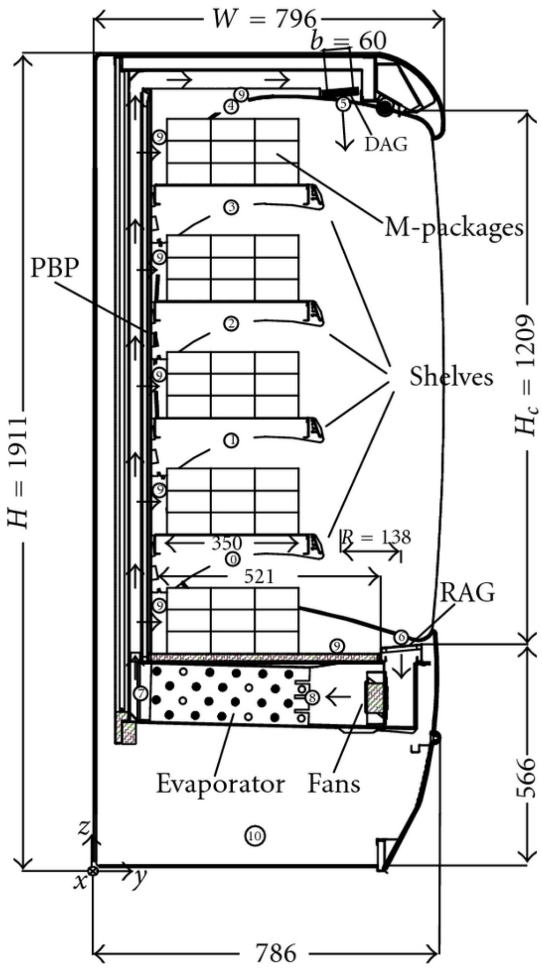
STUDY REPORT



- Food safety and quality prediction -

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TABLE OF CONTENTS

ACKNOWLEDGEMENTS

TABLE OF CONTENTS

FIGURE LIST

LIST OF APPENDICES

INTRODUCTION

I - BIBLIOGRAPHY

II – EXPLANATIONS OF PHYSICAL PHENOMENA

A) How the cooler works

B) Heat transfer – Methods

B-1) Study of the theoretical heat transfer modes

B-2) Setting up experiments in labs and stores

C) Heat transfer - Results

C-1) Lab

C-2) Stores

III – STUDY OF THE NORMAL BEHAVIOR AND TEMPERATURE PREDICTION

A) Methods

A-1) The Newton model

A-2) Origin of the formula

A-3) Forward model

B) Results

B-1) Results parameters

B-2) Results on the temperature

IV – STUDIES OF ANOMALIES

A) Importance of data collection

B) Anomalies detection

B-1) Explanation of the code created to detect anomalies - Methods

B-2) Results

C) Data visualization

CONCLUSION

BIBLIOGRAPHICAL REFERENCES

APPENDICES

SUMMARY

FIGURE LIST

Figures

Figure 1 – Air flow visualization
Figure 2 – Heat transfers
Figure 3 – Numbering of the shelves
Figure 4 – Position of each sensor
Figure 5 – Cartography of the average temperature
Figure 6 – Mapping of the average temperature (in front in red faced to the back in green) in the store of City
Figure 7 – The range of light and how the store and the products are enlightened
Figure 8 – Gradient when there is light above and below the shelf
Figure 9 – Position of the sensor on the shelf
Figure 10 – Values of Delta according to its position on the shelf
Figure 11 – Values of Q on different food groups
Figure 12 – Prediction by the model with actual measurements made in store
Figure 13 – Presentation of the meat in the shop window
Figure 14 – The front parameter corresponds more to reality
Figure 15 – The case of sliced fish
Figure 16 – Back settings on 8°C coolers
Figure 17 – Front settings on pastas coolers
Figure 18 – Defrosting time on model prediction
Figure 19 – Detection of anomalies by blue circles
Figure 20 – Drift observed from 2018-07-07
Figure 21 – There is no defrosting cycle around the 26th
Figure 22 – Missing values
Figure 23 – Cooler maintenance
Figure 24 – Outlier on the 27th, temperature too high
Figure 25 – Improved plotting versus normal plotting

LIST OF APPENDICES

APPENDIX I – Anomaly detection code on R

APPENDIX II – Data visualization code on R

APPENDIX III – Fragment of the model code on Mathematica

INTRODUCTION

One of the most common methods of preservation, is the use of cold. When we apply cold, deterioration reactions, including microbial activity, are slowed down, resulting in an extended shelf life of the food. The quality of chilled food, in terms of microbial, chemical, physical and nutritional properties, is clearly influenced by temperature variations in storage. Therefore, refrigerated storage at a constant temperature is essential to reduce perishable food losses. Due to insufficient cooling, 20% of global losses and 9% of relative losses in industrialized countries were recorded in 2009. (International Institute of Refrigeration, 2009).

Refrigerated storages as vertical open coolers are the critical point in the cold chain. They are the ones who maintain a desired low-temperature range.

In this project, temperature fluctuations of cooled food are determined by several sensors. Real-time measurements of air temperature allow conclusions to be drawn about the core temperature of food in vertical open coolers. Migros, the Switzerland's largest retail company, will be able to guarantee temperature safety in the future with fewer staff.

In order to create a model which would be able to predict the core temperature of foods without damaging the product on a large scale, it is necessary to understand the physical properties of thermal transfers. In this document, the heat transfer from the environment where the product stands to the centre of the food is studied in order to understand the influence on the temperature change over time.

But it requires knowledge of the evolution of temperature and food products throughout the vertical open cooler which can be done by investigation, experiments and statistical issues.

The following theoretical part deals with bibliographic research aimed at further explaining the importance of refrigeration on bacterial action and explaining the basics required to deal with the future model.

The next chapter will deal with the basis for the creation of the model and in particular the study of the normal behaviour of the cooler, i. e. how the cooler works, the different heat transfer mechanisms applied to the cooler and various tests in real conditions in the store.

Then comes the creation and explanation of the model with the results obtained and their interpretation.

Finally in the last part, called continuous improvement, we will use statistical resources to detect temperature anomalies potentially dangerous for products and we will also present a tool allowing the optimal visualization of huge datasets in time-series format.

We will try to understand the importance of studying the behaviour and influencing factors of a vertical open cooler to ensure optimal health quality.

I) BIBLIOGRAPHY

The main idea before starting this project was to understand why this project was born. What were his motivations and assumptions.

Thus the guiding idea was to ensure optimal food quality, through refrigeration. We then considered it useful to find out about the microbiological risks associated with refrigeration and understand why in this project the threshold temperature is 5°C.

Generally, the more we want to preserve, or store a food product for a long time, the more we need to lower the storage temperature (**Guiraud J-P**, 1998).Here our study was only about refrigeration and not freezing. The term refrigeration is used for storage temperatures above 0°C.

Refrigeration slows enzymatic and chemical reactions, and therefore also slows down the multiplication and metabolism of micro-organisms, consequently it only allows a relatively short storage period (a few days). Unlike freezing, which involves reducing the availability of "free" water by freezing water at negative temperatures, used for the growth of microorganisms (**Guiraud J-P**, 1998)

Some pathogenic microorganisms still develop at 6°C, such as Listeria monocytogenes, (**Federighi. M** , 2006), Yersina enterolytica , (**Carniel, E. et al.**, 2006*)* and salmonella, (**Federighi. M** , 2006). At this temperature, some Clostridium botulinum (**ANSES**, 2011- erratum 2016), are still able to produce its toxins. Among the spoilage germs, Pseudomonas, moulds and yeasts can develop in refrigerators.

In addition to the bacteriological risk, let us add the physical and chemical alterations that can make the product different and not encourage the consumer to make the purchase of buying it. At worst, the taste of the food changes which is frequent in using cold (rancidity, hydrolysis of fat)(**Vickie A. et al.**, 2014).

Microorganisms die gradually when cells are placed in an atmosphere at a very low temperature as freezing, and the death rate is in principle logarithmic in appearance, which is not the case for refrigeration, we must be careful. Especially because after low temperature storage, microorganisms must be exposed to a favourable temperature for a sufficiently long time before they can resume reproduction, active and normal growth. Typically what happens when the cold chain is broken, when a cooler breaks down or a product leaves the cooler enclosure. (**Vickie A et al.**, 2014)

Most moulds and yeasts belong to the group of psychrotrophic, microorganisms capable of actively multiplying at commonly used refrigeration temperatures, but fortunately, almost all pathogenic bacteria, with few exceptions, can no longer reproduce below about +5°C. Only coliforms can develop below +5°C or even up to 0°C (**Joffin C. & Joffin J-N,** 2010).

We have just seen that cold slows down cellular activity, enzymatic reactions and the development of micro-organisms, and why we usually use cold (until 5°C) to preserve common food.

Let us carry out the thermal balance, thanks to the first Fourier law, it is simple to demonstrate the formula of the cooling rate or also called Newton's cooling law. We will need this formula later to build a model to understand how fast it cools.

However it would be better to demonstrate this formula in order to enhance it and to add progressively parameters really useful in our study.

We have decided to work with Newton law of cooling but it requires some conditions. It generally works well in thermal conduction (where it is guaranteed by Fourier's law), but it is often only approximately true in conditions of convective heat transfer. However we decided to test it despite everything, because it remains the easiest way to solve this project and an approximate accuracy is sufficient at this early stage of the project. Later on, it may indeed be necessary to change this model, but to begin a project and make it understood by as many people as possible, a model like this one is sufficient

It states that the rate of change of temperature should be proportional to the difference between the temperature of the food and the ambient temperature, which is the cooler (**Feldman J. et al.,** s.d). Normally, in literature we find Newton's law of cooling described by the following formula but instead of $\frac{dT}{dt}$ we usually have $\frac{dQ}{dt}$, but knowing that $\frac{dQ}{dt} = C\frac{dT}{dt}$, we know this is equal.

So let's write it in mathematical terms. This sentence above makes some intuitive sense.

$$\frac{dTc(t)}{dt} = -k.(Tc(t) - Te(t))$$

$$\frac{dTc(t)}{dt} = k.(Te(t) - Tc(t))$$

We insert an additional parameter here, remember that here we use the bibliography to build the basic formula for the future model (in a mathematical point of view), the several parameters used will be explained later. So we insert Δ a position-time dependent parameter.

According to the literature this coefficient **k** is worth $\frac{hA}{m.Cp}$, we will simplify it later in $h.Q$, knowing that $C = m.Cp$ (**Bourdreux S.**, 2004) and $Q = \frac{A}{C}$. Thus we find the same formula as the one dedicated from Fourier (with our Δ parameter in plus).

$$\frac{dTc(t)}{dt} = h.Q.[Te(t) - Tc(t) + \mathbf{\Delta(t)}]$$

This derivative does not allow us to obtain the information we are looking for, namely the core temperature, easily. It must therefore be simplified and brought out in a "simple" equation, this unknown parameter. One option would be to apply to this equation a simple finite-difference forward Euler method.

For the sake of clarity and simplicity, the detail of the method is not explained here, only the result is shown below.

$$\mathrm{Tc}(\mathrm{t}+\mathrm{dt}) = Tc(t) + h.Q.(Te(t) - Tc(t) + \mathbf{\Delta}).dt$$

With so many parameters and new ones compared to Newton's basic formula, we had to face a dimensional analysis.

$$\mathrm{Tc}(\mathrm{t}+\mathrm{dt}) = Tc(t) + h.Q.(Te(t) - Tc(t) + \mathbf{\Delta}).dt$$

Either

$$\mathbf{°C} = \mathbf{°C} + \frac{\mathbf{W}}{\mathbf{m^2K}}.\frac{\mathbf{m^2K}}{\mathbf{J}}.(\mathbf{°C} - \mathbf{°C} + \mathbf{°C}).\mathbf{s}$$

By simplification

$$\mathbf{°C} = \mathbf{°C} + \frac{\mathbf{W}}{\mathbf{J}}.(\mathbf{°C}).\mathbf{s}$$

Knowing that $\frac{\mathbf{W}}{\mathbf{J}}$ it is worth to $\mathbf{Hz}$ and also to $\frac{\mathbf{1}}{\mathbf{s}}$, both parts of the equation are well in $\mathbf{°C}$

II) EXPLANATIONS OF PHYSICAL PHENOMENA

A) How the cooler works

An air curtain, in which cold air flows downwards, cools the products located in the front of the cooler, at the bottom of the cooler a part of the air curtain flows out of the cooler, and a part flows down into the return air grid and join again the fan to flow cooled air horizontally through metallic perforated panel and provides cooled air to the products in the back *(Fig.1)*.

Thus we expect to study a non-homogeneous place which is likely to impact the core temperature

B) Heat transfer - Methods

B-1) Study of the theoretical heat transfer modes

Without a physical barrier, like a door, an open cooler increases flow irregularities (due to heat transfer with the ambient air, because of the conduction, convection, radiation, lighting ...), and difficulties to control the air temperature and the energy consumption, which is noteworthy in a store.

For all these reasons, a deep comprehension of all the events inside the open cooler is necessary before testing under real conditions the impact of these mechanisms on food products.

We have to take into account different heat transfer mechanisms *(Fig.2)* :

1. Heat transfer by convection between the external air and the front product
2. Heat transfer by convection between the air of the cooler and the air from the perforated plate
3. Heat losses through the walls of the cooler
4. Heat transfer by conduction between the back and the front products
5. Heat transfer by radiation with the surrounding walls of the room of the store
6. Heat transfer by lighting (in the cooler and in the store)
7. External infiltration (customers or employees)

B-2) Setting up experiments in labs and stores

To prove the remarkable differences observed during the theoretical study we set up an experimental plan to see if these theoretical interactions are founded and observed also in practice

Fig. 3 shows the front view of the cooler used in our study which was equipped of one air curtain and 5 shelves: shelf 1 (top), shelf 5 (bottom) for the side with glass support and shelf 6 (top), shelf 10 (bottom) for the metallic support side.

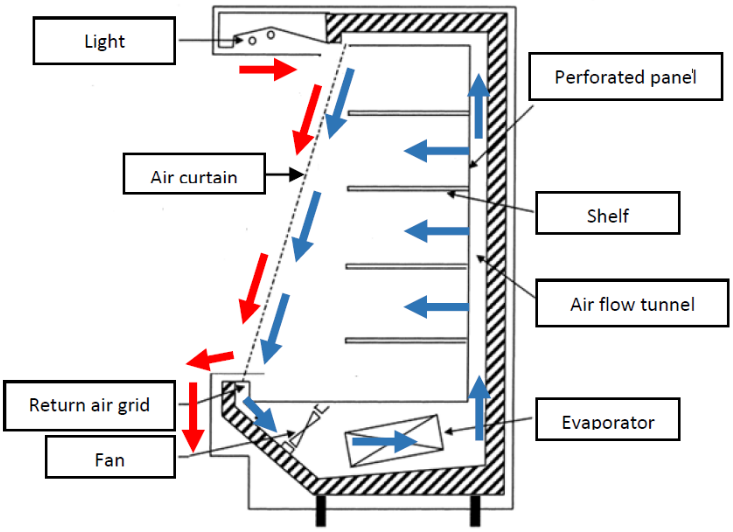


Figure 1 – Air flow visualization

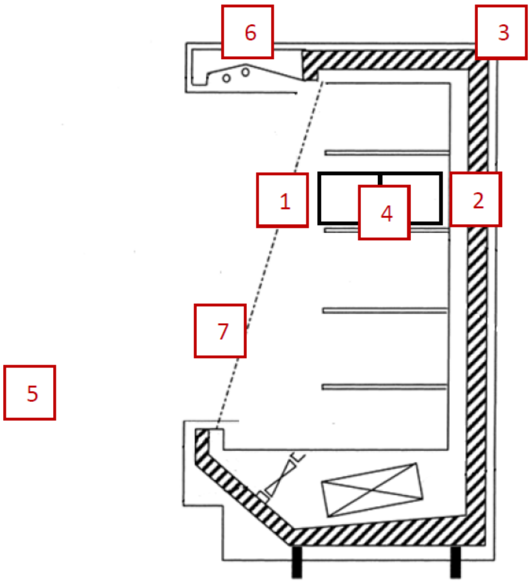


Figure 2 – Heat transfers

Figure 3 – Numbering of the shelves

The cooler was located in a room in which the ambient temperature was controlled at 25°C. The temperature of the air in the cooler was measured every ten seconds. Then, the average temperature was calculated over one hour. The goal was to have a map of the normal behaviour of the cooler (without defrosting or any incidence). The lighting in the cooler was turned ''on'' during the experiment showing the "normal day behaviour".

The position of each sensor is shown in the ***figure 4*** below.

STORE

We also tested under real conditions, to get an idea if theoretical transfers can also explain reality.The temperature of the core products in the cooler "GMZ-123519" was measured three times, each time on Tuesday, at the same hour (9.00). Then, the average temperature was calculated.

C) Heat transfer - Results

C-1) Lab

The average temperature is reported in ***Fig 5***

The air temperature increased from 1.1°C, at the top of the cooler, to 7.5°C, at the return air grid. This temperature increase is due mainly to the infiltration of external air, of the room where the cooler was, at a temperature of 25°C.

The products located at the front are more likely to be affected not only by convection with the air curtain but also to heat exchange by radiation with the wall of the room and to temperature increase due to light absorption on products with dark packaging. As a consequence, the temperature of products located at the front is higher than the ones in the back.

Concerning others remarkable things, if we focus on one shelf, the top is always cooler for products in front, because of the fact that the products are well protected by the shelf above and thus from the light. In the bottom shelf the temperature is higher because of some turbulences due to air return grid, the temperature increase mainly due to the infiltration of external air. However, it exists an exception, in the top, because of the light absorption the front products near the light are higher.

Because of the contact between products, heat transfer by conduction is also important and has to be taken into account.

First we have to highlight the fact the study was focused on "normal behaviour" without taking into account type of packaging, customers or employees, defrosting, or any other incidence. Here we used few parameters but all were controlled without any interferences, the goal was to simulate an "ideal cooler" and we are now able to give an experimental map of the temperature in the cooler in normal behaviour to compare to cooler in stores and see if we could find similarities.

It is a fact, temperature in front is higher than in the back of the cooler for the exposed reasons. Now we have to determine if it impacts the quality and safety of food for consumers.

Figure 4 – Position of each sensor

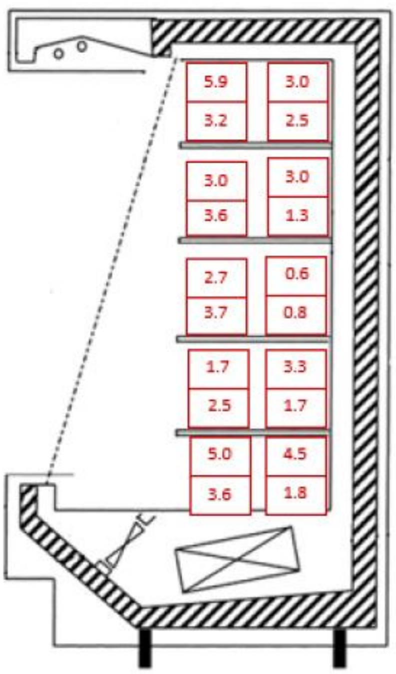


Figure 5 – Cartography of the average temperature on the metallic support side

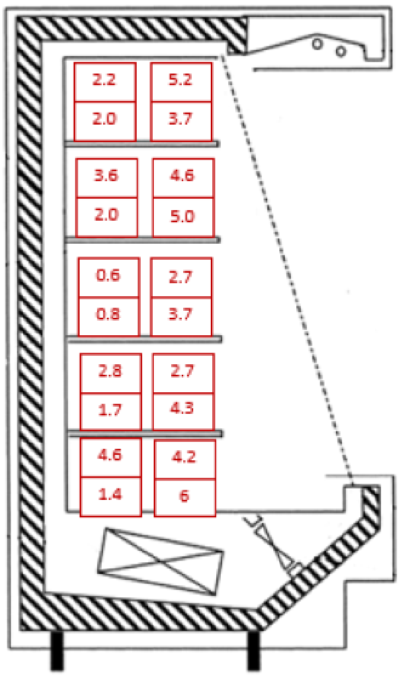


Figure 5 – Cartography of the average temperature on the glass support side

C-2) Stores

ZURICH

As shown *in Fig 6*.

Middle of the cooler (100A9 / 10048) seems to be a safe area, the temperature is the lowest, it coincides with the experimental results in the lab, this is the place where the range of the light couldn't reach the products or at least doesn't have enough energy to raise the temperature and this is a place where there is no turbulence.

The last shelf (100A5 / 10098), as far as we know regarding the experimental result in the lab, should be a high temperature place, in seeing the store result, it is more or less 5°C (we don't have to forget we have a mean value).This is a bit high but less than expected (bottom is a place of turbulences) because of the conduction between products, here we have many smalls products packed together (butter and liquid cream), thermal inertia may be the cause of it.

Then the first two shelves (1009D / 10117 / 10141) have the highest temperature because of the range of the light they are at the nearest point of the light, and radiations. If we look at the *figure 7* we could easily see the range of the light and seeing that beyond the first two shelves the products are less affected by the light when we have a look at the shadows. We also have to take into account the light of the store as shown.

Concerning 100F2 and 1010D it seems that they have an abnormal behaviour considering the position they have in the cooler and the test we had in the lab.

Let's take 100F2 first, it could be the fact that in this place there were less products and they were spaced apart. Cold air from the back could affect the temperature in front with spaces, maybe the convection from the back was powerful enough to face light absorption.

1010D now, the only explanation here would be that the product studied was "demi crème" in a pack of 3 and I was taking the temperature in the middle brick maybe this one was insulated by the two bricks on the side.

SCHLIEREN

Special mention for the coolers 822 and 823 in Schlieren where the products are not illuminated by a single light, at the top of the cooler but under each shelf. The result is a different gradient because the product is also impacted by a release of heat from the light under the shelf heating the metal support where the product stands, so here is the shape of the gradient *(Fig.8).*

CONCLUSION

Despite the differences related to the infrastructure of the two stores we can express common points, which can be useful to create a theorical model which will allow, thanks to the air temperature (only value available with the sensors) to simulate core temperature.

- The closer the product is to the light the higher the core temperature will be, this can be represented with a gradient as shown opposite.
- The closer the product is to the front the higher the core temperature will be.

Figure 6 – Mapping of the average temperature (in front in red faced to the back in green) in the store of City

Figure 7 – The range of light and how the store and the products are enlightened

III) STUDY OF THE NORMAL BEHAVIOR AND TEMPERATURE PREDICTION

The previous studies were essential to establish a reference and visualize all the phenomena useful for the construction of the model.

As it is difficult to quantify the light, and to generalize this study (due to the very different infrastructures of Migros stores), we will focus on the majority influence that is the difference front/back products.

A) Methods

A-1) The Newton model

We model the cooling process of a body using Newton's law of cooling. It states that the rate of heat loss of a body is proportional to the difference in temperatures between the body (Tc) and the environment (Te).

A-2) Origin of the formula

$$\frac{dT_c(t)}{dt} = h \cdot Q \cdot [T_e(t) - T_c(t) + \Delta(t)]$$

Where h and Q are model parameters describing the physical heat transfer process and the physical properties of the body being cooled, respectively. In this way, Q, values could be tabulated for the food products of interest (liquid dairy products, solid cheese, etc...) and then considered constant parameter, valid for all coolers. The other parameter h, could be ideally calibrated for cooler types, and then "assigned" to each cooler as a constant, clearly, it depends only on the cooler. Δ, is a time and position dependent offset. Indeed, as seen previously, it is this parameter that will refine the result by taking into consideration the position of the product in the cooler, because as seen before, whether the product is in front or behind it, it reacts differently to heat transfers.

The parameter Q is defined as $Q = \frac{A}{m \cdot C_p}$, where A is the surface area, m the mass, and Cp the specific heat capacity of the food item.

A-3) Forward model

We want to predict the core temperature Tc of food items knowing the air temperature Te at some predefined location in the cooler. As shown in the bibliography we have found this formula

$$T_c(t + dt) = T_c(t) + hQ \cdot [T_e(t) - T_c(t) + \Delta] \cdot dt$$

Which yields the core temperature of a food product at a time t+dt, given both its estimated temperature Tc(t) and the measured air temperature Te(t) at the preceding observation time t.

Now we have to determine h and Q to suppress unknown values.

A cooler could be filled up with several dummy objects with a known form factor Q. Knowing the form factor Q has the obvious advantage that we can observe directly the behaviour of the coefficient h, constant for the cooler, if we define that delta is 0 considering a reference position in the center of the cooler, which is the safest place and not subject to a lot of turbulence.

In addition, we expect the parameter Δ to be very strongly location dependent as said. We would like to capture this dependence and design a "map" $\Delta(x)$, and this is what we did in the first part, knowing the difference between back and front in normal behavior (average over several hours as already said in II). So for each place of the cooler we have the delta defined. It will only be necessary to determine the Q for each foodgroup because any other parameters will be known.
Thus we start the model with precise real measured values and it deduces the following ones according to the previous ones.

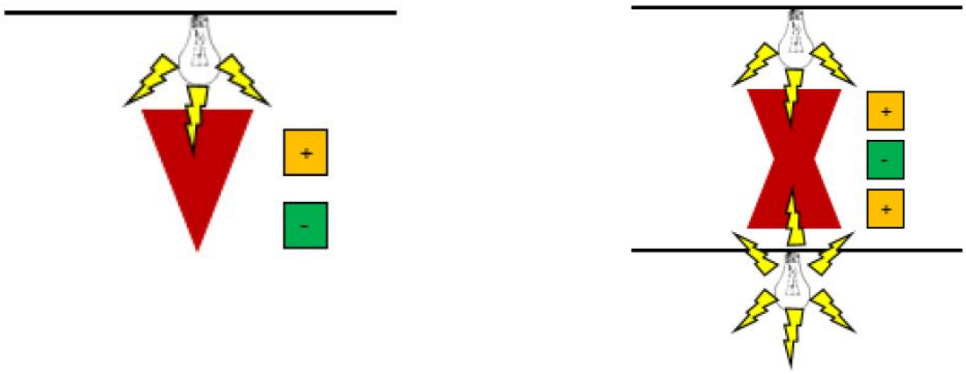


Figure 8 – Gradient when there is light above and below the shelf

B) Results

The purpose of this part is to validate the proper functioning of a heat transfer model to predict core temperature product in a cooler

B-1) Results parameters

The choice of parameters was more complex than expected because in practice sensors were at the very back of the shelves (for practical reasons : not enough space for products if we put sensors in the middle of the shelf) whereas the algorithm is optimized to work with known air temperature at the centre of the shelves (see *Fig.9*). Consequently, all core temperature measurements are carried out in front of the air temperature sensor and this is not the 'optimal' choice of parameters even if we have encouraging results it could be further adjusted.

As said previously, to use the formula : it was necessary to determine h, Q and Δ, so it would be easy to calculate the temperature at $t+dt$ (temperature intake every 5 mins) thanks to the current temperature of the environment and the previous core product. This allow to initiate the model that will use the previous simulated temperatures to deduce the following ones.

Thus to determine all the parameters, we have to follow a logical order. The deltas are known thanks to the map we created and the study of heat transfers. We know that what differs is the back and the front, the sides for a same surface (glass or metal) do not influence.

Another team worked on the extrapolation of the estimation of different deltas that are location dependent. They placed temperature sensors inside dummies objects and some selected food products and they tried to conclude with general appreciations of the delta estimation.

Here is what they found *(Fig.10).*

We also add their work on the day/night variable where the fabric curtain is closed and thus allows a better retention of the temperature within the cooler with less heat loss.

To calculate Q we used food products and several dummy objects with a known form factor Q, simple object to have a simple mass, a simple surface and a Cp found in literature. Knowing the form factor Q has the obvious advantage that we can observe directly the behaviour of the coefficient h, our last unknown parameter.

It is just necessary to deduce h simply from the equation, since all the other variables are now known and it will remain unique and constant for the cooler.

Once all the parameters are known, several Qs are tested to have a wide palette of Q corresponding to several foodgroups, because Q is describing the physical properties of the product in the formula *(Fig.11).*

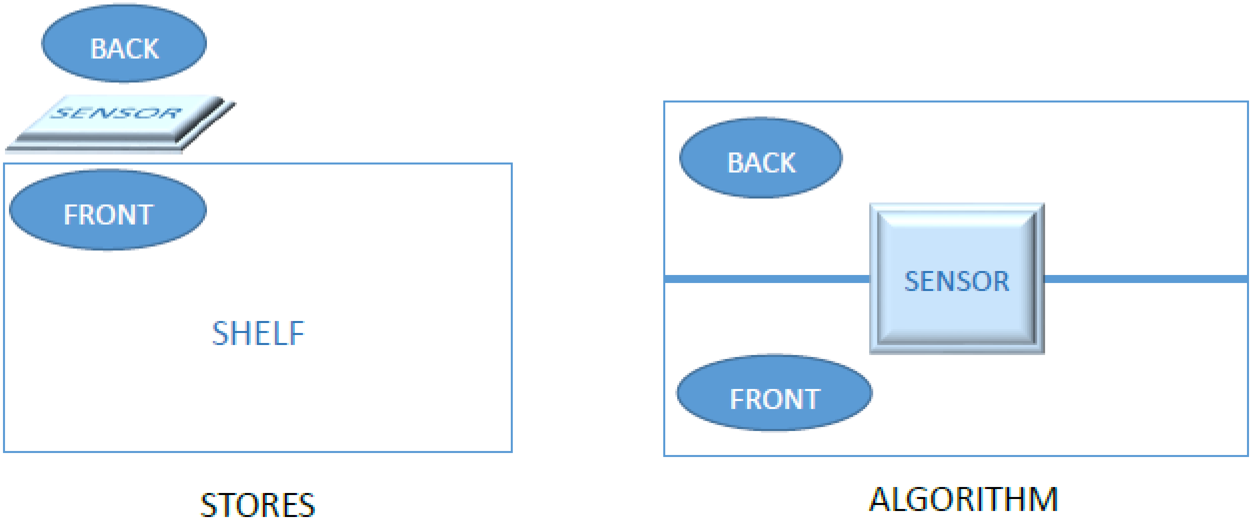


Figure 9 – Position of the sensor on the shelf

Location	Open curtain	Closed curtain
Front	$\Delta = 2.5 \pm 0.5$	$\Delta = 1.0 \pm 0.3$
Back (cooler centre)	$\Delta = 0.0 \pm 0.3$	$\Delta = 0.0 \pm 0.3$
Back (not centre)	$\Delta = 1.0 \pm 0.4$	$\Delta = 0.4 \pm 0.3$

Figure 10 – Values of Delta according to its position on the shelf

$$Q_{meat} = 6.9\times10^{-5}$$

$$Q_{fish} = 8.0\times10^{-5}$$

$$Q_{conv\_S} = 5.0\times10^{-5}$$

$$Q_{conv\_L} = 2.0\times10^{-5}$$

$$Q_{dairy\_S} = 4.2\times10^{-5}$$

$$Q_{dairy\_L} = 5.4\times10^{-5}$$

Figure 11 – Values of Q on different food groups

B-2) Results on the temperature

At the beginning, we worked on a particular cooler (519 – Dairy products). The choice of this cooler to be studied was not chosen randomly, in fact it is the only cooler to have several sensors, at defined and strategic places as seen before, in order to have an overview of the cooler through the study of the times series and the collected information, to have all the parameters useful for the model. Shown in the next figure, we have 3 manual temperature sessions (on the same day of the week, at the same time/hour) taken in front and back of the shelf in the core product to compare reality faced to the model.

The goal is to see if the temperatures recorded during these sessions are as close as possible to the temperatures predicted by the models

Then we extended the comparison to other food groups following the same methodology with others measurements/sessions, this time the coolers have only 2 sensors; one central and one on the top left

An acceptable result is characterized by a good agreement with the core temperatures recorded in stores, within the p/m 1-degree uncertainty of the theorical model, because it is not perfect, we claimed we could achieve speaking with MIGROS.

It works well on as shown ***(Fig. 12).***

Special cases

The cases of food groups such as meat and fish are special.

Indeed there is no shelf strictly speaking ***(Fig. 13)***, but rather floors with bars to hang the products, so the products are suspended on these bars and are most often at the front of the cooler, so for this type of food the front parameter corresponds more and allows a better prediction of the core temperature ***(Fig. 14).***

We have such good agreement for fish in one piece, however, care must be taken during interpretation, as some products that have undergone processing, react differently, as in the case of smoked fish, which are often sliced. Sometimes making manual measurement is difficult since the limits of the product body are blurred. Thus, results as shown in ***(Fig. 15)*** can reflect a bad temperature measurement and not a faulty model.

The wide variety of products in the convenience group makes the task more complicated. Indeed this group being less homogeneous than the previous ones, it is necessary to have a particular attention in the prediction

For coolers set at 8°C composed mainly of salads or other sauces, the back settings seem to be more appropriate, even if the products are in the front ***(Fig. 16).***

For products that are difficult to measure, such as spaghetti and products prepared in air-filled boxes, the front settings correspond more closely, same here, even if the products are in the back ***(Fig. 17).***

According to this *Figure 18* for some defrosting time, the model does not assume this change (slightly with regard to the error bar).

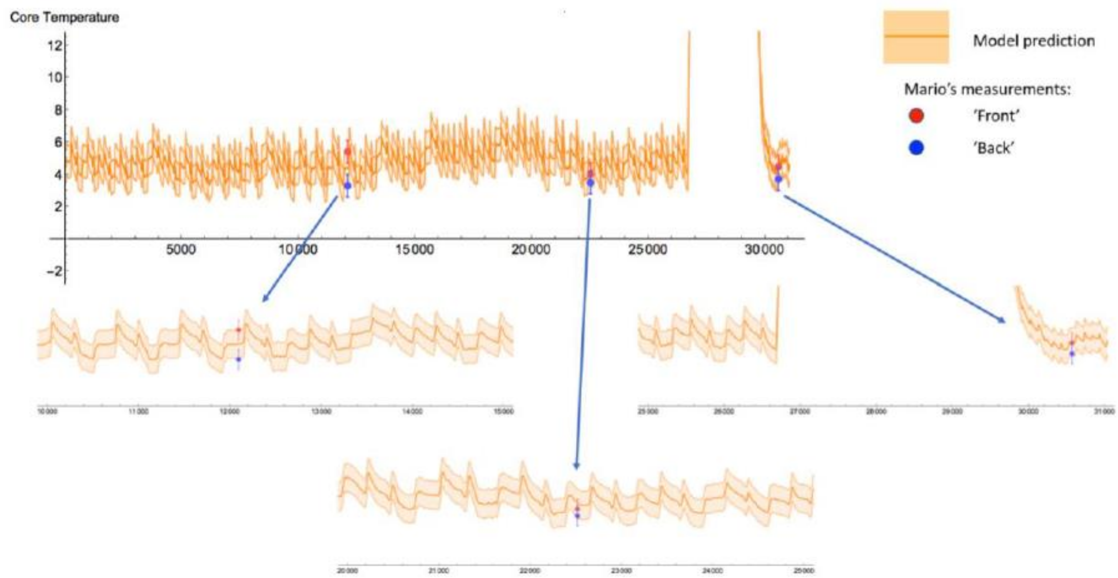


Figure 12 – Prediction by the model with actual measurements made in store

Figure 13 – Presentation of the meat in the shop window

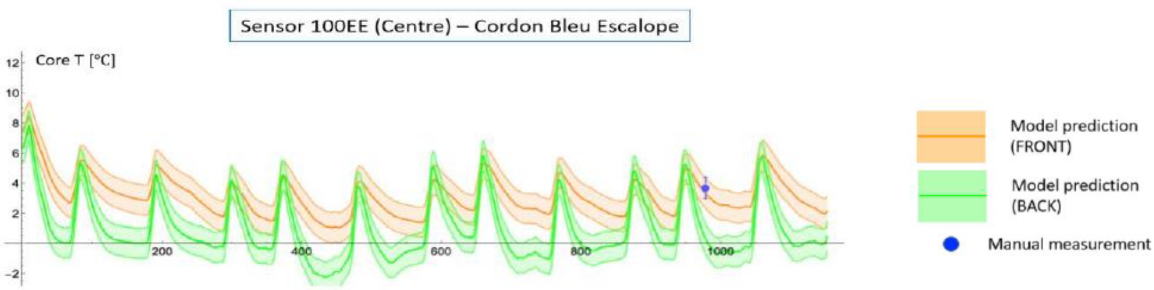


Figure 14 – The front parameter corresponds more to reality

For a total of 62 observations, there are eight differences in the model, i.e. 13 %.

However, among these eight, three are, as seen previously, due to products difficult to measure in view of their physical body (slices,...).

Three others of the measurement during a defrosting time, which is not a normal behaviour.

Finally, this would mean that only two observations do not correspond to the mathematical model, i.e. 3%.

These 2 inconsistent outputs predict warmer temperatures than the actual observations, which is better than opposite

To conclude, the model used slightly predicts the core temperature, with a very few difference between experimental and predicted. This difference may be due to two reasons:

- The precision when taking the temperature in the store and the precision of the thermometer (+/- 0.5 °C), as well as the type of products (sliced products express values to be taken with caution)
- Even if the model used to predict is complete, it remains a simplified mathematical model and cannot take into account all the hazards present in the store

Nevertheless, the model allows the prediction of the product temperature ranges and the trends.

IV – STUDIES OF ANOMALIES

A) Importance of data collection

Data collection is the process of gathering information on targeted variables, which then enables answering relevant questions.

Accurate data collection is essential to maintaining the integrity of research, in practice in this project the data collection was done through an online server managed by an external organization called AXINO.

This platform offers a whole bunch of variables thanks to its sensors that can collect various measurements.

It is therefore essential to choose the right variables to know how to detect anomalies that may impact food safety.

A time series is when you measure the same variable at regular intervals. So therefore the first variable is time, this one is known since it is taken every 5 minutes every day, and corresponds to the very principle of the time series.

Regulated by the principle that a product tends towards the temperature of the medium in which it is located, to detect anomalies and predict future temperatures, We chose as another variable, the air temperature of the cooler at each location of the sensor, because at that time the temperature predicted at the heart of the product by the model was not available in the axino software, we didn't finish it.

So we used to say that if a malfunction occurs within the cooler an anomaly detection can identify it, it implies a change of air temperature, then a change in core temperature knowing that product tends to the temperature where it stands.

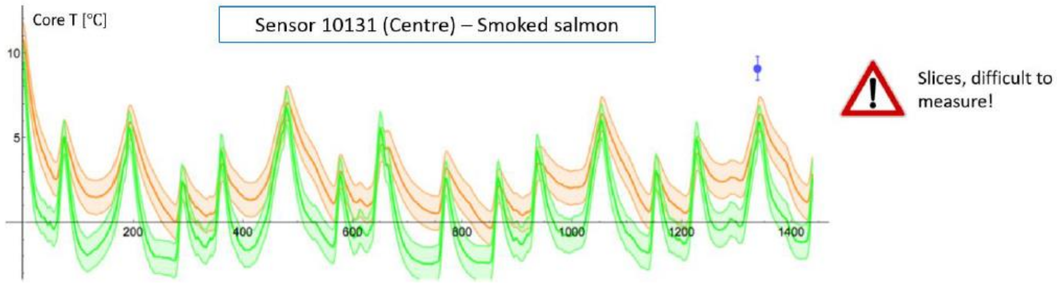


Figure 15 – The case of sliced fish

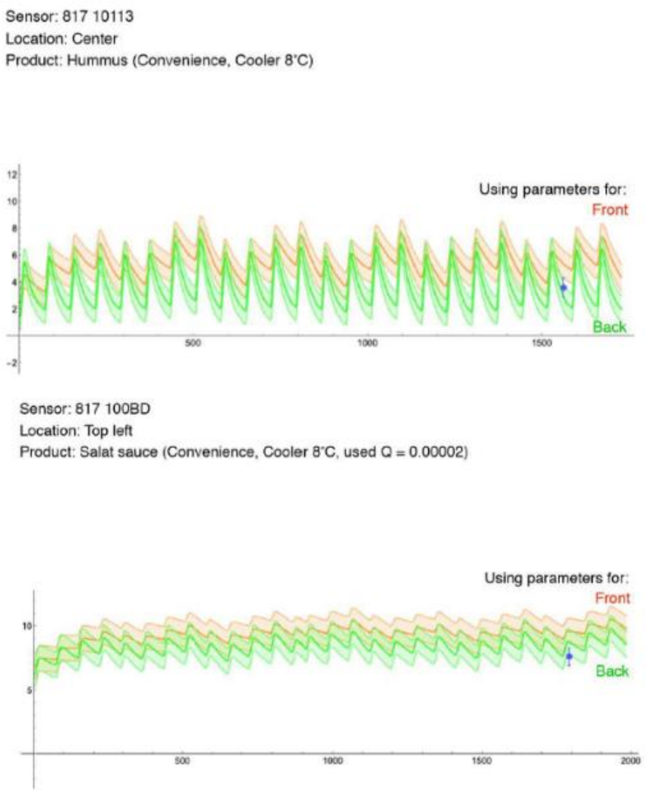


Figure 16 – Back settings on 8°C coolers

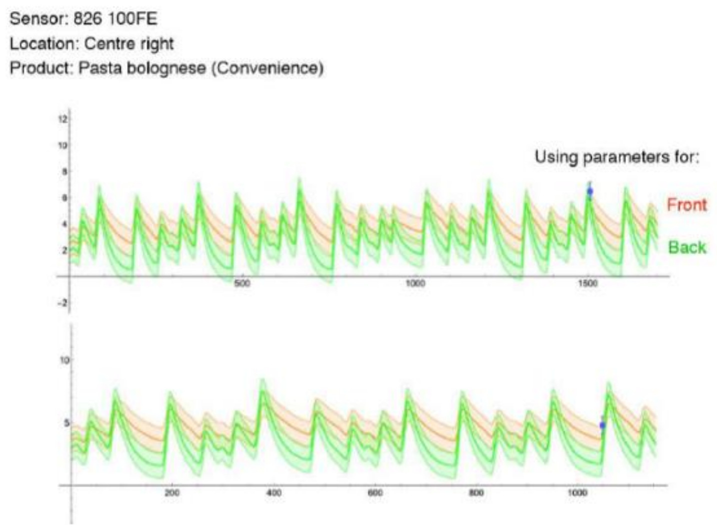


Figure 17 – Front settings on pastas coolers

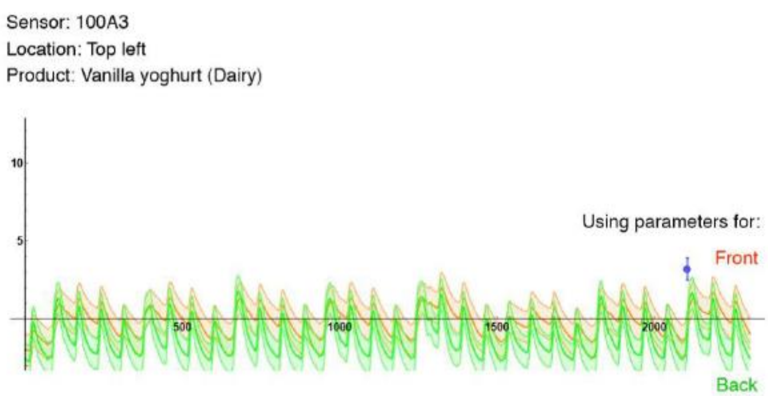


Figure 18 – Defrosting time on model prediction

B） Anomalies detection

B-1 ） Explanation of the code created to detect anomalies

AnomalyDetection is an open-source R package to detect anomalies where the input is a series of observations.

It can detect outliers within local short-term seasonal trends, as well as global outliers that fall far above or below all other values. This is robust, if there is the presence of seasonality and an underlying trend, which is the case in cooling cycle（**Github**, 2015）

This package is achieved by employing time series decomposition. Typically, a time series can be decomposed into three components: the trend, the seasonal variation and the residual（**Rafael G. Vieira et al.,** s.d.）

- The trend is the long-term change in the mean level in the serie
- The seasonal part is concerned with the periodic fluctuations in the series over a fixed period, as example in our study, day in a week versus week end.

Once the trend and seasonal components have been accounted for, the remaining data is attributed to a set of residuals.

- However, if anomalies are found in the input data, this procedure can potentially affect normality of the residual component, this is how the package could find anomalies

The object used to store data tables in R is the data frame. This is a list of vectors of the same size, potentially of different type（numeric, character）, in our example; Air Temperature, Date, Hour, Location, N° sensor. For each row, every 5 minutes, it is a new vector. So we used the AnomalyDetectionVec function to detect one or more statistically significant anomalies in a vector of observations.

In addition we must convert hours thanks to this line of code

Thanks to as.Date, the first column of the data frame（time of temperature measurements）is converted to the correct format and indicates to R how the start data set uses the time variable.

Then with posix calendar time( ), it is indicated that the second column are recorded from the origin

It only remains to decompose the second column with AnomalyDetectionVec function and use the filters to choose the degree of accuracy

B-2) Results

As shown from the plot *(Fig. 19)*, we observe that the input time series experiences both positive and negative anomalies and, it works well.

Now, we must classify the phenomena detected by the R code in order to know if they are due to incidents considered normal (due to traffic, season, maintenance,...) or to real anomalies likely to break the cold chain and make food unfit for consumption within the cooler, leading to a significant loss for the store.

When is a detected anomaly really an anomaly?

Plots of the sensor data were shown to a specialist and suspicious periods were discussed in order to gain an understanding whether the behavior in question is normal and can be explained.

In the following part, the questionable sequences are shown together with the categories found and some explanatory remarks.

Baseline

The mean temperature seems to be moving, whereas normally it should be stable due to the cooler cycle which should oscillate around a target value (outside defrosting time) *(Fig.20).*

The slight drift can be explained by high surrounding temperature, especially in summer as it is the case from June to August. A rise in the ambient temperature leads to an increase in the air and the core temperatures, because of ambient air infiltration, particularly at the front of the cooler.

Defrost cycle

The high peaks result from a longer defrosting cycle *(Fig.21)*. This usually happens when a lot of humidity entered the cooler.

The exchange of humidity is annoying, because a lot of energy is needed to maintain a satisfactory temperature in the cold room (simply because the water molecules in the air require cooling, too) (**Ronald H. Howell et al.,** s.d.).

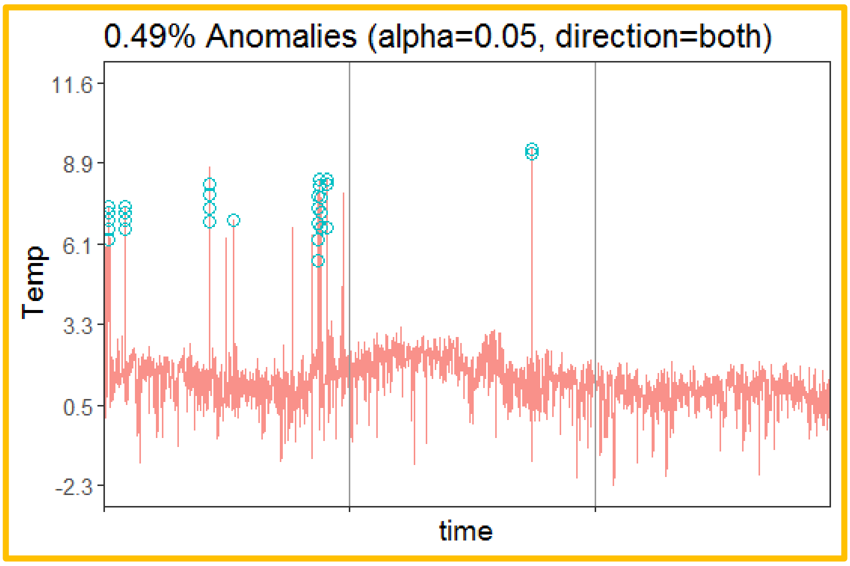
That's why the next defrosting peak is lower, the cooler works harder to cool food.

Missing values

Here the problem comes from the organization recording the data from the sensors located in the coolers *(Fig.22).*

Outliers

These are the phenomena that we should call anomalies *(Fig.24)*. But here again, it is necessary to differentiate between voluntary anomalies such as maintenance operations, the cooler was shut down during the weekend *(Fig.23)*.



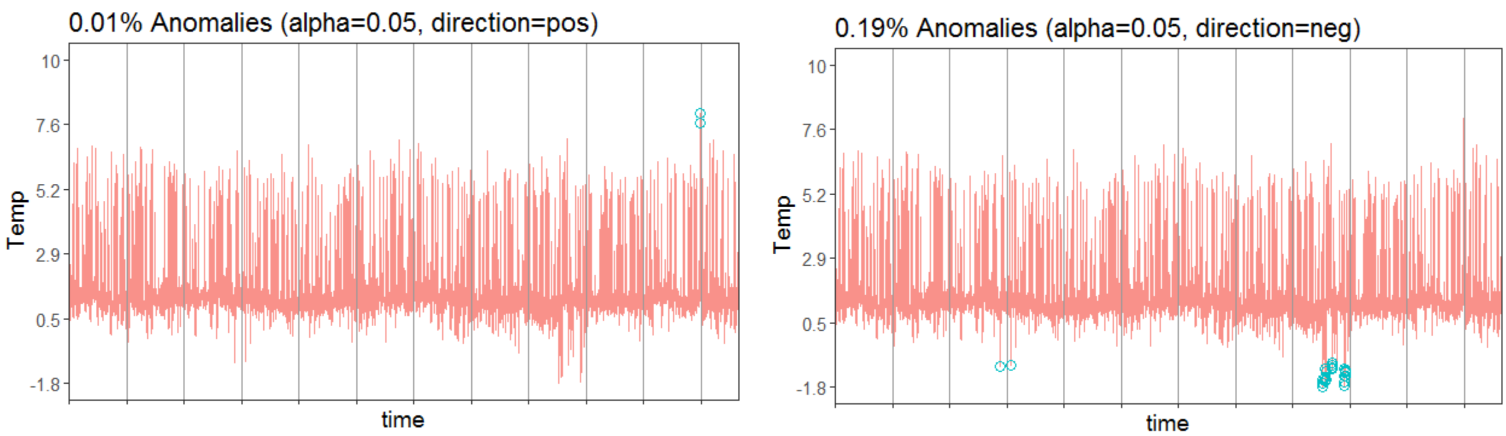


Figure 19 – Detection of anomalies by blue circles

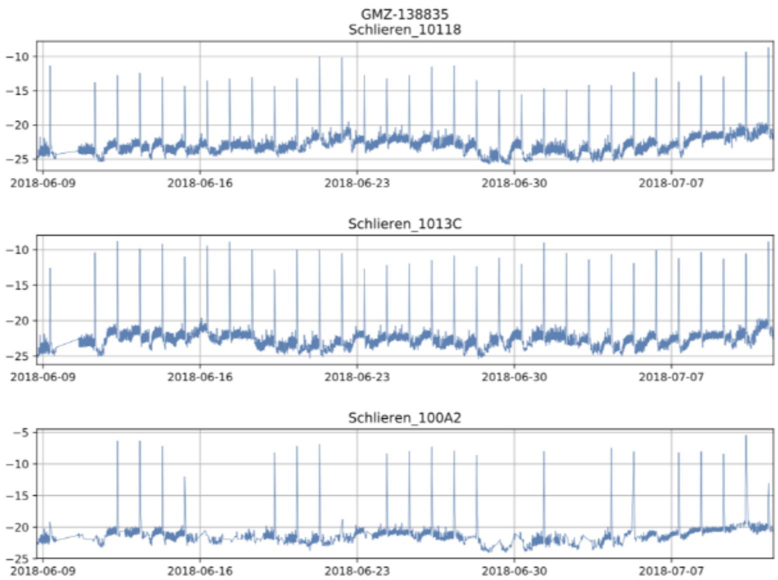


Figure 20 – Drift observed from 2018-07-07

C) Data visualization

We've been dealing with a problem because one area in which this package is lacking is data visualization with unreadable plots and an impossibility to see well the recurring patterns or anomalies for several months except when it brought the curve to extreme temperatures, so package dygraphs came up alongside the literature.

It permits a greater control on the exploration of time-series data. For example, you can drag vertical sections to zoom in on the plot, or simply using the slider on the bottom of the web page or double-click to reset.

In addition with digraph it is possible to label and highlight important time series areas, which is useful during meetings to present results on a particular day on dataset of several months with a measurement every 5 minutes let us remember it.

I figure the best way to show is to go through a few examples and show the normal plotting versus improved plotting, on the following figures *(Fig.25).*

All in all, we see how simple modifications greatly improves the plotting capacities of the AnomalyDetection package. Most of the work was to presenting information to non or less technical people. People who know nothing from a statistical technical point of view, in a first time and in a second one, about the path taken to move forward with this project.

These people simply want to continuously improve their systems and allocate a budget for this purpose but leave the different aspects of the project to specialists, and each specialist must vulgarly explain his work. And rather than writing to digest this information in a textual format from, as a report, in doing an interactive tool we allow anybody to do their own exploration of the data, zoom in on anomalies, trends, etc, by taking part more easily in the project for neophytes

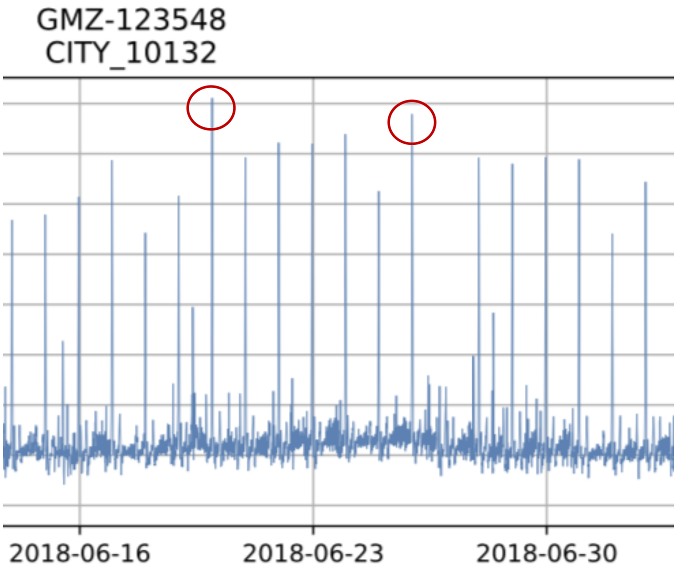


Figure 21 – There is no defrosting cycle around the 26th

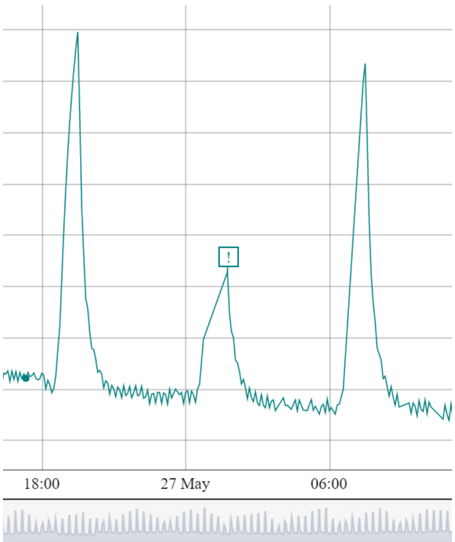


Figure 22 – Missing values

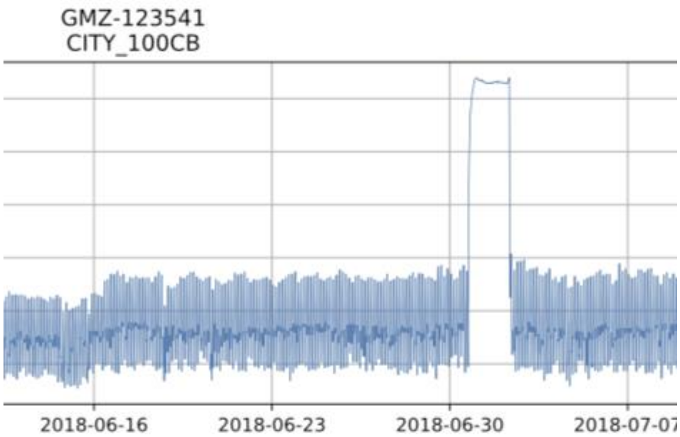


Figure 23 – Cooler maintenance

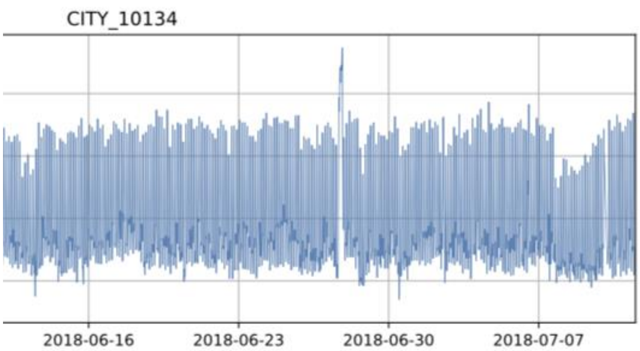
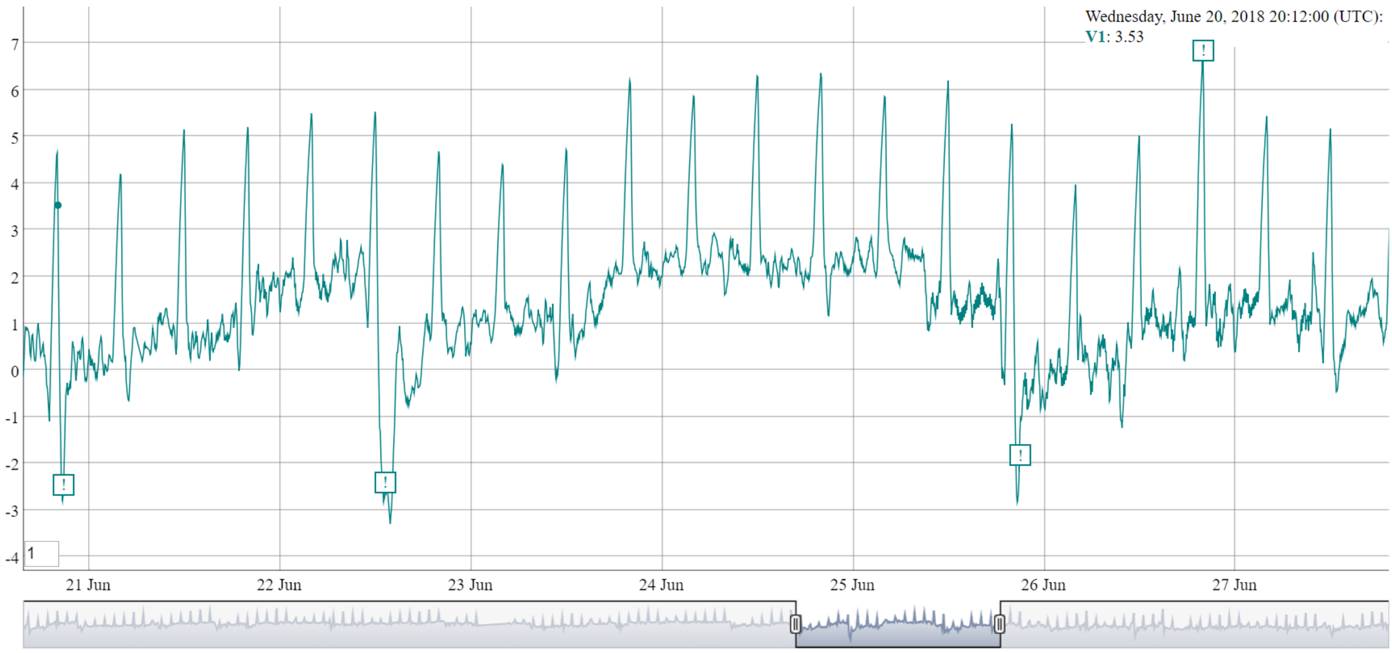


Figure 24 – Outlier on the 27th, temperature too high



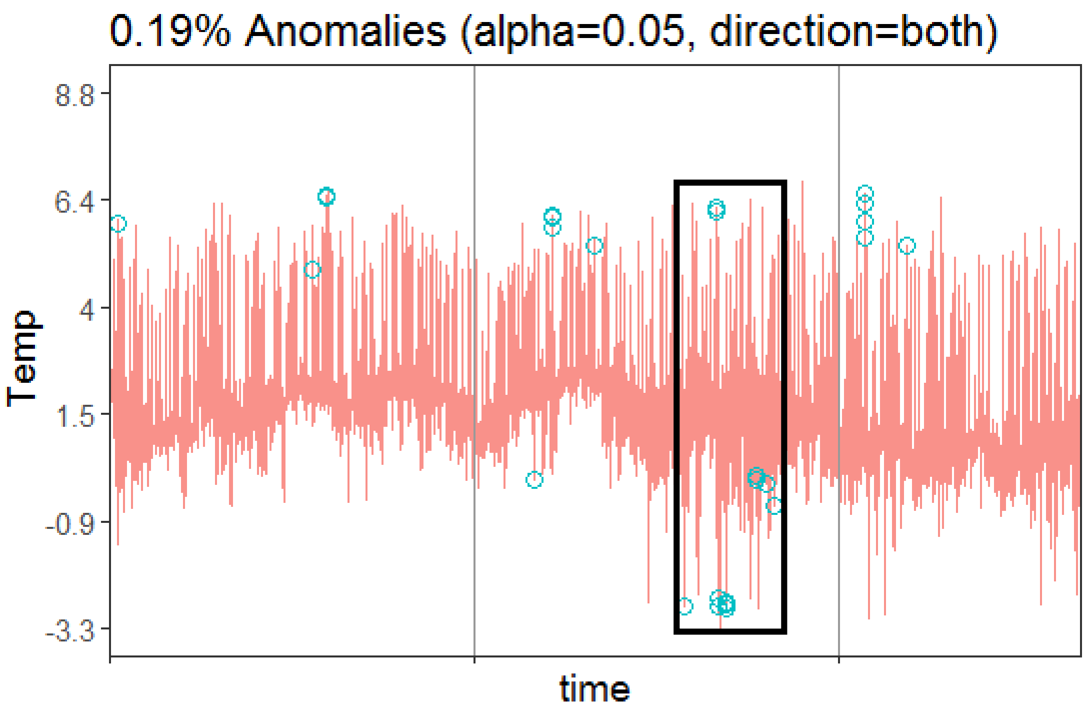


Figure 25 – Improved plotting versus normal plotting

CONCLUSION

A simplified heat transfer model was developed for a vertical open cooler equipped with an air curtain. This model takes into account the heat transfers, the position of the food within it, the type of cooler and the food groups associated. The objective was to predict the core temperature from the environment temperature, called air temperature in the document.

The model slightly under predicts the air temperature and over predicts the core temperature with very few outliers.

The only detections may be due to some reasons, it remains a simplified hypothesis, a simplified mathematical model, and the theory cannot perfectly match the experimental data. Nevertheless, the model allows the prediction of the product temperature ranges and the trends.

The detection of anomalies and its easy visualization also seem to work rather well, and allow first of all to get an idea of the causes and corrective actions to be implemented.

In order to construct a model of the part of the cold chain where temperature abuse is the most often observed in practice, the product temperature evolution and the potential incidences along the cold chain can be followed.

The transport, entry into the store and disposal of products on the shelves could also be a part where temperature/cold chain abuse is the most often observed in practice.

This is why developing and perfecting in the future what we have been working on can be beneficial. The cooling system should be more monitored closely with simple actions.

As improving the model with more sensors for increased accuracy, build an online and real-time detection algorithm with an alarm which is triggered if a certain temperature threshold is reached, to report an ongoing anomaly

As well as developing machine learning can be done, for ever more precision and decide if it is an anomaly or just a normal incidence (as defrosting or a different temperature the weekend when the curtain is closed)

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APPENDICES

APPENDIX I – Anomaly detection code on R

```r
install.packages("devtools")
devtools::install_github("cbgaindia/AnomalyDetection")
install.packages("dygraphs")
install.packages("xts")
install.packages("lubridate")
help(AnomalyDetectionVec)
library(dygraphs)
library(xts)
library(lubridate)

data <- S1011C
data$Sample.Time= as.Date(data$Sample.Time, format = "%d.%m.%Y %H:%M")
data$Sample.Time <- as.POSIXct(data$Sample.Time)
attr(data$Sample.Time, "tzone")
res <- AnomalyDetectionVec(data[,2], max_anoms=0.002,alpha=0.05,period =2000, direction='both', only_last=FALSE, plot=TRUE,xlabel = "time",ylabel = "Temp")
res$plot
```

APPENDIX II – Data visualization code on R

```r
series = xts(S1011C$Air.Temperature, order.by = as.POSIXct(S1011C$Sample.Time, "UTC", "%d.%m.%Y %H:%M"))
graf <- dygraph(series) %>%
  dyRangeSelector() %>%
  dyOptions(useDataTimezone = TRUE) %>%
  dyRoller(rollPeriod = 1) %>%
  dyAnnotation("2018-06-09 14:16", text="X", tooltip = "Blackout")%>%
  dyShading(from = "2018-06-09 14:16", to = "2018-06-10 14:01", color="black")
```

APPENDIX III – Fragment of the model code on Mathematica

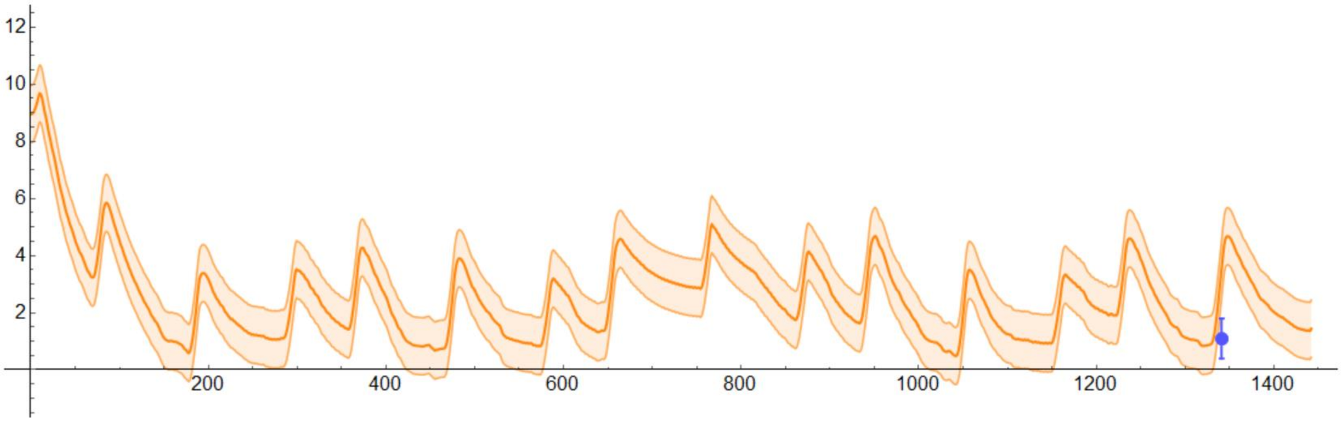
```
TknewF = Table[0, {i, dim}];

Δop = 2.5;
Δcd = 1.0;
hf = 1.2;
Q = 0.000069;

dt = 60.0 * 5;

index_cd[[1]]
index_op[[1]]

Timing[
 TknewF[[1]] = airT[[1]] + Δcd;
 Do[
  If[MemberQ[index_op, ix],
   Δtemp = Δop,
   Δtemp = Δcd
  ];
  TknewF[[ix]] = RKsolver[TknewF[[ix - 1]], airT[[ix - 1]], airTmid[[ix - 1]], airT[[ix]], Q * hf, Δtemp, dt]
  , {ix, 2, dim}]
]
```

```
{0.055449, Null}
```

```
Length[Tknew]
```

```
1442
```

```
Show[
 ListPlot[TknewF, Joined → True, PlotStyle → {Orange, Thickness[0.002]}, PlotRange → All],
 ListPlot[{TknewF + 1.0, TknewF - 1.0}, Joined → True, PlotStyle → {Lighter[Orange]}, PlotRange → All, Filling → True],
 (*ErrorListPlot[Table[{Transpose[{posTcoreF,coreTf}][[ix]],ErrorBar[0.7]},{ix,1,3}],PlotStyle→{Lighter[Red],PointSize[0.01]}],*)
 ErrorListPlot[Table[{Transpose[{posTcoreB, coreTb}][[ix]], ErrorBar[0.7]}, {ix, 1, 1}], PlotStyle → {Lighter[Blue], PointSize[0.01]}],
 PlotRange → {All, {-2.5, 12.0}}, AxesOrigin → {0, 0}, ImageSize → 1100, AspectRatio → 1 / 3, AxesStyle → Black, PlotLabel → None, LabelStyle → {16, GrayLevel[0]}
]
```



RESUME

Author	SEROUART Mario
Promotion	IN26
Document	15 pages – 25 figures – 3 appendices – 12 bibliographical references
Keywords	Heat transfer – Migros – Anomalies detection – Model Newton's law of cooling

The temperature in a vertical open cooler is very variable and directly influences the safety and quality of food products. This variability is due to the position of the product inside the cooler, fluctuations in the ambient temperature in supermarkets (day/night, opening hours, seasons, air conditioning, lights, etc.) and the surrounding conditions of the cooler (in front of another, customers, etc.).
In order to improve the performance of refrigerated display cabinet in improving the uniformity of food temperature, this study proposes a whole review of vertical open cooler behavior, more specifically, a heat transfer model to predict the load temperature in it and a work on anomalies detection.

Things was taken into account to create the model and test it as the functioning of all the heat transfers that the cooler undergoes as well as reasons for the temperature differences according to the position of products in the cooler.
The model was validated by comparing predicted values with experimental ones
Then it was used to predict the influence of various parameters for different food groups.

This approach can be used as a tool for quality and sanitary evaluation of products displayed in display cabinets, by evaluating trends and to see evolution.