Current status and future trends of computational methods to predict frost formation for demand defrost control systems

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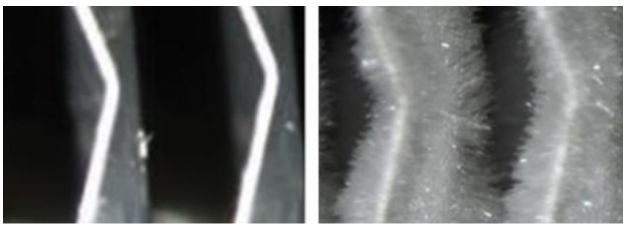
Abstract: *Nowadays, the increasing energy prices and associated environmental concerns lead the refrigeration systems' developers and manufacturers to develop more energy efficient and sustainable equipment and devices. On the most demanding systems, intense usage results in the fast accumulation of ice on the evaporator fins that reduces the efficiency and may even clog the system. These systems often have time-controlled defrost cycles, that heat the evaporator, melting the ice and allowing the system to keep working normally after the defrost cycle. This cycle consumes extra energy and causes a thermal imbalance on the refrigerated space, that may result in a worst refrigeration quality. If it was possible to avoid the defrosting cycle passively (without energy consumption) its efficiency would greatly increase, and the refrigeration temperature would be more stable. Currently defrost cycles cannot be avoided in an economically viable way, although new designs, materials and configurations show promising results, and are currently being investigated. These studies require experimental tests that may become expensive as several geometries, topologies, materials and surface treatment combinations should be evaluated. To access the efficiency before these experimental tests, computational models that simulate frost formation could predict with some accuracy which of the most promising configurations should be then tested experimentally. The present paper aims to review the computational methods to predict frost formation and compare them for possible usage in the computational study of evaporators. Additionally, the future trends of the simulations are discussed, taking into account physical and mathematical models, numerical procedures and the accuracy of the dynamic pattern of the predictions.*

Keywords: Demand defrosting, frost measurement, controlling strategy, frost detection, evaporator design, finned tube evaporators.

1. INTRODUCTION

The issue of frost formation in air conditioning and refrigeration systems, more specifically on the fin-and-tube evaporators, has been studied for several years and yet it still results in significant additional energy consumption [1-2]. As they are used in light commercial systems, these fin-and-tube evaporators have a large area-to-volume ratio. The demand for subfreezing operating temperatures causes the formation of a frost layer on the fin surface [3-4], as shown on Fig. 1.



(a) (b)

Figure 1: Visualization of fins surface before (a) and after (b) the frost formation process (adapted from [3]).

Being a porous medium comprised of ice crystals and pores filled with moist air, the frost buildup on the evaporators fin surface increases its air-side thermal resistance, decreasing the overall thermal efficiency of the system. If the frost is allowed to continue growing, the efficiency keeps decreasing due to not only the increment of the heat transfer resistance, but also to the blockage of the air passage between fins. This condition can lead to a full blockage if no defrost method is applied [5]. Several parameters can influence frost growth, but those with most influence are air relative humidity, velocity and supercooling degree (difference between inlet air dew point and fin surface temperature [4-8]. Although, other parameters such as fin shape and spacing [3], type of flow (laminar or turbulent) [9], or air cleanliness [10] may influence the frost growth. The lower refrigeration efficiency caused by the frost layer on fin surfaces results in a higher energy demand, and in extreme cases, system damage. Furthermore, the inability to cool the air to the desired temperatures, and sometimes the use of active frost removal methods that heat the evaporator result in an increase in the temperature of the refrigerated goods and thus higher product temperatures. Defrost methods are used to reduce the problem, although additional energy is usually consumed for their operation [11]. After literature review, the defrost methods were classified in two groups:

Restraint frost methods: methods for the retardation of the frost formation, by either changing the characteristics of the inlet air (humidity, velocity and temperature) [3], [12]; changing the features of the cold surface (temperature, morphology, position and treatment) [13-18]; and changing the interaction between the air, condensed water or frost and the cold surface (electric field [19], magnetic field [20], ultrasound [21]), etc.

Frost removal methods: methods that act upon the formed frost to remove it and return the working conditions to normal, therefore, ideally, are only used after the frost is formed. These defrosting operations usually result in undesirable temperature fluctuations on the refrigerated space [22]. There are several defrost methods, such as: compressor shutdown [23]; electric resistive heater [24]; reverse cycle[25-26]; hot gas bypass [27]; hot water [28]; air jet or air particle jet [29]; and ultrasonic vibration methods [30-32].

Both restraint frost and frost removal methods can be classified as passive or active: passive if no additional energy is required and active if some additional power input is required to remove the accumulated frost [33]. This classification is summarized on Fig. 2.

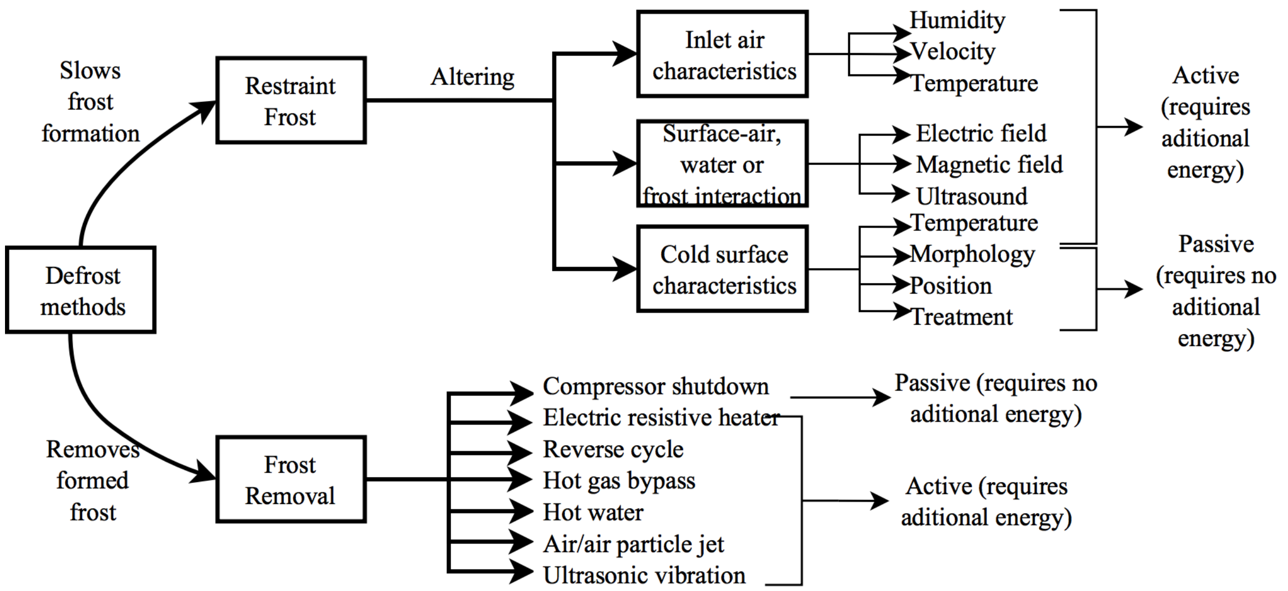


Figure 2: Classification of available defrost methods.

Time controlled with on-off defrosting and electric resistive heater or reverse cycle are the most used active defrost methods. Apart from these, none of the abovementioned methods has gained significant acceptance from the refrigeration industry, due to complex, expensive and unreliable sensing and prediction methods [34], [35]. The use of one of these methods can cause a huge impact on energy consumption, as the defrost operations are timed for the worst-case scenario (warm air with high relative humidity) and thus, as these air conditions vary during the year, the amount of defrosting cycles could vary as well. Tassou *et al.* [36] studied the frost formation and defrost control parameters for open multideck refrigerated display cabinets and concluded that the ideal time between defrosts varies greatly with air temperature and humidity. In Fig. 3, the comparison between time controlled defrosting operations and demand defrosting operations shows the amount of unnecessary defrosting operations for the case studied in [4]. As the ideal operation time between defrosts on this food display cabinet under the studied conditions can range from an average of 4 hours to around 9.5 hours at different times of the year.

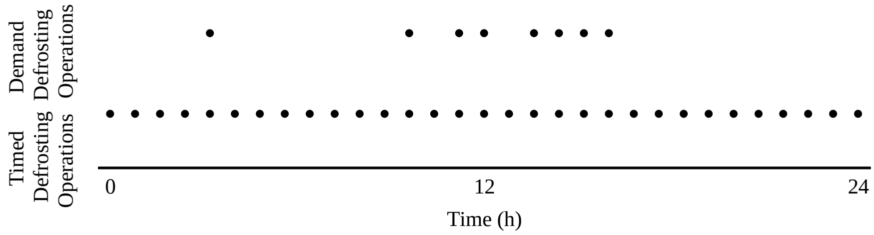


Figure 3: Time difference between defrosting operations in demand defrosting operations and timed defrosting operations in a 24 hour interval (each dot represents a defrosting operation) [4].

A time-controlled defrosting must have in consideration the worst-case scenario on time between defrosting operations. Demand defrost tries to solve this problem by predicting or measuring frost formation. This can be done by directly measuring frost on the evaporator coils. Alternatively, the frost formation can be predicted by processing the measured factors that influence frost formation (such as surface temperature, and inlet air characteristics: relative humidity, temperature and velocity) [37], computing the measurable system changes caused by the frost accumulation on the evaporator (temperature difference between the air and evaporator surface [38], pressure drop [39], degree of refrigerant superheat [40], fan power sensing [41] or both [42], using methods such as artificial intelligence [43-44] or numerical analysis [45-48].

2. PREDICTIVE METHODS

2.1. Artificial Intelligence

Artificial intelligence computes a large set of pre-obtained reliable data (parameters and results) to learns how to predict the desired parameters of frost formation when results are not given [43-44]. These methods can be, amongst others: Multiple linear regression (MLR); Artificial neural network (ANN) and Support vector machine (SVM). These methods are described in the following sections, while their comparison is performed later.

Multiple linear regression (MLR) method: It is a statistical method that can be used to model the relationship between two or more input variables (such as surface temperature, air temperature, relative humidity and time) and one output variable (such as frost thickness) by fitting a linear equation to the observed data [49, 44]. Fig. 4 shows the comparison of measured frost thickness and predicted thickness using the MLR method, this plot gives an idea of how accurate this method can be, as a perfect prediction would result in all points coinciding with the x=y line.

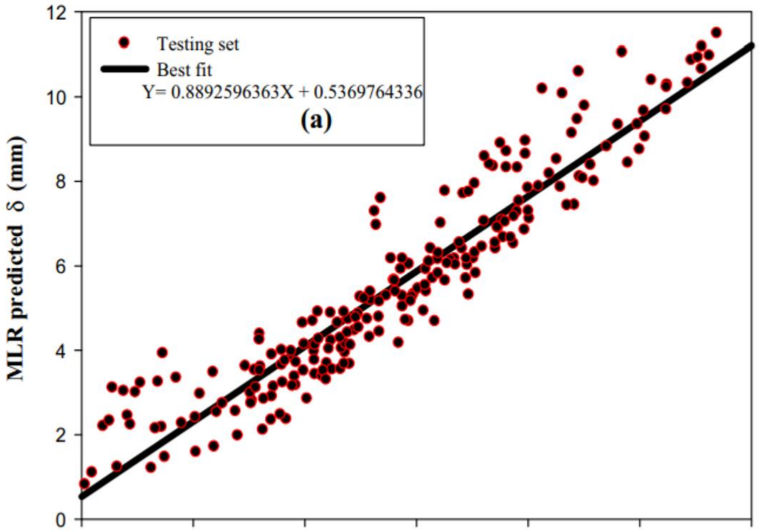


Figure 4: Comparison of measured frost thickness and predicted thickness using the MLR method [44].

Artificial neural network (ANN): ANN are inspired by biological nervous systems, which can learn and identify the correlated patterns by training and then present new values. The general goal of the approach is to find solution algorithms to complex problems, such as prediction, pattern recognition, and classification [50] Fig. 5 shows the comparison of measured frost thickness and predicted thickness using the ANN method performed by Zendehboudi *et al.* [44]. A Multilayer Perceptron-Artificial Neural Network (MLP-ANN) [43] was able to predict frost density on horizontal surfaces, within −7.79% and +5.1%; frost layer thickness on parallel surfaces, within 22.95% and −18.2%; and frost density on parallel surfaces, within −5.26% and +9.99%. In addition, 99.32% of data points related to the frost thickness on horizontal surfaces are within ±20%.

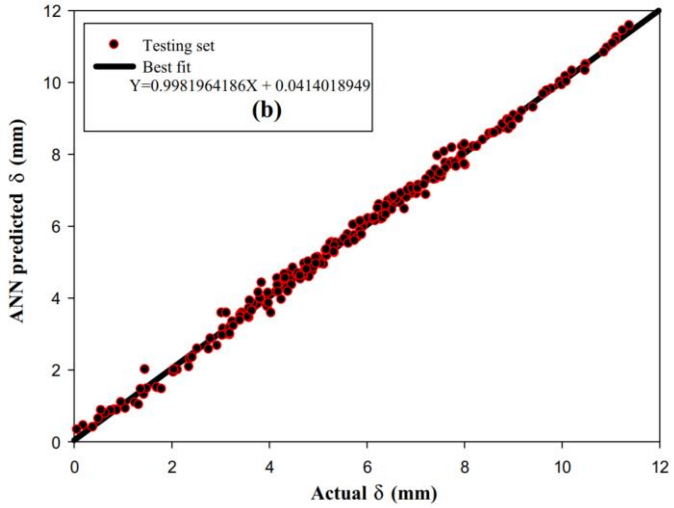


Figure 5: Comparison of measured frost thickness and predicted thickness using the ANN method [44].

***Support vector machine (SVM)*:** The Support Vector Machine learning algorithm is based on statistical learning and structural risk minimization concepts. By mapping nonlinear input variables to high-dimensional feature spaces, the algorithm finds a hyper plane via nonlinear mapping [51]. A modified version of SVM, the least squares support vector machine (LSSVM) has a high generalization capability, lower computational complexity, and higher solving speed [44]. Fig. 6 shows the comparison of measured frost thickness and predicted thickness using the GA-LSSVM method.

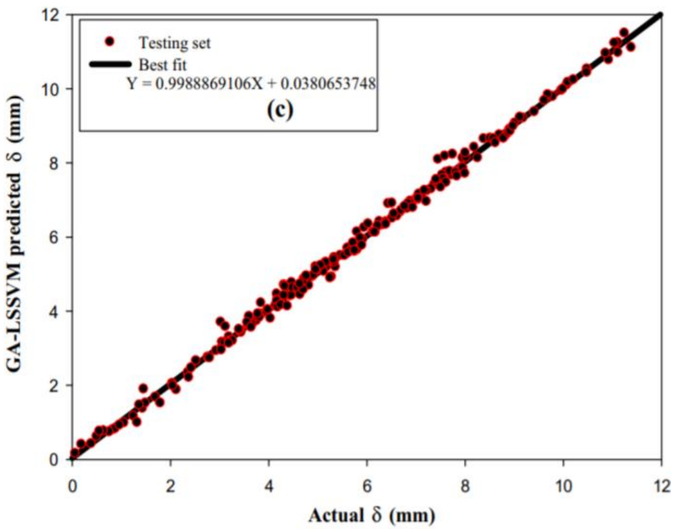


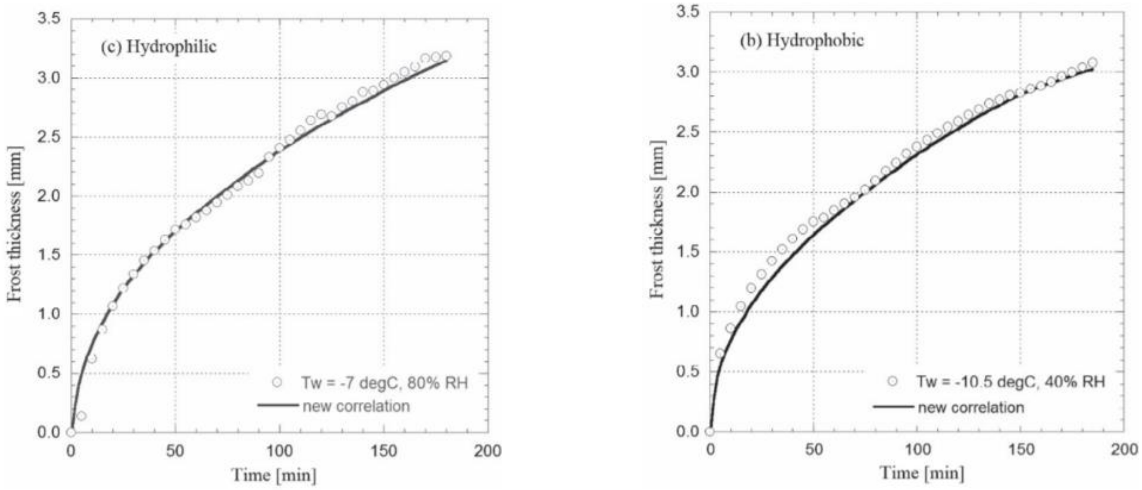
Figure 6: Comparison of measured frost thickness and predicted thickness using the GA-LSSVM method [44].

Concluding remarks: These models can be used to predict frost deposition in a wide range of different conditions with high accuracy. In addition, because models such as MLP-ANN can give results within 1 second, with high accuracy, the models can be used to design and enhance the thermal performance of heat pumps or heat exchangers in low ambient temperatures for refrigeration packages [43]. These models could

also be incorporated in refrigeration systems to compute a prediction of the frost layer in real time using the parameters already measured by refrigeration systems, and applying a demand defrost method based on these results.
As shown on Figures 4, 5 and 6, artificial intelligence methods can give different results, depending on the method and on the implementation. Less reliable results don't necessarily mean that these methods are unsuitable but may show better results if a different implementation is applied. For example, increasing the amount of data samples to train the models is one procedure that may improve model results.

2.2. Numerical analysis

Semi-empirical models: Semi-empirical models can be considered as numerical models enhanced by correlations derived from experimental data, as such derived by Hermes *et al.* [48]. These authors derived a correlation from three different surfaces, to include the surface wettability in a numerical model. Errors bounds of ±15%, and an average predictive error of 11.7% were obtained for different surfaces, which reveal how practical these models can be, as graphically shown on Fig. 7.



(a) Model validation for hydrophilic surfaces. (b) Model validation for hydrophobic surfaces.
Figure 7: Predicted frost thickness as a function of time versus the experimental data for hydrophilic and hydrophobic surfaces under different operating conditions [48].

Although these correlations can simplify the inclusion of a variable or parameter (such as in the case of [48] that includes the surface wettability in a frost prediction model), these incorporations must be carefully introduced, as frost formation is a complex phenomenon and these semi-empirical models might end up oversimplifying and/or introducing errors into the model [45]. Nevertheless, for complex simulations such as frost formation, correlations are usually used to account the huge number of factors that influence frost formation, and thus most of the following methods use empirical correlations in their models [46].

Finite volume method: The finite volume method is a numerical method used for solving partial differential equations. This method calculates the values of the preserved variables averaged across the volume. Bartrons *et al.* [46] used a finite volume method to predict the frost growth using dynamic meshes. The dynamic meshes change with every iteration to account for the frost layer. Application of the model and comparison with experimental data for validation are shown in Fig. 7. The transient numerical prediction provides a trend very similar to the experimental results.

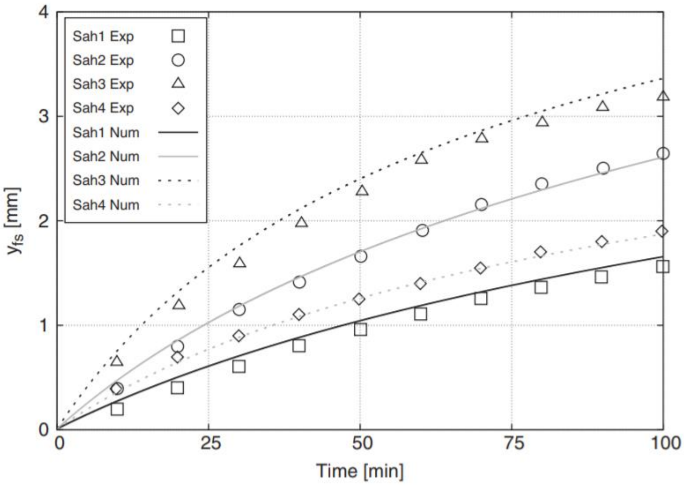


Figure 8: Comparison of measured frost thickness and predicted thickness using the finite volume method in [46] for different conditions.

Other variants of the finite volume method were studied in Negrelli *et al.* [52] in which experimental data was represented within the ±15% thresholds. Armengol *et al.* [45] obtained model predictions of the frost thickness as function of time agree with the experimental data within ±10% deviation for the case of intermediate plate temperature. Lee & Yang [53] developed a model that predicted the experimental data of the frost properties within a maximum error of 10%.

Euler multi-phase flow method: In a two-dimensional computational domain of a finite volume method, it is impossible to express the exact shape and position of the frost surface using a one-dimensional line, because the shape and position change in real time. This problem can be solved by using the Euler multi-phase flow method [47]. This method allows a two-phase flow in a single computational domain. The two considered phases are usually humid-air phase (dry air and water vapor) and a frost phase [47].
Ma *et al.* [54] developed a numerical investigation of frost formation on wavy plates using the Euler multi-phase flow method, leading to average frost thickness and frost weight differences between the simulations and experiments within ± 20%, as shown on Figure 9. It should be considered that this model works for wavy plates, as opposed to most of the reviewed models that work for flat surfaces.

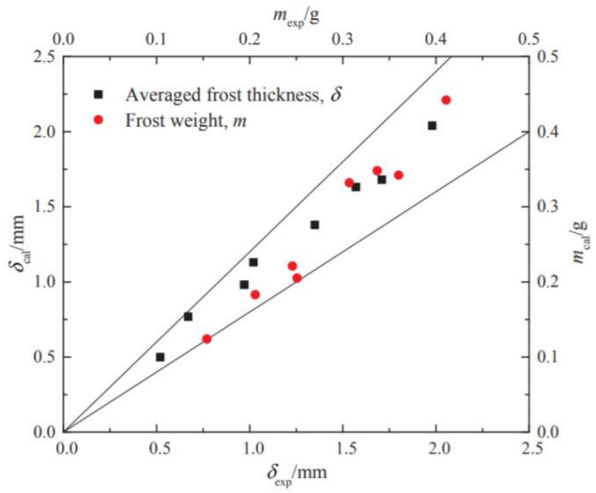


Figure 9: Experimental frost thicknesses versus simulated values using the model developed in [54].

Computational fluid dynamics and software: Although Computational Fluid Dynamics (CFD) can use the abovementioned numerical analysis methods, a special regard should be given to CFD software, as it is nowadays a great tool for simulation. Wu *et al.* [55] uses FLUENT to simulate frosting on fin-and-tube heat exchanger surfaces. This model predicts frost distributions on the heat exchanger surfaces, the temperature distributions and the air flow pressure drop. This model is based on the Euler multi-phase flow method and can be used in the development of a system for frost simulation during the design phase of heat exchangers, as shown in Figure 10. This method managed to achieve an average relative error between the predicted and measured pressure drops of -12.5%.

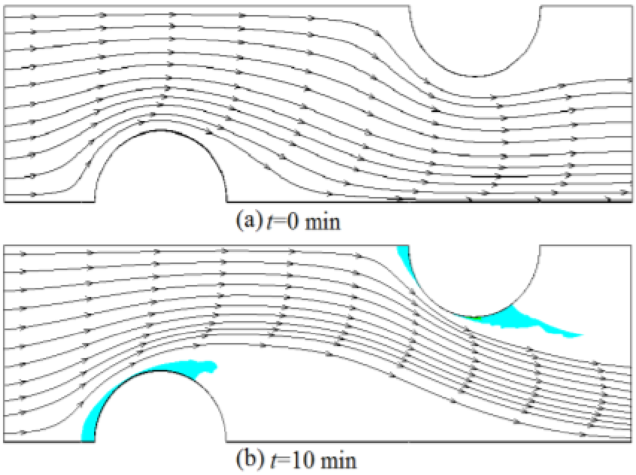


Figure 10: Humid air streamlines on the heat exchanger before and after frost accumulation [18].

Hu *et al.* [53] developed and simulated a phase change mass transfer model to predict the frost layer growth and densification using FLUENT. The difference between the predicted and measured frost weights is within 3.2–3.9%, which are good predictions values when considering the average accuracy of the state of the art reviewed models.

3. COMPARISON BETWEEN METHODS

It is difficult to achieve a comparison between methods as even different implementations of the same method may yield different results. Nonetheless, a general comparison between the method category can be developed based on the main differences between artificial intelligence and numerical methods, with the aim of implementing these methods in the prediction of frost formation in evaporators. This objective can be considered as a means of designing the systems for a better passive defrost, and as a means of implementing demand defrost systems, using the frost prediction to start defrosting operations, rather than time based. The comparison between frost formation prediction methods is shown in Table 1.

Table 1: Comparison between frost formation prediction methods (from ✓ to ✓✓✓ where ✓ is not very suitable for the purposed usage and ✓✓✓ is very suitable.)

Method	Artificial Intelligence	Numerical analysis
Required Computational Power	✓✓✓	✓
Accuracy	✓✓	✓✓✓
Implementation for evaporator design	✓✓	✓✓✓
Implementation in demand defrost systems	✓✓✓	✓

Artificial intelligence methods are the most suitable methods to implement in refrigerators for demand defrost control, as these are accurate enough for demand defrost control, while being simpler to implement and require less computational power (numerical models usually rely on software that is computationally heavy). On the other hand, numerical methods are those that can be reliable and accurate and at the same time better developed for application in a uniform software to aid the design of fin-and-tube evaporators, by allowing the frost formation prediction to dictate if the design will result in an inefficient system, or if it has reached a compromise between heat transfer efficiency and frost accumulation damages.

4. CONCLUSIONS

Different methods for frost prediction and simulation have been developed and are available on the scientific literature. Although, most of these models are for simple applications, mostly for a cold flat plate, with a few methods starting to approach tube fin evaporators and wavy fins. Besides, in the methods for frost formation prediction, there is not a single method that has been widely accepted as the most accurate or convenient, and thus, when talking about methods for frost formation prediction, several different approaches can be made, which causes the problem of not having a uniform solution. If further developed for the purpose, some of these methods can be applied in commercial refrigerators with relative ease. Many of the required sensors are already available in most the refrigeration systems. conditions. However, extra sensors may be required in refrigerator systems that still rely on the timed control method for defrosting operations. Evaporator frost prediction can be a solution to this problem, as a relatively accurate measurement with a safety factor would be more than likely enough to command defrosting operations.

During this review, no studies have been found regarding real implementation in commercial refrigerators. Having a system working in a laboratory doesn't mean it is suitable for implementation, therefore implementation studies should be carried out in the future. These studies should aim for the development of a model that can easily be implemented on an existing refrigeration system without requiring excessive personnel and capital costs, and thus having minimal impact on the sale price of the refrigeration system, while resulting in large energy savings in refrigeration and extended shelf life of the refrigerated products. Although prediction models usually require more than one input (air temperature and humidity, cold surface temperature, air velocity, …), some of these characteristics are already usually monitored by the refrigeration systems, and thus require no additional sensor installation, as opposed to the direct frost measurement systems that require the installation of a frost detection sensor on the system.

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