APPLICATION OF MONITORING, DIAGNOSIS, AND PROGNOSIS IN THERMAL PERFORMANCE ANALYSIS FOR NUCLEAR POWER PLANTS

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As condition-based maintenance (CBM) has risen as a new trend, there has been an active movement to apply information technology for effective implementation of CBM in power plants. This motivation is widespread in operations and maintenance, including monitoring, diagnosis, prognosis, and decision-making on asset management. Thermal efficiency analysis in nuclear power plants (NPPs) is a longstanding concern being updated with new methodologies in an advanced IT environment. It is also a prominent way to differentiate competitiveness in terms of operations and maintenance costs.

Although thermal performance tests implemented using industrial codes and standards can provide officially trustworthy results, they are essentially resource-consuming and maybe even a hind-sighted technique rather than a foresighted one, considering their periodicity. Therefore, if more accurate performance monitoring can be achieved using advanced data analysis techniques, we can expect more optimized operations and maintenance. This paper proposes a framework and describes associated methodologies for in-situ thermal performance analysis, which differs from conventional performance monitoring. The methodologies are effective for monitoring, diagnosis, and prognosis in pursuit of CBM. Our enabling techniques cover the intelligent removal of random and systematic errors, deviation detection between a best condition and a currently measured condition, degradation diagnosis using a structured knowledge base, and prognosis for decision-making about maintenance tasks. We also discuss how our new methods can be incorporated with existing performance tests. We provide guidance and directions for developers and end-users interested in in-situ thermal performance management, particularly in NPPs with large steam turbines.

KEYWORDS : Thermal Efficiency, In-situ Analysis, Condition-Based Maintenance, Turbine Cycle, Nuclear Power Plant

1. INTRODUCTION

Integrated information technology (IT) solutions for power plants are being installed not only for administrative purposes but also for plant operations and maintenance decision-making. Such a technical trend is not new or novel. Most power plants already use operator-aid solutions to facilitate operations and maintenance. However, the current trend clearly differs from conventional systems by (1) increasing data availability via massive but low-priced databases, (2) providing convenient data accessibility with advanced wired or wireless networks, and (3) promoting a reappraisal of the value of operator-aid solutions given the new big-data environment.

Given that the primary purpose of power plants is to produce electricity at a competitive price, the most typical operator-aid solutions in nuclear power plants (NPPs) is software to monitor thermal efficiency and diagnose performance degradation. A plant computer system (PCS) uses an algorithm to calculate the efficiency of a heat supply side and a power conversion side, along with performance indices associated with major components such as the reactor, steam generators, turbines, heat exchangers, pumps, and so on. The traditional algorithms embedded in PCSs calculate the performance metrics with measured signals and compare them with reference values. Performance metrics thus identify increasing or decreasing conditions from the reference values in periodic performance monitoring during day-to-day operation. An abnormal condition observed during performance monitoring or maintenance effectiveness, particularly before and after overhauls, needs to be checked using a special performance test conducted under well-ordered conditions with authorized codes and standards. The results of performance monitoring and testing initiate an engineering process to clarify the cause of deg-
radation and find appropriate maintenance activities. In conventional thermal efficiency management, periodic monitoring has focused on the preliminary detection of anomalies, and special tests have essentially determined whether such anomalies are problematic or not. The procedures for both performance monitoring and testing are provided in performance test codes (PTCs) from the American Society of Mechanical Engineers (ASME). Although several PTCs are in accordance with users’ purposes, Volumes PM, 6, and 6S are representative for evaluating overall electricity generation. PTC PM [1] addresses performance monitoring, and PTC 6 or PTS 6S [2, 3] are used for performance testing of NPPs with large steam turbines. Table 1 shows their representative features.

As Table 1 shows, performance monitoring and testing are complementary. The results analyzed by PTC 6 or 6S are reliable and officially accepted, but the performance test is a resource-consuming task. Conducting a performance test for a large steam turbine cycle requires meeting tough standards for sensor calibration, flow path isolation, and the stability of operational parameters [2, 3], which is not easy in most NPPs connected to the national grid. Despite such difficulties, performance tests are usually carried out before and after a scheduled overhaul to check the effectiveness of maintenance. While performance tests are necessary; however, strengthened performance monitoring can reduce the frequency of performance tests.

The concept of in-situ thermal performance analysis we are suggesting falls between performance monitoring and testing in terms of its purposes, measurements, and general procedures. The technical convenience and simplicity of conventional performance monitoring are inherited in the in-situ thermal performance analysis. The features of the proposed concept that distinguish it from conventional monitoring are: (1) it covers monitoring, diagnosis, prognosis, and decision-making for asset management, (2) it reduces measurement uncertainties using physical or empirical data validation models, and (3) it uses a plant simulation model in the entire analysis.

The ultimate goal of our in-situ thermal performance analysis is to fully support condition-based maintenance (CBM). CBM, sometimes called predictive maintenance, can save money by reducing time-consuming and unnecessary maintenance or testing activities and can also decrease human errors, which is vitally important for safety-critical systems in NPPs. The proposed methods can facilitate the CBM process for heat conversion cycles because the periodicity is much shorter than the progress of the usual degradation mechanism. Technical limitations in the signals coming from the sensors installed in a plant and the analysis under variable plant configurations are improved using advanced algorithms that use physical and empirical techniques. Because all the processes of in-situ thermal performance analysis should be managed on-line in real-time without an operator’s intervention, a high level of automation is required.

<table>
<thead>
<tr>
<th>Table 1. Comparison between PTC PM and PTC 6 or 6S</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Objective</strong></td>
</tr>
<tr>
<td><strong>Use</strong></td>
</tr>
<tr>
<td><strong>Measurement</strong></td>
</tr>
<tr>
<td><strong>Uncertainty of Results</strong></td>
</tr>
<tr>
<td><strong>Procedures</strong></td>
</tr>
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</table>
This paper explains the technological transition in thermal performance management, specifically the conceptual framework for in-situ thermal performance analysis highlighting the contribution of CBM. We also comprehensively explain several enabling technologies needed to implement the suggested framework. Even though we focus on large scale steam turbine cycles in NPPs, we expect our ideas to be shared with other power cycles.

2. FRAMEWORK FOR IN-SITU THERMAL PERFORMANCE ANALYSIS

The framework for thermal performance management in NPPs has already been established by industrial codes and standards such as ASME PTCs, Heat Exchange Institute standards, and so on. These codes were developed to provide guidelines for performance monitoring and testing. Performance tests are a series of calculations used to determine heat balance and find the performance indices at cycle or component levels. To guarantee their accuracy, tests must be conducted under strictly controlled conditions with qualified sensors. Depending on the purpose of the tests or upon a user’s request, a performance test can be followed by a full-scope procedure [2] or a simplified procedure [3]. On the other hand, the procedure for performance monitoring [1] focuses on surveillance of trends in a few significant performance indices and is much less stringent than performance testing. The present codes and standards are not relevant to in-situ thermal performance analysis aiming to effectively support CBM. This chapter describes the in-situ thermal performance analysis and how it compensates for the weaknesses of conventional performance monitoring and testing.

2.1 Terminology

This section defines terms related to in-situ thermal performance analysis to clarify their technical distinctiveness. Most of these terms are common, but we refine their definitions here to distinguish our use of them from their conventional uses.

Performance Testing vs. Performance Monitoring

Performance monitoring aims to detect variations in indices for cycles or components by periodic calculations, and performance tests are conducted in highly controlled conditions to calculate accurate and quantitative performance indices. The codes and standards for periodic surveillance are limited to calculating significant performance indices and monitoring their trends compared with reference indices.

The main benefit of performance monitoring is expected to be its short periodicity. Periodic checking permits observation of malfunctions in a timely manner because frequent performance testing is impractical because of its pre-requisites. Nonetheless, performance monitoring is less accurate than performance testing. In other words, the detection of performance variation is important in performance monitoring, whereas the absolute values of performance indices are significant in performance testing.

The in-situ thermal performance analysis we describe aims to achieve the accuracy and coverage of performance testing with the periodicity of performance monitoring. Therefore, the conventional codes and standards cannot be directly applied to in-situ thermal performance analysis. Nonetheless, those conventional codes and standards remain the technical basis for in-situ analysis.

Aging vs. Degradation

The meaning of aging and degradation, which both represent the decrease of an intended functionality, will sometimes be shared and sometimes distinguished in this paper. Aging is defined as the natural decrease of thermal performance over time. Most components go through aging due to various causes such as mechanical, electrical, and chemical stressors. Aging is, therefore, both inevitable and irreversible. On the other hand, degradation is defined as a performance decrease caused by factors that can be removed or corrected to restore the degraded component to its original functionality. Aging caused by degradation is not recovered, so a kind of hysteresis can occur in the functionality.

Controllable vs. Uncontrollable Loss

Regardless of theoretical or practical controllability, controllable loss is defined as loss due to degradation, and uncontrollable loss is caused by aging, which requires replacement or cleaning of a component to return it to a normal condition. The sources of controllable loss are incorrect settings of operating parameters categorized as (1) less than optimized operating conditions, (2) undesirable site conditions, and (3) a faulty flowpath causing an internal or external leak. For example, a controllable loss could be derated due to a poor condenser vacuum. Usually when a condenser vacuum deviates from its design condition, plant efficiency decreases. In this case, operators can use additional vacuum pumps or coolant circulation pumps to regulate the condenser vacuum. If operators fail to control the pumps, the controllable loss falls under less than optimized operating parameters. If such degradation is caused purely by the temperature of the ultimate heat sink, it could be considered an undesirable site condition. The poor condenser vacuum might also be caused by abnormal venting or emergency drains, which would make it a flowpath fault.

Achievable vs. Actual Performance

Fig. 1 shows a schematic diagram of plant efficiency under various operating conditions [4]. Fig. 1 also explains plant efficiency in terms of the combination of uncontrollable and controllable losses. The upper curve represents the achievable efficiency of a power plant without aging or degradation. Usually, the design heat balances provided by a vendor or the heat balance analyzed from
of controllable loss, less than optimized operating conditions and flowpath faults are eliminated by test pre-requisites. Undesirable site conditions are compensated using correction curves. The corrected efficiency can now be compared with the rated efficiency to observe whether the uncontrollable loss is acceptable. It should be noted that corrected is valid only when the differences between Condition_{ref} and Condition_{mea} are within certain narrow bands [4]. Beyond those limits, correction is not officially guaranteed. Because plant conditions during daily operation are likely to violate those narrow limits, the comparison between rated and corrected is irrelevant for in-situ thermal performance analysis.

Even if the comparison between a rated and corrected efficiency is recommended in a performance test, an other approach is possible to detect uncontrollable loss. Expected is defined as the point as indicating a plant’s condition with controllable loss only. In other words, the deviation between an expected and a measured efficiency also presents only uncontrollable loss, which is the same consequence as the conventional approach. The feasibility of this idea depends on how accurately we can simulate expected efficiency using component design parameters and operational parameters. Because a flexible expected value can be produced as long as a simulation model is qualified and supported, this approach is preferable for in-situ analysis.

2.2 Framework

The framework for the in-situ thermal performance analysis follows a series of supervision loops suggested by Isermann [5]. They are composed of fault detection, diagnosis, evaluation, and decision. Fig. 2 characterizes the framework for in-situ thermal performance management.
2.2.1 Monitoring module

The monitoring module calculates the measured and expected performances and compares them to identify the presence of uncontrollable loss. Uncontrollable loss is detected when deviation between the measured and expected performances becomes unacceptable.

Implementing this module raises two technical issues. The first is how to accurately calculate an expected performance. The expected performance is determined by calculating the heat balance for a clean and new power system considering all types of controllable losses. Clean and new means all components are in the condition guaranteed by vendors or measured in an acceptance test. Coping with controllable losses requires automatic data acquisition of parameters corresponding to controllable losses. For instance, the following list belongs to the parameters representing controllable losses in NPPs: steam conditions at steam generator outlets; the ultimate heat sink’s condition; makeup water condition; and flowpath valve arrangement. In summary, the inputs needed to calculate an expected performance are new and clean components and the parameter values representing controllable losses. The output is the expected heat balance and performance indices under those inputs. For credible estimation, we use a professional toolbox to simulate a heat balance [6-12]. Even though the expected performance can be calculated by simulation toolboxes, it should be noted that the accuracy of the expected performance depends strongly on engineers’ expertise in developing heat balance models. The heat balance model is also important in the diagnosis and prognosis modules, which will be explained in the next sections.

The second issue is how to accurately calculate a measured performance using uncalibrated sensors installed in the field. Because the proposed framework uses sensors installed in a power plant, signal validation is required. Furthermore, because all the processes should be performed on-line, signal validation should be carried out without an operator’s intervention. This step is called data reconciliation in Fig. 2. The purpose of data reconciliation is to detect signal anomalies and replace them with appropriate values, which is different from the management of systematic and random errors suggested by ASME PTCs [13]. We define signal anomaly as a condition that is physically impossible such that a heat balance calculation fails or provides physically unreasonable results if the raw data are used without any correction. Signal anomalies can be caused by systematic errors or...
random errors. Pressure measurements at a low-pressure turbine are likely to be anomalies caused by fluctuating vacuum conditions, for example. Such anomalies result in meaningless performance indices such as greater than 100% turbine or pump efficiency, which should make operators doubt the reliability of the whole solution. Another specific issue in NPPs is the estimation of feedwater flow rate [14-16]. The most significant parameter in calculating turbine cycle performance is feedwater or condensate flow rate, and it is likely to be overestimated due to fouling of the flow sensing element. Signal anomalies must thus be distinguished from conditions caused by the system’s aging or degradation. The role of data reconciliation should therefore be minimal so it does not eliminate the effects of aging or degradation. Limiting data reconciliation can be achieved using the periodic update scheme for plant models, which will be described in the next chapter.

After the expected and measured performance indices are produced, the detection of uncontrollable loss is the final step of the monitoring module. Monitoring of the residual, that is, the deviation between the performance indices of the measured and expected heat balances, can provide symptoms associated with uncontrollable loss as promptly as possible. This step is called early warning in this framework. The early warning can bring various uncertainties because it is the final calculation merged by all the parameters’ uncertainty, so it can be misinterpreted by operators. Therefore, statistical methods should be used to cope with the uncertain factors for trustworthy decision-making.

### 2.2.2 Diagnosis module

The diagnosis module begins working when the monitoring module warns that unexpected residuals in the performance indices are observed in the early warning annunciator. The residual represents change from a reference condition due to uncontrollable loss. The purpose of the diagnosis module is to address and determine the severity of the root cause of uncontrollable loss.

In this case, two challenges emerge: One is from the viewpoint of epistemic uncertainty. The diagnosis for thermal efficiency management is usually knowledge-based and represents the relationship between intrinsic causes and superficial consequences. In other words, a kind of supervised learning process is a pre-requisite. The knowledge base can be accumulated by simulation or historical records. However, no matter how we accumulate historical knowledge, the knowledge base itself could be incomplete for unforeseen causes and consequences. The closed loop of the Rankine cycle in NPPs makes it more difficult to find root causes because the effect of the fault in a component propagates to other components, so that any component could show abnormal performance indices [17, 18], which can easily lead operators to a wrong decision. Furthermore, the simultaneous occurrence of multiple causes makes it difficult to diagnose reliably [19]. The second challenge is the possibility of aleatory uncertainty, in other words, signal accuracy. Even if signals are qualified through data reconciliation, their accuracy is still doubtful for diagnostic purposes because data reconciliation does not estimate a true value but merely replaces damaged signals with an approximate value. Therefore, we have to indicate the resolution limits of the installed sensors. The sensors for thermal efficiency management provide only thermal-hydraulic properties such as pressure, temperature, flow rate, level, and so on. These sensors might not observe material-related degradation or be able to isolate a specific root cause.

Several diagnosis methodologies, from an expert system to advanced artificial intelligence, have been proposed, but the aforementioned limitations still hold for industrial applications. The methodology proposed by ASME is a type of expert system such as cycle interrelations or a logic tree [1]. Cotton [20] suggested a diagnosis matrix for large steam turbines. Both methodologies are qualitative approaches unrelated to the turbine cycles in NPPs. Research and outcomes for performance diagnosis in process industries are summarized in Table 2. In addition to the methodologies in Table 2, auto-associative kernel regression; auto-associative neural networks; an auto-regressive multivariate state estimation technique; neural expert systems; neuro-fuzzy systems; and genetic

<table>
<thead>
<tr>
<th>Expert system</th>
<th>Fuzzy</th>
<th>PCA, ICA</th>
<th>Multivariate Regression</th>
<th>ANN</th>
<th>SVM</th>
</tr>
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<tbody>
<tr>
<td>[22]</td>
<td>[19], [23], [24], [25], [26]</td>
<td>[27], [28]</td>
<td>[18]</td>
<td>[29], [30], [31], [32]</td>
<td>[21], [33], [34]</td>
</tr>
</tbody>
</table>

(ANN: Artificial Neural Networks, ICA: Independent Component Analysis, PCA: Principal Component Analysis, SVM: Support Vector Machine)

1The numbers in Table 2 are reference numbers.
algorithms have also been suggested [21]. Most of the methodologies are classification tools, which means they are unable to address unforeseen situations. Their accuracy and robustness differ depending on their pre-processing methods to reduce dimensions, transfer domains, or eliminate noise. Some of them focus on the degradation mode of a specific component, and others try to find the component causing overall performance degradation.

Several authors have attempted to infer degradation causes and their severity using quantitative and qualitative methods [17-19, 22]. However, no single method has fully overcome the limitations and showed satisfactory performance in field tests. From these experiences, we decided that for the thermal analysis diagnosis module: 1) the knowledge base should be updated periodically to cover unforeseen faults. A clustering tool is therefore necessary in order to distinguish a new case from the learned cases; 2) multiple algorithms, including expert judgment to determine root causes, should be provided in parallel; 3) system walkdown and inspection using advanced sensors should be used for more confident diagnoses.

2.2.3 Prognosis module

The prognosis module forecasts the pattern of uncontrollable loss for future operating conditions. The pattern is ultimately used to predict accumulated electric loss during a certain interval to compare the cost–benefit for specific maintenance tasks to improve asset management.

Three categories of methodologies have been suggested in reliability engineering depending on the information available for degradation modeling: 1) failure-data based prognosis, 2) stress-based prognosis, and 3) effect-based prognosis [35]. Because the failure-data based approach uses only generic data from industrial experience, it cannot benefit from condition monitoring. The stress-based approach makes a better prognosis model, but it still estimates approximated states of uncontrollable loss by observing external environmental conditions. Furthermore, it is not easy to figure out the relationship between many stressors and uncontrollable loss. Effect-based prognosis characterizes the lifetime of a specific unit or system operating in its specific condition [35]. Weibull analysis, the proportional hazards model, physics of failure models, regression analysis, a Markov chain-based model, LEAP-Frog, the particle filter model, the general path model, and the shock model have all been suggested as prognosis methodologies [36]. However, no accepted standard guarantees the performance of any of them.

The purpose of the prognosis module is to analyze the remaining useful lifetime below a certain probabilistic failure limit. As long as the failure limit is reasonably converted to an allowable limit in terms of thermal efficiency, the prognostics in reliability engineering can be applied.

2.2.4 Decision-making module

The purpose of the decision-making module is to provide cost–benefit analysis for maintenance tasks by integrating information from the diagnosis and prognosis modules. Given the results of the diagnosis and prognosis modules, the choice may be to promptly stop for maintenance or to continue operation until a scheduled overhaul with or without a change in operating parameters to compensate for electric loss (Fig. 3). The diagnosis module aims at providing significant causes for aging or degradation and inducing relevant maintenance tasks, which can affect the cost of the first choice. Meanwhile, the prognosis module provides the expected risk and proposes continuous operation if the risk is less than the benefit of maintenance. At this time, some operating parameters can be changed to alleviate electric loss.

The options that can appear in the decision-making
module are expressed in Fig. 4, where the vertical axis represents a loss of electric output. Case A, corresponding to the first choice, stops the plant for immediate maintenance followed by a plant restart. When a plant shuts down, the lost electricity that should be considered is the full capacity. However, uncertainty in calculating the expected cost for maintenance remains because the maintenance strategy determined by the diagnosis module might be incorrect.

Cases B and C correspond to the second choice. Case B depicts continued operation with changed controllable loss, which can temporarily reduce lost electricity, but a close examination is required to analyze whether such change accelerates aging or degradation, such as, for instance, structural reliability. Case C shows a pattern of continuous operation without specific maintenance tasks. Cases B and C save the costs associated with maintenance because maintenance tasks are not executed, but the saved costs must be less than the expected loss of electricity. To estimate the cost for power loss in both cases, it should be noted that the slope of Cases B and C can have uncertainty.

The decision-making module provides information for end users to determine the best decision by comparing the expected costs, including the uncertainties of both diagnosis and prognosis, as explained above. However, the calculation presented in Fig. 4 was solely conducted from the viewpoint of power plants’ thermal efficiency. The effects of reliability problems that could occur in the materials when degraded performance is maintained have been excluded from consideration. Therefore, making the final conclusion after review with experts in other areas is desirable.

3. ENABLING TECHNIQUES FOR ADVANCED THERMAL EFFICIENCY MANAGEMENT

Many methodologies for performance monitoring can be borrowed from performance testing. Therefore, this chapter describes unique methodologies for implementing the framework of on-line thermal efficiency management discussed in Chapter II.

3.1 Data Reconciliation

Data reconciliation is a special branch of data validation that replaces in advance any data that could cause noticeable problems in calculating the heat balance or performance indices. The range check is an example of data validation. In this method, a range in which certain data are meaningful is determined in advance, and any data that exceed that value are replaced by predetermined values. Ranges can be determined according to physical properties or operational characteristics. However, because the data are replaced by predetermined alternative values regardless of the value of the surrounding variables or the operational state of the power plant, mass and energy conservation might still be violated in calculating the heat balance. Data reconciliation considers that shortcoming.

![Fig. 4. Comparison of Options in the Decision-making Module](image)

Table 3. Comparison of Physical and Empirical Models

<table>
<thead>
<tr>
<th>Physical Model</th>
<th>Empirical Model</th>
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<tbody>
<tr>
<td>• White-box model</td>
<td>• Black-box model</td>
</tr>
<tr>
<td>• Calculation based on the first principles of physics, thermo-hydraulics, material science, etc., so more strict in terms of mass and energy conservation</td>
<td>• Prediction based on the previous dataset accumulated during sound operation</td>
</tr>
<tr>
<td>• Possible to predict unforeseen states</td>
<td>• Impossible to be implemented before plant operation</td>
</tr>
<tr>
<td>• A model is hard to develop and limits system customization</td>
<td>• Models are easy to generate with high customization flexibility</td>
</tr>
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</table>
Data reconciliation is performed before calculating a measured/expected heat balance using a data snapshot. Fig. 5 illustrates the information flow in the monitoring module. Once a set of raw signals is prepared, the random errors in those signals are alleviated by averaging. Systematic errors need to be handled differently. First, the expected values are obtained from models that show the normal states of the power plant. Those models are largely divided into physical models based on first principles and empirical models based on prior data from the power plant. To benefit from diverse algorithms and compensate for the weakness of other techniques, we suggest data fusion from two or more data reconciliation techniques. Fig. 5 explains how to merge the results from a physical model and an empirical model to generate final datasets. Table 3 summarizes the pros and cons of both models [1].

Although empirical models cannot be called data reconciliation in the strict sense because they cannot be guaranteed to accurately conserve mass and energy, they are included as data reconciliation in this study because they flexibly reflect power plant operating conditions. Whereas physical models use mass and energy conservation equations and various first principles to create an expected heat balance, empirical models use only the dataset previously accumulated while a plant was operating without uncontrollable loss [37-39]. For example, various linear/non-linear regression analyses, kernel regressions, and artificial neural networks have been successfully applied in various fields. If the final value made through these complicated stages shows a difference larger than the set point from the measured value, the measured value will be replaced by the final value.

One physical model we used was a simulation model that can be also applied to calculate expected heat balances. Data reconciliation based on physical models was first proposed a long time ago [40]. When we applied a conventional technique to the Rankine cycles of power
plants, we found the following difficulties: (i) Huge matrix for a full scope plant model, (ii) Nonlinear Jacobian matrix caused by enthalpy calculation, and (iii) Lack of redundant sensors. These difficulties can be practically resolved by iterative simulations, as published and applied to power plants [41].

The results from physical and empirical models can be different. Those cases require an appropriate technique to determine a final dataset. Sometimes in practical field applications, it is also necessary to manually override certain values, which can be part of data reconciliation.

The model that provides alternative values in data reconciliation is not the clean and new model mentioned in Fig 1. Because data reconciliation must be meaningful for models reflecting performance degradation to provide alternative values, it should be able to reflect the characteristics of the past most similar to current power plant conditions. Because alternative values eventually come from power plant conditions that are simulated by physical or empirical models, periodic updates of models are essential to conform to the purpose of data reconciliation. Therefore, if data reconciliation replaces many variables simultaneously, model reliability becomes uncertain, and a process to update model should be started.

An important variable in managing NPPs' thermal efficiency is main feedwater flow rates. Data reconciliation methods for main feedwater flow rates have long been studied. Here, we consider the importance of measuring main feedwater flow rates as an example of data reconciliation.

In most pressurized water reactors (PWRs), thermal reactor power is estimated using secondary system calorimetric calculations that rely on measurements of the feedwater flow rate. But it is essential to actually measure the feedwater flow rate in PWRs. Venturi flow meters measure the feedwater flow rate in most PWRs. However over time, corrosion product builds up near the meter orifice and induces measurement drift. These fouling phenomena increase the pressure drop across the meter and cause an overestimation of the feedwater flow rate. Whenever the calorimetric calculation is carried out during an operating fuel cycle, the thermal reactor power must be reduced to match the false feedwater flow rate measured by the Venturi meter, which causes NPPs to operate at lower-than-planned power levels.

According to the former 10CFR50 Appendix K for the emergency core cooling system (ECCS) evaluation model, the original thermal power margin required to evaluate an ECCS was 2%, irrespective of the demonstrated instrument accuracy. A revision to 10CFR50 Appendix K was made to allow a margin equal to the actual instrument accuracy. The revision of the 10CFR50 Appendix K encourages the use of advanced feedwater flow instruments in PWRs. Currently, ultrasonic flow meters are considered a competitive alternative to Venturi meters because they do not have fouling problems. However, ultrasonic flow meters are difficult to install in existing NPPs.

Fouling of the Venturi meter is the most significant contributor to the derating of the power level, up to 3% of full power in some cases [42]. The most common way of resolving this problem is to inspect and clean the Venturi meters every fuel cycle, but corrosion deposits near the orifice can appear as small as one month. Therefore, several on-line monitoring techniques have been presented to address the problem [14-16].

In this paper, we introduce on-line monitoring techniques for the feedwater flow rate. There are generally two approaches to estimating the feedwater flow rate. One is to use an analytical and mechanistic model and the other is to use data-based modeling that depends on the measured values. Data-based modeling, such as artificial intelligence, is preferred because it can model complicated processes that are difficult to describe using analytical and mechanistic models. Therefore, data-based models have been widely attempted, including the following three.

The first method is a fuzzy inference system (FIS) [14]. The FIS is constructed from a collection of fuzzy if–then rules. The FIS combines linguistic and numerical information (mainly input–output data pairs). Linguistic information can be directly incorporated, but the numerical information must be incorporated by training the FIS to match the target input–output data pairs. The FIS is trained using both the genetic algorithm and the least-squares method.

Second, Na et al. [14] presented a support vector regression (SVR) to estimate the feedwater flow rate. Support vector machines (SVMs) have generally been applied to function classification problems. However, with the introduction of Vapnik’s ε-insensitive loss function, SVMs have been extended and widely used to solve nonlinear regression estimation problems. The SVR maps the input data into a high-dimensional feature space in which the linear regression is then carried out.

Third, a group method of data handling (GMDH) model [16] was developed for soft-sensing the feedwater flow rate of a PWR. The GMDH algorithm can generally find interrelations in data to improve precision accuracy and select the optimal structure for the model or network. The GMDH algorithm uses a data structure similar to that of multiple regression models. The acquired data are usually divided into three subsets: a training data set, a checking data set, and a test data set. The GMDH model cross-validates itself to prevent over-fitting and maintains model regularization. The measured feedwater values are monitored using a sequential probability ratio test (SPRT).

Those three algorithms were confirmed using real plant startup data from the Hanbit Nuclear Power Plant Unit 3. The data consisted of signals measured from the

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The data-based models have several sources of uncertainty in their predicted values: the selection of the training data; model structure (including complexity); and noise in the input and output variables. Statistical uncertainty analysis generates many bootstrap samples for training and checking data sets initially and retrains the model parameters on each bootstrap sample. After repetitive sampling and training, the values predicted by the data-based models provide a distribution. That distribution is then used to calculate the prediction intervals.

To calculate the prediction intervals, 100 GMDH models were developed from 100 bootstrap sample sets. Fig. 7 shows the actual feedwater flow rate and the prediction intervals of the GMDH model. The prediction intervals are shown better in the partly enlarged graph. The actual feedwater flow rate was covered by the up-

Table 4. Performance of the Data-based Models

<table>
<thead>
<tr>
<th>Model</th>
<th>Data type</th>
<th>RMS error (%)</th>
<th>Relative maximum error (%)</th>
<th>Number of data points</th>
</tr>
</thead>
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<td>2.6978</td>
<td>1000</td>
</tr>
<tr>
<td></td>
<td>Verification data</td>
<td>0.1408</td>
<td>2.6978</td>
<td>1800</td>
</tr>
<tr>
<td></td>
<td>Test data</td>
<td>0.0581</td>
<td>0.4098</td>
<td>201</td>
</tr>
<tr>
<td>FIS</td>
<td>Training data</td>
<td>0.1018</td>
<td>1.2092</td>
<td>1000</td>
</tr>
<tr>
<td></td>
<td>Verification data</td>
<td>0.0838</td>
<td>1.2092</td>
<td>1800</td>
</tr>
<tr>
<td></td>
<td>Test data</td>
<td>0.3181</td>
<td>3.7025</td>
<td>201</td>
</tr>
<tr>
<td>SVR</td>
<td>Training data</td>
<td>0.2105</td>
<td>1.4278</td>
<td>1000</td>
</tr>
<tr>
<td></td>
<td>Verification data</td>
<td>0.1896</td>
<td>1.4278</td>
<td>1800</td>
</tr>
<tr>
<td></td>
<td>Test data</td>
<td>0.2085</td>
<td>1.2497</td>
<td>201</td>
</tr>
</tbody>
</table>
per and lower bounds determined by the statistical uncertainty method. At only one data point among 201 test data points did the actual feedwater flow rate exceed the predicted interval, indicating 99.5% coverage. Therefore, we expect that the data-based model can be applied successfully to validate and monitor existing feedwater flow meters.

3.2 Uncontrollable Loss Detection

Even though data reconciliation and uncontrollable loss detection look completely different, they are exactly the same in that both of them detect deviations between a measured value and an expected (or reference) value. In uncontrollable loss detection, measured values (where we are) correspond to performance indices obtained through heat balance calculations using measured data and coordinated data; expected values (where we should be) are performance indices calculated from clean and new models. All the performance indices observed in this step correspond to the key parameters in the diagnosis table that will be explained in the next section.

The process of uncontrollable loss detection focuses on time-series anomalies for an individual parameter. In other words, considering the statistical uncertainty contained in individual parameters, this process checks for any statistically significant deviation between the measured performance index and the expected performance index. Well-known examples of this method are sequential tests [46] and statistical quality control (SQC) charts [44]. SQC charts such as the Shewhart chart or Cumulative-Sum chart can track various behaviors in a single parameter and expose the hidden characteristics of plant processes by pattern types. As explained in the next section, methodologies are necessary to identify increases or decreases in variables. SPRT and SQC can also be used for this purpose.

Commercial products for uncontrollable loss detection are currently being sold [45-47]. In addition to study papers, those products can identify operation principles or technical methodologies from multiple patents [48-52].

3.3 Diagnosis Tables

Although diagnosis methods for thermal efficiency management have been extensively proposed, each of them had application limitations in terms of accuracy, credibility, or practicality. Even though ASME PTCs recommend diagnosis procedures, plant engineers struggle to develop customized methods that can take their specific plant conditions into account. In Chapter II, we mentioned the unavoidable limitations of our on-line diagnosis module. Although plant engineers want to be able to diagnose unforeseen degradation modes, the current systems do not effectively cover even the malfunctions commonly known and experienced.

In this paper, we call the knowledge-base containing the causes and consequences of thermal efficiency degradation a diagnosis table. The consequence is observed by monitoring the key parameters in the diagnosis table. We assume a root cause can be determined by observing the unique combination of changes (increasing, decreasing, or staying the same) in key parameters. As an example, Table 5 summarizes the changes of key parameters for diagnosing aging in high pressure turbines in a Rankine cycle [18]. The maintenance required is determined through this table by checking the area changes of each turbine stage. As depicted, the area of the first stage of the HP turbine might decrease when the throttle flow and first stage pressure decrease, which thus decreases the efficiency of the HP turbine. Thus, we can suspect deposit and peening at the first stage of the HP turbine.

In the same way, it is possible to diagnose performance degradation in heat exchangers. Table 6 and 7 show the diagnosis tables for a condenser and a feedwater heater [22].

The diagnosis tables presented in Tables 5, 6, and 7 are not in their complete forms because they will likely vary a little depending on power plant structures, and they can be expanded to other instruments with similar methods. In most cases, diagnosis tables can be analyzed using the professional simulation toolbox mentioned in section II.1. The professional simulation toolbox provides the degrees of changes in key parameters according to

| Table 5. Diagnosis Table for Steam Turbines |

<table>
<thead>
<tr>
<th>Cause</th>
<th>Key Parameter</th>
<th>Throttle Flow</th>
<th>P_t</th>
<th>P_1st</th>
<th>...</th>
<th>HP EFF.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area at 1st Stage Increased (SPE)</td>
<td>↑</td>
<td>-</td>
<td>↑</td>
<td></td>
<td></td>
<td>↓</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Area at 1st Stage Decreased</td>
<td>↓</td>
<td>-</td>
<td>↓</td>
<td></td>
<td></td>
<td>↓</td>
</tr>
<tr>
<td>(Deposits / peening)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(P_t: Pressure at Throttle Valve Inlet, P_1st: First Stage Pressure, HP EFF.: Efficiency of High Pressure Turbine, SPE: Solid Particle Erosion)
is not always the case. Therefore, the effects of multiple causes should be added to the diagnosis table as separate phenomena. The second issue is that ad hoc sensors are unlikely to be used because of the characteristics of in-situ analysis. Therefore, in some cases, performance degradation modes cannot be identified with sufficient resolution using the signals collected from the limited

![Fig. 8. Flowchart of Diagnosis](image)

The severity of each cause. Therefore, if the degrees of change in key parameters are known, the severity of each cause can be predicted by inverse calculation.

Fig. 8 shows the procedure for using the diagnosis tables. The SPRT or SQC used for uncontrollable loss detection enables judgment about the increases or decreases in key parameters presented in Tables 5, 6, and 7. If these observations match each other, the causes of degradation and actions to be taken can be identified. If they do not, we continue monitoring the key parameters. If the types of parameters registered in a diagnosis table are not enough to determine a specific cause, we can add more parameters to create another unique combination. The parameters to be added could be measured signals or calculated parameters.

Three issues might come up in using the diagnosis tables. The first one is diagnoses when multiple causes occur simultaneously. Although some performance degradation factors are unlikely to be left unattended, such as serious leakages, performance degradation factors that progress slowly, such as tube fouling, are quite likely to cause other performance degradation factors. Although the effects of certain causes occurring simultaneously can be predicted based on linear combinations, which

<table>
<thead>
<tr>
<th>Cause</th>
<th>Key Parameter</th>
<th>TTD</th>
<th>DCA</th>
<th>(\Delta T_{\text{tube}})</th>
<th>...</th>
<th>(T_{\text{subcooling}})</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Drain Level</td>
<td>↑</td>
<td>↓</td>
<td>↓</td>
<td>↑</td>
<td>↑</td>
<td>↑</td>
</tr>
<tr>
<td>Low Shell Pressure</td>
<td>↓</td>
<td>↓</td>
<td>↓</td>
<td>↑</td>
<td>↑</td>
<td>↓</td>
</tr>
<tr>
<td>Tube Leakage</td>
<td>↓</td>
<td>↑</td>
<td>↑</td>
<td>↑</td>
<td>↑</td>
<td>↑</td>
</tr>
</tbody>
</table>

(DCA: Drain Cooler Approach, \(\Delta T_{\text{tube}}\): \(T_{\text{tube_out}} - T_{\text{tube_in}}\), \(T_{\text{subcooling}}\): Difference between Saturated Temperature at Condenser Pressure and Temperature on Hotwell side of Condenser)
number of sensors installed. In such cases, providing several suspected causes simultaneously using weighting or credibility is expected to improve decision-making as the second-best plan. Finally, because the diagnosis table is based on known degradation phenomena, it is not classification through supervised learning. Therefore, new degradation phenomena cannot be accurately judged. In this respect, clustering through unsupervised learning is necessary. In the case of clustering, the fact that combinations of key parameters are neither normal, nor consequences of any cause in the diagnosis table, should be judged and made clear to the user. Although many studies on clustering have been conducted, a few power plant application can be used in thermal efficiency analysis [53].

3.4 Prognosis Using Linear Model

We introduced the concept of risk in forecasting the trend of uncontrollable loss by the next period. In engineering, risk is defined as the multiplication of likelihood and the consequence of a certain event. For thermal efficiency management, consequence is regarded as the loss of electric output or decreased efficiency, and likelihood represents the uncertainty level of a prognosis result.

The targets of prognosis can reasonably be shared with the key parameters defined in the diagnosis tables. The patterns of the key parameters, their increasing or decreasing status, can be stretched to the next scheduled overhaul in the prognosis module to calculate the accumulated loss of electric output using expected heat balances.

In this study, we used linear regression models to develop theories because they are the most intuitive to use. Linear regression can also determine whether parameters have increased, decreased, or stayed the same. Fig. 9 shows our overall prognosis scheme based on linear regression, and the equations for simple linear regression are shown below. Prognosis is predicting the degree of performance degradation should the equipment be continuously operated until the next overhaul or thereafter without correcting performance degradation factors. Therefore, in Fig 9, \( t=t_0 \) is regarded as the point at which abnormal conditions were detected by uncontrollable loss detection, and the present point is determined as a point \( t=t_1 \) between \( t=t_c \) and \( t=t_M \), which is the point at which the next overhaul begins. Here, because the linear model has been regarded as a prognosis model, future key parameter values can be predicted using the key parameter values observed between \( t=t_0 \) and \( t_c \).

At \( t=t_i \) for a key parameter, \( k, \overline{y}_{ki} \) estimated from the linear regression is

\[
\overline{y}_{ki} = \hat{a} + \hat{b} t_i
\]

where \( t \) is time,
\( \hat{a} \) is an intercept,
\( \hat{b} \) is the slope of the line.

The confidence interval given by the specified confidence level is

\[
y_{ki}^n = \overline{y}_{ki} \pm t_{(1-a),n-2} \cdot s \sqrt{\frac{1 + (t_i-t)^2}{n \sum (t_i - \overline{y}_i)^2}}
\]

where \( s \) is sample variance,
\( n \) is sample size. This is the number of data points in the period from \( t_i \) when degradation began to \( t_n \) when degradation was detected,
\( m \) is min or max. If \( m \) is min, choose ‘−’, and if \( m \) is max, choose ‘+’.
\( t_{(1-a)} \) is the critical value of t-distribution at confidence level \((1-a)\).

Estimated values of electric losses can be simulated using the estimated values of key parameters obtained through the prognosis. Equations (3) and (4) provide the electric losses expected to occur from the beginning of degradation to the overhaul as a range considering the uncertainty of the prognosis.

\[
P_{\text{loss}}^m = \sum_{i=t_0}^{t_n} \left[ f(y_{1i}, y_{2i}, \cdots, y_{ki}) \times d \right]
\]

\[
P_{\text{mean loss}} = \sum_{i=t_0}^{t_n} \left[ f(\overline{y}_{1i}, \overline{y}_{2i}, \cdots, \overline{y}_{ki}) \times d \right]
\]

where \( P_{\text{loss}} \) is electric loss [MWd],
\( f \) is the day-averaged power loss under key parameters using heat balance simulation [MW],
\( d \) is unit time [day].

The outputs of the expected electric loss, \( P_{\text{loss}} \) have the intervals \((P_{\text{loss}}, P_{\text{mean loss}})\) considering the uncertainty of the degradation estimation. This result will be provided for cost–benefit analysis for final decision-making, as described in the next section.
4. CONCLUSIONS AND RECOMMENDATIONS

This paper has suggested a framework and enabling techniques for in-situ thermal efficiency management, which is based on the industrial codes and standards of conventional performance tests, but requires additional methods to implement as in-situ analysis which is an online, automated, and intelligent procedure. Specifically, we described the detection of performance degradation and techniques for diagnosis, prognosis, and decision-making modules helpful for operator policymaking.

The framework and methods proposed here are already being applied in many Korean NPPs and fossil-fueled power plants. The algorithm of methodologies discussed is generically applicable, but some cases need to be adjusted according to the characteristics of individual plants. Although diverse methods were mentioned in this paper, the most important factor for the accuracy of efficiency management is including a sufficient number of high-quality sensors. Many enabling techniques are eventually required to enhance the quality of the data collected from sensors. Therefore, to effectively manage thermal efficiency with limited resources, enhancing the quality of the sensors and installing redundant sensors at important positions is recommended first. Fundamental technologies are the next most important factor, including models that can calculate the heat balance of power plants according to operating conditions. Although turbine cycle vendors currently provide heat balance diagrams for major loads on utilities, there are difficulties in managing utilities’ thermal efficiency because the heat balance simulation models used to prepare the heat balance diagrams are not disclosed. Although heat balance models per se should be manufacturers’ intellectual property, if the models could be provided through the toolboxes, it would be very helpful in effectively managing utilities’ thermal efficiency while protecting vendors’ intellectual property rights.

Dissemination of CBM stems from the increase of available data caused by IT development. Because mass storage devices were not installed until a few years ago, operator-aid solutions did not spread. But blind adoption of such solutions can waste money and have other negative effects. The most important goal is not to find a suitable efficiency management solution but to foster thermal efficiency experts to distinguish pros and cons in developing thermal management solutions for their particular plants.

Finally, this paper recommends preparing administrative backup so in-situ efficiency management can settle down into daily operation. The concept proposed in this paper has not yet been officially recognized internationally, and its accuracy can vary greatly according to the proficiency of its development. Furthermore, as mentioned earlier, sensor quality is a fundamental limitation of in-situ analysis. However, those problems should decrease as in-situ analysis becomes more widely used in power plants. Nonetheless, if new methodologies are not proceduralized, they cannot advance. Therefore, we emphasize that concrete administrative support is required until the methodologies settle down.

REFERENCES

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KIM et al.,  Application of Monitoring, Diagnosis, and Prognosis in Thermal Performance Analysis for Nuclear Power Plants

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