Rigorous modelling is at the core of computer aided food process engineering. As part of model building parameter estimation (PE) from experimental data is critical to achieve desired model predictive properties.

This work takes a new look into the PE problem in food process modelling: 1st is presented and 3rd tion

**CONCLUSIONS**

- This work presents a data-based protocol for model identification in food engineering intended to diagnose and to surmount the most common pitfalls.
- The protocol was validated with an example related to the thermal processing of packaged foods. Experiments were performed in our pilot plant at the IIM-CSIC.
- The application of the protocol is supported by software tools available from the authors.
- Methods and tools are general in the sense that they can be applied to any other food process model.

**REFERENCES**

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**ILLUSTRATIVE EXAMPLE**

Thermal processing of packaged food

**Mathematical model formulation**

\[ \frac{\partial T}{\partial t} = \frac{h}{\rho c} \left( T_{w} - T \right) \]

\[ \frac{\partial T}{\partial z} = \frac{h}{\rho c} \left( T_{w} - T \right) \]

**Reduced order model**

\[ \dot{\theta} = F(\theta, u, t) \]

**Structural identifiability analysis**

Use power series methods to check if parameters can be given unique values (M structurally identifiable).

**A protocol for model parametric identification**

**Practical identifiability analysis**

Sensitivity analysis, robust confidence intervals, correlation analysis and core predictions.

**Parameter estimation with global optimization**

Optimal experimental design

**Model validation**

Evaluate predictive capabilities comparing model core predictions with a new set of data.

**Optimal experimental design**

To design:

- i) Initial / boundary conditions
- ii) Observed / measured quantities
- iii) Control profile
- iv) Sensor locations / sampling times
- v) Experiment duration to maximize confidence on parameter estimates.

**Successful model**

Due to

\[ A \cdot \theta = y \]

**Common pitfalls**

Different parameter values lead to exactly the same fit. Due to lack of structural or practical identifiability.

Best parameter values result in a bad fit. Either the model is not correct or the solution is suboptimal (multimodal parameter estimation problem).

Good fit but unsuccessful validation. Related to over-fitting or to low reliability of parameter estimates. Data are scarce or non-informative.