DIAGNOSTICS AND PROGNOSTICS OF CENTRIFUGAL CHILLERS

Abstract

This paper deals with an effective methodology for organizations to diagnose and detect events that mandate the need for maintenance in their centrifugal chillers. This approach developed by Infosys uses a combination of different machine learning methods and chiller domain knowledge to detect chiller degradation, which requires maintenance, and perform diagnostics and prognostics. This approach was applied to chiller data collected at the Infosys Mysore campus. Once all the events were detected and diagnosed, a prognosis was formed by forecasting some of the key performance indicators. The methods developed were incorporated into Infosys' knowledge-based artifical intelligence platform – Infosys NiaTM – and deployed on the campus. This paper uses the data from one chiller to explain how to develop the approach for diagnostics and prognostics of centrifugal chillers by modeling the data, developing relevant machine learning methods and linking these with chiller domain knowledge.

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1.0 Introduction

Infosys' green initiatives leverage advanced technologies such as the Industrial Internet-of-Things (IIOT) to manage energy, water, waste, security, and transportation within the campuses and continuously improve efficiency. As part of this drive, Infosys saved nearly 46% of per capita energy consumption over a period of 7 years through state-of-the-art design and operations within their buildings and campuses [1].

However, air conditioning systems, particularly chillers, consume a major share of the total energy used in buildings. Infosys has been collecting historical data and maintenance records from more than 130 chillers on its campuses over several years. As chiller data is captured and stored every 5 minutes, this amounts to over a billion records and few terabytes of data storage.

Chiller data is analyzed using Infosys' knowledge-based artificial intelligence (AI) platform – Infosys Nia – to develop diagnostics and prognostics models for the chiller energy management system. This is done to improve operations and reduce maintenance cost by automating processes. We now have a data analytics model to understand chiller behavior, detect events that lead to performance degradation and maintenance, forecast future chiller behavior, and develop knowledge models for predictive maintenance.

The smart connected chillers shown in figures 2 and 3 illustrate the applications of predictive maintenance. However, we are not discussing in this paper the complete methodology required for such development. General event detection and forecasting methods are shown in figures 4 and 5. The event detection methods for chillers are presented in figure 6. However, these do not provide detailed decision-making and evaluation approaches. The application of neural network and MARS methods for general problems are discussed in figures 8 and 9. The aim of the current study on chiller data is to develop a robust method for chiller maintenance by developing techniques using statistical and machine learning methods as shown in figures 10 and 11.

2.0 Chiller operations and key performance indicators

Figure 1 describes the operation of smart connected chillers. Each chiller has two separate water loops, i.e., the condenser water loop and the evaporator water loop. There is also a refrigerant loop. While warm water is cooled in the evaporator, the refrigerant liquid evaporates when it reaches saturation temperature. The saturated refrigerant vapor is then compressed at high pressure in the compressor and cooled and condensed to a liquid in the condenser using cold condenser water (cooled in the cooling tower) that absorbs the heat. The cooling tower uses a large fan and operates in the open.
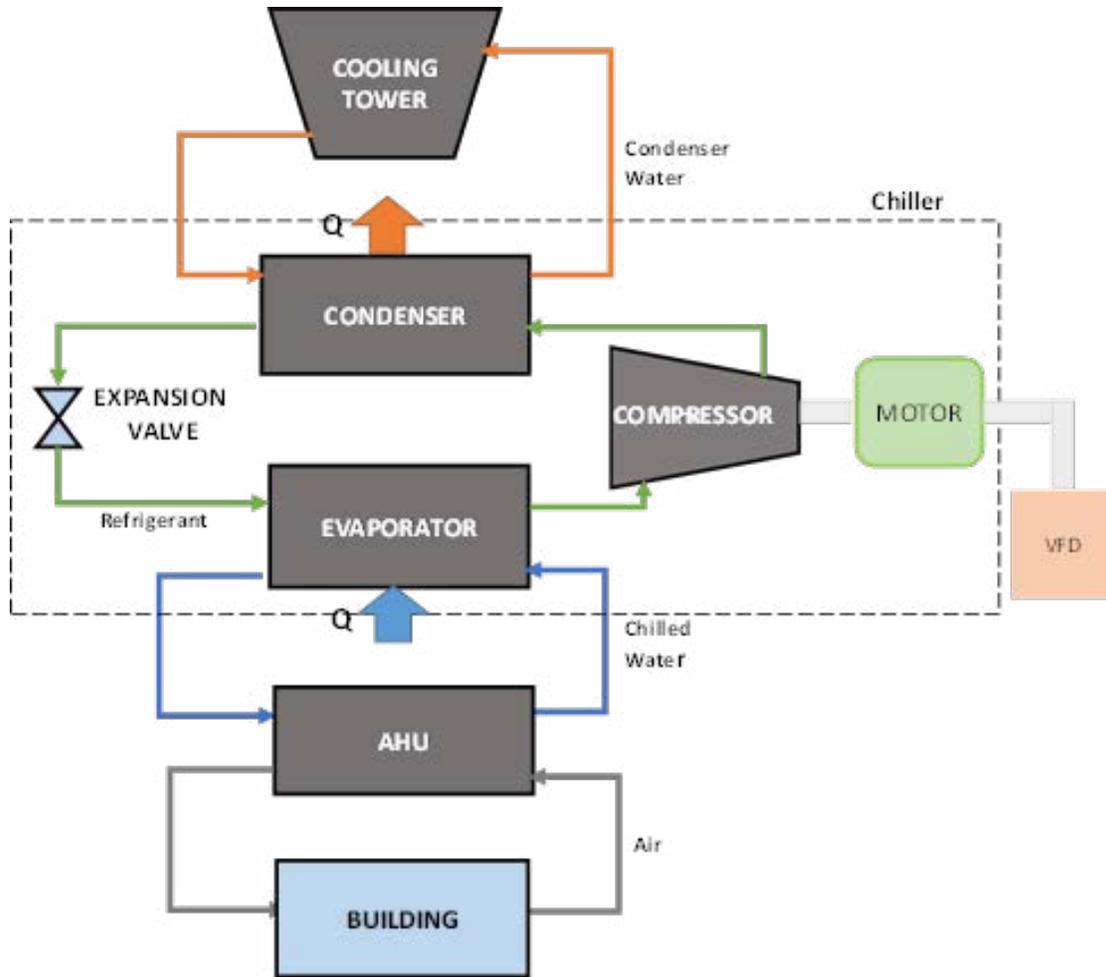

Figure 1: How a chiller operates

2.1 Key performance indicators

To manage chiller operational and energy efficiency, several key performance indicators were identified, monitored and analyzed such as:

a) ikW/TR: Power consumed in kilowatts (kW) per tonnage rating of refrigeration

b) Chilled water, small temperature difference: Difference between the saturation temperature of the refrigerant and the temperature of chilled water leaving the evaporator

c) Condenser water, small temperature difference: Difference between saturation temperature of refrigerant and the temperature of water leaving the condenser

d) Cooling tower effectiveness: Ratio of the difference in temperatures of water entering and leaving the cooling tower to the difference in temperature of water entering the cooling tower and wet bulb temperature (maximum possible cooling in cooling tower)

e) Chilled water temperature difference: Difference between the temperatures of water entering and leaving the evaporator

f) Condenser water temperature difference: Difference between the temperatures of water entering and leaving the condenser

Note: One ton of refrigeration is defined as the heat of fusion absorbed by melting 1 ton of ice within 24 hours, i.e., 1 Ton of Refrigeration = 3.517 kW.

3.0 Data sets and variables

The data set used consists of 9 chillers from Infosys' Mysore campus. The chiller specifications are shown in Table 1.

Chiller Name	Capacity (Tons)
GEC1_Chiller1	249
GEC1_Chiller2	249
GEC1_Chiller3	249
GEC1_Chiller4	249
GEC2_Chiller3	500
GEC2_Chiller4	500
SDB_4_Chiller1	225
SDB_5_Chiller1	400
SDB_5_Chiller2	400

Table 1: Specifications of 9 chillers

The parameters used in this analysis are:

1. Date and time (Time)

2. Percentage of full load (FLA)

3. Energy consumed per ton of refrigeration ikW/TR (IKWTR)

4. Condenser water, small temperature difference (CDW_STD)

5. Chilled water, small temperature difference (CHW_STD)

6. Cooling tower effectiveness (CTEffectiveness)

7. Condenser saturation temperature (CondSatTemp)

8. Evaporator saturation temperature (EvapSatTemp)

9. Leaving condenser water temperature (LCDWT)

10. Return condenser water temperature (RCDWT)

11. Leaving chilled water temperature (LCHWT)

12. Return chilled water temperature (RCHWT)

13. Compressor discharge temperature (CompDischargeTemp)

14. Outside wet bulb temperature (WetBulbTemp)

15. Outside dry bulb temperature (OutsideTemp)

4.0 Data analytics approach

Chiller data, collected every 5 minutes, was analyzed and found to be very noisy owing to data fluctuations observed during start and stop operations of the chillers (less than 50% FLA and FLA above 98%). This noise in the data was removed using the following steps:

a) Consider the data for FLA in the range of 50% to 98%, which amounts to about 95% of the data collected

and includes data in the steady state region.

b) Calculate the average of the data for each day

Outliers from the data were removed by observing the data for one day. The mean and standard deviation of the parameters were computed. To identify outliers, the upper control limit (UCL) is calculated using the formula

$UCL = Mean + 3 * standard\ deviation$

Any value outside the UCL range is considered as an outlier and is excluded from the data.

The data analytics approach consists of the following steps:

a) Exploratory analysis

b) Diagnostics and event detection

c) Prognostics

5.0 Exploratory data analysis

The objective of exploratory data analysis is to observe trends in the data and compare them with the physics. In figures 2, 3 and 4, KPI data for GEC1_Chiller1 are plotted and the maintenance events are indicated using dashed vertical lines to indicate changes occurring after maintenance. As seen in Figure 2, the condenser water, small temperature difference (CDW_STD) was high before the first maintenance and dropped to about 2^0C after maintenance.

Figure 3 shows that the chilled water small temperature difference (CHW_STD) reduced after the second maintenance event (refrigerant shortage). Figure 4 shows the variation of IKWTR values before and after the maintenance events.
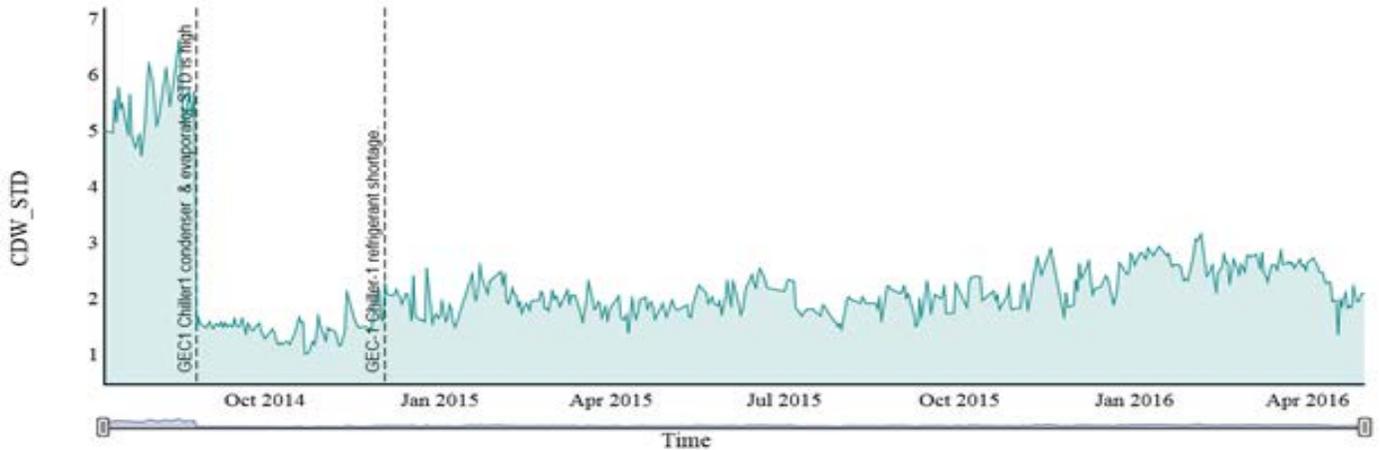
Figure 2: Condenser water, small temperature difference (CDW_STD) variation and maintenance events for GEC1_Chiller1
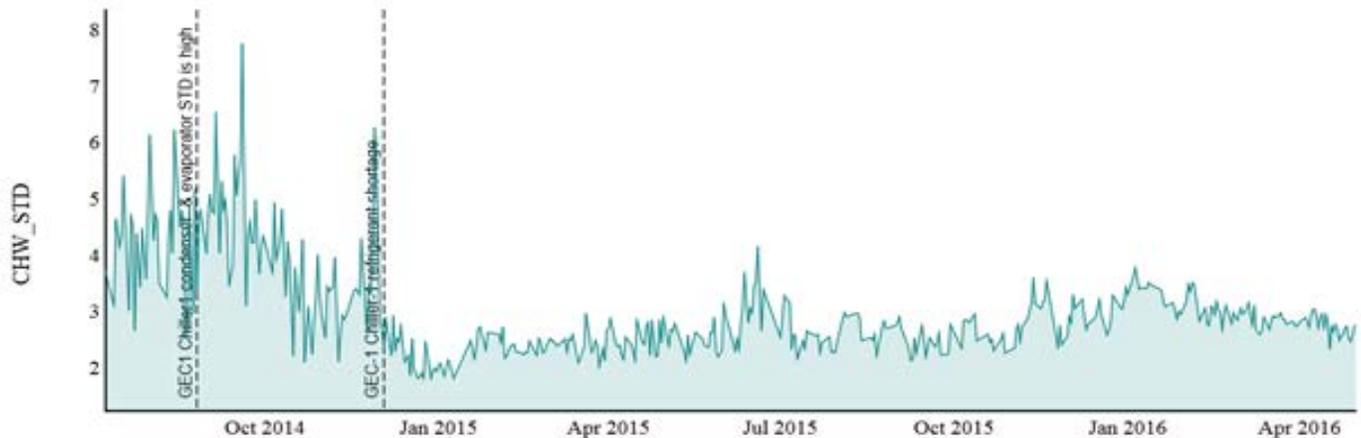
Figure 3: Chilled water, small temperature difference (CHW_STD) variation and maintenance events for GEC1_Chiller 1
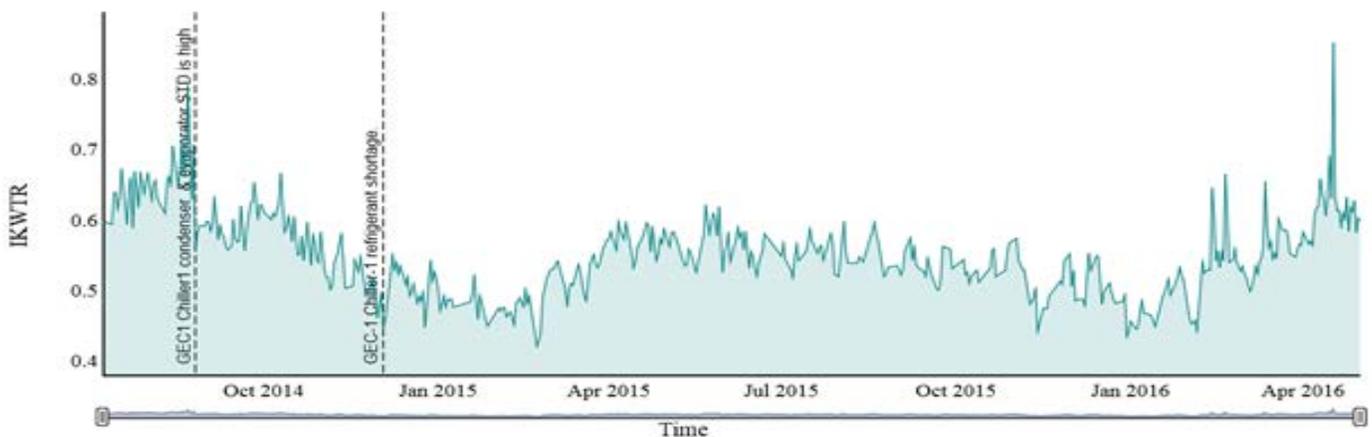
Figure 4: Energy consumed per ton of refrigeration (ikW/TR) variation and maintenance events for GEC1_Chiller1

5.1 Correlation

The correlation between the variables is computed and these results are shown in Figure 5. There is a strong correlation between IKWTR and wet bulb temperature, condenser saturation temperature and wet bulb temperature, LCDWT and wet bulb temperature, RCDWT and wet bulb temperature, and compressor discharge temperature and wet bulb temperature.
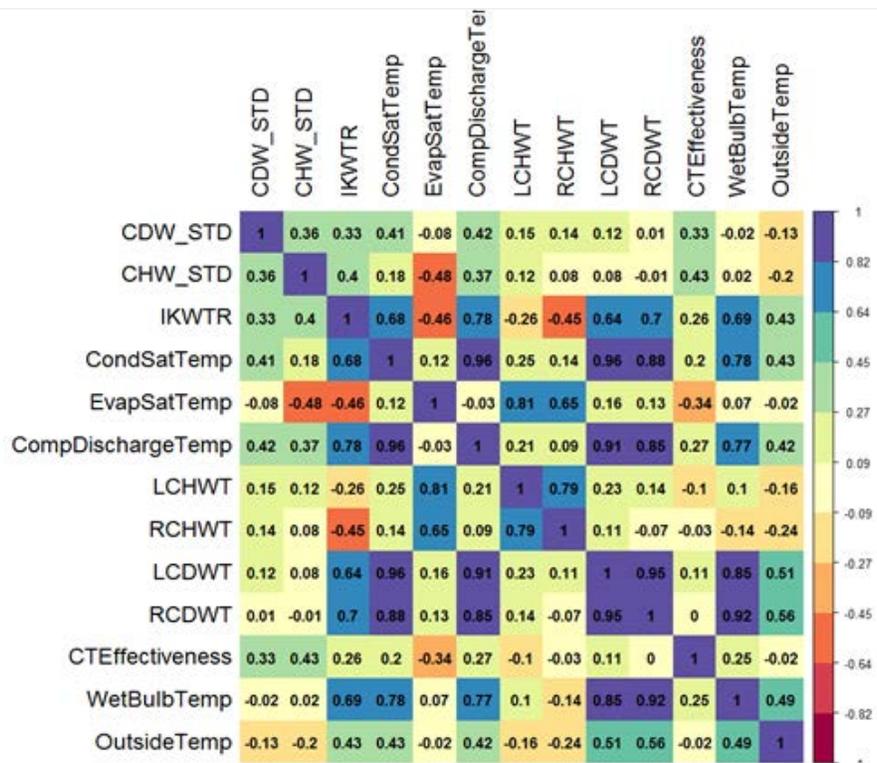

Figure 5: GEC1_Chiller1 correlation plot

6.0 Diagnostics

The first step in predictive maintenance is to diagnose poor chiller performance and detect the corresponding events. Comparing the results of the analysis can help arrive at the best diagnosis. In this case, analysis was performed using:

a) Regression through various methods

b) Hotelling's T^2 method – uni-variate and multi-variate

c) Quartile
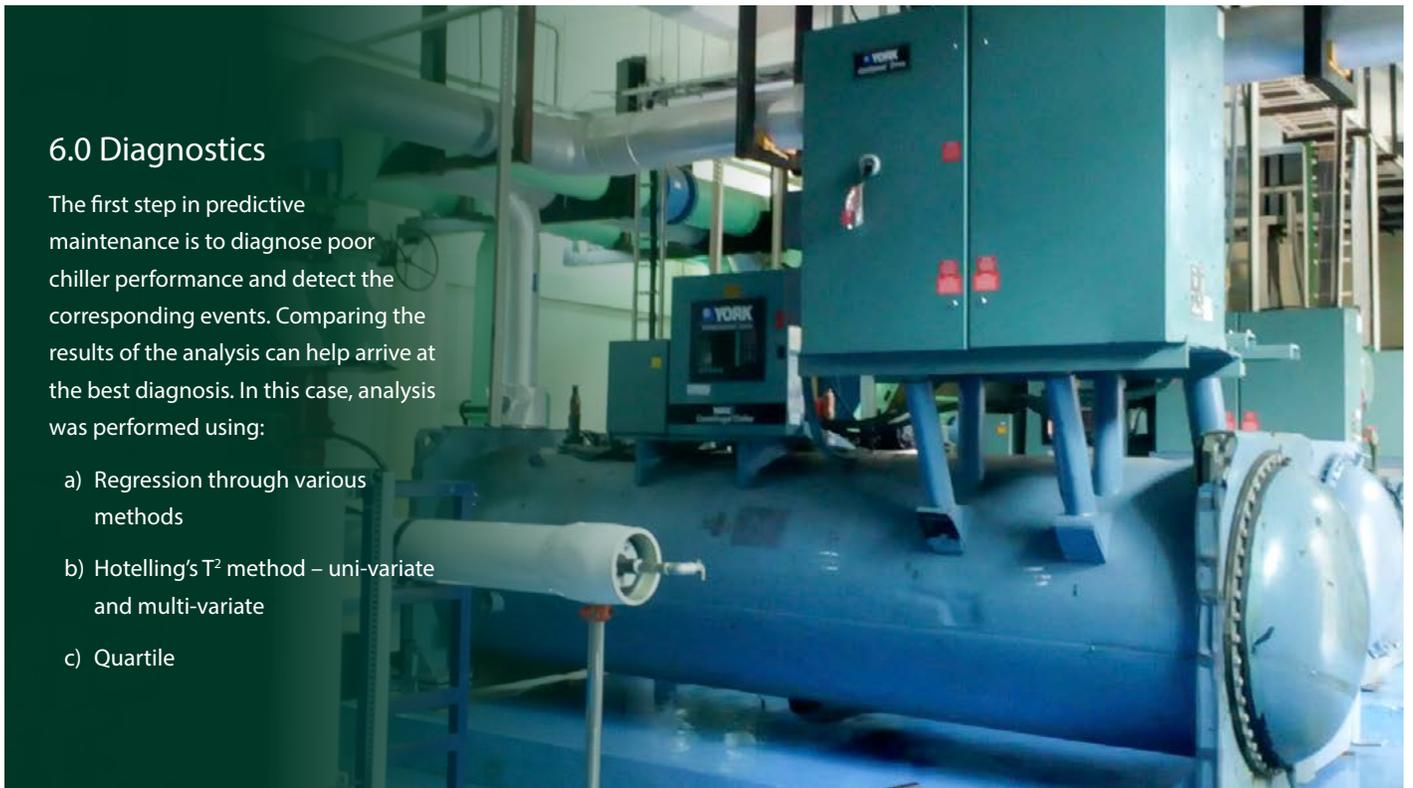
6.1 Regression

First, identify where the chiller operates efficiently, for example where IKWTR is below 0.6. Develop a regression model for this region by fitting the IKWTR value using the remaining 13 parameters. Apply the regression model to the complete duration of the chiller operation. Doing this produced large errors in the regions where chillers do not operate efficiently, indicating the need for maintenance. Chiller data was analyzed through regression methods such as:

a) Multi-variate linear regression

b) Multi-variate adaptive regression splines (MARS) method

c) Random forest method

The regression fit for IKWTR were computed utilizing the above three methods. Based on the difference between the fitted and actual values for IKWTR, it was observed that the errors were large before maintenance and very small after maintenance. Random forest regression (figure 6) detected both the maintenance events whereas MARS and linear regression methods could detect only the first maintenance event.
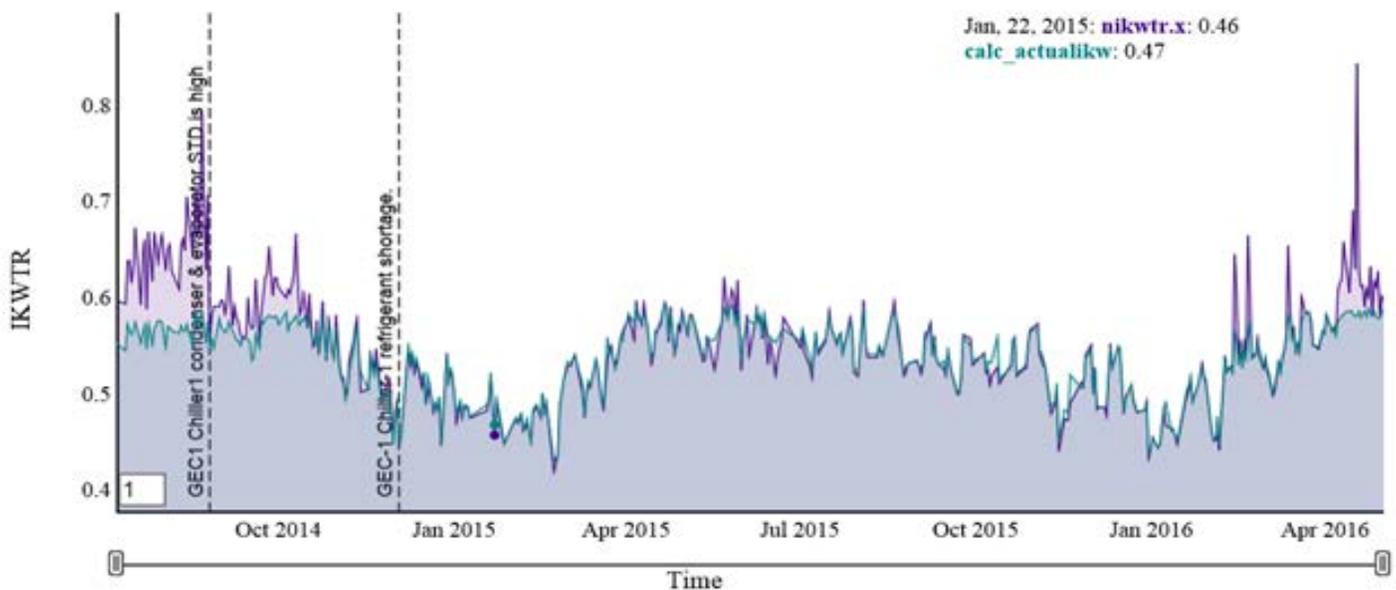

Figure 6: Random forest regression for IKWTR for GEC1_Chiller1

6.2 Hotelling T² method

This method provides an upper limit on computed T^2 value based on all parameters. Points where the T^2 value is beyond the upper limit are considered as events of failure or abnormality. The method can be uni-variate or multi-variate. Points where the T^2 values higher than UCL are anomalous and correspond to maintenance events. IKWTR values are above the UCL values just before both maintenance events. While this method could predict events for GEC1_Chiller 1, it could not do so for the other chillers.

6.3 UCL based on mean and standard deviation

In this method, the theoretical upper limit of the parameter values is computed as mean+3σ, where σ is standard deviation. Cases where the parameter value exceeds this limit are indicative of an event. While this method could predict the first event for GEC1_Chiller1, it could not predict the second event.

Quartiles

UCL values are computed using the region where chiller performs efficiently, i.e., where chiller works normally without any anomaly. This value is considered as UCL1. A second upper limit (UCL2) is derived based on quartiles as follows:

 a) Compute the quartiles

 b) IQR = Q3-Q1

 c) Upper limit (UCL2) = Q3 + 1.5*IQR

Event is detected as follows:

 a) Find the minimum of UCL1 and UCL2. This is considered as the upper limit.

 b) If the parameter value is above the 'upper limit' for 5 days out of 10 consecutive days, it indicates an event.

The results generated from using the above method for event detection in GEC1_Chiller1 are shown in figures 7-9. In these

figures, areas marked in red indicate points above the upper limit, leading to an event. It can be observed that both maintenance events can be detected through the event detection method for IKWTR, CDW_STD and CHW_STD separately. The parameter values are high before maintenance and drop afterwards to lower values due to the corrective action.
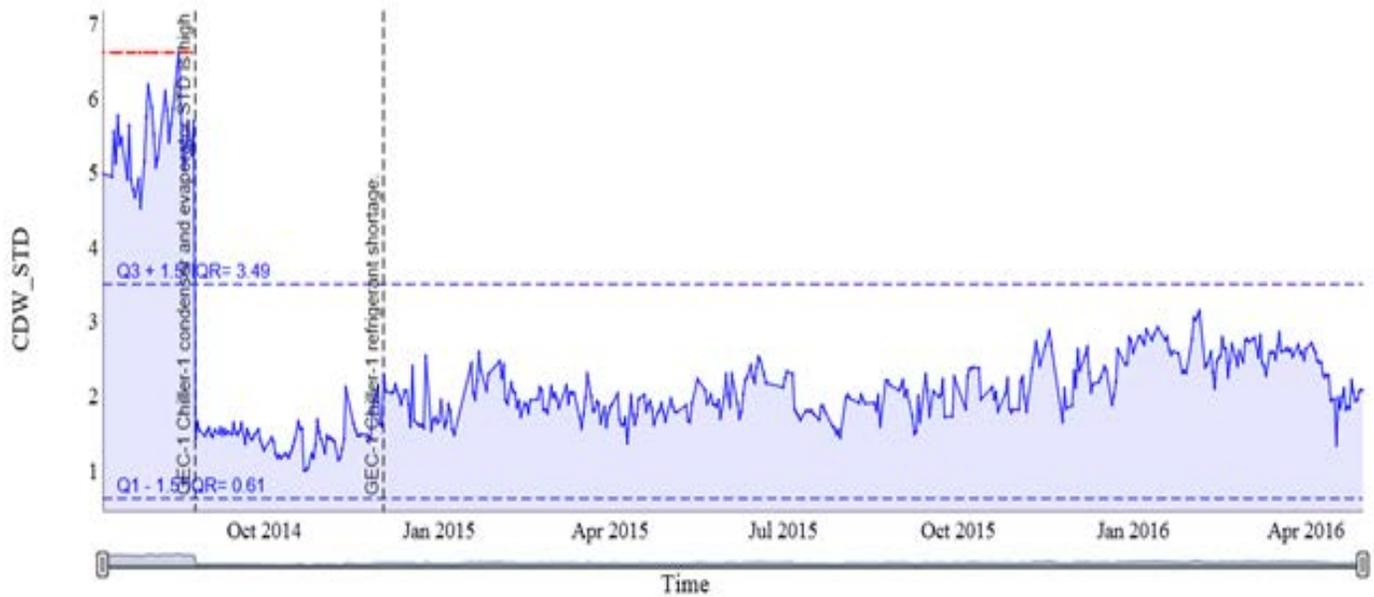

Figure 7: Event detection in the condenser of GEC1_Chiller1
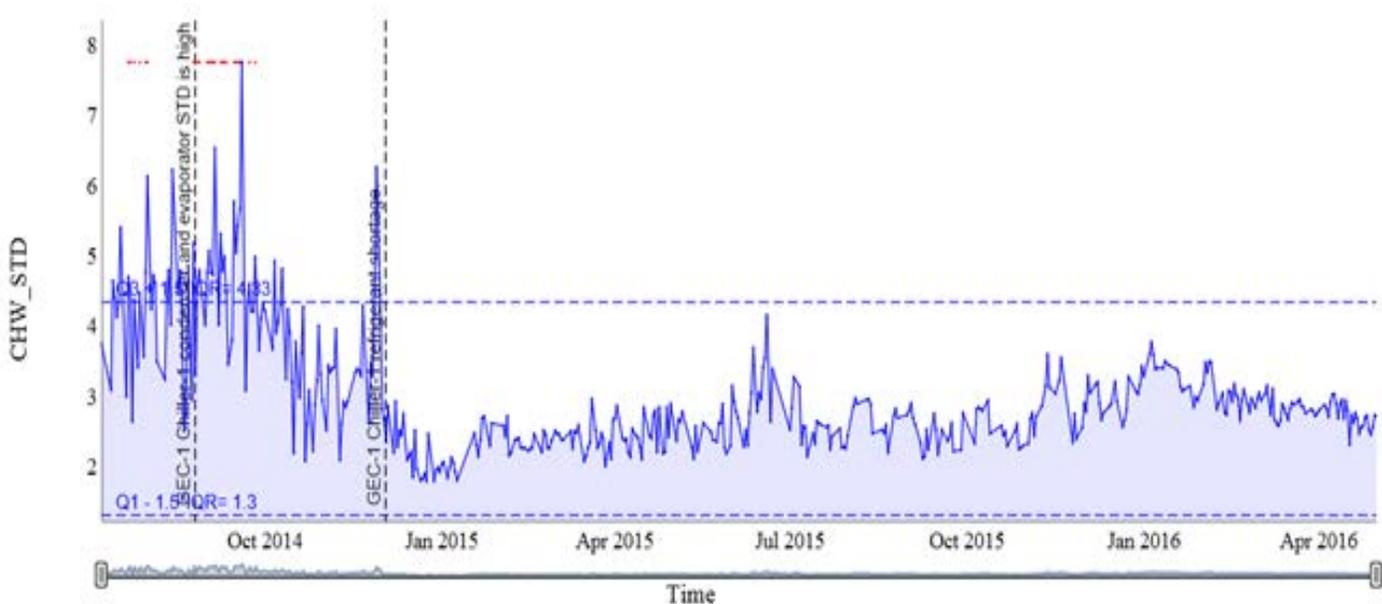

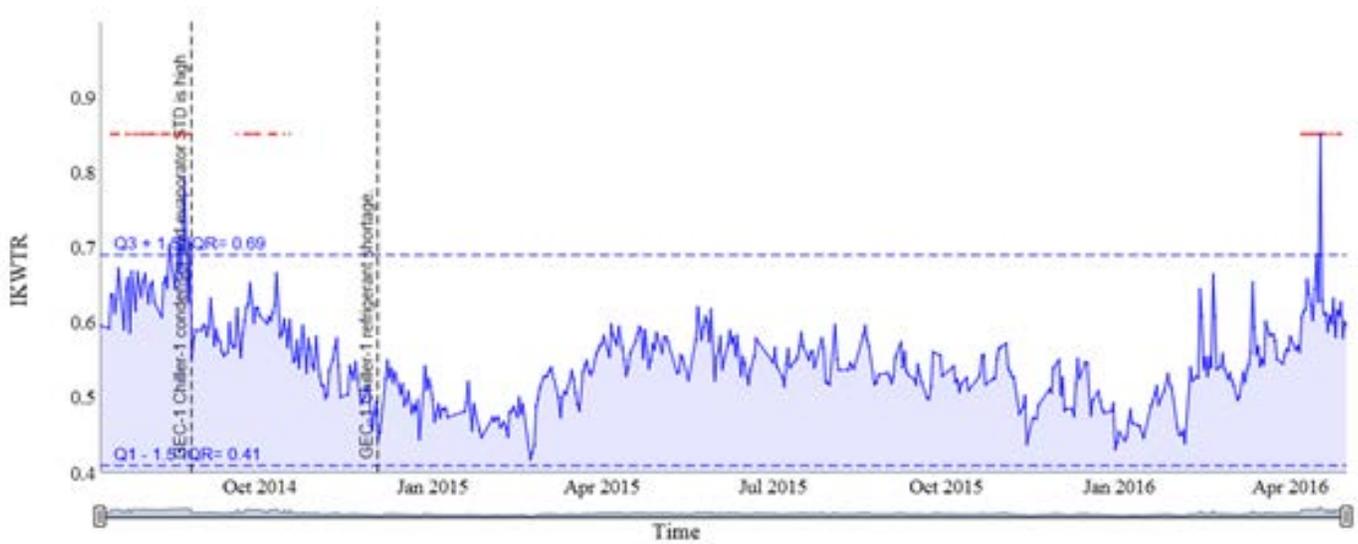Figure 8: Event detection in the evaporator of GEC1_Chiller1

Figure 9: Event detection using IKWTR for GEC1_Chiller1

This event detection method was applied to all the 9 chillers and successfully demonstrated events in all the cases. Hence, it was selected as the preferred approach for detecting events.

Prognostics

The objective of prognostics analysis is to forecast events that may occur in future. To perform predictive maintenance, it is important to forecast the results in the near future based on current data and verify whether the forecasted values indicate an event. Here, the strategy is to perform prognostics using one method while checking if other methods can provide better results. The following methods were studied to develop the forecasting model:

1. Neural networks auto regression

2. Exponential smoothing (ETS Model)

3. ARIMA

These methods were applied on the GEC1_Chiller1 data and forecasting was performed. The ARIMA method with the dependency parameter (xreg in R ARIMA models) yielded better results compared to other methods, provided the variable being forecasted depends on another variable. Correlation analysis reveals a high correlation between IKWTR and the wet bulb temperature. ARIMA model for IKWTR was developed with the wet bulb temperature as the dependent parameter (xreg = wet bulb temperature).

It was observed that the wet bulb temperature has an annual seasonal behavior. The ARIMA model was developed for wet bulb temperature with the seasonal component. First, the wet bulb temperature is forecasted for the near future. Then, the predicted wet bulb temperature values are used in the ARIMA model to forecast IKWTR with wet bulb temperature as the dependent parameter (ARIMA with xreg = wet bulb temperature).

CDW_STD and CHW_STD do not correlate strongly to the wet or dry bulb temperature. However, LCDWT and CondSatTemp strongly correlate to the wet bulb temperature. Thus, ARIMA models were developed for LCDWT and CondSatTemp with wet bulb temperature as the dependent variable. First, LCDWT and CondSatTemp are forecasted. CDW_STD is computed as the difference between LCDWT and CondSatTemp. CHW_STD is modeled in the ARIMA model no dependent parameters.

The results obtained using the ARIMA model for predicting wet bulb temperature are shown in Figure 10. Here, the three curves for forecasted values indicate the mean value (middle), lower and upper limits of the 80% confidence interval. The forecasted wet bulb temperatures are used to predict IKWTR using ARIMA xreg model. These results are shown in figures 11 and 12.

Figure 10: Wet bulb temperature forecasting using the ARIMA model with seasonal components for GEC1_Chiller1
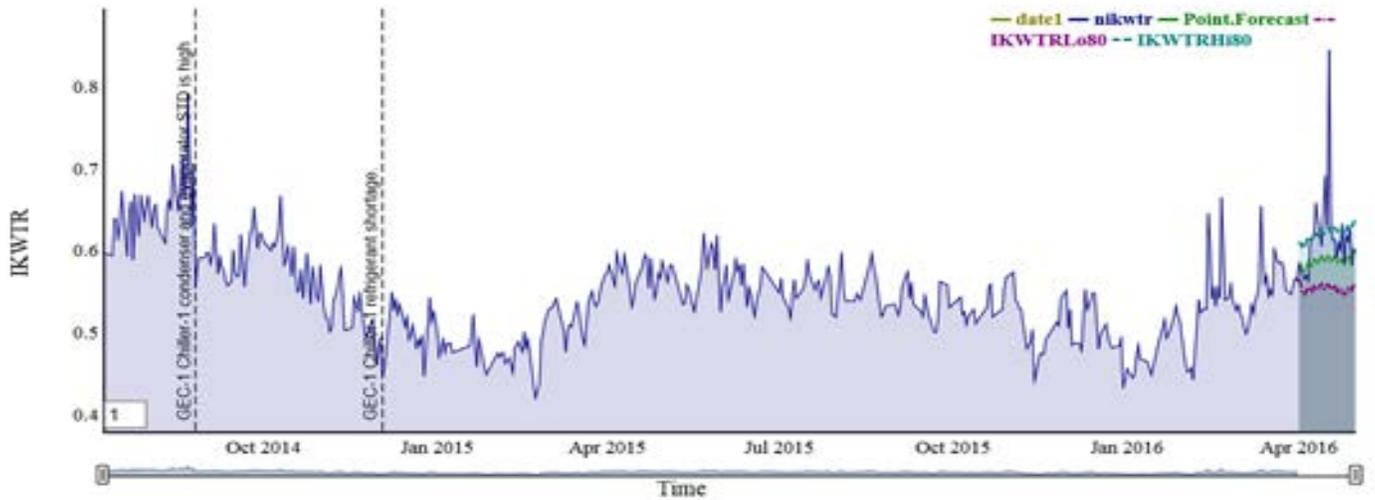

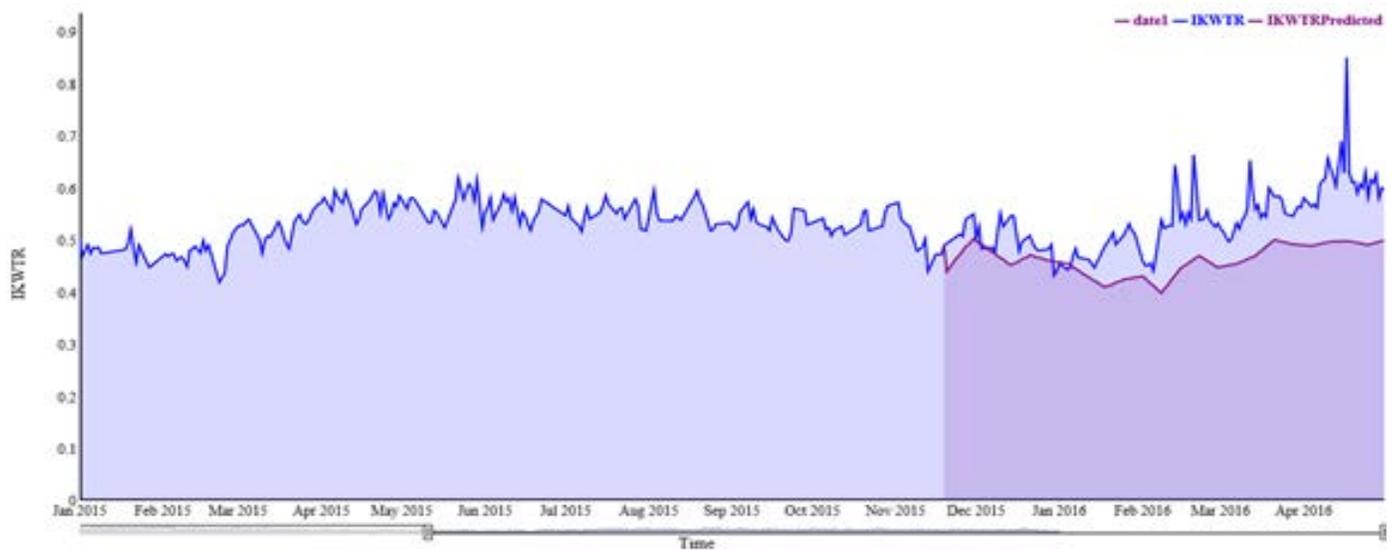Figure 11: IKWTR forecasting using ARIMA with xreg = wet bulb temperature for GEC1_Chiller1

Figure 12: IKWTR forecasting using ARIMA with xreg = wet bulb temperature for GEC1_Chiller1

8.0 Conclusions

As part of its green initiative to reduce energy consumption across campuses, Infosys leveraged IIOT in the chillers of air conditioning systems. Operational and maintenance data were collected over several years and used to develop advanced analytics approaches for chillers – from data cleansing to event detection and from diagnostics to prognostics. The final approach was validated using data obtained from chillers in the Infosys Mysore campus where all the events were detected. The quartile-based event detection method yielded favourable results and demonstrated all the events. In prognostics, using the ARIMA model with dependent variables provided better forecasts when the dependent variable was forecasted with another variable and used with ARIMA. Infosys plans to roll out this analytics approach to the remaining chillers (numbering over 120) with further refinements, if required.

Authors

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