# INTEGRATION AND ASSESSMENT OF COMPONENT HEALTH PROGNOSTICS IN SUPERVISORY CONTROL SYSTEMS

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## ABSTRACT

Enhanced risk monitors (ERMs) for active components in advanced reactor concepts use predictive estimates of component failure to update, in real time, predictive safety and economic risk metrics. These metrics have been shown to be capable of use in optimizing maintenance scheduling and managing plant maintenance costs. Integrating this information with plant supervisory control systems increases the potential for making control decisions that utilize real-time information on component conditions. Such decision making would limit the possibility of plant operations that increase the likelihood of degrading the functionality of one or more components while maintaining the overall functionality of the plant. ERM uses sensor data for providing real-time information about equipment condition for deriving risk monitors. This information is used to estimate the remaining useful life and probability of failure of these components. By combining this information with plant probabilistic risk assessment models, predictive estimates of risk posed by continued plant operation in the presence of detected degradation may be estimated. In this paper, we describe this methodology in greater detail, and discuss its integration with a prototypic software-based plant supervisory control platform. In order to integrate these two technologies and evaluate the integrated system, software to simulate the sensor data was developed, prognostic models for feedwater valves were developed, and several use cases defined. The full paper will describe these use cases, and the results of the initial evaluation.

*Key Words*: predictive risk monitor; supervisory control system; risk-informed decision making; valve prognostics

## 1 INTRODUCTION

Advanced reactors (AdvRx) generally encompass all non–light-water-cooled reactor (LWR) concepts, and are being considered as a longer-term option for meeting electrical generation and process heat needs in the United States [1]. AdvRx and AdvSMRs (based on modularization of advanced reactor concepts) with their passive safety features and the ability to incrementally add modules over time offer alternatives to traditional LWRs. However, the challenging environments found in AdvRx increase the possibility of degradation of safety-critical active and passive components adding to the challenges of their deployment and extended operation. For example, harsh environments within the primary and intermediate loops of AdvRx include high temperatures (in excess of 500°C), potential for fast spectrum neutrons, and corrosive coolant chemistry. These environments in proposed AdvRx concepts increase the possibility of degradation of safety-critical components and pose a challenge for deployment and extended operation of these concepts. Therefore, critical to longer-term adoption and ensuring wider deployment of AdvRx concepts are management of operations and maintenance (O&M) costs including the prediction and management of component integrity as a way to impact planning for maintenance activities and staffing levels. In general, the ability to monitor, assess, and predict component/equipment health in terms of probabilities of failure (POF) or planning O&M actions is fundamental in the ability to achieve overall enterprise risk management in AdvRx.

Health monitoring techniques are among a class of technologies that can be used to establish condition indicators; in combination with predictive estimates of component failure based on condition, such techniques can be applied to manage O&M costs through improved scheduling of maintenance activities and selection of operational decisions that minimize the risk of unplanned plant shutdowns. Recent research has focused on developing technologies in the areas of various condition monitoring methods for assessing component condition [2], predicting passive [3, 4] and active [5] component integrity, and development of a prototypic ERM framework [6-8].

In this paper, we describe an approach to integrating health monitoring and predictive risk estimation with a plant supervisory control system (SCS) framework. The SCS framework is specifically designed to address a need for plant control that accounts for component degradation in its decision making.

## 2 ENHANCED RISK MONITORS

Enhanced risk monitors (ERMs), as a component of overall enterprise risk management, is a proactive philosophy where greater situational awareness can be provided to plant supervisory control and O&M

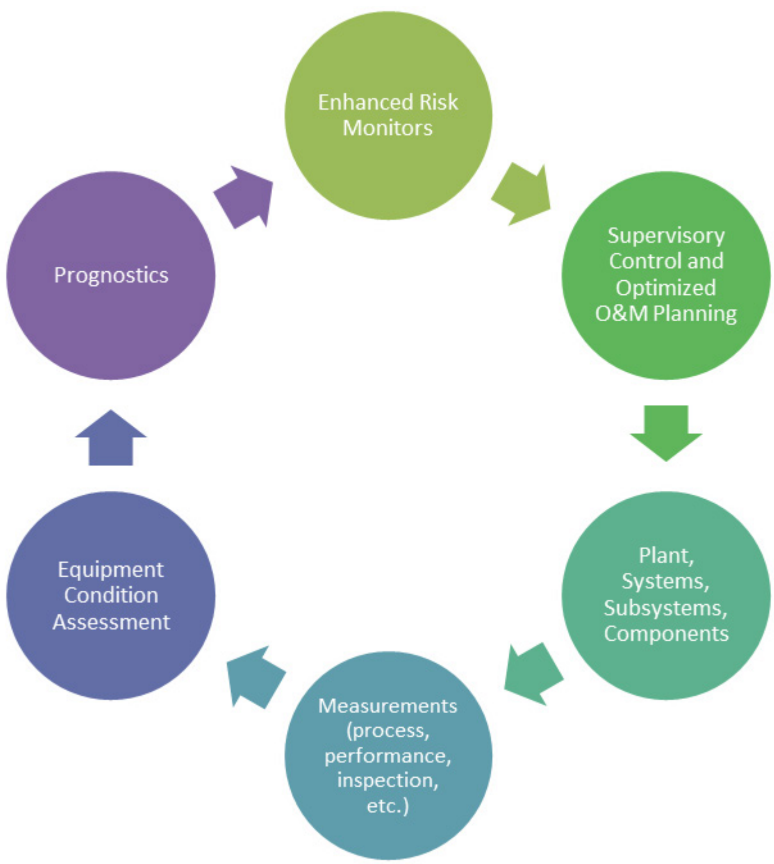


**Figure 1. ERMs can provide greater situational awareness to the plant supervisory control and O&M planning routines [5].**

planning routines as depicted in Fig. 1. Essentially, ERMs are predictive risk monitors that incorporate the time-dependent failure probabilities from prognostic health monitor (PHM) systems to dynamically update the risk metric of interest. Specifically for AdvRx, enhanced risk assessment of AdvRx that incorporates real-time degradation information of critical active components will greatly improve overall asset protection and management, allowing for safe, reliable generation during extended operating cycles and longer reactor lifetimes.

Risk monitors expand on probabilistic risk assessment (PRA) by incorporating changes based on day-to-day plant operation and configuration (e.g., changes in equipment availability, operating regime, environmental conditions). The PRA systematically combines event likelihoods and the availability of key components and, combined with the magnitude of possible adverse consequences, determines risk. Currently, most nuclear power plants have a PRA that reflects the as-operated, as-modified plant; this model is updated periodically.

Instead of using population-based POF (as is typically done) to estimate average plant risk over time, component-specific POF, if available, can provide a more accurate estimate of risk. ERM integrates the component-specific POF obtained using health monitoring techniques with predictive estimates of changes to POF, to calculate changes to future risk that are conditioned on the actual component condition. In their use of real-time component condition, ERM technologies differ from conventional risk monitors [9, 10] that use a static estimate for event probability and POF, typically based on historical observations and engineering judgment. More recently, time-based POF values derived from operating experience and traditional reliability analysis have been used [11, 12]; however, these are usually not specific to the component. Critical to the ERMs is a predictive estimate of POF of the component, which is precisely what PHM provides [13]. As a result, PHM technologies are likely to be applicable to achieving enhanced risk monitoring to obtain a realistic assessment of dynamic risk that is unit-specific and accounts for the operational history of the component [5-7].

## 3 SUPERVISORY CONTROL SYSTEMS

The SCS, as previously indicated, provides the overall coordination and control for plant operations. Focused on non-safety systems, the SCS integrates information from a number of sources, utilizes predefined success criteria, and calculates plant control actions to ensure that the plant operates within a defined operational envelope. This is especially important when dealing with AdvRx concepts that include multiple reactor modules. In this case, the control decisions need to account for the interconnected nature of the modules while ensuring that the objectives of the plant (electrical generation, process heat, etc.) are met.

The schematic of the SCS is shown in Fig. 2. This framework is composed of four main modules:

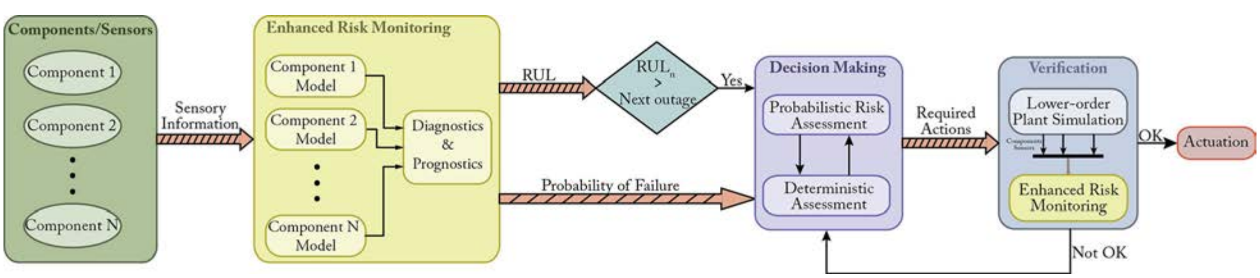


**Figure 2. Schematic of the general architecture of the supervisory control system.**

1. Components/Sensors: This includes components of interest that are required to be monitored for possible degradation. Each component has a set of sensors associated with it that provide sensory information and can be interpreted by the ERM system. The specific list of components may be derived from an appropriate risk model that determines the possible failure pathways and identifies the highest priority components for monitoring.
2. Prognostic Health Monitor/Enhanced Risk Monitor: The main purpose of this module is to perform diagnostics and prognostics on the components of interest based on the provided sensory information. This requires a mathematical model representing the component. Such a model can be a physics-based model, or a data-driven model using historical data of the component or related components. The desired output from diagnostics is an estimate of the POF for each component and the confidence in this estimate. The desired output from prognostics is an estimate of the remaining useful life (RUL) for each component and the confidence in this estimate. The ERM, if necessary, can also provide estimates of predictive risk using the POF and the RUL.
3. Decision Making: This module is invoked only if any of the RUL values is estimated to be larger than the time to the next outage. Decision making involves two steps—probabilistic risk assessment and deterministic assessment. Essentially, this module ranks possible action paths that will not trip the plant's safety system. See Cetiner et al. [14] and Muhleim et al. [15] for more information about the functionality of the decision-making module.
4. Verification: Once the decision-making module decides on a single solution for the operational strategy of the plant, the solution is verified using a low-order model of the plant. The required actions will be given as inputs to instantiate the low-order model. This model will output the states of the plant components. Sensor data from these components is then used, along with a separate instance of the PHM/ERM module to re-compute the RUL of all components, and to verify that they will fall within the prescribed criteria.

In the following sections, the functionality of the ERM module will be discussed in detail.

### 3.1 Evaluation Scenarios

The evaluation scenarios for the integrated SCS-ERM software are based on a two-reactor power block, with a common balance-of-plant (Fig. 3). Several scenarios may be considered, focused on the power conversion module. For initial integration evaluation, the following initiating events are considered:

1. Turbine control valve from reactor 1 drifts in closed direction
2. SG 1 FW FCV drifts in closed direction
3. SG 1 FW FCV drifts in open direction.

In all instances, it is clear that the initiating event is based on a valve failure and, therefore, the ability to monitor the condition of a valve and predict the time to failure is critical to ERM and its integration with SCS. To this end, the focus of the prognostic module was on valve prognostics, with several possible degradation modes considered in the prognostic analysis. This module is described next.

### 3.2 Valve Prognostic Modules

The prognostic module uses a Bayesian approach for predicting the remaining life, given the estimated condition of the component. The Bayesian module utilizes a component-specific degradation-state evolution model, and a measurement-physics model [16]. For the integration testing, as described earlier, condition assessment and prognostics for a valve were implemented.

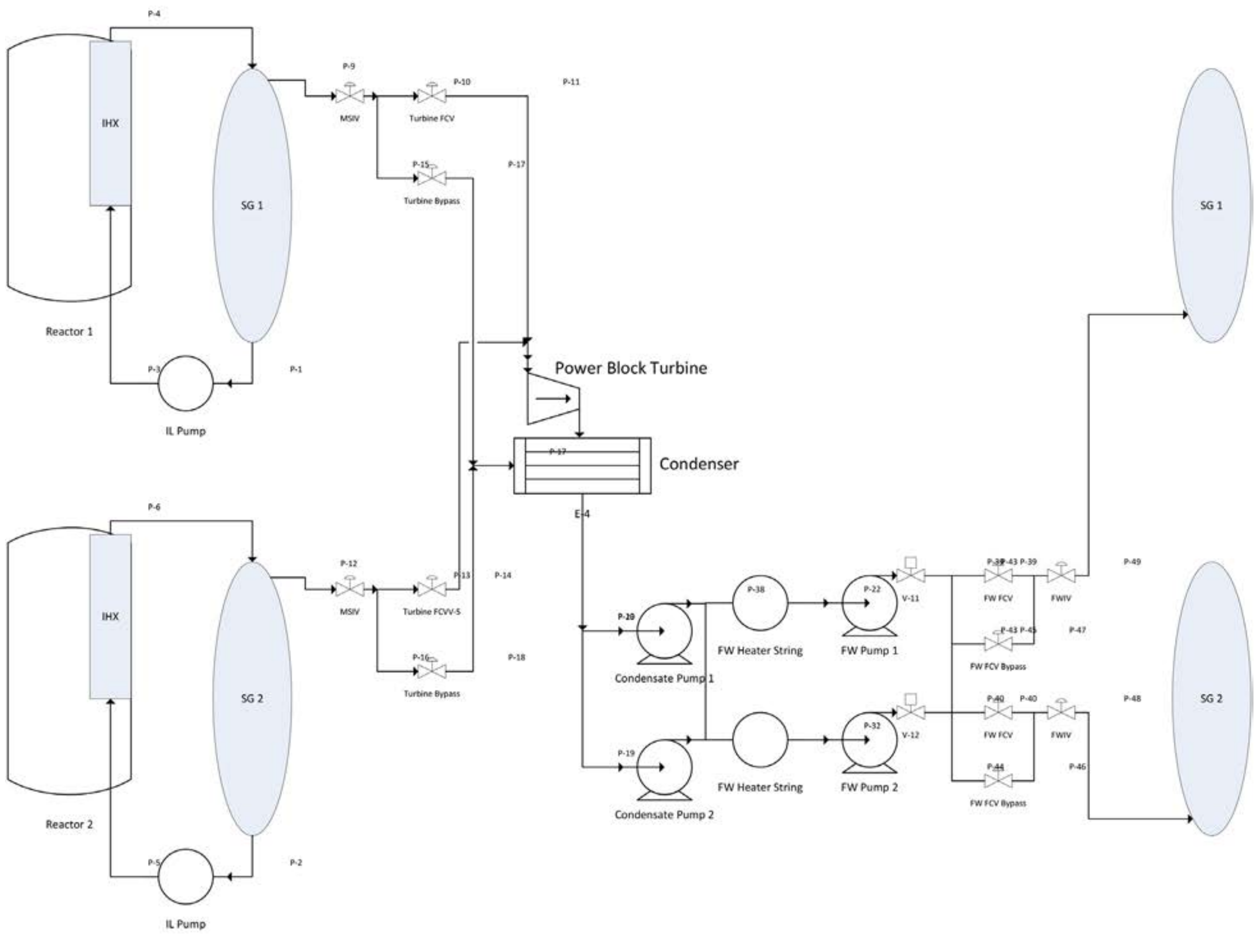


**Figure 3. Prototypic advanced reactor power block, used for the integration testing with the SCS.**

The valve degradation-state evolution utilizes a state dynamics model that relates the system state and material degradation accumulation rate (i.e., the states and degradation level at the next time instant given their values at all times up to and including the present time). The measurement-physics model represents the quantitative relationship between the measurement and the system states and degradation level at the present time instant.

Several state-dynamics models exist for valves. For the purposes of integration testing, a pneumatic valve mode [17] was utilized for simplicity of implementation and testing. This state-dynamics model is capable of accounting for multiple degradation modes. Further, the valve can be controlled using signals representing pneumatic pressure inputs that drive the valve to a desired valve position.

The dynamic evolution of system states and material degradation can be obtained by using the solution of state tracking problem [16, 18, 19]. For a linear system with Gaussian additive noise (uncertainties in the measurements and physical model), the optimal solution to the tracking problem can be shown to be the Kalman filter [18]. However, when the system is nonlinear and/or the noise terms are non-Gaussian (as is likely in the early degradation estimation problem), then more general solutions to the tracking problem are necessary, and include algorithms such as the extended Kalman filter, unscented Kalman filter, and the particle filter. A detailed description of the Bayesian approach used here is given elsewhere [18, 19], and its applicability to prognostics is discussed in Ramuhalli et al. [20] and Meyer et al. [21].

### 3.3 General Description of the Pneumatic Valve

The valve has a return spring that ensures that it is in the closed position by default when there is no air pressure applied to the valve. The valve has two chambers with orifices for the air flow that controls the position of the valve. This valve controls the fluid flow rate in the feedwater tube. This is done by a control system, which has a specified fluid flow rate set point, and a feed-back controller from the valve, which changes the air supply within the top and bottom chamber to reach the required flow rate set point.

The functional requirements are two-fold:

1. When air supply within the valve chambers is lost, the valve should be in the closed position.
2. The fluid flow rate going through the pipe should be achieved within a given time requirement.

Damage could happen within the valve, which may hinder its ability to satisfy its functional requirements. Four sources of damage are possible for this specific valve, and are included in the model used to simulate valve operation:

1. Friction Damage: The contact area between sliding bodies increases with time due to the wear down of surfaces. This results in an increase of the friction coefficient, which makes it harder to open/close the valve.
2. Spring Damage: The spring softens due to use, resulting in a decrease in the spring constant. This might result in the valve not being able to fully close when air supply is lost.
3. Internal Leaks: Internal leaks could result from the sliding wear near the seal surrounding the piston.
4. External Leaks: Connections for the pneumatic gas supplies at the top and bottom chambers in the valve are subject to corrosion. This might result in leaks, affecting the supply gas pressure going into the valve.

### 3.4 Evaluation of Valve Prognostic Model

To test the performance of the prognostic module, input data for the valve and measurements were synthesized to represent simplified measurements and inputs from a typical feedwater control valve. It is assumed that the plant operates in a load-following mode, and thus the position of the valve, which controls fluid flow-rate, changes based on demand.

Fig. 4 shows the control signal (pneumatic pressure) history for the valve, and corresponding measured valve position. In this instance, the valve damage parameters are increased as a function of time, and it can be seen from the figure that the valve progressively requires more time to open due to increased wear damage.

The prognostic evaluation using the measured valve position and the degradation accumulation model indicates that RUL estimate decreases over time, where the remaining life is computed based on an estimated time it would take the degraded valve to fail to meet its functional requirements. Fig. 5 shows the RUL estimates for this specific example.

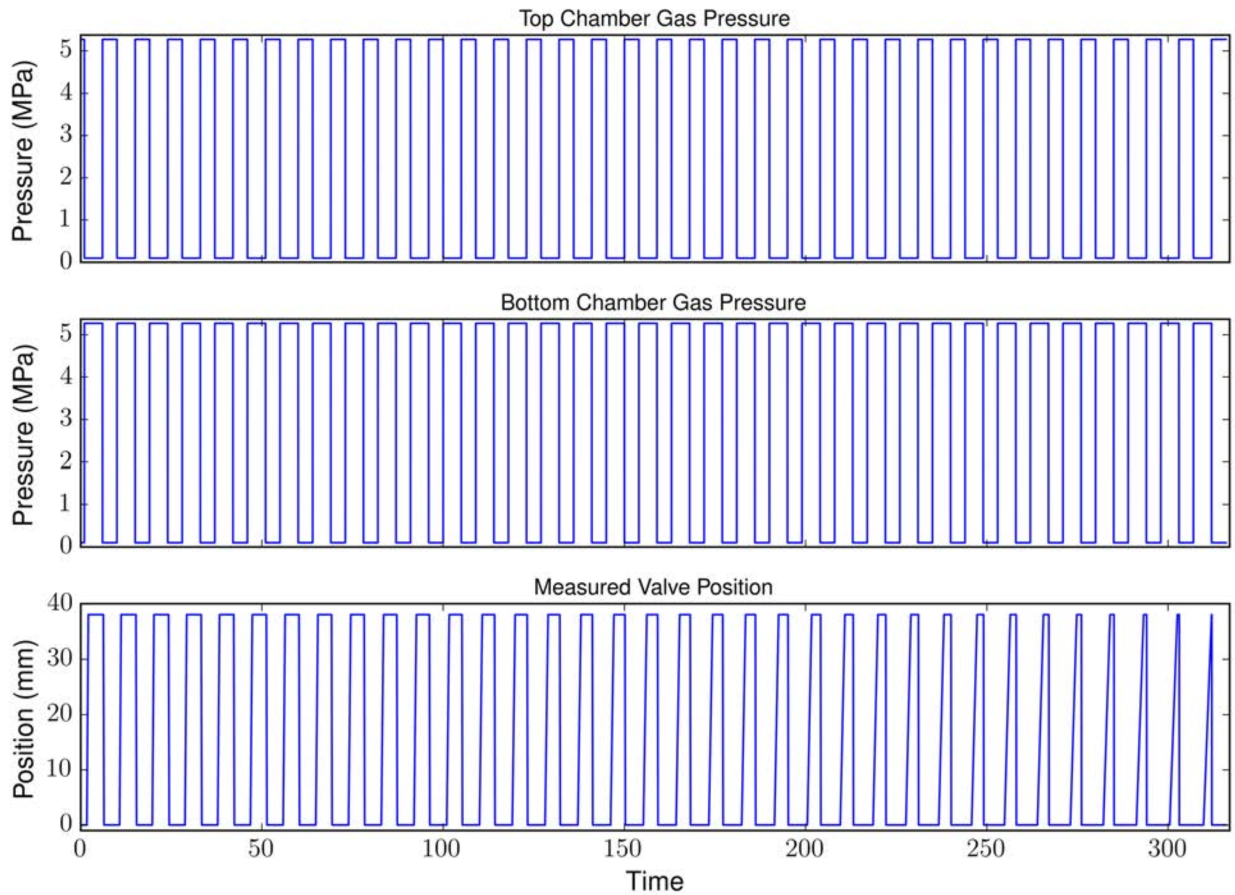


**Figure 4. Input pressure history for pneumatic valve with corresponding measured valve position.**

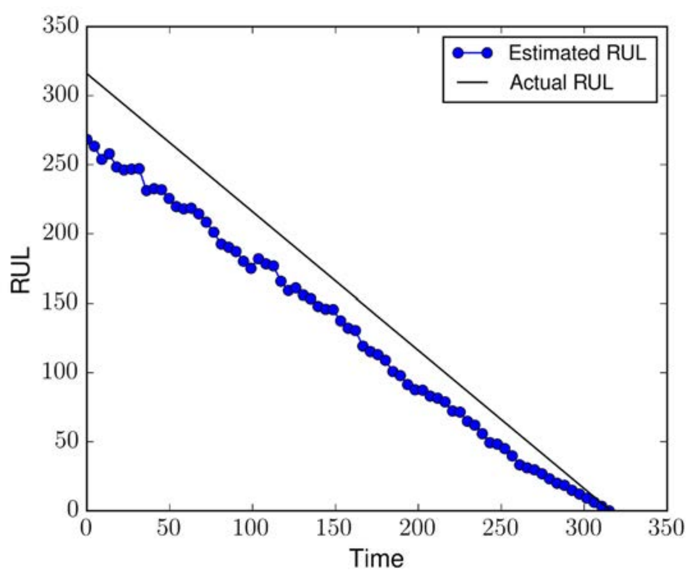


**Figure 5. Pneumatic value RUL estimates.**

In general, other possible demand profiles can be used to generate RUL estimates. Within the SCS, the expectation is that multiple demand profiles (representing expected demand variations in the future) will be used to estimate the RUL for degraded valves. The information across these estimates can be combined in several ways to provide a general estimate of POF as a function of time and incorporated into the risk models for SCS utilization.

These models can be readily integrated into the SCS framework, with initial integration complete and testing ongoing.

## 4 CONCLUSIONS AND FUTURE WORK

The need for an ERM methodology and the benefits of implementing it for developing an array of decision alternatives were identified. Implementation and integration of ERM with an SCS framework required modeling component operation, degradation accumulation, and degradation sensing for performing diagnostics and prognostics in addition to any need for component modeling by the SCS. As AdvRx concept development progresses further, there will be the need for additional research to model proposed plant components (active or passive) for performing diagnostics and prognostics in support of integrating an ERM methodology into the SCS. Sensor technologies for monitoring the condition of these components will also be needed to address the need for equipment/component condition assessment. Timely research on component modeling, health monitoring and prognostics, and improvements in the ERM methodology can complement advances in SCS research in its support to developing AdvRx concept designs and O&M strategies.

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