

## TACKLING FOULING CHALLENGES WITH THE ALFA LAVAL SMART HEAT EXCHANGER

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### ABSTRACT

Fouled heat exchangers account for up to 1 – 2.5 % of the global CO<sub>2</sub> emissions, where compensation costs for increased electricity consumption is estimated to be 0.25 % of the GDP of the industrialized nations [1].

This paper aims to showcase the Alfa Laval *Smart Heat Exchanger* solution, which offers real time monitoring of the performance and efficiency of the Gasket Plated Heat Exchanger, GPHE. This not only enables proactive and preventive services instead of reactive, but also introduces crucial insights in the operation of the cooling / heating process. With a smart solution of hardware combined with cloud-based algorithms, the Alfa Laval Smart Heat Exchanger provides several condition monitoring tools in an informative dashboard setting, working towards more precise and customized operations.

The installation used as a case for this paper, a manufacturing company, showed important learnings for maintenance and operation of the GPHE from the sensor values and algorithm outputs. The algorithm for measuring the thermal efficiency of the GPHE engaged the customer in optimizing cleaning strategies during months where biofouling negatively affected the cooling process. This would not only lead to increased costs but also a potential deterioration in product quality, as the cooling requirements were not met. Seasonal critical periods of cooling were pinpointed, where top thermal health was vital. From this information, fouling problems that occurred in the cooling tower cold loop could be prevented and mitigated. Ensuring clean PHE ahead of these periods together with the load optimization increased efficiency.

The AI algorithm for calculating the loss of cooling temperature, further validated seasonal patterns and efficiency losses due to fouling. From this data, actions could be taken for ensuring top performance and mitigating both electrical compensation costs and CO<sub>2</sub> emissions.

### INTRODUCTION

A fouled heat exchanger has a lower efficiency and sub-optimal heat transfer. This often leads to compensation costs in the form of higher water consumption, electricity costs in pumps, chillers or boilers as the cooling or heating requirements of the operation must be met. According to [1], fouled heat

exchangers account for up to 1 – 2.5 % of the global CO<sub>2</sub> emissions by increased compensation costs. Presented as an example and to put things in perspective, the data center industry is estimated to consume up to 205 TWh or 1 % of the global electricity consumption in 2018 [2]. Thus, power use efficiency is key to the economic performance and for this purpose reduced fouling and improved monitoring and maintenance is key. Hence, the fouling dilemma must be battled. Historically, the Plated Heat Exchanger (PHE) has been seen as a static object with no need for service, optimization or monitoring of the condition. Today, the data of [1] tells us that this must change.

With the climate crisis heating up our planet, Alfa Laval has set out on a path of mitigating these CO<sub>2</sub> emissions that result from heat exchanger fouling [3]. This is where the Alfa Laval digital platform *Smart Heat Exchanger* health monitoring system comes into play.

The purpose of this paper is to present the Alfa Laval Smart Heat Exchanger. The ambition of improving the operations and service strategies of PHEs, regaining efficiency and battle fouling, leading to mitigated compensation costs was initiated in 2015 in R&D Alfa Laval Technologies, Lund. Combining smart sensors with efficient algorithms together with the accumulated and extensive experience and knowledge of Alfa Laval became the targeted solution.

Since then, several sites and PHEs have been connected for pilot installations and in early 2023 the commercial offer was launched. The offer includes everything from hardware to software, from commissioning to insights and service recommendations.

As seen in many installations, the Connected Services offer great insights in the PHE operations, health and efficiency. For example, one HVAC customer having multiple GPHEs in parallel, distributing the flow according to a control system by the cooling load on the system, learned that long periods of under-design flow increased the fouling. The seawater on the cold side quickly built up fouling, and with these insights, a new operation strategy could be formed. This included among others, an optimization of the cooling process operations, namely running fewer units at higher flow and switching between the GPHEs.

Another installation experience showed that the loss of performance due to fouling led to dramatic deterioration of the cooling process. This had the potential of big negative impacts on the company, as whenever cooling requirements were not met, the production load had to be reduced, leading to financial loss and risk of damaging components.

The specific installation for this paper will be a manufacturing company, here referred to as BatteryX, which faced similar fouling challenges as in previously mentioned installations and applications. The paper will showcase the platform, the potential and the gain of the customer for the period of 2022.08.01 – 2024.01.01.

## BACKGROUND

Early in the starting phase of the Smart Heat Exchanger the customer, BatteryX manufacturing company, qualified as a good pilot installation. They were eager and curious to improve operations, monitor the condition of the cooling process and tackle their fouling challenges.

The heat exchangers at the site serves to cool the production line. If the cooling requirements of the production is not sufficiently met, the production is halted, and BatteryX cannot produce their product in the required quality.

Since the GPHEs are connected to a cooling tower, they had considerable problems with bio-fouling in the cooling system and in the GPHEs. BatteryX did not have a control room or monitoring system to check the status of the cooling process or the GPHE condition. This caused the maintenance decisions to be taken based on assumptions and previous experience.

The two (2) parallel-connected GPHEs were connected to the Alfa Laval digital platform in the hopes of measuring the GPHE performance, having better overview of the operations as well as planning what maintenance to do when. Alfa Laval were to serve the customer with a platform of hardware and software, giving them the opportunity to take actions based on KPIs generated from live sensor data and smart algorithms.

## HARDWARE

The hardware solution consists of two parts, the first being four (4) sensors, four (4) cables and one (1) sensor box as shown in figure 1. This sensor kit is produced by the company WIKA. The sensors are easily connected to the pipes of the connections, either by drilling a hole and welding a socket, or by mounting the sensors on instrument flanges, mounting one sensor per connection. The cables connect the sensor body to the sensor box, for easy data transmission. The sensor box is then magnetically attached on the GPHE and can be powered by both batteries and power cable.



Figure 1: The sensor kit, containing one sensor box and four sensors with cables from WIKA.

The second part of the hardware is the gateway in figure 2, a networking hardware that collects the sensor data from the sensor box via Bluetooth communication and then transmits the data points to the software platform of *ALIoT* via the mobile 3G/4G/5G broadband. The Alfa Laval gateway used in the Smart Heat Exchanger platform is manufactured by Cassia. The limit of the gateway is not in the number of sensor boxes, but the distance to it, recommended up to 50 m.



Figure 2: The Alfa Laval gateway for the Smart Heat Exchanger service, provided by Cassia. The limit of the gateway is not in the number of sensor boxes, but the distance to it, recommended up to 50 m.

The final mounting of the sensors and sensor box on a GPHE in a test environment is shown in figure 3 below.



Figure 3: The full installation of the sensor kit on a GPHE in a test-environment.

## SOFTWARE

The sensor data is transmitted from the sensor box to the gateway via Bluetooth and can be sampled at different frequencies. The data then flows from the gateway to the software platform ALIoT where it is processed, displayed and used as inputs to both physical and AI algorithms, developed by the competence of Alfa Laval.

Because of intellectual property, the detailed information on the pre-processing of data and the specifications of the implemented algorithms cannot be disclosed here. However, some generic pre-processing of data, physical properties of some data parameters and KPIs of algorithms are presented in the next section.

## Pre-processing

Correct pre-processing of data is a vital part in obtaining the optimal result for algorithms [5]. Making sure that the data set is free from noise and inconsistencies enables the best pre-requisites for high-quality output and more accurate predictions. Correct pre-processing can also significantly reduce the dimensionality of the data set, removing any irrelevant variables or features, resulting in faster computations and more efficient models.

The Interquartile Range method (IQR) is one pre-processing model for ensuring a good data set, by removing outliers. IQR is defined as the difference between the 75<sup>th</sup> and 25<sup>th</sup> percentile, shown in equation (1).

$$IQR = Q3 - Q1 \quad (1)$$

The outliers are then defined as data points outside the range of equation (2),

$$[IQR - 1.5 * Q1, IQR + 1.5 * Q3] \quad (2)$$

leaving the remaining set of good data to be data points within the range of eq. (2) [6]. The boxplot with a generic IQR and a generic probability function is shown in figure 4 below for representation. The data in the plot is not connected to actual data of this paper.

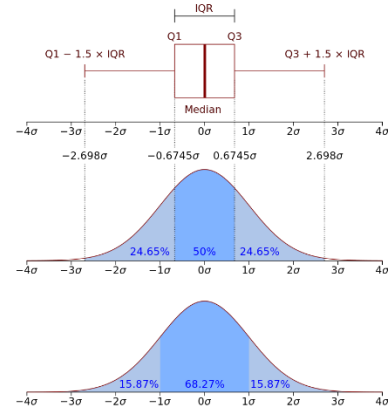


Figure 4: The generic IQR method from Wikipedia for removing outliers in a data set [6], shown in boxplot and with probability distributions.

## Sensor values

The sensors read temperature data, one temperature per connection, at a configurable sampling rate, by default specified to every 10 minutes. It is important to have the correct sensor connected to the right connection. If this is not the case, one could get crossing temperatures e.g., not having the hottest temperature measured at the connection where the media comes in at the hottest temperature. This would generate some errors for the logic of the algorithms. Good temperature data from BatteryX installation looks like figure 5.

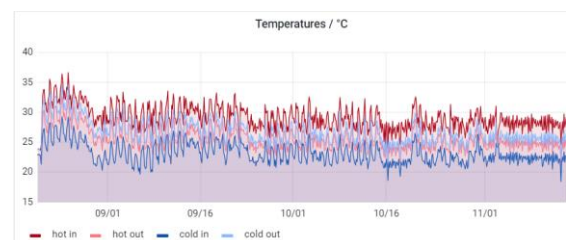


Figure 5: The temperature data for BatteryX between 2023.08.20 – 2023.11.14. Hot in temperature is the hottest, and cold in is the coldest, as expected.

It is also important to have the sensors connected as closely as possible to the pipe (and flow) of the media, as shown in the two lowest connections in figure 3. If the sensor is connected via a valve, rather than close to the pipe, there could potentially be less accurate measurements, since the sensor readings would be disturbed by the ambient temperature as the sensor membrane is too far away from the medium. There is also a delay in time

caused by the ambient temperature affecting the measurement. This physical phenomenon is described by Newton’s law of cooling. The temperature changes in time  $t$  and ambient temperature  $T_r$  as Figure 6 shows. Mathematically this is shown in equation 3 [7].

$$\frac{dT}{dt} = -k(T - T_r) \quad (3)$$

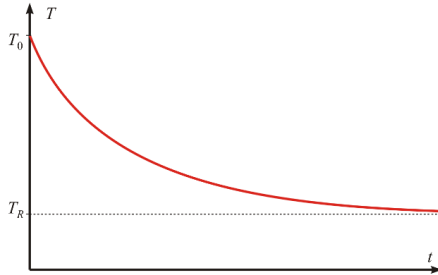


Figure 6: The temperature of an object  $T_0$  in ambient room temperature  $T_r$  according to Newton’s law of cooling [7].

This problem can however be somewhat relieved by insulating the valves. This is not an optimal solution, but a viable one. This can look like figure 7, from another customer installation.



Figure 7: Insulation of valves to relieve the problem that the sensors measure the ambient air temperature rather than the temperature of the medias, on a customer installation.

The sensors also measure pressure data at the ports. The risk of measuring faulty values is smaller for the pressure data, since there is no interference

from surroundings. Pressure data for the same period as in figure 4 is shown in figure 8.

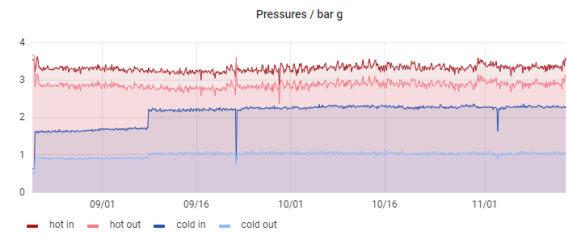


Figure 8: The pressure data for BatteryX between 2023.08.20 – 2023.11.14. The values vary somewhat, mainly on the cold inlet.

It is seen that the pressure data varies somewhat. This is expected as the cooling load also might vary. A varying cooling load can result in the customer managing a higher flow and pressure on the cold inlet.

### KPIs and algorithm output

The clean data can now be used as input to the Alfa Laval developed algorithms, some of which have been developed in the lab environment with expert knowledge, and some with the combination of AI. The logic will be briefly described, and their output KPIs in the dashboard environment will be shown for the BatteryX installation.

One of the most value-adding algorithms developed for the *Smart Heat Exchanger* platform is the *Thermal Health Algorithm*, which calculates the thermal health of the connected heat exchanger. Feeding this Alfa Laval developed algorithm with the measured sensor values, it evaluates the relative percentual health of the GPHE as compared to a reference period where it was in a clean state. I.e., this algorithm evaluates the efficiency of the GPHE. Figure 9 shows the Thermal Health Trend for the installation of BatteryX customer.



Figure 9: The thermal health trend from 2022.06 – 2024.01. Decline in thermal health indicates deteriorating efficiency of the PHE.

The declines in thermal health indicate that fouling is building up in the GPHE, which results in less efficient thermal exchange. The steep increases in the graph typically show that some cleaning has been made, yielding a higher thermal exchange, and a more efficient GPHE. Another plot of the thermal health for the period 2022.05 – 2023.06, a sub-set of the data in figure 9 is shown in figure 10 below.

Figure 10 also includes some smoothing by moving median to reduce noisy data.

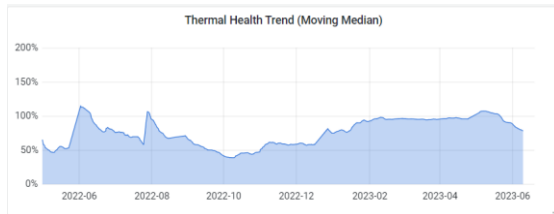


Figure 10: The thermal health trend from 2022.05 – 2023.06 shows the varying efficiency of the connected GPHE.

Another value-driving algorithm is the *Temperature Drift*, which is based on Artificial Intelligence. Having set a period for which the GPHE is deemed as clean as a reference period, the AI-algorithm is trained on this data, learning and replicating the pattern of the input sensor values. If the GPHE is later fouled, the algorithm still replicates the sensor values as if the GPHE had been clean. This is displayed as the *Temperature Drift*.

Depending on the application of the GPHE whether it is cooling / heating, the temperature drift then equals the *Cooling / Heating Temperature Loss*, a measurement proportional to the amount of thermal power lost due to fouling. The evaluation of the temperature drift for the BatteryX cooling application is shown in Figure 11.



Figure 11: The *Temperature Drift* output for BatteryX cooling application, showing the cooling temperature loss. The drift is high at 2022.10, when the thermal health trend in figure 9 is at a low, as one would expect.

The cooling temperature loss is zero in the beginning of the chosen period, i.e. 2022.08. This is the period for which the algorithm was trained, when the GPHE was deemed as clean, as per Figure 9. Annotated in figure 9 and figure 11 is the training period. This evaluation of the temperature drift of the GPHE is typically the reverse of to the evaluation of the Thermal Health Trend. The drift output is high at 2022.10, when the thermal health trend in figure 10 is at only 50 %, as one would expect. This shows that fouling was most likely built up, generating a loss in GPHE thermal performance and cooling power. The dramatic spike just after 2023.07 is represented in both figures which is satisfactory. However, the spike is most likely due to some sensor data error, one would not expect such

dramatic and fast variations in fouling and PHE efficiency.

## RESULTS

Looking at Figure 9 it is seen that the efficiency of the connected PHE varies over time, which is as expected. Different methods of cleaning at the customer site result in improvements in the PHE efficiency. Figure 12 shows the same view as figure 10, but with the cleaning measures marked for an easy overview. It is clear that the efficiency is greatly improved in 2022.06, obtaining a thermal health at around 100 %. This was after a documented cleaning of the cooling towers where the bio-fouling is reduced in the GPHEs, number one (1) in the figure. After this cleaning, a decline is noticed up to 2022.08. The decline is at a pace one could expect for the bio-fouling during the warmer summer months. During this time, some biocide additives were used in the cold loop, i.e. the cooling tower water, event two (2) in figure 12. The improved thermal health in 2022.08 is because of a cleaning-in-place strategy, event three (3) in figure 12. It is seen that the efficiency is once again at around 100 %. The decline in efficiency following this cleaning-in-place strategy is at the same pace as between 2022.06 and 2022.08.

In 2022.10, the bio-fouling is not as prominent as during the warmer summer months which is why the decline is less dramatic. During this time, BatteryX also invested in chlorine-additives in the cooling tower water, which would mitigate the bio-particles growth, number four (4) in the graph.

The following months, the thermal health is improved at a slow pace. This might be explained both by the chlorine additives and the colder months not enabling the bio-fouling growth. Some undocumented event seem to happen at number five (5) in the figure, when the Thermal Health increases.

The small increase in thermal health in 2023.05 is because of a documented mechanical cleaning of plates. As seen, the increase in efficiency is somewhat small from an already high level. This will be commented further.

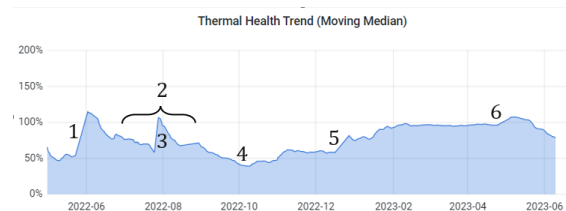


Figure 12: The Thermal Health Trend for the same period as in figure 10 but marked with the different cleaning measures described. The measures all result in better health.

The algorithm of the *Cooling Temperature Loss* shown in figure 11 is trained on the data for the

period of 2022.08, and we see that the output is zero at this time. At 2022.10 it is at a high point, when the thermal health is at its lowest. All of this is satisfactory. The temperature drift is then reduced, as the thermal health algorithm shows an increase in efficiency. This is all aligned with the cleaning strategies mentioned in the previous section of this paper.

## CONCLUSION

The results presented and brought forward in the Result section show that the algorithms generate useful insights and knowledge, and that the platform of the *Smart Heat Exchanger* creates value for the customer in terms of improved business and cost savings. The increases and decreases in the *Thermal Health Trend* are aligned with the *Cooling Temperature Loss* algorithm as well as with the documented cleaning and maintenance strategies mentioned. This gives the customer confidence that the algorithms show accurate numbers and KPIs. For the specifics of BatteryX it is interesting to address the effects of the different cleaning measures made. The cleaning of the cooling tower (1) and the cleaning-in-place (3) as well as the chlorine additives (4) all seem to be beneficial actions.

The value of the biocide additives (2) and the mechanical cleaning (6) are interesting to investigate further, as they do not seem to add too much value. The gain of the biocide additives is however hard to determine, since it is not clear how fast the fouling would build up without this additive. Also, the mechanical cleaning system does not seem to add much value, since the GPHE was already quite clean. Upon discussions with BatteryX, they were advised from the analysis that this mechanical cleaning might not bring much benefit. This event was however a part of their long-term scheduled maintenance, and it was requested that they provided pictures of the plates upon opening. These pictures served as a validation for the algorithms, as the pictures were aligned with the findings from the *Smart Heat Exchanger Platform*, telling the story that the GPHE was in a rather clean condition, making a costly maintenance such as mechanical cleaning unnecessary.

Thus, the solution of the *Smart Heat Exchanger Platform* offers great potential and value. Especially for customers wanting to optimize their operation and maintenance of their GPHEs and structure more efficient cleaning strategies. Further work will be done in connecting more GPHEs to sensors and the *Smart Heat Exchanger* platform and validating the solution, learning from customers on the field and advising on potential cost savings for customers where fouling creates a headache. Alfa Laval also enables customers to deep-dive in their potential savings with the *Energy Hunter Program* [4], where

data from both the connected platform and the customer specific inputs on their facility is used. This opens the door for even more detailed cost savings.

This offering not only brings value for the customer but also contributes to mitigating CO2 emissions, the key in tackling the global problem of climate change. In this arena, the Alfa Laval *Smart Heat Exchanger* offers a key solution.

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