Time-Dependent Reliability Analysis of Nuclear Hybrid Energy Systems

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Abstract: This paper focuses on developing a framework for comprehensive time-dependent reliability analysis of a nuclear hybrid energy system (NHES) design. Subsystem interactions of this complex integrated system under stochastic electricity demand and load-following operation capabilities require dynamic reliability assessment of the NHES at the component, subsystem, and system levels. In order to capture the dynamic operational behavior of critical systems and components, a detailed thermal hydraulic model of the NHES was generated using Modelica and was tested under different electricity demand histories generated using RAVEN. The physical data (e.g., valve position, flow rates, inlet outlet water temperatures) gathered from Modelica were used to calculate time-dependent failure rates by fitting data into the piecewise Weibull distribution. The optimum maintenance interval was calculated, and maintenance cost estimates based on the calculated reliability metric were made for the selected component. Component time-dependent failure rates were fed into the subsystem reliability model, which was built with non-Markovian Stochastic Petri Nets. The component and subsystem failure rates were calculated and updated every hour to characterize the system's behavior and to aid in understanding operational reliability of the NHES design at a given time.

Keywords: Nuclear Hybrid Energy System, Time-dependent Reliability, Maintenance Cost

1. INTRODUCTION

Nuclear Hybrid Energy Systems (NHESs) have been proposed to provide significant benefits in minimizing cost and volatility of energy production while simultaneously reducing greenhouse gas emissions. This complex, integrated system includes a nuclear reactor(s), renewable energy generation, and industrial processes to fulfill the need for grid flexibility (baseload and load-following capabilities). Technical (electric power frequency stability, load following response) and economic (net present value, internal rate of return) figures of merit (FOMs) were identified to optimize the design and the operations of the NHES design alternatives during the 2014 INL-NREL workshop [1]. The primary FOM driving the design optimization process is the total energy cost. Reliability was introduced as a new FOM by Oak Ridge National Laboratory to minimize reliability-related costs (operational and maintenance [O&M] costs) over lifecycle cost by assuring reliable operation of the NHES from early in the design phase.

The NHES reliability analysis began with a component-level assessment. Early prediction of component reliability is a challenging problem because of many uncertainties associated with a system under development and under different types of operation (baseload and load-following). It has been observed that load-following influences the aging of certain operational components (e.g., valves), so an increase in maintenance costs can be expected [2]. This paper addresses the challenges in developing a component reliability analysis framework to track the simulated condition of a component to identify

its departures from normal operation, to update the change in failure rates at each time step, and then to map this into a cost optimization model.

The Modelica simulation of the NHES [3,4] captures the typical dynamic characteristics of the selected component and the model used to predict system performance. The simulated operational data were fit into the piecewise Weibull distribution to estimate the failure rate of the component. Failure events were taken into account by Weibull parameters (the characteristic lifetime and the shape parameter) of the failure model. Failure events for non-constant hazard rate functions with respect to time are best represented by Weibull distribution because of its versatility to represent different failures according to the value of the shape parameter. The estimated failure rates were used to quantify the normalized cost of repairs, replacements, or other O&M actions through the cost forecasting model. The reliability model coupled with the optimizer model in the Risk Analysis Virtue Environment (RAVEN) [5] was developed at Idaho National Laboratory. The optimum maintenance intervals were estimated as a function of failure rate during a given time and net present value change based on maintenance cost. Reliability of the turbine control valve (TCV) in the balance of plant subsystem was analyzed to demonstrate the feasibility of the framework.

This paper summarizes the NHES modeling and simulation work underway, emphasizing the time-dependent reliability model that has been developed and tested for an individual component and proposed for the overall system. Section 2 briefly introduces the NHES configuration and describes the selected subsystem and component. Section 3 discusses a dynamic reliability model for the simulated data and investigates the statistical inferences of the model parameters. Case study results are used to demonstrate reliability related cost analysis in Section 4. Section 5 draws conclusions based on the results and discusses future work associated with developing the system level's reliability model.

2. SYSTEM DESCRIPTION

The current NHES design configuration can be categorized in four main subsystem groups: (1) nuclear heat generation source, the pressurized light-water cooled, medium power reactor (1000 MWt) IRIS (International Reactor Innovative and Secure) reactor plant; (2) power conversion (electricity generation); (3) industrial processes; and (4) interface or storage technologies. The Modelica modeling language, relying on thermal-hydraulic Modelica-based libraries such as TRANSFORM [6], is used as the modeling and simulation environment to construct and simulate the dynamic models of the selected NHES. Figure 1 illustrates the NHES Modelica model under development [4]. NHES can be designed in numerous configurations to meet diverse technical specifications; it can be adapted based on the needs and opportunities of a given local market.
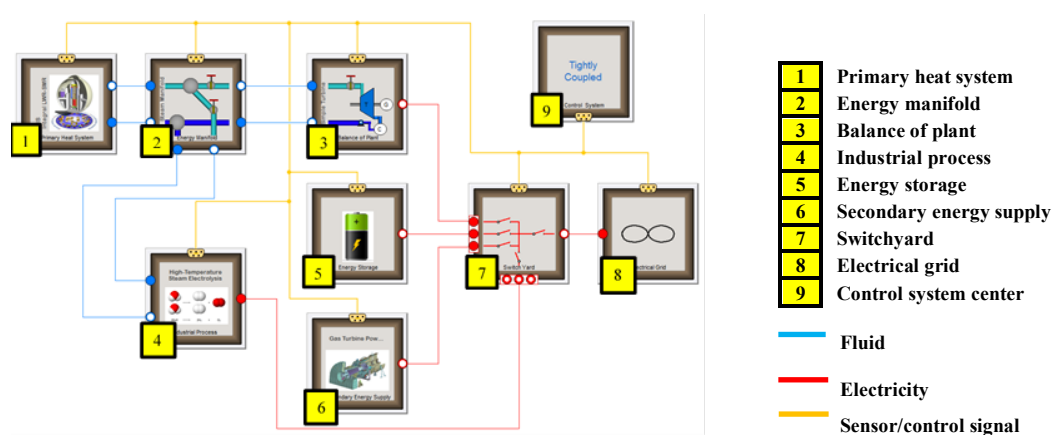

Figure 1: The NHES Configuration

The reliability analysis was focused on the balance of plant (BOP), which is marked as subsystem 3 in Figure 1. The BOP generates the primary share of electrical energy in the NHES. The current NHES BOP Modelica model contains a steam turbine, a condenser, a feedwater heater system, and a control and a bypass valve (circled in red), as seen in Fig. 2 [7].
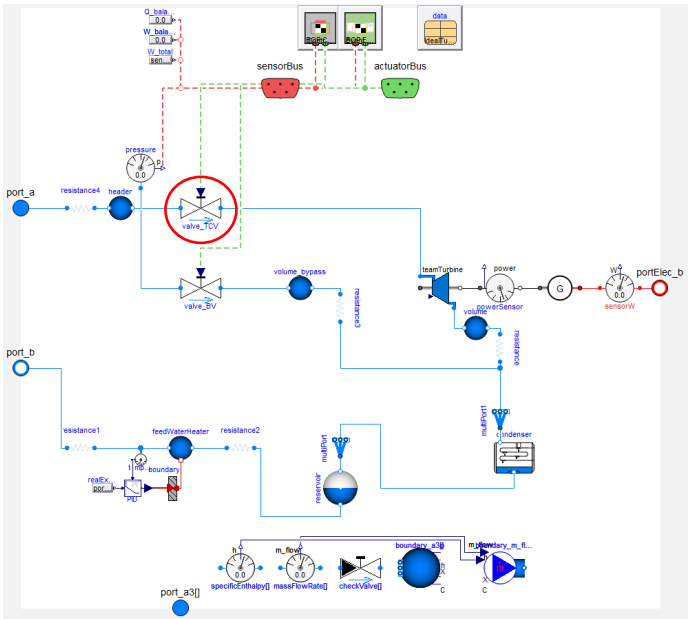

Figure 2: Modelica Model of the Balance of Plant of the NHES

2.1. Selected Component: Turbine Control Valve

The turbine control valves (TCVs) are the most essential components of the steam turbines in regard to the operation, reliability, and safety of the plant. The TCVs regulate the mass flow rate entering the first nozzle of a turbine to control and protect the main turbine. These valves are responsible for small, fast control modulations. The current NHES design has only one TCV (indicated with red circle in Fig. 3) instead of multiple parallel trains of TCVs and bypass valves that typically exist in operating nuclear reactors. Therefore, the TCV was selected for the component reliability analysis due to its lack of redundancy and its increased possibility of failure under stochastic demand.

Failure modes of the TCV were identified, and the reliability model was defined according to the failure mode of the component. There are limited common control valve failure modes: the dominant problems are usually related to leakage, speed of operation, or complete valve failure. The reference failure rate was assumed as 2.5E-2/demand, which is the only failure to open/close the TCV. This rate is reported in the component reliability database [8]. Only functional failure is being considered in this work, which is a failure to support a process need (flow of fluid, provide electrical power, etc.). Failure mechanisms such as stress corrosion cracking are not considered since current simulation capabilities have not yet included failure mechanisms. This approach complies with the US Nuclear Regulatory Commission's maintenance rule [9], which includes a performance measure based on functional failure.

3. RELIABILITY MODELING AND ANALYSIS

The proposed reliability model of the NHES combines the stochastic processes of degradation and fluctuating load, which are combined to evaluate time-dependent reliability. The component degradation process was modeled with piecewise Weibull distribution by using operational parameters (valve position, flow rate, etc.) from the Modelica model to estimate the Weibull parameters in every selected time step. The stochastic process of loads was generated by a Poisson process which is widely used to

model loads for structural analysis due to memoryless and randomness properties. Details of the model are given in Section 3.1, and implementation of the approach for the TCV is given in Section 3.2.

3.1. Component Reliability Analysis

The procedure of the component reliability analysis includes four main steps:

1. Create synthetic operational time series data, or gather data from Modelica
2. Fit the data set to the Weibull distribution and determine the scale and shape parameters
3. Model accuracy tests on the distribution to determine the acceptance of the statistical model
4. Calculate mean time between failures (MTBF), reliability, and availability metrics

The assumptions described below pertain to the basis for the proof-of-concept analysis and are applicable to other component assessments. If the intended operating mode of the component/system is known, then duration of the operation can be specified. Otherwise, a default value of 1 hour was used. The data set created from the Modelica model and three representative groups were used to test the model. The Weibull distribution was fitted to the time-series data using median rank regression (MRR).

Weibull analysis is a technique in which a statistical distribution is fitted to the data, allowing predictions to be made about the failure rate of the component. The two-parameter Weibull analysis was conducted on each data set to determine a shape parameter (β), scale parameter (η), the characteristic life, and the MTBF. The β and η parameters are used in reliability equations to determine lifecycle qualities of the data sets. The corresponding probability density function is given by

$$f(t|\beta,\eta) = \frac{\beta}{\eta^{\beta}} t^{(\beta-1)} \, exp\left\{-\left(\frac{t}{\eta}\right)^{\beta}\right\}, \text{for } \eta > 0, \text{and } \beta > 0. \tag{1}$$

Beta values represent the failure behavior of the component, where $\beta > 1$ wear-out, $\beta = 1$ chance failures, and $\beta < 1$ infant mortality failures are indicated. Knowledge of the failure behavior will help to improve overall reliability and availability. This will aid in decisions regarding whether preventive or predictive maintenance techniques should be applied to the component. The Kolmogorov-Smirnov goodness-of-fit test was performed on the same set of data and showed that the Weibull distribution is a good fit; high p-value (>0.5) is the case for the groups.

Because of its uses in lifetime analysis, a more useful function is the probability that the lifetime exceeds any given time: P (T > t). This is called the *survival function* or in the *case* of a product, reliability. For the Weibull distribution, the reliability is calculated as follows:

$$S(t) = R(t) = 1 - P(T \le t) = 1 - F(t|\beta,\eta) = exp\left\{-\left(\frac{t}{\eta}\right)^{\beta}\right\} \tag{2}$$

3.1. Test Case

According to the proposed approach, the first step (Section 3.1) is to collect the real-time position of the internal turbine control valve as discrete values each hour for three time periods (t_1, t_2, t_3). The charts presented in Figure 3 show the Weibull fit results for the first data sets; the axes in these charts represent the Weibull parameters estimate equation, which is equal to $\beta \log(t) - \beta \log(\eta)$ and the logarithmic frequency of the valve position data. Calculated Weibull parameters for each time interval are listed in Table 1, along with the reliability percentages.
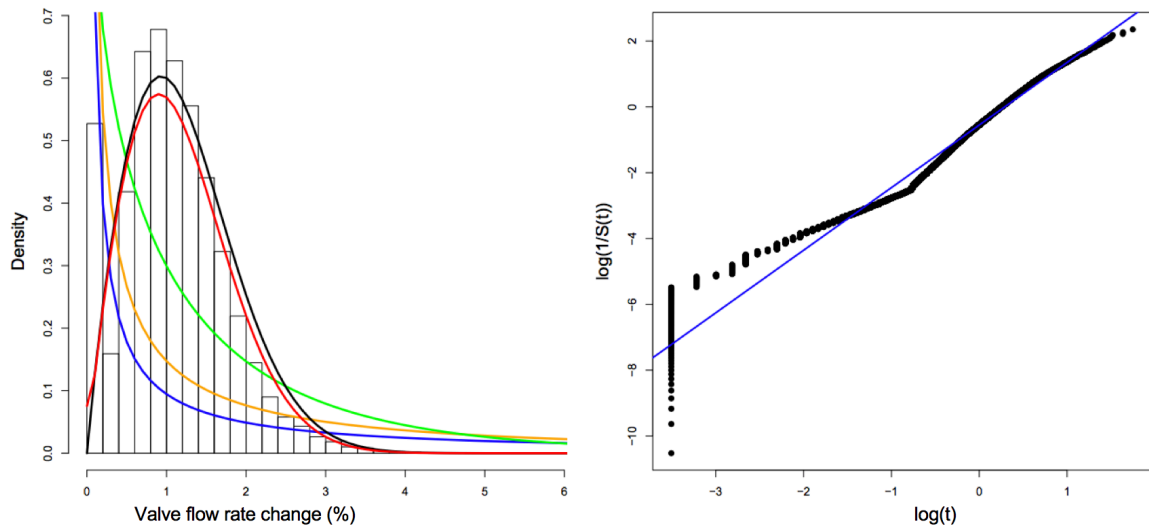
Figure 3: Weibull Analysis Results and Fitting Statistics for TCV at t_1

In Figure 3, the dot distributions at the regression line graphs imply the presence of more than one failure mode for the TCV failure or degrading component's health.

Table 1: Weibull Parameters and Reliability Estimations

Time Interval	Beta (β)	Eta (η) hours	R (%)
Period #1	1.358	90,129	76.63
Period #2	1.372	79,797	69.26
Period #3	1.383	68,854	63.71

Estimated Weibull beta values imply wear-out conditions (at the bathtub curve). These results are consistent with actual behavior, as degradation increases with time. The estimated eta values consistently decreased at each period, representing an accelerated deterioration process. The characteristic lifetimes of the component for different time histories are calculated as 10.29, 9.11 and 7.86 years.

Glasser's optimum replacement equation, shown in Eq. (3), was used to convert Weibull failure data to reliability cost data [10]: results for each data set are listed in Table 2.

$$O_r = \frac{C_p * e^{-(t/\eta)^\beta} + C_{up} * (1 - e^{-(t/\eta)^\beta})}{\int_0^t e^{-(t/\eta)^\beta} dx} \tag{3}$$

The first term of the numerator is the lower cost planned maintenance, C_p, and the replacement cost off-line before failure, multiplied by reliability; this term decreases with time. The second numerator term is the high cost of an unplanned, C_{up}, online, failure multiplied by the unreliability; this term increases with time. The denominator of the optimum replacement equation is the mean time to failure within the replacement interval. This relationship is valid up to the age of the characteristic life of the component and does not reflect the second replacement, which often occurs after the characteristic lifetime has been reached.

The optimum maintenance intervals for the all data sets are listed in Table 2. While component resistance decreases due to operational degradation, the replacement interval decreases, leading to a

lower net present value for the NHES system. This replacement interval is fed into the RAVEN CashFlow module for lifecycle cost analysis.

3.2. Integration of the Reliability Metrics into the Cost Optimization

An economic evaluation of NHES was performed to investigate the minimum cost of a hybrid system using Modelica/RAVEN optimization routines [11]. The reliability model introduced in Section 3.1 is written in the Python language and is used as an external model in RAVEN, which is tightly coupled with the CashFlow module.

Integration of the reliability tool into the overall methodology is outlined in Figure 4; RAVEN supplies the dynamic model demand time histories for specific subsystems, along with subsystem capacities. The dispatch then operates the overall system to meet the required demand. At the end of the simulation, various FOMs (e.g., ability to meet demand, reliability based on operation of components, maintenance intervals) are passed to RAVEN. The CashFlow module computes economic indicators such as internal rate of return (IRR) or net present value (NPV) and passes them back to the Optimizer in RAVEN. The reliability model output updates the O&M costs and the other economic indicators.
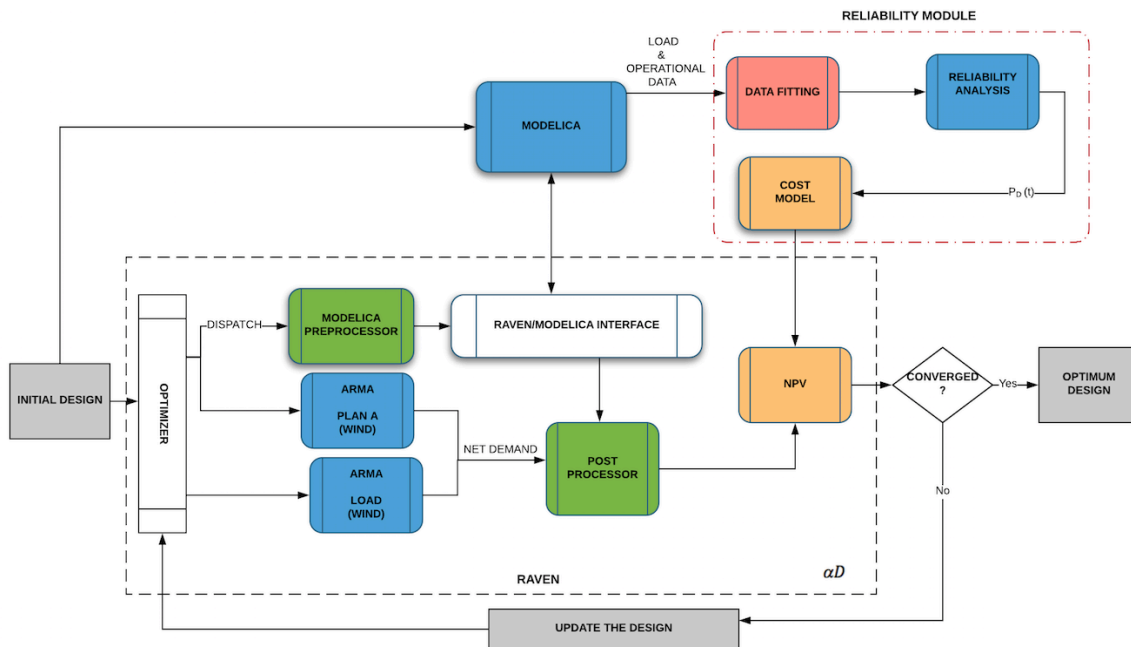

Figure 4: Reliability Model Integration into the Overall Optimization Methodology

In the RAVEN CashFlow module, the nuclear reactor has an assumed lifetime of 60 years. The tax and inflation rates are assumed to be 39.2% and 4%, respectively [9]. For the computation of the NPV, a weighted average cost of capital (WACC) of 5% has been assumed. Two O&M costs are modeled for the nuclear reactor: the fixed O&M cost and the variable O&M and fuel cost. Taxes are applied to both costs. The reference fixed O&M cost is for a 1100MWe plant with yearly a yearly cost of $93.5 million. The economy of scale factor for nuclear plants is 0.64. The variable O&M for the reactor is 0.5 $/MWh.

Within the nuclear industry, the performance of a lifecycle cost analysis (LCCA) typically results in calculating the NPV of both the benefit and the cost of a proposed change. Knowing the net cash flow (CF) and discount rate (DR) associated with each failure event, the value NPV_C from discounted cash flow for the current maintenance policy, which is based on the CF and failure rate, can be calculated [12]:

$$NPV_c = \lambda_c CF - \sum_i \left[\frac{(t_i + t_0)^{\beta_c}}{(1+DR)^i} - \frac{(t_{i-1} + t_0)^{\beta_c}}{(1+DR)^i} \right], \tag{4}$$

where i refers to the year the cash flow occurs, and the subscript c refers to the current maintenance policy. Planned and unplanned costs are given in Table 2 based on assumptions due to lack of real data.

Table 2: Planned and Unplanned Cost Estimation and NPV Changes

	Planned Replacement Cost ($) C_p	Unplanned Replacement Cost ($) C_{up}	Optimum Interval (Years)	NPV change
Period #1	250,000	400,000	5.83	-3,484%
Period #2	250,000	400,000	5.21	-4,171%
Period #3	250,000	400,000	3.73	-4,633%

The NPV changes listed in Table 2 do not represent realistic NPV changes due to the high demand simulated in the time series and in the data uncertainties and assumptions. However, it provides an insight into how the reliability of degrading components can impact lifecycle costs.

4. CONCLUSION

To ensure the high reliability and economic competitiveness of design, component reliability should be estimated and analyzed. To capture overall system reliability, the NHES model decomposed the subsystems and components, and reliability analysis was conducted, beginning with development of the component reliability model. This paper describes the development and implementation of a Weibull model to (1) maintain and improve the reliability of the NHES based on operational demand and to (2) assure the safety of operations.

The model is implemented with the turbine control valve (TCV) as a case study due to the valve's importance in the balance of plant system of the NHES. The time-dependent reliability of a TCV is calculated for 3 data series, and the proposed approach is feasible to apply to other NHES components for larger data sets.

Once this component-level, time-dependent reliability information is available for critical components of the BOP, simulation can be expanded and performed to determine the reliability of the NHES BOP using non-Markovian Stochastic Petri Nets.

Acknowledgments

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