Nuclear cycle length economics strategy using stochastic and deterministic Monte Carlo computation models

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INTRODUCTION

Nuclear power plants (NPP) have historically been a low cost base-load electricity source because of their high fuel density and operational reliability. [1] In the United States, NPPs typically run 18- to 24-month cycles to limit outage times and maximize capacity factor. [13,21] Recently, however, increased volatility in energy and fuel prices, lower natural gas prices, higher material costs, and new energy sources are challenging the nuclear industry. [1,15] This warrants a study in developing a more robust cycle length and fuel burnup strategy to make NPPs more competitive. Most recently, the Clinton Power Station, operated by Exelon, is scheduled to transition from a 24-month to a 12-month cycle starting in May 2015. [19] Exelon expects to save fuel costs by utilizing the fuel more efficiently and reducing the overall fuel throughput. [19] Similarly, this study calculates the expected net present value (NPV) of a typical NPP for a 24-month cycle and a 12-month cycle strategy. The purpose of this study is to establish a robust cycle length economics model for individual NPPs. Future studies will evaluate dynamic cycle lengths to maximize the expected NPV under a competing mechanism among an entire fleet of NPPs.

BACKGROUND & ASSUMPTIONS

Attributes and Assumptions of a Nuclear Power Plant

This study assumes a Boiling Water Reactor Type 5 (BWR-5) that generates 1,300 MWe (4,000 MWth) and operates with a 24-month cycle length. Varying the cycle length changes different variables that impact NPV, where NPV is the sum of present values of all the cash flows through cost (capital, operations and maintenance (O&M), decommissioning, and fuel costs) and revenue (generation). [16] This study compares NPV between a 24-month and 12-month cycle case. For simplicity, we assume that all incurred construction and capital costs are paid off in full. Therefore, the expected NPV can be represented by equation (1) assuming revenue R_n, O&M cost O_n, and fuel cost B_n. $P/F, r_d$, n is the present value equation with discount rate rd, daily increments n, and length of forecasting window tl. The forecast window in this study is between April 2012 and April 2014.

$$NPV = \sum_{n=0}^{t_l} \left(\frac{P}{F}, r_d, n\right)(R_n - O_n - B_n) \quad (1)$$

This study uses MathWorks' MATLAB to forecast electricity prices, electricity generation, O&M costs, and fuel costs with stochastic and deterministic Monte Carlo simulation models. Studsvik's CASMO/SIMULATE lattice physics code is used to determine the batch sizes through core design.

The purpose of this study is to design an accurate cost model; hence, real data is not necessary. All data used in this study is either public information or an approximation.

Revenue

Revenue R_n is the product of electricity spot price en and electricity generation G_n ($R_n = e_n \times G_n$). MATLAB was used to forecast e_n and G_n. Forecasting an accurate long-term e_n is difficult due to various inherent volatility such as limited storability and transmission constraints, weather dependency and seasonality, spikes in prices and consumption, inverse leverage effect, and Samuelson effect where volatility of forward prices decreases with maturity. [18] This study uses long-term seasonal component (LTSC) electricity spot price forecasting method based on wavelet-based models to capture volatility [5,6]. e_t at time t is the sum of LTSC T_t, the periodic short-term seasonal component (STSC) s_t, and a stochastic component X_t ($e_t = T_t + s_t + X_t$). [6] Figure 1 represents the LTSC forecast window based on a Coiflet wavelet of order 2, slow exponential decay (λ =1/180) to the median, Symmlet

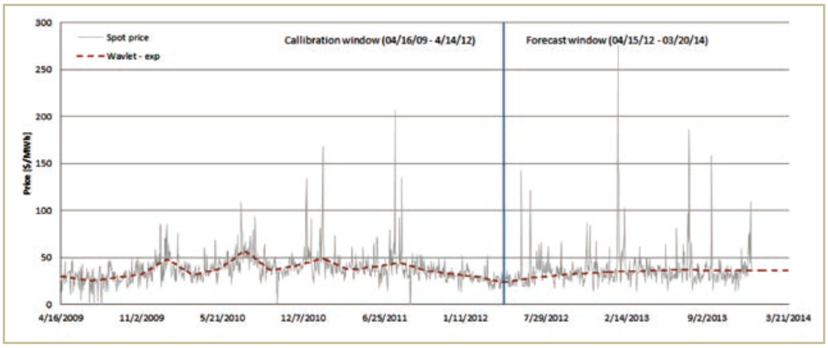

Figure 1. LTSC forecasting model results for the NYISO market in the Central New York region with a 3-year calibration window.

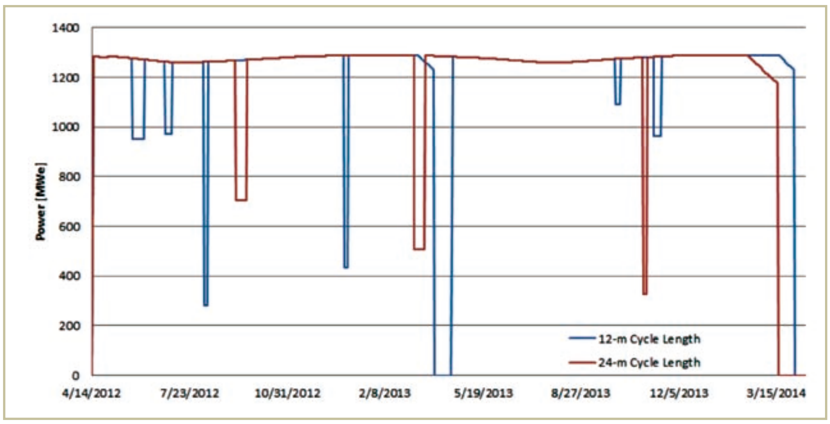

Figure 2. 2-year electricity generation forecasting period for a 12-month and 24-month cycle length case based on a chronological state transition using two-state continuous time Markov chain with failure and repair rate.

Case	Revenue (2012 $M)	Fuel Cost (2012 $M)	O&M Cost (2012 $M)	NPV (2012 $M)
12m[1]	650	($67)	($165)[2]	$418
24m	652	($85)	($157)[2]	$410

1. 12m cycle is spread into two years of operation
2. 10% discount rate applied to reflect 2012 $ [11]

Table I. Net present value of 12m and 24m case over 2 years.

approximation of order 6, and anomalous data replaced by the upper/lower 2.5% quantiles of the deseasonalized prices under a three-year calibration window (1095 daily mean electricity spot price). [5,7] Daily data for the calibration window is based on mean regional daily spot prices, also known as the Locational Based Marginal Pricing (LBMP) from the New York Independent System Operator (NYISO) in the Central New York region. [14]

Daily electricity generation G_n is forecasted by calculating the mean of n independent cases of a continuous sequential Monte Carlo model with state duration sampling process. [17,22] The operating state is based on the chronological full power load $u(t)$ that follows a two-state continuous-time Markov chain with failure rate λ (online duration) and repair rate μ (downpower duration) [8,9,10,22]. $u(t)$, λ, and μ are deterministic data based on previous three cycles of operation. Notice the local maximum of full power $u(t)$ during the winter seasons because of the higher thermodynamic efficiency during colder weather. [12] This seasonality phenomenon was captured by incorporating a Coiflet wavelet function. Figure 2 represents two sample cases to illustrate power during start-up, full power, downpower, and coastdown operation. The conventional 24-month case refuels every other year and assumes 702 days of operation and 28 days of refueling outage. The 12-month case refuels every year and assumes 350 days of operation and 15 days of refueling outage.

Fuel Cycle Cost

Fixed fuel cost $B_{f,n}$ is composed of front-end (mining, material, and fabrication) and back-end (spent fuel storage) cost. [2] For the purposes of this study, the cost of bundles was estimated with a single stream of bundle type using current market prices. Variable fuel cost $B_{v,n}$ is determined by the fuel efficiency during operation (enrichment and number of fuel bundles). $B_n = (B_{f,n}+B_{v,n})$ can be reduced with higher energy yield and lower material, storage, and service cost. Cycle length reduction is a simple and cheap method to increase energy yield and reduce material throughput [20] because reduced cycles allow more fuel bundle shuffling and more efficient core designs. Increased efficiency in fuel usage (higher core average burnup) ultimately reduces the batch size. The number of fresh bundles required for each cycle was simulated using the CASMO/SIMULATE lattice physics code. Some countries like Spain have additional incentives to reduce batch size because back-end cost is dependent on the mass of discharged bundles. The United States, however, has less of an incentive to produce less discharged bundles because back-end cost is dependent on burnup and not mass. [20]

O&M Cost

Typical O&M cost models are divided into fixed O&M cost $O_{f,n}$, (cost of preventive and scheduled maintenance) and variable O&M cost $O_{v,n}$, (cost of normal operation). [2,3] However, this is inaccurate in terms of a time-dependent cost analysis. For example, the average O&M cost per day could cost 4 to 5 times more during an outage than when a reactor is at full power operation. The O&M cost (O_n) model in this study captures the time-dependent variants by dividing the O&M cost between during operation and during outage. O_n is highly correlated to the schedule and workload. Hence budgeting O&M expenses using previous experiences provides a good estimate. [4] For the purpose of this study, the O&M cost is based on the median cost and duration of each task from previous data that results at approximately 80% fixed and 20% variable O&M cost. [2,23] Further study and additional data is needed to develop more robust cost distributions for O_n models.

RESULTS

Net Present Value

From Table 1, the revenue for the 12-month case was slightly lower than the 24-month case due to the additional maintenance outage length. The fuel cost for the 12-month case was greatly reduced because the throughput of fuel bundles was reduced through additional shuffling and increased core efficiency. The O&M cost for the 24-month case was lower because of shorter outage duration throughout the 24-month period. In conclusion, the 12-month case saves approximately $8M largely from reduced fuel throughput. Note that this is a preliminary study, and it is important to consider other relevant factors that impact NPV such as contractor scheduling issues, fuel contract costs, and more realistic operation, fuel, and outage costs.

CONCLUSION & FUTURE STUDIES

It is important to develop an accurate fuel cycle economic model to better understand how to make nuclear power more competitive. The purpose of this study was to design a robust cost model for a single NPP to compare the expected NPV between different cycle lengths using Monte Carlo simulations. Future studies will evaluate dynamic cycle lengths among an entire fleet of NPPs to maximize the overall expected NPV under a competing mechanism. Ultimately, we must have a better understanding of the supply and demand chain to make nuclear more competitive under volatile energy markets.

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