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Machine learning-based virtual sensors for reduced energy consumption in frost-free refrigerators

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Abstract

This study explores Machine Learning (ML) integration for household refrigerator efficiency. The ML approach allows to optimize defrost cycles, offering energy savings without complexity or cost escalation. The paper initially presents a State-of-the-Art of ML potential to improve functionality and efficiency of refrigerators. Since frost is the cause of significant energy losses, a ML-based Virtual Sensor was developed to predict frost formation on the evaporator also in low -level refrigerators. The results show the environmental significance of ML in enhancing appliance efficiency.

Keywords: artificial intelligence (AI), sustainability, case study, virtual sensors, machine learning

1. Introduction

The increasing number of buildings, especially in emerging economies, is one of the key factors for the continuous growth of electricity consumption by appliances. Currently, most households own refrigerators, averaging 0.9 units per household, and it has become common to own more than one television, with an average of 1.3 units per household (International Energy Agency, 2023). Since refrigerators have 24-hour functioning, they are responsible for significant electricity consumption: for instance, it has been estimated that in India, they account for 461 kWh on average (Prayas (Energy Group), 2021), representing approximately 27% of yearly consumption in a household.

The introduction of the Energy Star Program in the early 1990s, led by the United States Environmental Protection Agency (EPA), marked significant progress in improving appliance efficiency. This initiative aimed to identify and promote energy-efficient products, including refrigerators. As a result, consumers were encouraged to choose greener options, leading manufacturers to compete in producing energy-efficient models. In successive years, improved insulation materials, advanced compressors, and better temperature control systems have become standard features of home refrigerators. The industry has also seen the adoption of cyclopentane and other foams with reduced global warming potential (GWP), reducing the refrigerant's environmental impact (Faruque *et al.*, 2022).

Although regulations and technological advances in the field have led refrigeration systems to use relatively low power for regular operation, different studies have recognised external factors that affect refrigerators' energy consumption during everyday use, such as room air temperature, unit ageing, design practices, and user interactions (Anjana *et al.*, 2015). Consequently, studies that minimise the impact of these factors have gained attention in recent years (Hueppe *et al.*, 2021), especially because the European energy system is currently addressing an unprecedented crisis. It is worth mentioning that despite the identified relevance of the influence of these factors on the additional energy consumption of domestic refrigerators, there are no robust published data in this respect (Harrington *et al.*, 2019).

In addition to optimising control based on factors such as user interaction, room air temperature, and unit ageing to enhance efficiency, the increased appliance intelligence is driven by other trends. These include focusing on food quality, sustainable lifestyles, and healthy eating practices.

To address efficiency and adapt to new trends, a potential solution involves integrating specialised sensors to enhance the information level available for the appliances and consequently improve controls and features. While this is technically feasible, it would cause an increase in the complexity and cost of the appliances. Hence, the addition of dedicated sensors seems to be possible only for high-end refrigerators and not for the most diffused ones (medium-low cost). This last category is the most promising in terms of potential environmental impact.

This work presents an original analysis of the main external factors that impact energy consumption in household refrigerators during regular use based on a literature review and other identified sources. Likewise, it delves into a case study that explores the opportunity of exploiting Machine Learning (ML) as an innovative solution to increase the energy efficiency of these appliances without the need for extra sensors, avoiding increased complexity and cost. This is highly relevant for low and medium-price appliance market segments, accessible for most households. The possibility of adding valuable information for better control logic without adding physical sensors is a well-known idea, but has not yet been applied in domestic refrigerators. This paper is divided into five main sections. Section 1 (this section) introduces the context and motivations of this research. Then, Section 2 reports the State of the Art of household appliances in terms of energy efficiency improvements through the application of ML. The same section also anticipates a case study and the rationale behind its selection. Section 3 describes the experimental setup and the experimental campaign. Section 4 illustrates how the mathematical model for the case study has been created and validated. Finally, Section 5 discusses the potential impacts and presents conclusions.

2. Impactful situations analysis and case study selection

Artificial Intelligence (AI) and ML have already been integrated into modern refrigerators to improve their functionality and user experience. Some existing solutions in domestic refrigerators include (i) Adaptive Cooling based on usage patterns (a real example is R31831I by Asko) and external factors to optimise food preservation and reduce energy consumption, (ii) smart inventory management systems that analyse refrigerator contents, track expiration dates, and suggest recipes based on preferences or available ingredients to minimise food waste and facilitate meal planning (Samsung Newsroom US, 2020; Soh *et al.*, 2020), and (iii) optimisation of **e**nergy **e**fficiency to reduce electricity consumption and a lower environmental impact (SureChill, 2023)**.**

Despite the promising advancements, there are still some limitations to AI implementations in home refrigerators; narrow affordability as advanced AI-powered refrigerators are cost prohibitive for a large portion of consumers, limiting widespread adoption; and product complexity translated into challenges for users in understanding and using the full potential of their smart refrigerators.

A comprehensive literature review was conducted, drawing from 21 different sources of information, such as academic research paper databases (Google Scholar, Science Direct, and ResearchGate), government reports, and manufacturers' websites. This comprehensive approach allowed the consideration of insights from academic sources as well as industry practitioners and works of industrial relevance. The search queries encompassed terms related to the appliance, including different variations of its name such as "fridge", "refrigerator", and "refrigeration". Modifiers such as "domestic", "household", or "home" were added to narrow the focus on domestic appliances. Additionally, specific searches were conducted using keywords such as "energy consumption", "evaluation", "environment", "user interaction", and "food safety" to target relevant content in the research.

Based on the literature review, a structured classification was made to describe all situations that impact energy consumption in household refrigerators during regular use. Table 1 shows an excerpt of such classification.

The table has been structured to outline the key drivers of energy consumption in household refrigerators. Each row corresponds to a specific situation, systematically labelled with 'Category'. The 'Situation' column provides a descriptive name for each scenario, while the 'Sources' column references the sources from which this information has been extracted. To quantify the influence of each situation

on energy consumption, the ‘Energy Impact’ column shows the percentage of impact reported in the respective sources. In the ‘Brief Description’ column, concise descriptions elucidate the nature of each situation. Eventually, the last column of the table is dedicated to other effects.
A design approach to problem solving brings a holistic perspective to each of the reported situations, emphasising the interconnectedness of systems to go beyond immediate energy impacts and identify broader consequences, such as additional effects on health and the environment. This integrated approach allows for uncovering hidden complexities and potential risks, ensuring that solution proposals are energy-efficient and consider a larger context of sustainability and well-being.

Table 1. Situations that impact energy consumption (excerpt)

Category	Situation	Sources	Energy Impact	Brief description	Other effects
1. User interactions	1.1. Door opening	(Harrington *et al.*, 2019; James *et al.*, 2017)	5% to 7%	Warm air and water vapour entering the appliance (sensible and latent heat load)	Temperature change in food that accelerates the degradation
	1.5. Placing warm food items	(James *et al.*, 2017)	8%	Heat load	During cooling time, bacteria can multiply and cause foodborne illnesses
2. Ambient air	2.1. Changes in room air temperature and humidity throughout the day	(Harrington *et al.*, 2018b; Hassan *et al.*, 2015)	3% to 8%	Reduced efficiency. Warm air and water vapour entering the appliance (sensible and latent heat load)	Food temperature fluctuations can accelerate spoilage. Changes in temperature and humidity can create conditions conducive to bacterial growth, increasing the risk of foodborne illnesses
3. Design-related	3.1. Automatic defrosting	(Bansal *et al.*, 2010; Harrington *et al.*, 2018a)	18%	Internal temperature increase, resulting in insufficient compressor operation and wasted energy	Reduction in the refrigerator’s overall lifespan. Temperature fluctuations caused by automatic defrosting can affect the quality and safety of stored food items
4. Ageing	4.2. Obsolescence.	(Harrington, 2017; Harrington *et al.*, 2019)	30% to 80%	Older refrigerators tend to be less energy-efficient compared to newer models	Disposal of old refrigerators and their components that may contain harmful chemicals poses risks to human health and the environment

Among the various identified situations, the authors selected “Automatic defrosting” as a case study. This situation refers to the presence of a defrost cycle in frost-free refrigerators. This cycle implicates a temporary increase in the temperature in the region close to the evaporator. On the one hand, the change in temperature makes the accumulated frost on the evaporator melt. This solution avoids any manual operation by the user and removes the frost layer on the evaporator that causes efficiency drops in the case of excessive thickness. On the other hand, the rising temperature causes the compressor to run more frequently to cool the appliance back down, leading to increased energy consumption. In some cases, particularly for middle-low level refrigerators where the control logic is simple, automatic defrost systems operate even when there is minimal frost build-up, wasting energy.
From an experimental point of view, conducting a data acquisition campaign for a solution based on either a physical model or ML entails significant effort. However, when considering the mathematical aspect, implementing a physical model requires extrapolating an explicit equation that can be challenging to use and process by the refrigerator. Conversely, by employing suitable ML algorithms, it’s possible to extrapolate complex relationships between variables precisely and represent them in a

tabular form that can be easily integrated into refrigerator controls. Hence, ML offers superior management of both the required memory and computational power needed to address the issue of Automatic defrosting. ML algorithms can analyse the temperature and other data inside the fridge to detect early signs of frost formation. Once identified, the system could be used to optimise automatic defrost cycles, adapting them to the real needs of each specific case instead of relying on pre-set timers. Developing an AI-powered system to identify frost formation in home refrigerators can significantly benefit users thanks to increased energy savings and reduced maintenance efforts. In addition, the environment will be positively affected by the generation of lower carbon emissions due to reduced energy consumption. Finally, it can also create a competitive business advantage by attracting the attention of investors, customers, and industry leaders.
The general objective of the selected project is to develop a system for accurately predicting frost formation on the evaporator of a household refrigerator under regular operation conditions with the help of an ML model without integrating any additional sensor into the appliance.
The Specific Objectives are:
Machine Learning Algorithm Development: design and implement an AI algorithm capable of analysing temperatures and other data to accurately detect frost formation in different stages.

- Reliability and Accuracy Validation: conduct comprehensive testing and validation to ensure the system's reliability, accuracy, and robustness in diverse household environments and usage scenarios.
- Preliminary considerations on Dynamic Defrost Optimisation: set the basis of an optimisation mechanism that adjusts defrost cycles based on actual frost levels.

3. Experimental campaign

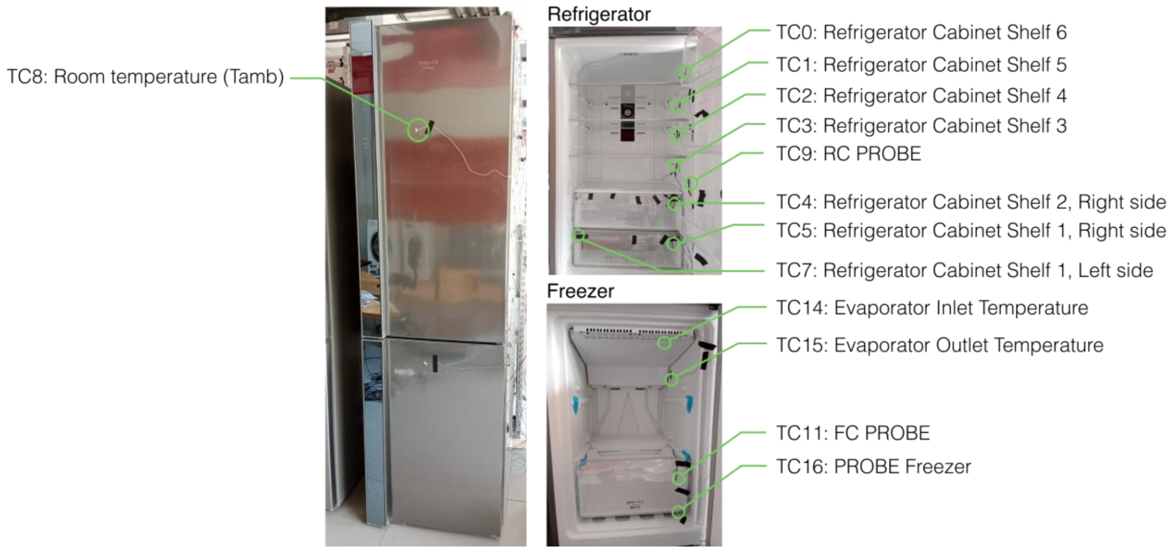

Figure 1. Location of the thermocouples

A total of 620 hours of tests were conducted to collect the valid data needed to build a ML model that predicts frost formation on the evaporator of a household refrigerator under the conditions described below. For data collection, an empty, no-frost refrigerator Hotpoint Ariston of 368 L-total net capacity and nominal 281 KWh-yearly energy consumption was placed in a room with ambient temperatures ranging between 20-24°C and air humidity between 50-60%. The freezer is located at the bottom. As Figure 1 illustrates, the room temperature and internal temperatures at different refrigerator points were measured employing thermocouples type T (often used in low-temperature applications as their temperature range is from -75°C to 250°C, with a tolerance value of ±1.0°C) and registered with the help of a National Instruments Real-Time CompactRIO system. Temperature values were stored in CSV format files for further analysis. Type T thermocouples are stable and often used in applications such as cryogenics or freezers.

The refrigerator in off-status was placed on top of a high-resolution balance (model Xtrem F4-200 with a maximum load capacity of 200 kg and resolution of 5 g) and tared to zero. In this way, every change in the mass reflects the frost mass formation levels. To accelerate humid air entering the freezer and simulate frost build-up on the evaporator, some tests followed a data acquisition protocol involving a 1.5-minute freezer door opening every 30 minutes. While this protocol is widely accepted for accurate models (Malik *et al.*, 2021), there is a concern that the algorithm might be limited to predicting frost formation only under these precise conditions. To address this, additional tests were conducted with data acquisition during sporadic door openings, capturing a more diverse range of situations that better reflect a refrigerator's regular usage conditions, thus ensuring a robust and realistic model design. Moreover, additional tests were conducted under different ambient conditions (room temperature ranging between 14 and 40°C, humidity ranging between 31 and 72%).

Since ambient temperature plays an influential role in refrigerator performance, additional tests were conducted with the refrigerator placed in a closed room, where the internal ambient temperature was adjusted using an air conditioner (to simulate colder ambient temperatures) and a space heater (to simulate warmer ambient temperatures). Multiple points within the room were monitored to ensure reduced temperature variability. This experimental setup aims to reproduce real-world conditions for household refrigerators, offering practical and realistic simulations. The experiment adhered to a rigorous methodology, incorporating controls and careful data collection processes, making it adaptable for replication in diverse environments. While acknowledging limitations, such as temperature and humidity variations, this approach allows the acquisition of realistic and practical data that reflect the variability experienced by consumers in their daily lives, ensuring that the data derived from this setup remains valid and highly applicable to real-world scenarios.

4. Machine learning model

This project adheres to the CRISP-DM methodology throughout its execution, but this paper does not report all the iterations and considerations for space limitation issues.

Among the available ML techniques, Random Forest was chosen for its versatility and compatibility with the domestic refrigeration application since a model generated with this algorithm can be easily converted into a readable format for the appliance's motherboard. Additionally, given these appliances' typically limited memory and computational power, computational complexity is a crucial consideration. Random Forest outperforms other methods in Prediction computational complexity. In contrast, methods like Neural Networks (ANN), Hierarchical Clustering (HC), and DBSCAN that could be suitable to solve the frost formation problem have higher computational complexities(Zaki and Meira, 2014), resulting in greater memory space demand and longer predicting operation times. While methods like Decision Trees offer lower complexities, they often lack robustness for complex data. Thus, Random Forest was selected for its balance of performance and computational efficiency. The structure of the models created using this algorithm is easily implementable on a real motherboard. Moreover, the complexity of the model can be regulated through various hyperparameters, fitting it with the available resources. Other algorithms have been considered and tested for a comparison with the Random Forest, but they are not reported in this paper, since the objective here is not the optimisation of the model, but rather a reflection on the design implications of embedding ML algorithms in simple systems such as low-cost household appliances.

Renowned for its simple implementation, the Random Forest method aligns perfectly with the goals and practicalities of optimising refrigerator performance and energy efficiency.

The first step in creating a robust ML model is data understanding and exploration. The most valuable insights that emerged in this process are:

- The frost build-up on the evaporator closely reflects the expected physical phenomena since it progressively increases as warm, humid air enters the cabinet. Later, the mass decreases to zero grams following a defrost cycle, indicated by a substantial temperature change.
- The door opening process introduces measure noises: the balance measures the mass changes due to the door openings. A noise removal process is necessary to obtain a meaningful curve.
- Partial or short defrosts are encountered during the regular working process of the refrigerator.

- There is a potential correlation between the temperatures recorded in the evaporator (TC15), the temperature probe (TC9), and the compressor working cycles.
- The evaporator temperature (TC15) shows an interesting pattern (see Figure 2) with a repetitive shape that reveals a cycle. The cycle is composed of two sub-cycles with different shapes. This paper refers to these sub-cycles as "sharp" and "round". The length and amplitude of the sub-cycles seem to be affected by the quantity of frost on the evaporator, among other factors. This characteristic could be fostered to describe the problem's main element behaviour.

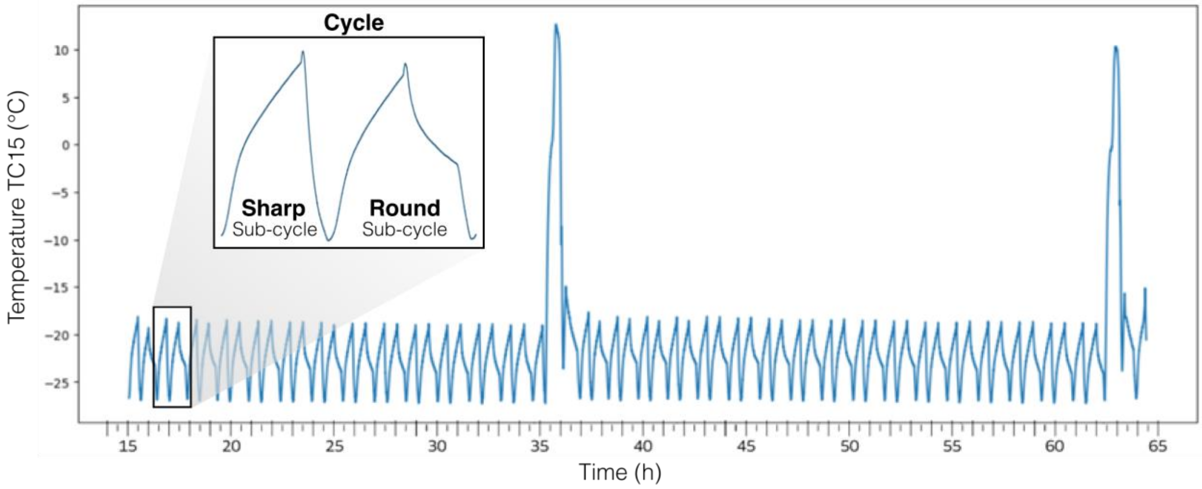

Figure 2. Evaporator temperature (TC15) with a zoom on the repetitive cycle

The mass data coming from the experimental campaign were treated using a moving average with a window size of 600 data points (10 minutes), removing the noise related to door openings.

4.1. Feature engineering

A typical step in the ML pipeline is feature engineering, where new features are defined starting from the original data. In this case study, the main effort has been focused on new features derived from the evaporator temperature (TC15). In particular, the shape of the sub-cycles is mathematically described with the first derivatives after 30, 60, 120, 180, 240, 300, and 600 seconds. The idea behind this kind of feature is to synthesise the characteristics of the cycle with relatively simple mathematics. All functionalities are designed considering two fundamental aspects: they involve computationally light calculations (in this case, arithmetic differences), and they derive from physical variables obtained from sensors already present in standard refrigerators.

4.2. Feature selection

Taking advantage of an inherent feature of the Random Forest technique, the feature selection procedure is embedded in the algorithm. It is possible to define the weight of each feature in the structure of the Forest and then select the necessary features that describe 90% of the model. For this, a model with all the features was created with a subset of the available data. This process with the collected data leads to the selection as a feature of:

- Sharp60, Sharp180 and Sharp600: 3 derivatives of the sharp sub-cycle with temporal differences of 60, 180 and 600 seconds
- Tamb: room temperature of the refrigerator
- Round30: derivative of the round sub-cycle with a temporal difference of 30 seconds

4.3. Discretisation of the target variable

Since the exact amount of frost on the evaporator is not of industrial interest, for the sake of model simplicity and practical usage, the target variable (Mass) has been discretised. Different discretisation techniques lead to different models; thus, the mass variable is discretised using three different strategies.

1. (M1) 4-Bin Uniform Discretization: each bin has the same length.
2. (M2) 3-Bin Uniform Discretization: coarser level of granularity compared to M1.
3. (M3) 4-Bin Constant Frequency Discretization: each bin contains the same amount of data.

4.4. Modelling

The global dataset was divided into a training set and a test set, following a common practice of allocating 80% of the data for training the machine learning model and 20% for testing or evaluating how well the model generalises to new unseen data. Feature selection was performed on a shuffled portion of the training set using cross-correlation to improve the quality of the performance estimation. A subset of 30% of the training set is used as a validation set. This set is not used to train the model but to validate or assess its performance during training. It provides an unbiased evaluation of a model fit on the training data set while tuning the model's hyperparameters. In this manner, it helps when deciding how to adjust the model for better performance. Based on the 3 discretisation strategies (M1, M2, and M3), 3 ML models were trained, validated and tested using the Random Forest algorithm. A summary of the performances and the characteristics of each model is reported in Table 2.

Table 2. Summary table of the developed models and their performance

Model	M1	M2	M3
Number of categories	4	3	4
Overall accuracy	73%	75%	56%
Advantages	Acceptable overall accuracy. Excellent prediction of class 3. No confusion between class 0 and class 3	Acceptable accuracy	Acceptable prediction of minimum and maximum mass levels
Drawbacks	Low accuracy prediction of classes 1 and 2	Sometimes it misclassifies between class 0 and class 3	Low overall accuracy. Sometimes exhibits confusion between class 0 and class 3

Figure 3 shows the confusion matrix of model M1 on the test set. Label 0 indicates the "No Frost" class, label 1 corresponds to the "Low-Frost" class, label 2 is the "Medium-Frost" class and finally label 3 is the "High-Frost" class. This is the best model among the three proposed ones since the overall performance is good and the confusion in classification predominantly occurs between adjacent classes, with no instances of confusion between class 0 (No Frost class) and class 3 (High Frost class). This distinction is crucial, as real-world scenarios demand precise classification to avoid unnecessary (if the actual case is class 0 and the predicted one is class 3) or delayed defrosts (if the actual class is class 3 and the prediction is class 0), which could lead to energy waste.

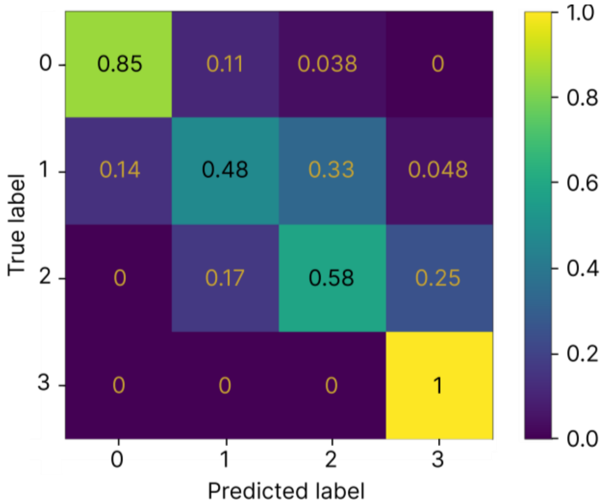

Figure 3. Confusion matrix of model M1 on the test set

5. Discussion and conclusions

The proposed model (M1) offers a practical solution that can be applied across various refrigerator models. This balance is essential for future real-world applications where low computational power and memory are available and only firmware programming modifications are required, avoiding the need to increase appliance manufacturing process complexity and associated costs.

Potential energy savings were estimated by comparing the energy consumption associated with the current defrost technique. Two defrost types were identified during the refrigerator's functioning:

1. Soft (short) defrost: it lasts for 20 minutes and consumes 100W on average, causing an increase of TC15 up to 0°C (0.033 kWh during defrost). It is usually performed when our algorithm M1 predicts class 2.
2. Hard defrost: it lasts for 30 minutes and consumes 150W on average, causing an increase of TC15 up to 15°C (0.075 kWh during defrost). It is usually performed when our algorithm M1 predicts class 3.

With the developed algorithm, it would be possible to change the defrost cycles in terms of intensity and frequency. A potential new control logic would be the reduction of the soft defrost cycle time from 20 to 10 minutes, with the consequent increase in the frequency of this type of defrost cycle. It is reasonable to assume that the frequency will increase 1.5 times (at the same time that the current control logic performs 2 cycles, the new logic will perform 3 cycles). Under these hypotheses, the expected energy savings for each cycle would be approximately 33%. In this way, the energy saved per cycle would be 0.0167 kWh, but increasing the frequency would reduce this positive impact. In the case of hard defrosts, it would be possible to completely avoid them by predicting the amount of frost on the evaporator and replacing hard defrosts with soft ones. It is reasonable to assume that, in this case, the defrost frequency will remain the same as the current control logic. Introducing the developed algorithm for these situations would save 0.042 kWh for each correctly planned defrost. It is obvious that to obtain a better estimate of the possible savings in energy terms, it is necessary to develop a new control logic that includes the developed algorithm and test it in real conditions.

This study offers an original analysis of the external factors impacting energy consumption in household refrigerators, sourced from an extensive literature review and other identified sources. The findings highlight 4 categories of these key drivers that encompass (i) user interactions, (ii) ambient air, (iii) design practices, and (iv) appliance ageing. Moreover, it identifies opportunities for the application of AI in these appliances, exemplified through a case study focused on developing a ML model with low computational requirements for predicting frost formation on household refrigerator evaporators. The developed ML model can predict frost formation in the refrigerator evaporator with acceptable accuracy. By leveraging historical data on temperatures from already embedded sensors in the appliance, the model effectively anticipates the occurrence of frost accumulation.

Through rigorous experimentation and analysis, it has been demonstrated that it is not necessary to introduce additional sensors to create a robust predictive model. The evaluation of the model across various usage scenarios and changing environmental conditions revealed its consistent and robust performance. Likewise, this study establishes the foundation for a system with optimised defrost cycles based on real-time frost level predictions. By integrating the predictive model into the refrigerator's control mechanism, the system could adjust defrost cycles and minimise energy consumption while ensuring efficient cooling performance. This holds especially true for low- to medium-level refrigerators, where cost and complexity constraints often lead to the use of basic control techniques. By using this method, enhancements can be achieved in these appliances without incurring extra costs and introducing minimal additional complexity, primarily at the firmware level. It's worth mentioning that with the conducted study, it is not possible to state whether the model could become capable of distinguishing frost accumulation more finely through a more extensive data acquisition campaign or whether the dynamics of the system and the measured signals constitute a limitation to the potential of the Random Forest model. Nevertheless, the model is applicable to other refrigerators with similar characteristics where the evaporator temperature measurements can be accessed; the number of levels in which the ice accumulation can be discretised must be verified.

However, a more precise estimate of potential energy savings requires the development of a new control logic incorporating the developed algorithm and subjecting it to real-world testing. This represents a promising avenue for future exploration.

Finally, this research not only delves into the factors influencing frost formation but also demonstrates the potential of ML applications in household refrigerators without the need for extra sensors. The project offers exciting prospects for designing intelligent refrigeration systems with optimised features such as defrost cycles, underlining the practical and environmental significance of this innovative approach. More generally, it represents an example of how ML algorithms can be exploited in the design of more efficient products without requiring the introduction of new physical resources.

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