

# Advanced Methods for Predictive Modeling of Growth of *C. perfringens* in Cooked Meats during Cooling

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# Predictive modeling – different perspectives

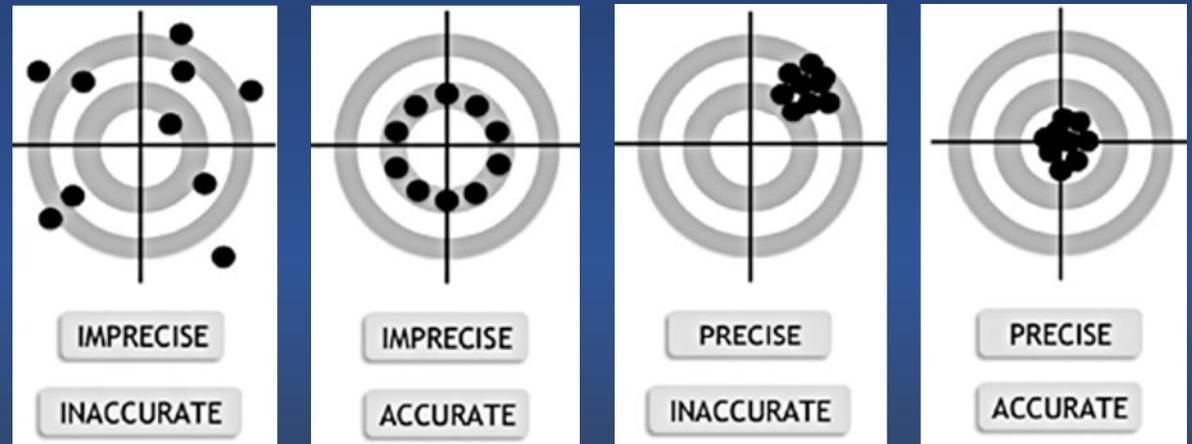
- End users (FSIS) – the persons who use models/tools
  - A **model/tool** with necessary **parameters** to make a meaningful **prediction**
  - Forward problem or forward analysis
- Developers (ARS) – the persons who develop models/tools
  - Performing kinetic analysis (data collection)
  - **Identifying** a **model/tool** and **determining** kinetic **parameters**
  - Inverse problem or inverse analysis – **digging information from laboratory data**
  - Two aspects to work together
    - Biological: growth kinetics
    - Physical: time-temperature history

# Thrusts of our research

To do things well, one needs to perfect his tools.

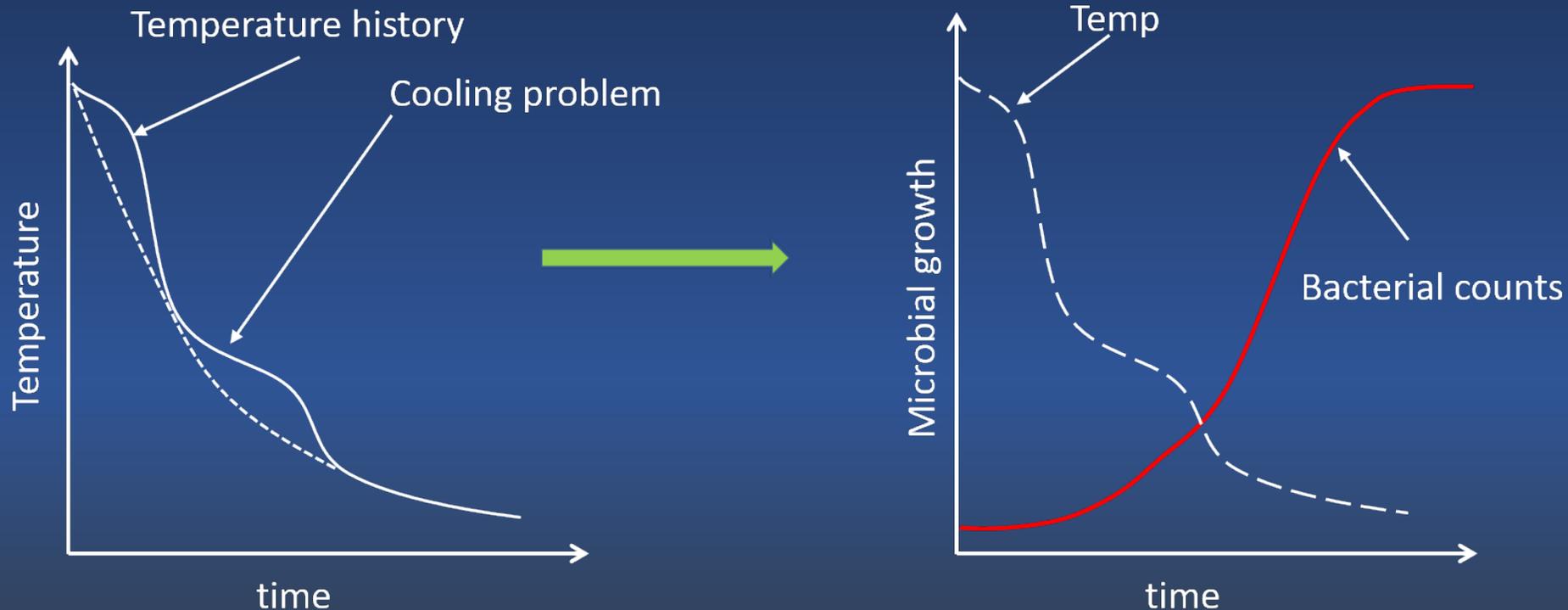
## One-Step Dynamic Analysis

- More accurate models
- Faster model development
- More efficient development
- More useful models
- All validated



# One-Step Dynamic Analysis

- Dynamic conditions to expose the bacteria to a wide range of temperature conditions (such as cooling)
- Dynamic analysis – solving differential equations numerically
- Numerical optimization



# Dynamic CP models - validation

## Point-by-point comparison

- Documented temperature profiles
- Continuous curves, either isothermal or dynamic curves, compared point-by-point
- Very accurate (internal and external validation)

## Single-point comparison

- No documented temperature profiles
- Two points (**initial** and **end points**)
  - Only relative growth is reported
  - No complete temperature history
- Not as accurate
- These data are not so scientifically convincing

Take-home message to FSIS: Time-temperature history is very critical for reliable food safety evaluation

# One-step Dynamic Analysis and Cooling

## Direct Dynamic Kinetic Analysis and Computer Simulation of Growth of *Clostridium perfringens* in Cooked Turkey during Cooling

Lihan Huang and Bryan T. Vinyard

Journal of Food Sci. 2016

**Abstract:** This research applied a new 1-step methodology to directly construct a tertiary model that describes the growth of *Clostridium perfringens* in cooked turkey meat under dynamically cooling conditions. The kinetic parameters of

Growth of *Clostridium perfringens* in roasted chicken and braised beef during cooling – One-step dynamic analysis and modeling<sup>☆</sup>

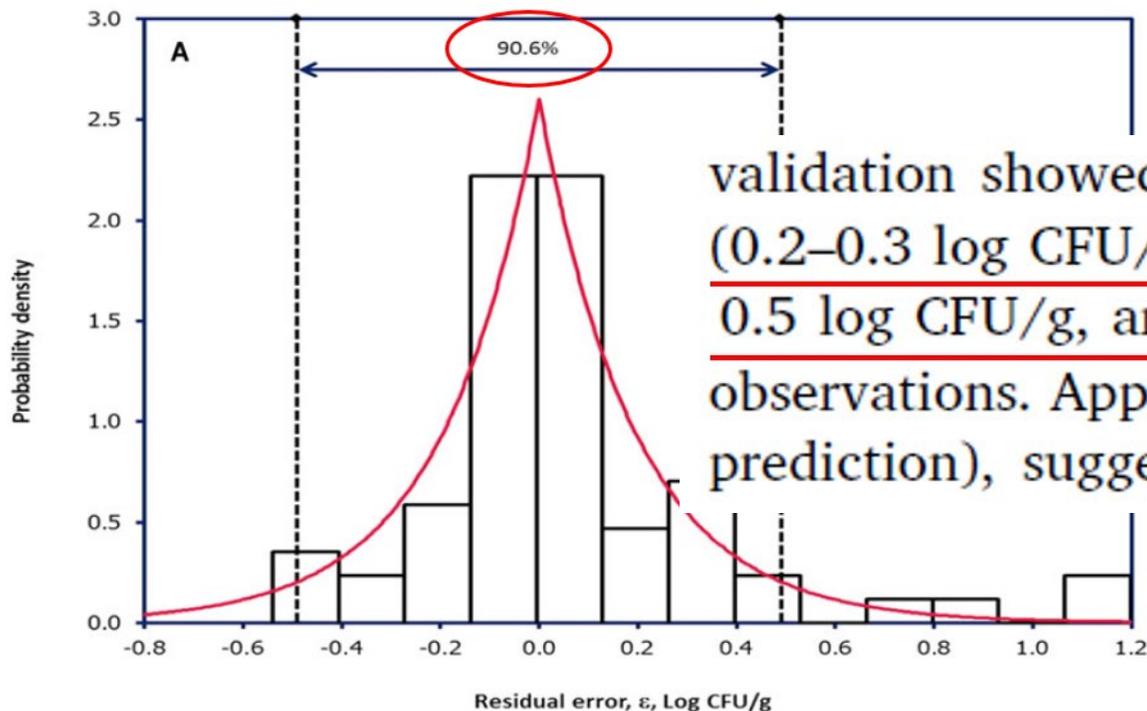
Miaoyun Li<sup>a,\*</sup>, Lihan Huang<sup>b,\*</sup>, Yaodi Zhu<sup>a</sup>, Qingying Wei<sup>a</sup>

Food Control, 2019

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Residual errors of prediction  
Laplace(0,0.27163)



validation showed that the RMSE of predictions were relatively low (0.2–0.3 log CFU/g), with 94% of the residual errors falling within  $\pm 0.5$  log CFU/g, and 76% within  $\pm 0.3$  log CFU/g of the experimental observations. Approximately 73% of the predictions are positive (over-prediction), suggesting that the predictions are mostly fail-safe. The

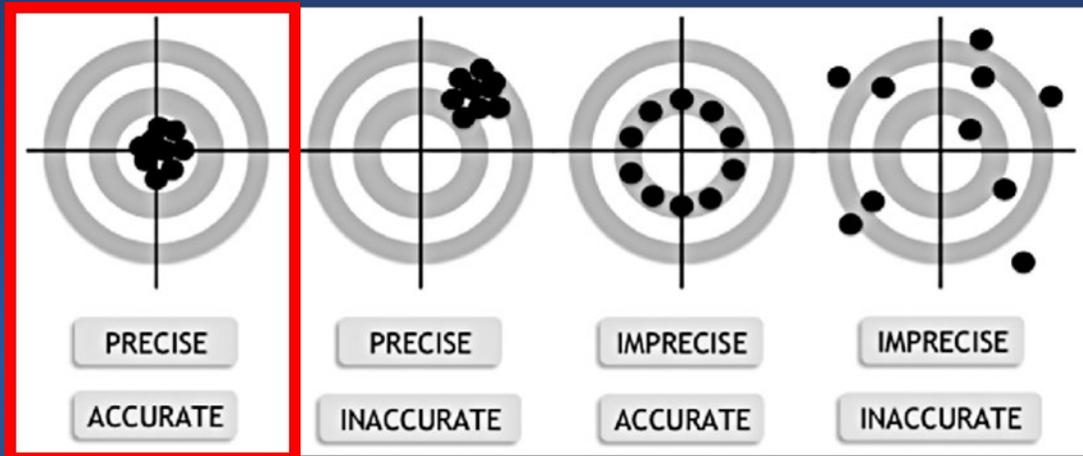
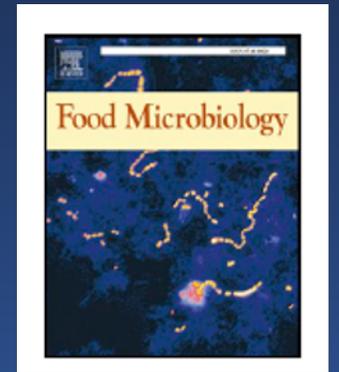
# One-Step Dynamic Analysis (2)

- We have firmly established the methodology
- We have reasonably defined residual errors
- 60-94% of residual errors of prediction is within  $\pm 0.5$  log CFU/g
- But is that all?
- Can we do better than  $\pm 0.5$  log CFU/g?
- We have to rely on other modeling methods

# Bayesian Analysis and Markov Chain Monte Carlo Simulation of Dynamic Growth of *C. perfringens* in Cooked Chicken during Cooling

Significantly improved accuracy and precision

Prediction errors are 100% within  $\pm 0.25$  log CFU/g!



Growth of *Clostridium perfringens* in cooked chicken during cooling: One-step dynamic inverse analysis, sensitivity analysis, and Markov Chain Monte Carlo simulation<sup>☆</sup>

Lihan Huang<sup>a,\*</sup>, Changcheng Li<sup>b</sup>

Benefit to FSIS: more reliable predictions and food safety management

# For $C_p$ prediction, temperature history is critical

- The best way
  - Direct measurement (sensors and data loggers)
- The alternative
  - A typical unsteady state (transient) heat transfer problem
  - Engineering analysis
    - Finite element method
    - Finite difference method



## 6 Impact of refrigeration operations on the microbial ecology of foods 142

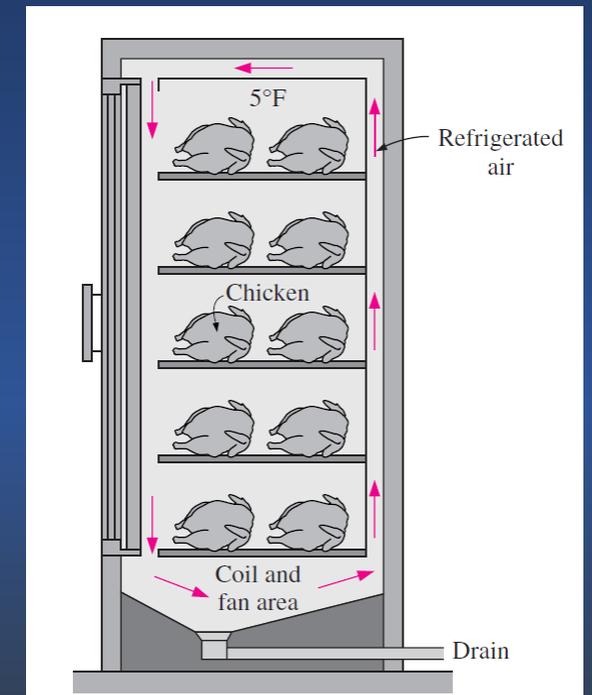
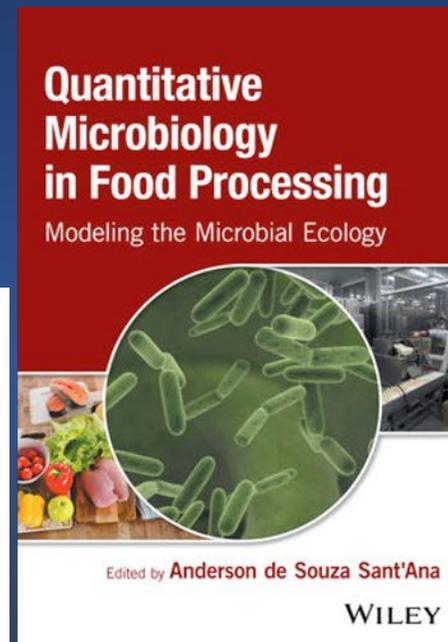
L. Huang

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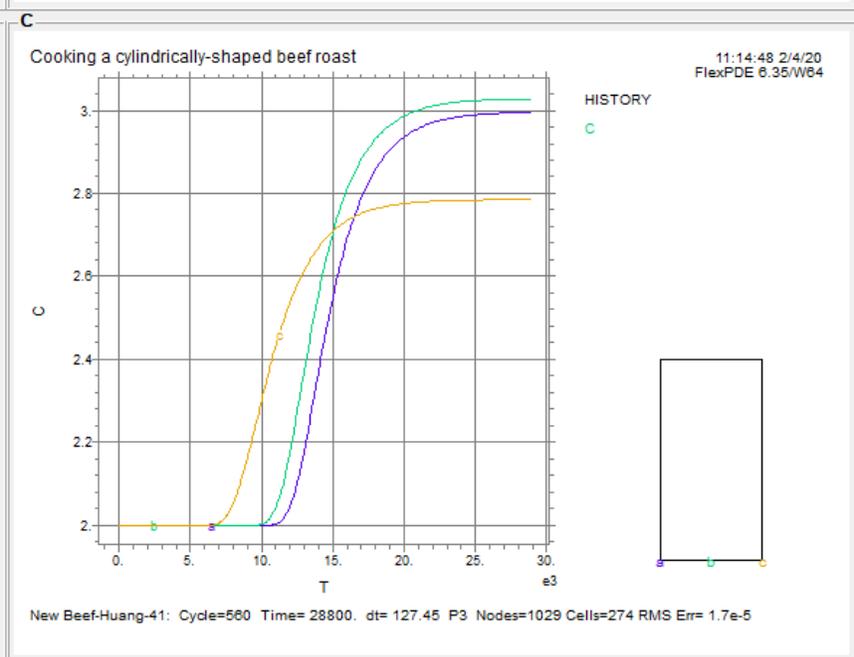
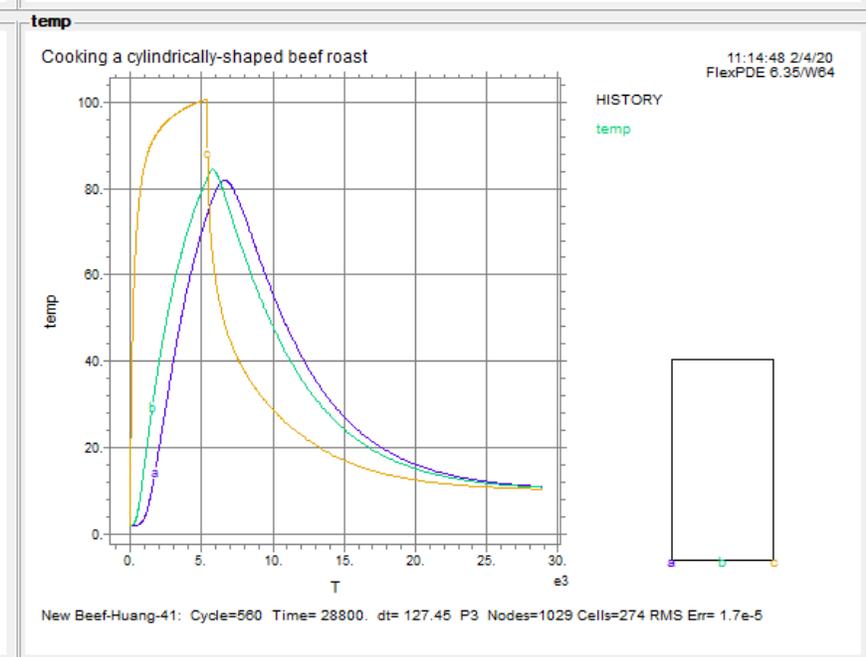
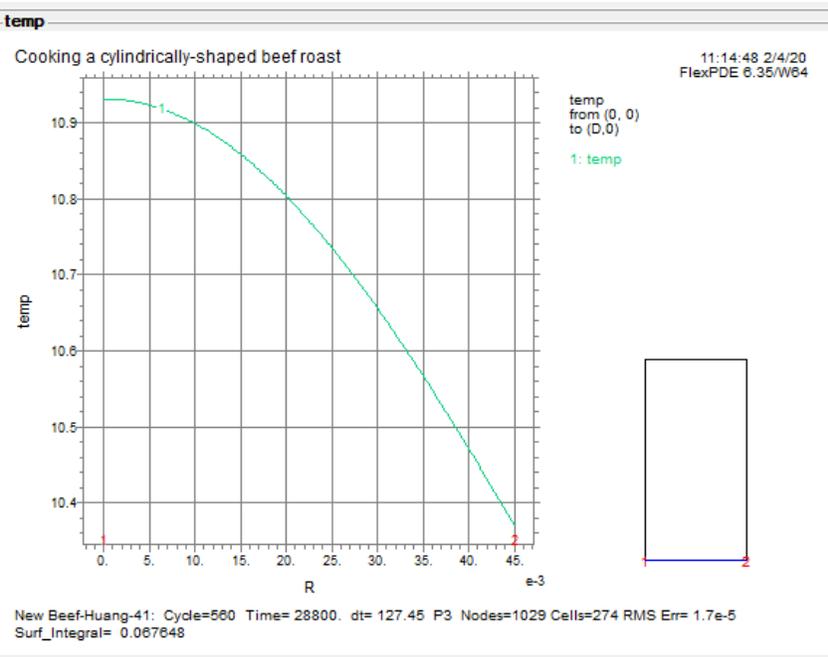
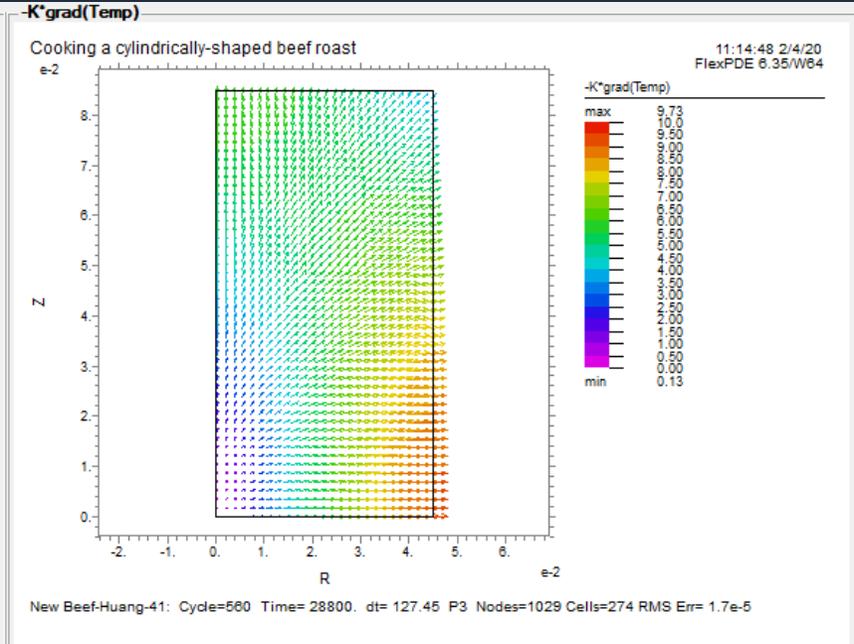
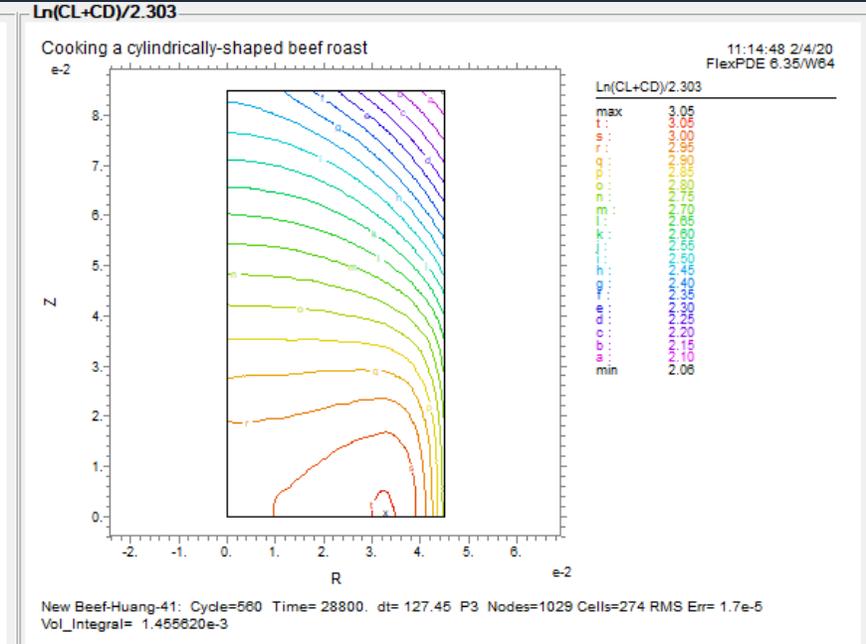
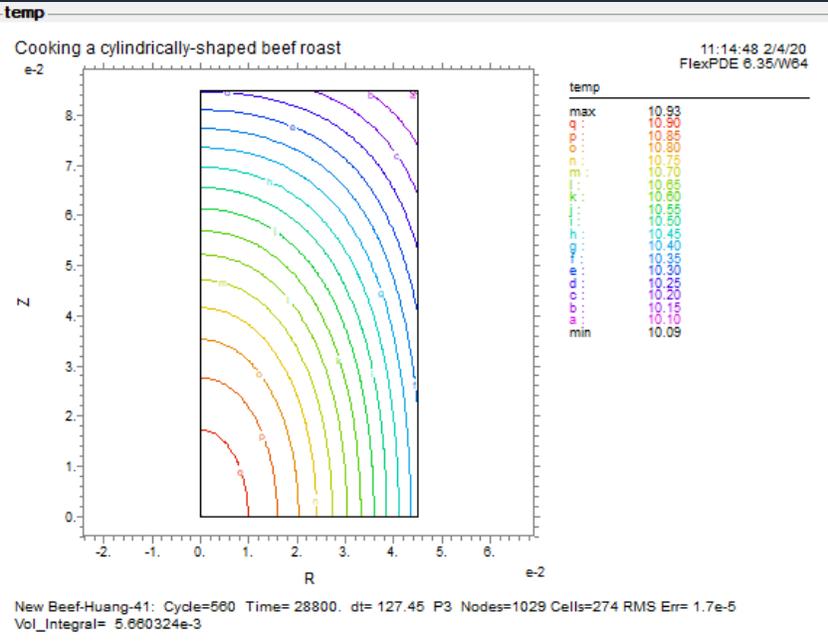
6.2 Refrigeration as a unit operation 143

6.3 Dynamic effect of chilling on growth of *C. perfringens* during cooling 147

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# Finite Element Analysis (based on physics)



# Computer simulation

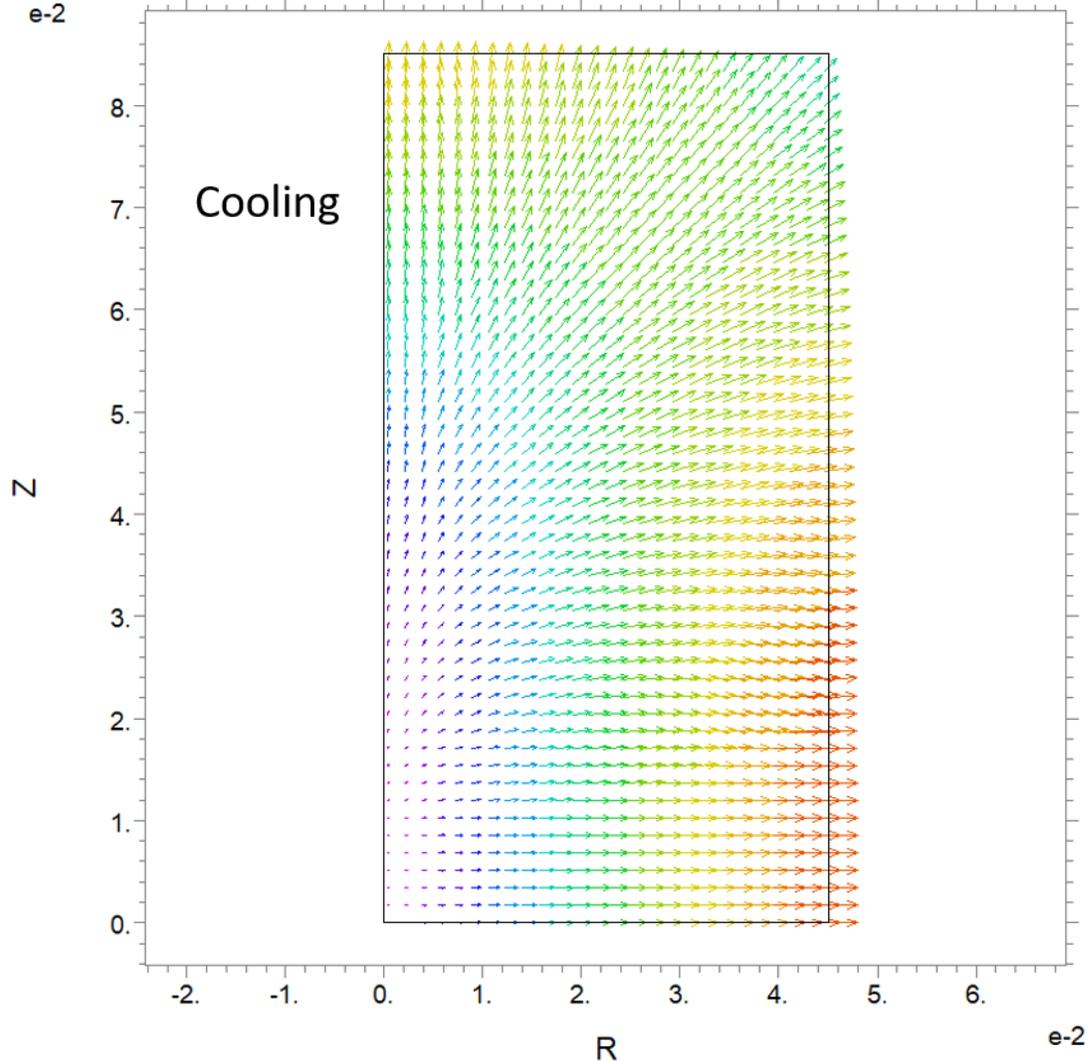
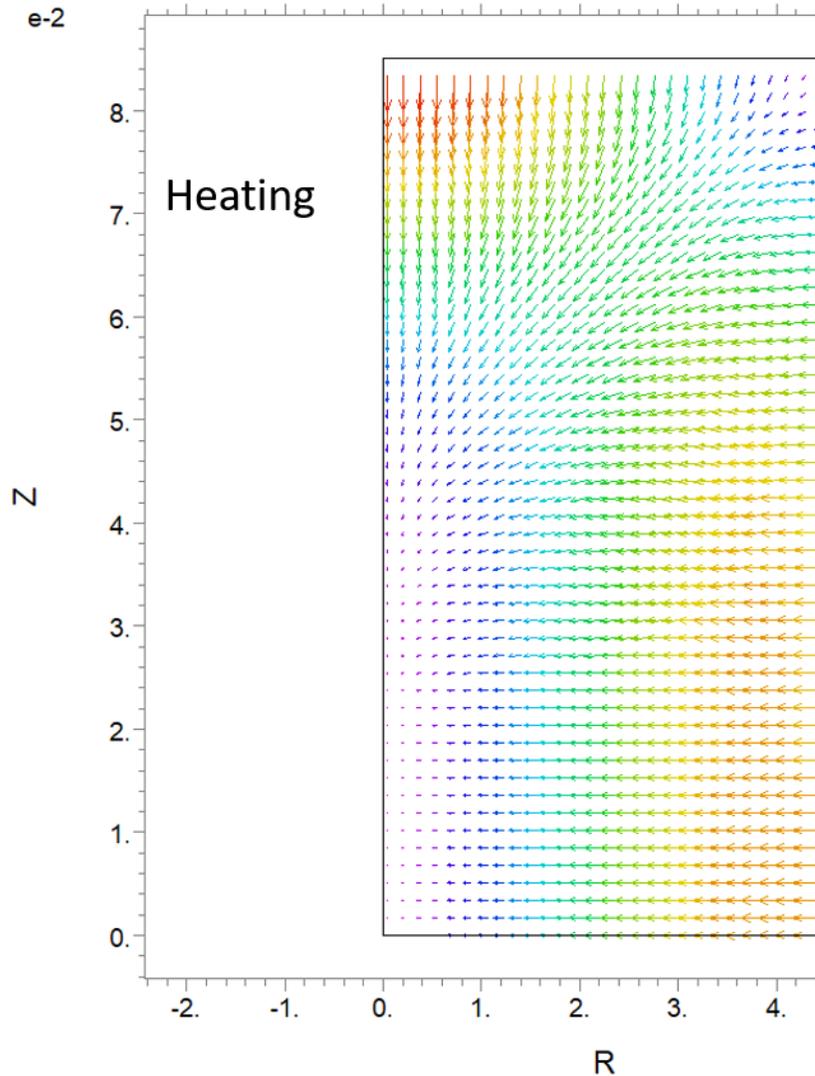
11:14:48 2/4/20  
FlexPDE 6.35/W64

-K\*grad(Temp)

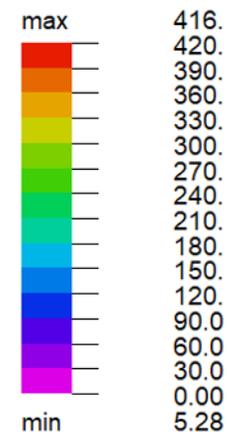
-K\*grad(Temp)

Cooking a cylindrically-shaped beef roast

Cooking a cylindrically-shaped beef roast



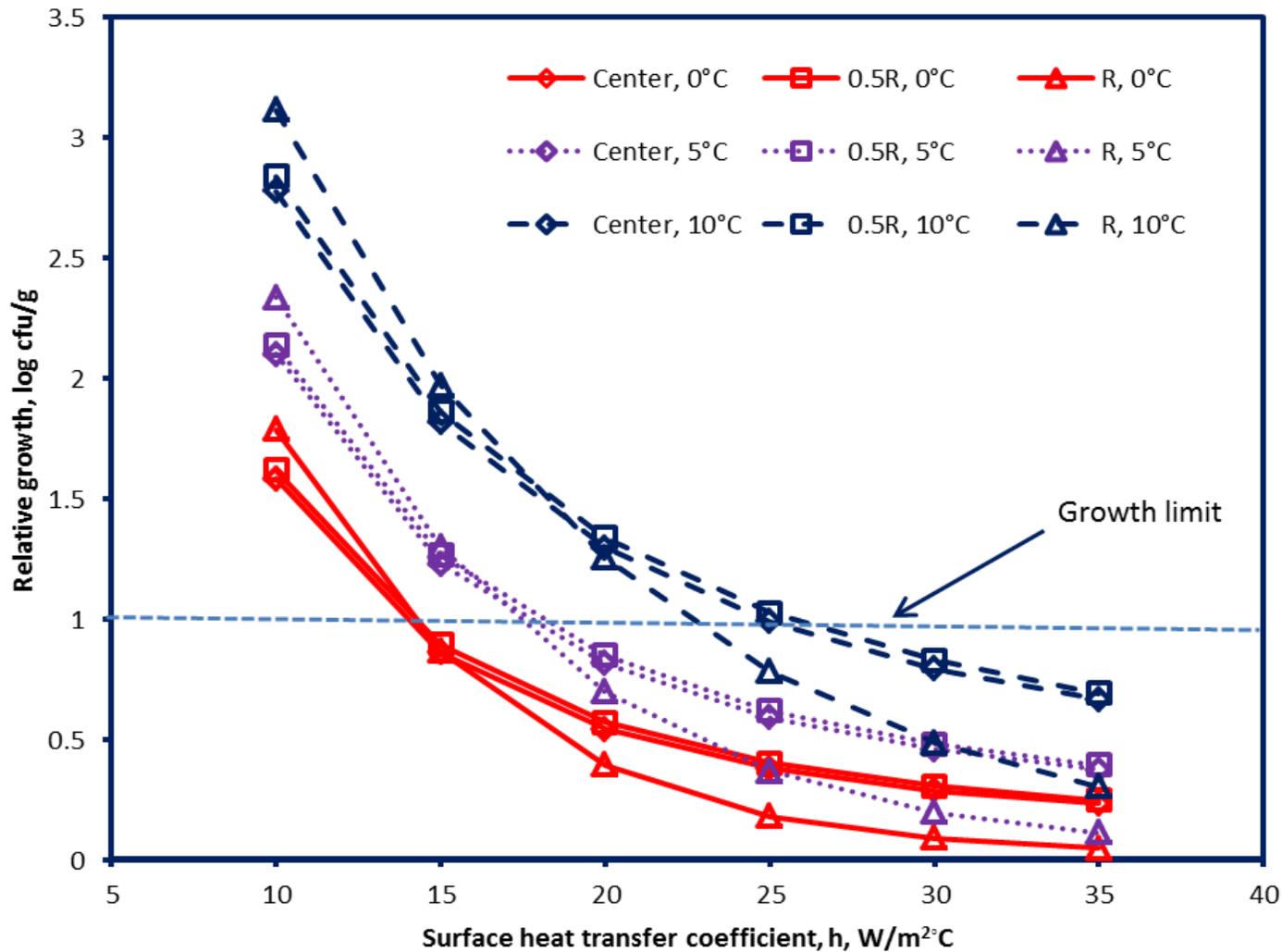
-K\*grad(Temp)



New Beef-Huang: Cycle=202 Time= 2322.0 dt= 21.482 P3

New Beef-Huang-41: Cycle=431 Time= 10656. dt= 90.227 P3 Nodes=1029 Cells=274 RMS Err= 2.6e-5

# Effect of Cooling Conditions on Relative Growth of *C. perfringens* in cooked beef



## Cooling operational conditions:

- Air temperature
- Air flow rate
- Surface heat transfer coefficient
- Cooling time

## Physical properties:

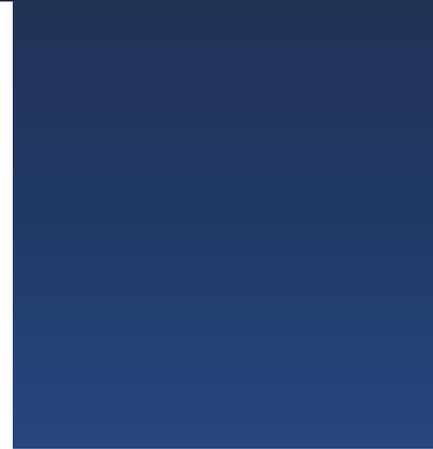
- Dimension
- Heat conductivity
- Heat diffusivity
- Heat capacity
- Density

# Direct measurement

Multi-Channel Hi-Temp Oven Logger



Embeddable miniature dataloggers, possible real-time data analysis



Thank you!