Mathematical and Statistical Applications in Food Engineering

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CRC Press
Taylor & Francis Group
Boca Raton London New York

CRC Press is an imprint of the
Taylor & Francis Group, an **informa** business
A SCIENCE PUBLISHERS BOOK

Contents

CHAPTER 2

Evolutionary Optimization Techniques as Effective Tools for Process Modelling in Food Processing

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1. Introduction

Most food processing firms are making persistent efforts to maximize their returns and minimize their process costs to compete in the existing market scenario. Consequently, these industries need to opt for advanced alternative technologies for improving, monitoring, optimizing and controlling process parameters like nutrients, moisture content, temperatures, etc. (Rodríguez-Fernández et al., 2007). Processing operations in these industries are conducted in a dynamic, unpredictable environment, subject to a large number of constraints, i.e., quality of the final product, financial, environmental, safety aspects, etc. Therefore, extracting an optimal solution from a large set of options for a food processing problem is an arduous task. Hence, a useful model-based optimization tool is essential to accomplish it. An exhaustive evaluation of the cons of the existing tools has been summarized below:

1.1 Limitations of mathematical optimization techniques

Specific characteristics of the food processing operations, like those mentioned below, make it difficult for application of mathematics-based optimization tools:

- Most of the processes are conducted in a batch or semi-batch mode. Hence, the models employed need to be dynamic, non-linear models with discrete events.
- Many process variables of these studies (temperature, pH, concentration, etc.), are more often spatially distributed and coupled with transport phenomena, thus making it difficult for mathematical models using only partial differential equations.
- Complicated nonlinear constraints issued from safety and quality aspects associated with food processing operations cannot be effectively represented in mathematical optimization models.
- Also, the food processes more often involve coupled time-dependent transport phenomena, making it even more difficult.

Thus, optimization of such processes requires an alternative physics-based model capable of being used in a systemic search approach in conjunction with explicit and implicit constraints.

1.2 Empirical equation-based models

Operational barriers limit extensive use of statistical, empirical equation-based models (Garlapati and Roy, 2017; Chauhan and Garlapati, 2014; Sharma et al., 2016) for optimization in food process engineering operations. Most of the simulators consequentially developed using these tools trail the traditional path of employing low-level languages. These tools are both highly resource-consuming and error-prone, thereby making them non-applicable for plant-wide simulation.

1.3 Challenges in extensive utilization of tools and simulators in food industries

Modern-day simulators can increase productivity much more effectively in comparison to the traditional modelling approach. These high-level modeling systems are advantageous in terms of (i) better and ease of maintainability, (ii) flexibility in facilitating effective communication between co-workers and partners, (iii) ease in development, reusability, etc.

- In spite of their advantages, many of these models lack robust and efficient optimization solvers and, hence, preclude a more widespread use for optimization studies in the food industry.
- Another type of barrier arises from human-resources and knowledge issues:
  In most food processing industries, the managerial and technical human resources are often not familiar with these simulation and optimization tools. Even competent people with the relevant technological know-how are skeptical in applying these tools for food industries as these processing operations are incredibly complex.
- The food industries are need dynamic models that mimic their processes because, for a long time, there have been a lack of tailor-made modeling and optimization software tools. These may be like the tools developed by de Prada (2001) for the sugar industry.
- Most of the real-world problems of food processing operations have multiple, often competing for objectives as the raw materials involved are complex and of wide variations, making it difficult.
- Food processing operations more often encompass multiple suboptimal and equivalent solutions, thus posing a major challenge in developing an optimization model for them adequately.

Non-convex problems of these industries are solvable using conventional global optimization methodologies but, for issues of non-identifiability, the complexibility to be dealt with persists. Additionally, the desired process performances of these operations encompass variables and constraints that attribute to the economic impact on efficiency product quality and safety. A class of linear search algorithms, i.e., Evolutionary Algorithms (EAs), are seemingly vital tools for challenges that make things difficult in existing search and optimization situations. These algorithms have gained popularity in recent times because of their ease in the way of handling multiple objective problems, irrespective of the multi-objective optimization problems being constrained or unconstrained (Karaboga, 2004; Saputelli et al., 2004). Thus, evolutionary optimization tools may be successfully applied to these food processing industries.

2. Evolutionary Algorithms/Optimization Tools

These computational biological-inspired optimization algorithms, based on natural evolution and selection principles, are popularly used for solving non-differentiable, intermittent and multimodal optimization problems.

Salient aspects of EAs include

- They operate on a population of potential solutions and yield effective and improved results using evolutionary-like operations that work on the principle of survival of the fittest (selection, reproduction and mutation) (Ronen et al., 2002).

- These optimization tools can generate Pareto optimal solutions for complex processes with many objective functions and constraints and, hence, can be used for optimization processes (Garlapati et al., 2017; Garlapati and Banerjee, 2013; Garlapati et al., 2011).
- Evolutionary algorithms (EAs) are the ultimate tool to overcome limitations (Price, 1999; Boillereaux et al., 2003; Mariani et al., 2008) of a situation lacking problem-solving technique because of multiple local minima due to unidentified process parameters.

EAs differ from the traditional methods in the following aspects

- These algorithms work with coded versions of the parameter set and do not operate with the parameters themselves directly.
- Optimal search is made from a population of points and not a single point.
- Objective functions are used, not derivatives or other ancillary information.
- Probabilistic transition rules are applied instead of deterministic rules.

3. Basic Operational Characteristics of Evolutionary Algorithms

An evolutionary algorithm is a biologically inspired, generic, population-based optimization algorithm. Its mechanism includes:

- **Reproduction/procreation:** The process of producing new "offspring" from their "parents".
- **Mutation:** Alteration in the order of the process being considered (e.g., organism, production or business process, code).
- **Recombination:** A process of exchange of information between two processes yielding a new combination of processes (e.g., operations in a workflow process).
- **Selection:** A method by which traits become either more or less common in a population as a function of the influence of traits concerning the intended goal (e.g., increased production efficiency in a production process). Selection is a key evolution mechanism. Probable solutions of the optimization problem for which an evolutionary algorithm is employed to arrive at, are viewed as entities in a population. A fitness function is used to assess its suitability as a solution. **A fitness function** is an objective function that is used to summarize how close a given solution is to fulfilling the optimization goals. All the stated operators are applied several times in the process and, hence, the term "evolutionary".

The evolutionary process thus involves

- **Generation** of the initial population (i.e., first-generation) of individuals randomly.
- **Evaluation of the fitness** of each entity of the population based on the optimization criteria given.
- **Repetition of the fitness evaluation** on this generation till its termination, wherein the termination criteria can be time limit, etc.
- **Selection of the best-fit individuals**, i.e., parents for subsequent reproduction.
- **Breeding of** new individuals through crossover (for bringing in variation from one generation to the other) and mutation (for varying the programming from one generation to the next) operations to yield offspring from the best fit individuals.
- **Evaluation of** the new individuals fitness.
- **Replacement of least-fit population** with new individuals.

➤ This sequence of the evolutionary process is repeated until an individual fulfilling the fitness criteria within the given parameters is obtained.

4. Types of Evolutionary Algorithms

Evolutionary algorithms are robust global optimal solutions that help in overcoming the limitations of traditional methods. The various evolutionary optimization techniques available include: Genetic algorithm (GA), differential evolution (DE), particle swarm optimization (PSO), artificial neural networks (ANNs), fuzzy logic (FL), and ant colony optimization (ACO) (Bhattacharya et al., 2011; Adeyemo, 2011; Sarker and Ray, 2009; Kennedy and Eberhart, 1995).

4.1 Genetic Algorithm (GA)

GAs, as depicted in Fig. 1 below, are optimization algorithms that mimic natural evolution (Holland 1975, 1973; Mohebbi et al., 2008; Babu and Munawar, 2007). They have been employed to obtain near-optimum solutions for a large number of situations (Gen and Cheng, 1996). One limitation of GAs is the long processing time required for the near-optimum solution to evolve.

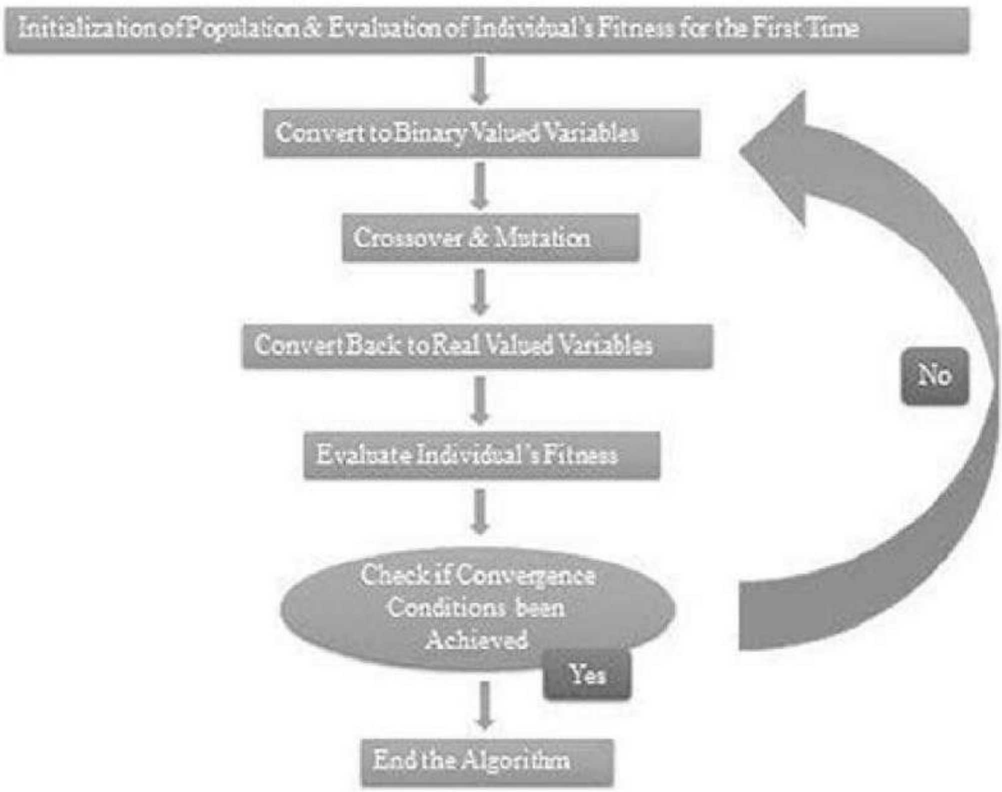

Figure 1: Flow chart of GA.

4.2 Differential Evolution (DE)

DE algorithm is a stochastic, population-based optimization method like GA; optimization functions with real variables and multiple local optima (Storn and Price, 1997; Pierreval et al., 2003) can be effectively optimized with this algorithm. A mutation is the primary search mechanism (Godfrey and Babu, 2004) for these search optimization tools. DE is self-adaptive (Karaboga, 2004). These algorithms have many advantages (Abbass et al., 2001; Strens and Moore, 2002). DE exhibits more convergence speed than genetic algorithms (Abbass et al., 2001; Strens and Moore, 2002; Karaboga, 2004). Its process flowchart has been depicted in Fig. 2 below.

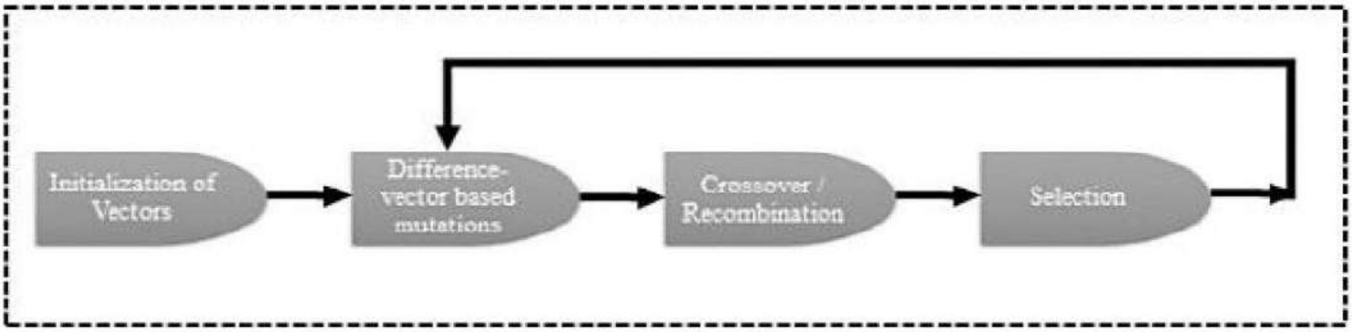

Figure 2: Sequence of events in DE.

4.3 Fuzzy Modeling (FM)

It is a robust method, encompassing scientific and heuristic modelling approaches. It mimics human control logic wherein they utilize the data and expert knowledge. Its input data may be an imprecise, descriptive language as a human operator (Huang et al., 2010). Fuzzy systems have been extensively applied to solve different problems. The present trend is towards enhancing their effectivity by employing soft-computing methods, such as fuzzy genetic systems.

4.4 Particle Swarm Optimization (PSO)

These are metaheuristic algorithms. PSO's mimic the social behavior of flocks of birds and schools of fish. Its process flowchart is depicted by Fig. 3.

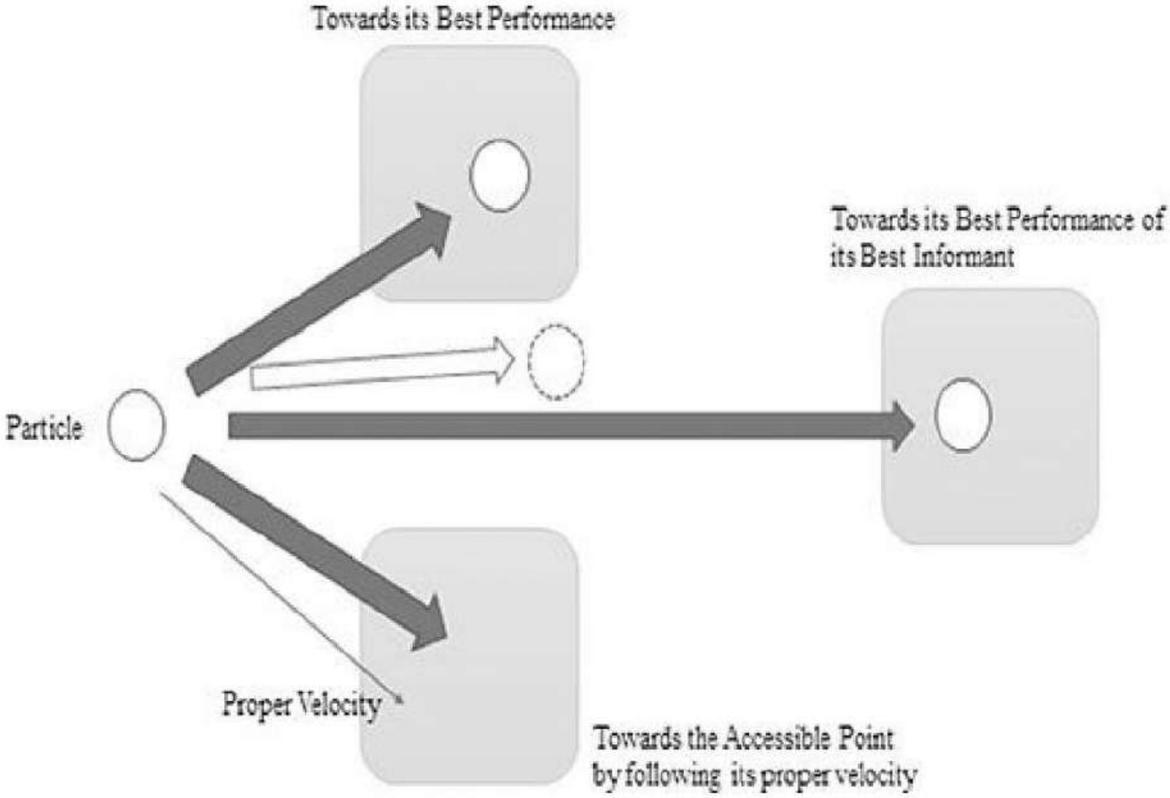

Figure 3: Process events in PSO.

5. Overview of Application of EA's in Food Processing Industries

Food processing industries involve a large number of unit operations, each **governed by a series of dynamic conditions** that include mass, heat and momentum transfer operations. Likewise, **market-driven parameters**, like cost, demand and consumer acceptability factors and **the regulatory norms** on the quality parameters of the product, all **dictate the decision of fixing the operable strategy** for a product. Thus, modeling and optimization of these processes are highly challenging with the development of models governed by laws of mass, energy, etc., and capable of predicting the physicochemical, quality properties and safety aspects of the products. Kinetic models reflect the **change in relevant state variables** with time and position when the food sample is subjected to **different processing conditions** (Tijskens et al., 2001; Wang and Sun, 2003). The **Shelf life of products** impact, shortage and surplus of goods which in turn may impact income for the manufacturing units and, hence, this aspect also needs to be considered. Therefore, it may be summarized that optimization techniques are essential tools in food processing operations, used to enhance the economic values of processing and for the marketing of food.

Table 1: Comparative summary of evolutionary algorithms/optimization techniques.

Algorithm	Pros	Cons
Genetic algorithms	• Alter information (crossover or mutation) • Effective to solve continuous process issues	• Lack retention • Early convergence • Meager local search ability • Effective and impressive computational effort • Challenging to translate a problem in the form of a chromosome
Particle swarm optimization	• Possesses memory • Convenient for execution as it employs a simple operator • Promising to resolve continuous problems	• Early convergence • Poor local search ability
Ant colony optimization	• Retains the information • Yields good solutions rapidly • Effective in solving discrete and varied types of problems	• Untimely convergence • Ineffective local search ability • Yields changes in probability distribution with iterations • Ineffective in cracking the continuous problems

Currently, there lies a pressing need to ensure admirable product quality. Consequentially, the food industries are focusing more attention on improving their processing operations (e.g., Effective methods for drying, wetting, heating, cooling and freezing of foods are necessary (Doganis et al., 2006). Thus, it is becoming imperative to implement advanced optimization tools like EAs and the related techniques thereof, in the complex operations of modern food processing industries. EAs, like Differential evolution (DE) algorithms, have been successfully applied to solve several optimization problems of chemical and biological processes (Liu and Wang, 2010; Cheng and Ramaswamy, 2002; Chiou and Wang, 2001; Lu and Wang, 2001) while other similar EA tools have been used for the fuzzy-decision making problems of fuel ethanol production (Wang and Cheng, 1999), fermentation process (Wang and Cheng, 1999) and other engineering issues (Garlapati et al., 2010; Garlapati and Banerjee, 2010a,b; Babu, 2004, 2007; Angira and Babu, 2006; Babu and Angira, 2002; Babu and Jehan, 2003; Sarimveis and Bafas, 2003). These studies concluded that these techniques are less time consuming than the existing techniques and can adequately estimate the optimal parameters. Summarized below is the current status of application of these tools in various operations.

5.1 Role of EA's in food-based fermentation

Fermentative processes are dynamic and involve a large number of process variables (e.g., media parameters and process parameters like aeration rate, temperature, duration of incubation, etc.). These processes are governed by mass transfer, heat transfer principles, kinetic models and operational constraints. Traditional optimization techniques for resolving the multiple intended objectives of these operations are mostly non-lucrative. Evolutionary algorithms (EAs) are preferred alternative methods for monitoring the state variables of these dynamic fermentative operations (Soons et al., 2008). Artificial neural networks (ANNs) and genetic algorithm (GA) that mimic different aspects of biological information processing for data modelling and media optimization have proven to be effective for optimization problems of these sectors (Baishan et al., 2003). Impressive results have been obtained from ANN-GA for simultaneous maximization of biomass and conversion of product, e.g., pentafluoroacetophenon with *Synechococcus* PCC 7942 (Franco-Lara et al., 2006), and fermentative production of xylitol from *Candida mogii* (Desai et al., 2006; Baishan et al., 2003), exopolysaccharides production by *Lactobacillus plantarum* isolated from the fermented *Eleusine coracan*. In the latter application, Plackett Burman (PB) was applied to identify the three most influential media components, ANN for modeling the nonlinear relationship between the operating variables and the intended objectives, finally the ANN model was used as an input for the optimization through GA. The optimization of hydantoinase production from *Agrobacterium radiobacter*, lipase production from a mixed culture and glucansucrase production from *Leuconostoc dextranicum* NRRL B-1146 was performed with ANN–GA model using RSM-based data by Nagata and Chu, 2003; Haider et al., 2008; Singh et al., 2008, respectively. Kovarova-Kovar et al., 2000 demonstrated optimization using hybrid algorithms in the fed-batch process for riboflavin production. GAs with their multi-objective problem-solving capabilities have been applied in synthesis and optimization of non-ideal distillation systems (Fraga and Senos, 1996), computer-aided molecular design (Shunmugam et al., 2000), optimal design of xylitol synthesis reactor (Baishan et al., 2003), estimation of parameters in trickle bed reactors (González-Sáiz et al., 2008), on-line optimization of culture temperature for yeast fermentation (Yüzgeç et al., 2009) and optimal ethanol production (Guo et al., 2010; Rivera et al., 2006).

5.2 *Evolutionary optimization for extrusion-based processes*

RSM integrated GA-based optimization was reported to be effective in predicting the optimal process conditions with the intended quality of an extruded fish product. The conditions yielded a product with more desirable features than those obtained by specific condition optimization. Process variables taken for consideration included: Screw speed, feed moisture content, expansion ratio, water solubility index, barrel temperature, bulk density, hardness, and fish contents for single-screw extrusion cooking of a fish and rice flour blend (Shankar and Bandyopadhyay, 2004).

5.3 *EA's application in the dairy industry*

Preparation of different types of milk powder, i.e., whole milk powder, spray dried milk powder, skimmed milk powder, etc., in the dairy industry involves operations with multi-process parameters affecting the final product quality. Independent parameters required may include screw speed, process temperature, milk powder feed rate to the drier, addition rate of additive, etc. (Koc et al., 2007). The depended parameters include free fat content, lactose crystallinity, particle size and colour, while the constraint was desired power consumption. The intended multi-objectives include maximization of free fat content, the crystallinity of lactose and minimization of particle size (Koe et al., 2007). Fuzzy logic was also used in the real-time control of a spray–drying of whole milk powder processing. The algorithm used controlled the process at the desired power consumption and yielded entire milk products with the desired attributes (Queiroz and Nebra, 2001).

5.4 *Application of EA's in oil processing*

Neural network-based genetic algorithm optimization tools have been employed for multi-objective estimations during oil processing. Experimental data from vegetable oil hydrogenation process plant was used to develop the model and the intended objectives included minimization of isomer and maximization of cis –oleic acid (Izadifar and Jahromi, 2007).

5.5 *EA tools for food product quality evaluation*

Quality parameters of the final food product play an important role in the consumer acceptability and approval by the food safety standard norms. Quality parameters may vary for the type of food products and the processing conditions also affect these parameters. Artificial neural networks have been applied in predicting the selected intended quality parameters with variations in process conditions during different unit operations for varied types of food products, e.g., extruded products (Linko et al., 1992), rheological dough properties in bakery operations (Ruan et al., 1997), meat quality (Yan et al., 1998), bakery products (Cho and Kim, 1998) and post-harvest processed products (Morimoto et al., 1997a,b). The impact of thawing conditions on Thermal properties of gelatin was determined using artificial neural networks (Boillereaux et al., 2003). Mittal and Zhang, 2000 developed a feed-forward neural network to predict the freezing and thawing time of food products with simple regular shapes. The results demonstrated that the developed ANN-GA-based models were useful for the estimation of parameters that were usually considered for foods of varied structural, morphological configurations and compositions.

5.6 *Utilization of evolutionary optimization tools in drying operations*

Performance of a drying process in the food industry is assessed from improvement in manufacturing quality and reduction in energy consumption. Optimization techniques, when applied to drying operations, are intended for reduction of drying time and occasionally the process cost. Nonlinear predictive control genetic algorithm and the like have been developed and reported (Yüzgeç et al., 2006, 2009; Na et al., 2002; Potocnik and Grabec, 2002; Mankar et al., 2002; Quirijns et al., 2000). The intended objective was final product quality enhancement, minimal energy consumption during drying and reduced process cost by developing a control procedure for the drying process.

In recent times, ANNs have been receiving more considerable attention in modelling the drying operations (Chen et al., 2000; Kaminski et al., 1998; Sreekanth et al., 1998), food rheology (Ruan et al., 1995) and thermal processing (Sablani et al., 1997a,b). Structural identifiability analysis of model methods for improvement in the efficacy and robustness of the model parameter has been proposed and demonstrated in many reports (Rodríguez-Fernández et al., 2007; Movagharnejad and Nikzad, 2007). ANN model was reported to be more accurate than empirical correlations in describing the drying behavior of tomato.

The optimization of multiproduct batch plants design issues for protein production using fuzzy multiobjective algorithm concepts was demonstrated by Dietz et al., 2008. The model developed provided an up-and-coming framework that could take imprecision into account during the new product development stage and finally in making the decision. Kiranoudis and Markatos, 2000 considered the multi-objective design of food dryers using a static mathematical model for simultaneous minimization of economic measure and the colour deviation of the final product.

6. Case Study of EA in Thermal Processing Operation

Thermal processing is an active food preservation strategy, for inactivation of microbial spores that are a public health concern or of microbial species responsible for spoilage of foods in containers. These operations are conducted at temperatures well above the ambient boiling point of water. For these purposes, pressurized steam retorts/autoclaves are operated at conditions not detrimental to food quality (Simpson et al., 2003; Holdsworth and Simpson, 2007; Abakarov et al., 2009). For obtaining the extended shelf life of products and their intended safety, cost-efficient treatments are widely preferred in industries. The imperatives, like health value, drive these thermal treatment operations and the economic aspects of sustainable food supply, they also minimize food-borne illness and food waste and retain or enhance nutritive quality to ensure affordability. Thermal treatments are mostly capable of catering to the imperatives mentioned above. There is an increasing concern regarding the harmful effects of these thermal treatments, i.e., compromised nutritive quality, deteriorating effects on essential nutrients and unique bioactive phytochemicals.

6.1 Basic objective

Thermal treatment optimization is a **dynamic process** where the **intended objective** is to determine the **optimal heating temperature-time combination** that effectively **maximizes the final nutrient retention** of a per packaged conduction heated food. The operable **constraint** involved is that the heating temperature should be effective **to impart microbiological lethality**.

Thus, there are two contradictory demands: To obtain the **desired minimum lethality**, all the sections of the food must be subjected to a high enough temperature for sufficient duration. However, the same exposure is likely to destroy nutrients; therefore, it is desired to **minimize that undesirable effect**.

6.2 Challenges

- Thermal destruction of microbes is conventionally proven to follow a first-order semi-logarithmic rate. Consequentially, it is not likely that, theoretically, a sterile product can't be produced with certainty even after exposure of the food product for long process time.
- If the intended product is to be rendered utterly void of microorganisms, then the thermal treatment is likely to yield a product which is unwholesome or inferior in quality. Thus, commercial sterility or shelf stability of the products is the most preferred or sought-after objective by the processing authorities of industries.
- Thermal destruction issue is dynamic and, hence, it implicates dynamic optimization techniques to determine optimal operating policies. The EA techniques are more effective than the traditional (constant temperature) processes. The optimal strategies can enhance the quality of the final product, and/or reduce the processing time to yield the desired quality level. Reduced-order models have generated cost-effective simulations (Banga et al., 2003). With these "accelerated" models, the dynamic optimization issue can be performed in just a few seconds. Since EA tools are capable of minimizing the complexity of a process model which seems promising for food process operations with a new avenue for real-time optimization and control.
- Treatments engaged in thermal destruction of microbes encompass a multi-objective optimization problem where the reduction of total process time and significant retention of several nutrients and quality factors need to be deliberated simultaneously (Fryer and Robbins, 2005). To this effect, Sendín et al., 2006, 2010 proposed and applied a novel multicriteria optimization method to the thermal processing of foods.

6.3 Background and principle

Designing an effective thermal processing strategy makes it imperative to have an extensive understanding of process methods, the heating behavior of the product and its impact on a target microorganism. Thus, the dependable factors for gauging the severity of any thermal process must be known and they include:

- **The physical characteristics of the food product**.
- **The type and thermal resistance of the target microorganisms**.
- **The changes in intrinsic properties of the food which affect the survival of microbes in thermal processes**.

6.4 Basic design premise and concerns of thermal processes

For design optimization studies, the user should be reminiscent of the following:

- The **heat resistance of microorganisms** for each specific product formulation and composition. Thermal inactivation kinetics of microorganisms is essential and may be obtained from a survivor curve, i.e., a logarithmic plot of the number of microorganisms surviving a given heat treatment at a given temperature against the heating time. Thermal inactivation generally follows a first-order reaction. Two key parameters (D and z values) are then determined by the survivor and resistance curves, respectively.
- **The heating rate of the specific product:** This is essential for mathematical modeling of experimental data, which aids in understanding the impact of process parameters, on relevant pathogens. The effective heating rate of the product is accomplished from a detailed analysis of product and system parameters affecting the heating behavior of the product.
- **The conditions for which such models apply** and
- Their **limitations** since food matrices are complex and can influence microbial resistances in different ways.

Design concerns include

- Simple, Robust, flexible models operable for process deviation analysis and ensuring appropriate levels of public safety are becoming popular. A single "fit-all-data" model is not effective for explaining or describing the complex behavior of microbes when subjected to external agents (such as temperature, salt, pH, etc.), and their interactions.
- Varied time-temperature combinations, processing methods, systems or techniques may yield the desired lethality. However, these variations are also likely to impact the quality of the end product to different extents. Therefore, minimal changes to the desired sensory and organoleptic attributes of food products are always intended through process optimization routines and thereby determine system appropriateness using kinetic data for the most heat-sensitive nutrient.
- The time-temperature history of a product undergoing thermal treatment will depend on several factors that include but are not limited to: (i) the processing system (conventional, static or agitating retorts, etc.), (ii) the heating medium (steam, water immersion, etc.), (iii) product characteristics including consistency, solid/liquid ratio, and thermophysical properties, (iv) product initial and heating medium temperatures, and (v) container type, shape and size.

6.5 Guidelines for applying evolutionary algorithms for thermal process optimization studies

Step 1: Identification of process parameters affecting the process under consideration.

Step 2: Collection of data from experiments conducted based on chosen Design of experiments (DOE). Selection of DOE is from amongst Plackett Burman, Factorial designs, Central composite design, etc., to have representations from the significant combinations of the process parameters (Kumari et al., 2013; Chauhan et al., 2013; Mahapatra et al., 2009).

Step 3: Developing the thermal process schedule, i.e., model development using the experimental data from the heat penetration and kinetic data (z and Freq values) by the conventional methods. Formula methods have been currently developed and employed to impart flexibility to establish times to achieve the desired cumulative lethality. Incidentally, these formula methods have limited implementation in optimization studies and automatic control systems as they are incapable of defining dynamic functions during the entire processing. Artificial neural networks (ANN) are effective to computerize mathematical aspects of thermal process calculations. These models mitigate the need for a large storage space while computerizing.

Step 4: Application of optimization tool to the developed model.

The main factors/selected objective functions taken into consideration during the optimization of thermal processing include **final product quality and safety, consumption of energy** and **total processing time**. The diversity of the sighted processing objectives imposes different optimal conditions to sterilization/thermal processing. Hence, an algorithm capable of considering various objective functions is preferred for the determination of the optimal thermal processing of food. These software packages are intended to ascertain the optimum variable temperature profiles concerning the intended objective functions, geometric options and constraints chosen by the processor/user. The packages should facilitate/automate **the calculation of heat transfer coefficient** for irregular or regular geometries, various shapes and heating conditions, **predict moisture loss, shrinkage, yield loss, internal temperatures** and **lethality for different sizes of product**. These capabilities would make them a useful tool in taking processing decisions. These algorithm packages should be proficient at simulating food safety by combining a physics-based model of food processes, with the microbial kinetics and chemical transformations to provide a microbial count and/or nutrient and/or undesired chemicals amounts at any time and in any location in the food during processing.

Step 5: Mathematical formulation of the Problem statement for thermal sterilization of foods.

In canning operations, the problems mentioned below may be addressed using modeling and optimization techniques:

- Estimation of a retort function, where the final quality retention or surface quality retention is maximized, while the final process lethality is held to a specified minimum.
- Determination of a retort function, such that the final process time is minimized subject to the same lethality requirement, while the quality retention does not fall beneath some specified minimum.
- Fixation of a retort function, where the cooked value is minimized, while the final process lethality is held to a specified minimum.
- Fixation of a retort function, such that the final process time is minimized subject to the same lethality requirement, while the quality retention is not below some specified minimum, and the energy consumption is not above a specified maximum; minimum and maximum values are computed at constant retort temperature profiles.
- The thermal process optimization problem is, thus, posed as a multi-objective optimization problem.

In each of these cases:

- **The lethality constraint** is specified as: (i)

F0(t)=∫0tf10T−Teffzfdt

where $F_{0(t)}$ is the final required lethality which is calculated using: ∫0tf10T−Teffzfdt

where T is the temperature at the critical point or cold spot, normally the geometric center of the container (in the case of conduction-heated canned foods), Teff is the reference temperature and Zf the thermal resistance of the microorganisms.

- **The quality retention constraint** is specified as:

Cav(tf)=1Vt∫0Vtexp[−ln10Drefc∫0tf10T−TreffZcdt]dVt

where Cv is the desired volume-average final quality retention value and is calculated using the equation given above, where Treff is the reference temperature, z c and D are kinetics of the degradation of nutrients.

- **The surface retention is given by**

S(tf)=exp[−ln10Dfefs∫0tf10T−TrefsZsdt]

where Trefs is the reference temperature, z and D are kinetics of the degradation of nutrients, and the surface retention constraint can be specified as S(t), which is the desired final surface retention value.

- Also, a common relationship for estimating quality losses is the "Cook or Cvalue", which is calculated using ……… C(tf)=∫0tfT−TrefvZqdt

where z and Trefv represent the z-value and reference temperature for the most heat-labile component. The z-value for cooking degradation within the given range corresponds to sensory attributes, texture softening, and color changes. The z-value of 33.1ºC and Tref equal to 100ºC are often used to compute a cook value to describe the overall quality loss. The cook value constraint is specified as Cd, where Cd is the desired minimum final cook value.

These expressions are standard model equations and, for consideration of new process parameters, model equations may be obtained using regression analysis or artificial neural network algorithms. The obtained models are then subjected to numerous iterations within the set range of the individual parameters and subject to the constraint of the individual problem statements to attain the set levels of the objective functions. The iterations are performed using evolutionary optimization techniques until the deviations between the set and predicted values are minimal enough to achieve the optimal conditions, which are further validated by performing the processes at those conditions.

7. Advantages of EA's

Evolutionary computation techniques only require an evaluation of the objective function and not an exhaustive mathematical requirement on the optimization problem. There are zero order methods capable of handling nonlinear problems and dependent on discrete, mixed or continuous spaces, irrespective of whether they are unconstrained or constrained using operators that are global in scope.

- Evolutionary algorithms are a potential source of breakthroughs for most of the food industrial engineering processes that include challenging, unstructured, real-life problems to be modeled as they include unfamiliar factors ranging from risk factors to aesthetics. They have the potential to provide many near-optimal solutions at the end of an optimization run which facilitates selection of the best solution later, based on criteria that were either incoherent from the expert or poorly modeled. The efficiency of EA's can be enhanced because of their flexibility and comparative ease of being hybridized with domain-dependent heuristics.
- These optimizers are global optimization methods that can be scaled up to higher-dimensional problems. EAs are robust concerning noisy evaluation functions, and can effectively handle evaluation functions which do not yield a sensible result in a given period.
- The algorithms are incredibly flexible and, hence, can be moderated, changed and customized to fit the problem at hand. They are applicable in many complex problem-solving applications, unlike classical search and optimization techniques.
- EAs are inspired by natural evolution and, hence, conceptually flexible and straightforward.
- EAs use prior information and, thus, outperform the methods which utilize the prior information minimally and with restricted search space.
- EA is representation independent, i.e., applies to constrained or unconstrained sets and to sets whether discrete or continuous, unlike most of the numeric techniques.
- Evaluation in Evolutionary optimization processes is performed as a parallel operation and only operations

of the selection process are serially processed.
- Evolutionary algorithms that develop adaptability to yield a solution in changing environment are robust, unlike the traditional optimization tools which vary according to variations in the surrounding environment.
- EAs are capable of solving problems without any human intervention, hence, handy tools. However, these tools do not perform satisfactorily for automating problem-solving routines.

8. Disadvantages of EA's

- Evolutionary algorithms do not always assure an optimal solution to a definite problem within the anticipated time. There lies a great need for tuning of parameters by trial-and-error, thereby necessitating lots of computational resources.
- The performance of evolutionary search methods in the optimization of food engineering problems is highly impacted as the majority of these are constrained problems.
- The confirmatory conclusion of the best suited evolutionary algorithm for a given problem remains unanswered. The standard values provide good performance, but, interestingly, a variation in configurations tends to yield better results. The adverse configuration may lead to premature convergence, generating local optima and not the global optima.

9. Conclusion

This chapter provides an overview of the use of computational-based optimization algorithms in major real-world applications, intending to find global optimum solutions for food processing industry issues. Multi-objective optimization problems of modern food processing operations, whether constrained or unconstrained, have been resolved using new hybrid optimizers. Process treatments affect product quality, safety and marketing. Hence, the use of new techniques for the optimization of food treatment processes becomes vital. Consequentially, basic research on the modeling, simulation, designing and evaluation of parameters affecting different food processes is vital. It is suggestive that EA's are likely to have a positive impact on solving real-world issues/challenges in the food processing industries shortly. Also, it is noteworthy that, though these EA's are extensively applicable in many areas, these too come with marginal success in performance. Hence, the current efforts are focused on the application of some parallel algorithms along with Evolutionary Algorithms, that is, to hybridize two or more algorithms or to improve the existing algorithms.

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