A Hybrid RBF_GPR_EWMA Model for Data-driven Fault Detection in Centrifugal Chiller Systems

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***Abstract*—Fault Detection and Diagnosis (FDD) are vital for maintaining the energy efficiency and reliability of centrifugal chillers. This study proposes a hybrid data-driven approach that combines Radial Basis Function (RBF) regression and Gaussian Process Regression (GPR) to develop an accurate residual-based reference model. Deviations in thermodynamic parameters are continuously tracked using an Exponentially Weighted Moving Average (EWMA) control chart to detect condenser fouling and refrigerant leakage at multiple severity levels. The proposed RBF_GPR_EWMA framework was validated using the ASHRAE RP-1043 dataset and real chiller data obtained from a hospital in Ho Chi Minh City. The results demonstrate high prediction accuracy ($R^2 > 0.99$) and reliable detection of early-stage performance degradation. The proposed framework does not require fault labels or complex feature design, offering robustness and interpretability. The simplicity and adaptability of the framework make it suitable for integration into building management systems to support condition-based maintenance and energy-efficient operation of heating, ventilation, air conditioning, and refrigeration equipment.**

***Keywords*—Fault Detection and Diagnosis (FDD), Exponentially Weighted Moving Average (EWMA) control chart, radial basis function, Gaussian process regression, ASHRAE RP-1043 dataset**

I. INTRODUCTION

Chiller systems are among the most energy-intensive components in heating, ventilation, air conditioning, and refrigeration applications, accounting for 30%–40% of the total annual cooling energy in large commercial buildings [1, 2]. This substantial energy share implies that even minor degradations in performance can result in considerable increases in electricity consumption, operational costs, and peak demand charges. Thus, effective Fault Detection and Diagnosis (FDD) is essential for ensuring operational reliability, minimizing energy waste, and extending the lifespan of equipment. Despite decades of research [3–7], chiller FDD remains a challenging task due to the system's inherent nonlinear dynamics, time-varying operating conditions, and complex thermodynamic interactions.

Conventional methods, such as rule-based diagnostics and linear regression models, offer interpretability; however, they fail to capture the nonlinearities inherent in chiller thermodynamics. These nonlinearities stem from refrigerant phase transitions, compressor characteristics, and heat exchanger dynamics. Consequently, linear models often exhibit poor generalization capability, high false-alarm rates, and low sensitivity to incipient faults under varying loads. To address these limitations, nonlinear regression and machine learning models have been increasingly adopted for chiller FDD application [8–10]. Among these, Support Vector Regression (SVR) and its variant, Least-Squares SVR (LSSVR) [11, 12], Gaussian Process Regression (GPR), also known as Kriging in geostatistics literature [13, 14], and Radial Basis Function (RBF) networks [2, 15] have demonstrated strong capability in modeling these complex relationships. Recent deep learning approaches, including Long Short-Term Memory (LSTM) networks [16], autoencoder-based anomaly detection [17], and Generative Adversarial Network (GAN)-assisted FDD methods [8], have demonstrated promising performance in HVAC fault diagnosis. However, these approaches generally require large-scale labeled datasets, extensive training procedures, and high computational resources, which may limit their practical deployment in real-time chiller monitoring systems. In addition, many deep learning models suffer from limited interpretability, making it difficult to associate prediction deviations with physical thermodynamic behavior. Therefore, there remains a need for a computationally efficient, interpretable, and robust hybrid framework capable of

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detecting incipient chiller faults under varying operating conditions while maintaining practical applicability for industrial deployment.

However, each standalone modeling paradigm involves inherent trade-offs. For example, while metaheuristic optimization can enhance the predictive accuracy of LSSVR [12, 18, 19], it introduces substantial computational overhead and exhibits high sensitivity to parameter initialization [4]. GPR provides valuable probabilistic uncertainty quantification; however, it suffers from cubic computational complexity, which limits its scalability for large datasets or real-time applications. RBF networks, while effective as universal approximators, are sensitive to the selection of basis function centers and spread parameters, which can reduce robustness under fluctuating conditions. Thus, relying on a single modeling approach often necessitates a compromise between accuracy, robustness, and computational efficiency. To address these limitations, this study proposes a hybrid reference modeling framework based on a sequential stacking architecture that integrates the RBF and GPR models. The theoretical justification for this combination is grounded in the bias-variance decomposition of generalization error. RBF networks are universal function approximators with localized receptive fields. By representing the target function as a weighted sum of radial basis functions distributed throughout the input space, RBF networks effectively reduce prediction bias. The RBF-based approach captures the sharp, localized nonlinearities typical of chiller thermodynamics, such as refrigerant phase changes, compressor performance curves, and heat exchanger behavior. However, since RBF generalization depends strongly on the density of training samples near each center, prediction variance tends to increase in data-sparse regions of the operating space or under thermal load conditions that were poorly represented during training. GPR overcomes this limitation by using a nonparametric Bayesian framework that places a prior over possible functions and updates it with observed residuals, producing a posterior that is smooth and adapted to local data density. When trained on RBF residuals—the systematic errors RBF misses—GPR provides a principled probabilistic correction exactly where RBF performs weakest. Thus, the two models complement each other structurally: RBF and GPR address different parts of the prediction error, and their sequential combination effectively reduces bias and variance in a coordinated, non-redundant way. Note that accurate modelling must be paired with sensitive residual monitoring to detect incipient faults. Conventional methods such as Shewhart charts and t-statistics are generally effective for abrupt shifts but are less sensitive to small, gradual drifts that typically precede severe chiller faults. Accordingly, the proposed framework incorporates an Exponentially Weighted Moving Average (EWMA) control chart for residual monitoring, as described in detail in Section II. The major contributions of this study are as follows: (a) the development of a hybrid residual-learning RBF-GPR reference model integrating nonlinear approximation with probabilistic residual compensation; (b) improved prediction robustness and residual stability under varying operating conditions through sequential residual correction; (c) integration of an EWMA residual monitoring framework for sensitive detection of incipient and gradual faults; and (d) validation using both the ASHRAE RP-1043 benchmark dataset and real chiller operating data from a hospital in Ho Chi Minh City, Vietnam, demonstrating practical applicability under real-world conditions.

In summary, the proposed RBF-GPR-EWMA framework advances the state-of-the-art in chiller FDD by integrating a hybrid nonlinear-probabilistic model with statistically sensitive monitoring. The proposed approach is robust, scalable, and interpretable, and it enables early detection of real-world anomalies, reduces energy waste and operational costs, and enhances reliability in commercial buildings and other critical applications.

II. Methodology

This section presents the proposed hybrid RBF_GPR_EWMA framework for chiller FDD. The methodology integrates nonlinear thermodynamic modelling, probabilistic residual correction, and statistical residual monitoring to improve fault sensitivity and diagnostic robustness under varying operating conditions. The overall framework comprises four core components: (i) RBF-based thermodynamic prediction, (ii) GPR-based residual correction, (iii) EWMA residual monitoring, (iv) fault diagnosis and validation through the benchmark ASHRAE RP-1043 dataset and real chiller operating data.

A conceptual overview of the workflow is shown in Fig. 1. The sequential process of the proposed hybrid RBF-GPR FDD framework is as follows: (a) data acquisition and preprocessing, (b) RBF-based thermodynamic prediction, (c) GPR-based residual modeling, (d) hybrid residual-corrected prediction generation, (e) EWMA-based residual monitoring, and (f) fault identification and interpretation. This structured framework ensures both modeling accuracy and monitoring sensitivity, thereby establishing a unified and adaptive diagnostic system for centrifugal chillers.

In the offline training phase, high-quality fault-free data are collected and normalized to eliminate noise and ensure consistent scaling among input variables. For model development, the datasets were divided into training, validation, and testing subsets. Approximately 70% of the data were used for model training, 15% for validation and parameter tuning, and the remaining 15% for independent testing. The validation dataset was employed to optimize model hyperparameters and reduce overfitting risk before final performance evaluation on unseen testing data.

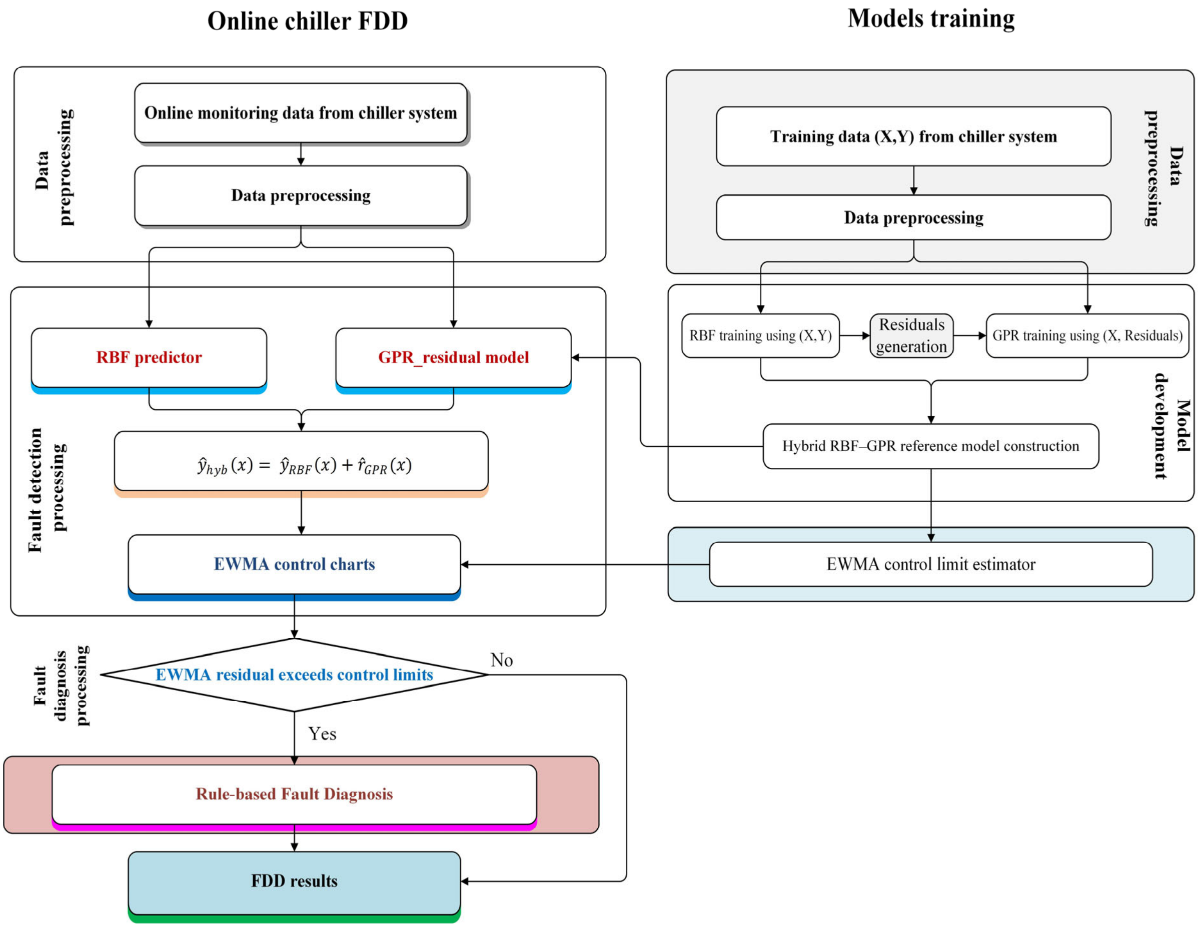

Fig. 1. FDD flowchart for hybrid RBF-GPR.

During the online monitoring stage, real-time operational data are continuously input to the trained hybrid RBF-GPR model to generate predicted responses of key Diagnostic Indicators (DIs) under normal conditions. The deviations between the measured and predicted values, referred to as residuals, are subsequently evaluated using the EWMA control scheme. Persistent or systematic deviations beyond the established control limits indicate abnormal operating behavior. When such anomalies are detected, the fault classification module is activated to identify the specific fault type, e.g., condenser fouling or refrigerant leakage, based on the characteristic residual patterns.

Overall, the proposed hybrid RBF_GPR_EWMA approach integrates nonlinear learning, probabilistic inference, and statistical process control to establish a robust and sensitive FDD framework. It enhances early fault detection capability, reduces false-alarm rates, and provides a reliable foundation for intelligent chiller operation and maintenance.

A. RBF Model

The RBF network is a widely adopted nonlinear modeling technique for function approximation because of its simple structure and fast learning ability. In principle, the model represents the target function as a linear combination of RBFs located at certain centers. This structure enables RBF models to capture local nonlinear behavior effectively, such as the complex relationships among chilled water temperature, condenser water inlet temperature, and cooling capacity in a chiller system.

However, a major limitation of RBF models is their sensitivity to the selection of center locations and kernel widths. Poor parameterization may result in unstable model performance under varying operating conditions. To address this limitation, the RBF network is combined with a statistical regression model, i.e., the GPR model, such that both local flexibility and global smoothness can be achieved.

The RBF network is employed as a nonlinear regression model to approximate the relationship between the input and output variables of the chiller system. Here, for an input vector $x \in \mathbb{R}^D$, the RBF predictor is defined as:

$$\hat{y}(x) = \sum_{i=1}^{M} w_i \emptyset\left(\frac{\|x-c_i\|}{\sigma_i}\right) + b \tag{1}$$

where: M denotes the number of RBFs; $c_i \in \mathbb{R}^D$ represents the center of the i-th radial function; σ_i is the spread (or radius) parameter; w_i represents the regression weights; and b is a bias term; $\phi(r)$ is typically selected as a Gaussian kernel:

$$\emptyset(r) = \exp(-r^2) \tag{2}$$

To improve model generalization capability and mitigate overfitting risk, the RBF hyperparameters were optimized using Leave-One-Out Cross-Validation (LOOCV)-based RMSE minimization. Specifically, the shape parameter α and ridge regularization parameter λ were systematically tuned through a grid-search procedure to obtain the optimal nonlinear approximation performance. The RBF model captures localized nonlinear features, which are highly useful when describing chiller thermodynamic processes. Model training involves solving a regularized least-squares regression problem to determine the weighting coefficients, while the spread parameter is adjusted through the hyperparameter optimization procedure described above.

B. GPR

GPR is a nonparametric Bayesian modeling framework that defines a prior distribution over possible functions and updates this prior using observed data. It models the underlying mapping between the inputs and outputs as a Gaussian process fully characterized by a mean function and a covariance (kernel) function. The covariance structure determines the degree of correlation between data points and thus governs the smoothness and generalization properties of the predictive function.

In this study, the GPR model is constructed using an Automatic Relevance Determination (ARD) squared-exponential kernel, which provides adaptive scaling for each input dimension. The ARD mechanism allows the model to automatically assess the relative importance of each feature by learning individual characteristic length scales. This capability enhances the model's effectiveness in capturing the nonlinear relationships among the thermodynamic parameters of the chiller system. This kernel can be expressed as

$$k(x_i, x_j) = \sigma_f^2 exp\left(-\frac{1}{2}\sum_{d=1}^{D}\frac{(x_{i,d}-x_{j,d})^2}{\ell_d^2}\right) \tag{3}$$

where ℓ_d^2 denotes the characteristic length-scale associated with the d_{th} input variable, σ_f^2 represents the signal variance, and D denotes the dimensionality of the input space.

For the training data $D = \{X, Y\}$, where $X = \{x_1, x_2, \dots, x_N\}$ and $Y = \{y_1, y_2, \dots, y_M\}$, the predictive mean for a new sample x_* is expressed as:

$$\hat{y}(x_*) = k(x_*, X)[K(X, X) + \sigma_n^2 I]^{-1} y \tag{4}$$

with the corresponding predictive variance:

$$\sigma^2(x_*) = k(x_*, x_*) - k(x_*, X)[K(X, X) + \sigma_n^2 I]^{-1} k(X, X_*) \tag{5}$$

where, $K(X, X)$ is the covariance matrix with entries $k(x_*, x_*)$, (x_*, X) is the covariance vector, and σ_n^2 is the noise variance.

Unlike deterministic regression models, GPR yields a mean prediction and quantifies predictive uncertainty with the variance term $\sigma^2(x_*)$, providing a probabilistic interpretation of model confidence. This uncertainty estimation is particularly useful in fault detection, because it enables differentiation between model uncertainty and actual abnormal system behavior. The hybrid RBF–GPR framework mitigates these individual limitations by coupling the localized nonlinear mapping of RBF networks with the global probabilistic robustness of GPR. By utilizing GPR to model the systematic residuals left unresolved by the RBF component, the proposed sequential architecture ensures high fidelity in data-sparse operating regions while maintaining robust uncertainty quantification against measurement noise.

C. Hybrid RBF–GPR Residual-Learning Architecture

Although the RBF model provides strong nonlinear approximation capability, small residual deviations may still remain under varying operating conditions due to measurement uncertainty and unmodeled nonlinear dynamics. To further improve prediction robustness and residual stability, this study adopts a sequential residual-learning strategy integrating GPR model.

The RBF model captures localized nonlinear patterns between thermodynamic parameters, providing high sensitivity to subtle operational variations. Subsequently, the residuals between measured outputs and RBF predictions are modeled using GPR to estimate probabilistic residual corrections. The proposed framework adopts a sequential residual-learning architecture. First, the RBF model is trained to approximate the primary nonlinear thermodynamic behavior of the chiller system. Subsequently, the residuals between measured outputs and RBF predictions are modeled using GPR. The final hybrid prediction is obtained by combining the RBF prediction with the GPR-based residual correction.

$$\hat{y}(x) = \hat{y}_{RBF}(x) + \hat{r}_{GPR}(x) \tag{6}$$

where $\hat{y}(x)$ denotes the final hybrid prediction, $\hat{y}_{RBF}(x)$ represents the prediction generated by the RBF model, and $\hat{r}_{GPR}(x)$ denotes the residual correction estimated by the GPR model.

The proposed residual-learning integration preserves the localized nonlinear approximation capability of the RBF model while improving prediction robustness through probabilistic residual compensation provided by GPR. The RBF weighting coefficients are estimated using ridge regression, corresponding to a convex optimization problem with a unique closed-form solution. This property improves numerical stability and mitigates overfitting during nonlinear thermodynamic modelling. The GPR hyperparameters are automatically estimated through marginal likelihood optimization during model training, enabling probabilistic modelling of the residual distribution and improved generalization performance under varying operating conditions. Furthermore, GPR provides uncertainty-aware regression capability, which is beneficial for handling measurement noise and operational variability commonly observed in real chiller systems. Unlike a parallel weighted-average fusion that requires a manually tuned scalar weight β, the proposed stacking formulation eliminates β entirely. The overall hybrid model is nonlinear because both the RBF and GPR components are individually nonlinear functions of the input variables.

D. EWMA

The residuals between the predicted and actual measurements are monitored using EWMA control charts. The EWMA statistic accumulates past information with a smoothing factor λ, making it more sensitive to small, gradual shifts than conventional Shewhart charts. The smoothing parameter λ directly influences the sensitivity of the EWMA chart. Smaller λ values provide stronger noise filtering but slower fault response, whereas larger λ values improve responsiveness at the expense of increased false-alarm sensitivity. In this study, $\lambda = 0.15$ was selected as a compromise between detection sensitivity and monitoring stability based on validation experiments and recommendations from previous EWMA-based chiller FDD studies [2, 12]. This property is particularly important for chillers, where incipient faults, e.g., refrigerant leakage or condenser fouling often begin as minor deviations before escalating into severe efficiency losses.

After the hybrid RBF-GPR model is trained, the residuals between the measured and predicted outputs are monitored using EWMA charts to detect faults. The EWMA statistic at time *t* is expressed as follows:

$$Z_t = \lambda e_t + (1-\lambda) Z_{t-1} \tag{7}$$

where $Z_o = \mu_e$ is the expectation of the residuals; μ_e denotes the in-control mean of the residuals, $e_t = y_t - \hat{y}_t$ is the residual, and $\lambda \in 0{,}1$ is the smoothing parameter.

The control limits of the EWMA are calculated based on residuals obtained under normal operating conditions. The Upper Control Limit (UCL) and Lower Control Limit (LCL) defined as follows:

$$UCL = \mu_o + L \cdot \sigma_e \sqrt{\frac{\lambda}{n(2-\lambda)}} \tag{8}$$

$$LCL = \mu_o - L \cdot \sigma_e \sqrt{\frac{\lambda}{n(2-\lambda)}} \tag{9}$$

where σ_e denotes the standard deviation of the residuals, and L is the width multiplier typically set to 3 (i.e., 99.73% confidence interval). A fault alarm is triggered if the EWMA residual exceeds these thresholds.

E. ASHRAE RP-1043 Dataset

To evaluate the proposed framework, this study uses the benchmark dataset provided by ASHRAE RP-1043. This dataset was generated from full-scale chiller experiments conducted under carefully controlled conditions, covering both normal operation and artificially induced faults. The RP-1043 dataset has been widely employed in previous chiller FDD studies and is recognized as a reliable reference for model validation [4, 20, 21]. Its controlled fault scenarios provide a strong basis for testing and benchmarking advanced diagnosis methods. Although the RP-1043 dataset includes multiple types of chiller faults, this study specifically focuses on refrigerant leakage and condenser fouling. The rationale for this selection is fourfold. First, these faults are among the most frequently encountered in real-world chiller operation and are associated with substantial efficiency degradation. Second, both fault types evolve gradually, making early detection essential for minimizing energy waste and reducing maintenance costs. Third, they represent two distinct mechanisms: refrigerant-side degradation (leakage) and heat-exchanger-side degradation (fouling). Finally, focusing on two representative fault types ensures that the study remains feasible and practical, while still testing the generalizability of the proposed hybrid diagnostic framework.

F. Diagnostic Procedure

The diagnostic procedure focuses on analyzing two key thermodynamic indicators used as fault diagnostic indices: the heat exchanger efficiency of the sub-cooling (ε_{sc}) and the condenser Logarithmic Mean Temperature Difference ($LMTD_{cd}$), which are defined in Table I. These diagnostic parameters have been widely adopted in chiller FDD research because of their strong sensitivity to variations in system thermal performance under fault conditions. The ε_{sc} is computed using Eq. (10), where T_{sub} denotes the refrigerant sub-cooling temperature, T_{cd} denotes the condensing temperature, and TCI denotes the condenser inlet water temperature. Similarly, the condenser logarithmic mean temperature difference is calculated by Eq. (11), which quantifies the effective temperature driving force for heat transfer between the refrigerant condensing T_{cd} and the cooling water flowing through the condenser, accounting for the logarithmic variation of the temperature difference along the length of the heat exchanger.

TABLE I. DIAGNOSTIC INDICATORS IN CENTRIFUGAL CHILLER FAULTS [2, 12]

Diagnostic Indicators	Formulations		Faults type	
			Condenser Fouling (CdFoul)	Refrigerant Leakage (RefLeak)
ε_{sc}	$\varepsilon_{sc} = \frac{T_{sub}}{T_{cd} - TCI}$	(10)	↓	↓
$LMTD_{cd}$	$LMTD_{cd} = \frac{TCO - TCI}{ln\frac{T_{cd} - TCI}{T_{cd} - TCO}}$	(11)	↑	↓

Note: ↓ and ↑ represent a decrease and increase relative to normal operation, respectively.

Under normal operating conditions, the residuals of ε_{sc} and $\mathrm{LMTD_{cd}}$ fluctuate randomly around zero within their control limits. However, under faulty conditions distinct deviation patterns emerge, as summarized in Table I.

In case of condenser fouling, thermal resistance increases due to the accumulation of scale or deposits on the condenser tubes, causing the condenser pressure and temperature T_{cd} to increase. This results in a higher $\mathrm{LMTD_{cd}}$ and reduced ε_{sc} due to reduced heat transfer efficiency in the condenser. Conversely, for refrigerant leakage, the loss of refrigerant charge lowers both suction and discharge pressures, reducing the condensing temperature and overall heat rejection rate. Consequently, both $\mathrm{LMTD_{cd}}$ and ε_{sc} decrease. The EWMA residual charts detect deviations when the residuals of ε_{sc} and $\mathrm{LMTD_{cd}}$ exceed their respective control limits. An increasing $\mathrm{LMTD_{cd}}$ residual combined with a decreasing ε_{sc} residual indicates condenser fouling, whereas simultaneous decreases in the residual of both parameters correspond to refrigerant leakage.

This residual-based diagnostic mechanism allows the early detection of performance degradation, even under small or incipient fault conditions, without requiring prior knowledge of fault severity levels. Although this study focuses on condenser fouling and refrigerant leakage, the proposed residual-based monitoring framework is fault-agnostic: any deviation from normal operation generates detectable residual signatures, provided that appropriate diagnostic indicators (e.g., ε_{sc}, $\mathrm{LMTD_{cd}}$, or TCA) are defined for the target fault types. Consequently, the proposed hybrid RBF_GPR_EWMA framework enhances both reliability and practicality of real-time chiller monitoring and predictive maintenance in building energy systems.

G. Evaluation Metrics for Regression-based Fault Detection

To ensure a fair comparison with previous chiller FDD studies [2, 11, 12], the performance of all regression models was evaluated using two widely adopted statistical indicators: the coefficient of determination (R^2) and standard deviation of residuals (σ).

The R^2 value represents the degree of correlation between the predicted and actual outputs, and σ reflects the variability of the model residuals. σ is also used to establish the control limits in the EWMA residual monitoring stage. A higher R^2 and a smaller σ indicate a more accurate and stable model.

The standard deviation of residuals σ is calculated as follows:

$$\sigma = \sqrt{\frac{1}{n-1}\sum(e_i - \overline{e})^2} \tag{12}$$

where n denotes the number of samples, e_i is the individual residual between the measured and predicted values, and $\overline{e}$ represents the mean residual.

The coefficient of determination R^2 which quantifies the goodness-of-fit between predicted and measured data, is calculated as follows:

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{13}$$

where y_i denotes the measured value, $\hat{y}_i$ represents the predicted value, and $\bar{y}$ is the mean of the measured data.

III. Results and Discussion

A. Benchmark Results on ASHRAE RP-1043

1) Development of reference models

The proposed FDD strategy was evaluated using the experimental Normal2 dataset from the ASHRAE RP-1043 research project. Here, performance was benchmarked against the SVR_EWMA [11], RBF_EWMA [2], and DE_LSSVR_EWMA [12] methods by employing the same DIs and diagnostic criteria, with a confidence level of 99.73% (3σ) to detect and diagnose condenser fouling and refrigerant leakage faults.

Fig. 2 compares the predicted and measured values of the two DIs, (i.e., $\mathrm{LMTD_{cd}}$ and ε_{sc}) obtained using the ASHRAE RP-1043 Normal2 dataset. The regression plots demonstrate that the predicted values closely align with the 45° reference line, indicating strong correlation and accuracy in the model predictions. Both Fig. 2(a) and (b) show that the proposed RBF-GPR hybrid model achieves high coefficients of determination, with $R^2 = 0.9946$ and 0.9554 for $\mathrm{LMTD_{cd}}$ and ε_{sc}, respectively, confirming the model's excellent capability to capture the nonlinear behavior of the chiller system under normal operation conditions.

Table II summarizes the results for the comparative performance analysis of the SVR_EWMA, RBF_EWMA, DE_LSSVR_EWMA, and proposed RBF_GPR_EWMA methods. In terms of fitness metrics, the proposed hybrid model achieved the highest R^2 values and the lowest standard deviation of residuals (σ) for both parameters. Specifically, for $\mathrm{LMTD_{cd}}$, the R^2 value improved from 0.9897 (RBF_EWMA) and 0.9868 (SVR_EWMA) to 0.9946, and the σ value decreased from 0.1390 (RBF_EWMA) to 0.1046. Similarly, for ε_{sc}, the R^2 value increased from 0.8556 (RBF_EWMA) and 0.8355 (SVR_EWMA) to 0.9554, and the σ value decreased to 0.0237, representing the most stable residual distribution among all tested methods. The UCL and LCL values presented in Table II further demonstrate the higher stability of the proposed model. The control bands of the RBF_GPR model are narrower (±0.0442 for $\mathrm{LMTD_{cd}}$ and ±0.0104 for ε_{sc}) than those of the other three models, indicating smaller residual dispersion and higher reliability of the predicted reference values. In EWMA-based monitoring, narrower control limits indicate enhanced sensitivity to subtle deviations, which is crucial for early fault detection.

These results demonstrate that integrating the RBF network and GPR successfully combines the nonlinear approximation strength of RBF with the uncertainty quantification and statistical robustness of GPR. Consequently, the hybrid model enhances prediction accuracy and improves residual stability, providing a more reliable reference baseline for subsequent EWMA-based fault detection.

In summary, the proposed RBF_GPR_EWMA framework outperformed all compared methods in terms of both prediction accuracy and statistical consistency. The strong agreement between the predicted and measured values, (Fig. 2), and the superior regression statistics (Table II) demonstrate that the hybrid model provides a robust and effective foundation for detecting chiller faults under varying operating conditions.

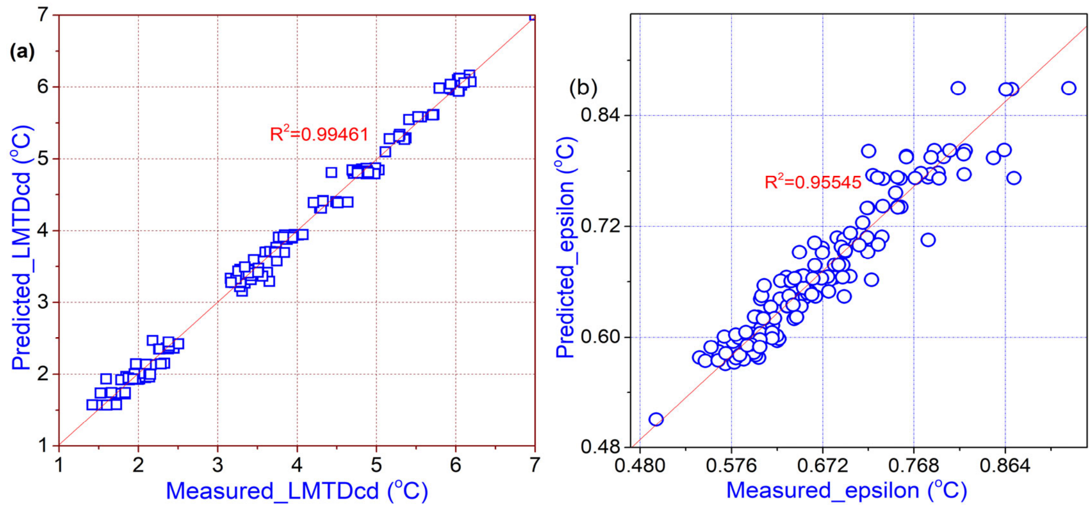

Fig. 2. Predicted and calculated values of diagnostic indicators obtained using RP-1043 "Normal2" dataset. (a) condenser logarithmic mean temperature difference (LMTDcd); (b) heat exchanger efficiency of the subcooling (ε_{sc}).

TABLE II. FITNESS METRICS AND CONTROL LIMITS FOR LMTDcd AND ε_{sc} OBTAINED BY THE RBF [2], SVR [11], DE_LSSVR [12], AND PROPOSED RBF_GPR HYBRID MODELS USING THE ASHRAE RP-1043 "NORMAL2" DATASET

Model	Metrics	LMTDcd	ε_{sc}
RBF_EWMA	R^2	0.9897	0.8556
	σ	0.1390	0.0309
	UCL	0.1157	0.0255
	LCL	−0.1217	−0.0252
SVR_EWMA	R^2	0.9868	0.8355
	σ	0.1517	0.0325
	UCL	0.1288	0.0285
	LCL	−0.1288	−0.0285
DE_LSSVR_EWMA	R^2	0.9937	0.8697
	σ	0.1084	0.0281
	UCL	0.0463	0.0120
	LCL	−0.0463	−0.0120
Proposed RBF_GPR_EWMA	R^2	0.9946	0.9554
	σ	0.1046	0.0237
	UCL	0.0442	0.0104
	LCL	−0.0442	−0.0104

Note: R^2: coefficient of determination; σ: standard deviation of residuals; UCL/LCL: upper/lower control limits calculated under 3σ confidence level (99.73%).

2) FDD results

This section evaluates the FDD performance of the proposed RBF_GPR_EWMA framework using experimental datasets from the ASHRAE RP-1043 research project. Three chiller operating conditions were considered, i.e., normal operation, condenser fouling, and refrigerant leakage. Following the classification defined by Comstock and Braun [22], the two fault types were categorized into four severity levels (SL1–SL4) to reflect progressively increasing fault magnitudes. During the FDD process, the residuals of the two monitored parameters, i.e., $LMTD_{cd}$ and ε_{sc} were derived using the hybrid RBF_GPR model and evaluated using EWMA control charts at a 99.73% confidence level ($\pm 3\sigma$). A sample was diagnosed as faulty if either residual exceeded the control limits, and correct diagnosis rates were computed as the proportion of correctly classified samples over the total number of test points for each condition.

The framework's behavior under normal operating conditions is illustrated in Fig. 3, which shows EWMA charts for LMTDcd and ε_{sc} using the RP-1043 Normal2 dataset. As shown in Fig. 3(a) and (b), all EWMA residuals remain within the prescribed UCL and LCL throughout the observation window. This indicates that the RBF_GPR model accurately reproduces the thermodynamic behavior of the chiller under fault-free operating conditions, with no spurious fault alarms. Furthermore, the residual distributions are symmetrically centered around zero, which confirms that the hybrid regression model provides unbiased estimates of the thermal performance metrics. Additionally, the narrow control limits indicate low process variability and strong model stability. Collectively, these results validate the proposed reference model as a reliable foundation for subsequent fault detection under abnormal conditions.

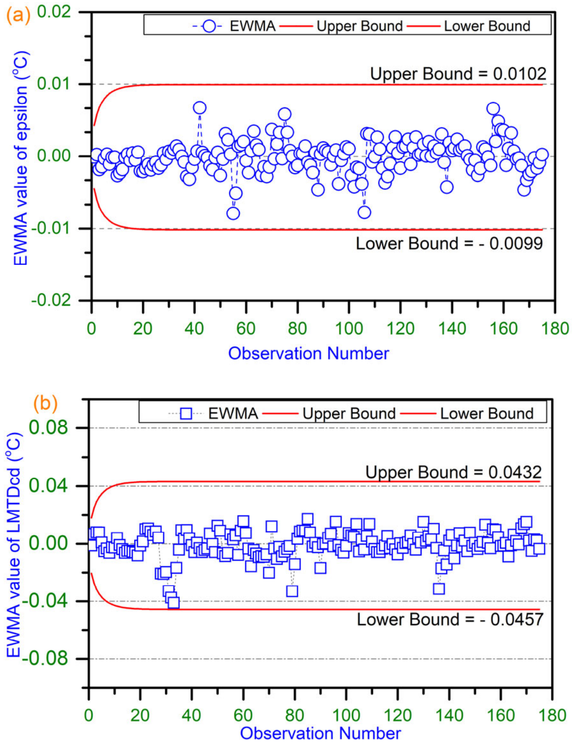

Fig. 3. Residual variation of $LMTD_{cd}$ and ε_{sc} using RP-1043 "*Normal2*": control charts of (a) ε_{sc} and (b) $LMTD_{cd}$. $LMTD_{cd}$: condenser logarithmic mean temperature difference; ε_{sc}: heat exchanger efficiency of the subcooling; EWMA: exponentially weighted moving average.

A quantitative comparison between the proposed model and previously reported benchmark methods, namely RBF_EWMA, SVR_EWMA, and DE_LSSVR_EWMA, is summarized in Table III. As can be seen, the proposed method achieved a 100% correct classification rate under normal operation, consistent with the benchmark models. This indicates that the hybrid model provides a reliable baseline for subsequent fault detection.

TABLE III. DIAGNOSIS RATES OF FDD METHODS AT 99.73% CONFIDENCE LEVEL (3Σ) FOR VARIOUS CHILLER HEALTH CONDITIONS AND FOUR SLS

Chiller Health Condition	FDD Method	Diagnosis Rates				
		Normal (%)	SL1 (%)	SL2 (%)	SL3 (%)	SL4 (%)
Normal operation	RBF_EWMA	100.0	-	-	-	-
	SVR_EWMA	100.0	-	-	-	-
	DE_LSSVR_EWMA	100.0	-	-	-	-
	Proposed method	100.0	-	-	-	-
Condenser fouling	RBF_EWMA	-	0.0	19.7	65.5	100.0
	SVR_EWMA	-	7.7	45.2	60.7	100.0
	DE_LSSVR_EWMA	-	16.67	29.17	76.79	100.0
	Proposed method	-	0	11.9	88.1	100.0
Refrigerant leakage	RBF_EWMA	-	25.0	31.6	95.3	100.0
	SVR_EWMA	-	20.1	36.2	88.3	100.0
	DE_LSSVR_EWMA	-	37.43	39.77	100.0	100.0
	Proposed method	-	22.81	47.37	100.0	100.0

The diagnostic performance of the proposed method for condenser fouling is shown in Fig. 4, where the EWMA residuals of both parameters are presented across the four severity levels. For ε_{sc}, as shown in Fig. 4(a), the residuals exhibit an upward shift at SL1and SL2 and become progressively more negative at SL3 and SL4, clearly exceeding the control limits as the fault severity increases. Similarly, the residuals of $LMTD_{cd}$ (Fig. 4(b)) exhibit pronounced deviations from the control limits starting from SL2, with large excursions observed at SL3 and SL4.

The physical basis for these residual patterns can be interpreted through the thermodynamic mechanism of condenser fouling. As scale or deposit accumulates on the inner surfaces of the condenser tubes, the overall thermal resistance of the condenser increases progressively. This impedes heat transfer from the condensing refrigerant to the cooling water, causing the condensing pressure and consequently the condensing temperature T_{cd} to rise above its normal operating value. The elevated T_{cd} directly increases $LMTD_{cd}$ (Eq. (11)), since the temperature differential between the condensing refrigerant and the cooling water stream expands, producing a positive residual drift. Simultaneously, the higher T_{cd} narrows the available sub-cooling margin at the condenser outlet, reducing ε_{sc} (Eq. (10)) below its normal value and producing a negative residual drift. These two opposing thermodynamic effects, positive $LMTD_{cd}$ deviation and negative ε_{sc} deviation, are precisely the residual signatures captured in Fig. 4, providing direct physical interpretability for the observed EWMA patterns.

These patterns demonstrate that the proposed method can sensitively detect condenser fouling progression. As shown in Table III, the proposed method achieved 88.1% and 100% correct diagnosis at SL3 and SL4, respectively, outperforming the RBF_EWMA and SVR_EWMA methods at higher severity levels. This performance improvement highlights the benefit of integrating the nonlinear approximation of RBF with the probabilistic uncertainty estimation of GPR, thereby enhancing fault sensitivity.

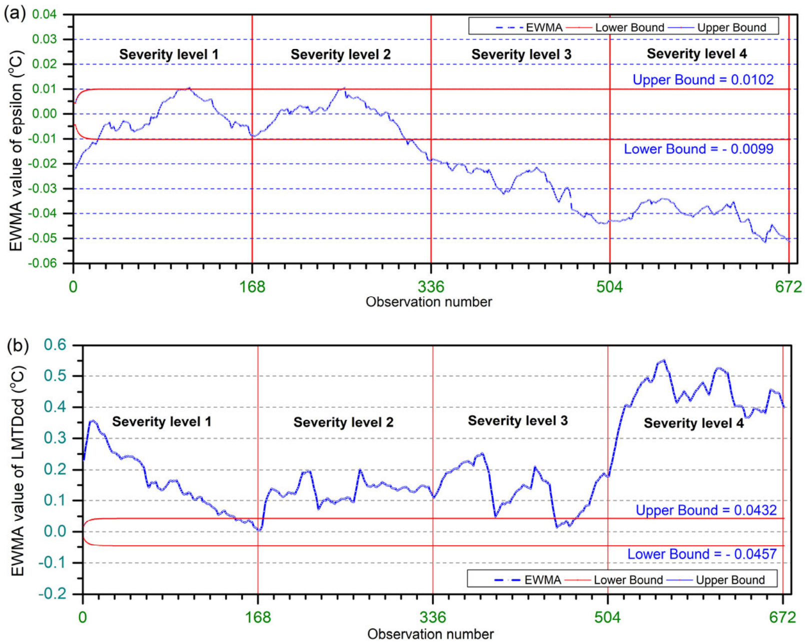

Fig. 4. Residual variation of $LMTD_{cd}$ and ε_{sc} under condenser fouling at four severity levels. (a) control chart of ε_{sc} and (b) control chart of $LMTD_{cd}$.

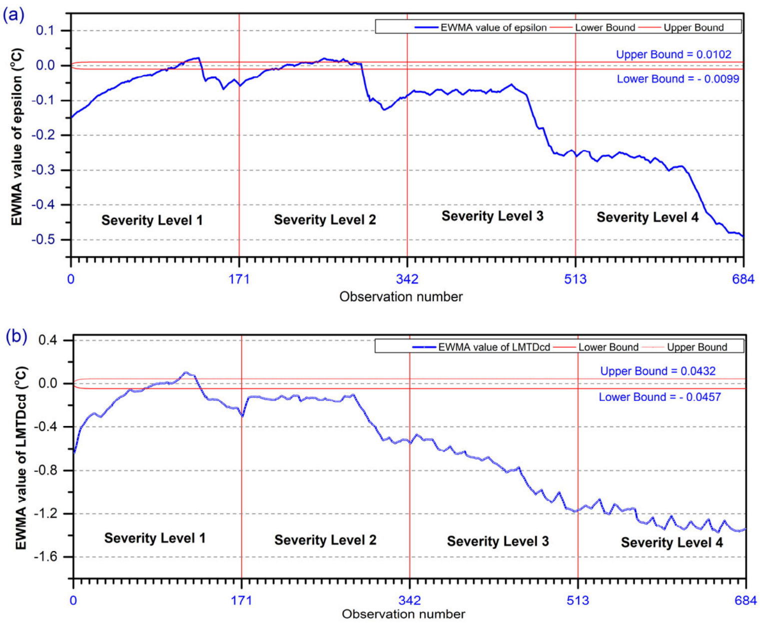

Fig. 5. Residual variations of $LMTD_{cd}$ and ε_{sc} under refrigerant leakage at four severity levels: control chart of (a) ε_{sc} and (b) $LMTD_{cd}$. LMTDcd: condenser logarithmic mean temperature difference; ε_{sc}: heat exchanger efficiency of the subcooling.

Fig. 5 shows the residual behavior of the proposed method for the refrigerant leakage case. For ε_{sc} (Fig. 5(a)), the residuals initially remain close to zero but exhibit a clear downward shift at SL2 and continue to deviate at SL3 and SL4, consistently breaching the LCL. A similar trend is observed for $LMTD_{cd}$ (Fig. 5(b)), where the residuals shift negatively as the leakage severity increases, crossing control limits from SL2 onward. The dual-negative residual signature observed in Fig. 5 is thermodynamically consistent with the refrigerant leakage mechanism. As refrigerant charge is progressively lost, the mass flow rate circulating through the system decreases, lowering both the suction pressure at the compressor inlet and the discharge pressure at the outlet. The lower discharge pressure causes the condensing temperature T_{cd} to decrease below its normal value. This reduction simultaneously affects both diagnostic indicators in the same direction: LMTDcd decreases as the temperature differential between the condensing refrigerant and the cooling water narrows (Eq. (11)), while ε_{sc} also decreases as the sub-cooling margin between T_{cd} and the condenser inlet water temperature TCI diminishes (Eq. (10)). This simultaneous negative drift in both residuals—thermodynamically distinct from the opposing-direction signature of condenser fouling—forms the physical basis for fault type discrimination in Table I.

The distinct separation between normal and fault conditions enables reliable detection of refrigerant leakage. As shown in Table III, the proposed method achieved a correct diagnosis rate of 47.37% at SL2 and reached 100% detection accuracy at SL3 and SL4, performing comparably or better than the benchmark methods at high fault severity levels. This result confirms the robustness of the hybrid model in identifying refrigerant leakage even under small-signal conditions.

Overall, the results shown in Figs. 3–5 and Table III demonstrate that the proposed RBF-GPR-EWMA framework delivers superior diagnostic capabilities compared with conventional approaches. The two fault types produce thermodynamically distinct two-dimensional residual signatures in the (LMTDcd, ε_{sc}) diagnostic space: condenser fouling generates opposing residual directions (positive LMTDcd, negative ε_{sc}) reflecting heat-exchanger-side degradation, while refrigerant leakage generates aligned negative residuals in both indicators reflecting charge-side degradation. This directional discrimination enables reliable fault classification based solely on residual pattern, without requiring fault-labelled training data. In normal operation, the proposed framework maintains low residual variability and avoids false alarms. Under condenser fouling and refrigerant leakage conditions, the residuals exhibit systematic, severity-proportional shifts beyond control limits, enabling early detection and accurate classification. Although the benchmark methods such as RBF_EWMA and SVR_EWMA perform adequately at SL3 and SL4, their sensitivity diminishes at SL1 and SL2. In contrast, the hybrid model combines the nonlinear modeling capability of RBF with the Bayesian inference of GPR, yielding more stable residuals and tighter control limits in healthy conditions and more pronounced deviation signatures under faulty conditions. This synergy translates to more reliable FDD across diverse operating conditions. While the ASHRAE RP-1043 benchmark provides a controlled and standardized evaluation environment, real-world chiller systems operate under more complex and variable conditions, including fluctuating ambient temperatures, varying occupancy loads, water quality changes, and sensor noise. To assess the practical applicability of the proposed framework beyond controlled laboratory settings, Section III-B presents a validation study using historical operational data from a 420-RT centrifugal chiller installed in a hospital in Ho Chi Minh City, where ground truth is established through maintenance records rather than controlled fault injection.

B. Validation of Proposed FDD Strategy Using a Hospital Building Chiller System

To validate the practical applicability of the proposed hybrid RBF_GPR_EWMA FDD framework, historical operational data from a 420-ton centrifugal chiller installed at a hospital in Ho Chi Minh City, Vietnam, were analyzed. This chiller undergoes scheduled maintenance twice annually, typically in March and September, during which the condenser is mechanically cleaned. To establish a reliable baseline for the FDD strategy, datasets collected immediately after condenser cleaning were assumed to represent fault-free operation and were employed for model training, while data from subsequent fouling periods were reserved for testing and validation.

1) Chiller system description

The system comprises two water-cooled centrifugal chillers, each rated at 420 Refrigeration Tons (RT), supported by two open cooling towers, three condenser water pumps, and three chilled water pumps. Condenser cooling water is supplied from the municipal network and treated with chemical additives. However, inadequate maintenance of the water treatment system has resulted in recurrent condenser fouling. System operation and data acquisition are managed through a Building Management System (BMS), which records sensor readings and operational status at hourly intervals. All sensors undergo biannual recalibration to maintain measurement integrity. Temperatures are measured using resistance temperature detectors with a full-scale accuracy of ±0.2°C, and water flow rates are monitored using ultrasonic flow meters with a full-scale accuracy of ±1%. For this study, one 420-RT centrifugal chiller was selected as the test unit, and its historical operational data were used to validate the proposed FDD framework, with particular emphasis on the detection and diagnosis of condenser fouling.

2) Model training using fault-free data

For practical implementation in the hospital chiller system, the Temperature Condenser Approach (TCA), which is a direct measurement from the BMS, was selected as the characteristic parameter instead of the derived $LMTD_{cd}$. This selection allows for real-time application using existing sensor infrastructure. After data preprocessing, 391 samples collected after cleaning were used to train the hybrid RBF_GPR model. As shown in Fig. 6, the model exhibited excellent predictive performance with an R^2 value of 0.99367, indicating strong agreement between the predicted and measured TCA values. This confirms that the proposed hybrid model can accurately represent normal chiller operation.

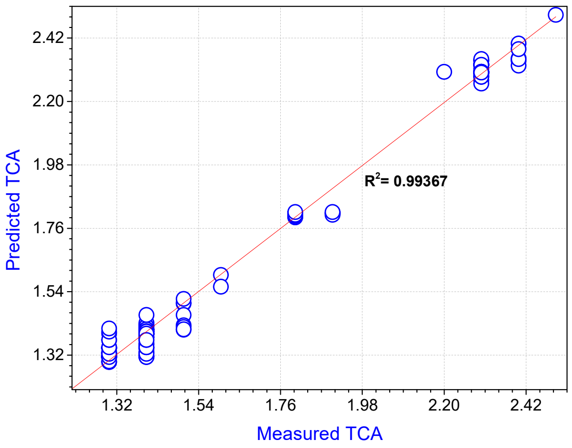

Fig. 6. Comparison between predicted and measured Temperature Condenser Approach (TCA) values using building operating data.

3) *Evaluation under post-cleaning conditions*

The trained model was subsequently applied to six months of operating data to monitor the residuals of the TCA parameter. Fig. 7(a) shows the EWMA control chart of the TCA residuals under the post-cleaning conditions. As shown, nearly all residual points remain within the control limits, while the few points outside the limits are randomly scattered without a consistent trend, indicating that no actual fault occurred. This confirms that the chiller operated under stable and fault-free conditions during this period, and it demonstrates the ability of the proposed framework to distinguish normal fluctuations from true anomalies.

To evaluate the effectiveness of the proposed strategy for fault detection, the TCA residuals were monitored over an extended operating period encompassing a full condenser fouling and cleaning cycle. As shown in Fig. 7(b), the residuals during the normal (post-cleaning) period remain well within the control limits. However, they gradually increase and exceed the UCL as the condenser fouling progresses. This steady upward shift reflects the accumulation of scaling in the condenser tubes due to inadequate water treatment, which accelerates fouling. After the scheduled cleaning event, the residuals promptly returned to the normal range, confirming that the fault condition was eliminated.

These results indicate that the proposed hybrid RBF_GPR_EWMA framework can effectively detect and track the progression of condenser fouling in real time. In addition, the EWMA control chart reveals that the current twice-yearly cleaning schedule may be insufficient to prevent significant fouling, as demonstrated by the early residual excursions beyond the control limits. By implementing the proposed strategy in real time, maintenance personnel could be alerted to clean the condenser at the optimal moment, thereby maintaining higher chiller performance and reducing energy consumption.

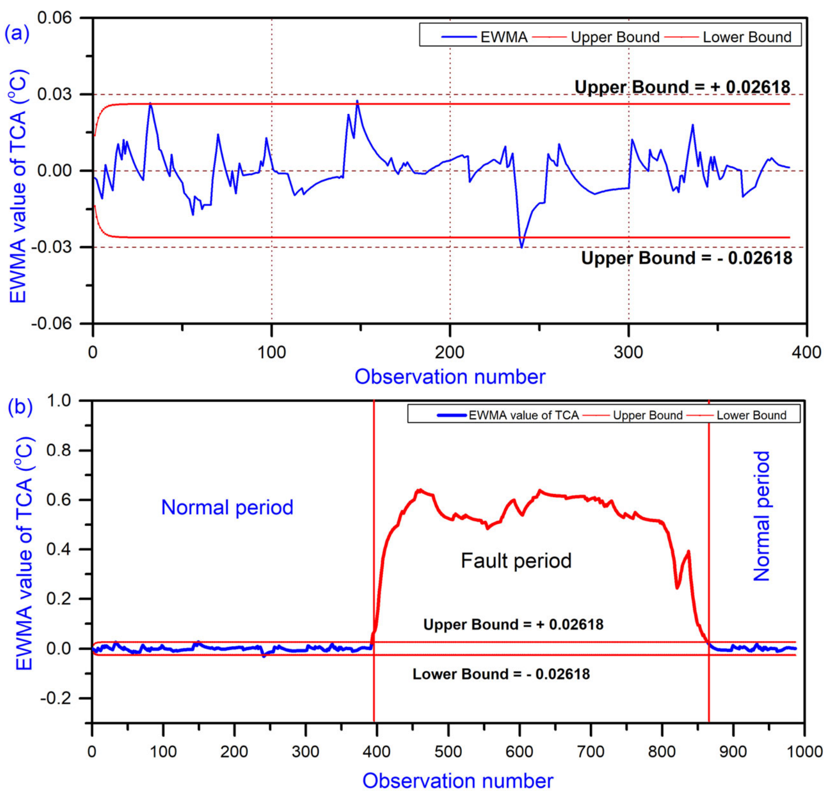

Fig. 7. Residual variations of TCA for operational data: (a) fouling-free condition and (b) normal and condenser fouling operating periods.

IV. Conclusions

This study proposed a hybrid FDD framework that integrates RBF regression, GPR, and EWMA control charts to improve chiller monitoring reliability. By combining nonlinear regression and probabilistic inference with statistical process control, the proposed RBF_GPR_EWMA framework achieves high sensitivity to incipient faults while maintaining stability during normal operation. Validation using the ASHRAE RP-1043 benchmark dataset showed that the hybrid model outperformed the RBF_EWMA, SVR_EWMA, and DE_LSSVR_EWMA methods in terms of prediction accuracy ($R^2 > 0.99$) and residual stability. Furthermore, the narrow control limits of EWMA confirmed its superior responsiveness to small deviations, enabling early detection of condenser fouling and refrigerant leakage. Tests conducted using operational data from a hospital chiller system further demonstrated accurate reproduction of the TCA ($R^2 = 0.9937$) and consistent identification of fouling progression aligned with maintenance records. Because the proposed framework requires only normal operation data, it simplifies implementation in BMSs, thereby providing intuitive visualization through EWMA residual trends. Overall, the hybrid model is lightweight, explainable, and robust, offering strong generalization capability from benchmark to real-world data and supporting adaptive, energy-efficient maintenance in large-scale heating, ventilation, air conditioning, and refrigeration systems. The proposed framework also maintains a relatively lightweight online monitoring structure because only residual estimation and EWMA updating are required during operation, making it potentially suitable for practical deployment in building management systems.

Despite its high diagnostic accuracy and lightweight computational footprint, certain limitations remain to be addressed. First, the framework assumes that fault-free training data can be isolated immediately following scheduled maintenance; in poorly documented chiller systems where the exact timing of maintenance is unknown, initializing an unbiased reference model remains challenging. Second, the Automatic Relevance Determination (ARD) squared-exponential kernel utilized in the GPR component assumes smooth, continuous thermodynamic variations. Consequently, highly abrupt or discontinuous fault events, such as sudden compressor surge or catastrophic refrigerant loss, may not be effectively captured. Third, while cross-system transferability was demonstrated, deploying the framework to systems with substantially different capacities, refrigerant types, or mechanical configurations still requires a localized baseline retraining phase utilizing fault-free data.

To overcome these constraints, future research will focus on developing self-initializing, adaptive residual-learning strategies that mitigate the reliance on strict post-maintenance timelines. Additionally, automatic parameter optimization algorithms and adaptive kernel selection methods will be investigated to extend the framework's capability toward capturing highly dynamic, abrupt anomalies, as well as validating its generalizability across a broader matrix of chiller capacities and diverse operational conditions.

Conflict of Interest

The authors declare no conflict of interest.

Author Contribution Statement

DATT proposed the research problem, developed the theoretical framework, provided technical and methodological guidance; NHS conducted the literature review, collected and processed the data, and prepared the original manuscript draft; HNTC supervised the research, validated the methodology and results, and critically reviewed and revised the manuscript. All authors discussed the results, contributed to the final manuscript, and approved the final version for publication.

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