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extrACT

Automatische Funktions- und Ertragskontrolle für thermische Gebäudesysteme - Effizienzsteigerung Datenextraktion

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1 Inhaltsverzeichnis

2 Einleitung

Today's thermal building systems collect a remarkable amount of data in their controllers. However, the evaluation at runtime is usually limited to raising alarms in case of severe errors, but do not pinpoint data problems or inefficiencies. Therefore this project develops algorithms for common systems with solar heating and cooling components that detect errors and inefficiencies automatically and mainly independent of the actual system. The algorithms are tested in systems by partner Pink and with data from solar cooling installations in two office building installations.

2.1 Relevance for Project with Regard to Call

The project contributes to "*Schwerpunkt: 2 Erneuerbare Energien*": it aims at automated analysis of monitoring data in existing HVAC systems and develops algorithms that perform fault detection and data analysis. This supports the ability to constantly check the data and optimize the performance

2.2 Tender Goals

The algorithms that are developed in the project are primarily used and tested for renewable energy systems, namely solar heating and cooling systems. The generic design of algorithms and automatic detection of new system topologies ensures a high degree of usability. The knowledge gained here will help to make such innovative solutions available for the market and thereby increase the penetration and affordability. The project contributes both to meeting the energy, climate and technology policy guidelines of the Austrian Federal Government as well as to increase the affordability of sustainable energy and innovative energy technologies.

2.3 Data Analysis in Energy Systems

Today current installations of cooling devices have the problem, that the implemented monitoring and the previous state of the art methods for fault detection are not adequate. Only for a few faults it is possible to raise accurate alerts that point directly to the right cause within the cooling system. Additionally there are many fault scenarios that could not be diagnosed correctly yet. These could be caused by faulty sensors, which conveyed wrong values or configuration issues. These wrong measurements cause shut downs of devices, although the operation itself had not been faulty. The opposite case was also true: there are situations when components fail that cause a real fault of the system, but still the monitoring is not able to detect these error situations. Only trained engineers could pinpoint fault situations after time costly investigations of all relevant points of measurement. Often a time consuming and very costly on-site investigation could determine the problem, so it was not possible to determine beforehand, which modules would be needed to be replaced and therefore often a second visit was inevitable.

These situations were specifically troublesome with solar thermal powered cooling devices, since in contrast to traditional cooling devices the cooling could only be performed for a few hours a day. If the available time for cooling based on the availability of solar irradiation could not be used efficiently because of system faults, the cooling had to be postponed to the next day. Therefore, it is very important that faults can be identified and resolved quickly.

In summary, the algorithms and methods developed within the project will lead to a much higher operational safety of cooling devices, because the monitoring system based on project results' will have, in addition to traditional fault alerts (1), new methods of sensor data analyses (2) and advanced data analysis (3).

	Existing, real fault of the installation	Monitoring shows a fault	Fault can be detected currently	Fault will be detected in future
(1)	yes	yes	yes	yes
(2)	**no**	**yes**	**no**	**yes**
(3)	**yes**	**no**	**no**	**yes**

In the past there have been specifically false positives for faults alerts, caused by defective flow and temperature sensors. These false positives caused unnecessary shutdowns and maintenance operations, although the system would have been able to run completely within the specified boundaries of operation (category 2). Based on the implementation of the algorithms developed within the project into the machines, these scenarios become fewer in future. The analysis of energy balance within the cooling device should help in determining if a single sensor is faulty or the overall system has a problem. In the first case a continuing emergency operation is possible until maintenance can be performed. A shut down of operation will only occur if inevitable.

An example for category (3) is a single component fault (such as pump of the solution or injector valve) or faults of the overall system (recooler) happening repeatedly. These faults cannot be identified by a dedicated alert using state of the art monitoring. Within this project it was possible to develop algorithms that support the detection of these situations. This will lead to more accurate alerting and faster response and repair times in production.

3 Inhaltliche Darstellung

This chapter starts with an introduction of the developed visual workflows and an example of visualizing cycle characteristics and then moves on to cycle detection. Cycles are required for most of the following error detection analysis. The error detection comprises of analysis such as calculating the thermal energy efficiency ratio and detecting sensor faults through detection of outliers and stuck-at-values. Histograms are used for checking sensor boundaries. The analysis is then refined by a CoP analysis on duty cycles as well as looking at the Carnot efficiency. The analysis ends with the creation of an energy balance and the detection of duty cycle outliers. The chapter is concluded with an introduction and outlook on robustness analysis.

3.1 Interactive, Quick Assessment Workflows

The goal is to allow the energy expert to relatively quickly and in an interactive fashion utilize building blocks to make a first assessment of the chillers' operation. As such the general mode of operation is of interest as seen in Figure 2 below. The workflow in Figure 1 extracts relevant date and time and creates a pivot of days against minutes. As can be seen in Figure 2 the individual cycles are quite regular but rather short (35-55 Minutes) which can impact the performance negatively.

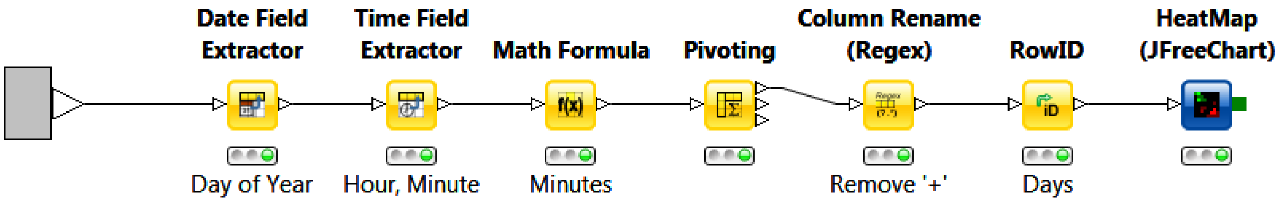

Figure 1 Heatmap workflow

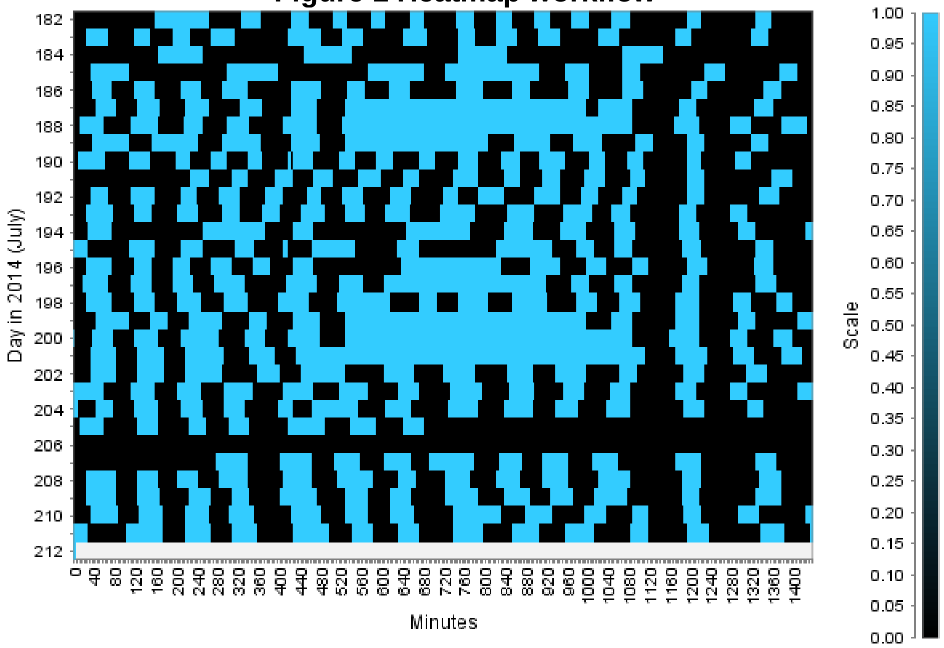

Figure 2 Heatmap of cycle characteristics Privathaus, July 2014

Next, the high and low temperature cycle thermal capacity and the resulting thermal energy efficiency ratio (EER) are calculated for the same system but for the whole of 2014. Figure 3 shows the workflow of calculating and visualizing the thermal performance. The sorted view shows values of between -3.59 and -2.67 that are due to recordings being stuck over two days. The remaining values below 0 and above 1 are due to transient states. The statistics node (showing minimum, mean, median, maximum, std. dev., skewness, kurtosis, no. missing, no. +∞, no. -∞, histogram) indicates an overall mean EER_th of 0.41 for 2014. Low values that are not due to transient state as well as views of individual days can now be filtered and further investigated.

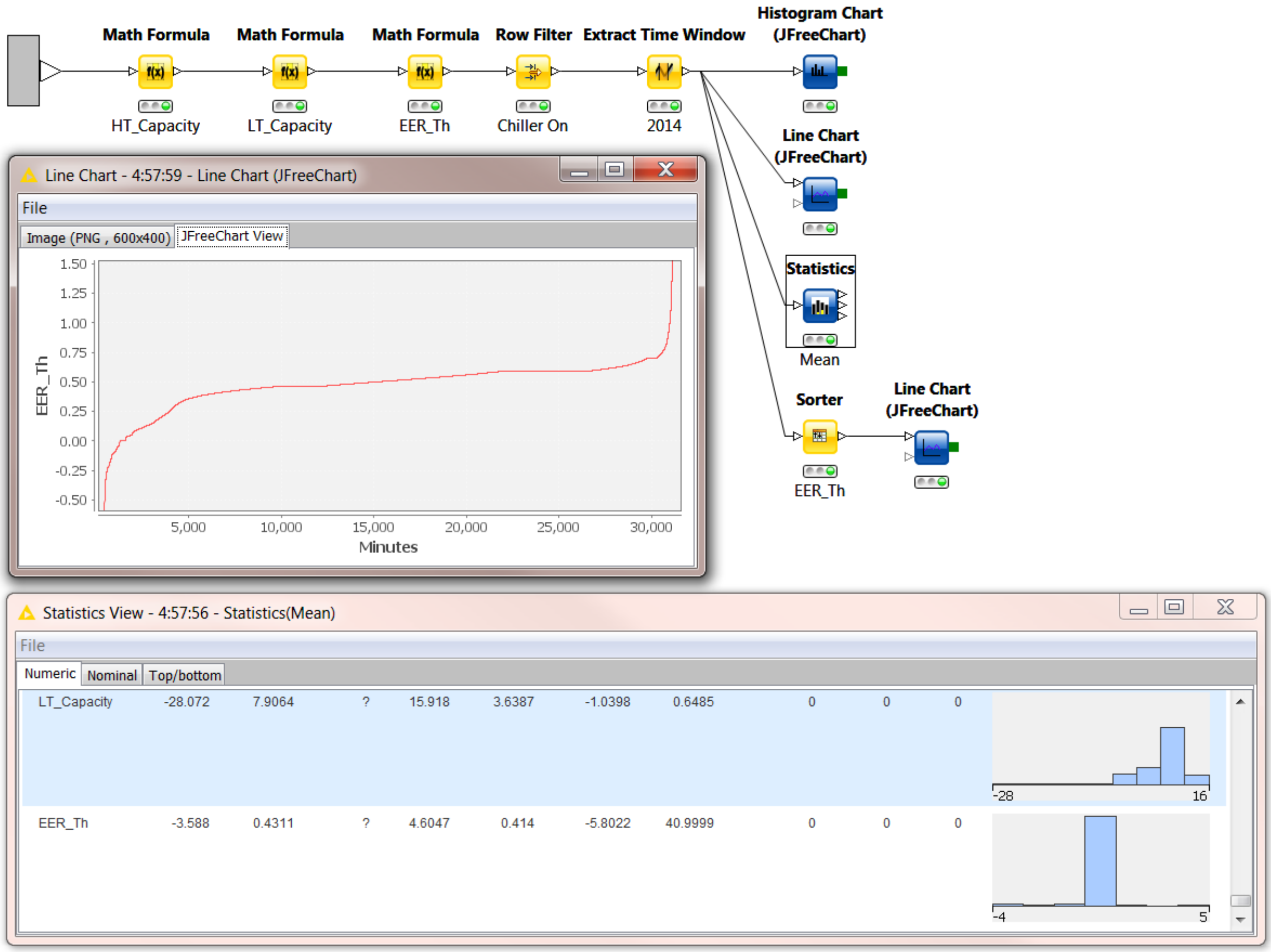

Figure 3 Calculation of EER_Th for on cycles 2014

3.2 Error Detection Pink Chillers

All installations within the project that use the PinkChiller by Pink GmbH have been examined during operation concerning various different recurring faults. As was already mentioned in chapter 1, there are different categories of faults. Category 1 is already covered by the currently existing monitoring system and can be interpreted correctly:

- Missing mass flow in one of thy hydraulic circulations (HT, MT, LT) caused by bad venting of the system or by filters needing replacement.
- Overload of single system components such as the solution pump, the hydraulic circulation pump or the cooling tower fans.
- Since the cause of the fault can be figured out easily and the resolution of the problem is easily possible, this category of errors has not been covered within this project

For category 2 the monitoring system reports a fault, although there is no real fault. These situation occur mostly because of faulty sensors, but the problem would not need a downtime for the chiller system. The sensor batch used for measuring the energy balance turned out to be unreliable and to fail often. As a result the rate for false positives was high. After switching from the back than newly available combinations of flow sensors (vortex measurement principle) and temperature sensors to according to the manufacturer more reliable sensors, the problem could still not be solved. Eventually, after switching to sensors for the manufacturer HUBA (another exchange of sensors was needed) the measurement of the mass flow and therefore the efficiency measurement of the chillers could be increased to a needed level.

The result of wrong measurements is quite problematic, since a missing or to low flow in one of the three hydraulic circuit leads to a complete stop of the machine. This is a safety measure, since an inadequate flow in the cooling circuit (LT) and in the recooler circuit (MT) can lead to damage of the chiller. Damage has to be prevented at all costs, especially since ammonium is used as cooling agent.

As example data points of the same hydraulic circuit are shown in Figure 4. The data points are before and after the exchange of the sensors. It can be seen clearly that the measured values in the left part of the figure vary a lot. After the replacement the mass flow can be measured correctly. Also the control / safety related shut downs can be seen (gaps within the green bar, which shows the period of duty of the chiller device.

Defective sensor | correctly working sensor

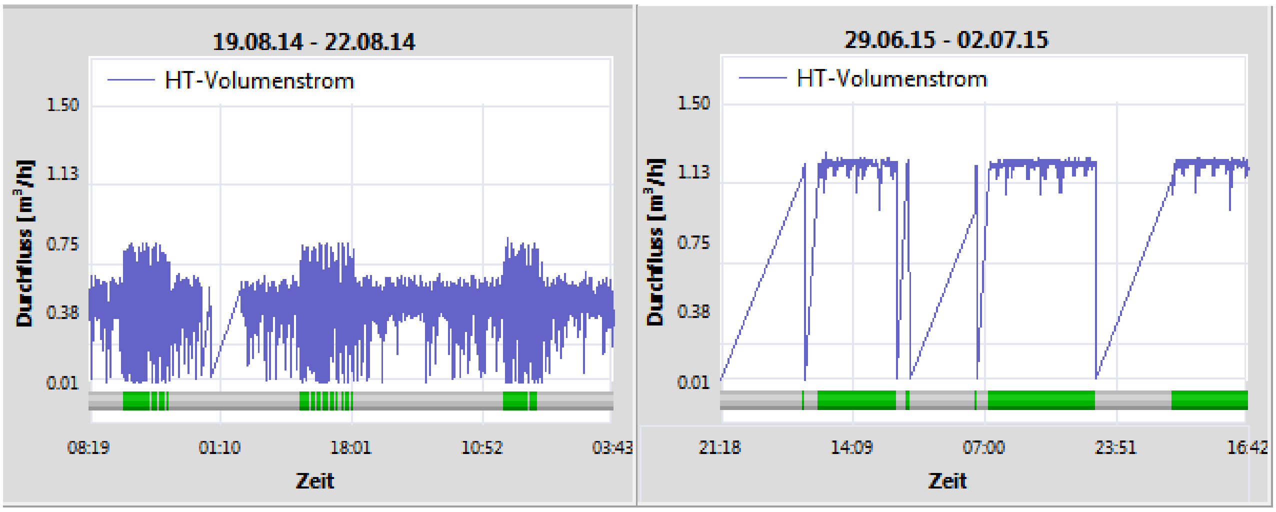

Figure 4 Sensor comparison

Since a power calculation is needed in all three circuits of the pink chiller, it is possible to get information about the measurement errors by calculating the balance of in and outgoing power. As an example a day with a correct power balance over the duty periods of the whole day is shown. (see Figure 5).

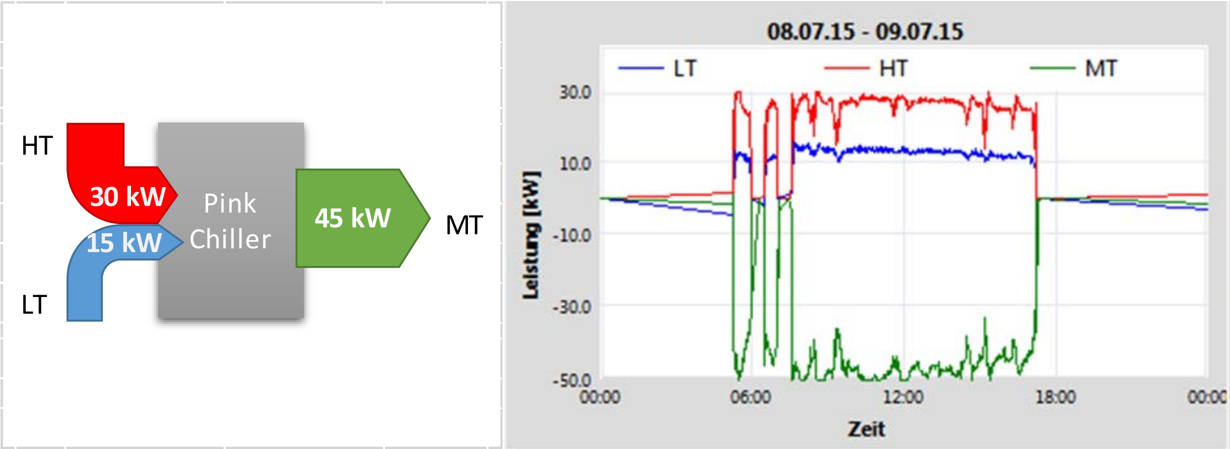

Figure 5 Power balance with working sensors

3.3 Analysis: Detection of Duty Cycles

The behavior of chiller varies in On and Off state, which can also be seen in the data monitored. In order to detect these two states, K-Means clustering algorithm is used to find the two clusters (On/Off) in the data. Before applying the K-Means algorithm the data is normalized using Min-Max normalization. The number of cluster for K-Means clustering is taken as 2 with the Euclidean distance function as we expect 2 clusters in data, as can be observed in Figure 6 below. The dotted line shows the On and Off status of the chiller. The behavior of the temperatures at the Low Temperature (LT), Medium Temperature [MT] and High Temperature [HT] cycle are responding according to the detected On/Off state. The dotted rectangle shows one On cycle of the chiller between 2010-07-21 and 2010-07-22. It is evident that during the detected On cycle, the LT temperatures decreases indicating cooling operation while at the same time, the temperatures increase in the HT and MT cycle of the chiller. This change pattern in temperature, is a clear signal for the algorithm that the chiller is in operational mode.

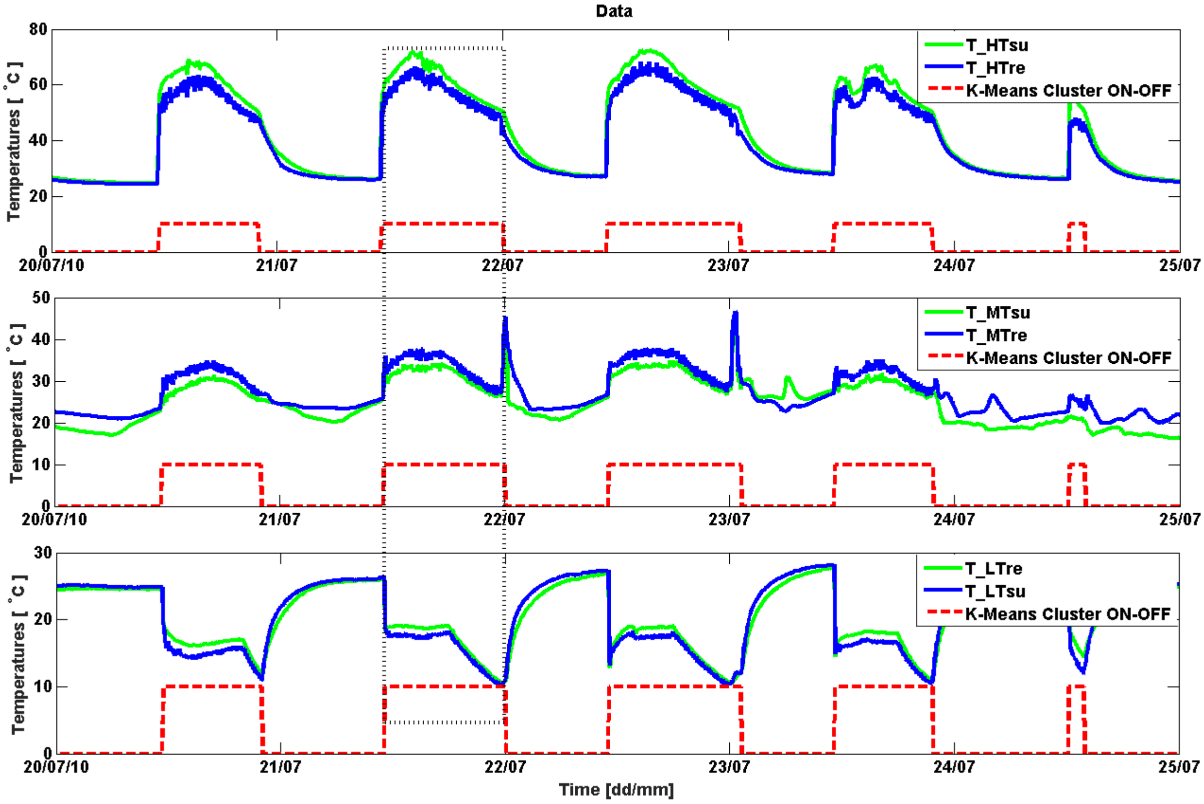

Figure 6 K-Means On/Off state detection

3.4 Analysis: Point Based Outlier Detection

The outlier detection process described here uses Z-scores [1]. It operates automatically and does not require configuration. However, the performance of the outlier detection benefits from the duty cycle detection: z-score considers the mean and standard deviation of the whole data for normalization; this way outliers are better distinguishable from normal behavior, thus improving the clustering algorithm that identifies the outliers. In this project we define the duty cycle Z-score (i.e. the z-score specific to one On- or Off state) as following:

$$1)\quad \text{Z-Score}_{Cycle} = (X - \mu_{Cycle}) / \sigma_{Cycle}$$

Where Z-Score_{Cycle} is the z-score for each cycle when the system is either On or Off, X is the value of the sensor, μ_{Cycle} is the population mean of each Cycle, and σ_{Cycle} is the standard deviation of each Cycle. Figure 7 shows the improved outlier detection: While the standard Z-score detects only one outlier (at about 1:00 on Jun 18th), the cycle Z-score detects a second outlier (at about 18:30 on Jun 17th), which would otherwise go undetected.

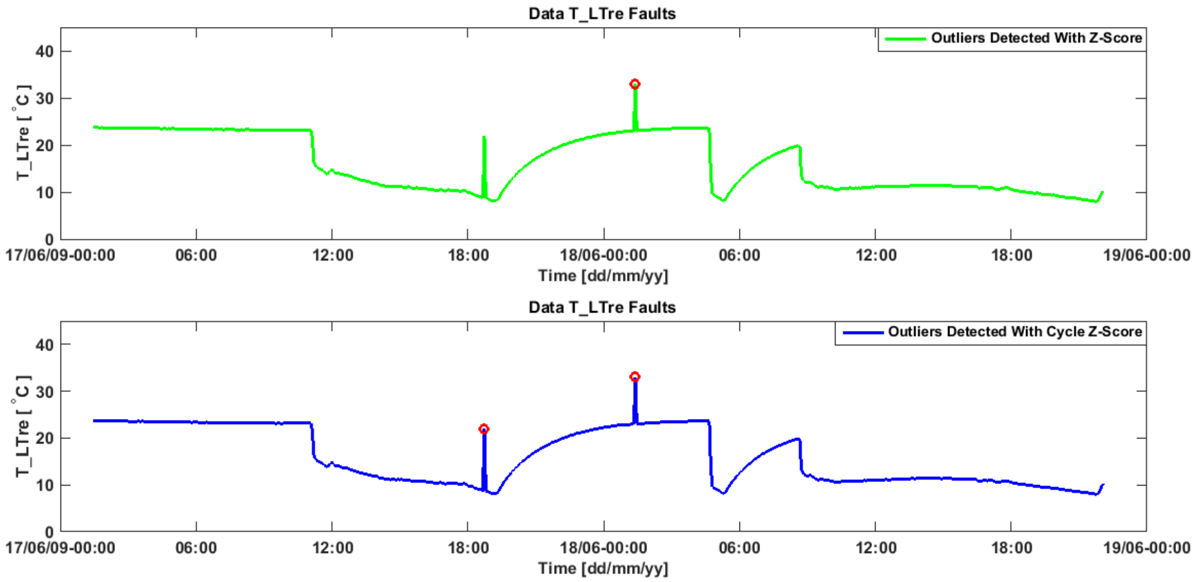

Figure 7 Outlier detection with cycle based Z-Score

3.5 Analysis: Stuck-at Value Detection

Sensors that are deployed in the field run the risk of getting damaged, thus can record faulty data. It is important to detect there errors as this will help in the detailed analysis of the energy systems. The stuck-at value is can be observed in the patterns of data, as seen in Figure 8 below. For detecting such faults, the On/Off cycle information is used, because the detection of stuck-at errors is only relevant in the On-state of a machine.

The On/Off state is found using K-Means algorithm. The behavior of the chiller varies in these two states (On/Off), the pattern (behavior) in On state with the preceding Off state pattern. If the patterns in two consecutive (On/Off) cycles have same kind of patterns, then this will be considered as stuck-at value fault of sensor. For pattern (behavior) comparison the data is transformed using symbolic aggregate approximation (SAX). Then the symbols are represented using Bag of Word Representation (BoWR) for each consecutive cycle (On/Off). At the end the consecutive BoWR of cycles are checked for similarity by using the Manhattan distance function. If the distance between two consecutive cycles is zero then these instances are marked as stuck at value error as can be seen in Figure 8 below with the line at top of the figure: The red bar indicates that a stuck-at error has been detected.

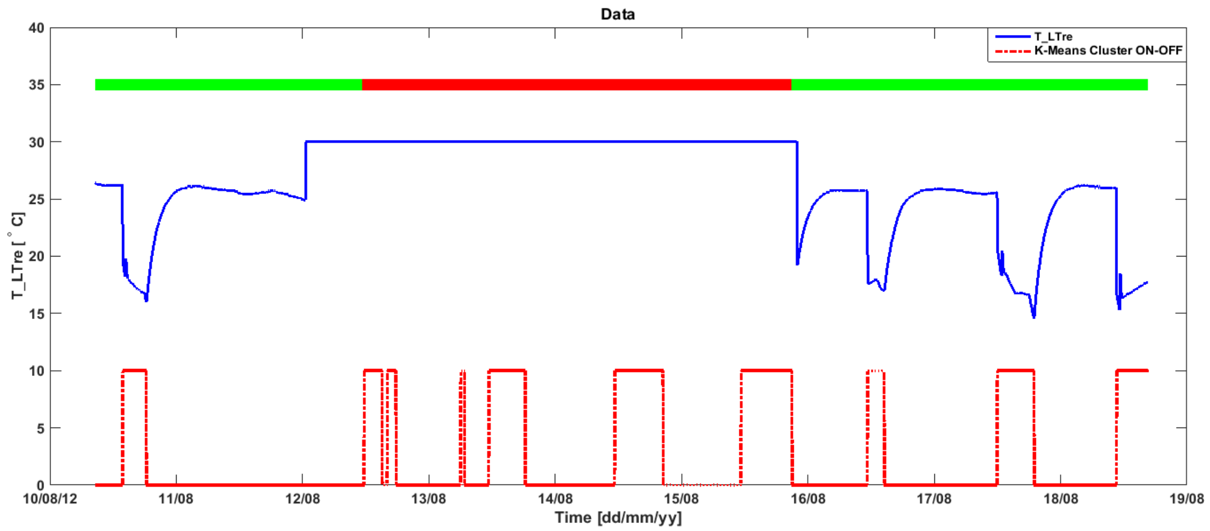

Figure 8 Sensor stuck-at value detection

3.6 Analysis: Histogram

The adapted histograms are suggested to visualize the statistical information of the data distribution. The information of duty cycle detection provides a swift way of visually checking data plausibility. Only data from the On-state of the system is visualized. As a result, the number of process limit violations is reduced, giving insight into the real operation of the system. Figure 9 below shows a system temperature in a specifically adapted histogram: The data within the process limits are equally divided into ten bins in the middle, while the upper and lower boundary *process limits violation bin* that contains all remaining outliers. For better visualization these two bins are drawn with red bars, as can be seen in Figure 9 where only a minor part of the data is outside the process limits and shown as a red bar on the right. By combining the On/Off state detection with the improved histogram, an energy expert can quickly assess that the overall data quality of the supply temperature on the hot side of the chiller is adequate.

3.7 Analysis: CoP per duty cycle

The thermal Coefficient of Performance (COP_{therm}) is another analysis method to improve data quality and to identify faults. The thermal COP (COP_{therm}) of adsorption chillers has to be in a range between 0 and 1, a COP_{therm} outside this range is physically not possible and therefore a good indicator for low data quality. Following the naming convention that has been adapted from IEA Task 38 the COP_{therm} can be calculated through the following equation:

$$CoP_{therm} = \frac{Q7_{KW}}{Q6a_{KW}}$$

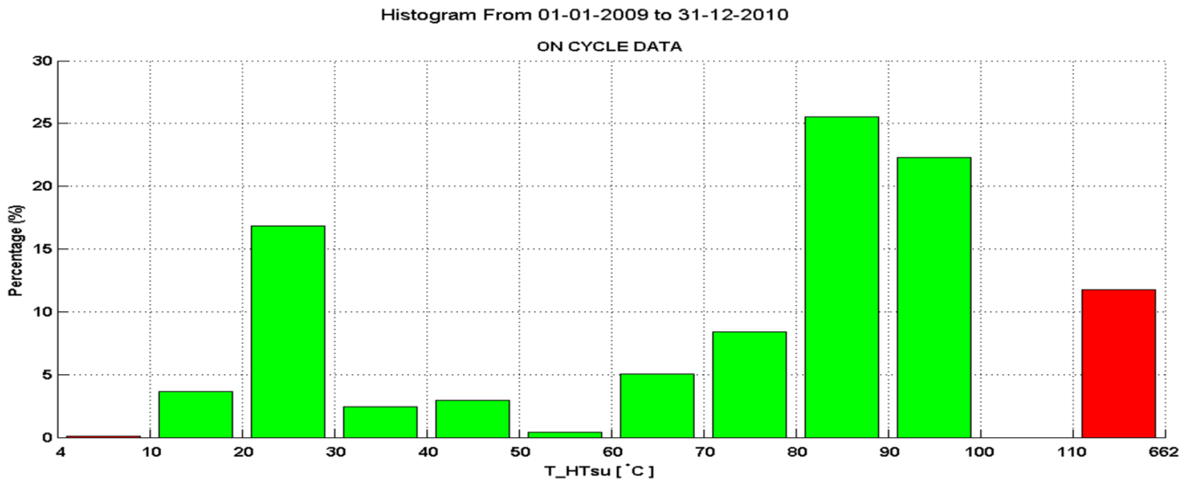

Figure 9 Histogram of the supply temperature in the high temperature cycle containing outliers

Commonly the COP is calculated coarsely over a longer operation period. By using the duty cycle detection we have the ability of calculating a more detailed COP. Figure 10 shows the thermal COP derived on a sample-by-sample base (blue graph) and averaged over the On-state of a duty cycle (red graph). It also shows that the calculation of the COP on a sample-by-sample base is overambitious, since the high time resolution results in a highly dynamic and noisy signal. This is mainly due to the intrinsic delays in the system, i.e. the energy that is put into the system does not affect the output in the same time step, but rather with a short delay. As a result, values can exceed the maximum value of 1. It has therefore been decided that a sample-by-sample COP is not feasible. Instead, the single samples are averaged over a whole duty cycle, as shown in the dotted red line. This parameter gives a good indication of system performance on a single cycle base.

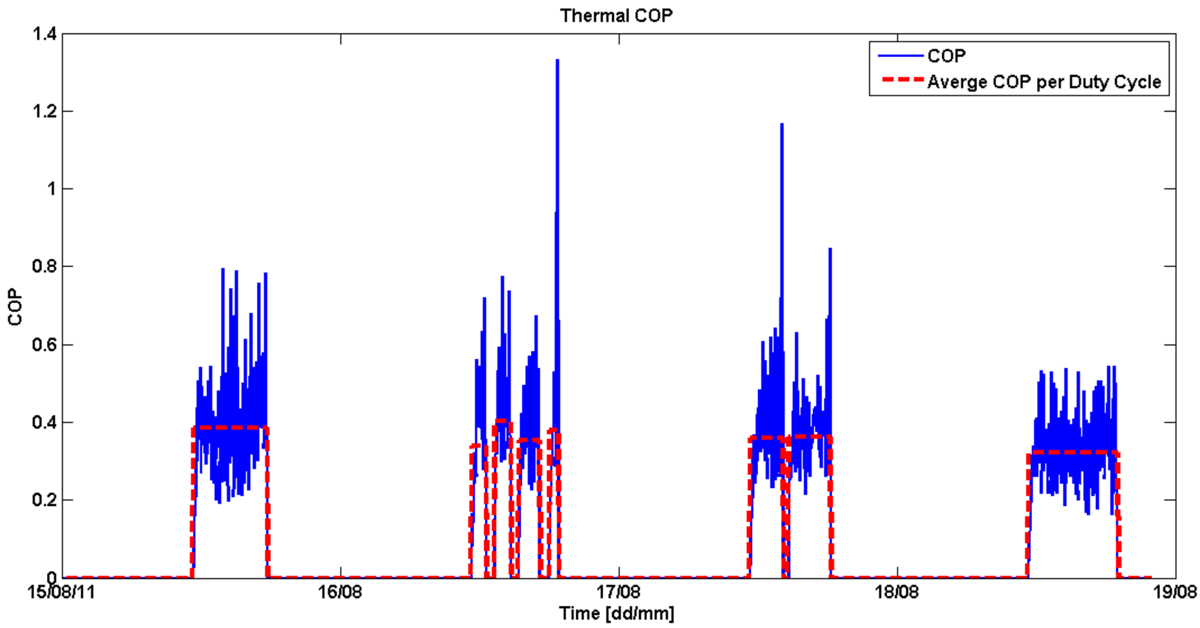

Figure 10 Average COP per cycle

Analysis on-cycle sequences

Detailed analysis of sensor data during operation of the chiller systems is valuable for the detection of operational anomalies as well as for the localization of defect parts in the system architecture. As a result of this detailed analysis process for each recorded data point a specific template is generated. The characteristics of these templates are derived from system on cycles already stored in the database. Depending on the type of the metering point (pressures, temperatures, flow values, etc.) the template includes various statistical measures as well as time and frequency domain characteristics. Finally with the help of the template three tasks may be achieved.

1. If a new on-cycle sequence of the chiller is monitored, the recorded data samples can be verified against the stored template. If there are any deviations from the template which are larger than defined tolerances the dedicated on-cycle sequence may be marked as faulty. If faulty chiller operations occur sequentially a system error report (alarm) can be sent to an operator. Data points of faulty on -cycles which are not compliant with the defined template may be a starting point for further manual inspection. Thus, eventually slight damages of components can be maintained before the full system break down and run into a fatal error state. Second, the location of the faulty component in the system structure may be identified. Sequences of faulty data points are correlated. For example, if the motor of a compressor unit is not working properly the recorded data for pressure may be too low at a simultaneously too high electrical power consumption. Under consideration of such correlations the location of damage may be identified to specific structures of the full system architecture.
2. Due to an interruption of the communication channel between sensors and process control system the identification part of a data stream may get lost. Thus, an anonymous data series is monitored. With the help of the templates the process controller can evaluate potential candidates for matching the received data stream to a registered data point. Strictly speaking, available characteristics of the received data stream (values, shape, durations, etc.) tried to be matched to a template. This process results in a specific identification probability for each stored template representing a data point.
3. The number of stored on cycles is essential for the quality of the described template. Thus, each monitored on cycle which is not marked as faulty refines the template of dedicated data series.

The so called on-cycle periods is identified by two Boolean values in the measurement data streams. First, the “system on” bit identifies if the full system is switched on and ready for operation. Due to corresponding environmental sensor data the chiller is in standby mode. Second, the “chiller on” bit states if the cooling process is active. For the following analysis, where on-cycle periods of the system are extracted and compared to each other, both of the mentioned bits must be logical true.

For all of the following analysis and template extraction processes on-cycle sequences are inspected individually. Thus, if a “system on = true” and “chiller on = true” state is identified in the sensor data stream a new on-cycle sequence data record is created. In our case, we perform a post process analysis of all previously monitored system data. These data is available and exported from the JEVis system in 5-minutes aligned csv files. Figure ABC illustrates exported on cycles for data points *LT_Power* and LT_Temp_in for the Behmann system. The diagram in Figure 11 shows 500 minutes of each on-cycle.

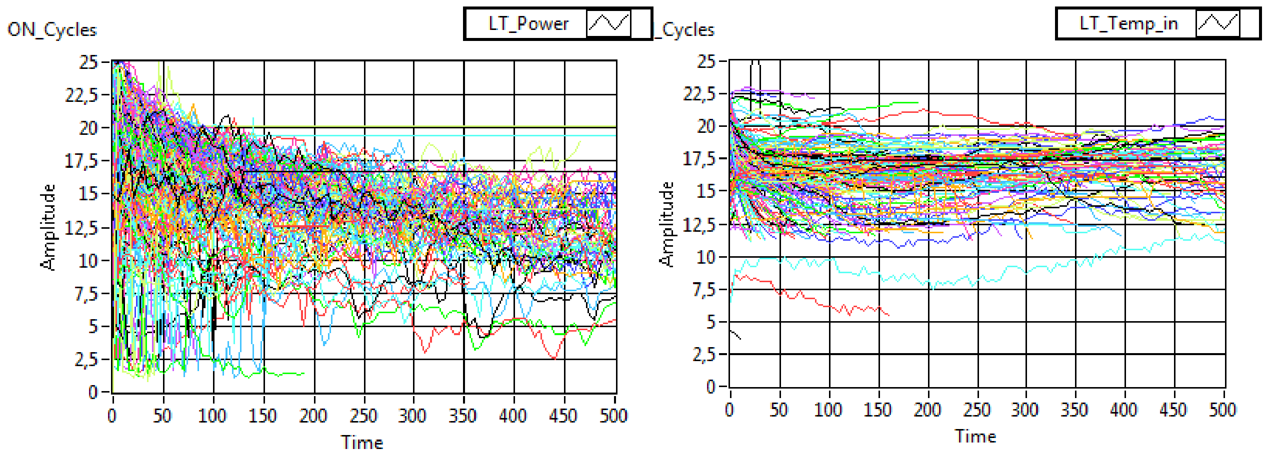

Figure 11 Statistical on-cycle analysis

Temporal Analysis

Within this type of analysis on-cycle data series are explored in time domain. The Behmann system, which is the running example for the description of analysis methods and template generation, includes 493 sequential on-cycles. First analysis type mentioned here is the measurement of the RMS (root mean square) value over a full on-cycle period. This statistical value is a significant measure if the expected value of a specific data point is approximately constant over a full on-cycle period. If there is an exponential trend the single RMS value is not a valuable characteristic for the data series. Thus, RMS analysis and especially a meaningful contribution to template generation depend on the global trend of the data series, which is related to the physical type of the value.

Figure 12 below illustrates the RMS plot and a histogram of the HT Flow data series. The left diagram plots the RMS values of the according on-cycle. As a result of the histogram it can be seen that the mean of all available RMS values is located at 2.53 m^3/s having a standard deviation of 0.49. It can be seen that after approximately 400 cycles the RMS values gets somehow larger speeded which bay be caused by some changes within the system structure.

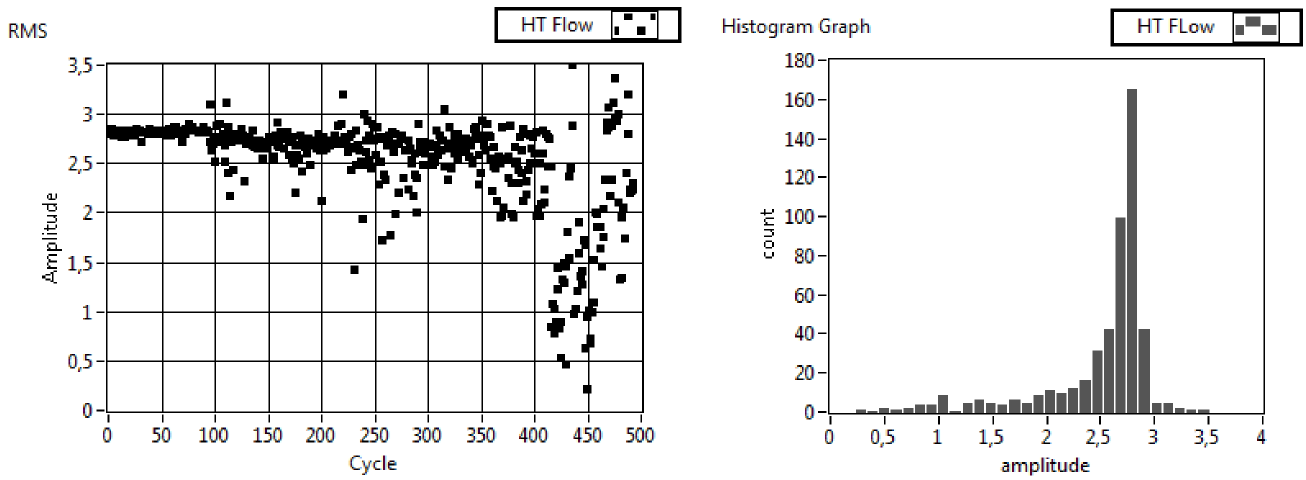

Figure 12 HT Flow RMS

A similar analysis can be evaluated for minimum and maximum values occurring within all recorded on-cycles. Figure 13 illustrates the minimum and maximum values of the HT Flow data point. It indicates that the minimum and the maximum occurring value over the according period are close together. This indicates a more or less constant trace of the HP flow data series. The minimum has an estimated average of 2.20 m³/s with a standard deviation of 0.56. The maximum average value of all on-cycles of HT flow has a value of 2.72 m³/s with a standard deviation of 0.49.

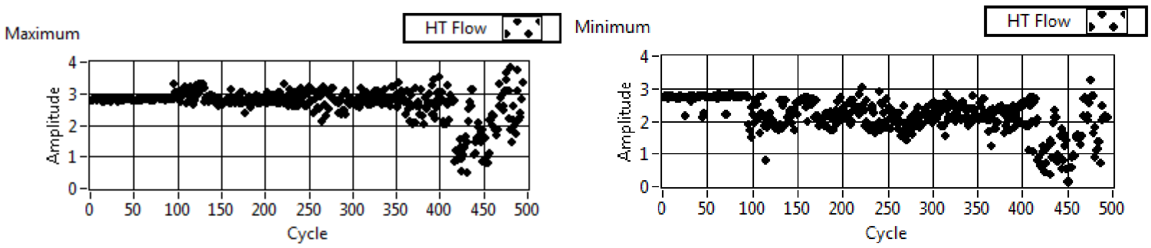

Figure 13 HT flow amplitude

Based on this detailed temporal analysis method the following evaluations have been applied on the resulting waveforms. In contrast to the specified observation of single operation cycles the following methods process data specified over various periods.

Frequency domain analysis: Processes characteristic frequency domain ratios indicating the occurrences of the activated cooling processes. Due to a significant impact whether these are processes during or outside of the cooling season (summer or winter) the analyzed portion of the time waveform must be at an appropriate length. Strictly speaking, the analyzed partial timing waveform must be focused on time interval where weather conditions (especially outside temperature) are assumed to be constant.

Correlation analysis over sequential on cycles: If various cooling cycles are taken into account, several correlations regarding characteristics parameters of the process can be evaluated. Especially in the temporal domain a specified subset of monitored metering points correlate more or less each other. For example cooling characteristics as time constants, thermal influence of the outside temperature, etc. may correlate over various cooling cycles.

Extraction of templates: Based on the analysis results for the prediction of internal system faults characteristic process parameters are evaluated. If these parameters (process properties) are violated the user may get an indication where to start further verification of the process and prevent potential resulting system faults.

Visualization for decision makers

For the ease of use for decision makers the data has also been integrated into dynamic Microsoft Excel documents with embedded MATLAB (Figure 14). The documents allows to select the device, the month of interest and creates diagrams that can also be integrated in documentations about the device performances. The following figures show the configuration and interface and some examples of diagrams.

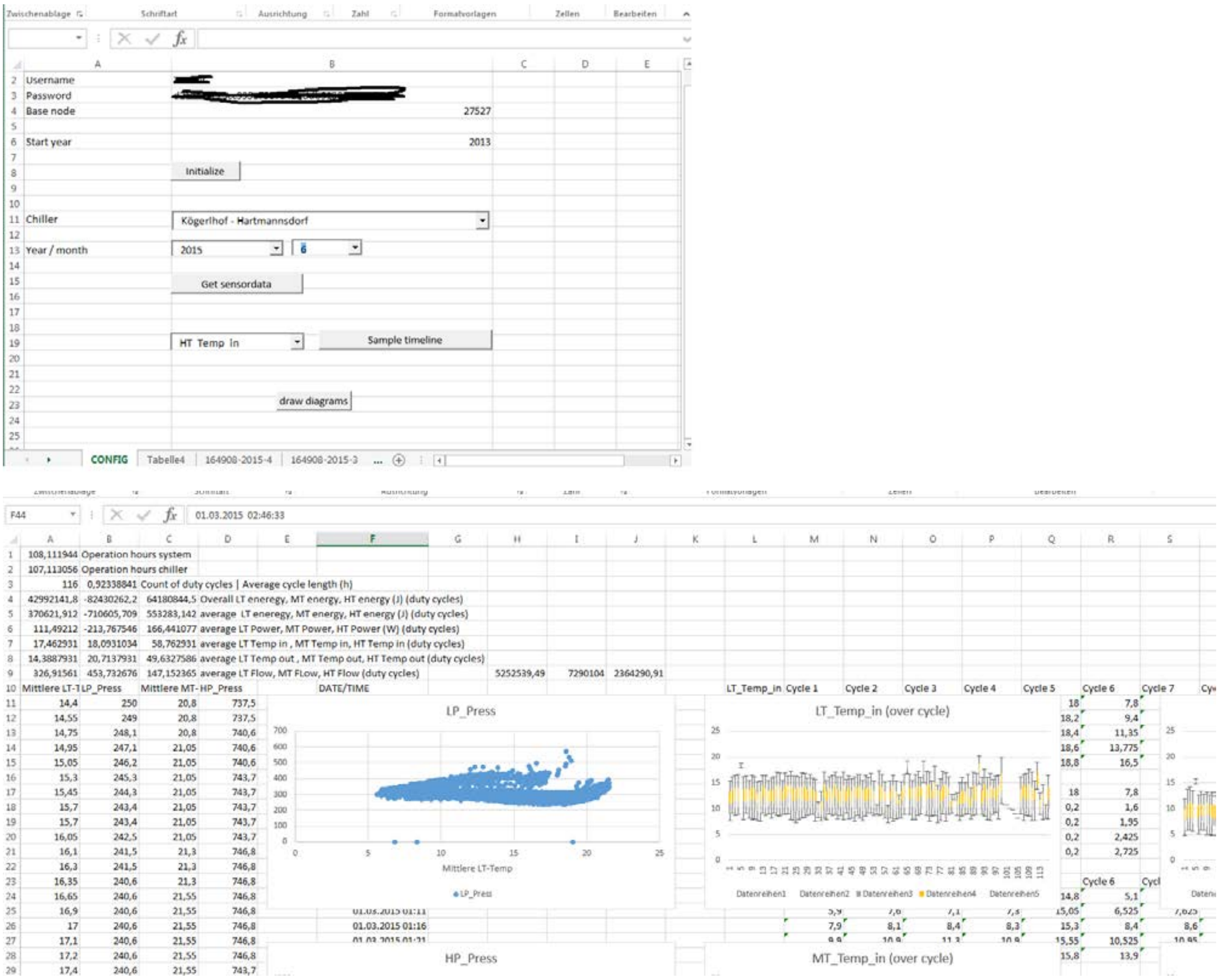

Figure 14 Visualization of monthly analysis

3.8 Analysis: Carnot Efficiency, Constant per Duty Cycle

Carnot efficiency puts the actual performance in relation to the theoretical performance of an ideal, frictionless machine. It is calculated using the following equations:

$$COP_{carnot(therm)} = \left(\frac{T\_HT_{su} - T\_MT_{su}}{T\_HT_{su}}\right) * \left(\frac{T\_LT_{re}}{T\_MT_{su} - T\_LT_{re}}\right)$$

$$CoP_{therm} = \frac{Q7\_KW}{Q6a\_KW}$$

$$Efficiency_{carnot} = \frac{COP_{carnot(therm)}}{CoP_{therm}}$$

Figure 15 shows Carnot efficiency derived on a sample-by-sample base (blue graph) and averaged over the On-state of a duty cycle (red graph). Similar to COP_{therm}, it exceeds 1 on a sample basis but not on averaged basis.

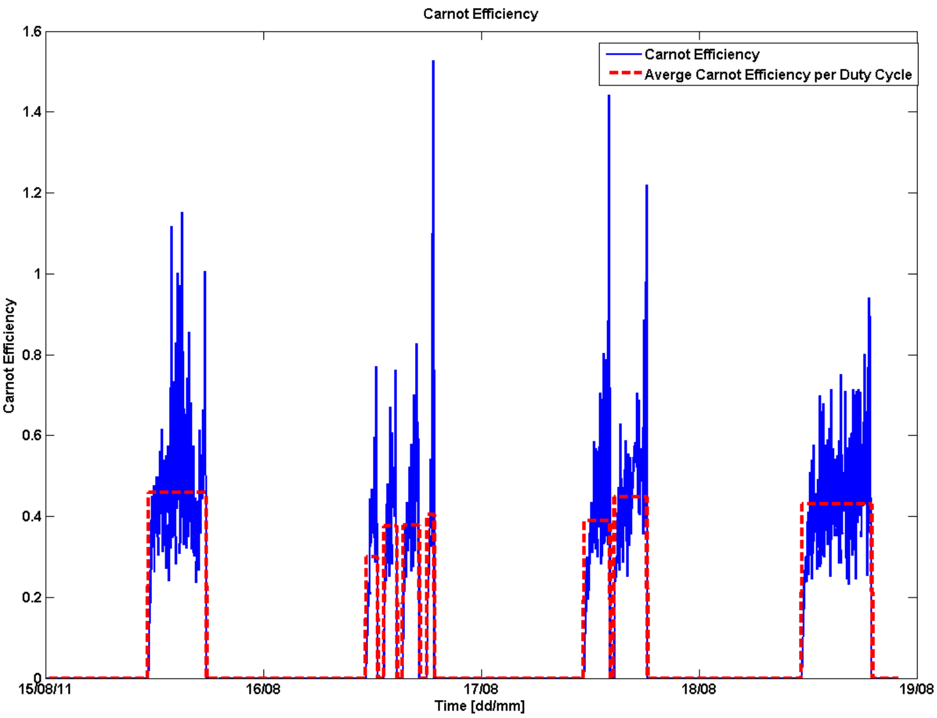

Figure 15 Average Carnot efficiency per cycle

3.9 Analysis: Energy Balance Analysis

The first law of thermodynamics can be used as first principles for detection of faults in the data, given that the system boundaries are known and all relevant parameters are measured. There are three heat meters measuring the heat flux in the low, medium and high temperature cycle in the system used for this research, thus allowing defining a system boundary where only the losses are unknown.

$$Q7\_KW + Q6a\_KW - Q12\_KW + \Delta E = 0$$

Therefore

$$\Delta E = Q7\_KW + Q6a\_KW - Q12\_KW$$

Here ΔE represents the combination of losses and changes in the stored energy. Since the chiller does not have significant thermal capacity, the assumption to verify is that ΔE should be close to 0. Figure 16 below shows that the values have high dynamics when deriving the energy balance on a sample-by-sample basis (blue graph). This is expectable due to the various delays in thermal dissipation and mass flows. The average value (red dotted line) is close to zero, therefore, the measured data is resilient. The energy balance is plausible and the metering data can be used for further analysis. The automated detection of the duty cycle contributes to this analysis, since the data in Off-state are commonly not relevant for energy balance analysis.

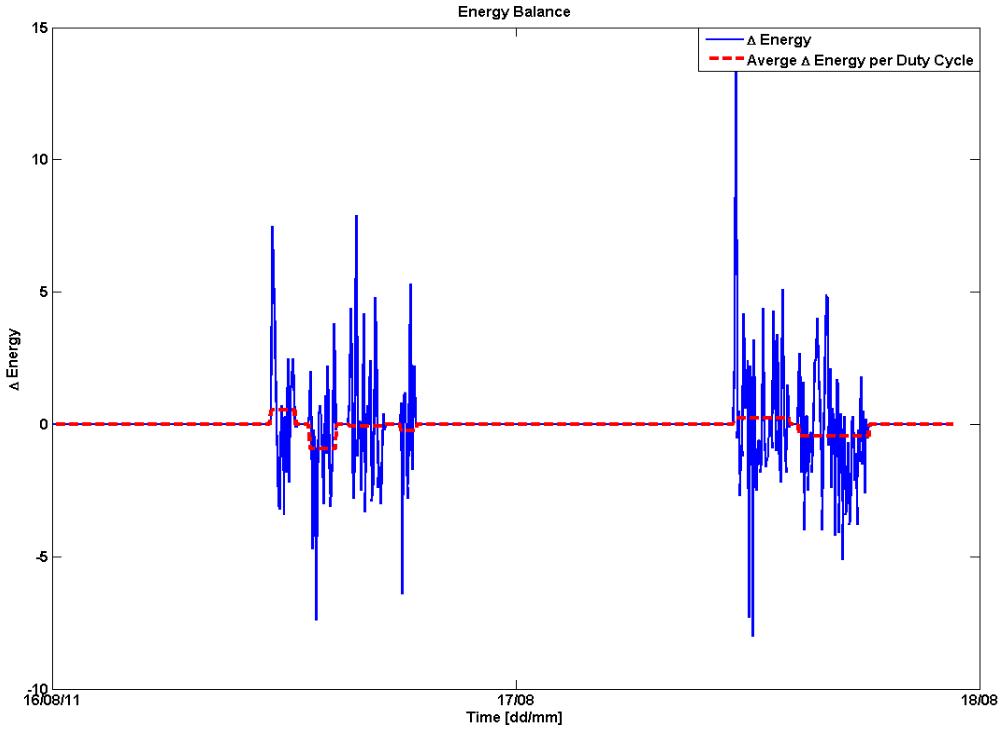

Figure 16 Average ΔE per cycle

3.10 Analysis: Detection of Duty Cycle Outliers

Another approach has been research to detect duty cycles that are as a whole not within regular process boundaries. To do so all the duty cycles were scaled to a uniform length with respect to all other duty cycles. The length to be used to be the new length of all duty cycles is the median length of all lengths of all retained duty cycles. To scale the length of all duty cycles, a linear interpolation on the duty cycles was performed. Then X-Means clustering algorithm on the scaled-in-length duty cycles was run. For visualization a heat map visualizations where each row corresponds to a duty cycle was created as shown in Figure 17. The rows were arranged in such that those that belong to the same cluster were grouped in order to show efficient clusters and allowing outlier analysis on the cluster model obtained from X-Means. Based on this, additional boxplots, line plots, and scatterplots were created to obtain more details on the cluster models. Finally, quantitative relations on the clusters of the model were done by performing Pearson Product moment correlation on each pair of clusters from the model. In practical discussion with energy experts it was shown that the heat map proved useful, especially the clustering of similar duty cycles.

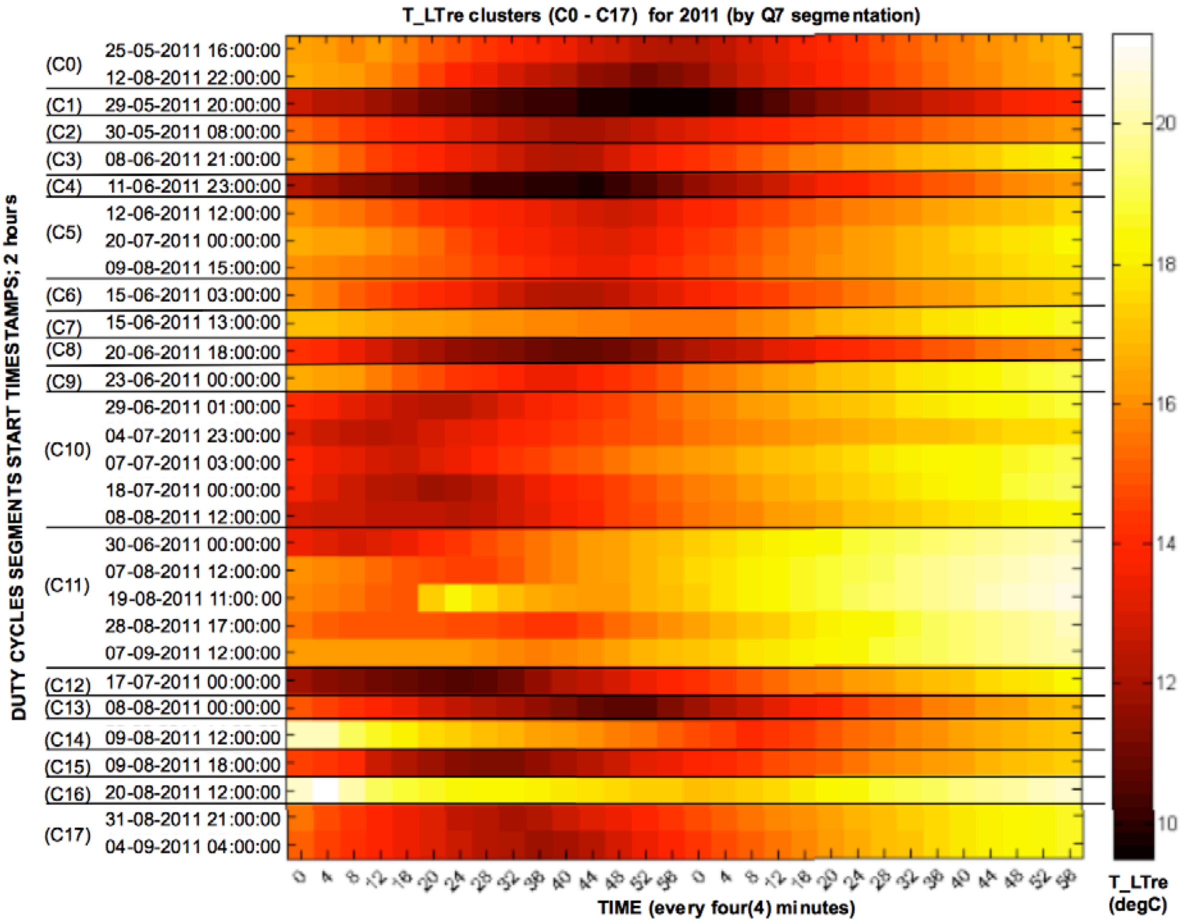

Figure 17 T_LTre monitoring data X-Means cluster model

3.11 Robustness Diagram

Developed by Doug Rosenberg, the ICONIX Framework offers a minimalist, streamlined approach to Use Case-driven UML modelling centered at using Robustness Diagrams. It focuses on the use of a subset of the UML diagrams for object-oriented analysis and design. Its major component in accomplishing its task is the usage of robustness analysis. Robustness analysis provides capabilities to remove ambiguities in use case descriptions by ensuring that domain models are consistently represented both in structure and behavior in the UML diagrams. Shown in Figure 18 is the ICONIX Framework. This framework shows a Robustness Diagram bridging the gap between modelling the static information derivable from domain models as represented by class models, and their dynamic information as represented in a collection of sequence diagrams. One sequence diagram typically models one scenario of system behavior showing its basic course and all alternative process flows and exceptions.

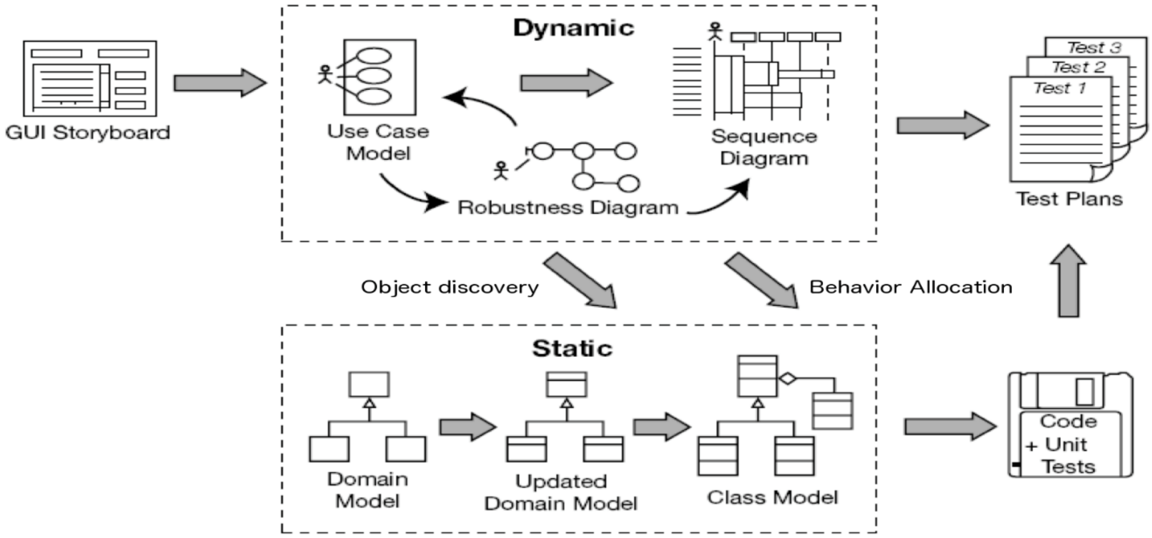

Figure 18 The Robustness Diagram of the ICONIX Framework (Source [2])

Shown in Figure 19 are the components of a Robustness Diagram. These components are connected by using arcs for any pair of nodes except between two nouns.

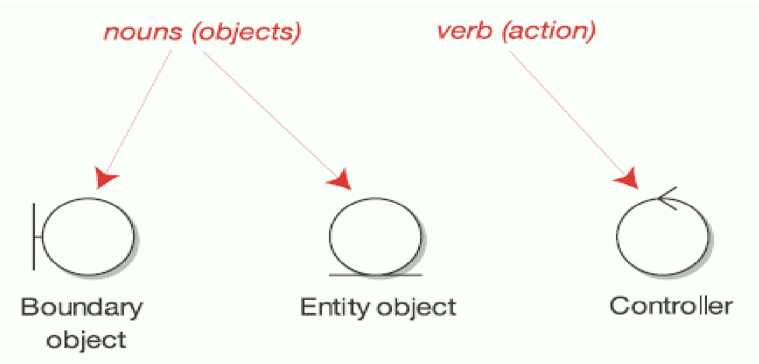

Figure 19 Boundary and entity objects, and controllers composing a Robustness Diagram

In this project, we developed an extension of Robustness diagram with labeled and timed arcs and objects. These are used to obtain different activities done by a system throughout its operation. The adsorption system and its corresponding model using the proposed Robustness diagram extension is in Figure 20 and Figure 21. For further details on the framework of modelling as well as the results, refer to the following published works [3], [4].

Figure 20 shows the scenario extraction process where the integers on the arcs represent the time of enabled transition from one process to another as represented by the controllers of the model.

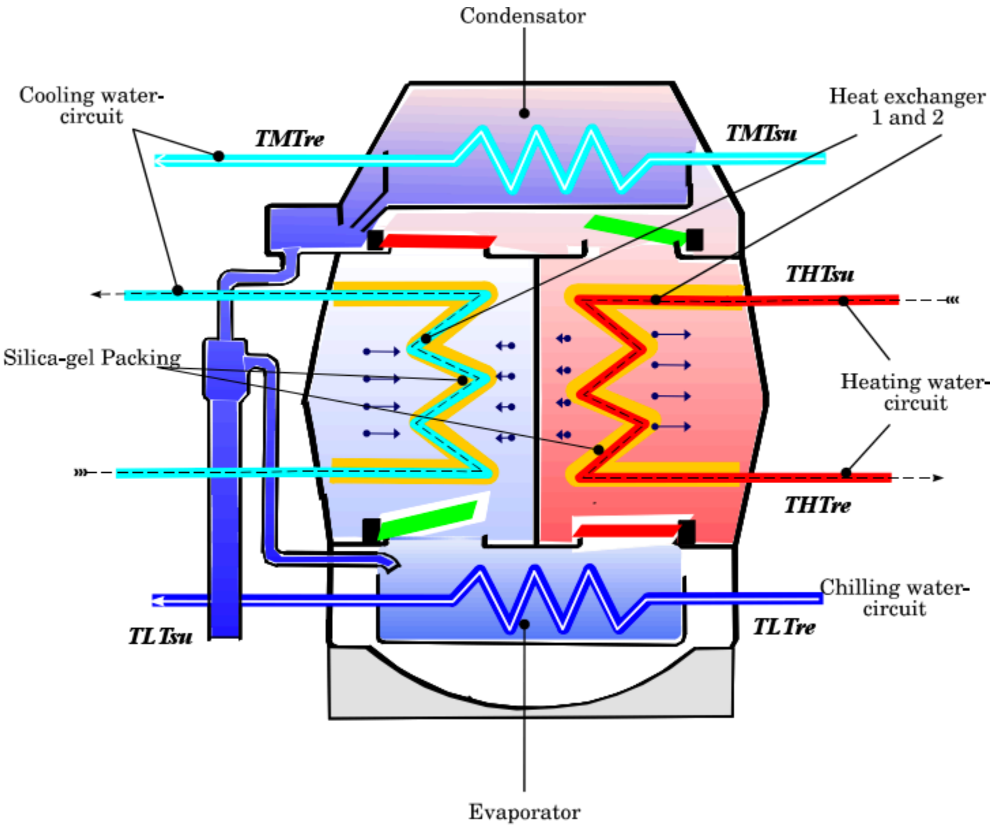

Figure 20 Adsorption chiller with colored temperature lines (chilling water (blue), heating (red), cooling water (light blue))

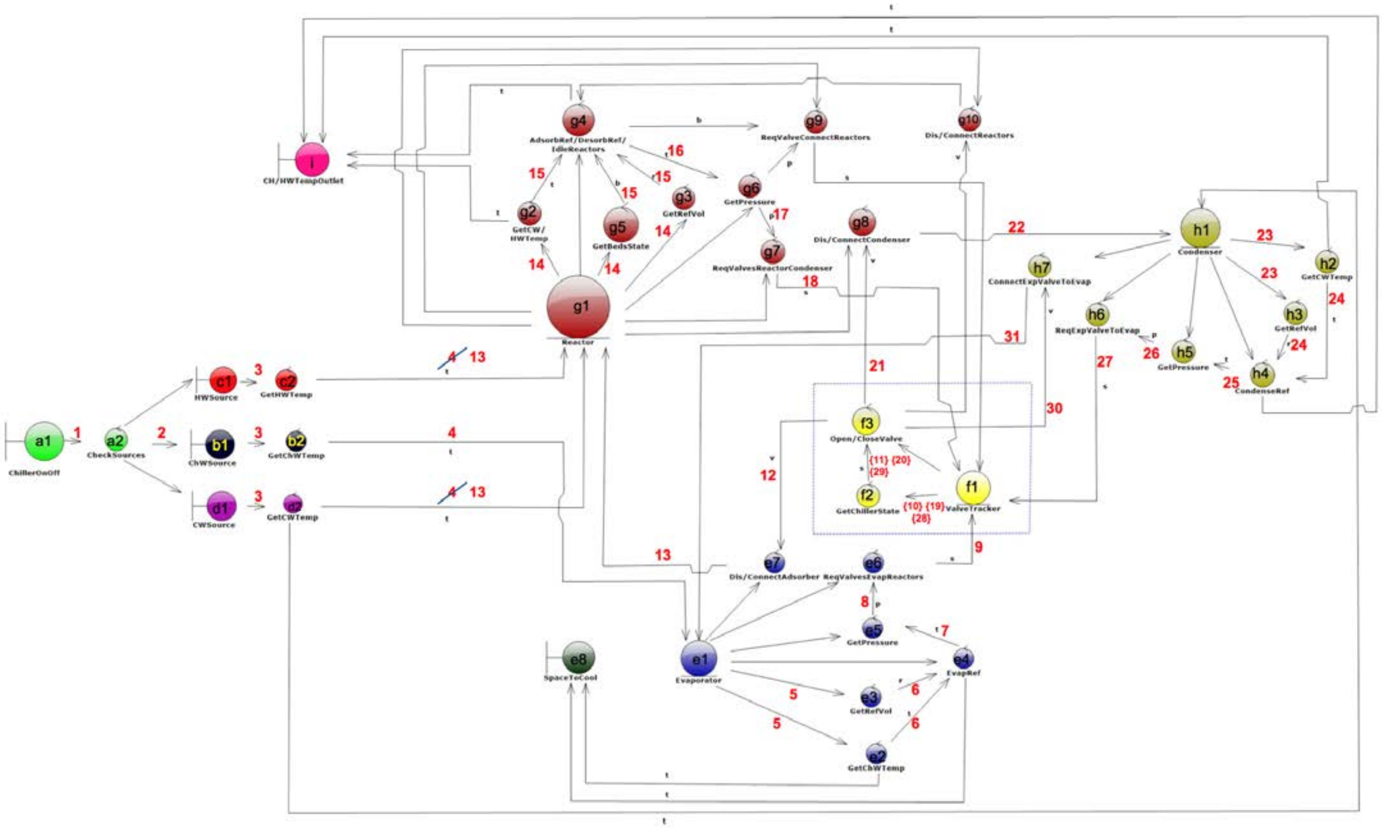

Figure 21 The Robustness diagram of the adsorption chiller

4 Ergebnisse und Schlussfolgerungen

The project developed a robust set of algorithms for automated data quality check and data analysis. These methods are widely applicable to energy systems in general and are therefore a significant result of the project. Comparing with the original project goals it was necessary to put more effort into data sanitation because of low quality of available monitoring data. This also yielded good results and allows to identify data problems with little configuration effort. Therefore, the goals of the project were fully achieved.

A highlight of the project was a user friendly workflow of data analysis using the KNIME platform. This way an energy expert can work with a graphical interface instead of computer programming and visualize the results with little effort. Results can also be visualized conveniently through Excel report integration with the monitoring system to give non experts also a good general overview about the efficiency and the reliability of the cooling systems.

Based on these general results, focusing on Pink GmbH, the considerations done during the project are going to lead to important performance improvements of the cooling machines operated and serviced by Pink GmbH right now and are also going to improve the performance of machines installed in future.

The resulting algorithms have been scientifically disseminated, most prominently in the paper “Sanitation and Analysis of Operation Data in Energy Systems”, published in the journal “MDPI Energies”, which has an Impact Factor (IF) of 2.072 (2014).

4.1 Company Partner Pink

The comprehensive analysis of the data and the generation and description of useful algorithms and the description of possible methods for fault detection will help all operators of thermally driven chillers. The current ways to detect faults causes unnecessary long downtimes. This is caused by erroneous interpretation of the data or delayed repairs, because the real cause of a fault can only be detected on site, after manual investigations. Sometimes situations are assessed wrongly (real fault -> but no maintenance / no fault in fact -> maintenance) which leads to wrong actions. The resolution of the fault situation can often only be done by expert engineers with lots of detail knowledge, because the resolution can be arbitrary complex. It is often possible that chillers run inefficiently for a long time, before the wrong behavior gets noticed by the operator.
In these areas a huge improvement of the quality of fault management can be expected with the methods developed within this project. The overall amount of time Pink GmbH engineers need to monitor the chillers should decrease by a fair amount.

4.2 Scientific Partners AIT and ICT

The scientific partners were responsible for the scientific dissemination of results. This has been successfully been achieved with two journal publications and five conference papers (as listed below). Furthermore the data analytics methods are used as a foundation for future research, manifesting in new research project such as ADA-EE (Advanced Data Analytics for Energy Efficiency, FFG Project Nr: 849968).

<u>Journals</u>

G. Zucker, U. Habib, M. Blöchle, F. Judex and T. Leber, “Sanitation and Analysis of Operation Data in Energy Systems”, MDPI Energies Journal. [Accepted]

J. A. Malinao, F. Judex, T. Selke, G. Zucker, J. Caro, and W. Kropatsch, Pattern mining and fault detection via COPtherm-based profiling with correlation analysis of circuit variables in chiller systems, Computer Science Research and Development, DOI 10.1007/s00450-014-0277-5, ISSN 1865-2034, Springer Berlin Heidelberg. (2015)

<u>Conferences</u>

U. Habib, G. Zucker, “Finding the different patterns in buildings data using bag of words representation with clustering”, FIT 2015-I3th IEEE International Conference on Frontiers of Information Technology. [Accepted]

U. Habib, G. Zucker, M. Blöchle, F. Judex, “Outliers Detection Method Using Clustering in Buildings Data”, IECON 2015 – 41st Annual Conference on IEEE Industrial Electronics Society, Yokohama (Japan), November 2015.

J. Malinao, F. Judex, T. Selke, G. Zucker, H. Adorna, J. Caro, and W. Kropatsch, „Robustness Diagram with Loop and Time Controls For System Modelling and Scenario Extraction with Energy System Applications, To appear in Proceedings in CUE2015 Applied Energy Symposium and Summit 2015.
G. Zucker, U. Habib, M. Blöchle, A. Wendt, S. Schaat, L.C. Siafara, “Building Energy Management and Data Analytics”, ComForEn 2015 - 6th Symposium on Communications for Energy Systems, September 2015.

G. Zucker, J. Malinao, U. Habib, T. Leber, A. Preisler, and F. Judex, “Improving energy efficiency of buildings using data mining technologies,” in 2014 IEEE 23rd International Symposium on Industrial Electronics (ISIE), 2014, pp. 2664–2669.

5 Ausblick und Empfehlungen

The extrACT project contained some valuable insights into the operation of buildings. The main learning was that the analysis of data is only the second step. Before any type of analysis the data quality needs to be assessed. This very often results in necessary adaptations in the sensory equipment, the commissioning or the data storage. The impact of extrACT is therefore mainly in the development of low-effort algorithms for data sanitation and data analysis.
On the foundation of extrACT it is now possible to implement more advanced algorithms. The path of developing abstracted analysis mechanisms that can be used for a whole class of energy systems (e.g. chillers) shall be continued in follow-up projects for more energy systems. Data analysis would greatly benefit from having a “library” of algorithms for different types of energy systems.
It also became clear that meta-data are vital for the understanding of monitoring data. Follow-up activities therefore concentrate on extending the IEA Task 38 naming scheme and introducing semantic information for energy systems. This greatly simplifies the efforts for data import and analysis. Along these lines there are also activities to develop a recommendation for a monitoring protocol for building operation data, which defines all necessary data and meta-data from the data value up to the overall structure of the monitoring data. For example, the definition of the textual representation of the unit to be used, can be unified. This eliminates the ambiguity of defining units, which are currently written in many different formats (e.g. m^3/h, m3/h, m3h, etc) and allows for automated processing of data rows.

The customers or operators of the chillers will benefit indirectly from results of this project, the exploitation of the results will be done by Pink GmbH for the PinkChiller product group. For the exploitation the project results (algorithms and methods for automatic fault detection), need to be integrated into the real monitoring and control system. The integration can happen in different ways.
One possible way is the direct implementation of the generated methods into the “Speicher programmierbaren Steuerung” (SPS) of the chillers, directly on site. This has the advantage that it can be adapted to the individual needs of the customized chillers. Customizations are the system configuration (type of recooling, is buffering available, …) and control strategies (is a higher order control available or does the PinkChiller control the whole system autonomously). For this type of

implementation there is also no external access needed, which is good, if a customer is concerned about security aspects. A lot of system administrators do not like to have a channel open to the outside all the time. A disadvantage is the increased effort of implementing the feature on all existing devices, although project has already led to a simplification. All the existing chillers now run the same software release now, they didn't in the past. Therefore an update of the SPS-software would be feasible.
Another way to exploit the results of the project would be to integrate the methods and algorithms in the real remote monitoring system that runs on the servers of Pink GmbH. It is a centralized system for all chillers. This would reduce the effort needed for adapting the systems, since the changes are centralized, and all chillers would benefit from the changes at once. A disadvantage would be the missing flexibility concerning individual chillers. Only installations with remote access would benefit from the improvements. New realizations about faults or inefficiencies would not directly influence the control algorithm on site, but there would be an indirect influence, which would lead to a delay and perhaps a second control loop.
The advantages and disadvantages of a centralized or a decentralized adoption of the algorithms have to be evaluated concerning the before mentioned aspects in correlation to the amount of time needed and the costs. What also needs to be done, is to decide which degree of detail is really needed in the real control loop. Perhaps some points can be skipped in the real implementation. To give the customers and operators full advantage, the implementation of the results has to happen before the next cooling season.

6 Literaturverzeichnis

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7 Kontaktdaten

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