Transformer Health Monitoring Using Dissolved Gas Analysis: A Technical Brief

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Abstract

As integral components of any power plant, transformers supply the generated electricity to the grid. However, a transformer's cellulose-based paper insulation and the mineral oil in which it is immersed break down over time under standard operating conditions—or more rapidly due to potential faults within the system. As the transformer's mineral oil breaks down, gases are released that can be measured and monitored. This technical brief exhibits a collection of diagnostic and prognostic techniques that utilities can adopt in lieu of labor-intensive periodic preventive maintenance routines. Furthermore, prognostic models have been incorporated using the latest version of the Institute of Electrical and Electronics Engineers (IEEE) standard (IEEE, 2019) for dissolved gas analysis (DGA), thus expanding it to include estimation of the time to maintenance. Overall, four different methodologies are explained, each of which aids in determining a transformer's state of health. These methodologies include the Chendong model, the IEEE thermal life consumption model (IEEE, 2012), a diagnostic model for DGA, and a prognostic model for DGA that uses an autoregressive integrated moving average (ARIMA) model. An additional improvement for estimating missing system parameters by using monitoring data (i.e., a tool for parameter estimation utilizing Powell's method) is presented, enabling the IEEE thermal life consumption model to benefit not only the collaborating power plant, but also the power industry at large.

1. Introduction

Transformers supply generated electricity from power plants and are critical to the reliability of the electric transmission grid (Coble, Ramuhalli, Bond, Hines, & Upadhyaya, 2015). However, a transformer's cellulose-based paper insulation and the mineral oil in which it is immersed break down over time under standard operating conditions—or more rapidly due to potential faults within the system. As the transformer's mineral oil breaks down, gases are released. Key dissolved gases (e.g., methane, hydrogen, ethylene, ethane, carbon monoxide, carbon dioxide, oxygen, nitrogen, and acetylene) are monitored, and the rates at which they are produced can be indicative of the transformer's state of health. With the installation of a dissolved gas measurement system, these measurements can be taken more frequently, and online monitoring has been enabled. Dissolved gas analysis (DGA) is the premier diagnostic approach to monitoring and detecting faults within oil-immersed transformers (Wani et al., 2021).

This technical brief expands on the work previously published in (Agarwal, Lybeck, Pham, Rusaw, & Bickford, 2015), which demonstrated the Chendong model and the Institute of Electrical and Electronics Engineers (IEEE) thermal life consumption model on plant data, with simulated drift to represent primary winding insulation degradation, as part of the Electric Power Research Institute's Fleet-wide Prognostic and Health Management Suite software (Electric Power Research Institute (EPRI), 2012). This research expands on that work by enabling broader usage, incorporating (IEEE, 2019) to enable prognostic models, and then testing the models on actual plant data. Additionally, Wani et al. provided an excellent review of state-of-the-art nonlinear techniques for DGA-based transformer fault diagnosis, but failed to mention linear techniques such as autoregressive integrated moving average (ARIMA), which is covered in this brief (Wani et al., 2021).

The main contributions of this brief are summarized as follows:

1. Showcasing of four complementary techniques (i.e., the Chendong, thermal life consumption, diagnostic, and prognostic models) for determining and predicting a transformer's state of health, and these techniques are demonstrated using 5 years worth of plant data.
2. Development of a parameter estimator that uses Powell's

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method to approximate missing plant parameters within the IEEE thermal life consumption model, thus enabling broader usage of the model within industry.

3. Utilization of (IEEE, 2019) to develop a prognostic model to calculate remaining time until maintenance, based on dissolved gas measurements.

After a transformer's state of health is estimated using dissolved gas and temperature measurements, maintenance can be scheduled proactively, thus leading to cost savings, as failures and unplanned outages can be avoided. Use cases were developed using actual plant data to demonstrate how these methodologies can be applied to a power plant transformer, and how these models synergize to diagnose and predict transformer conditions.

The rest of the paper is organized as follows. Section 2 describes the data used in this technical brief. Section 3 introduces the four methods and the parameter estimator, outlines their methodologies, and explains their expected contributions and value by using sample data from a nuclear power plant (NPP). Section 4 summarizes the work and outlines the path forward.

2. Data Description

Online dissolved gas analyzers were installed in three transformers, with help from the collaborating NPP. These sensors recorded gas concentrations and insulating oil temperatures over a 5-year period, using an initial hourly sampling frequency that was reduced to one sample every 8 hours for the final year. The measurements were first cleaned of any outliers by using a rolling median filter, then interpolated to produce an even sampling frequency throughout the data. The recorded measurements included the quantity of key gases such as hydrogen, methane, nitrogen, acetylene, ethylene, ethane, carbon monoxide, carbon dioxide, oxygen, and water, along with other relevant parameters such as ambient temperature and oil pressure/temperature. The level of 2-Furaldehyde required for the Chendong model was not a measurement recorded by the online monitoring sensor. This value was recorded yearly during a more intensive oil analysis.

3. Methodology

The primary objective of this research was to leverage previous knowledge to develop a deployable package for use by industry. Additionally, prognostic models were incorporated using the latest version of the IEEE standard (IEEE, 2019) for dissolved gas analysis (DGA), thus expanding it to include estimation of the remaining time until maintenance. An additional improvement for estimating missing system parameters from monitoring data (i.e., a tool for parameter estimation utilizing Powell's method) is presented, enabling the IEEE thermal consumption model to benefit not only the collaborating NPP but also the power industry at large, in cases in which some of the system parameters are unknown.

Each of the five different methodologies contributes to the health monitoring of transformer systems and the determination of a transformer's remaining time until maintenance. These methodologies are:

1. The Chendong model for calculating the remaining useful life (RUL) of a transformer's insulation by relating the 2-Furaldehyde level to the degree of polymerization (Chendong, 1991).
2. The IEEE thermal life consumption model for estimating the hot-spot temperature within the insulation, based on the ambient temperature and the transformer's load conditions, to estimate an accelerated aging factor (Agarwal, Lybeck, & Pham, 2014; IEEE, 2012).
3. A parameter estimator that predicts any single missing plant parameter within the IEEE thermal life consumption model. Many plant-specific variables (e.g., the ratio of load losses, thermal heat capacities, and transformer losses) are required for this model. Some of these parameters may not be known, available, or even measured by the utility.
4. A model for diagnosing the cause of high gas concentrations and rates, based on information in the IEEE Guide for the Interpretation of Gases Generated in Mineral Oil-Immersed Transformers (IEEE, 2019).
5. An ARIMA prognostic model for predicting future key gas concentrations to indicate when maintenance may become necessary (Naim, Mahara, & Idrisi, 2018).

The following subsections summarize the implemented and demonstrated models, and describes the key aspects of the methodology used in each approach. Each model incorporates different inputs and produces actionable outputs. Figure 1 lists the expected outputs and value gained by using each model, and visually illustrates their synergy for transformer health monitoring. Additional information on each model can be found in the cited references.

3.1. Chendong Model

As the paper insulation in the transformer ages, the cellulose polymer chains break down into shorter lengths, decreasing the tensile strength. The average length of these cellulose polymers is referred to as the degree of polymerization (DP), which is also the average number of glucose monomers in the polymer chain. Directly testing for either tensile strength or DP is difficult (Stebbins, Myers, & Shkolnik, 2003); however, via Eq. 1, the Chendong model relates the 2-Furaldehyde level in the transformer's oil—an organic compound that is readily measurable—to the DP of the insulating material:

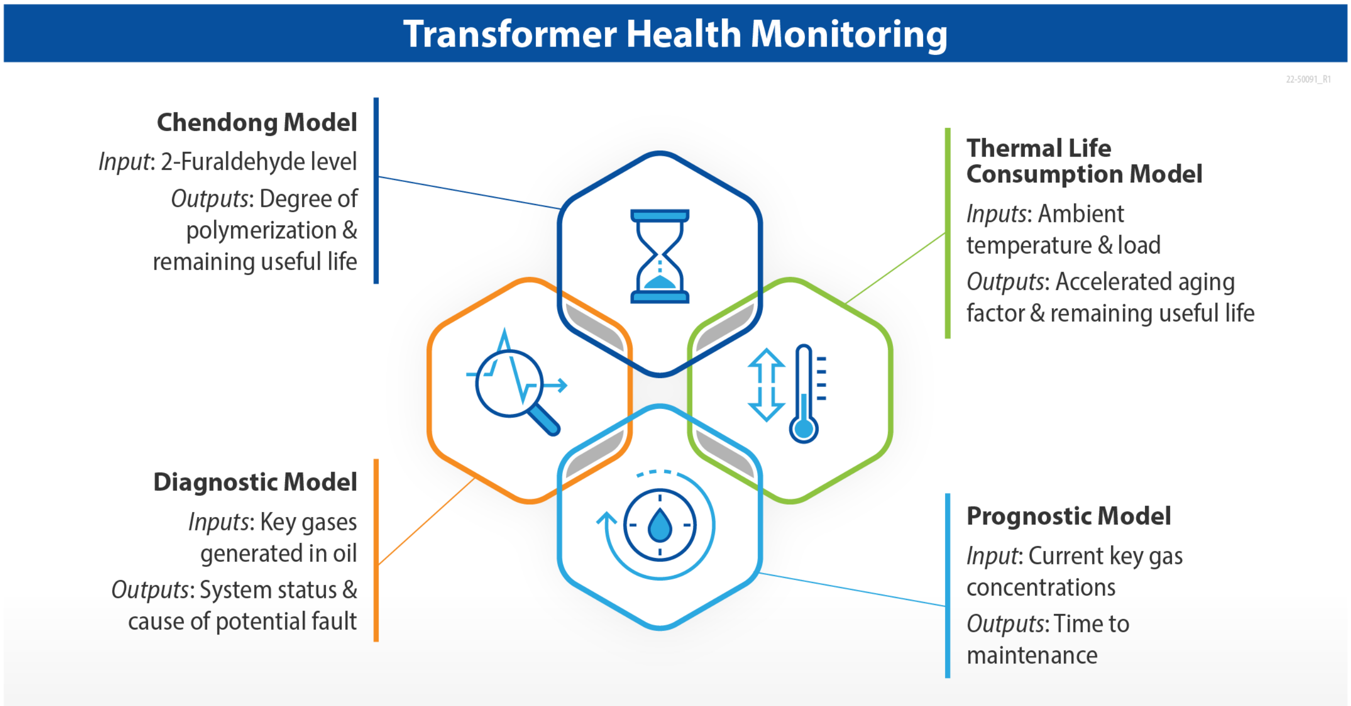

Figure 1. These four models synergize with regard to transformer health monitoring by incorporating different inputs to produce actionable outputs.

$$DP_t = \frac{log_{10}(2FAL) - 1.51}{0.0035}, \quad (1)$$

where DP_t is the DP, $2FAL$ is the 2-Furaldehyde level, and 1.51 and 0.0035 are empirical constants from the original calculation and are used to relate DP_t and $2FAL$ (Chendong, 1991). A lower DP means that more deterioration has occurred and that a lower tensile strength is expected. To calculate the insulating material's RUL in years, the ratio of the measured DP (DP_t) to the initial DP (DP_0) is determined via Eq. 2:

$$RUL = 20.5 * \frac{DP_t}{DP_0}, \quad (2)$$

where 20.5 is the average insulation life expectancy (in years) assumed in (IEEE, 2010). The Chendong model is expected to receive two inputs for calculating RUL: the amount of 2-Furaldehyde (in parts per million) and the DP_0. The Chendong model has three outputs: current DP, RUL, and significance of the results. The significance of the results attempts to describe the current DP in more descriptive, actionable terms (e.g., healthy insulation, moderate deterioration, extensive deterioration, and end-of-life criteria), as per Table 1 (Abu-Siada, 2011). The calculated DP was 800 for this transformer, which is listed as "healthy insulation" in Table 1. Assuming the original DP of the new transformer was 1200, then the RUL according to Eq. 2 would be 13.67 years. Each transformer varies in terms of the DP that it begins with, so this value should be estimated early in the transformer's lifecycle to achieve the most accurate prediction.

Table 1. Significance criteria for DP.

Description	DP_t
healthy insulation	700–1200
moderate deterioration	450–700
extensive deterioration	250–450
end-of-life criteria	<250

3.2. IEEE Standard C57.91-2011 Thermal Life Consumption Model

The thermal life consumption model, originally presented in (IEEE, 2012), estimates how much life has been "consumed" as a result of exposure to higher temperatures (IEEE, 2012; Aizpurua, Stewart, & Mcarthur, 2019). This model calculates transformer insulation hot-spot temperatures by using the ambient air temperature, hot-spot reference temperature, load, and transformer-specific parameters to arrive at an aging acceleration factor.

The hot-spot reference temperature refers to the winding hot-spot temperature that produces an aging acceleration factor of 1.0. This hot-spot temperature may vary from asset to asset, and should thus be calibrated. A reference hot-spot temperature of 55°C was chosen for this analysis, based on the decrease in the estimated RUL of the transformer following the first year of operation. For a healthy transformer, the RUL is assumed to decrease by one year for each year of use.

Fourteen separate variables are required as inputs for the IEEE thermal life consumption model. If a specific variable is unknown, the parameter estimator (see Section 3.2.1) can solve for the missing values, assuming that the top-oil/ambient temperature is known. The IEEE thermal life consumption model first estimates the thermal hot-spot temperature by using the ambient air temperature, load, and other plant parameters. The aging acceleration factor (F_{AA}) is then estimated via Eq. 3:

$$F_{AA} = e^{\frac{15000}{T_{HS}+273} - \frac{15000}{T_H+273}}, \tag{3}$$

where T_{HS} is the reference hot-spot temperature, T_H is the calculated hot-spot temperature, 273 is the conversion from Celsius to Kelvin, and 15,000 is an empirical value for the insulation degradation and is akin to the activation energy within the Arrhenius reaction rate equation (Agarwal et al., 2014).

For a normal insulation life of 20.5 years, the RUL is calculated as being 20.5 years minus the amount of time that has already transpired and taking the aging acceleration factor into account. Figure 2 shows the RUL prediction that was based on the thermal life consumption model for a transformer at the plant site.

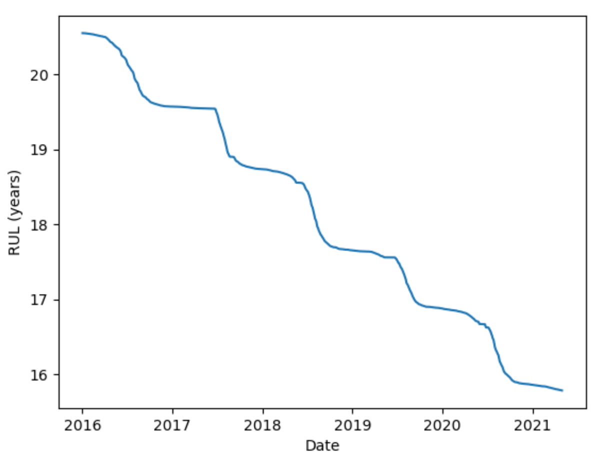

Figure 2. Transformer RUL prediction using the thermal life consumption model. The cyclic behavior is due to rapid RUL decrease during hotter summer months.

In Figure 2, a cyclical pattern is evident. In general, higher temperatures increase the speed at which the transformer insulation degrades. This can be seen in Figure 2, as the insulation's RUL decreases more rapidly in summer than in winter. Higher temperatures and loads lead to increased aging acceleration factors and a quicker decline in RUL. This model enables easy calculation of the transformer insulation's RUL as a function of ambient temperature, load, and plant-specific parameters.

3.2.1. Parameter Estimator

The parameter estimator was developed to estimate any plant-specific parameters contained within the IEEE thermal life consumption model. This estimator will enable further deployment of the thermal life consumption model in other NPPs, even when certain parameters are unknown. Certain plant-specific parameters may not be measured by the utility (e.g., ratio of load loss at specific taps) or may perhaps be more theoretical (e.g., a thermal time constant). The parameter estimator uses the known parameters, in combination with the ambient and top-oil temperatures, to form a constrained optimization problem, then solves a part of the thermal life consumption model via Eqs. 4, 5, and 6:

$$min(|(\Delta T_{TO,U} - \Delta T_{TO,i})(1 - e^{\frac{-t}{\tau_{TO}}}) + \Delta T_{TO,i} - \Delta T_{TO}|) \tag{4}$$

$$\Delta T_{TO,U} = \Delta T_{TO,R}\left[\frac{(K_U^2 R + 1)}{(R+1)}\right]^2 \tag{5}$$

$$R \geq 0 \tag{6}$$

where ΔT_{TO} is the top-oil temperature rise over the ambient temperature following a load change, $\Delta T_{TO,U}$ is the ultimate top-oil temperature rise over the ambient temperature following a load change, $\Delta T_{TO,i}$ is the initial top-oil temperature rise over the ambient temperature before a load change, $\Delta T_{TO,R}$ is the top-oil temperature over the ambient temperature at rated load, t is the time duration, τ_{TO} is the top-oil thermal time constant, K_U is the transformer load ratio between the ultimate load and the rated load, and R is the ratio of load loss at rated load to no-load loss at the tap position. In this example, because the ratio of load loss (R) is unknown, it is constrained as positive definite and then estimated via the parameter estimator algorithm. Without knowing each variable within the thermal life consumption model, it cannot be used for RUL estimations. A deeper explanation of the formulation of the thermal life consumption model itself is found in (Agarwal et al., 2014).

The estimator attempts to solve the constrained optimization problem by using Powell's method to minimize the error between the functional output and the known temperatures (M. J. D. Powell, 1964). This minimization produces an estimation of the missing parameter, in units suited to the desired thermal life consumption model. In this case, the plant-specific parameter estimated is withheld due to NPP sensitivity. However, the ability to determine unknown plant parameters can increase the IEEE thermal life consumption model's applicability to other NPPs.

3.3. IEEE DGA Diagnostic Model

The IEEE DGA diagnostic model combines two internal functions (i.e., the DGA status function and Duval triangle) and was developed using the information in (IEEE, 2019).

The DGA status function takes the gas concentrations, production rates, and transformer age, and then compares them against the alarm threshold tables given in the IEEE-2019 standard. The threshold values in these tables are based on manual measurements that may be more conservative than necessary for continuous online monitoring, since the frequency in which the manual measurements are taken is lower than for online monitoring. The DGA status function returns a value of either 1, 2, or 3, which correspond to "healthy," "watch," and "warning," respectively. "Healthy" represents gas concentrations and rates associated with what is considered a healthy state for transformers of a given age. "Watch" is a recommendation that manual samples be taken more frequently, or that online monitoring be implemented to better capture fast-moving trends or to more closely monitor gases with higher concentrations than expected. Because online monitoring is currently used for this NPP, the word "watch" is no longer strictly appropriate, yet it serves as a useful designation that more attention may be needed. The "warning" threshold indicates a recommendation that the plant be surveyed for potential faults.

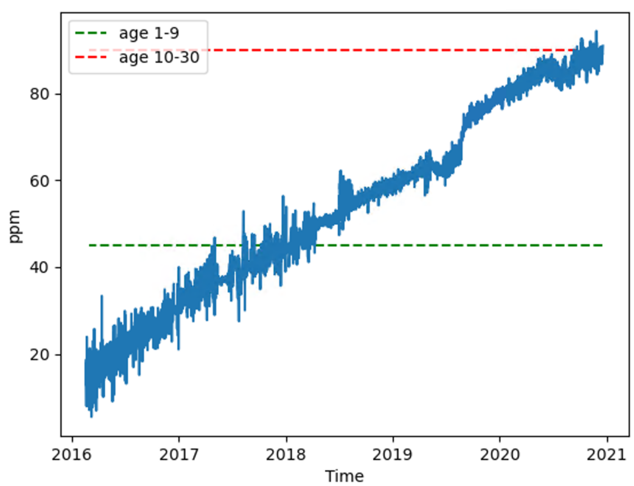

Figure 3. The methane concentration in the transformer appears to steadily increase. Alarm threshold tables given in the IEEE-2019 standard.

Once the "warning" threshold is breached due to either a high concentration of gas or an excessive gas production rate, gas

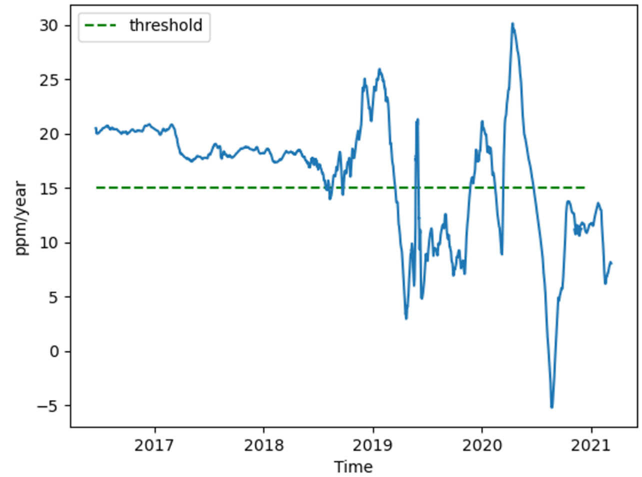

Figure 4. The methane production rate in the transformer exceeds the healthy threshold for much of the recorded period.

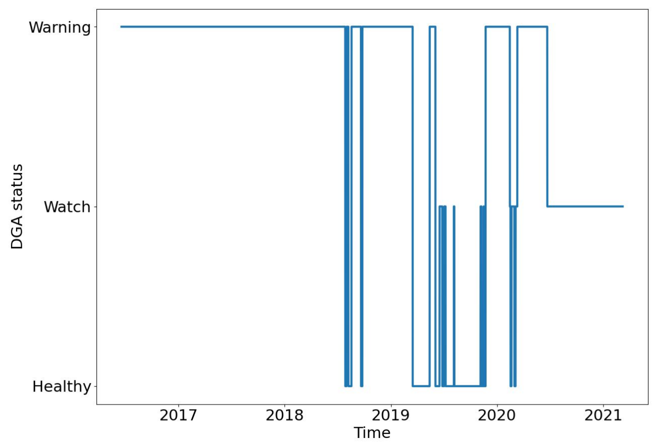

Figure 5. The transformer's DGA status contains large amounts of "warnings" due to the elevated methane production rate.

concentrations and rates are passed to the Duval triangle function. Based on the concentrations and ratios of certain gases (i.e., methane, ethane, and ethylene), the Duval triangle returns a diagnosis of the cause of the fault (Duval, 2002). The Duval triangle can differentiate from among faults such as partial discharges, electrical faults, and thermal faults, based on faults simulated in a laboratory environment. The Duval triangle functions as a lookup table. Such diagnoses give the plant maintenance team a better understanding of potential faults that may ultimately reduce transformer's service life. The Duval triangle should not be used unless a fault is known to be present, since it always returns a diagnosis, no matter what. In the case of healthy gas concentrations/rates, the diagnosis would be a false one. However, the Duval triangle is the most accurate traditional interpretation technique when compared to others such as Doernenburg ratio, IEC ratio, and Roger's ratio (Gouda, El-Hoshy, & Hassan, 2018). Figure

3 shows the concentration of methane in a transformer increasing over a 5-year period. The dotted lines signal different "warning" thresholds, depending on the transformer's age. The figure indicates that, for a transformer less than nine years old, the "warning" threshold was exceeded by mid-2017. Figure 4 shows the production rate (parts per million/year), as calculated via a moving average for the amount of methane produced in the transformer over a 4-month period. A 4- to 9-month moving average was recommended by the IEEE-2019 standard when using manual measurements. Any time the production rate of a gas exceeds the specified threshold given in the IEEE-2019 standard, the DGA status immediately changes to "warning." Figure 5 shows the expected DGA status when using the gas concentrations and rates from the transformer. Since the methane is increasing at a higher-than-advisable rate, the DGA status is "warning" (level 3) over much of the recorded data for this particular transformer. This status may fluctuate as the rate of production changes. Once the fault was flagged as a warning, the gas concentrations were sent to the Duval triangle, which diagnosed the cause as a thermal fault of under 300°C.

Overall, this diagnostic model possesses the tools to determine whether gas concentrations and production rates fall within advisable limits. Once these limits are crossed, the Duval triangle can diagnose the potential cause of the gas concentration increase, thus enabling more targeted maintenance.

3.4. IEEE DGA Prognostic Model

Built on similar tenets as the diagnostic model, the IEEE DGA prognostic model calculates the remaining time to maintenance. First, the prognostic model predicts future gas concentrations using an ARIMA model (Naim et al., 2018). The ARIMA model is useful because it only requires prior data for the particular time series to be forecasted. These concentrations are forecast into the future at an hourly time interval, until they cross the same "warning" threshold featured in the IEEE DGA diagnostic model. The forecasted feature includes the estimated value as well as the uncertainty of the parameter of interest. The remaining time until maintenance is calculated as the difference between the current time and the time at which the forecasted value crosses the "warning" threshold. The prognostic model should be used to estimate when maintenance will likely be needed, not to estimate specific faults. Diagnosing faults based on these conditions is not recommended, as the physics relating to damage and gas production were not considered when developing this data-based prognostic model. The forecasted values were estimated via an ARIMA model based on past values.

Figure 6 shows an example (using carbon monoxide [CO] data from the transformer) of forecasting into the future until the "warning" threshold is crossed. The magenta line represents the predicted extrapolation, with uncertainty bounds positioned on the upper side of the forecast. Gases do not typically leave the transformer in significant amounts unless the transformer is being actively de-gassed. Only the upper confidence interval and forecast are shown to be conservative in the estimate of when maintenance must be performed. Figure 6 shows that the CO concentration will not become an issue for this transformer for several years, since the expected forecast does not cross the "warning" threshold until 2029. The 95% confidence interval crosses earlier (i.e., in 2025). However, this is still significantly far in the future, allowing for additional monitoring before a maintenance action must be considered. This estimation should be made for each of the monitored gases.

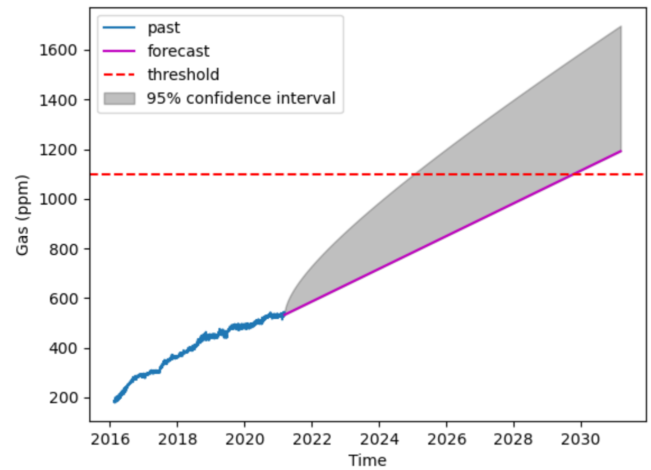

Figure 6. Forecasting of CO concentrations in the transformer. The ARIMA model estimates that the "warning" threshold will be crossed in 2029.

The prognostic model tracks and forecasts gas concentrations, enabling estimation of when maintenance or de-gassing should be performed, based on the earliest crossing of the "warning threshold." This can enable maintenance to be planned well in advance, thus introducing new cost-saving opportunities.

4. CONCLUSION

This technical brief describes four models that synergize with regard to transformer health monitoring. Using these models, the transformer's remaining time to maintenance can be estimated and potential problems diagnosed. Each of these models uses a different set of inputs (e.g., gas concentrations, temperatures, loads, and 2-Furaldehyde level) to estimate the transformer's state of health; thus, a combination of models would provide the best results. This technical brief applied each model to a singular, operating transformer to determine when maintenance may be required. Although the Chendong model and the thermal life consumption model estimated that the insulation was healthy, the diagnostic model determined that a high production rate of methane was most likely due to a thermal fault under 300°C.

Due to the tools' modularity and robustness to inputs, they can be implemented into a monitoring and diagnosis center for multiple power plants that feature similar oil-immersed transformers. The default values for each parameter within the models are plant-specific. But in the case of the IEEE thermal life consumption model, a single missing plant-specific parameter can be estimated using the parameter estimation tool, assuming that the ambient and top-oil temperature—both common measurements—are known.

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BIOGRAPHIES

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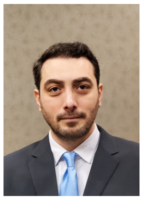

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Vivek Agarwal, Ph.D. is a senior research scientist and the technical lead of the Fission Battery Initiative. He specializes in cross-cutting applications and the advancement of inter-disciplinary research to enable resilient real-time measurement and control of process variables within the nuclear industry and other critical industries. Dr. Agarwal received a Bachelor of Engineering in Electrical Engineering from University of Madras, India in 2001; a M.S. in Electrical Engineering from the University of Tennessee, Knoxville in 2005; and a Ph.D. in Nuclear Engineering from Purdue University in 2011. He joined INL as a researcher in 2011 and has since led projects under multiple DOE programs such as the Light Water Research Sustainability project, the Nuclear Energy Enabling Technologies – Advanced Sensors and Instrumentation Program, and the Technology Transition Office. Dr. Agarwal was awarded the 2019 Presidential Early Career Award for Scientists and Engineers, as well as the 2016 Laboratory Director Early Career Achievement Award. He also received the American Nuclear Society Human Factors, Instrumentation, and Control Division's Ted Quinn Early Career Award in 2019. He has authored 80 peer-reviewed publications. He has one U.S. patent and has co-authored a book chapter. He is a member of the American Nuclear Society.