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ScienceDirect

Procedia Food Science 7 (2016) 41 – 46

Procedia Food Science

9th International Conference on Predictive Modelling in Food

Modeling *Salmonella* Inactivation in Low Moisture Foods: Using Parameter Estimation to Improve Model Performance

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ABSTRACT:

Validating *Salmonella* inactivation processes for low moisture foods is a critically important food safety requirement, due to *Salmonella* persistence in these systems. Application of microbial inactivation models for this purpose is complicated by critical interactions between product water content and activity, temperature, and process humidity. Several models have been proposed; however, very few can handle or have been tested under dynamic conditions. One previously published model accounted for product surface temperature and process dew point, to predict *Salmonella* inactivation on almonds, but did not incorporate dynamic water activity. The goal of this study was to apply improved parameter estimation techniques to reduce correlation and relative standard errors of the parameters (RSEP), and to propose a more robust model for this application. Model fitting was performed using nonlinear regression, and the root mean squared error (RMSE), RSEP, variance-covariance matrix (VCM), and scaled sensitivity coefficients (SSC) were used to evaluate model performance in terms of parameter quality and robustness. Results indicated a reasonable performance of the model (RMSE = 1.6 log), with RSEP below 7.5%. However, VCM and SSC indicated correlation among the parameters. Therefore, multivariate optimization was applied to minimize the correlation, with the sum of the RSEP used as the objective function. Two of the elements on the VCM were reduced from around -0.5 to < 0.1, and the RSEP of the associated parameter also reduced from ~7.5% to < 3.5%. The remaining matrix elements did not change, which indicates an inherently larger correlation among those parameters (0.91). Post-fitting analysis of estimated parameters and optimization of reference values for inactivation models are useful to improve model performance and reliability. An attempt to reparametrize the correlated parameters, accounting for the effect of product water activity, is underway. This modification accounts for process conditions, product characteristics, and interactions with product surface temperature.

KEYWORDS: modeling; inactivation; *Salmonella*; parameter estimation.

Peer-review under responsibility of Department of Food Science, Faculty of Food Engineering, University of Campinas.

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doi:10.1016/j.profoo.2016.02.083

1 INTRODUCTION

Salmonella in low-moisture foods and ingredients is an emerging and difficult challenge, as reflected in nationwide outbreaks and recalls involving almonds, pistachios, peanut products, pet food, and other dry ingredients [1–4]. Unfortunately, even rigorous hygiene and sanitation practices are insufficient to ensure product safety; therefore, processing interventions are an emerging imperative to reduce the risk of *Salmonella* in low-moisture products. Validation of such processes soon will be a requirement embedded in the rules associated with the U.S. Food Safety Modernization Act (FSMA). However, very sparse data and tools are available to enable robust validation of such processes, either by challenge tests or predictive microbiology.

Modeling microbial thermal inactivation in low-moisture products, (e.g., almonds, pistachios, wheat flour, etc.) is challenging due to the characteristics of the products and processes involved. In particular, the dynamics of moisture exchange between the product and the process environment can significantly affect *Salmonella* thermal resistance [5], but is rarely well documented or understood for the various processes.

Most of the modeling efforts on thermal inactivation had been carried out under isothermal conditions. Extrapolating such results to non-isothermal conditions is feasible, but sometimes fails to account for some nonlinearities in the data [6]. Also, under isothermal treatments, other variables (e.g., water dynamics, process humidity, etc.) are commonly ignored because they "appear" to be insignificant. Industrial-scale processes, however, are highly dynamic in nature, and some of the variables that can be "ignored" at the laboratory scale under isothermal conditions became relevant and even critically important.

Modeling and estimating parameters from dynamic data offered an opportunity to develop models that are based on data more representative of commercial-like conditions. As those models became sufficiently reliable, the likelihood of real application by the industry and regulators is thereby improved.

A previously published model [5] successfully modeled thermal inactivation of *Salmonella* on almonds under dynamic temperature and moisture conditions. The model accounted for the effect of almond surface temperature, and for moisture based on the difference between the surface temperature and the dew point of the process air (quantifying the occurrence and rate of condensation or evaporation).

In this work we fit the proposed model, analyzed the fitting, and showed one possible approach to resolve inherent limitations due to the correlation of the parameters.

2 MATERIALS AND METHODS

2.1 The model:

An inactivation model (1), previously proposed by Jeong, [5] that accounts for the effects of surface temperature and process humidity was used,

$$log\left(\frac{N}{N_0}\right) = -\int_0^t \left(1/D_{ref} * 10^{\left\{[T_{ref}-T_S(t)]/Z_T\right\}+\left\{\left[(T_{d,ref}-T_d)-\left(T_{ref}-T_S(t)\right)\right]/Z_M\right\}}\right)\cdot dt \qquad (1)$$

where D_{ref} is the reference decimal reduction time, T_{ref} is the reference temperature, T_s is the surface temperature of the product at any time t, Z_T is the change in temperature needed to change D_{ref} by 90%, $T_{d,ref}$ is a reference dew point temperature, T_d is the dew point of the system, and Z_M is the change in dew point causing a change in D_{ref} by 90%.

2.2 The data:

An extended data set from Jeong [5], consisting of 233 *Salmonella* inactivation data points and temperature profiles ($\Delta t = 0.2$ s) was used. The data covered the experimental space defined by process temperature (121, 149, 177, 204 and 232°C), oven humidity (moisture by volume fraction, %Mv, of 5, 30, 50, 70, and 90%, corresponding to dew points of 32.8, 69.2, 81.2, 90.0, and 97.0ºC, respectively), and sampling times to achieve nominally 0.5, 2.0, 3.5, 5.0, or 6.0 log reductions. The data were generated using *Salmonella* Enteritidis phage type 30 inoculated on intact almonds processed in a custom-designed, computer-controlled,