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Challenges and opportunities in food engineering: Modeling, virtualization, open innovation and social responsibility ☆

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ABSTRACT

Food engineering should shed its historical mindset, embrace new challenges and opportunities that the 21st century holds. Unabated scientific progress and breakthroughs highlight mounting challenges with some vital paradigm shifts. Four main challenges have been identified: modeling, virtualization, open innovation (OI) and social responsibility (SR). The shift from empirical to physics-based food modeling is paramount to benefit from new sensor technology, proliferation of the 'Internet of Things', and big-data information. An overriding part of modeling continues to be food uniqueness and complexity, consumer needs and expectations, health and wellness, sustainability and SR. Virtualization is to significantly benefit from expanding computational power, dedicated software, cloud computing, big data, and other breakthroughs. Collaboration and partnerships with all innovation ecosystem stakeholders are paramount. Academia's role as a 'startup university' requires revising its intellectual property models, curricula rejuvenating, OI, creativity, employability and SR. Food engineers are at a verge of a very prosperous future.

1. Introduction

Today, food engineering faces numerous challenges while offering many opportunities for its practitioners. This article is based on a plenary session held during the conference "Virtualization of Processes in Food Engineering" at the University of Salerno, Italy (1–3 Oct 2014) and presents the author's views on four main topics: modeling, virtualization, *Enginomics*, OI, SR, as well as on the future of food engineering. These topics and the accompanying challenges and opportunities will play an important part in creating the paradigm shifts required to reshape the food engineering domain.

2. Modeling

A model is an analog of a physical reality, albeit typically more simple and idealized. Models can be physical or mathematical and are created with the goal of gaining insight into reality more conveniently (Datta and Sablani, 2007). An observation made more than three decades ago, which still applies today, stipulated that devising a formal scheme to produce a general kinetic/mathematical model is beyond our knowledge. It outlined the following general steps for structuring a model (Saguy and Karel, 1980): (i) defining the problem; (ii) applying the theory that governs the phenomenon; (iii) expressing that theory in mathematical terms; (iv) writing a suitable computation algorithm; (v) verifying the model by comparing its results with actual experimental data. It is worth noting that fitting a model with no theoretical basis is merely data fitting, and should not be confused with a physics-based approach. Modeling verification is the last step; it is an essential and cardinal part of the modeling process and should not be circumvented. Moreover, the verification step should use a different dataset than that used to construct the model itself. These observations are trivial, but nevertheless bear mentioning.

Despite a very large number of scientific publications on modeling, their applicability to food products and processes is far from straightforward (Bimbenet et al., 2007). Food modeling remains a complicated task due mainly to a lack of knowledge concerning its mechanisms, the difficulty involved in experimentation and obtaining reliable data, and the natural variability and uncertainties surrounding most food properties. For a long time, food processing was mostly dedicated to product safety, stabilization and operation scale up in the industry. Process engineers applied concepts from chemical engineering and focused on time–temperature diagrams to predict and limit residual spores or

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microorganisms in foods (Datta and Sablani, 2007; Trystram, 2012). A new modeling paradigm known as multiscale modeling might alleviate some of these difficulties. Multiscale models are essentially a hierarchy of interconnected submodels that describe a material's behavior on different spatial scales (Ho et al., 2013).

Another topic that needs additional consideration is data availability, reliability and accuracy. In many cases, food engineers lack accurate data for their systems, and consequently use previously reported data with little control of the system used, and/or fit the wrong type of model. A good example is the utilization of Fick law claiming that diffusion is Fickian, and that the diffusion coefficient is a function of concentration. With new tools, methods, monitoring devices, accurate and adequate data collection is becoming feasible. Thus, one should expect to see more benefits of modeling, and even more of multiphysics that would furnish the possibility to test different types of data and deriving the sensitive parameters.

Modeling of foods and food processing are expected to undergo a significant shift due to the widespread proliferation of computers, lower cost, availability of dedicated and sophisticated software (e.g., Comsol, http://www.comsol.com/products), and the enormous potential of big data, microprocessing, sensing devices and connectivity (Saguy et al., 2013). Emerging technologies are already available for the development of a new generation of intelligent sensors for real-time detection and monitoring of changes in a product or process. However, the major shift will occur when experimental or "observation-based" models, where the starting point is the experimental dataset from which the model was built, undergo a significant modification toward physics-based and/or mechanistic models. The latter is based on the universal physical laws that describe the presumed physical phenomena (Datta and Sablani, 2007; Trystram, 2012).

The physics-based approach (also known as deductive, mechanistic, first-principle-based, or 'white box') stems from models of transport phenomena coupled with models describing the physicochemical changes in the product as a function of operating variables (Broyart and Trystram, 2003; Purlis, 2014). The empirical modeling approach (also known as 'black box') ignores the reactions and mechanisms occurring during the process, while aiming to find a relationship between inputs (operating process conditions, product characteristics) and outputs (final quality attributes) using an experimental dataset and mathematical and statistical tools, and linear and/or nonlinear techniques, response surface methodology (RSM), artificial neural networks, etc. A combined model may also be applied (Broyart and Trystram, 2003; Purlis, 2014). While the black-box approach seeks simplified relationships to correlate an output variable with one or more input variables, it ignores and/or circumvents the process's physical and thermodynamic mechanisms, as well as chemical and biochemical reactions. The opposite approach, termed 'white box', takes into consideration the physical changes and other reactions occurring during the process.

Physics-based modeling can be extended by using multi-physics, which involves multiple physical models or multiple simultaneous physical phenomena (e.g., drying, microwaving), and the solving of coupled systems of partial differential equations. This approach holds the potential for generality as no empirical correlations are used at the interfaces. Multi-physics mathematical modeling can drive innovation in very specific applications, and several food applications are already available (e.g., mild drying, devoted to the processing of high-added-value food products, microwaving; Marra, 2012; Marra et al., 2010).

To highlight some of the issues related to empirical modeling, here are two typical examples that are quite frequently used and yet should be considered carefully, if not scrutinized or challenged. They are the Arrhenius model and RSM.

- The Arrhenius equation has been widely used as a model of temperature's effect on the rates of chemical reactions and biological processes in foods (e.g., Clemente et al., 2014; Labuza, 1984; Saguy et al., 2005; van Boekel, 2009). However, the applicability and usefulness of the Arrhenius equation to chemical reactions and biological processes in foods, especially solids, and the relevance of the statistical–mechanical assumptions on which it is based can be challenged on several grounds (Peleg et al., 2012). Furthermore, most, if not all reported rates vs. temperatures traditionally described by the Arrhenius equation can also be described by a simpler exponential model (Peleg et al., 2015, 2014), without sacrificing the fit as judged by statistical criteria. As in the Arrhenius equation, in the exponential model the rate constant is chosen at selected reference temperature. In contrast, however, both temperatures are in degrees Celsius (not Kelvin), and the exponential constant is expressed in degrees Celsius reciprocal. The use of the exponential model eliminates the need to reverse the temperature axis direction and compress its scale. It is important to note that the use of the exponential model also makes it unnecessary to assume that the degradation's energy of activation, is universally temperature-independent, an assumption rarely if ever supported by experimental evidence (Peleg et al., 2015). Worth noting however, that the Arrhenius equation (or model) can be still be used interchangeably, but one should be aware of its several limitations.
- The second example focuses on RSM. This is a statistical technique that uses regression analysis to develop a relationship between the input and output parameters by treating it as an optimization problem (Datta and Sablani, 2007). Although modeling using RSM is very effective and useful for formula optimization in new product development, and in improving processing conditions to obtain a certain objective function and/or quality, it provides no insight into the underlying mechanisms and it is merely an experimental relationship that can be very far from, and in some cases even unrelated to the physics-based model that describes the various phenomena and/or processes. Moreover, changes in formulation and/or the conditions under which the RSM was derived are not possible. It has been previously indicated that physics-based modeling can be an important tool for food product, process, and equipment designers by reducing the amount of experimentation and providing a level of insight that is often not achievable experimentally (Datta, 2008). Hence, RSM should probably be restricted to a handful of practical and limited cases.

The above two typical examples highlight the need for a paradigm shift toward enhancing the utilization of physics-based modeling and simultaneously limiting, as much as possible, the application of empirical models. However, it is quite true that empirical models may be the only feasible and practical approach to coping with food system and process complexity, nonlinearity and natural variability. Cost may be another factor (Pantelides and Renfro, 2013) in the use of empirical modeling. As this issue is of the utmost importance to almost all industrial applications, it highlights the paramount prerequisite for careful consideration.

Utilizing an empirical-based model that is tailor-made for a unique process and industrial applications can deliver some of the benefits of a physics-based approach in a more cost-effective, reliable and sustainable manner. For example, applications for optimization using much simpler models, combined with coordination of linear multivariable controllers, have been found to be less costly to implement while still delivering a significant proportion of the benefits (Pantelides and Renfro, 2013). Nevertheless, striving for the better characterization, understanding and insights gained from physics-based modeling is one of the challenges in