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Cold chain break detection and analysis: Can machine learning help?

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ABSTRACT

Background: The impact of the cold chain breaks on food products is widely documented with multiple stakes: health, environmental and economic. The emergence of Internet of Things (IoTs) will enable more rigorous temperature monitoring in real time but raises new questions about the processing of the generated data.
Scope and approach: Different definitions and challenges associated with the detection of cold chain breaks are presented and discussed. Machine learning methods applied to cold chains are described in order to highlight the issues related to these data. In addition, these studies allow us to bring out the different data sources that can be used to train the learning models.
Key findings and conclusions: The field of cold chain generates experimental and numerical data that have a great potential to train machine learning models. To our knowledge, although machine learning methods have been used to predict temperature, these methods have not been used to detect breaks in the cold chain. However, several methods already exist to detect anomalies in time series data. Learning from these data would be a step forward: on one hand, to get a better knowledge of cold chain breaks, and on the other hand to alert operators at the right time.

1. Context and motivation

Refrigeration is crucial as it extends perishable food shelf life and provides consumers with safe food of a high organoleptic quality. Indeed, low temperatures reduce the rates at which changes occur in perishable foods such as growth of micro-organisms (e.g. pathogens and spoilage flora), ripening rates, browning reactions or water losses (James & James, 2010; Laguerre et al., 2013).

As the use of refrigeration has expanded during the last decades in most developed and developing countries, perishable food product supply chains have expanded to keep pace. Nowadays, refrigerated or frozen food product supply chains, usually called the cold chain, are global, and billions of tons of food products are transported between regions, countries and continents.

The term “chain” is intended to emphasize the importance of low-temperature control throughout the various links in the chain: production plant, warehouse, transport, cold room, display cabinets and domestic refrigerators. A failure in the temperature control in one link can jeopardize the efforts devoted to all other links and may lead to product deterioration. These failures, known as disruptions, breaks, abuses, interruptions or spikes, may have different causes such as refrigeration system outages, incorrect temperature settings in refrigeration systems, very irregular temperature distribution due to uneven air distribution or exposure to ambient air during delivery loading and unloading (Brenner, 2015; Commere & Billard, 2008; Mercier et al., 2017).

Several field studies (see Table 1) identified temperature breaks along the cold chain (Ndraha et al., 2018). For example, in France, Derens et al. (2006) observed that around 12% of products in transport and in platforms had an average temperature above the recommended value. However, as this field study was conducted without the supervision of an operator, the cause of the breaks, i.e. irregular temperature distribution in the equipment, improper temperature setting or equipment malfunction, could not be identified. Moreover, there was no information on potential breaks caused by the time intervals between two different links in the cold chain (e.g. where products await delivery loading/unloading). Hence, in spite of the fact that cold chain breaks were detected, their characteristics such as occurrence, the cold chain break level (gap between recommended and actual temperature) and

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their duration are still poorly known, especially for temperature breaks caused by products remaining at ambient temperature during deliveries. Yet, many studies have been carried out under laboratory to evaluate the impact of cold chain breaks on food products quality and shelf-life (Table 2). Of the 27 studies reported in this table, only 10 have based their temperature break scenarios on field study temperature data. Various types of products (meat, fish, fruit and vegetables) and several quality criteria, such as spoilage, health risks, sensory, vitamins and shelf life were studied. Depending on the product type, cold chain breaks of 2 h can reduce the shelf life by 10 to 40%. For highly perishable products, the occurrence, the cold chain break level and the duration can highly impact the product quality. Hence, it is necessary to better characterize temperature breaks in the food cold chain in order to correctly estimate and prevent food commodity quality deterioration.

Nowadays, with the emergence of IoT (Internet of Things), wireless temperature sensors are now widely commercialized at affordable prices, and temperature measurements in real-time throughout cold chains by these sensors are now possible (Bouzembrak et al., 2019; Sarac et al., 2010). Yet, although temperature field data on the cold chain will become available in the coming years, the imminent arrival of these new sources of data raises several questions regarding the definition of a temperature break, the positioning of the sensors so as to account for the whole load in a refrigerated equipment, or the methods to use to detect and characterize temperature breaks. Artificial intelligence with its new set of methods might be one means of answering those questions. This review paper intends to identify how artificial intelligence may be used in order to both characterize and detect cold chain breaks. In Section 2, different definitions of cold chain disruptions from the literature are analyzed. Studies using artificial intelligence in the cold chain are then reviewed in Section 3.

Section 4 presents how to build a learning sample in order to detect breaks: firstly, how to generate/collect thermal data and secondly, a way to label them (i.e tag the data with "cold chain break" or "no cold chain break"). From the data available and existing studies, different directions for further work are then discussed in Section 5.

2. Cold chain breaks

2.1. Definition of a cold chain break

The European Regulation (EC) N° 852/2004 (European Parliament and Council 2004) specifies that "*Raw materials, ingredients, intermediate products and finished products likely to* support *the reproduction of pathogenic micro-organisms or the formation of toxins are not to be kept at temperatures that might result in a risk to health. The cold chain is not to be interrupted*". In other words, any overshoot of this temperature is therefore considered to be a break. However, the regulation also specifies that "*limited periods outside temperature control are permitted, to accommodate the practicalities of handling during preparation, transport, storage, display and service of food, provided that it does not result in a risk to health*". An overshoot is thus tolerated as long as proof that the product does not pose a health risk is provided.

According to Commere and Billard (2008), cold chain breaks concern several situations which share the fact that the product no longer meets customer expectations in terms of hygiene, shelf life and organoleptic quality (color, appearance, taste, etc.). Similarly, many other studies considered the impact on the quality in their definition (Freiboth et al., 2013; Ruiz-Garcia et al., 2009; Thompson, 2002). One issue with this type of definition is that it is dependent upon the product considered and therefore that there are as many types of cold chain breaks as there are food products. Still, even without an agreed-upon definition of these breaks, methods to detect them have been proposed in the literature.

2.2. How can cold chain breaks be detected?

Considering a cold chain break as an event that impacts product quality, the easiest way to detect a cold chain break would be to measure directly the product quality. However, measuring the product's biochemical and sensory qualities is complicated, invasive and expensive. As an alternative, Time-Temperature Integration (TTI) was developed in the last decade to evaluate food quality through the integration of the measurement of the temperature over time. One advantage is that

Table 1
Field studies of the influence of cold chain break on food quality and shelf life.

Country	Product	Data type	Quality indicator	Sensors (sampling interval)	Stage	Reference
Thailand	Chain restaurant product Yoghurt and meat product	Temperature profile, Structure of the chain Temperature profile	–	Data loggers, Thermal infrared images Data loggers	cold storage, temperature-controlled truck	Chaitangjit and Ongkunaruk (2019) Derens et al. (2006)
France	Smoked salmon	Temperature profile	Microbiological	Data loggers	all stages	Morelli and Derens (2009)
	Pasteurized Milk	Temperature profile	Microbiological	Electronic temperature-monitoring data loggers	transportation to retail retail storage domestic storage	Koutsoumanis et al. (2010)
China Australia	Vacuum packaged chilled beef	Temperature profiles, food quality	Microbiological, Chemical, sensory	25 min, 15 min	processing, shipping, distribution network	Frank et al. (2019) - Data Paper
South africa	grapes, plums, pome fruit	Temperature profile, Structure of the chain, food quality	Respiration rate	Data loggers (30 min)	harvest (orchard) until the port of destination	Goedhals-Gerber et al. (2015)
Spain	Cooked meat	Temperature profile, Structure of the chain	Microbiological,Chemical	Data loggers	domestic refrigerators	Jofré et al. (2019)
USA	Oysters	Temperature profile coupled with predictive microbiology, Structure of the chain	Microbiological	Data loggers	six different types of supply chains	Love et al. (2020)
Taiwan	Frozen shrimps	Temperature profile, Structure of the chain, food quality	Microbiological, Chemical, Sensory	Electronic data loggers (continuous recording)	home delivery	Ndraha et al. (2019)
Belgium	Endive	Temperature profile coupled with predictive microbiology	Microbiological	Data loggers (1min)	from harvest to restaurant	Rediers et al. (2009)
USA Spain	Packaged Fresh-Cut Romaine Mix	Temperature profile	Microbiological	TempTale4 sensors	commercial transport, retail	Zeng et al. (2014)

Table 2
Laboratory studies of the influence of cold chain break on food quality and shelf life.

Country	Product	Recommended temperature storage (°C)	Tested[1] (°C)	Duration of the cold chain break	Quality indicator	Shelf life impact (% of shelf life)	Authors, date
Germany	Poultry Pork	4	7 or 15*	5% of shelf-life	Microbiological	−3 to 31.1% −6.8 to 27.7%	Bruckner et al. (2012)
Spain	Poultry	1 4	15 → 4* 15 → 10 20 → 7	6 h→ 112 h 6 h→ 96 h 6h→96 h	Microbiological	–	Alonso-Hernando et al. (2013)
	Pears	1–4	8*	5 d	Chemical, Sensory, Microbiological	–	Colàs Medà et al. (2016)
Benin	Atlantic Horse mackerel	−18 4	Power cut	(3 h or 6 h or12 h) per day x 3	Chemical, Sensory	–	Martinien Hospice Mahussi Assogba (2019)
Portugal	Watercress Frozen strawberries	−18	4, −10, 25 *	15min to 1 h	Chemical, Sensory	– –	Cruz et al. (2009)
China	Post-harvest brocoli Chicken breast	1 4	4, 10, 25 4→ 28→ 4	13 days 1 2 h→ 7h→53 h	Chemical, Sensory Microbiological	Impact higher during 60 d Pre-storage –	Gao et al. (2018) Li et al. (2017)
China USA	Fresh-cut cantaloupe, honeydew, watermelon, pineapple, radish	4	8, 12, 35	7 d, 7 d, 2 h	Microbiological	–	Huang et al. (2015)
Ireland	cooked and fresh vegetable products	3	3→ 12→ 8	24, 96 168 h → 12 h → 48 h	Chemical, Sensory, Microbiological	–	Thomas and O'Beirne (2000)
Vietnam	Pangasius filet	1	1 * 9 * 28–30	48 h/27 h/50 h 5min-2h 2 h/1min-30min-2h	Chemical, Sensory, Microbiological	–	Mai and Huynh (2017)
Malaysia	Unfinished UHT milk		15, 25, 35	2 h, 4 h, 6 h	Chemical, Microbiological	–	Siti Norashikin et al. (2018)
Iceland	Arctic char	1	18	24 h	Chemical, Sensory, Microbiological	−10%	Odoli Ogombe Cyprian et al. (2008)
	Frozen atlantic meckerel	−25	−12	1 month	Chemical, Sensory	–	Romotowska et al. (2017)
	Chilled fish (saithe) fillets	2	16	0 h 1 h 2 h -	Chemical, Sensory, Microbiological	– −22% −44%	Mu et al. (2017)
Italy	Precooked chicken fillets	4	30	1 d	Microbiological	–	Degli Esposti et al. (2018)
France	Fresh chicken liver and breast fillets	−18	4 or 20	0.5,1,2,4,6,8 h	Microbiological	–	Faullimel et al. (2005)
Chile	Hass avocados	7	15 25	24 h or 48 h	Sensory	no reduction early softening	P. Undurraga, J. A. Olaeta and P. Canessa (2007)
Iran	Yogurt	5 20	interrupted cold chain	24 h	Chemical, Sensory	–	Ferdousi et al. (2013)
India	Rocket leaves	5	13	24 h (2 times, at day 2 and day 6)	Chemical	–	Mastrandrea et al. (2017)
Hungary	Vacuum-packaged pork ham slices	5	15, 25, 35 *	1 h 3 h	Microbiological	- 6days - 50%	Géczi et al. (2017)
New Zealand	fluid pasteurized skim milk	5	25 *	8 h	Microbiological, Chemical	reduction	Sadhu (2018)
South Africa	avocado fruit	4 to 8		5 h/20 h/10 h	Sensory	–	Lemmer and Kruger (2010)

[1] Tested cold chain break: scenarios noted with * are actual cold chain break scenarios (based on previous field studies).

Time-Temperature Integrators are small and inexpensive devices based on chemical or biological markers that can be attached to food or food packages. They are designed to match the biochemical activity related to the product's quality evolution and aim at indicating the remaining shelf life using a color stamp (Taoukis & Labuza, 1989) or if the product is still consumable. TTI offers a cost-effective and user-friendly means of detecting any problematic points in the cold chain (Giannakourou et al., 2005). However, even though TTIs have been recognized as effective monitoring tools and have been subjected to regulatory guidelines or standards like in France, the estimate of the real evolution of the product is always approximate, so this has been an obstacle to their wide acceptance in cold chains.

To detect breaks, cold chain operators measure the temperature at one or several positions of a pallet at a given time (e.g. during delivery or shipping). However, these local measurements may not provide a good indication of temperature abuse in the whole pallet. Indeed, very irregular temperature distribution can be observed within a pallet or the load in a refrigerated equipment (Laguerre et al., 2014). Moreover, these measurements at a given time cannot detect prior temperature breaks. Consequently, some operators use data loggers to monitor the temperature throughout the cold chain and an alert signal can be sent to them in the case of temperature abuse. The time-temperature profiles recorded by data-loggers allow the analysis of the characteristics of the break. For example, Goedhals-Gerber and Khumalo (2018) identified the influence of logistics activities on cold chain breaks during exports of fruit in South Africa. These authors determined the percentage of temperature abuse at each stage of the chain by considering that a cold chain break occurred when the ambient temperature was above 2 °C for more than 90 min.

Recently, the development of IoT such as Wireless Sensor Technologies (WST), Wireless Sensor Networks (WSN) and Radio Frequency IDentification (RFID) technology has allowed real-time measurement and transmission of temperature to web platforms (Abad et al., 2009; Ruiz-Garcia et al., 2009). Most of those devices are "active", meaning that they have their own energy source enabling them to operate. While a few years ago, the use of these devices was out of the question, mainly because of their price, stakeholders are now beginning to deploy them in the cold chain and it is expected that this deployment will continue over the coming years. However, they are mainly used to measure the air temperature continuously in a given link in the cold chain and they do not allow the measurement of product temperature throughout the entire chain. The ideal solution would be to measure the temperature of all the products using "passive" devices with no energy source of their own, enabling the data to be read remotely, e.g. a tag placed on the surface of a product pack. Yet, because of their cost, the use of these passive devices has remained limited so far in spite of their potential.

The main advantage of these devices is that automatic alerts can be sent to the operators to rapidly implement remedial actions and avoid deterioration of food quality. However, the criteria defining alerts must be well-defined; a definition that is too lenient may imply undetected alerts and lead to health risks or food wastage due to poor organoleptic quality at the time of consumption. On the other hand, a definition that is too stringent may cause false alerts and not only lead to high logistic costs but also to food waste. Interestingly, both lenient and stringent definitions would lead to food waste. In the case of a lenient definition, waste would mostly be at the expense of the consumer, while in the case of a stringent definition, waste would be at the expense of the chain operators. In conclusion, to define an efficient alert system that limits food waste, health risks and logistic costs, the total number of both undetected and false alerts needs to be minimized (Haflidason et al., 2012).

Whether it is to collect temperature data at one or several positions, to analyze cold chain breaks through data-loggers (Goedhals-Gerber & Khumalo, 2018) or to detect the breaks in real-time (Haflidason et al., 2012), there are many issues related to the representativeness of the measured temperatures with regards to the temperature of the whole pallet or the whole load in a refrigerated context. Indeed, while it is commonly the ambient temperature that is measured, the product temperature might be different, especially in dynamic systems such as the cold chain ("on" and "off" working cycle of the refrigeration system, door openings, sequence of stages with different temperature settings). Since numerous studies show that the temperature inside a refrigerated equipment is heterogeneous (for instance see Laguerre et al. (2013)), one issue is how temperature measurements made at one location can be representative of what happens in the whole load.

In conclusion, to implement an efficient system to detect temperature breaks, the primary focus should be on an appropriate definition based on the type of product, and secondly, a robust solution regarding the methodology used to determine the product temperature and the temperature distribution within a load has to be developed.

3. State of the art of machine learning in the cold chain

3.1. Brief overview of machine learning

Artificial Intelligence (AI) refers to a set of concepts, methods and tools that aim to achieve better understanding intelligence and to endow machines with faculties that are qualified as intelligent when performed by humans or other living creatures. One way to reach a capacity for intelligent decision-making is to learn from examples. Machine Learning is the subfield of Artificial Intelligence that studies approaches and algorithms to do so (Aggarwal, 2015; Alpaydin, 2020; Géron, 2019; Theodoridis, 2020). Prominent among the existing Machine Learning techniques is *supervised learning*. The goal is to find a relationship between inputs and outputs. More formally, one would like a machine to be able to predict the output y when given an input x. For instance, given the characteristics and symptoms of a patient, one would like to be able to predict the diagnosis. Or, closer to our concerns, given the evolution of the temperature of a payload of fresh food over the past 12 h, the aim is to be able to generate an alert if a significant cold break has occurred.

Methods of supervised learning learn a function between the input variables x and the target variable y from a sample of such mappings $S = \{(x_i, y_i)\}_{1 \leq i \leq m}$. When the output variable y is discrete, one speaks of a *classification* task, while when $y \in R$, this is called a *regression* task. The former case could correspond to the prediction that a cold chain break occurred or did not occur, while the prediction of the temperature inside a food product from diverse external measurements is an example of the latter. For either task, numerous techniques have been applied, often successfully, in a broad spectrum of domains. The challenge is to be able to learn a function that applies to any given input x from a limited amount of training examples $S = \{(x_i, y_i)\}_{1 \leq i \leq m}$. To achieve this, the type of functions that the learning system is able to consider should be expressive enough so as to be able to capture the existing dependencies between inputs and outputs, while not being too expressive and risking to learn irrelevant coincidences in the training set.

In many applications, the measurements that define an input x are assumed to be independent, as when collecting information about a client such as: age, profession, number of children, salary, and so on. For some applications however, there exist dependencies among the measurements. This is the case of time series when the measurements are made over time. Here, changing the order of the measurements would alter completely the nature of the input in many cases.

When such dependencies exist between the measurements that compose out an input, the learning method must be able to take into account these relationships. In the case of time series, methods have been developed, such as grammars, Markov chains and, more recently, specialized types of so-called neural networks (Weigend, 2018).

Artificial neural networks have been part of Artificial Intelligence since its beginning in the 1950s. However, a breakthrough occurred in 1985 with the invention of the back propagation algorithm for multi-layer perceptrons, which enabled neural networks to start to achieve significant learning tasks, in particular from noisy data, a feat that was beyond most existing learning techniques at that time. The last ten years have seen a spectacular rise in interest in artificial neural networks thanks to the conjunction of very large training databases, the huge increase in computing power, and new technical features that improve the optimization process forming the basis of these neural networks. "Deep learning" is often the term used to refer to these new neural networks. This is to indicate that they are able to extract relevant descriptors that make it possible to capture important regularities in the data. However, most of the time, this achievement necessitates very large training data sets. In parallel, a set of new methods has been developed in order to deal with time series: Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are the most widely used (Chung et al., 2014; Gers, 1999). One can also cites WaveNet, a Neural Network initially designed for speech and sound generation (Oord et al., 2016). Recent developments in attention-based deep Neural Networks may also be useful for times series analysis and predictive tasks (Vaswani et al., 2017).

3.2. Examples of machine learning in cold chain studies

Table 3 presents examples of the application of machine learning to cold chain studies. Nunes et al. (2014) trained neural networks by using the recorded ambient temperature to predict the product temperature

Table 3
Examples of machine learning applied to cold chain studies.

Models	Target	Type of data	Sensors	Reference
Back Propagation Neural Network	Predict temperature shifts and trends Monitor temperature variations	Univariate Time series Temperature data	RFID	Chen and Shaw (2011)
Neural Network	Temperature prediction inside a pallet from a single sensor	Multivariate Time series Temperature data	-	Mercier and Uysal (2018)
Neural Network	Temperature estimation accross the pallet	Thermal image	Thermal camera	Badia-Melis, Qian, et al. (2016)
Firefly algorithm	Reduce risk automatically	Temperature Geospatial data	Zigbee RFID	Sichao Lu and Xifu Wang (2016)
Neural Network	Predict the product temperatures inside the pallet for shelf life prediction from sensors outside the pallet	Time Series Temperature data	RFID	Nunes et al. (2014)
Kernel Logistic Regression	Decision making support to Optimize quality with minimum cost	Time Series Temperature data	-	Mohebi & Marquez (2014)
Neural Network	Temperature prediction	Time Series Temperature data	RFID	Badia-Melis, Mc Carthy, and Uysal (2016)
Compressed Sensing	CO_2 signal reconstruction	CO_2	RFID WSN	Draganic et al. (2017)

(here, of berries) in a pallet. The same approach was used by Badia-Melis, Mc Carthy, and Uysal (2016) to estimate the product temperature distribution during a failure of a refrigeration system. The data were obtained by recording various actual events in cold chains, including cold chain breaks such as refrigeration failures. Good performances were obtained using artificial neural networks in comparison with Kriging algorithms and capacitive heat transfer methods. Moreover, the performance increases along with the number of sensors. The results obtained were also influenced by the positions of the sensors. These two studies showed that using neural networks brought good predictions of both functioning (refrigeration) and malfunctioning (cold chain breaks) refrigeration system conditions.

In Mercier and Uysal (2018), simulated temperatures at different locations obtained from a heat transfer model, implemented using Comsol Multiphysics 5.1 software, were used as the training data of a neural network to estimate the temperature distribution in a pallet. This heat transfer model had been validated previously (Mercier, Marcos, et al., 2017). The experiment consisted in placing several temperature sensors at different positions in the pallet and in identifying the optimal sensors' positions, which achieve the best temperature prediction in the entire pallet. They also found that the number of sensors and their positions were a determining factor for the precision of the prediction of the temperature distribution in a pallet. To overcome the issue of the cost of temperature sensors and the difficulty inherent in the implementation of measurement, a thermal camera can be used to provide a snapshot of temperatures in refrigerated equipment. Badia-Melis, Qian, et al. (2016) used the temperature measured at some points in a thermal image to predict the temperature of an entire load of apples. These predicted results were compared with that estimated using neural networks and it turned out that the maximum difference between the prediction and the true value was 0.7 °C.

Mellouli et al. (2019) developed a neural network using the external conditions as input variables such as external temperature, demand-response period, compressor working cycle to predict air and product temperatures. The objective of this study was to optimize demand response of the refrigeration processes of the cold room.

Compressed Sensing is a signal processing technique for efficiently acquiring and reconstructing a signal. Compressed sensing and machine learning methods can be combined and we found it relevant to include existing work in our review. While some methods compress information after acquisition to optimize memory, *Compressed Sensing* aims to acquire and compress information at the same time, resulting in fewer measurements. Xiao et al. (2016) used this method in the chilled fish cold chain to improve the prediction of product shelf life (via a WSN system). However, *Compressed Sensing* was not used to select the optimal sensor positions but instead to reduce the amount of stored data: in this context, the temperature is measured at multiple locations in the refrigerated equipment. When the number of sensors is high, and real-time analysis is required, data traffic becomes heavy and the prediction of remaining shelf life becomes less efficient. Here, *Compressed Sensing* provides a method to acquire "compressed" data and to reconstruct all the temperatures once the data have been transmitted. Draganic et al. (2017) used a Compressed Sensing method in the grape cold chain to predict CO_2 levels, reducing the number of measurements to be made, i.e. reducing the number of sensors needed and avoiding communication overloading. They showed that the entire signal can be reconstructed from 45% of the samples.

All the studies cited above demonstrate that machine learning can be used to estimate the temperature distribution inside a pallet in several links of a cold chain. However, the providing of high-precision predictions for the temperature distribution in a pallet using a limited number of temperature sensors is a challenge for machine learning. In addition, the providing of optimal sensor positions that will allow better temperature prediction is another challenge. The input temperature data from several sources for training are presented in Section 4.

4. How to obtain the cold chain data for machine learning?

Overall, the airflow and temperature distribution inside a refrigerated equipment in the cold chain has been extensively studied experimentally and numerically. In this section, the data produced by these studies are described. The potential and the limitations of these data to be used to inform an algorithm able to detect and characterize temperature breaks are also discussed.

In order to build a learning sample that can detect breaks, we propose a formalization to build a variable to predict with the temperature data.

4.1. Measured temperature

In most of the experimental studies, the airflow pattern and the temperature field in refrigerated equipment are studied simultaneously as the latter depends on the former. The airflow pattern is often studied using a hot wire anemometer (Duret et al., 2014), LDV (Laser Doppler Velocimetry (Merai et al., 2018; Pham et al., 2019), or PIV (Particle Imagery Velocimetry (Chaomuang et al., 2017), in both empty and loaded refrigerated display cases or vehicles. The air and product temperatures are in general measured using thermocouples. Mostly, the experimental protocol consists in an installation of a refrigerated system in a test room in which the ambient temperature (and sometimes the velocity) during the experiment is controlled (Laguerre et al., 2013). Analysis of the data obtained provides a better understanding of the heat transfer and airflow phenomena in the installation investigated. It also enables validation of the model by comparing the experimental values with the predicted ones.

The cold chain domain can generate a lot of experimental data that can be used for machine learning algorithms. However, the data of the previously existing studies cannot be used in the case of cold chain break analysis because the experiments were conducted under the normal operating regime of the refrigeration system. A specific experimental set-up that causes cold chain breaks used to generate data must be developed as Badia- Melis, Mc Carthy, and Uysal (2016a) did.

4.2. Temperatures predicted from physical-based models

As an alternative to experimentation, CFD (Computational Fluid Dynamics) or simplified models can be used to generate data on the temperature change of products exposed to different cold chain break scenarios. While a few years ago the geometries in CFD models were simplified because of numerical limitations (Hoang et al., 2015; Nahor et al., 2005; Verboven et al., 2006), enhanced digital capacities now make it possible to refine the mesh and to have more realistic geometries such as palletized polylined fruit packages (O'Sullivan et al., 2017). Moreover, by combining X-ray computed tomography with CFD models, it is now possible to include the product shape and the filling pattern variability in the models (Gruyters et al. 2018, 2020). CFD models are also capable of computing the product temperature evolution in a pallet throughout the various links in the cold chain (Wu et al., 2018). These models provide the detailed temperature distribution in a pallet. However, this approach requires a computation time ranging from several minutes to several days, as well as powerful computers and the expertise of numerical scientists. The use of a CFD approach in order to generate temperature data under numerous temperature conditions encountered in the logistic cold chain to be used in a machine learning application is promising but might not be the most efficient methodology because of the large amount of expertise and numerical resources required. One solution designed to overcome this issue is to develop simplified models based on a simplified (zonal) approach. These models, also physics-based, allow the prediction within seconds of the product temperature in different areas in a refrigerated equipment. (Chaomuang et al., 2019; Laguerre et al., 2014; Lecoq et al., 2016). While these simplified models provide a less detailed description of the temperature field within the products, their reduced computation time allows the generation of temperature data using numerous scenarios that can be used as training data for the application of machine learning techniques.

4.3. Cold chain break formalization

As seen in section 3, machine learning, more specifically supervised learning, predicts an output variable y from an input variable x. Specifically, y could be a binary variable "break" or "not break", and x the temperature of one or more products as a function of time.

Some possible formalizations are presented in Table 4 to label the data. The construction of y is proposed as follows:

Table 4
Several formalizations of f function.

$f(T_p(t))$	$\int_{t_1}^{t_2} f(T_p(t))dt$
$\mathbb{1}_{(T_p(t)>T_c)}$	number of times the product temperature exceeds the critical temperature T_c
$(T_p(t)-T_c)\mathbb{1}_{(T_p(t)>T_c)}$	classical time-temperature integration
$\left(\frac{T_p(t)-T_{min}}{T_{ref}-T_{min}}\right)^2$	microbiological growth simulation where T_{min} and T_{ref} are the minimum and reference growth temperature (McMeekin et al., 1993)
$exp\left[-\frac{E_a}{R\left(\frac{1}{T_p(t)}-\frac{1}{T_c}\right)}\right]$	vitamin C loss simulation based on the Arrhenius equation where E_a is the activation energy and R is the universal gas constant (Dermesonluoglu et al., 2015)

$$y_{[t_1,t_2]} = \frac{1}{t_2-t_1}\int_{t_1}^{t_2} f\left(T_p(t)\right)dt > threshold$$

where T_p is the product's temperature, and *threshold* is a characteristic threshold chosen beforehand. Thus, $y_{[t_1,t_2]}$ is a binary value indicating whether there was a break between time t_1 and t_2.

One can use more complex formalizations that take into account several quality criteria, or even the formalization of remaining shelf-life of the product. However, the formalizations presented in Table 4 take into account the temperature of a single product item while for operational purposes, it is necessary to extend it to the scale of a shipment/pallet. This can be completed in the following way, where $(T_p^i)_{i\in[1,n]}$ are the n products in a shipment/pallet:

$$F(T_p) = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{1}{t_2-t_1}\int_{t_1}^{t_2} f\left(T_p^i(t)\right)dt\right]$$

$$G(T_p) = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{1}{t_2-t_1}\int_{t_1}^{t_2} f\left(T_p^i(t)\right)dt > threshold\right]$$

$F$and G provide two complementary pieces of information: F indicates the average condition of the products, while G represents the proportion of the shipment subjected to a cold chain break.

At the shipment level, y can be built as follows: all products are subjected to a cold chain break as soon as s% of the product items in a shipment are subjected to a cold chain break.

$$y_{[t_1,t_2]} = G(T_p) > s$$

This formalization, which takes into account only the product temperature, supervised learning can enable to detect cold chain breaks in three distinct ways:

1. Training a learning model to predict the temperature of all the products (in this case we train a regression model) and from to these temperatures, we calculate f or/and F.
2. Training a model to predict the output y: this is a classification task.
3. Predict $f(T_p)/F(T_p)$: thus, we are dealing with a regression task which aims at estimating product's/shipment's deterioration.

For example, predicting F would enable operators to claim "less than 5%" or "more than 60% of the products in a shipment were submitted to temperature breaks".

5. Possible roles of artificial intelligence in cold chain break analysis

5.1. Temperature prediction

One challenge is to use machine learning techniques to predict with high precision the changes in product temperature during cold chain breaks using a limited number of sensors. From this predicted temperature, it should be then possible to predict the evolution of the quality of the food product. The information brought by these learned models would help operators in the food supply management when breaks are detected.

As discussed in section 4.2 physical models such as CFD models are used to predict air and product temperatures in refrigerated equipment. However, CFD models require high numerical resource, as example, there are 4.2×10^5 cells for a refrigerated truck loaded by palettes and 3 days calculation with 450 MHz processor (Moureh & Flick, 2004). This makes the CFD fail to predict temperature in real-time while this is a key factor in providing operators with a decision support tool.

Other engineering based methods, on the other hand, allow this real-time prediction. For example, kriging (an interpolation method from geostatistics) or capacitive heat transfer (method based on the electrical analogy) allow this prediction. However, previous works (Badia-Melis, Mc Carthy, & Uysal, 2016; Nunes et al., 2014) have noticed that these methods gave less accurate prediction during temperature variations in comparison with machine learning methods.

Other methods such as dynamic thermal networks (Chaomuang et al., 2019; Masana, 2001) or impulse-response (Laguerre et al., 2008) could also be used to predict temperature in real-time. However, these methods were validated for a specific type of pallet or equipment. Machine Learning methods, in addition to enable real-time prediction, could bring more flexibility in product configuration using only one model (e.g. whatever packaging type, ambient temperature and air velocity). The limitation to achieve this flexibility is that data is needed as much as possible, with numerous temperature profiles, equipment and packaging. To our knowledge, the performances of thermal models were not compared yet with machine learning methods.

5.2. Cold chain break detection

It is possible to be even more ambitious and to envision the *prediction* of likely cold chain breaks, rather than "merely" detecting them. This is what is done in predictive maintenance in other application domains such as aircraft maintenance. Indeed, it is possible that cold chain breaks may be predicted knowing the present condition of the links in the chain and/or of the past history of the chain considered. On-line prediction algorithms suitable for this task exist, that aim at the early classification of time series (Achenchabe et al., 2020; Dachraoui et al., 2015).

Machine learning models used in the cold chain have applied two methods to generate learning data: the experimental method, which consists in simulating cold chain scenarios on real or simulated products in the laboratory, and the numerical method, which consists in using physical models to generate temperature profiles. Some questions are raised, such as: what is the desired output which indicates a cold chain break? When did it begin and when did it end? What event caused the break (door opening, breakdown, loading-unloading)?

The classification methods could make it possible to identify the nature of the breaks, for example, a break during product transfer from one link in the cold chain to another, a power cut, etc. The frequency of different breaks can be identified and corrective measures can be implemented. The application of these methods also raises several questions: Do we prefer to detect breaks with certainty even if we omit some? Do we prefer to detect as many breaks as possible, even if the product quality is not significantly impacted?

The answers to these questions depend on the detection algorithm and the operator's preference criteria. Indeed, in real time detection, one does not want to raise an alert if a break is detected with uncertainty. If the analysis is performed remotely, detecting a break may have no immediate impact on practice in the field. Chandola et al. (2009) reviewed the various ways of handling this issue along with the associated methods.

These methods for detecting breaks could influence the way the cold chain is managed. Currently, once a break is detected, operators can destroy the product or orient product towards a different chain, for example, transform products (e.g. with a heat treatment to ensure the safety of the product), or shorter logistic chain. With a better knowledge of these breaks, the decision could be more adapted to reduce food waste instead of product destruction. Finally, a better monitoring of the products could be used to feed broader cold chain optimization tools.

6. Conclusions

Temperature control in the cold chain is essential in order to reduce food waste and health risks, and to ensure product quality at the consumer level. Current temperature control practice is complex because of irregular temperature distribution in a refrigerated equipment. To our knowledge, in spite of the rich potential of the cold chain domain to generate data, no automatic learning models have been developed to specifically detect cold chain breaks. Very few studies have used the machine learning approach to predict temperature from a limited number of sensors and to choose the optimal sensor positions. This approach should be further developed to detect and analyze cold chain breaks.

Wireless temperature sensors and data transmission are expected to be widely used in cold chains and will provide a large amount of data. This make the real time-temperature analysis possible by the aide of the compressed sensing method. This enables the automatic warning systems to take into account the temperature variability within an equipment and time-temperature thresholds for the alert. Furthermore, it will become possible to classify breaks according to their cause: product transfer between two links in a cold chain or incorrect temperature setting in a refrigerated equipment.

In the long term, data analysis based on a machine learning approach will enrich knowledge of cold chain breaks: occurrence, temperature abuse level, and duration. Currently, this information remains rare. Such knowledge will make it possible to optimize cold chain management, reduce food waste and operating costs, and ensure consumer safety.

While this paper is dedicated to the detection and prediction of cold chain breaks, it might be worthwhile in conclusion to mention other roles for which artificial intelligence could be useful. One of them is in the operational management of warehouses where AI could be used to automatically decide to which client each food package should be sent given its temperature history. Likewise, in this period dominated by the Covid-19 pandemic, problems raised by the logistics of bringing vaccines under controlled temperature to the population have become prominent. For some vaccine brands, ensuring the quality of the cold chain is paramount, with few days left to use the vaccine when very low temperatures (-70 °C, for example) are not ensured anymore. In this case, not only temperature sensors and AI with real-time capabilities could significantly improve the management of the cold chains, but also, it could provide decision aids as where and when best to send the vaccines batches depending on their temperature history.

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