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Research Paper

Neural network models for predicting perishable food temperatures along the supply chain

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ARTICLE INFO

Article history:
Received 11 August 2017
Received in revised form
5 April 2018
Accepted 20 April 2018

Keywords:
Perishable food
Cold chain
Quality-driven distribution
Temperature prediction
Neural network
Heat transfer

Monitoring the temperature of perishable food along the supply chain using a limited number of temperature sensors per shipment is required for wide-scale implementation of quality-driven distribution. In this work, we propose to leverage the theoretical foundation and generalisation ability of a physical heat transfer model to develop a flexible neural net framework which can predict temperatures in real-time. More specifically, the temperature distribution inside a pallet subjected to different ambient temperatures are generated from a validated heat transfer model, and used to train a neural network. Simulations show that the neural network can predict the temperature distribution inside a pallet with an average error below 0.5 K in a one-sensor-per-pallet scenario when the sensor is properly located inside the pallet. Placing the temperature sensor at the corner of the pallet provides a high information content with strong correlations to the other locations inside the pallet to maximise the accuracy of the temperature estimates. The application of an ensemble operator to combine the predictions from multiple randomly seeded neural networks improved by up to 35% the accuracy of the temperature estimates. Finally, the introduction of small Gaussian noise in the training data is an efficient approach to improve the generalisation ability of the neural network and improved by nearly 45% the accuracy of the temperature prediction in the presence of noisy temperature sensors.

1. Introduction

Temperature is the factor with the highest impact on perishable food quality and safety. For many perishable food products, the knowledge in real-time of their temperature can be translated into an estimate of their remaining shelf life. The remaining shelf life can subsequently be used to improve supply chain management, for instance through First-Expired-First-Out inventory management, dynamic expiry dates and dynamic pricing systems (Dittmer, Veigt, Scholz-Reiter, Heidmann, & Paul, 2012; Mercier, Villeneuve, Mondor, & Uysal, 2017; Nunes, Nicometo, Émond, Badia-Melis, & Uysal, 2014, Tromp, Rijgersberg, Pereira da Silva, & Bartels, 2012;

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https://doi.org/10.1016/j.biosystemseng.2018.04.016

Wang & Li, 2012). Supply chain management based on temperature measurements can significantly decrease food waste, which is of critical importance given that, for some products, waste can reach up to half of their production (NRDC, 2012). More efficient supply chain management can also save water and energy, increase return-on-investment, improve consumer satisfaction and support compliance with recent regulatory requirements (Dittmer et al., 2012; Mercier, Villeneuve, et al., 2017; Nunes et al., 2014; Tromp et al., 2012; Wang & Li, 2012).

However, low-cost and high-resolution monitoring of perishable food temperature along the supply chain represents a significant challenge. Wireless sensors, notably RFID tags, are increasingly performant and accessible, but realistic implementations of temperature measurement systems along the supply chain remain limited to one sensor-per-pallet or one sensor-per-shipment scenarios (Bollen et al., 2015; Musa & Dabo, 2016; Nunes et al., 2014; Ruiz-Altisent et al., 2010; Ruiz-Garcia & Lunadei, 2011). A single sensor is not sufficient to estimate accurately the state of the food and implement efficient management systems based on temperature measurements, because a wide range of temperatures is generally observed within pallets and shipments. As an example, Tanner and Amos (2003) reported a temperature variability of up to 7.5 K during sea transportation of kiwifruits in refrigerated containers, creating a wide range of remaining shelf life for fruits within the same shipment. Similarly, Margeirsson, Lauzon, et al. (2012) reported a temperature variability of up to 8.5 K depending on the location of fishes inside a pallet, and Nunes et al. (2014) estimated that the remaining shelf life of First Strike Rations (high-calorie military food products) at the corner of a pallet was up to 15% shorter than the shelf life of those near the centre.

A combined measurement-modelling strategy is a promising solution to improve temperature resolution while limiting the number of temperature sensors. The objective is to develop a model able to use the temperature measured by a limited number of sensors placed at strategic locations within a shipment for the estimation of the temperature at locations where no measurement is taken. Jedermann and Lang (2009) and Jedermann et al. (2011) quantified the accuracy of temperature estimates obtained using different weighted interpolation schemes. These authors showed that interpolation with the Kriging method, where weighting is based on the statistical dependency between the locations where the temperature is measured and predicted, performed better than inverse distance weighting or multiple linear regression. However, the authors estimated that approximately 20–30 temperature sensors were required to map with a sufficient resolution the temperature distribution, a number remaining significantly high for a cost-effective commercial implementation. Nunes et al. (2014) estimated the temperature inside a pallet of First-Strike-Rations from temperature measurements taken around the pallet. The authors compared the accuracy of Kriging interpolation, an exponential decay model and predictions using a neural network. The neural network provided the most accurate temperature mapping, and an average estimation error below 0.5 K was achieved for a pallet subjected to a winter or a summer temperature profile. A similar analysis was performed Badia-Melis, McCarthy, and Uysal (2016) for pallets of synthetic strawberries and oranges stored inside a refrigerated container. The authors showed the high accuracy of the neural network approach, and achieved an average estimation error below 0.5 K when using eight temperature sensors inside the container. Badia-Melis, Qian, et al (2016) showed that a neural network can also be trained to predict accurately the distribution of temperature inside a pallet from the measurement of its surface temperature. Mercier, Marcos, et al. (2017) developed a strategy to map the temperature inside a pallet using a heat transfer model and a convection heat transfer coefficient estimated from a temperature sensor placed near the corner of the pallet. Simulations for different measurement noises and positional errors of the sensor indicated that an average estimation error below 1 K could be achieved.

Previous works on combined measurement-modelling strategies highlighted the promising application of neural networks for temperature estimation (Badia-Melis et al., 2016; Badia-Melis, McCarthy, et al., 2016; Nunes et al., 2014). The hypothesis behind a neural network is that it can learn the nonlinear relationship between the input (temperature measurements provided by a limited number of sensors) and output (temperature estimated where no measurement is taken) given enough training samples (previous temperature measurements). The limitation of neural networks is that, given the complexity of the nonlinear and strongly-coupled physical phenomena governing the temperature distribution inside pallets and shipments, the amount of measurements required to train neural networks can be very large. Furthermore, neural networks have limited generalisation abilities: as an example, when the food product or the packaging is changed, a new neural network has to be trained, meaning that a new large set of measurements for this given product or packaging needs to be collected. In contrast, a physics-based model, developed from first principles, can be generalised across multiple food products and packaging by the proper adjustment of the transport properties, which have well-defined physical meanings. A possible solution to decrease the amount of measurements required to train neural networks could be to first develop a physics-based model describing the heat, mass and momentum transfer mechanisms controlling the temperature distribution. The physics-based model promotes a detailed comprehension of the underlying physical phenomena and requires a limited amount of temperature measurements for its validation. Once a validated physics-based models has been developed, it can be used to generate the data required to train the neural network (Chen & Ramaswamy, 2002a, b; Mittal & Zhang, 2000). In such a sequential physics-based model – neural network development, these two modelling approaches are not seen as distinct methodologies, but as complementary approaches allowing one to benefit from the theoretical foundation and generalisation ability of the former, and from the flexibility and near real-time temperature estimates of the latter.

The application of neural networks for temperature mapping from a few temperature sensors requires careful selection of the number of sensors to use and where to place them. The optimal number of sensors and their location to provide accurate temperature estimates while remaining