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Introduction

1.1. Evolutionary computation in food science and technology

Food is a major factor for health and public well-being. It is one of the most important sectors of industry and deals with chemicals, agriculture, animal feed, food processing, trade, retail and consumer sectors. Providing an adequate food supply to a growing world population is one of the greatest challenges our global society has to address. Enterprises need to continuously provide safe, tasty, healthy, affordable and sustainable food in sufficient volumes. This requires adapt on to a range of factors, such as the increase in human population and health requirements, and the reduction in crops and livestock due to environmental factors and changes in the sociopolitical scene [VAN 14]. Besides, there is a need for an integrated vision looking at these factors from multiple scales and perspectives:

– from the emotion and pleasure generated when eating food to the nanostructures of a food emulsion or food microbial ecosystems;

– from regional organization to nutritional and sociological impact;

– from health considerations to intercrop culture and microbial complexities, within the human body and in relation to food microbial ecosystems.

Under these conditions, creativity, pragmatism and robust optimization methods are crucial for reaching breakthrough innovations and sustainable solutions. There is a huge opportunity for evolutionary computation, in particular for developing efficient integrative models and decision-support tools [PER 16] to address the aforementioned challenges. Nonetheless, the specific characteristic features of food systems pose a significant challenge to evolutionary computation heuristics:

– the uncertainty and variability (in process, data and available knowledge) that severely influences the dynamics and emergence of various properties;

– the heterogeneity of data, from big volumes at the genomic scale to scarce samples at a more macroscopic level (i.e. process scales). To give an indication of size, an ecosystem of nine microorganisms can be characterized using 40,000 genes, and its dynamics with 10 aromatic compounds;

– the complexity of qualitative and quantitative information, for instance for social and environmental evaluation, at various scales in space and time;

– the variety of perspectives, types of models, research goals and data produced by conceptually disjointed scientific disciplines, ranging from physics and physiology to sociology and ethics.

1.2. A panorama of the current use of evolutionary algorithms in the domain

The potentials of evolutionary optimization methods for the resolution of complex problems in the food domain are demonstrated by a number of publications. A 2004 overview on optimization tools in food industries [TAR 05] mentioned the community interest in evolutionary approaches. Important journals such as the *International Journal of Food Engineering*, *Journal of Food Process Engineering* and *Journal of Food Engineering* regularly publish papers based on evolutionary techniques (more than a dozen papers per year in the last 10 years).

The main focus of these works is issues related to modeling using various model schemes. Evolutionary optimization is mainly used for building models (structure and parameter learning) or exploring the behavior of models, to find some mono- or multiobjective optima, for decision-making purposes (sustainability issues).

There are also other applications, for instance for classification or signal detection [BAR 06], that used genetic algorithms (GAs) to identify the smallest discriminant set of variables to be used in certification process for an Italian cheese (validation of origin labels), or genetic programming to select the most significant wave numbers produced by a Fourier transform infrared spectroscopy measurement device in order to build a rapid detector of bacterial spoilage of beef [ELL 04].

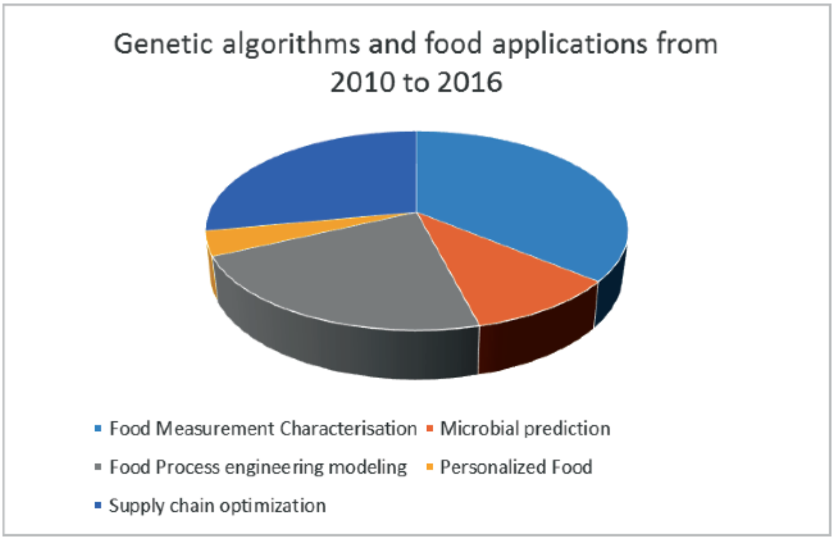

Figure 1.1. *Genetic algorithms and food applications from 2010 to 2016. Research focuses on the core collection of the Web of science, with the topics* (genetic algorithm) *and* (food) *and research domains* (computer science) *or* (engineering) *or* (food science technology)*; 403 records. For a color version of this figure, see www.iste.co.uk/lutton/algorithms.zip*

An analysis of the current publications related to evolutionary optimization in food science provides an interesting panorama. Evolutionary algorithms (EAs) are rather commonly used for single and multiobjective optimization for various purposes, including constrained optimization and modeling (structure and/or parameter learning). The multiobjective non-sorting genetic algorithm II NSGA-II tool is regularly cited. EA techniques are also often coupled with artificial neural networks, response surface models or fuzzy expert systems. Figure 1.1 highlights five main topics for the period 2010–2016:

– *Decision support for supply chain optimization*: on this topic, evolutionary computation is used as a pure optimization tool to provide optimal solutions for difficult, and often multiobjective, problems related to decision making. [NAK 16] is a typical example: the aim is to manage both the quality of perishable products and product cost (in this paper, GAs have been compared to simulated annealing). Work on the development of biodiesel and other alternatives to petroleum fuels also relies on multiobjective evolutionary optimization. See, to find the case study presented in [WOI 14], where GAs are used to find an optimal economical, environmental and social biodiesel production design from soybean oil.

– *Non-destructive measurement of food*: the focus here is on the use of EAs for learning predictive models by turning the learning task into an optimization. This topic is well represented in the literature. The models can be of any type, from white-box models that strongly rely on a precise knowledge of the underlying mechanisms (differential equations or other explicit mechanistic models) to black-box models. For example, for measuring the loss in apple moisture content during conservation, [TRI 14] use a GA to learn neural networks (NNs). Both the structure and weights of a NN are optimized by a GA with the help of a variable length genotype. Experimental results show the predictive model has high precision. There are many other applications based on similar strategies, for example [ABB 12], applied to predict the properties of wheat-flour dough. Partial least square (PLS) models are also widely used, like in [LIU 14], where it is used to extract relevant information from a near-infrared hyperspectral image; or like in [RAD 15], where it is used for predicting the sugar content of potatoes; or even in [GHA 14] for the qualitative characterization of beer.

– *Food microbial detection and prediction*: as mentioned earlier, EAs are used for learning about various models of microbial food contamination. The models considered are mostly NN and PLS, models, as in [FEN 13], where near-infrared measurements are used. There are also more sophisticated model combinations, like in [ALG 15] where a NN is coupled with a neuro fuzzy inference system to predict the population dynamics of *Pseudomonas aeruginosa* in a complex food system.

– *Food process modeling for process optimization*: in this category, EAs are not only used as discussed previously to build models (model learning), but also to run models, in order to find optimal conditions (model exploration). Here, a model can be used response surface method (RSM) as in [AGH 11], applied to optimize spray dryer operational conditions for the production of fish oil microcapsules. The aim is to simultaneously get the highest values for both encapsulation efficiency and energy efficiency. NNs are also a favorite tool in this category, as, for example, in [MOH 11a] for modeling the oil content of pretreated fried mushrooms, or in [MOH 11b] for modeling and then optimizing a process for dehydrating of carrot slices.

– *Personalized food*: EAs are also used for building decision support systems for personalized diet advice. For example in [LEE 15], a model relying on fuzzy sets and linguistic rules is learned (structure and parameters) using a GA.

Sustainability is a particularly challenging task for evolutionary computation. Multiobjective methods are quasi-mandatory for dealing with incompatible constraints. Datta *et al.* [DAT 07], for instance, propose an evolutionary multiobjective strategy with three objectives for the ecological management of soils: maximization of economic return, maximization of carbon sequestration and minimization of soil erosion. The use of evolutionary computation for eco-design is rather common in domains like architecture[1], or ecology [CHE 10]. In the agrifood domain, however, issues are so complex that the vast majority of work does not rely on optimization heuristics but on manual trial-and-error processes referring to huge international databases of process evaluations. There is a huge field of application for interactive and multiobjective EAs.

1 See http://eccogen.crai.archi.fr/wordpress/publications/.

1.3. The purpose of this book

This book is an attempt to address some questions related to optimization in the specific domain of food science. We try to show how evolutionary computation tools pave the way to new solutions because of their versatility and robustness, and by offering new ways to better integrate what can be called the “human factor”.

After a brief introduction to EAs, three examples from our own experience are presented in order to illustrate some new usages of EAs in food science, with a focus on the issues related to human expertise and to co-operative co-evolution strategies.

A first example is given in Chapter 3, where it is shown that a visualization of the behavior of an EA during optimization yields important information for modeling. This simple experiment stresses the fact that an appropriate visualization is important for understanding and revisiting model design and data-fitting steps. Within an iterative modeling process, expert users play an important role, and efficient and appropriate visualizations are important for the ease of the process.

User interactions can be more closely integrated into a computational process than a succession of autonomous computations followed by user interaction. Chapter 4 presents a modeling tool based on an interactive EA.

Finally, Chapter 5 develops two strategies for dealing with modeling issues based on cooperative–co-evolution schemes, another way of performing optimization with an EA.