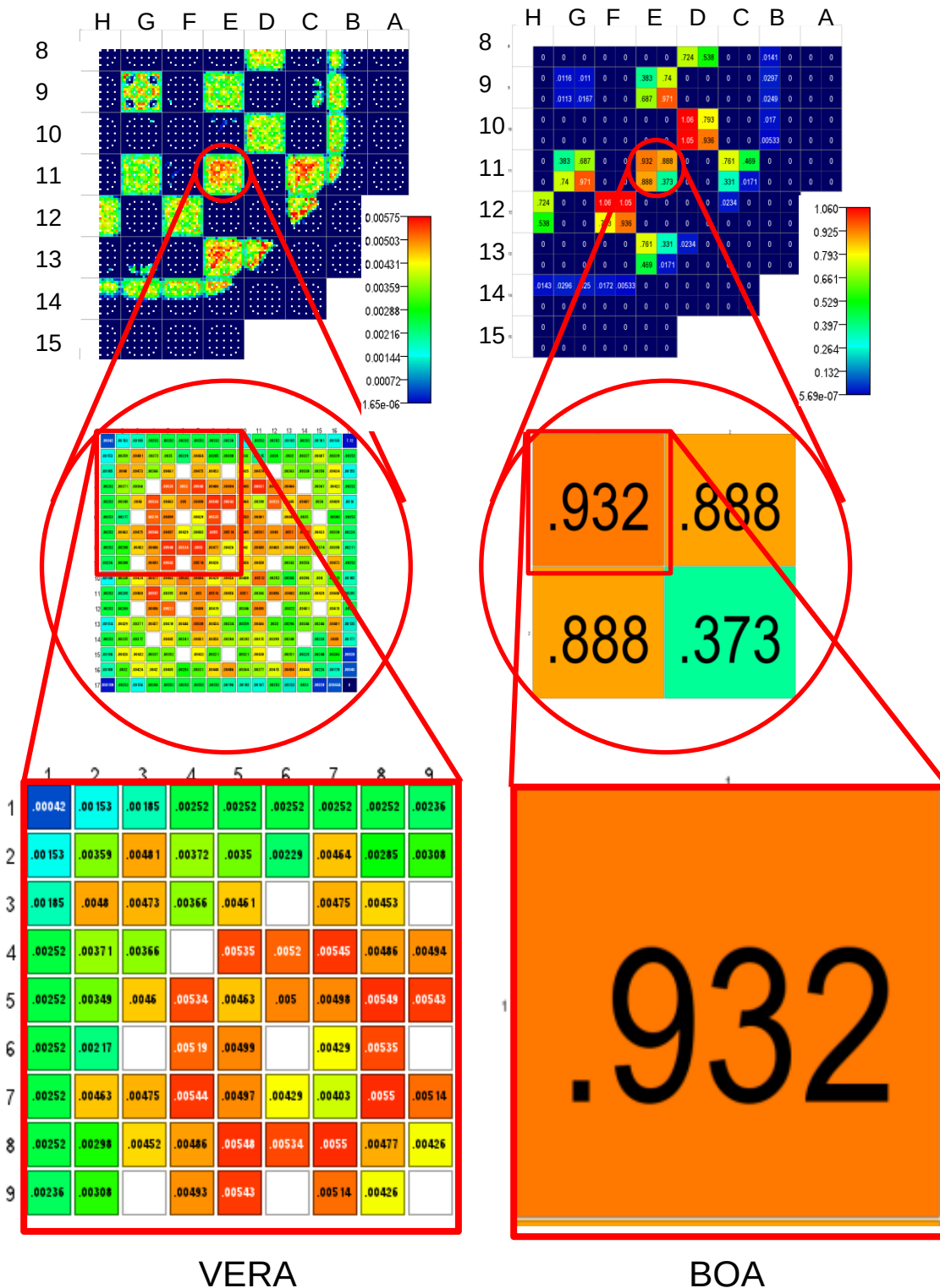


Figure 5-4 Comparison of Resolution of VERA and BOA for Radial Boron Mass 300cm from the Bottom of the Core at 350 EFPD. VERA is in units of kg/m^2 and BOA is in units of $\text{lbm} \times 10^3$.

Figure 5-5 shows that both BOA and VERA calculate the boron mass to be deposited in the upper spans of the fuel assembly. Each depression in boron mass seen in Figure 5-5 corresponds to a fuel assembly grid that suppresses power and increases heat transfer, therefore inhibiting crud growth and boron deposition. The spikes in boron mass are located at areas in between fuel assembly grids. Notice that the total core boron mass for the channel is approximately the same when summed axially. However, the distributions are distinctly different. BOA has three boron mass spikes at approximately 275, 300, and 325 cm from the bottom of the core. The largest amount of boron by far is deposited at ~300 cm. VERA shows a much lower magnitude of distribution of a larger number of upper spans in the fuel. VERA has five spikes in boron mass deposition that are all similar in magnitude. The boron mass spikes located approximately 250, 275, 300, 325, and 350 cm from the bottom of the core. It is believed that the physical feedback in VERA causes the axial boron distribution to be different. The slight misalignment in the spikes is due to the differences in axial meshing. When the boron begins to deposit earlier in the cycle, it acts as a strong local poison and pushes the power down where it was deposited. This reduces boiling and slows the boron precipitation in that spot. When the power is pushed to another location it increases boiling in the adjacent fuel spans that then begins accelerated deposition of boron until the boron deposition is significant to provide negative neutronic feedback and again push the power down locally. This multi-physics feedback limits strong spikes in boron mass axially and creates a larger number of lower magnitude spikes as shown by VERA in Figure 5-5.

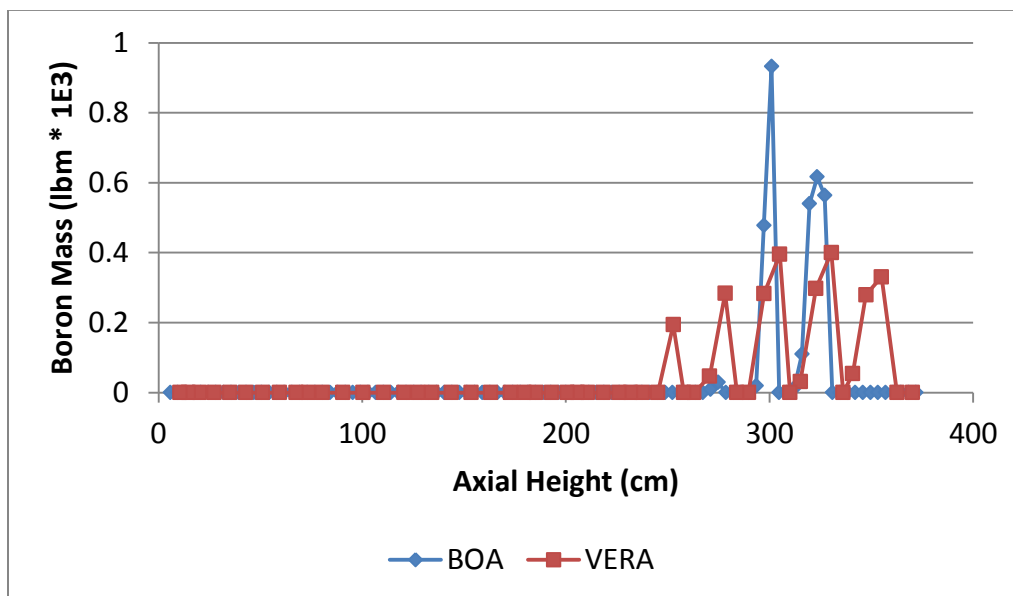


Figure 5-5 Axial Distribution of Boron Mass at 350 EFPD in the Top Left Nodal Channel of Assembly E11

This difference in axial boron deposition has effects that will carry on in the current cycle and into the next cycle. The axial burnup and therefore reactivity of the fuel at the end of the cycle will be affected differently depending on the boron mass distribution.

5.1.4 TOTAL CORE STEAM RATE DENSITY

Another global reactor parameter that shows significant signs of feedback from using multiple physics with VERA is the total core steam rate density, which is the total steam production in the core per unit area per second. A comparison of the VERA simulation without CIPS (called the “non-CIPS cycle” below) and the VERA simulation with CIPS of the low risk design matching the BOA maximum total core boron mass was performed to determine the impact of boron deposition on steaming rate. The comparison of the total core steaming rate densities of the two VERA cases is shown in Figure 5-6.

The total core steaming rate density for the simulation without CIPS shows typical behavior for a well behaved non-CIPS cycle. However the simulation with CIPS shows a deviation of up to 24% from the non-CIPS cycle. As the boron begins to build up in the core the steam rate density begins to decrease compared to the cycle with no boron buildup. The core steam rate density actually begins to decrease as the boron mass buildup reaches its maximum. A local minimum in the total core steam rate density corresponds to the maximum of total core boron mass at 350 EFPD. As the boron begins to dissolve out of the crud layer the core steaming rate density begins to increase again. Near the end of the cycle the CIPS cycle actually surpasses the non-CIPS cycle in steaming rate density. This is likely due to the reactivity effects of the boron buildup. Since the boron decreased the power in some of the fuel assemblies in the middle of the cycle, once it disappears there is extra reactivity present at that location compared to the non-CIPS case. This extra reactivity makes local locations of higher power at the end of the cycle that creates hot spots of steaming. The inclusion of multiple physics, particularly the coupling of the boron deposition to the neutronics, shows that core steaming is significantly affected by feedback during a CIPS occurrence.

5.1.5 AXIAL OFFSET

An unanticipated negative shift in the AO is considered the defining characteristic for CIPS. The threshold for the onset of CIPS is considered 3.0% deviation from predicted AO. Since BOA does not calculate time dependent AO behavior, an analysis was done to compare the AO for the VERA simulations with and without CIPS. This analysis allows a direct comparison of the same core design and to determine the expected effects of a specific amount of boron hideout in the core. The specific amount of boron hideout for this core design is 0.292 lbm,

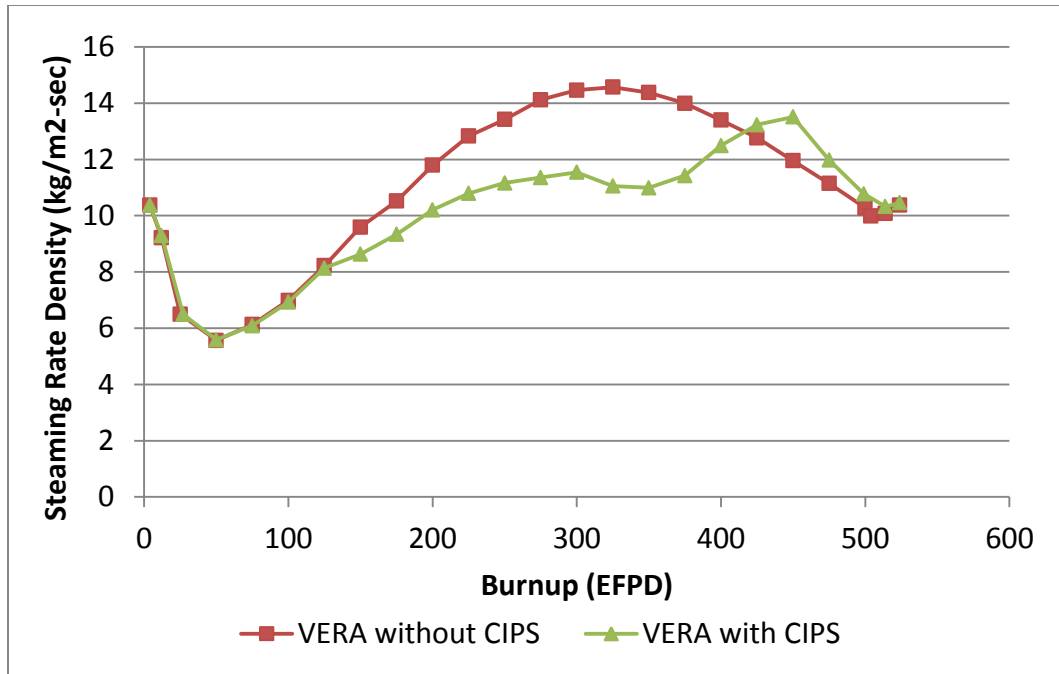


Figure 5-6 Comparison of the Total Core Steaming Rate Density Calculated by VERA for the Low Risk Core Design with and without CIPS

corresponding to the BOA simulations for the low-risk core design. The goal of this analysis was to quantify the additional AO deviation from predicted for a non-CIPS cycle of the same core design. The AO for the CIPS and non-CIPS cycles in VERA for the low risk core design is shown in Figure 5-7.

The AO calculated by VERA for the CIPS cycle shows the classical CIPS characteristic observed in plants. The AO begins to deviate by being more negative than predicted in the middle of the cycle. The maximum in AO deviation from the non-CIPS case occurs at 325 EFPD with a -2.0% deviation. This maximum deviation occurs very closely to the maximum core boron hideout at 350 EFPD. After 350 EFPD the AO begins to swing positive as the boron mass hideout decreases. This positive swing in AO has also been observed in plants with CIPS cycles. The AO near the end of the cycle is approximately 1.2% more positive for the CIPS cycle than for the non-CIPS cycle. This shows that the effect of CIPS on the core, through impacts on the burnup distribution, is present even as the cycle shuts down. These effects will carry over to the next cycle through the once and twice burned fuel that is carried over. Capturing these effects of a CIPS cycle on the fuel is important in planning and designing subsequent cycles.

5.1.6 COMPARISON OF VERA AND BOA SUMMARY

Using the same total boron mass, the comparison of VERA and BOA has shown that the codes largely agree with trends in global reactor behavior. There are a number of key differences though. VERA's use of multiple physics with feedback allows deeper insight into how the occurrence of CIPS affects local and global parameters that BOA does not currently capture. Using VERA in conjunction with BOA could help industry design cores that will be better understood and predicted in their local and global behavior. This increased understanding could help increase safety through advanced recognition of warning signs and help increase efficiency by decreasing uncertainty in critical parameters that currently cannot be modeled to this fidelity.

5.2 CIPS COMPARISON OF LOW, MEDIUM, AND HIGH RISK CORE DESIGNS

After comparing the results from BOA and VERA for the low risk design, a comparison was performed for the low, medium, and high risk designs with VERA. BOA results were not available for the medium and high risk designs other than their maximum total core boron values.

The CIPS analysis using VERA was performed in order to quantify the differences between the core designs. BOA categorized the different designs as the designs as low, medium, and high risk. VERA was used to calculate what

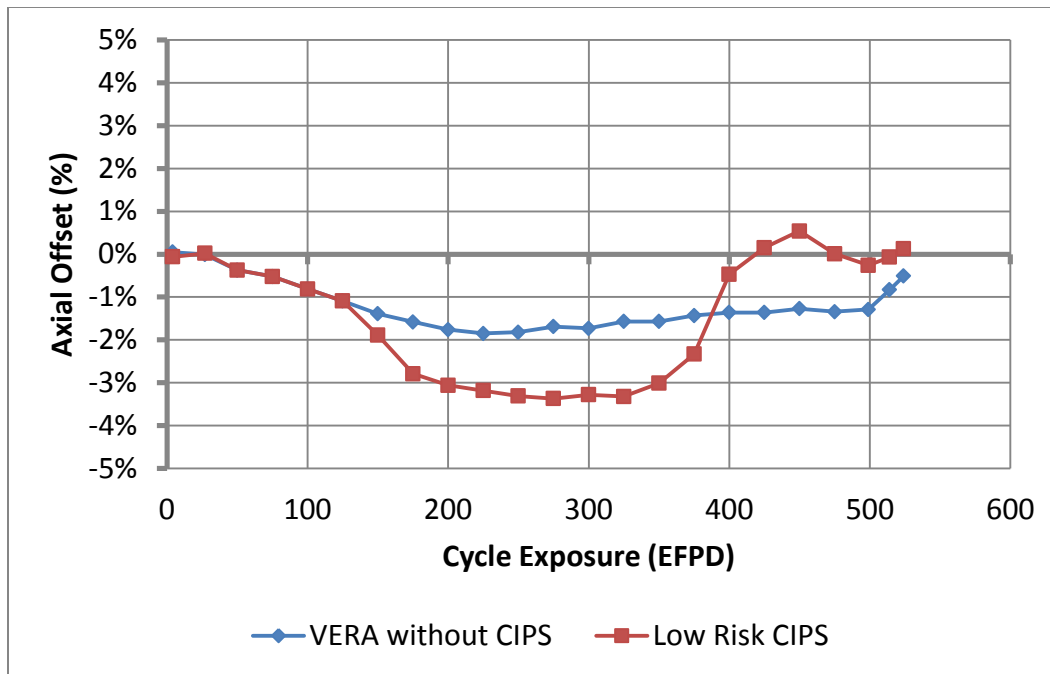


Figure 5-7 Axial Offset Calculate by VERA for the Low Risk Core Design with and without CIPS

effect that would have on the AO and what amount of additional AO deviation would translate from BOA's categorization.

The CIPS simulations with the multiple core designs were performed the same way for each design. All simulations used the same EOC data file for cycle 21 and shuffled in the fuel according to their design. The meshing was the same as the previous cycles with 16 radial partitions and 60 axial levels.

5.2.1 BORON MASS DISTRIBUTION

The different core designs were each calibrated to have the maximum total core boron deposition as calculated by BOA. The calibration process is described above in Section 5.1. Each of the core designs was analyzed to investigate the effects of getting CIPS with their associated boron mass hideout.

The three boron mass distributions for the low, medium, and high risk core designs were compared radially, shown in Figure 5-8, and axially, shown in Figure 5-9. The figures have the same scale for all the visualizations so that they can be compared visually.

The radial comparison of the low, medium, and high risk boron mass distributions show some specific trends. The high risk core has the largest area of the radial figure covered with boron mass at the high end of the scale. However, the local maximums in the low risk core are nearly as high as the high risk core; there are just fewer locations with that magnitude of deposition. Surprisingly it appears that at this location in the core, the medium risk core has lower local maximum boron deposition than both the low and the high risk designs. This suggests that higher maximum total core boron does not mean higher maximum densities of boron deposition. The density of the boron may be lower and more spread out but still have larger total core boron mass.

For the axial boron deposition in Figure 5-9 the same trend can be observed. The maximum local boron density in the low risk pattern is higher than the maximum local boron densities in the medium risk pattern. The high risk pattern has a wider spread of local high boron locations. A general trend is that the boron appears to spread out axially as the core designs increase in risk. The low risk pattern has boron that is limited axially between about 245 cm and 350 cm. The medium risk design begins to have boron deposited at further axial extremities in the fuel being bounded around 220 cm on the bottom and 360 cm high on the top. The high risk pattern has boron deposits at 220 cm all the way up to 370 cm in the core. This would explain how the medium risk core design could have lower local

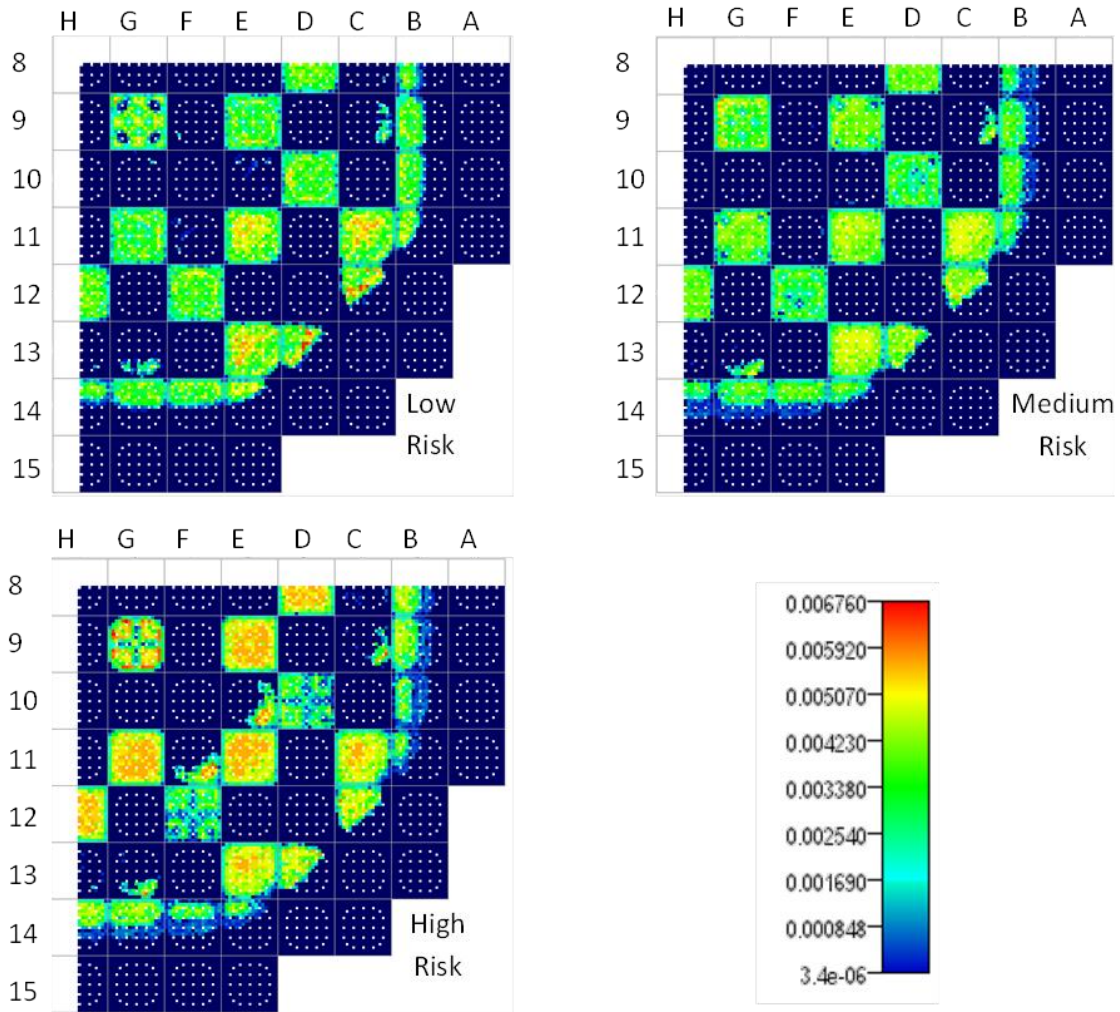


Figure 5-8 Radial Deposited Boron Mass Density through a Slice in the Core at an Axial Height of 300 cm and at 350 EFPD for the Low Risk, Medium Risk, and High Risk Core Designs measured in kg/m

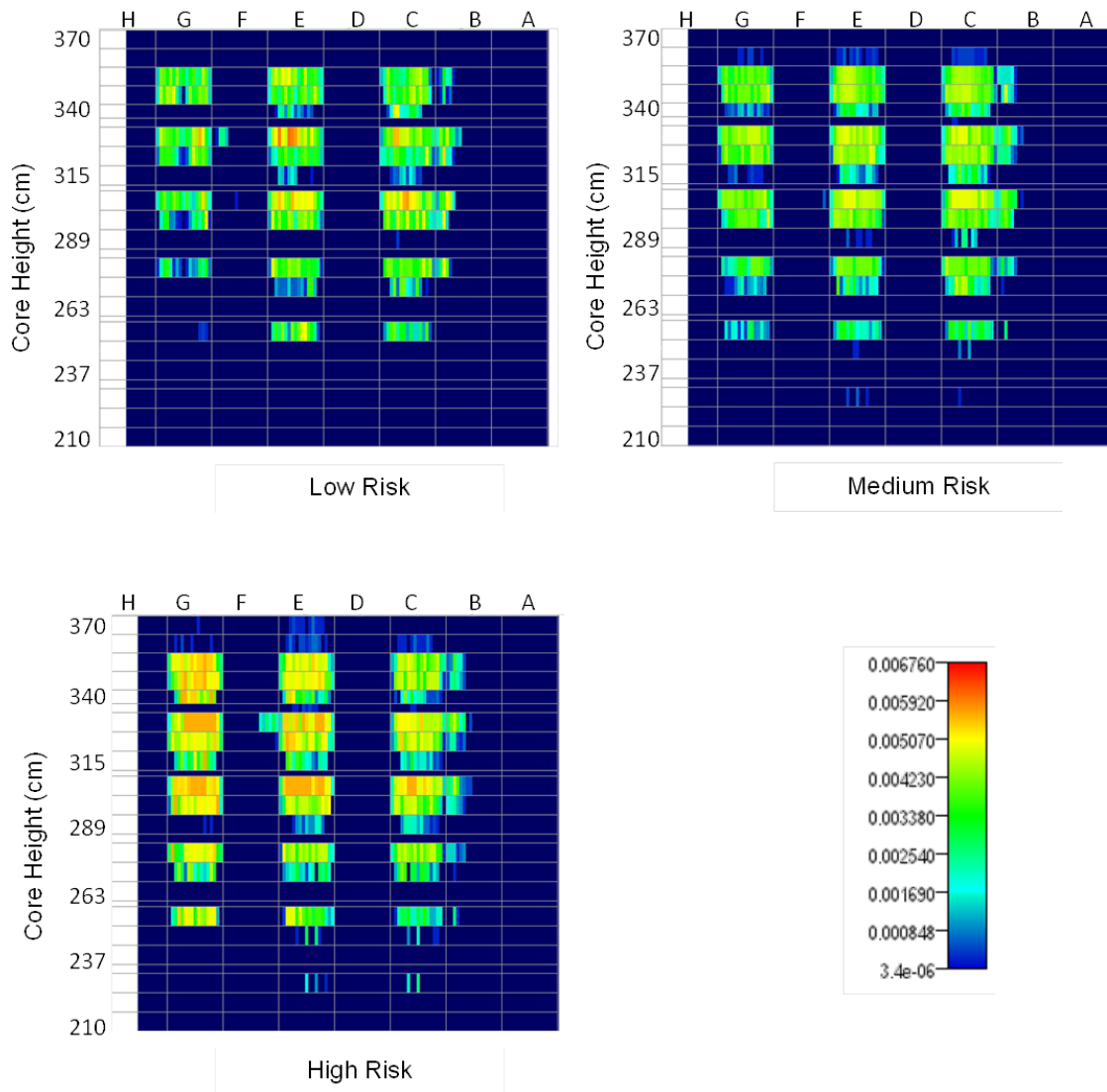


Figure 5-9 Deposited Boron Mass Density for the Top of the Core through an Axial slice of the Core at Row 11 at 350 EFPD in kg/m^2

densities of boron buildup but still have larger total core boron than the low risk core.

It appears that the boron deposition spreads to the top extremity of the core rather than building up lower in the core. This makes sense as it is increased steaming rate that accelerates boron deposition and the boiling is more likely to increase on geometries further along the fluid flow since the fluid is increasing in temperature.

Some of the differences in neutronic properties of the geometry can be seen by the differences in the boron deposition between the low, medium, and high risk designs. The depression in boron buildup due to the spacer grid effects is clearly seen in the axial figures for all three designs. The spacers have multiple effects that inhibit crud growth and therefore boron hideout. The main effect is likely due to enhanced heat transfer due to the mixing properties of the grids. This greatly reduces boiling and therefore inhibits crud growth. The enhanced mixing of the coolant also causes increased turbulent kinetic energy which erodes any crud that is present at an accelerated pace. Finally the spacer grids also depress the power due to the non-trivial absorption cross sections of the materials used in the grid structure.

Overall, the boron deposition in the core designs show some expected and unexpected trends. The boron deposition occurs more broadly over the fuel rods as the total boron on the core increases. However, greater total core boron does not require local locations of high boron density compared to a lower total core boron design.

5.2.2 AXIAL OFFSET

The operational indicator of interest from CIPS is the AO. The threshold for CIPS and the degrees of severity estimates on the effect of CIPS on the AO deviation from predicted. The AO deviation can become limiting if it is so severe that it violates the operational technical specifications. Severe AO shift has caused down rating a plant to 70% power for the last 1/3 of the cycle. The amount of AO is critical information in making decisions related to CIPS affected plants.

Due to the critical nature of the AO value it is used as the key parameter for the comparison of the three core designs. Specifically, what amount of additional AO can be expected from a given increase in maximum total core boron mass? The AO for the CIPS cycles for the three core designs is graphed in Figure 5-10.

Figure 5-10 shows that the AO for the three separate core designs behave very similarly. This is due to the fact that each core design was simulated under the same nominal conditions with no power maneuvers. Notice that the AO's follow

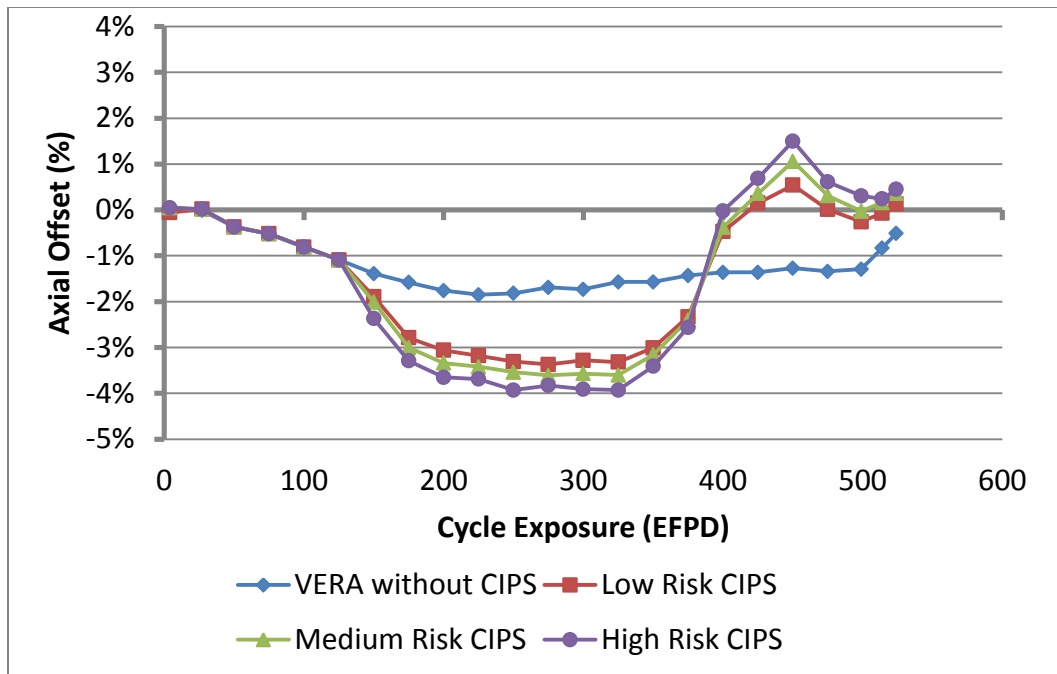


Figure 5-10 Axial Offset Behavior over the Length of the Cycle for the Low Risk, Medium Risk, High Risk, and VERA without CIPS Simulations

very similar trends until the boron begins to deposit at 150 EFPD. Then the AO behavior begins to follow an expected trend: the lower the total core boron mass, the smaller the AO deviation and vice versa. VERA calculates that an increase of total core boron mass does increase the severity of AO deviation.

Notice that the positive shift in AO begins near the time when the boron begins dissolving out of the crud layer and the total core boron begins to decrease. The power shifts quickly to the top of the core and then begins to balance back out again at 450 EFPD for all three designs. The strong positive shift in AO can be just as concerning from an AO deviation perspective depending on where the AO is predicted to be. However, the more common limiting point in AO deviation is the negative deviation in the middle of the cycle.

The increase in AO deviation calculated by VERA for each core design is broken down in Table 5-1. The “Max Core Crud Boron” column summarizes the maximum total core boron hideout calculated in VERA in pounds mass. The “Additional Boron” column calculates the amount of boron over the amount of boron in the low risk core design. This shows the delta increase over the low risk pattern for comparison with the AO affect. The “Additional AO Deviation” column shows the delta AO from the non-CIPS case for a comparison. The “Normalized AO Deviation” column is the data that shows the magnitude of the AO affect due to a CIPS cycle of the specified total core boron mass. This last column is the data of interest to this research. It answers the question of: how much additional AO affect can be expected from choosing a medium or high risk core design over the low risk design?

VERA calculates that in comparison to the low risk core design, the medium risk core design has an increased total core boron mass of 0.059 lbm and an additional 0.28% AO deviation from a predicted AO from the low risk design. The high risk design, in comparison to the low risk design, would have an increase of 0.118 lbm boron and an additional AO deviation of 0.61% over the low risk core design.

The “Additional AO Deviation” column is a measure of the predicted AO over a simulation of the same design run with no crud buildup or boron hideout at all. This no crud and no boron hideout simulation would be what the AO for the cycle is predicted by and would be the base comparison for calculating the deviation during the cycle. VERA calculates that even the low risk design shows some significant AO from the non-CIPS cycle with a deviation of -1.75%. This is misleading since cores are designed to have 0.292 lbm in BOA and are not expected to see any significant AO deviation during that cycle. This suggests that the 0.3 lbm limit in BOA is not directly correlated to a physical reality in the core of 0.3 lbm boron hideout in the crud, but rather is used as a calibrated risk factor. This is consistent with the intent and use of BOA, however there has been some

Table 5-1 Statistics for Axial Offset Calculations by VERA for the Low, Medium, and High risk core designs

BOA Risk Level	Max Core Crud Boron (lbm)	Additional Boron (lbm)	Additional AO Deviation	Normalized AO Deviation
Low Risk	0.292	0	-1.75%	0.00%
Medium Risk	0.351	0.059	-2.03%	0.28%
High Risk	0.410	0.118	-2.36%	0.61%

misunderstanding in industry as to whether or not the 0.3 lbm boron threshold is a physical reality in the core or not. Therefore the process of taking the maximum total core boron mass in the crud from BOA and calibrating VERA to it may need to be re-evaluated since the total core boron mass calculated in VERA may not directly correspond to the risk factor calculated by BOA.

The historical plant data that BOA was based on, shown in Figure 2-8 is compared to the data calculated by VERA in this analysis, shown in Figure 5-11. The data points are from VERA simulations using the three core designs in this research. They were simulated multiple times during the MAMBA-1D calibration and provide multiple data points of differing total core boron mass and AO deviation. The dotted trend line was fit to the VERA data in order to compare it to the solid BOA trend line calculated by using many data points of AO data from plant histories that had been modeled in BOA to calculate to total core boron mass hideout.

The trend lines in Figure 5-11 for VERA and BOA agree reasonably well. VERA's trend line intersects the origin and has low spread around the trend line. This does suggest a strong linear relationship of AO deviation with total core boron mass hideout for these core designs. However, the three core designs analyzed by VERA were similar in design and shared some cycle depletion conditions assumed in VERA and taken from BOA as inputs. This may contribute to an artificially strong linear correlation. BOA's limits are based on dozens of comparisons with real plant data and therefore are much better benchmarked than VERA at this time. VERA requires many more simulations compared to plant data with the advanced models being developed in order to reach a level of maturity in benchmarking achieved by BOA over decades of comparisons. However, this research shows some of the importance of being able to capture feedback from utilizing multiple physics during a CIPS occurrence.

5.2.3 SHUTDOWN MARGIN

While AO is the primary operational indicator of CIPS, the main safety concern caused by CIPS is the loss of shutdown margin (SDM). Shutdown margin is defined by the NRC as, *"The instantaneous amount of reactivity by which the reactor is subcritical or would be subcritical from its present condition assuming all full-length rod cluster assemblies (shutdown and control) are fully inserted except for the single rod cluster assembly of highest reactivity worth that is assumed to be fully withdrawn"* (Nuclear Regulatory Commission, 2017). The reactor core designers analyze the core for SDM throughout the life of the cycle to ensure sufficient amounts of required SDM for safe operation. The current industry analysis incorporates conservative assumptions to ensure sufficient SDM in all realistically possible states that would make the reactor contain the most reactivity.

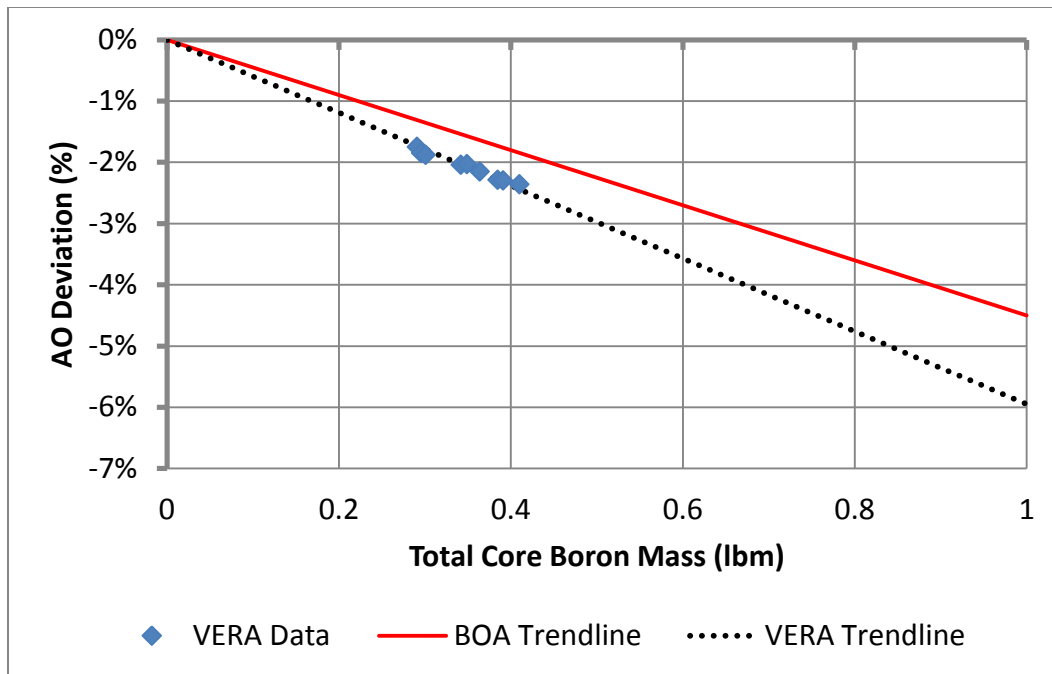


Figure 5-11 AO Deviation as a Function of Boron Mass for BOA and VERA

These assumptions include:

- The rod cluster assembly with the largest negative reactivity fails to be inserted into the core
- The coolant boron concentration is at the normal operating conditions since the highly borated water has not yet been injected into the core
- Xenon and samarium are at equilibrium concentrations in the fuel
- Coolant flow remains at operational conditions

CIPS affects many of these operating conditions. Due to the dissolution of boron in the crud layer when power decreases, additional reactivity is added to the core during and after shutdown. The additional reactivity due to boron dissolution and burnup effects in the fuel from CIPS needs to be quantified to ensure sufficient SDM. Due to the complex, 3D physical interactions, the effects of CIPS during shutdown on SDM have not been quantified. Using VERA with MAMBA1D, it is possible to calculate the additional reactivity in the core after shutdown and the boron dissolves out of the crud layer, and therefore that additional penalty to SDM that should be accounted for to ensure the reactor remains within regulatory limits.

The penalty on SDM due solely to the effects of CIPS is calculated here by simulating both a CIPS and non-CIPS cycle for each of the three core designs. During each of these simulations, restart files are written at multiple state points throughout the cycle that are used for comparison in the post-analysis. VERA uses the restart files to simulate a shutdown at each state point for both the CIPS and non-CIPS cases. The effect of CIPS is isolated by calculating the difference in core reactivity between the CIPS and non-CIPS simulations at the same point in the cycle. The VERA shutdown simulations are performed under the following conditions:

- All control rods are fully inserted
- The coolant boron concentration is at the normal operating conditions for that state point
- Xenon and samarium are at equilibrium concentrations in the fuel
- Coolant flow remains at operational conditions

These conditions are the same outlined above in the current industry methods, except for the single most reactive control assembly remaining fully withdrawn. Since industry methods already take into account the penalty from the most reactive control assembly withdrawn during shutdown, this research will not duplicate that calculation. This analysis solely calculates the penalty on SDM from CIPS. The SDM is calculated with Equation 4-2 where k_{test} is the k-effective calculated by VERA for the ARI HZP state point immediately following shutdown of the CIPS simulation and k_{base} is the k-effective calculated by VERA for the ARI HZP state point immediately following shutdown of the non-CIPS simulation.

This reactivity difference between the two cases is considered the SDM penalty due to the presence of CIPS.

The results of the calculated SDM penalty due to CIPS are shown in Figure 5-12. The CIPS SDM penalty is shown as positive reactivity because the CIPS core, when all rods are inserted and the reactor is shut down, is more reactive than the non-CIPS core, thereby decreasing its ability to be subcritical. Figure 5-12 shows a non-trivial amount of lost SDM due to CIPS for all core designs after 300 EFPD, particularly at 375 EFPD where the loss of SDM is highest. The low, medium, and high risk core designs have a maximum loss of SDM due to CIPS of 224 pcm, 275 pcm, and 326 pcm, respectively. This is significant since the cores are normally designed with a few hundred pcm SDM above their administrative limit of 1300 pcm SDM. The technical specifications only require 1000 pcm SDM, which leaves a conservative cushion for unexpected cases, just like CIPS.

The results shown in Figure 5-12 show that a non-trivial amount of SDM can be lost due to a CIPS occurrence, particularly in the last 200 EFPD of the cycle. This amount of SDM loss due to CIPS can, and should, be taken into account to ensure that administrative limits and technical specifications are maintained.

Similar to the AO, the CIPS SDM penalty for the medium and high risk designs has been normalized to the low risk cycle. Figure 5-13 shows the results of this normalization. The normalized CIPS SDM penalty follows the same trend as the overall CIPS SDM penalty, growing to a maximum near 375 EFPD and then dropping and leveling out at the EOC.

A summary of the CIPS SDM penalty statistics is given in Table 5-2. All three core designs have a maximum SDM loss at 375 EFPD. This corresponds closely to the total core boron buildup in the crud, which had its maximum at 350 EFPD for each core design

The additional loss of SDM compared to the low risk design due to increased CIPS is 51 pcm for the medium risk design and 102 pcm for the high risk design. While this amount of additional SDM loss is non-trivial, it is small enough adjustments can be made to ensure sufficient SDM, if any adjustments are needed at all, when moving from the low risk to the medium or high risk designs.

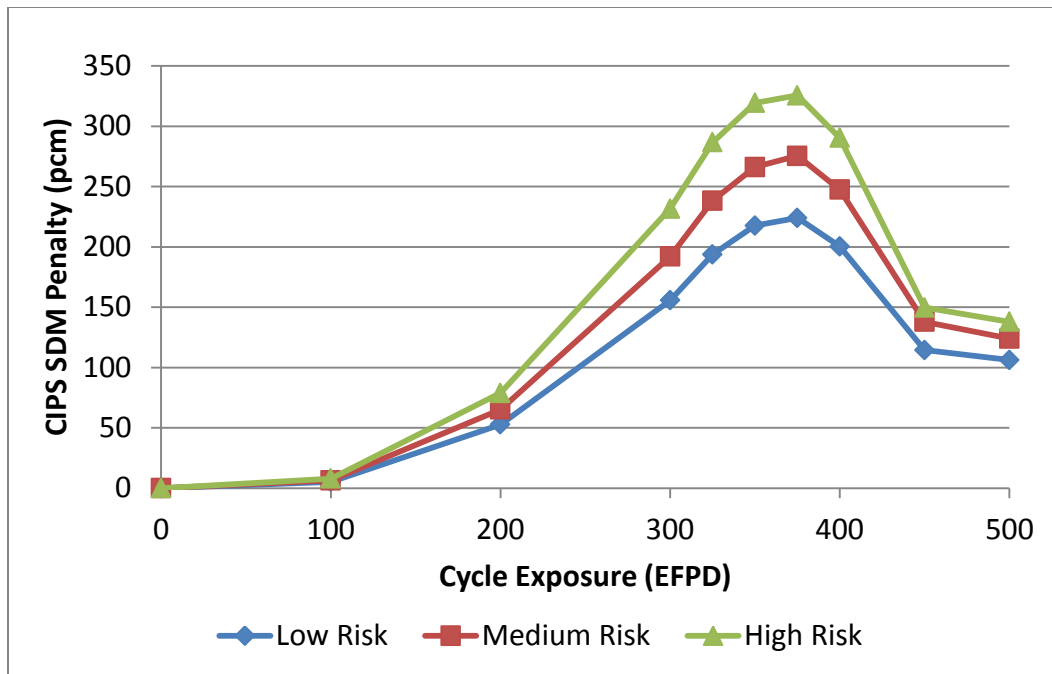


Figure 5-12 Penalty on SDM due to CIPS for Low, Medium, and High Risk Designs

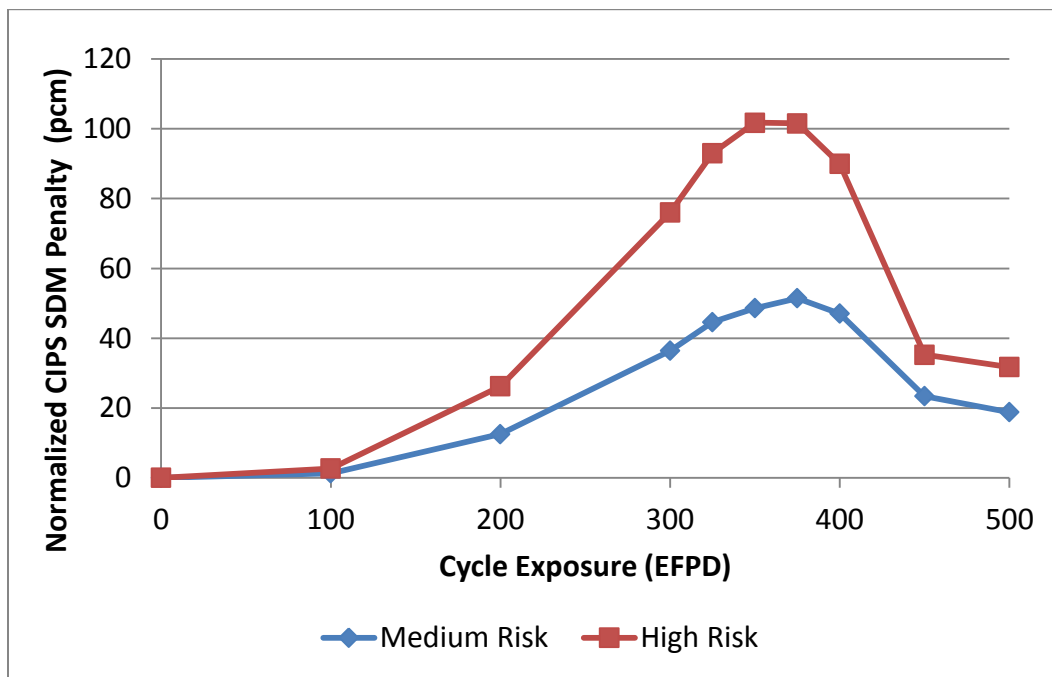


Figure 5-13 Penalty on SDM due to CIPS that is Normalized to the Low Risk Design

Table 5-2 Statistics for SDM Penalty due to CIPS for Low, Medium, and High Risk Core Designs

BOA Risk Level	Max Core Crud Boron (lbm)	Max CIPS SDM Penalty (pcm)	CIPS SDM Penalty (pcm) Normalized to Low Risk Design	Cycle Exposure at Max CIPS SDM Penalty (EFPD)
Low Risk	0.292	224	0	375
Medium Risk	0.351	275	51	375
High Risk	0.410	326	102	375

CHAPTER 6. NUCLEAR FUEL COST AND MONTE CARLO SCENARIO ANALYSIS

A Monte Carlo scenario analysis was performed by following the method described in Chapter 3 in the Section “Economic Analysis Methodology” to investigate the impacts of the higher risk core designs on the fuel cycle economics. The modeling information and results are presented below.

6.1 MODEL DESCRIPTION

The model used for the economic scenario analysis requires a number of inputs to be taken from the CIPS risk analysis model for the characteristics of the three core designs. Particularly the number of fuel sub-batches, the number of assemblies in each sub-batch, the enrichment of each sub-batch, and the mass of uranium in each fuel assembly are used for each core design. This data is proprietary and not presented here.

Many other variables are needed for the model. The fuel fabrication cost is assumed to be constant at \$200/kg. This was decided upon due to reports from 2006 (Nuclear Energy Agency, 2006) and 2009 (EPRI, 2009) and was confirmed as a good approximation by industry (Cameron, 2016). The geometric Brownian motion model requires an initial price for the market prices that it will simulate. These initial prices for uranium and SWU were taken from the uranium market report published in 2016 by the U.S. Energy Information Agency (Energy Information Agency, 2016). The initial conversion price was chosen to be \$8.50 per kg of uranium because Figure 2-11 shows that as the spot price near the beginning of 2014 which was approximately the time the decision for choosing between these core designs would have taken place. Some characteristics of the past market behavior for each price simulated is needed as well. The standard deviation of the past market data was taken by using Figure 2-11 and taking quarterly data for the natural uranium conversion spot price for 2012 to the present and calculating the sample standard deviation. The uranium and SWU standard deviations were calculated by taking the prices reported in the 2011 through 2015 Energy Information Agency’s annual uranium market reports and calculating the sample standard deviation from those.

Each history simulation consists of 18 months of simulated market price movements with 3 time steps per month. The geometric Brownian motion simulates market movement for all three resources. An example of the uranium price movements for 10 histories is shown in Figure 6-1. Then the optimal fuel price is calculated for each core design. The fuel prices are then compared and

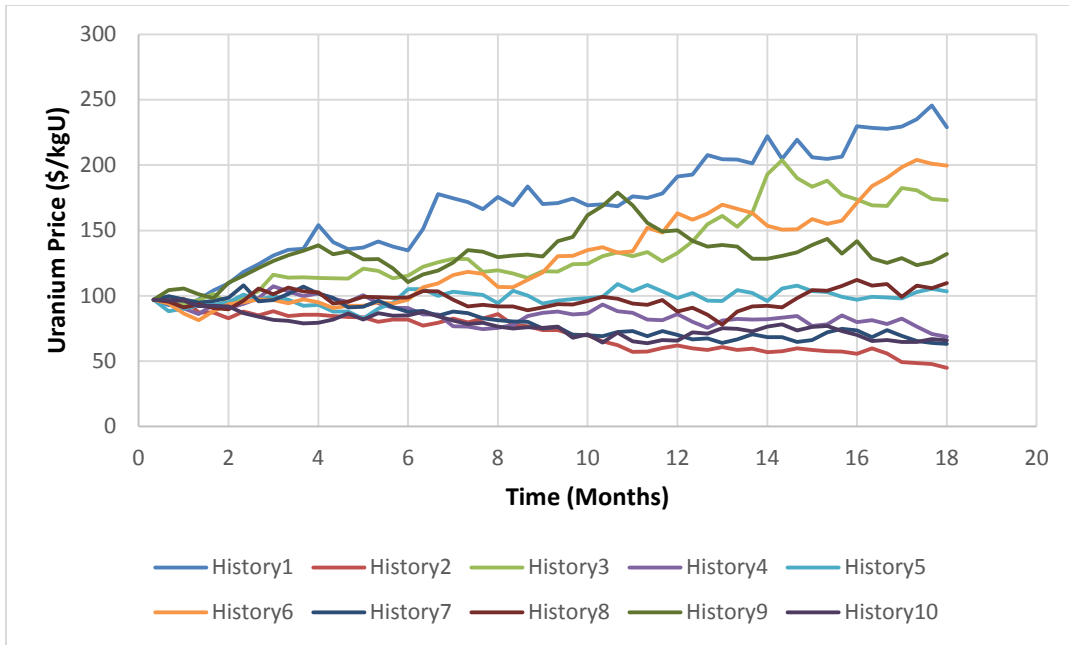


Figure 6-1 Ten Histories of Simulated Uranium Price Data

that completes one history. In total, 100,000 histories are simulated in the analysis.

6.2 RESULTS

The results of the 100,000 histories of the Monte Carlo scenarios have been analyzed to determine the correlation of each randomly generated resource price with the total fuel cost, the response surfaces of the fuel cost, the distribution of cost differences, the value at risk, and the expected shortfall. Each is presented below.

6.2.1 CORRELATION COEFFICIENTS

The correlation of each of the uranium price, SWU price and conversion prices was calculated with respect to the total fuel cost. The correlation coefficients are summarized in Table 6-1.

Correlation coefficients can range from -1 to +1. A positive correlation coefficient means there is a positive linear relationship between the variables and a negative correlation coefficient represents a negative linear relationship between the variables. The closer the correlation coefficient is to +1 or -1, the stronger the relationship is. As can be seen in Table 6-1, all of the correlation coefficients are positive. This is expected since the fuel cost should increase if any of the prices of the variables increase. The correlation coefficients between each core design are nearly identical. This is due to the relatively small differences in the core designs. Each core design has 72 feed assemblies with varying enrichments. It is possible to have more or less feed assemblies between core designs. This would change the effects of the variables on the core costs. However, as these cores are designed, they are rather similar in the resources needed for the cores.

The magnitudes of the correlation coefficients in Table 6-1 show the strength of the relationships between the variables and the fuel costs. The largest magnitude correlation coefficient is the price of the uranium at approximately 0.89. This means that the movement of the uranium price had the largest effect on the total fuel cost. The relationship between uranium price and fuel cost is shown as a scatterplot in Figure 6-2. The strength of the positive correlation between uranium price and fuel cost can be seen. This agrees well with the correlation coefficient for uranium price and fuel cost.

The correlation coefficient for the price of SWU has the next greatest magnitude at approximately 0.45. This suggests that there is a fairly strong positive relationship between SWU prices and fuel cost. However, the strength of the positive relationship is only about half that of the uranium price. Figure 6-3 shows a scatterplot of the SWU price and the fuel cost. A positive correlation can be

Table 6-1 Correlation Coefficients with respect to Total Fuel Cost for 100,000 Histories

Correlation Coefficients with Fuel Cost			
Core Design	SWU	Uranium	Conversion
Low Risk	0.454432	0.890712	0.008446
Medium Risk	0.454105	0.890879	0.008450
High Risk	0.454113	0.890875	0.008450

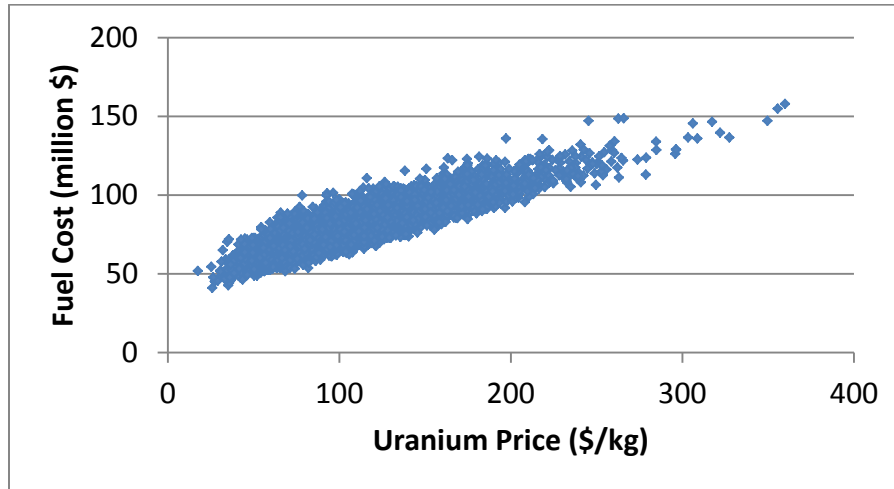


Figure 6-2 Scatterplot showing Relationship of the Uranium Price and Fuel Cost

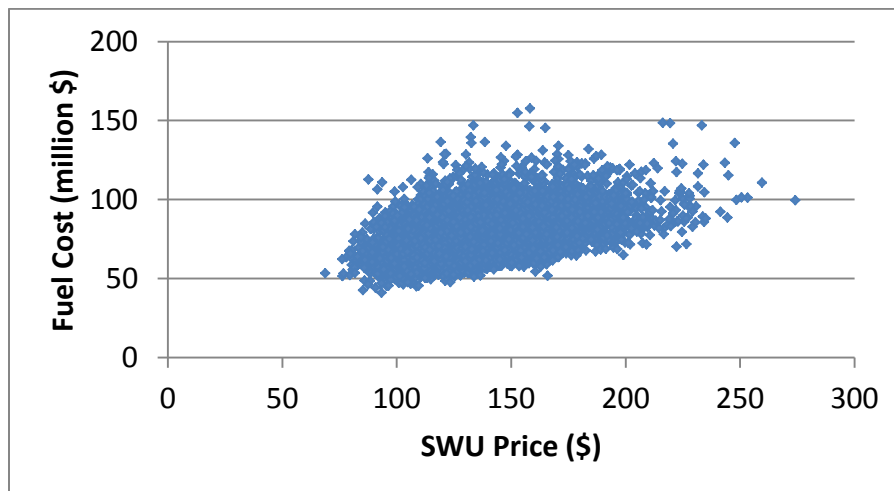


Figure 6-3 Scatterplot showing Relationship of the SWU Price and Fuel Cost

seen between the variables; however it is not as well defined as Figure 6-2. This is to be expected from the comparison of the correlation coefficients.

Finally the conversion price has a very low magnitude positive correlation coefficient at 0.0084. This is likely due to the relatively low price of conversion per kilogram of uranium and required volume compared to the uranium and SWU. This shows that the price of conversion has a small effect on the total cost of the fuel. Figure 6-4 shows a scatterplot of the conversion price and the fuel cost. This plot corresponds to a variable with nearly no correlation as expected. Each of the scatterplots only contains the first 1000 data points out of the 100,000 histories for simplicity to help show the relationships.

6.2.2 FUEL COST RESPONSE SURFACES

The response of the fuel cost was calculated by varying two of the variables while holding the third constant in order to get a surface response. The surface responses show how the effect on the fuel cost of varying the two variables being analyzed. The surface response shows the relationship of changing certain variables on the fuel cost. Each unique pair of variables was used to generate a response fuel cost response curve: uranium-SWU, uranium-conversion, and SWU-conversion. Each response surface was generated by calculating the optimal fuel cost for the low risk core design. A summary of the ranges and increments for each variable in the three response surface calculations is shown in Table 6-2. The uranium and the SWU prices were varied from \$2 to \$200 in \$2 increments for each response surface calculation in which they were used. The conversion price was varied from \$1 to \$100 by \$1 increments. These values were chosen because they are representative of the ranges of the prices for these markets historically and in order to have a grid of 100x100 data points for the response surfaces.

6.2.2.1 URANIUM-CONVERSION RESPONSE SURFACE

The contour plot for the response surface is shown in Figure 6-5. The transition lines between colors are constant fuel cost lines. Every point on the transition between two colors is the same fuel cost. Looking at the constant fuel cost lines, Figure 6-5 shows that the relationship between uranium price and conversion costs is linear. The slope of the constant cost lines shows that the conversion price must change significantly more than the uranium price to have the same magnitude effect on the fuel costs. It is expected that the relationship of the conversion and uranium prices would be linear since the conversion process is performed on the total mass of uranium used in the fuel manufacturing process.

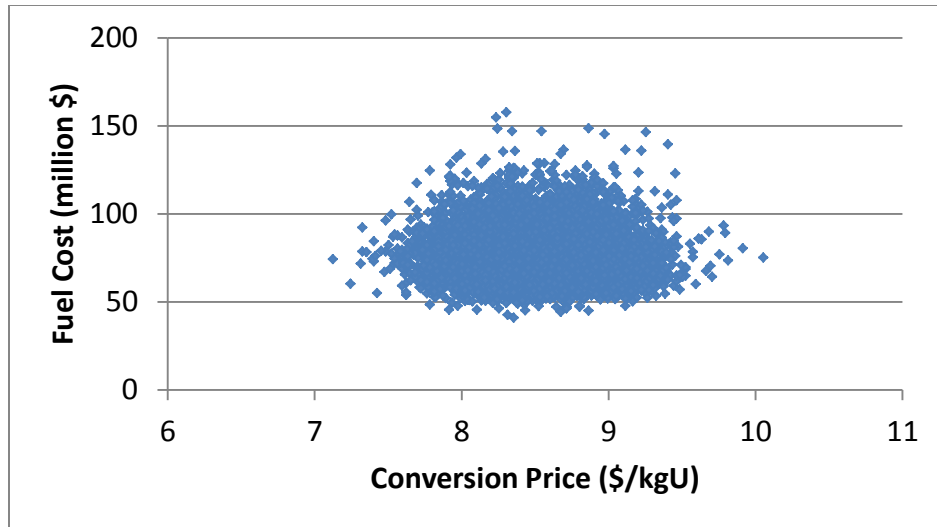


Figure 6-4 Scatterplot showing Relationship of the Conversion Price and Fuel Cost

Table 6-2 Setups for each Fuel Cost Response Surface Calculation

Response Surface Setups			
	Uranium	SWU	Conversion
Uranium-SWU	\$2-\$200 x \$2	\$2-\$200 x \$2	constant @ \$6/kgU
Uranium-Conversion	\$2-\$200 x \$2	constant @ \$50/SWU	\$1-\$100 x \$1
SWU-Conversion	constant @ 66\$/kg	\$2-\$200 x \$2	\$1-\$100 x \$1

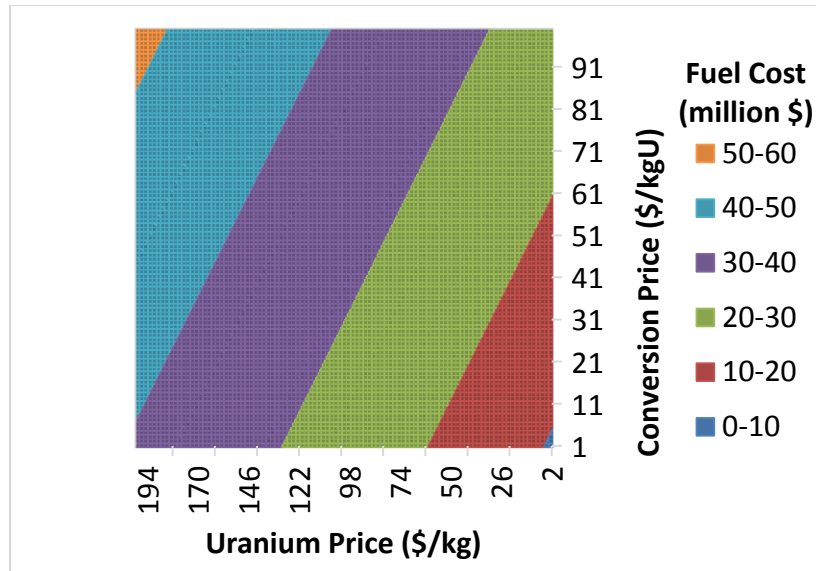


Figure 6-5 Fuel Cost Contour Plot of Uranium-Conversion Calculations with a constant SWU of \$50/SWU

6.2.2.1 SWU-CONVERSION RESPONSE SURFACE

The relationship between SWU and conversion is shown in Figure 6-6 and differs from that of the uranium-conversion relationship in that it is not linear. The relationship between SWU and conversion is instead curvilinear. The curvilinear nature of the relationship still reflects a stronger effect of the SWU price on the fuel cost than the conversion price. A small drop in SWU price requires a large increase in conversion price in order to keep the fuel cost constant for the most part. However, the region of high SWU prices and high conversion prices has a nearly linear relationship for a constant fuel cost. An entire band of color represents a \$10 million increase in fuel cost. Figure 6-6 shows that the bands get narrower at the higher conversion prices than the lower conversion prices. This suggests that at high conversion prices it takes less increase in SWU prices to add an additional \$10 million to the fuel costs. This can be explained by the calculation of the optimal fuel price for a given cost of uranium. If the SWU price increases but the uranium stays constant, then the optimal fuel will require more uranium and less SWU. The increase in uranium proportionally increases the amount of conversion needed. Therefore at high conversion prices it requires less of an increase in SWU to increase the total cost of the fuel by the same \$10 million.

6.2.2.2 URANIUM-SWU RESPONSE SURFACE

The contour plot of the fuel cost response surface for the uranium-SWU calculations is shown in Figure 6-7. This plot shows that the major relationship between uranium and SWU on fuel cost is curvilinear. The relationship is much less linear than the relationship between SWU and conversion prices. The constant fuel cost lines in the color transitions show that the curvilinear relationship is strongest at the region with low uranium and low SWU prices. In the region of the high uranium and high SWU prices, the fuel cost surface has a much more linear relationship. This suggests that at concurrently high prices for the uranium and SWU, the correlations of these variables with the total fuel cost becomes more equal in magnitude. Additional analysis of the relationship of these variables with the total fuel cost would provide additional insights.

6.2.3 FUEL COST DIFFERENCE DISTRIBUTIONS

In the Monte Carlo scenario analysis the optimal fuel costs for each core design were calculated given the simulated market prices and the core design characteristics. The fuel costs were then compared and analyzed to see what the difference between the core designs is. This difference is fuel cost between core designs was calculated for every simulation of the 100,000 histories. The distribution of fuel cost differences is given and discussed below.

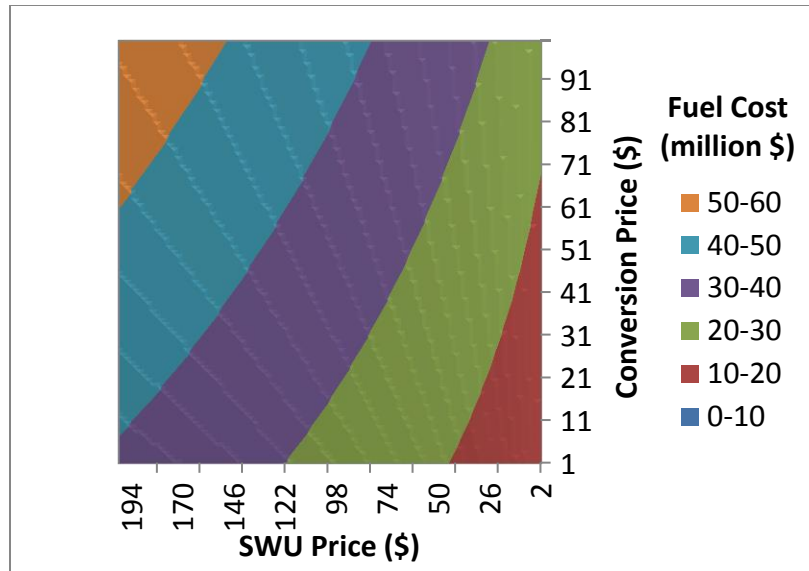


Figure 6-6 Fuel Cost Contour Plot of SWU-Conversion Calculations with a constant Uranium Price of \$66/kg

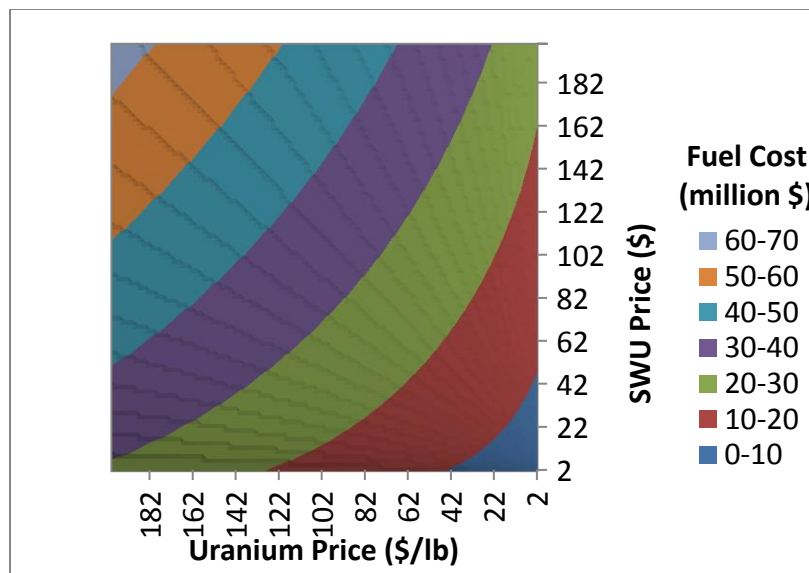


Figure 6-7 Fuel Cost Contour Plot of Uranium-SWU Calculations with a constant Conversion Price of \$6/kgU

6.2.3.1 *LOW RISK CORE COMPARED TO MEDIUM RISK CORE*

The low risk core was found to have the highest fuel costs. This is expected since the average fuel enrichment is highest for the low risk core design. Therefore, the fuel cost difference is calculated by subtracting the cost of fuel for the medium risk core design from the cost of fuel for the low risk core design. The fuel cost difference distribution is shown in Figure 6-8. The distribution is a histogram of the frequency of occurrence for cost differences that reside within bins of \$1000 increments. Statistics on the fuel cost difference distribution is given in Table 6-3.

Figure 6-8 and Table 6-3 show that the fuel cost difference distribution is positively skewed. This suggests that the model calculates a greater range of cost differences above the mean than below the mean. The minimum cost difference in the distribution is \$128,465.

This fuel cost distribution shows that for the developed model given above the fuel cost difference, or potential fuel cost savings if the medium risk core is chosen over the low risk core, has an average of \$256,188.

6.2.3.2 *LOW RISK CORE COMPARED TO HIGH RISK CORE*

The fuel cost difference between the low risk core and the high risk core was also calculated for each history. The difference was calculated as the high risk core design fuel cost subtracted from the low risk core design fuel cost. The resulting fuel cost difference distribution is shown in Figure 6-9.

The cost distribution is very similar to the cost distribution in Figure 6-8. Both are positively skewed. Although the fuel cost distribution for the low risk/high risk comparison is slightly less skewed positively. The low risk/high risk distribution is also has a lower positive kurtosis than the low risk/medium risk distribution which suggests there are less extremely high or low cost differences. This can also be seen in the differences of standard deviation. The low risk/high risk distribution has a lower standard deviation suggesting that the cost differences are more closely distributed around the mean.

A significant result is that the mean fuel cost difference, or fuel cost savings if the high risk core design was chosen over the low risk core design, is \$243,380. This is lower than the mean of the low risk/medium risk fuel cost difference distribution mean. This suggests that while there is a potential for cost savings with the high risk core design, the cost savings would be lower on average than the medium risk core design and it would come with greater risk. This would suggest that the high risk core design should never be chosen since the expected cost savings would be lower while incurring greater risk.

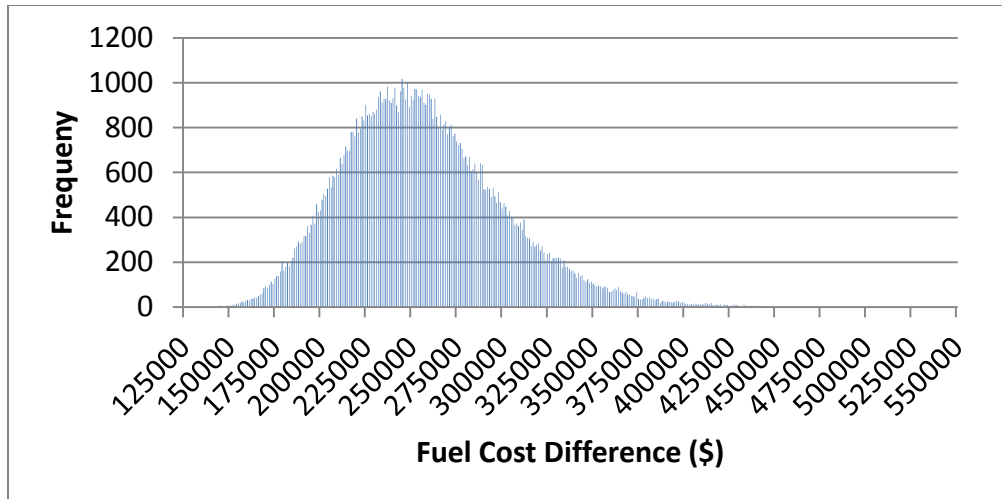


Figure 6-8 Fuel Cost Difference Distribution for Low Risk and Medium Risk Core Designs

Table 6-3 Statistics for the Fuel Cost Difference Distributions

Fuel Cost Difference Distribution Statistics				
	Mean	Standard Deviation	Skewness	Kurtosis
Low Risk - Medium Risk	\$ 256,188	\$ 44,269	0.6500	0.8094
Low Risk - High Risk	\$ 243,380	\$ 42,730	0.6486	0.8050

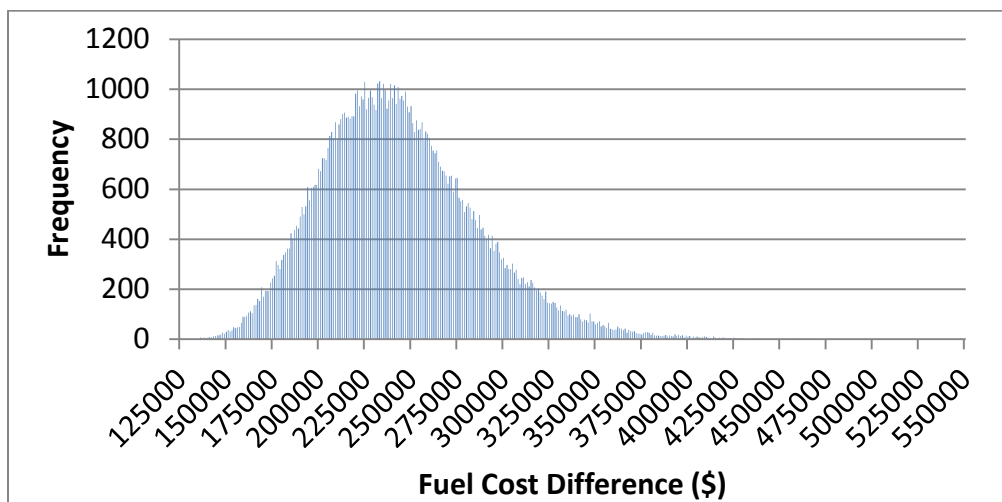


Figure 6-9 Fuel Cost Difference Distribution for Low Risk and High Risk Core Designs

CHAPTER 7. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

7.1 SUMMARY OF WORK AND KEY RESULTS

The physical mechanisms responsible for CIPS are varied with interactions spanning neutronics, thermal-hydraulics, and chemistry. Each phenomenon contributing to CIPS has an effect on the others creating complex feedback loops that requires high resolution, coupled physics codes to simulate accurately. The goal of this research was to develop and apply of an advanced CIPS risk methodology that builds upon the current industry methods with advanced, coupled multi-physics modeling and simulation the use of VERA. VERA was first benchmarked against measured operational data from cycles 18-21 of Catawba Nuclear Station Unit 2 through the use of the “jump-in” method. The benchmarking results showed good agreement with ZPPT and cycle depletion core parameters, providing confidence in VERA’s ability to simulate normal plant operations.

A CIPS analysis of three separate core design patterns was then performed with VERA where each design was a candidate for cycle 22. The potential core candidates were assessed by quantifying their behavior with respect to key CIPS parameters including AO and SDM. The analysis was performed for a full quarter-core rod-by-rod model for each core design, utilizing the realistic fuel depletion histories generated by the benchmarked models for the prior cycles from the “jump-in”.

Improvements were made to MAMBA-1D through the addition of a boron hideout dissolution model and the integration with CTF. These additions allowed for the capture of key CIPS behavior that had not been previously modeled in VERA. This resulted in a much more consistent comparison with the industry code, BOA, and facilitated calibration of MAMBA-1D to BOA boron mass results.

The VERA CIPS analysis has been effective in quantifying the effect of CIPS on the relevant core parameters. The first noteworthy result is that VERA calculated an increase of total core boron of 0.06 lbm from the low risk to the medium risk core loading pattern, resulting in an additional AO deviation of roughly 0.3%. Similarly, an increase of maximum total core boron mass of 0.12 lbm from the medium risk to the high risk loading pattern resulted in an additional AO deviation of roughly 0.6%. While this does indicate an increase in the AO from CIPS, these are relatively small compared to the overall simulated AO for the low risk design. The second noteworthy result is that VERA calculated an increase in CIPS SDM penalty of 51 pcm from the low risk to the medium risk core design. A total of 102 pcm additional CIPS SDM penalty was calculated for the high risk

core design when compare to the low risk. Although this loss of SDM due to CIPS is non-trivial and should be taken into account, it is manageable and both regulatory and administrative limits could be maintained.

A Monte Carlo model was developed to be applied in a scenario analysis to calculate the potential economic tradeoffs between the three core designs. The constituent models for the geometric Brownian motion and the fuel cost calculation were described in detail. The scenario analysis was performed by simulating 100,000 histories of stochastic market conditions and the corresponding differences in the fuel costs calculated for each core. The results of the analysis show that the high risk core has lower economic incentive than the medium risk core for all scenarios. This result effectively makes the high risk core less desirable than the low risk core in all cases since it offers lower economic incentive with higher risk. The medium risk core was found to have a fuel cost distribution that is positively skewed and has a mean of \$256,188 lower than the low risk core. For the developed fuel cost model, this means that there is a potential average fuel cost savings of \$256,188 by choosing the medium risk core design and accepting a potential increase in AO of deviation of -0.28%. This is significant since it is the first time that a cost for a corresponding amount of CIPS risk has been quantified. Additionally, the results show that larger economic incentive is not directly correlated to higher risk, i.e. more risk does not always equal better economics.

7.2 CONCLUSIONS

The methods and analysis presented in this research show a considerable advancement from the current industry capabilities in addressing CIPS, which are enabled by VERA and its high fidelity, multi-physics coupling. The use of these methods allows multiple core designs to be analyzed for key information to be used for making decisions when measuring the economic benefits against the risk and severity of effects from CIPS.

Key conclusions from this work are:

1. VERA shows excellent agreement in key parameters in comparison to three operating cycles of data from Catawba Unit 2 providing confidence in the ability of VERA to simulate normal plant (non-CIPS) operation.
2. The “jump-in” method allows simulation of later operating cycles and saves considerable time and effort yet provides accurate results that can be used for subsequent cycle simulations.
3. VERA, with coupled neutronics, thermal-hydraulics and crud capabilities can provide rod-by-rod simulations of rod power distributions, burnup distributions, and crud distributions with significantly improved resolution over currently-available industry tools.

4. The calibration of MAMBA-1D and the limited availability validation data resulted in limited confidence in its overall ability to simulate crud mass. Therefore, an application methodology based on parametric analysis and the use of industry standard code (BOA) calculated boron masses had to be applied.
5. VERA calculations with the BOA provided boron masses resulted in significantly more AO deviation than would be expected based on the industry CIPS risk methodology. This is attributed to the methodology using the BOA-calculated boron mass as a parameter based on previous operating history, rather than a prediction of the actual boron mass.
6. VERA analysis results for three core designs show relatively small differences in additional AO deviation and manageable SDM penalties for the more aggressive core designs. With improved confidence and validation, these results could support an industry decision to pursue a more aggressive core design resulting in savings in fuel cost.

7.3 RECOMMENDATIONS FOR FUTURE RESEARCH

This research has investigated many aspects of CIPS analysis in the core design process and quantified the potential impact on AO and SDM for a given boron mass deposition in the core. The following recommendations to improve the analysis of CIPS and its operational and economic effects are given below:

- **Improve the ability of MAMBA to predict total core boron mass:** In this research, the total core boron mass from BOA was used to calibrate the VERA results. This allowed for a meaningful analysis to be done with the current MAMBA-1D version implemented in VERA. Further development of MAMBA to allow it to be directly used to calculate total core boron mass with confidence is needed. This capability would need to be validated with experimental and plant data.
- **Perform power maneuvering for AO benchmarking:** One of the assumptions made in the VERA simulations was that there are no power maneuvers during the CIPS cycles. However, significant CIPS occurrences often lead to corrective mitigating actions resulting in plant operation at reduced power and or plant shutdowns. For more reliable application of VERA during a plant CIPS occurrence, power maneuvers during CIPS should be modeled with VERA and properly benchmarked.
- **Expand VERA benchmarking cases using historical plant data:** VERA is still under active development and requires additional validation and benchmarking before reaching the level of maturity of BOA. However, there is confidence that as VERA grows in capability and benchmarking

maturity, its higher fidelity and coupled physics capabilities will constitute a significant advancement in the industry capability to model CIPS and find more cost effective mitigating actions than with the standard tools.

- **Apply VERA to more aggressive core designs:** The three core designs analyzed in this work provide the basis of an approach for the direct simulation of CIPS to support the core reload design process. The actual AO deviation simulated between these three core designs was relatively small. A useful analysis would be to analyze an even more aggressive design, perhaps with reduced reload assemblies and further reduced fuel costs. This could demonstrate the potential use of VERA for even more substantial costs savings.
- **Use of VERA to improve industry CIPS risk assessment approach:** The results of this work provide an initial methodology that can be used to support the development of an improved industry CIPS risk assessment approach. The current methodology sets guidelines based on the past occurrence of CIPS in operating plants. This new capability based on VERA, along with improvements and validation recommended above, could be used to consider reducing overall CIPS risk conservatism and provide a basis for industry decisions to use core designs that save on fuel costs.

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