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Review Article

A Review of Stochastic Optimization Algorithms Applied in Food Engineering

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Mathematical models that represent food processing operations are characterized by the nonlinearity of their dynamic behavior with possible discrete events, the existence of several variables of interest that are usually distributed in space, and the presence of nonlinear constraints. These features require robust optimization methods to resolve these models and to identify the optimum operating conditions of the processes. Stochastic optimization methods, often referred as metaheuristics, are effective and reliable tools to perform the global and multiobjective optimization of process units and operations involved in food engineering. In this way, this paper surveys recent advances and contributions that have applied stochastic methods for solving global and multiobjective optimization problems in food engineering. The description of the most used stochastic algorithms in food engineering is provided including the application of those methods classified as random search techniques, evolutionary methods, and swarm intelligence methods. It was observed that evolutionary methods are the most applied in solving food engineering optimization problems where the genetic algorithm and differential evolution stand out. Finally, remarks on the limitations and current challenges to improving the numerical performance of stochastic optimization methods for food engineering applications are also discussed.

1. Introduction

In process modeling, the simulation, design, control, equipment sizing, and maintenance of any engineering system usually imply the resolution of multivariable and nonlinear mathematical problems. The engineers must address these problems to make technological and managerial decisions either to minimize the inputs required and/or to maximize the desired benefits and target characteristics for the process at hand [1]. From a specific set of alternatives, the decision choice that provides the best solution under a specific operating scenario is defined as optimization. Several optimization methods can be easily applied and adapted to handle the mathematical problems related to the food processing operations, provided that the changes during a process can be predicted mathematically [2].

In an optimization procedure, the goal is to maximize or minimize a predefined criterion, such as product quality, profits, energy, or any process attribute/metric. This criterion is expressed as a mathematical function of certain decision variables, known as the objective function [1, 3]. The decision variables, that can be continuous and/or discontinuous, are those controlled and used by the optimization method to specify the alternatives for the system under analysis [2]. The viable solutions to the optimization problem can be restricted to satisfy a set of requirements, called constraints (e.g., safety requirements, environmental criteria, and performance limitations). Therefore, the optimization procedure consists of identify a specific set of values of the decision variables representing the system's degrees of freedom that either maximizes or minimizes a predefined objective function while adhering to all established constrains [3].

Formally, an optimization problem with a single target criterion, whether global or local, can be expressed as follows:

Find $X = \{x_1, x_2, \ldots, x_n\}$ that optimizes (i.e., minimizes or maximizes) $f(X)$ subject to the constraints

$$\begin{aligned} &X_L < X < X_U, \\ &g_j(X) \le 0; \quad j = 1, 2, \ldots, m, \\ &l_j(X) = 0; \quad j = 1, 2, \ldots, p, \end{aligned} \tag{1}$$

where X is an n-dimensional vector named design vector, X_L and X_U are its lower and upper bounds, $f(X)$ represents the objective function, $g_j(X)$ and $I_j(X)$ are the inequality and equality constraints, respectively, and m and p are the corresponding numbers of these constraints [1].

Certain engineering processes may require more than one criterion to be optimized simultaneously. In this case, the optimization problem has multiple objective functions f_j that are usually in conflict [1]. This multiobjective optimization can be stated as follows.

Find $X = \{x_1, x_2, \ldots, x_n\}$ that optimizes simultaneously (i.e., minimizes and/or maximizes) $f_1(X), f_2(X), \ldots, f_k(X)$ subject to the constraints

$$\begin{aligned} &X_L < X < X_U, \\ &g_j(X) \le 0; \quad j = 1, 2, \ldots, m, \\ &l_j(X) = 0; \quad j = 1, 2, \ldots, p. \end{aligned} \tag{2}$$

A wide number of design and decision-making problems of food engineering can be formulated as single or multiobjective optimization problems. They include a wide spectrum of objective functions, decision variables, and constraints.

Concerning the solution of the objective function, an optimization problem can have just a single optimum (i.e., a minimum or maximum depending on if a minimization or maximization is conducted, respectively) or multiple optima. In this last case, one of the solutions is the global optimum and the others are local optima. The global optimum is the best solution to the optimization problem whereas the local optimum would have a better objective function value than those of the points in its neighborhood but worse than the global optimum [4]. Therefore, global optimization deals with the aim to find the best global solution to problems with nonconvex objective functions (i.e., that have multiple optima), which is known as the multimodal optimization problem [3]. The methods proposed for the resolution of global optimization problems can be divided into two main groups: deterministic and stochastic techniques [4].

Deterministic global optimizers guarantee finding the global optimum solution within a specified tolerance based on the mathematical properties of the defined objective function. Although they can search for the solution in a systematic predefined way, they require some assumption for their success like the objective function continuity [3–5].

Stochastic global optimization (SGO) techniques, also called probabilistic, use randomness during the iterative generation of new vectors of decision variables in the search for the global optimum in contrast with deterministic optimization approaches [3, 4]. This means that SGO techniques theoretically need infinite iterations to guarantee the convergence to the global optimum, but they can often converge to an acceptable solution within a reasonable computer time [4]. The greatest advantage of stochastic optimization approaches is that they do not require any prior knowledge or assumption regarding the mathematical structure of objective function proposed. Consequently, they can effectively solve problems with different complexities [3, 4]. SGO techniques have also other attractive features. They are simple to understand and implement in computer programs, they can be adapted for multiobjective optimization problems, they can handle both continuous and discontinuous decision variables, and they are robust for highly nonlinear problems even with a large number of variables [4].

Due to the inherent complexity of food processing, characterized by nonlinear dynamics, discrete events, multiple interacting variables, and a mix of continuous and discontinuous constraints, robust, and efficient optimization techniques are essential for food engineering. Although deterministic global methods may encounter challenges, stochastic approaches show promise by accelerating the optimization process and accommodating the inherent variability in food engineering problems. By addressing these challenges, it will be progressively possible to simplify optimization problems, leading to reduced operational workload and improved industry processes.

This review provides a survey of stochastic methods widely applied in food engineering problems. A brief description of different stochastic optimizers is presented, highlighting their capabilities and limitations in addressing challenging food engineering optimization problems. Different applications of these methods are described, and the performance of the algorithms is also discussed and analyzed.

2. Stochastic Global Optimization (SGO) Methods in Food Engineering

The vast number of stochastic optimization algorithms makes a universally accepted classification system elusive [6]. This review adopts Rangaiah's [4] proposed division, which categorizes SGO methods into the following four groups: random search techniques, evolutionary methods, swarm intelligence methods, and others. Table 1 summarizes the SGO algorithms applied in food engineering based on this classification.

Random search techniques include the following algorithms: pure random search, adaptive random search, two-phase methods, simulate annealing, and tabu search [4]. The random search method, also called adaptive random search (ARS), is one of the earliest stochastic optimization techniques, finding popularity in chemical and process engineering during the 1960s and 1970s [124]. Simulated annealing (SA) is also a mature technique but is more recent than AR since its application was introduced in 1983 [4, 124]. The advantages of both ARS and SA rely on that

Table 1: Summary of applications of stochastic optimization methods in food engineering.

Group	SGO method	Application
Random search technique	Multicanonical jump walk annealing	Batch fermentation [7]
	Novel simulated annealing	Batch fermentation [8]
	Hybrid artificial neural network simulated annealing	Fed-batch bio-reactor [9]
	Hybrid constraint programming and tabu search and simulated annealing (CP-TS/SA) (the authors also compared some hybrid techniques (CP/TS, CP/SA, and TS/SA); for most instances, the CP-TS/SA hybrid yielded the best solution quality in the shortest CPU time)	Sugarcane rail operations [10]
	Adaptive random search	Thermal sterilization [11]
	Modified adaptive random search (the authors also compared with the random search algorithm, but their modification improved the optimal solution in terms of both process time and the number of objective functions)	Thermal processing [12]
	Modified complex method	Thermal processing [13]
	Modified algorithm of complex method for multicriteria optimization problems with the weighting method and lexicographic ordering	Thermal processing [14]
	Modified complex method	Thermal processing [15]
	Heuristic approach based on the tabu search	Vehicle routing problem [16]
	Two-phase method based on GRASP (greedy randomized adaptive search procedure) and path-relinking metaheuristic strategies (GRASP-PR) (the authors also compared tabu search, scatter search, and VNS methods; GRASP-PR outperformed them by finding the best-known solution in more instances with a lower mean deviation)	Vehicle routing problem [17]
	Simulated annealing	Percolation process [18]
	Adaptive random search	Thermal processing [19]
	Tabu search based procedure (the authors also compared local search, linearization, and linearization + local search methods, but tabu search yielded the best solutions)	Structure of cold chains for distribution [20]
	Integrated controlled random search for dynamic systems	Air drying [21]
Evolutionary methods	Differential evolution (DE), opposition based on differential evolution (ODE), adaptive differential evolution (ADE), adaptive opposition based on differential evolution (AODE) (the authors also compared genetic algorithms (GA) but found that all the DE algorithms outperformed the classical GA)	Fed-batch fermentation [22]
	Modified genetic algorithm (MGA) (the authors also used ACO and random search for comparison, but MGA showed a better performance)	Production scheduling [23]
	Hybrid differential evolution (HDE) (the authors also compared a direct search method (BCPOL subroutine in IMSL Math/Library), the original DE, and a Fortran GA); and hybrid differential evolution (HDE) with a multiplier updating method including adaptive penalty parameters (the authors also compared the HDE with the penalty function method (PFM), the HDE with a multiplier updating method including fixed penalty parameters, the DE with the PFM, the BCPOL with the PFM, and the simple GA with a PFM)	Batch and fed-batch fermentation [24]
	A multiobjective evolutionary algorithms (MOEAs) based on Pareto sets of solutions	Batch fermentation [25]
	Hybrid differential evolution (HDE) and HDE with an adaptive multiplier updating method, including an adaptive penalty parameter strategy	Fed-batch fermentation [26]
	Genetic algorithm	Batch fermentation [27]
	Genetic algorithm	Batch fermentation [28]
	Multiobjective differential evolution	Fed-batch bioreactor [29]
	Hybrid improved genetic algorithm (HIGA) (the authors also compared the simple GA and the HIGA without a local search)	Fed-batch bioreactor [30]
	Differential evolution	Fed-batch bioreactor [31]
	Evolutionary program, based on a real-code genetic algorithm (the authors also used the first-order gradient algorithm for dynamic optimization for comparison)	Fed-batch bioreactor [32]
	Differential evolution	Fed-batch fermentation [33]
	Differential evolution (DE) (authors also tested the real-valued evolutionary algorithm and fully informed particle swarm, yet DE/rand variants consistently outperformed, even when other algorithms showed insignificant differences)	Fed-batch bioreactor [34]
	Two variants of genetic algorithm (GA-I and GA-II)	Fed-batch fermentation [35]
	Multiobjective differential evolution (MODE III)	Solid-state fermentation [36]
	Differential evolution (DE)	Fed-batch fermentation [37]
	Artificial neural network (ANN) model-coupled genetic algorithm (GA) (the authors compared the hybrid regression GA but concluded that the ANN-coupled GA was a superior approach to regression models)	Batch fermentation [38]
	Real-valued genetic algorithm	Fed-batch fermentation [39]
	Modified genetic algorithm	Drying process in batch fluidized bed [40]
	Nondominated sorting genetic algorithm-II (NSGA-II) (the authors also used the ridDE and ridPSO for comparison, but the performance of NSGA-II appeared to be the best)	Pasteurization [41]
	Genetic algorithm	Microfiltration [42]
	Response surface method combined with the genetic algorithm	Emulsion preparation procedure [43]
	Genetic algorithm (GA) (the authors also used LINGO for comparison; the developed GA was efficient in terms of computational time and quality of the obtained solutions)	Storage and transportation [44]
	Genetic algorithm coupling neural networks	Batch fermentation [45]
	A hybrid genetic algorithm based on NSGA-II	Packaging problem [46]

Table 1: Continued.

Group	SGO method	Application
Evolutionary methods	Genetic algorithm	Hydrolysis process [47]
	Differential evolution	Solid-state fermentation [48]
	Coupled artificial neural networks and genetic algorithm	Thermal processing [49]
	Hybrid artificial neural networks and the genetic algorithm	Thermal processing [50]
	Modified genetic algorithm	Fed-batch fermentation [51]
	Hybrid differential evolution (HDE) with the multiplier updating method (HDE-MUM), HDE including the penalty function method (HDE-PFM), and DE with penalty function method (DE-PFM) (the authors also used GA with penalty function method (GA-PFM) for comparison, but the optimal result obtained by GA-PFM were worse than HDE-MUM; the optimal solutions from HDE-PFM and DE-PFM were very close to that of HDE-MUM)	Fed-batch fermentation [52]
	Ad-hoc genetic algorithm	Feature selection in potatoes classification by computer vision [53]
	Radial basis function neural network architecture and a specially designed genetic algorithm	Time series sales forecasting [54]
	Differential evolution (the authors also compared response surface methodology (RSM))	Solid-state fermentation [55]
	Genetic algorithm	Fermentation [56]
	Genetic algorithm (GA) (the authors also explored GA's efficacy in enhancing RSM models but found that GA optimization could not significantly enhance accuracy and precision of RSM prediction models)	Prefry microwave drying and frying in a fryer [57]
	Genetic algorithm	Hydrogenation [58]
	Genetic algorithm	Single screw extrusion cooking [59]
	Genetic algorithm	Storage process [60]
	Genetic algorithm	Heat treatment [61]
	Genetic algorithm	Heat treatment [62]
	Genetic algorithm and sequential quadratic programming	Dehydration-impregnation-soaking (DIS) process [63]
	Differential evolution	Batch fermentation [64]
	Memetic or hybrid algorithms that use genetic algorithms (referred to by the authors as PDSP-MA1 and PDSP-MA2) (the authors also used CPLEX and PDSP-GA for comparison)	Integrated production and distribution scheduling problem [65]
	Genetic algorithm	Enzymatic interesterification in supercritical carbon dioxide [66]
	Genetic algorithm (the authors also compared the response surface methodology)	Enzymatic acidolysis reaction [67]
	Algorithm based on the genetic algorithm (era-gas)	Pig food formulations [68]
	Genetic algorithm (the authors also compared response surface methodology)	Ultrasound-assisted extraction bath system [69]
	Genetic algorithm (the authors used variables trends based on response surface plots for comparison)	Single-screw extrusion cooking [70]
	Design of experiment (DoE)-guided multiobjective genetic algorithm of kind II	Manufacturing supply chain [71]
	Nondominated sorting genetic algorithm of kind II (NSGA-II) (the authors compared MOGA-II and a "hybrid" approach with NSGA-II. NSGA-II emerged as the best optimizer according to the Pareto frontier). Design of experiment (DoE) was coupled with the optimizers	Distribution network for a two-layer supply chain [72]
	Hybrid differential evolution	Fed-batch fermentation [73]
	Genetic algorithm	Classification of rice grain (Zernike moments) [74]
	Improved genetic algorithm	Transportation routing [75]
	Hybrid genetic algorithm	Economic lot scheduling problem (ELSP) [76]
	Genetic algorithm	Drying process [77]
	Genetic algorithm (GA) (the authors compared the ability of GA with the traditional gradient search optimization; GA was faster in reaching an optimal solution)	Supercritical CO_2 extraction [78]
	Genetic algorithm	Supercritical CO_2 extraction [79]
	Algorithm based on adapting biogeography-based optimization (the authors used the genetic algorithm for comparison)	Distribution planning in cold chains [80]
	Artificial neural network coupled with the genetic algorithm	Pectinase-assisted low-temperature extraction of cashew apple juice [81]
	Multiobjective differential evolutionary algorithm with angle-based objective space division and parameter adaption (MODE-ASP) (the authors also compared the results of MODE-ASP with decomposition multiobjective evolutionary algorithm (MOEA) with covariance matrix adaption evolution strategy (MOEA/D-CMA), a clustering-based adaptive MOEA (CAMOEA), inverse modeling multiobjective evolutionary algorithm (IMMOEA), MOEA based on decision variables (MOEA/DVA), nondominated sorting and local search (NSLS), and a decision space-based niching NSGA-II (DN-NSGA-II) on benchmark functions; the authors also compared the results of MODE-ASP with MOEADCMA, CAMOEA, IMMOEA, MOEADVA, and NSLS in the fermentation process of sodium gluconate)	Sodium gluconate fermentation process [82]

Table 1: Continued.

Group	SGO method	Application
Evolutionary methods	Nondominated sorting genetic algorithm (NSGA-II)	Batch cooling crystallization of citric acid anhydrate [83]
	Genetic algorithm/correlation analysis	Oil palm production [84]
	Artificial neural network hybridized with a genetic algorithm	Lipase production from Penicillium roqueforti ATCC 10110 in solid-state fermentation [85]
	Nonsorted genetic algorithm (NSGA-II)	Confectionery stoving to produce soft-jelled candies [86]
	Metaheuristic based on nondominated sorting genetic algorithm II and nondominated sorting genetic algorithm II	Distribution of perishable products [87]
	Genetic-algorithm and fuzzy-logic methodology (the authors also compared response surface method)	The production of phycobiliproteins (PBPs) from cyanobacteria [88]
	Hybrid differential evolution algorithm involving a genetic operator with fuzzy logic controller (the authors compared Lingo, traditional differential evolution, and genetic algorithm in certain test problems, including the integer linear programming test)	Vehicle routing problem in the beverage logistics industry [89]
	Nondominated sorting genetic algorithm-II. The compromise solution of the experimental conditions was determined using the fuzzy c-means clustering algorithm	Ultrasonic probe extraction of phenolic compounds from olive leaves [90]
	Chaotic-based differential evolution (CDE) (the authors compared CDE with the classic differential evolution, particle swarm optimization, artificial bee colony, simulated annealing, and the touring ant colony optimization algorithm using benchmark functions from literature and compared CDE with DE in the optimization problem of baker's yeast drying process)	Baker's yeast drying process [91]
	Improved genetic algorithm (the authors also compared a traditional genetic algorithm)	Transportation route of fresh food [92]
	Genetic algorithm	Feature selection in seed discrimination [93]
	A novel evolutionary algorithms	Fed-batch bioreactor [94]
	Differential evolution	Enzymatic production of acylglycerols [95]
	Hybrid genetic algorithm (HGA) and hybrid harmony search (HHS) (the authors also used Lindo for comparison, but though Lindo was faster than HGA and HHS, the quality of HGA's and HHS's solutions was higher than that of Lindo; and, comparing HGA with HHS, the quality of HHS's solution was higher than that of HGA's solution, whereas HGA was faster than HHS)	Location-inventory supply chain for perishable products [96]
	Differential evolution (DE) (DE was compared to particle swarm optimization (PSO) and artificial bee colony (ABC), but overall, results showed that DE can outperform both PSO and ABC)	Fermentation process for xylitol production [97]

Table 1: Continued.

Group	SGO method	Application
Swarm intelligence methods	Ant colony system	Batch fermentation [98]
	Iterative ant-colony algorithm	Foreign protein production [99]
	Modified particle swarm algorithm through integrating the hybrid Monte Carlo sampling and path integral	Batch fermentation [100]
	Hybrid of the ant colony optimization algorithm and flux balance analysis (ACOFBA) (the proposed method surpassed OptGene, which was in line with the results achieved by another algorithm, CBAFBA)	Identification of gene knockout strategies [101]
	Artificial bee colony	Cold food chain logistics [102]
	Multiobjective particle swarm optimization	Deep-fat frying [103]
	Ant colony optimization with ABC customer classification (ABC-ACO) (the authors used ACO separately for comparison)	Distribution problem in metropolis [104]
	Two-grade delayed particle swarm optimization	Logistics system [105]
	MHPV (hybrid of multiobjective particle swarm optimization and adapted multiobjective variable neighborhood search) (the authors used a nondominated ranked genetic algorithm, a multiobjective genetic algorithm and a nondominated sorting genetic algorithm II for comparison)	Sustainable supply chain network [106]
	Particle swarm optimization and ant colony optimization	Bakery production planning (scheduling tasks) [107]
	Standard particle swarm optimization and quantum-behaved particle swarm optimization	Enzymatic pretreatments using viscozyme L [108]
	A proposed method that combines LINGO and a particle swarm heuristic (the author used Lingo for comparison)	Production and distribution planning [109]
	Ant colony system based heuristic (the authors used greedy heuristic for comparison)	Cooperative transportation planning for the German food industry [110]
	Hybrid of the artificial bee colony algorithm and the minimization of metabolic adjustment	iJO1366 *Escherichia coli* metabolic network [111]
	Ant colony optimization combined with interval partial least squares (ACO-iPLS) (the authors also compared full-spectrum PLS, iPLS, and genetic algorithm-iPLS)	Anthocyanins content prediction from near-infrared (NIR) spectra [112]
	Hybrid structure of inverse modeling embedded with ant colony optimization (the authors also compared linear transformed method)	Cr(VI) adsorption process on sustainable adsorbent derived from waste biomass (sugarcane bagasse) [113]
	Hybrid particle swarm optimization (HPSO) (the authors used the original binary PSO for comparison)	Supply chain network [114]
	Hybrid of bat algorithm and flux balance analysis	Metabolic engineering [115]
	Hybrid inverse modeling with evolutionary ant colony optimization (the authors also used linear transformed method (LTFM) for comparison)	Cr(VI) adsorption process on sustainable adsorbent derived from waste biomass (sugarcane bagasse) [113]
	Ant colony optimization algorithm modified by the characteristic wavebands selection principle (the authors also used successive projection algorithm method for comparison)	Classification of citrus fruit blemishes [116]
	Firefly algorithm	Osmotic dehydration process of mushrooms [117]
	Evolutionary Firefly algorithm	Osmotic dehydration parameters of papaya [118]
	Hybrid of artificial bee colony and flux balance analysis	Gene knockout identification [119]
Other methods	Strawberry algorithm	Batch fermentation [120]
	Improved hill climbing algorithm	Batch fermentation [121]
	Variable neighborhood search approach with the key steps of local search and shaking	Vehicle routing problem in fresh food e-commerce [122]
	Hybrid harmony search (HHS) and hybrid genetic algorithm (HGA) (the authors also used Lindo for comparison, but though Lindo was faster than HHS and HGA, the quality of HHS's and HGA's solutions was higher than those of Lindo, and comparing HGA with HHS, the quality of HHS's solution was higher than that of HGA's solution, whereas HGA was faster than HHS)	Location-inventory supply chain for perishable products [96]
	NIMBUS	Molecular distillation of olive pomace oil [123]

they are relatively well tested, thus proving their efficacy in several problems. Note that some information on the parameter settings of these algorithms can be found more easily when compared with more recent optimization methods [124]. Table 1 indicates that ARS and SA appear to be the random search techniques commonly used in food engineering and, consequently, detailed information on these algorithms is presented in the following topics covered by this review.

The evolutionary methods are algorithms inspired by features and processes of biological evolution and include the genetic algorithm (GA), differential evolution (DE), evolution strategy (ES), genetic programming, and evolutionary programming [4, 125–127]. Both GA and DE are the most used optimizers in food manufacturing optimization.

The swarm intelligence methods are inspired by swarm intelligence or social behavior. This group includes, for example, the following algorithms: particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC), firefly algorithm (FA), bat algorithm, fish swarm optimization algorithm, whale optimization algorithm, artificial algae algorithm, chicken swarm optimization, and grey wolf optimizer [4, 127–131].

Lastly, the other stochastic methods include algorithms such as harmony search, memetic algorithms, cultural algorithms, scatter search, tunneling methods, and other novel optimizers (e.g., artificial immune systems, method of musical composition, strawberry algorithm, and based on hill climbing algorithm) [4, 132, 133].

This review has identified adaptive random search (ARS), simulated annealing (SA), genetic algorithm (GA), differential evolution (DE), particle swarm optimization (PSO), and ant colony optimization (ACO) as prevalent stochastic techniques for tackling global and multiobjective optimization problems in food engineering. To provide a deeper understanding, a concise analysis of their descriptions, search procedures for finding the global optimum, and relevant applications in this field were presented.

2.1. Adaptive Random Search (ARS). Adaptative random search (ARS) is a method to solve nonlinear programming (NLP) problems [4]. It relies on generating decision variables from a specific probability distribution, minimizing computational efforts to find the global solution during the search process [134]. In addition, some versions are also capable of handling mixed-integer nonlinear programming (MINLP) problems [135, 136].

The procedure of the ARS algorithm can be described as follows [12] (Algorithm 1):

In step 2, the modification of the pedestal probability distribution is performed using some equations. The probability density h^j for step j, $j \epsilon 1{:}\ N_s$ is given by [12]

$$h^j = \frac{\left(1-\mathrm{p}^j\right)}{\left(1-\mathrm{v}^j\right)}, \tag{3}$$

where v^j is the volume of the perspective domain of random search in step $j\,(v^0 = 1)$ and p^j is the assumed probability in step j (where the optimal point belongs to the current domain I).

To calculate the currents v^j and p^j, the following expressions are used [12]:

$$\begin{aligned}
q^0 &= \frac{1}{2},\\
q^{j+1} &= q^j\,(2\varepsilon)_s^{1/\mathrm{N}}, \quad \text{where } \varepsilon \text{ is the given accuracy},\\
v^j &= \left(2q^j\right)^n,\\
p^j &= \left(\frac{s^j\,(p_{\min}-1)}{s_{\min}}\right) + 1, \quad \text{if } 0 \le v^j \le v_{\min},\\
&\left(\frac{v^j\,(1-p\min)}{(1-v\min)}\right) + \left(\frac{(p\min - v\min)}{(1-v\min)}\right), \quad \text{if } v\min \le vj \le 1,
\end{aligned} \tag{4}$$

where $p_{\min}$ and $q_{\min}$ are heuristic parameters that allow tuning the algorithm performance to different types of optimization problems.

The adaptive random search method proves particularly adept at tackling food engineering optimization problems due to its ability to handle nonlinear objective functions and identify multiobjective solutions that satisfy all constraints [11, 12, 19].

For instance, Simpson et al. [19] applied ARS to optimize the thermal processing of canned food. This stochastic optimizer was effective in searching the ideal retort temperature profile to either maximize quality retention (subject to achieving minimum target lethality) or to minimize processing time (subject to maintaining a specific quality retention level) [19].

(1) Set the total number of random search iterations (N_s), center point (x_i^0, $i \epsilon 1 : n$) of initial perspective subdomain I (Cartesian product of sets $I_i \subset$ domain X, $i \epsilon 1 : n$), and iteration counter $(s) = 1$.
(2) Generate a new vector ($x^j \epsilon$ domain X) from the current pedestal probability distribution $P_j(x^{j-1}, x^0)$, $j \epsilon 1$: N_s.
(3) Compute the objective function value $\Phi^j = \Phi(x^j)$ and identify the minimal objective function value $\Phi^j_{min} = \min\{\Phi^j, \Phi^j_{min}\}$ in step j, $j \epsilon 1 : N_s$.
(4) If $\Phi^j_{min} < \Phi^{j-1}_{min}$, then the center point $x^0 = x^j$.
(5) While $j < N_s$, go to step 2.
(6) End.

Algorithm 1: Adaptive random search.

This optimization technique was also successfully used by Abakarov et al. [11] for solving the multiobjective problem of the thermal processing of packaged food. In this problem, the goal was to find the optimum combination of constant retort temperature and processing time that would maximize the quality of pork puree (specifically, thiamine and texture retention) while minimizing the processing time needed.

To address challenges encountered with multimodal or dynamic optimization, Abakarov et al. [12] proposed a modification of the ARS method that incorporates a logistic function. This modification aimed to improve the method's performance, and it was tested on the optimization of thermal processing of canned foods. The goal was to find the optimal variable retort temperature profile for two distinct problems. The first problem searched for maximizing the final thiamine retention, while the process final lethality was kept to a specified minimum. The second problem focused on minimizing the process time subject to the same lethality requirement and maintaining a minimum quality threshold.

2.2. Simulated Annealing (SA). SA is an optimization method developed by Kirkpatrick et al. [137] to obtain better solutions for combinatorial optimization problems. The method simulates the thermodynamic principles of producing an ideal crystal and it utilizes the metropolis algorithm, which replicates the behavior of atoms in thermal equilibrium at a given temperature [124, 137, 138]. This temperature is the control parameter of SA, which starts at a high value, resulting from the "melting" of the system at the beginning of the process to be optimized. Gradually, the temperature decreases in controlled steps to produce a crystal, until the system "freezes" and stabilizes [124, 137]. A rapid decrease in temperature generates irregularities in the crystal structure, which could represent failure to find the global optimum solution for the tested objective function. Conversely, an extremely slow decrease results in higher computational efforts but favor the identification of the global optimum. A key characteristic of SA is its ability to accept worse solutions during the optimization process, thus helping to diversifying the search and avoid getting trapped in local optima. However, as the temperature decreases, the probability of accepting these worse solutions should drop. This encourages the algorithm to focus on refining the best solutions found and favors the convergence [124].

Food engineering often deal with complex optimization problems in cooking, where factors such as frying time, temperature, and oil amount have numerous and potentially noisy input and output parameters. The simulated annealing stochastic method, combined with artificial neural networks, offers a powerful solution for handling these intricate datasets [139].

The SA algorithm has been used by Russo et al. [18] to optimize the quality of espresso coffee by pod obtained via a percolation process. An adaptive neurofuzzy interference system (ANFIS) was utilized as a tool to model the process, and SA was employed to solve the complex nonlinear multicriteria optimization problem. The goal was to determine the extraction temperature, time, and composition of the coffee mixture that minimizes the difference between the sensorial attributes of the espresso coffee and the target values of the properties. The coffee quality was measured by sensorial attributes including color intensity, body, olfactive intensity, acidity, astringency, texture, roast intensity, and bitterness.

A novel simulated annealing based on published MATLAB® code (Optimization Techniques in Engineering, 2015) was developed by Rodman and Gerogiorgis [8] to find the optimal temperature profile capable of maximize final ethanol concentration and minimize bath time in a beer fermentation process. As a result, it was possible to reduce the processing time by 16 h, increasing the ethanol concentration and still maintaining byproduct concentrations below threshold values.

SA was also used with constraint programming (CP) and tabu search (TS) to solve large-scale sugarcane rail scheduling instances [10]. In short, this hybrid algorithm starts constructing an initial solution using the CP-depth-first search technique. All constraints and time windows of the train operations were identified and checked using constraint propagation. A backtracking procedure was used to remove any conflicts through the rail systems. Then, the first iteration solution of TS was developed by constructing a new neighborhood of the CP schedule. The first initial solution of TS was compared with the CP solution. The best solution in the makespan value (equivalent to the throughput of sugarcane transport) was integrated with the first iteration of SA to obtain another solution by generating a new neighborhood. The solution of this last step was used as an initial solution to start the second iteration of TS and so on, until satisfying the termination criteria [10].

2.3. Genetic Algorithm (GA). In GA, each possible solution is represented by a string of genes called chromosome. The genes represent the decision variables of a given optimization problem and are encoded with binary bits [140, 141]. The number of bits depends on the required precision [141]. The representation of a GA candidate solution is illustrated in Figure 1. In some cases, the solution can be represented by more than one chromosome [141]. GA starts by generating individuals that are candidate solutions for the optimization problem and these solutions constitute the initial population. There are several approaches to generate this initial population as those commonly used are random, uniform, and biased [141]. More details about these sampling methods are discussed by the authors in [141].

A chromosome's quality, or how well it solves the problem, is determined by the fitness function, which is directly based on the problem's objective function [140, 141]. The fitness value is used to drive the chromosomes to evolution by a selection operating [140, 141]. Individuals with higher fitness should have a greater chance to be selected than those with lower fitness [140]. There are different selection schemes such as roulette wheel, tournament selection, truncation selection, fitness scaling, and ranking selection [142, 143]. For example, the probability of selecting an individual in roulette wheel selection is equal to their aptitude of the average fitness in the population. On the other hand, the probability of selecting an individual in ranking selection is determined according to its fitness value rank in the population. In tournament selection, the population is divided into subgroups and the best individuals, according to their fitness values, are selected. This selection procedure is repeated until the desired number of individuals for the new population is reached [141].

After the selection process, GA performs a recombination operation, also known as crossover [141]. It consists of recombining usually two selected chromosomes from a population to produce one or more members of the successor population. So, the offspring is constructed from the characteristics of the first parent [140, 141]. Crossover operations can be handled in different ways. Figures 2 and 3 illustrate the single-point and the two-point crossover operations [140, 141].

There is another crossover operation called uniform crossover. In this case, a random binary mask is created first, as shown in Figure 4. The child chromosome is constructed based on the bit-by-bit comparison between the parent and the mask. If there is a zero in the mask bit and a zero in the corresponding parent 1 bit, this bit is copied to the child chromosome. Similarly, if there is a number one in the mask bit and a number one in the corresponding parent 2 bit, this bit is copied to the child chromosome. A second child is made of the unused bits of parents 1 and 2. Comparing these three crossover techniques, the uniform crossover is the one that produces a more explorative effect, thus contributing to enhancing the success rate for finding the global optimum [141].

After the crossover operation, the created children (new chromosomes) will be passed on to the mutation stage, thus enabling GA will maintain the population diversity [140, 141]. In the case of binary representations, the mutation operator replaces each position in the chromosome with a randomly selected bit if a probability test is passed [141]. That is, if a randomly generated number in the interval [0, 1] is greater than a predetermined "mutation rate," no mutation is applied. If the random number is smaller or equal to the mutation rate, then the bit is replaced, as shown in Figure 5 [140].

The summary of a GA flowchart can be as follows [140]:

(1) Generate an initial population of N chromosomes randomly.

(2) Calculate the fitness of each chromosome in the initial population.

(3) Create a new empty population and repeat the following steps until N chromosomes have been created.

   (a) Using a selection method, select two chromosomes, $c1$ and $c2$.
   (b) Apply crossover operation to $c1$ and $c2$ to generate a child chromosome c.
   (c) Apply mutation operation to c to obtain c'.
   (d) Add c' to the new population.

(4) Replace the initial population with the new population.

(5) Return to step 2 until satisfying the stopping criteria.

Concerning the applications of GA, it has several uses in food science. In 1997, Morimoto et al. [60] proposed an intelligent control technique including GA and neural networks for the optimal control of the fruit-storage process. Neural network was first used to identify and model the water loss and the fungal growth of fruit, as their functionality with relative humidity. Then, GA was utilized to search the optimal setpoints of relative humidity to minimize water loss and the development of lesions by fungi and bacteria of the fruit. These authors concluded that the algorithm searched for the optimal setpoints in a quickly and successfully way.

Morimoto et al. [61] used GA and neural networks to optimize the heat treatment for fruit during storage. In this study, a neural network was used to identify the time-history change in surface color of tomatoes as a function of temperature. Then, GA allowed the optimal eight-step setpoints of temperature to be successfully searched to delay the ripening process of tomatoes. In this work, the authors also tested three different search procedures of GA. The evolution curves from the three procedures showed that combining two specific crossover techniques significantly improved the search performance. This involved adding 50 individuals from another population to the original one and performing the crossover in two steps.

Heat treatment was also investigated by Morimoto et al. [62] for reducing tomato water loss during storage. An artificial neural network was firstly used to identify the dynamic change in the rate of water loss and its relationship with temperature. Then, GA was used to find the optimal combination of temperature setpoints that minimize the

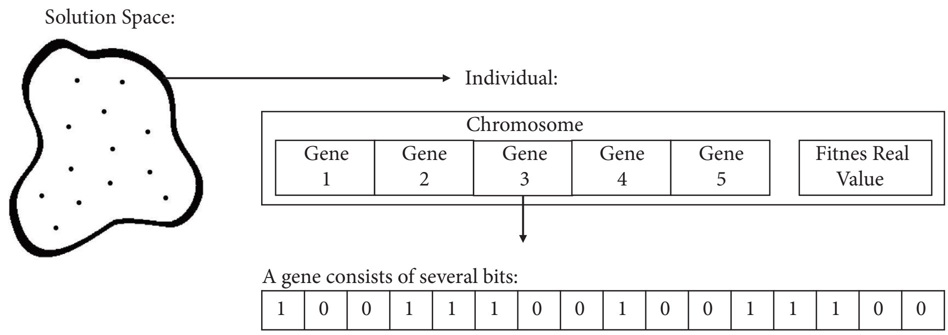

FIGURE 1: Representation of a GA candidate solution mapped into an individual that consists of one or more chromosomes [141].

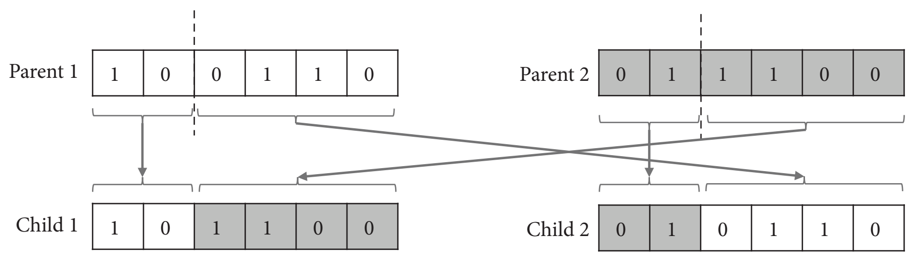

FIGURE 2: Single-point crossover [141].

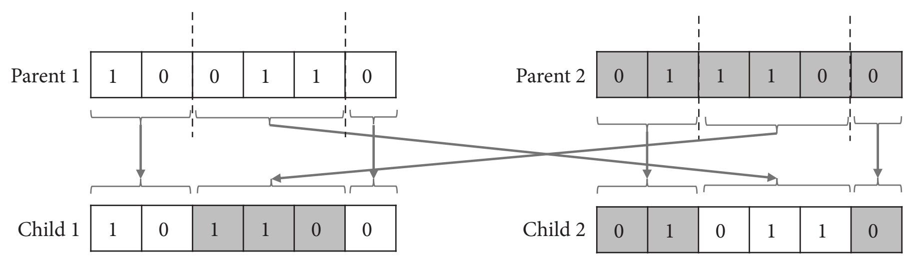

FIGURE 3: Two-point crossover [141].

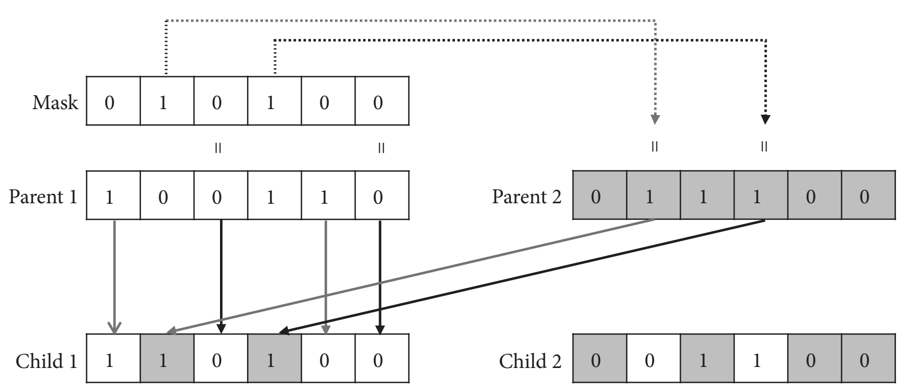

FIGURE 4: Representation of uniform crossover [141].

water losses. The results showed that the fruit freshness could be maintained during storage through the application of heat stress.

There are also many applications of GA or its variants in fermentation processes, both in batch ([27, 28, 38, 45, 56]), fed-batch operations ([39, 51, 77]), and in solid-state fermentation [85]. Carrillo-Ureta et al. [27] employed GA to optimize the temperature profile during beer fermentation, aiming to achieve the desired ethanol levels while adhering to operational and quality constraints. Desai et al. [28] used GA to determine the optimum media composition and inoculum volume for the fermentative production of exopolysaccharide from

Parent	1	0	0	1	1	0	Child	1	0	1	0	1	0

Figure 5: Representation of random mutation [141].

Lactobacillus plantarum. Haider et al. [56] enhanced lipase production by a soil microorganism using GA to search for the best media constituents. Pappu and Gummadi [38] used GA to find the optimum fermentation conditions (time, pH, agitation, aeration, concentration of biomass, and glycerol) to enhance xylitol production. Baishan et al. [45] also studied xylitol production but optimized the medium composition in a stirred tank bioreactor for improving the product yield.

Concerning fed-batch fermentation, Tochampa et al. [39] optimized the production rate of xylitol using the real-valued GA to establish optimal substrate feeding profiles. Another example is the application of two GA variants to find the optimal feed flow rate to maximize the *Saccharomyces cerevisiae* concentration and minimize ethanol formation [35]. The concentration of *Saccharomyces cerevisiae* at the end of the fermentation process was also optimized in the work of Chen et al. [51], which used a modified GA to find the optimal feed rate profile. Another example is the work of Zuo and Wo [144] that brings the optimization and control of a fed-batch fermentation system using hybrid neural networks and GA. This system produces thuringiensin, a bioinsecticide and one of the major exotoxins of *Bacillus thuringiensis*.

An example of GA application in solid-state fermentation was reported by Menezes et al. [85]. They utilized an artificial neural network hybridized with GA to optimize the lipase production from *Penicillium roqueforti* ATCC 10110 by finding the optimal fermentation time, incubation temperature, and percentage moisture content.

GA was also used as an optimization tool in supercritical CO_2 extraction by Zahedi et al. [78] to obtain nimbin from neem seed and by Bashipour and Ghoreishi [79] to obtain β-carotene from *Aloe vera*. Specifically, the first study showed that GA was more robust when compared to a traditional gradient search (GS) optimization technique, especially when considering computational effort [78].

Other studies involving GA-based optimization of extraction processes can be found in literature. Tao et al. [69] used GA to optimize the extraction of phenolics including anthocyanins from wine lees in an ultrasound-assisted process. Vural et al. [90] utilized the nondominated sorting genetic algorithm-II (NSGA-II) to optimize the ultrasonic probe extraction of phenolic compounds from olive leaves.

Another application of GA or its variants includes the food classification ([53, 74, 93]). Chtioui et al. [93] used GA for the feature selection in seed discrimination to maximize classification rates. Wee et al. [74] applied GA to reduce the number of features of Zernike moments for maximizing the performance of a neural network classification of rice grain. Dacal-Nieto et al. [53] utilized GA for feature selection in potatoes classification by computer vision.

GA-based optimizers have been also implemented to solve logistical problems ([44, 65, 71, 72, 75, 87, 92]). Wu et al. [75] used an improved GA algorithm to determine the optimal transportation routing for fresh food to minimize transportation costs. Asgari et al. [44] employed a GA to optimize wheat transport in Iran. Their model determined ideal monthly quantities transported between producing and consuming provinces to address a real-world supply chain challenge. Validi et al. [72] used NSGA-II to minimize carbon emissions and total costs on the distribution chain of the dairy industry in Ireland by finding the optimal routes and vehicle/truck types. The same authors further used a multiobjective GA to address both economic and environmental factors. Their approach aimed to minimize carbon emissions while optimizing distribution costs for transporting products from plants to consumers [71]. Devapriya et al. [65] presented a comparison of two heuristics that use GA in solving the integrated production and distribution scheduling problem. Nisperuza et al. [87] used a metaheuristic based on NSGA-II to a perishable goods vehicle routing problem. The goal was to minimize both the number of damaged products and the total distance travelled by the vehicles. Finally, Peng [92] used an improved version of GA to find the optimal logistics transportation path combination to minimize the total cost of cold chain logistics transport (transportation cost, cargo damage cost, and power consumption cost).

NSGA-II has also been successfully applied to optimize the scheduling of a heat exchanger network under milk fouling conditions [41]. A comparison of NSGA-II, a mixed-binary version of DE (ridDE), and a mixed-binary version of PSO (ridPSO) in the search for optimum solutions for this problem were performed. In the numerical study of single-objective optimization, NSGA-II demonstrated to maintain a good balance among the three measures of the cleaning cost, energy loss, and the flow rate of the heating medium. On the other hand, ridDE could schedule the heat exchanger network at the lowest cleaning cost but with a compromise on energy consumption and steam flow rate, while the solutions of the ridPSO were also associated with a significantly large amount of energy consumption and steam flow rate. In the numerical study based on a multiobjective scenario, the ridPSO could not achieve improvements up to the level of none of NSGA-II and ridDE [41].

GA was also applied to a single screw extrusion cooking to optimize the production of a fish and rice flour blend by Shankar and Bandyopadhyay [59] and Tumuluru et al. [70]. In both applications, GA was able to resolve the corresponding optimization problems.

GA has also been applied as an optimization tool to control a baker's yeast drying process [77], to find optimal reaction parameters in the vegetable oil hydrogenation process [58], to produce bioethanol via cassava starch hydrolysis [47], and to optimize the acidolysis reaction between mustard oil and capric acid using *Thermomyces lanuginosus* lipase [67].

Finally, Hecker et al. [23] compared the performance of a modified GA against random search and ACO in solving the production scheduling problem for a bakery case study. They concluded that the modified GA seemed to be the most promising method since it provided the best objective function values for both makespan and total idle time of machines. However, even though the modified GA method provided the overall best solution for all the optimization runs for makespan, all the three methods generated better results for this optimization problem than the initial product sequence, even considering their worst performances.

Other applications of GA and its variants including hybridized versions with other algorithms can be found in Table 1 ([23, 30, 32, 40, 42, 43, 46, 49, 50, 54, 57, 63, 66, 68, 76, 81, 83, 84, 86, 88, 96]).

2.4. Differential Evolution (DE). DE is a stochastic optimization method introduced by Price and Storn in 1995 [145]. The algorithm starts by choosing the initial points, $x_{i,j}$, randomly [146, 147]. Each point represents a possible solution for the optimization problem where $i \epsilon \{1, 2, \ldots, \mathrm{NP}\}$ and $j \epsilon \{1, 2, \ldots, D\}$, being NP the number of population members and D is the number of decision variables [147]. The generation of new points is based on the perturbation of existing points. The scaled difference of two randomly selected population vectors is added to a third randomly selected population vector [146]. This strategy is named mutation, and this mutant vector is obtained using the following equation:

$$\mathrm{v}_{\mathrm{i,j}} = \mathrm{x}_{\mathrm{r1,j}} + \mathrm{F}_{\mathrm{DE}}\left(\mathrm{x}_{\mathrm{r2,j}}\text{-}\mathrm{x}_{\mathrm{r3,j}}\right), \tag{5}$$

where F_{DE} is the mutant amplification factor that controls the amplification of the differential variation ($\mathrm{x}_{\mathrm{r2,j}} - \mathrm{x}_{\mathrm{r3,j}}$); i, r1, r2, r3 $\epsilon \{1, 2, \ldots, \mathrm{NP}\}$ and $\mathrm{i} \neq \mathrm{r1} \neq \mathrm{r2} \neq \mathrm{r3}$ and $j \epsilon \{1, 2, \ldots, D\}$, respectively [147].

To increase the diversity of the population members, a crossover step is used. It consists in generating a new solution vector, $u_{i,j}$, by copying some elements of the mutant individual to the target individual with a crossover probability constant [147, 148], where

$$\begin{aligned} u_{i,j} &= v_{i,j}, \text{if } \mathrm{rand}(j) < \mathrm{CR}, \\ &\quad ui, j, \text{otherwise}, \end{aligned} \tag{6}$$

where rand $(j) \epsilon [0, 1]$ is the j^{th} evaluation of a uniform random number generator and $\mathrm{CR} \epsilon [0, 1]$ is the crossover probability constant given by the user [147].

The population is then updated using the greedy criterion, where the objective function values of $u_{i,j}$ and $x_{i,j}$ are compared and the solution vector that provides the best value for the optimization problem is retained [147].

As observed for GA and its variants, DE and its improved versions also have several applications in the optimization of fermentation processes ([24, 26, 34, 36, 37, 40, 48, 52, 55, 64, 73, 82, 97]). DE applications in batch fermentation can be found in the works of [33, 37, 64, 82]. Chaitali et al. [37] proposed DE to determine the initial batch volume and the feed concentrations of the substrate to maximize xanthan gum formation by *Xanthomonas campestris* in a fed-batch fermentation process. Mandal et al. [33] used DE to maximize the expressions of catalase while keeping protease expressions within threshold limits in fed-batch fermentation of *Aspergillus niger*. Oonsivilai and Oonsivilai [64] applied the DE algorithm to design the temperature profile for beer fermentation in a batch process. Batch fermentation was also optimized by Guo et al. [82]. They employed a multiobjective DE algorithm with angle-based objective space division and parameter adaption to get higher conversion rate and utilization rates of equipment in the fermentation process of sodium gluconate.

Apart from these examples in batch applications, several authors worked with DE and fed-batch processes. Particularly, there are many applications of DE for fermentation fed-batch processes involving ethanol production ([24, 26, 52, 73]). The ethanol production rate was improved by Chiou and Wang [52]. They compared the use of the hybrid DE (HDE) with the multiplier updating method (HDE-MUM), HDE including the penalty function method, DE with penalty function method, and GA including the penalty function method (GA-PFM) to determine the optimal solutions in the fed-batch fermentation process by *Zymomous mobilis*. HDE-MUM showed better results for the maximum ethanol produced rate than GA-PFM. Also, Wang and Cheng [73] used hybrid DE to optimize the fermentation by *Saccharomyces cerevisiae*, determining the feeding rate and operation parameters to maximize the ethanol production rate and minimize the processing time. Wang et al. [24] applied a hybrid DE to estimate the kinetic model parameters of the fed-batch fermentation for ethanol and glycerol production using *Saccharomyces diastaticus* LORRE 316. The same authors also introduced the hybrid DE with a multiplier updating method including adaptive penalty parameters to determine the feasible feed rates for the fed-batch optimization problem. Hunag et al. [26] used a hybrid DE with an adaptive multiplier updating method, including an adaptive penalty parameter strategy, to find the optimal feed rate, the initial sugar concentration, and fermentation time to improve ethanol production in a fed-batch *Saccharomyces diastaticus* LORRE 316 fermentation.

There are also applications of DE in the optimization of other fermentation fed-batch processes ([34, 35, 97]). Particularly, Yuzgeç et al. [35] compared four different DE algorithms (the classical DE technique, the opposition based on DE, the adaptive DE, and the adaptive opposition based on DE) and GA in determining the optimal feeding flow profile in a baker's yeast fermentation process. They showed that all the DE algorithms have better performance than GA for the same fermentation process [35]. Koop et al. [97] applied DE to optimize the performance of a fermentation process for xylitol production by *Candida mogii* yeast using a fed-batch reactor. These authors also compared the numerical performance of DE with the results obtained using PSO and ABC and showed that DE can outperform both PSO and ABC in this case.

DE was also applied in solid-state fermentation processes by Garlapati and Banerjee [55] and Bhattacharya et al. [48], which optimized the extracellular lipolytic enzyme production by *Rhizopus oryzae* NRRL 3562 and the laccase production from a locally isolated hyperactive strain of *Pleurotus* sp., respectively. Another study by Gujarathi [36] employed a multiobjective DE strategy (MODE III) on two solid-state fermentation cases. Each case aimed to achieve two conflicting objectives to maximize enzyme activity while minimize the fermentation time and to maximize the product to the cell yield coefficient while minimize the fermentation time.

DE was also utilized by Sun et al. [31] to find optimal glucose and inducer feed rates to yield maximal economic benefit in foreign protein production using recombinant bacteria. Finally, DE was applied by Koop et al. [95] for the optimal control of substrate feed rate in glycerolysis of vegetable oils to improve monoacylglycerols and diacylglycerols production.

Other applications of DE variants and hybridized versions with other methods are described in Table 1 ([29, 82, 89, 91, 113]).

2.5. Particle Swarm Optimization (PSO). The particle swarm optimization (PSO) algorithm, introduced by Kennedy and Eberhart [149], shares similarities with GA in their use of randomly chosen initial populations. However, on PSO, each particle representing a potential solution is assigned a velocity, allowing it to dynamically move through the search space. This velocity introduces an additional element of exploration compared to GA's static individuals, which is advantageous for the food engineering field [150].

In the PSO algorithm, each particle remembers the best solution found by itself and by the whole population, along the search trajectory. The particles adjust the velocities (*ve*) by the following equation [149, 151]:

$$\mathrm{ve}_{i+1,j} = \mathrm{wve}_{i,j} + c_1 r_1\left(x_{i,j}^{\mathrm{local}} - \mathrm{x}_{\mathrm{i,j}}\right) + c_2 r_2\left(x_{i,j}^{\mathrm{global}} - \mathrm{x}_{\mathrm{i,j}}\right), \tag{7}$$

where r_1 and r_2 are two random numbers, w is the inertia weight parameter introduced by Shi and Eberhard [152], c_1 and c_2 represent the positive acceleration constants from the cognitive and social terms (respectively), $x_{i,j}^{\mathrm{local}}$ is the particle that has achieved the best fitness so far, and $x_{i,j}^{\mathrm{global}}$ is the best solution vector from all the swarm [151]. Recalling that, $i \epsilon \{1, 2, \ldots, \mathrm{NP}\}$, where NP represents the number of population members and $j \epsilon \{1, 2, \ldots, \mathrm{D}\}$, where D is the number of decision variables. Then, the new position $(x_{i+1,j})$ is given by

$$x_{i+1,j} = x_{i,j} + \mathrm{ve}_{i+1,j}. \tag{8}$$

In terms of food engineering applications, the PSO algorithm was efficient for optimizing the conditions of enzymatic pretreatment of oat bran [108], where the carbohydrase Viscosyme L was used to enhance protein extraction from it. Liu et al. [108] optimized the enzymatic pretreatment conditions using the standard PSO and also investigated the results obtained for the same problem using the quantum-behaved PSO (QPSO) [153]. In the quantum model of PSO, the state of a particle is represented by a wave function instead of position (vector x) and velocity (vector *ve*). Although QPSO demonstrated faster convergence and improved computational efficiency, it showed the same effectiveness as the standard PSO.

A modified PSO via the integration of the hybrid Monte Carlo sampling and path integral was proposed by Wang et al. [100] to maximize the production of 1,3-propanediol in batch fermentation. However, according to these authors, the convergence analysis and reliability of this algorithm are needed to be investigated.

PSO was also adapted by Hecker et al. [107] to optimize the production planning of an example bakery. The authors presented the modeling of the production processes that scheduled the workflow of a given product sequence and the optimization was performed with two different cost functions of economic interest.

The supply chain problem was also optimized using two-grade delayed PSO [105], hybrid PSO [114], hybrid of multiobjective PSO, and adapted multiobjective variable neighborhood search [106], and particle swarm heuristic [109].

Other PSO applications included the minimization of the system of distribution of fresh agriproducts cost [105], the minimization of production and transportation costs of the agrifood supply chain network [114], the minimization of logistic costs and environmental impacts of CO_2 emissions [106], the definition of the production quantities, the distribution centers to be visited, and the delivery quantities for each planning period in a way to minimize the total cost and the trip for perishable products [109]. For the resolution of this last problem, the authors proposed a heuristic method where the production submodel was solved using LINGO and the distribution submodel was optimized using PSO [109].

Finally, PSO was used by Amiryousefi et al. [103] to solve a multiobjective problem in deep-fat frying process. The goals consisted of minimizing the shrinkage percentage and the fat content of the deep-fat frying ostrich meat plates while keeping their moisture content within a legal range [103].

2.6. Ant Colony-Based Methods. Ant-based algorithms were first introduced by Dorigo et al. [154] and Dorigo et al. [155] as an approach to handling difficult combinatorial optimization problems. They draw inspiration from the foraging behavior of real ant colonies. These social insects collaborate to find the shortest paths between their nest and food sources. As ants travel, they leave behind a chemical trail called pheromone, creating a scent pathway. Other ants are more likely to follow paths with stronger pheromone concentrations, effectively sharing information about food sources. This collective behavior allows the colony to efficiently locate resources, and these algorithms mimic this process to solve optimization problems, especially in the food engineering field [156].

Specifically, the ant colony system (ACS) was introduced by Dorigo and Gambardella [157] and, in brief, it proceeds as follows: m ants are initially positioned on n cities chosen according to some initialization rule (e.g., randomly). Each ant constructs a tour, which is a feasible solution to the problem to be optimized by repeatedly applying a stochastic greedy rule, the state transition rule (for more details, see [157]). While building its tour, each ant changes their pheromone level by applying the local updating rule. When all the ants have finished their tour, the globally best ant, defined by the shortest tour, modifies the amount of pheromone on the visited edges according to the global updating rule. Thus, ants are guided in constructing their tours based on heuristic information, preferring to choose short edges and pheromone information where the edges with a high amount of pheromone are preferred [157].

Table 1 shows that ACS was used by Xiao et al. [98] and Sprenger and Monch [110]. Xiao et al. [98] applied ACS to optimize the temperature profile for beer fermentation, aiming the maximization of ethanol production, minimization of the byproducts concentration, and reduction of spoilage risk. On the other hand, Sprenger and Monch [110] applied ACS to improve a greedy heuristic used to solve a cooperative transportation planning problem motivated by a scenario found in the German food industry.

In 1999, Dorigo et al. [156] introduced the ant colony optimization (ACO) metaheuristic. The algorithm mimics real ants in many aspects. First, by using a colony of cooperating individuals, since the ants cooperate through the information, they read and write concurrently about the problem states they visit. Second, the algorithm makes use of an artificial pheromone trail for local stigmergic communication since the artificial ants change some numeric information locally stored in the problem's state they visit. Third, ACO uses a sequence of local moves to find the shortest paths since artificial ants move step by step through "adjacent states" of the problem to find the shortest one. Finally, ACO uses a stochastic decision policy employing local information. This is because the artificial ants decision policy depends on a priori information represented by the problem specifications (equivalent to the terrain's structure for real ants), and the local modifications in the pheromone trails induced by past ants [156].

In the ACO algorithm, there are also some characteristics of artificial ants that differ from real ones, i.e., they live within a discrete world, moving between discrete states, while real ants move in continuous space; artificial ants store information about past actions, aiding in decision-making that real ants often lack; they deposit "pheromone" amounts proportional to the quality of the solution found; and in ACO, pheromone updates can be adjusted based on the problem, e.g., they update pheromone trails only after having generated a solution [156].

Optionally, the ACO metaheuristic can comprise some extra components that use global information, named *daemon*. By the observation of the ant's behavior, a *daemon* can collect global information to deposit additional pheromone information, based, in this way, on the ant search process from a nonlocal perspective. By the observation of the solutions generated by the ants, the *daemon* can also deposit additional pheromone "offline" concerning the pheromone that the ants deposited online [156].

The ant's generation and activity, the pheromone evaporation, and the *daemon* actions also may need some kind of synchronization, as using strictly sequential scheduling of the activities in nondistributed problems [156].

ACO algorithm modified by the characteristic wavebands selection principle was successfully used in a problem of classification of citrus fruit blemishes [116]. Hecker et al. [107] used ACO and PSO separately to analyze and optimize the production planning of an example bakery, and both algorithms provided optimized results for the problem. Hecker et al. [23] also compared ACO with a modified GA and random search for optimizing the production planning of a bakery production line. Even though the modified GA provided better results, ACO was capable to generate a significant reduction in makespan compared to the initial value, and it was able to minimize the total machine idle time, which were targets of most economical interest. Lu et al. [101] used a hybrid ACO algorithm and flux balance analysis to optimize microbial strains. The authors presented a case study that used *Saccharomyces cerevisiae* as the model organism to optimize the rate of vanillin production. Other food engineering applications related to ACO can be found in Table 1 ([101, 104, 112, 113]).

3. Remarks on SGO for Food Engineering Optimization

From the research carried out on the Science Direct and Scielo platforms adding the works published by the authors of this article, 118 references were found related to food engineering optimization problems resolved with stochastic optimizers from January 1994 to February 2021. Figure 6 shows the contribution of publications by journal articles, conference/symposiums papers, and book chapters.

As stated in Table 1, these publications were classified into four groups: the random search techniques, the evolutionary methods, the swarm intelligence methods, and the other methods. Figure 7 shows that the evolutionary methods dominate, among the stochastic optimizers, as the common stochastic optimization tool in food engineering.

Particularly, 53 of 76 publications that apply evolutionary algorithms are related to GA or its variants and 18 used DE or its variants. GA and its improved and hybridized versions represent nearly 45% of the total publications presented in this review, while DE-based methods represent about 14% of these applications. In general, GA-based methods find wide-ranging applications, including optimization tasks such as refining operating conditions and various metrics across different processes (such as fermentation, extraction, and heat treatment), food categorization, and solving logistical problems. Concerning DE and its variants, most of the research has focused on the optimization of fermentation processes in food engineering.

Swarm intelligence methods are the second group most applied in food engineering (23 publications). Among the optimization methods of this group, PSO and its variants stand out with 35% of the reported applications, which

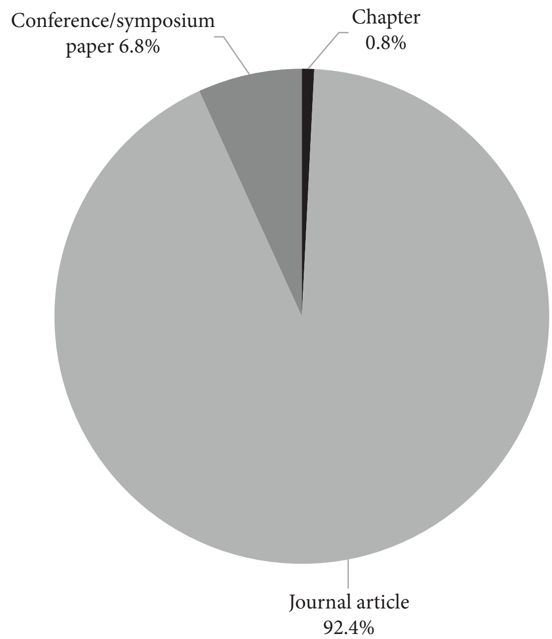

Figure 6: Contribution of publications by journal articles, conference/symposiums papers, and book chapters on food engineering optimization with stochastic optimization methods. Period: January 1994–February 2021.

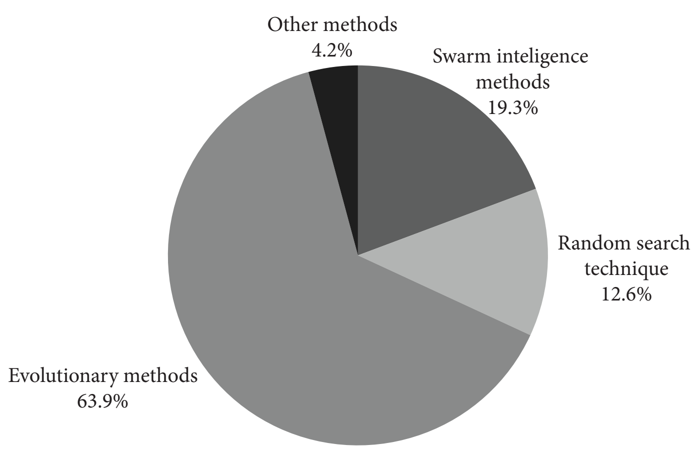

Figure 7: Number of publications per type of stochastic optimization method. Period: January 1994–February 2021.

included enzymatic pretreatment, fermentation process, deep-fat frying, production planning, and supply chain problems. ACO-based optimizers are also commonly used by the food engineering community to resolve diverse problems such as distribution problems [104], identification of gene knockout strategies [101], anthocyanins content prediction from near-infrared spectra [112], classification of citrus fruit blemishes [116], and Cr(VI) adsorption process on sustainable adsorbent derived from waste biomass (sugarcane bagasse) [113].

15 publications reported the application of random search methods where SA or its variants was used in 4 publications and adaptive random search in 2 publications and modified adaptive random search was used in one publication (see Table 1).

For illustration, Figure 8 shows the number of publications on food engineering optimization with stochastic methods in the period 1994–2020. Table 2 gives an overview of the articles published in 2014 where the evolutionary and swarm intelligence methods were commonly applied and, in particular, GA-based optimizers were preferred.

Table 3 shows the distribution of articles published by country on this research topic. As noted, China and India lead the research on food engineering optimization with stochastic optimizers followed by the United States of America.

Finally, Table 4 presents a summary of the applications of stochastic optimizers in the resolution of food engineering optimization, the decision variable(s) selected for each problem, and the respective objective function.

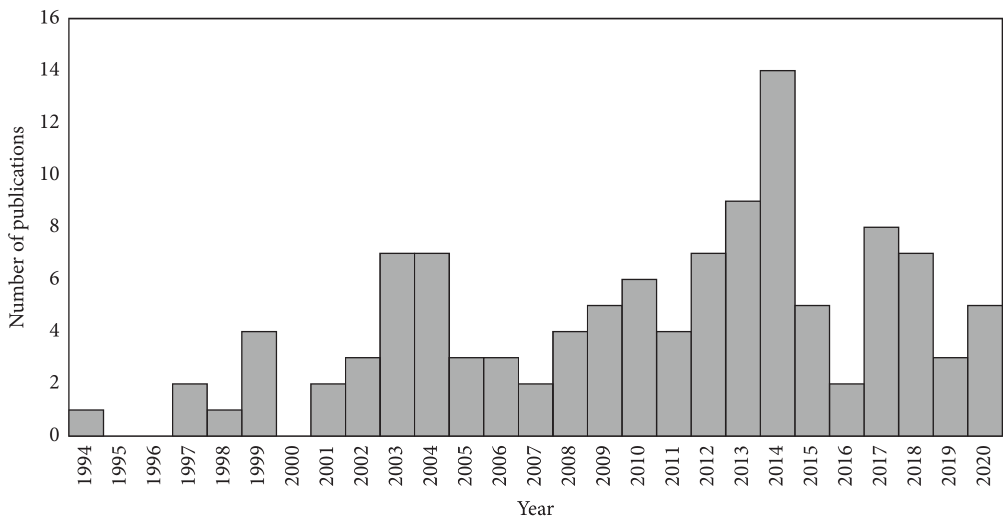

FIGURE 8: Number of publications per year on food engineering optimization with stochastic optimization methods. Period: 1994–2020.

TABLE 2: Survey of publications on stochastic methods applied to food engineering problems.

Reference	Application	Stochastic method	Group
[103]	Deep-fat frying of ostrich meat plates	Particle swarm optimization	Swarm intelligence methods
[106]	Sustainable supply chain network of perishable food	Hybrid of multiobjective particle swarm optimization and adapted multiobjective variable neighborhood search	Swarm intelligence methods
[23]	Bakery production scheduling	Modified genetic algorithm	Evolutionary methods
[101]	Vanillin production by the Baker's yeast Saccharomyces cerevisiae	Hybrid of the ant colony optimization algorithm and flux balance analysis (the proposed method was able to outperform OptGene, which was consistent with the results obtained by another algorithm, namely, CBAFBA)	Swarm intelligence methods
[34]	Fed-batch fermentation processes	Evolutionary algorithms	Evolutionary methods
[109]	Integrated production and distribution planning model for perishable products	LINGO and a particle swarm heuristic	Swarm intelligence methods
[57]	Prefrying microwave drying and frying conditions of French fries	Genetic algorithm	Evolutionary methods
[66]	Cocoa butter analog synthesis variables	Artificial neural networks and the genetic algorithm	Evolutionary methods
[67]	Acidolysis reaction between mustard oil and capric acid by using thermomyces lanuginosus lipase	Genetic algorithm	Evolutionary methods
[110]	Cooperative transportation planning	Ant colony system	Swarm intelligence methods
[69]	Ultrasound-assisted extraction of phenolic compounds from wine lees	Genetic algorithm	Evolutionary methods
[72]	Sustainable food (milk) supply chain distribution system	Nondominated sorting genetic algorithm of kind II	Evolutionary methods
[112]	Calibration models to measure the total anthocyanins content in flowering tea	Ant colony optimization combined with interval partial least squares (ACO-iPLS) (the authors also used full-spectrum PLS, iPLS, and genetic Algorithm-iPLS for comparison)	Swarm intelligence methods
[117]	Osmotic dehydration of mushrooms	Firefly algorithm	Swarm intelligence methods

Publication year: 2014.

Table 3: Publications of stochastic methods applied to food engineering problems in food by country.

Country	Number of publications
China	21
India	20
United States of America	14
Turkey	10
Iran	9
Canada	8
Malaysia	7
Japan	6
United Kingdom	6
Germany	5
Taiwan	5
Spain	4
Thailand	4
Australia	3
Chile	3
Ireland	3
Portugal	3
Russia	3
Brazil	2
France	2
Greece	2
Italy	2
New Zealand	2
United Arab Emirates	1
Belgium	1
Brunei Darussalam	1
Colombia	1
Denmark	1
Iraq	1
Mexico	1
Singapore	1
Sultanate of Oman	1
The Netherlands	1

Period: January 1994–February 2021.

4. Final Remarks and Future Perspectives

This review explored the role of optimization in food engineering, a field characterized by complex processes with nonlinear dynamics, multiple variables, and mixed constraints. Due to these complexities, the need for robust optimization techniques in this area was highlighted. Unlike deterministic methods, stochastic techniques can handle the inherent variability present in food processing. They offer advantages such as being adaptable to multiobjective problems, handling various decision variable types, and performing well with highly nonlinear problems.

It was evaluated that evolutionary algorithms, particularly genetic algorithms (GAs) and its variants, are the most widely used (45% of reviewed publications) and they address various tasks in food engineering, such as process optimization, food categorization, and logistics. Swarm intelligence methods (23% of the publications) are the second most common, with particle swarm optimization (PSO) being popular for optimizing processes, production planning, and supply chain problems. While less frequent (15% of publications), random search methods like simulated annealing (SA) are also used.

Particularly, genetic algorithms (GAs) and differential evolution (DE) emerge as particularly popular choices for tackling food engineering optimization problems, demonstrating their effectiveness in real-world applications. These methods excel due to their well-rounded capabilities. They efficiently find good solutions for complex problems, even as the problem size increases. This efficient scaling, sometimes nearly linear, makes them ideal for tackling large and intricate optimization tasks. In addition, their inherent parallel nature allows them to run on multiple processors simultaneously, significantly accelerating the optimization process.

The main drawback of these optimization methods relies on the tradeoff between success performance to find the global optimum solution and the corresponding numerical effort. Overall, all the stochastic methods utilized heuristics and arbitrary parameters as stopping criteria. This context has a direct impact on the algorithm performance since the probability to find the global solution for a given objective function increases with the numerical effort (i.e., computer time) performed by the optimizer. For the case of food engineering optimization with several decision variables, it could be expected that the reliability of stochastic optimization methods would be significantly affected by the defined stopping criterion. Therefore, it is necessary to develop proper stopping conditions to improve the performance of these numerical tools for optimization problems with several decision variables.

From a business perspective, extensive computational efforts to solve optimization problems can present challenges. While it might not guarantee finding the absolute best solution, it can significantly extend analysis times, leading to delays and potentially impacting profitability. In addition, with some problems, multiple solutions might be equally optimal, requiring further analysis to identify the most suitable option for the process.

It has been also observed that systematic performance comparisons of different stochastic optimization methods have not been reported using food engineering optimization problems. The selection or application of a specific optimizer is commonly not based on the feedback from numerical studies that justifies its reliability and efficiency to solve the problem under analysis. It appears that GA has been widely used in food engineering optimization due to its wide applications in other fields. However, it has not been proved that this method can offer the best performance for solving different optimization problems in food engineering.

Presently, no stochastic algorithm is universally effective for all food engineering problems. Moreover, there is a lack of characterization regarding the optimal algorithm for specific challenges such as global and multiobjective optimization problems within the food industry. Research studies are required to assess and categorize the performance of novel stochastic optimization methods in the resolution of food engineering optimization problems with different characteristics as decision variables and the presence of constraints. This evaluation is required to identify better optimizers that can resolve multivariable challenging functions with the lowest numerical effort.

Table 4: Description of the objective function(s) and decision variable(s) of food engineering optimization problems resolved with stochastic optimization methods.

Reference	Application	Decision variables	Objective
[11]	Thermal sterilization of packaged foods	Constant retort temperature and process time	Maximize food quality factors (thiamine and texture retentions of pork puree) and minimize processing time
[12]	Thermal processing of canned foods	Variable retort temperature profile	Maximize final retention of a specified quality factor (thiamine) and minimize final process time
[81]	Pectinase-assisted low-temperature extraction of cashew apple juice	Incubation time, incubation temperature and enzyme concentration	Maximize yield, clarity, ascorbic acid content, polyphenol content, protein content, and total soluble solids and minimize turbidity, viscosity, pH
[43]	Fish oil microencapsulation by spray drying	Aqueous phase content, oil proportion in total solids, and emulsification time	Maximize exergy efficiency and encapsulation efficiency
[103]	Deep-fat frying of ostrich meat plates	Microwave power, temperature, and frying time	Minimize shrinkage percentage and fat content of deep-fat frying ostrich meat plates and keep their moisture content in a legal range
[46]	Simultaneous lot sizing and scheduling of perishable products (yogurt) problem	Variables as quantity of products produced, quantity of stock products, quantity of stock of product that spoils and production to stock of product, among others and depending on the model used	Minimize the total production costs and maximize the average freshness of delivered products
[25]	Batch beer fermentation	Temperature profile	Minimize the risk of beer spoiling by *Lactobacillus plantarum*, minimize abrupt changes of temperature, minimize of both total and instant heat cost of the process, minimize the maximum difference of heat between two successive intervals (it is used to assume uniform consumption and to smoothen the energy cost) and minimize the total time of the process
[44]	Logistical management problem of wheat	Amounts of wheat to be transported from each producing province to each consuming province per month across the year	Minimize the total cost including the storage cost in warehouses which belong to the government trade corporation, warehouses which belong to the village's cooperation organization (VCO) and warehouses assigned to the flour factory, as well as the transportation cost between provinces and VCO charges
[45]	Bioreactor for batch production of xylitol (fermentation process)	Medium composition	Maximize the xylitol yield
[21]	Air drying of foods	Air dry bulb temperature and its relative humidity	Maximize the nutrient or enzyme retention, minimize the processing time, and maximize the energy efficiency
[79]	Supercritical extraction of β-carotene from *Aloe barbadensis* Miller	Operating conditions (temperature, pressure, and carbon dioxide flow rate)	Maximize the amount of β-carotene extraction yield
[102]	Cold food chain logistics problem	Vehicle number route for distribution and also quantities distributed by each vehicle to each market	Minimize the associated logistics transportation costs from depot to markets together with the safety loss costs in the cold chain logistics system
[47]	Hydrolysis of cassava starch by α-amylase from *Aspergillus niger*	Starch concentration, reaction temperature, and reaction time	Maximize the yield of hydrolysis

Table 4: Continued.

Reference	Application	Decision variables	Objective
[48]	Solid-state fermentation for laccase production	Surfactant concentration, pH, particle size, liquid to solid ratio, and incubation period	Maximize laccase activity
[27]	Batch beer fermentation	Temperature profile	Maximize ethanol levels
[37]	Fed-batch bioreactor (fermentation)	Feed rates of carbon source, nitrogen source, and oxygen source and the initial batch volume	Maximize xanthan gum formation
[51]	Fed-batch fermentation	Feed rate profile	Maximize the amount of biomass (backer's yeast *S. cerevisiae*) quantity at the end of the reaction
[122]	Vehicle routing problem in fresh food e-commerce	Routes to deliver various products from a depot to multiple customers	Minimize total cost (including the fixed cost, the travel cost, the refrigeration cost, and the carbon emission cost)
[49]	Thermal processing of canned foods	Variable retort temperature (VRT) function parameters	Minimize process time (or heating time) and surface cook value
[50]	Thermal processing of canned foods	Parameters of retort temperature profiles	Minimize process time and surface cook value
[52][a]	Fed-batch fermentation	Feed flow rate, feed concentration, initial glucose concentration and initial volume, and fermentation time	Maximize ethanol production rate
[93]	Feature selection in seed discrimination	Subset of features	Maximize classification rates
[115]	Metabolic engineering (microorganisms manipulation towards the desired phenotype)	Set of gene knockouts	Maximize the production of the desired metabolites (succinate and lactate)
[53]	Feature selection in potatoes classification	Feature combination that is important to classify potatoes	Maximize the classification percentage (better feature combination reducing the number of features of the classifier)
[96]	A location-inventory supply chain for perishable products	Quantity of specific perishable product from specific warehouse to a specific retailer, quantity of specific perishable product from specific plant to specific warehouse, quantity of excess demand for specific perishable product at specific retailer, and quantity of excess supply for specific perishable product at specific retailer, among others	Minimize total cost
[41]	Scheduling of a heat exchanger network in milk pasteurization	Operational status (heating or cleaning) of each heat exchanger at every time instant; final outlet temperature of the heating medium (steam) at every time instant; final outlet temperature of the processing fluid (milk) at every time instant	Minimize the cleaning cost, overheating of milk (energy consumption), and flow rate of steam
[28]	Fermentation for batch production of exopolysaccharide	Media composition and inoculum volume	Maximize exopolysaccharide yield
[65]	Integrated production and distribution scheduling with a perishable product	The number of trucks, their routes, and the production sequence	Minimize the total cost of distribution
[54]	Time series sales forecasting for short shelf-life food products (applied to fresh milk)	Subset of variables to build a model that can predict the sales volumes	Minimize the prediction error
[13]	Thermal processing	Process temperature profile	Maximize the volume average retention of thiamine in conduction-heated foods
[14]	Thermal processing	Process temperature profile	Maximize the volume average retention of thiamine for different shapes (a sphere and a finite cylinder)

Table 4: Continued.

Reference	Application	Decision variables	Objective
[15]	Thermal processing	Process temperature profile	Minimize the processing time and/or maximize quality retention for a specified level of lethality in thermal processing of conduction-heated foods (spheres and finite cylinders)
[55]	Solid-state fermentation for extracellular lipolytic enzyme production by *Rhizopus oryzae*	Temperature, liquid to solid ratio, pH, and incubation time	Maximize lipase activity
[104]	Perishable food vehicle-routing problem with time windows	A set of vehicle routes	Minimize the distribution overall cost
[105]	Inventory facility location for perishable food distribution centers	Select the distribution centers	Minimize the system of distribution of fresh agriproducts cost
[106]	Sustainable supply chain network of perishable food	The location of facilities, the size of each shipment, and the most efficient vehicle routes	Minimize logistic costs and environmental impacts of CO_2 emissions
[36]	Solid-state fermentation process for production of protease enzyme by *Aspergillus niger*	Airflow rates, air temperature, moisture content, parameters for cooling, and pressure	Maximize enzyme activity versus minimize fermentation time and maximize productivity to cell yield coefficient versus minimize fermentation time
[82]	Sodium gluconate fermentation process	Operating conditions	Maximize conversion rate, maximize utilization rate of the equipment, and minimize reaction time
[56]	Enhancing lipase production by a soil microorganism fermentation	Media constituents	Maximize lipolytic activities of a soil microbial culture
[107]	Bakery production planning	The starting times of all products on all stages (best possible schedule setup); 40 different products and 26 different production stages	Minimize the makespan (which represents the required time to complete the given production goal and equals the highest end time of the products), minimize the total idle time of machines (which the time span a machine or stage is ready and free to process a job but has to wait for a product that has not finished its processing on a previous stage yet)
[23]	Bakery production scheduling	The starting times of all products on all stages (best possible schedule setup); 40 different products and 26 different production stages	Minimize the makespan (which represents the required time to complete the given production goal and equals the highest end time of the products), minimize the total idle time of machines (which the time span a machine or stage is ready and free to process a job but has to wait for a product that has not finished its processing on a previous stage yet)
[83]	Batch cooling crystallization of citric acid anhydrate	Crystallizer temperature profiles	Maximize mean crystal size and minimize variance in size
[84]	Oil palm production	Identify the relevant variables and search for the best combinations for modeling to examine the potential of oil palm production	Maximize the intercorrelation and minimize intracorrelation
[80]	Distribution planning for perishable foods (chilled meat) in cold chains	Amount of food within the specific quality level delivered to specific customer, shortage amount of specific food to specific customer, time of arriving at specific customer, load of the vehicle, among others	Minimize the overall cost which arises from vehicle-related and product-related aspects
[26]	Fed-batch fermentation to producing ethanol	Feed rate, feed total initial sugar concentration, and fermentation time	Maximize ethanol production rate

Table 4: Continued.

Reference	Application	Decision variables	Objective
[58]	Vegetable oil hydrogenation process	Reaction temperature, H_2 pressure, catalyst concentration, agitation frequency, expected iodine value, and content of initial unsaturated fatty acids including oleic, linoleic, and linolenic acid	Minimize total trans isomer and maximize cis-oleic acid formation during the hydrogenation process
[113]	Cr (VI) adsorption process on sustainable adsorbent derived from waste biomass (sugarcane bagasse)	Estimation of parameters from a nonlinear isotherm/kinetic model	Minimize two statistical metrics called Pearson's chi-square measure (χ^2), and root means square error (RMSE)
[123]	Molecular distillation of olive pomace oil	Pressure and temperature	Maximize tocopherols and minimize squalene concentrations in the oil
[40]	Baker's yeast drying in large scale batch fluidized bed	Flow rate of inlet air and temperature of the inlet air	Maximize product quality while minimizing energy consumption
[97]	Fermentation process for xylitol production	Substrate feed rate; substrate feed rate and the operating time	Maximize the xylitol production
[95]	Enzymatic production of acylglycerols	Feed rate profiles	Maximize monoacylglycerols yield; maximize de sum of monoacylglycerols and diacylglycerols yields; maximize the diacylglycerols yield
[119]	Gene knockout identification for producing high yields of succinate and lactate in *Echerichia coli*	Gene knockout identification	Maximize yields of lactate in *E.coli*
[86]	Confectionery stoving to produce soft-jelled candies	Airflow rate and percentage of outdoor air used in the stove	Minimize energy usage and initial cost
[108]	Enzymatic pretreatments of oat bran	Viscozyme L concentration, incubation time, pH, and incubation temperature	Maximize protein extraction
[101]	Vanillin production by the Baker's yeast *Saccharomyces cerevisiae*	Sets of gene knockouts	Maximize production of vanillin
[42]	Milk microfiltration	Operating variables (temperature, pressure, cross-flow velocity)	Maximize the flux for whole and skim milk
[33]	Fed-batch fermentation of *Aspergillus niger*	Initial batch volume, the fermentation time, feed rates of sucrose, nitrogen source, and oxygen	Maximize expressions of one of the products (catalase) while keeping the other product (protease) expressions within threshold limits
[10]	Sugarcane transport scheduling system	Amount of food within the specific quality level delivered to specific costumer, time of arriving at specific customer, load of vehicle, among others	Minimize the makespan (equivalent to maximizing the throughput of sugarcane transport)
[85]	Lipase production from Penicillium roqueforti ATCC 10110 in solid-state fermentation	Fermentation time, incubation temperature, and percentage moisture content	Maximize lipase production
[60]	Fruit-storage process	The relative humidity in the storage house	Minimize water loss and the development of lesions by fungi and bacteria in the fruit
[61]	Heat treatment for fruit (tomatoes) during storage	Temperature	Minimize the change of the color representing the ripening of fruit
[62]	Tomato cool storage	Step setpoints for temperature	Minimize the rate of water loss
[87]	Distribution of perishable products	Customer service routes	Minimize the number of accumulated damaged products along the routes and minimize the distance travelled by the vehicle
[63]	Pork meat dehydration–impregnation–soaking process	Operating conditions	Minimize the total process duration, maximize the final mass yield

Table 4: Continued.

Reference	Application	Decision variables	Objective
[64]	Beer fermentation process (batch fermentation)	Temperature profile	Minimize the operation time and optimize the quality of beer
[16]	Vehicle routing for the distribution of fresh vegetables	Number of vehicles and number of the customers for vehicle	Minimize overall distribution cost
[17]	Vehicle routes in a bakery company	Delivery dates	Minimize the total distance travelled for the daily routes over the week
[38]	Xylitol production by *Debaryomyces nepalensis* in bioreactor	Fermentation conditions (time, pH, agitation, aeration, concentration of biomass, and concentration of glycerol)	Maximize xylitol production
[29]	Fed-batch bio-reactors for secreted protein production	Fed-batch operation time and the substrate feed rate at discrete interval points	Maximize productivity and maximize yield; maximize productivity and minimize fed-batch time; maximize yield and minimize fed-batch time; maximize productivity, maximize yield and minimize fed-batch time; maximize productivity and end minimize endpoint substrate concentration
[92]	Transportation route of fresh food	Logistics transportation path combination	Minimize the total cost of cold chain logistics transport (transportation cost, cargo damage cost, and power consumption cost)
[94][b]	Fed-batch fermentation processes	Feeding trajectory	Maximize the product concentration
[34][c]	Fed-batch fermentation processes	Feeding rate profile	Maximize the productivity/final amount of product
[8]	Beer fermentation	Temperature profile	Maximize ethanol production and minimize process time
[120]	Beer fermentation	Temperature profile	Minimize batch time and maximize product ethanol concentration
[121]	Anaerobic fermentation of glucose in a suspended cell culture	Modulation of enzymes	Maximize the production rates of ethanol, glycerol, and carbohydrates by *Saccharomyces cerevisiae*
[32][d]	Fed-batch bioreactor	Feed trajectory	Maximize foreign protein production
[18]	Quality of espresso coffee by pod	Extraction temperature, time and the composition of the coffee mixture	Minimize the difference between espresso coffee's sensory attributes and target property values
[88]	The production of phycobiliproteins (PBPs) from cyanobacteria	Concentration of ferric ammonium citrate, K_2HPO_4, and trace metals	Maximize phycobiliproteins production
[9]	I: production of secreted heterologous protein by a yeast strain in a fed-batch bioreactor; II: fed-batch production of induced foreign protein using recombinant bacteria; III: isothermal CSTR with complex reactions; IV: fed-batch growth of yeast	Feed flow rate, nutrient and inducer feeding strategy, four control variables, glucose feeding policy	Maximize the total secreted protein, maximize the profitability of the process for a specific final time, maximize the economic benefit of the isothermal CSTR, and maximize the profit defined as the difference between the product value (cell mass) and the operating cost
[89]	Vehicle-routing problem in the beverage logistics industry	Route for sequencing customers to be visited by each vehicle	Minimize total cost, which is related to the travelled distance
[109]	Integrated production and distribution planning model for perishable products	Production quantities, the distribution centers that must be visited and the quantities to be delivered to them	Minimize the total cost

Table 4: Continued.

Reference	Application	Decision variables	Objective
[57]	Prefrying microwave drying and frying conditions of French fries	Microwave power, microwave time, frying temperature, and frying time	Minimize oil content, moisture content, and textural property, and maximize luminosity color component, chromatic color component, and chromatic component
[59]	Process variables during single screw extrusion cooking of a fish and rice flour blend	Extruder barrel temperature, extruder screw speed, fish content, and moisture content of the feed	Maximize expansion ratio, minimize bulk density, minimize hardness, and maximize the water solubility index
[7]	Media composition for the production of α-amylase from this strain	Process operating variables: yeast extract concentration, starch concentration, K_2HPO_4 concentration/percentage, and $MgSO_4$ percentage	Maximize amylase yield
[66]	Cocoa butter analog synthesis variables	Process variables: pressure, temperature, tristearin/camel hump fat ratio, water content, and incubation time	Minimize the difference between the main TAG of cocoa butter analog and the main TAG of natural cocoa butter
[67]	Acidolysis reaction between mustard oil and capric acid by using *Thermomyces lanuginosus* lipase	Substrate ratio, time, temperature, enzyme content, and stirring speed	Maximize incorporation of capric acid into mustard oil
[19]	Thermal processing of canned foods	Variable retort temperature profiles	Maximize quality retention of a specified quality factor (thiamine); minimize process time
[110]	Cooperative transportation planning	Tour plans for external transportation between the locations of the manufacturers and intermediate distribution center	Maximize the efficiency of the transportation operations
[68]	Pig food formulations	Blending of various ingredients	Minimize the cost under the conditions of the ingredient prices and pig's nutritional requirements such as energy, fat, protein, minerals, and vitamins. The requirements and the average price of pig food are primarily considered as multiple objectives for Era-GAs scheme
[30][e]	Production of secreted protein in fed-batch bioreactor	Nutrient feed-rate profile	Maximize the secreted heterologous protein
[31][f]	1: yield of the intermediate product B at the end of operation in a batch reactor; 2: foreign protein production using recombinant bacteria	Temperature profile, glucose feed rate, and the inducer feed rate	Maximize the yield of the intermediate product B and maximize the economic benefit
[111]	Metabolic engineering	Sets of gene knockouts	Maximize the production rate of succinate and lactate
[69]	Ultrasound-assisted extraction of phenolics from wine lees	Extraction time, extraction temperature, solvent-to-solid ratio, and ethanol concentration	Maximize extraction yield of total phenolics or total anthocyanins
[39]	Fed-batch production of xylitol	Feeding profiles fed with glucose and xylose (separate feeds of xylose and glucose and another case with a single-feed stream consisting of a mixture of the two substrates)	Maximize the production rate of xylitol
[70]	Fish and rice flour coextrudates during single-screw extrusion cooking	Process variables: barrel temperature, screw speed, fish content, and feed moisture	Minimize the moisture and fat and maximize the protein content of the extrudates
[72]	Sustainable food (milk) supply chain distribution system	Routes and vehicle/trucks type	Minimize CO_2 emissions from transportation and total costs in the distribution chain
[71]	Irish dairy manufacturing supply chain distribution system	Routes from "plants" to "consumers"	Minimize the sum of carbon emissions (i.e., maximize "greening" effect) and minimize the sum of costs associated with product distribution

Table 4: Continued.

Reference	Application	Decision variables	Objective
[90]	Ultrasonic probe extraction of phenolic compounds from olive leaves	Amplitude, irradiation time, solvent (MeOH/EtOH) concentration, probe position, and duty cycle	Maximize the total phenolic content, oleuropein content, and total antioxidant activity in the extraction
[73]	Fed-batch fermentation process to produce ethanol by *Saccharomyces cerevisiae*	Feeding rate and operation parameters	Maximize the production rate and minimize fermentation time
[24]	Batch and fed-batch fermentation for ethanol and glycerol production	Kinetic parameter estimation; feed rates and fermentation time	Minimize the weighted least-squares error; maximize the ethanol production rate
[100]	Microbial fermentation in batch culture	Dilution rate	Maximize the yield of the 1,3-propanediol
[74]	Classification of rice grain	Zernike moments	Maximize the classification performance and minimize the input features to neural network
[75]	Transportation routing for fresh food	Transportation routing	Minimize transportation cost
[98]	Beer fermentation	Temperature profile	Maximize final ethanol production and minimize byproducts concentration and spoilage risk
[112]	Calibration models for measuring the total anthocyanins content in flowering tea	Set of intervals (i.e., features) for the PLS model	Minimize the correlation coefficient between predicted and measurement of PLS for the calibration set
[76]	Economic lot scheduling problem	Production frequency for a specific item and basic period in the production planning horizon	Minimize cost
[117]	Osmotic dehydration of mushrooms	Process parameters (temperature, concentration, and duration)	Maximize the percentage of water loss while the salt gain needs to be as close to 2.98% as possible
[118]	Osmotic dehydration of papaya	Process parameters (temperature, concentration, and duration)	Maximize the percentage of water loss while the sugar gain needs to be as close to 4% as possible
[77]	Baker's yeast drying process	Air temperature and air humidity	Maximize the quality of the dried end product and minimize the energy consumption during drying
[35]	Fed-batch fermentation process	Feed flow rate	Maximize biomass concentration and minimize ethanol (byproduct) formation
[22]	Baker's yeast fermentation process	Feeding flow profile	Maximize the biomass concentration, minimize total ethanol formation, and obtain the average substrate growth rate close to the critical growth rate
[91]	Baker's yeast drying process	Air temperature and the humidity of the air	Minimize energy consumption and maximize quality (in terms of product activity and moisture content)
[78]	Supercritical fluid extraction of nimbin from neem seeds	Operating values of temperature, pressure, carbon dioxide flow rate, and particle size	Maximize profit

Table 4: Continued.

Reference	Application	Decision variables	Objective
[20]	Structure of deep-frozen and chilled food chain	Goods flow over a long-term planning horizon (locate the central and distribution cold stores, allocate the central cold stores to plants, as well as allocate the distribution cold stores to central cold stores or plants)	Minimize the total operating costs for warehousing and transportation
[99][g]	Foreign protein production	Glucose feed rate and inducer feed rate	Maximize economic benefit
[116]	Classification of citrus fruit blemishes	Wavelength combination	Minimize the correlation relationship between wavelengths
[114]	Design of agrifood supply chain network	Amount of raw agricultural products collected within a specific region, amount of moving raw agricultural products from a specific location into another by specific transportation mode, the production amount of finished product with a specific type in a specific plant, among others	Minimize the sum of production cost and transportation cost of agrifood supply chain network

Period: January 1994–February 2021. [a]It is not clear if the ethanol production of the strain of *Zymomous mobilis* considered in this study can be used for the food industry. [b]Although the fermentation model described in this publication has as a product a biopharmaceutical product, perhaps it can be used in food industries. [c]Although the authors [94] of this fermentation model describes the product as a biopharmaceutical product, perhaps it can be used in food industries. [d]Maybe β-galactosidase produced by *Escherichia coli* D1210 and plasmid pSD8 can be used in food industries [158]. [e]This model of secreted protein production was obtained using SEY2102 as a model host yeast and SUC2-s2 as a model secretory protein [159]. Maybe SUC2-s2 can be used in food industries. [f,g]Maybe β-galactosidase produced by *Escherichia coli* D1210 and plasmid pSD8 can be used in food industries [158].

Another challenge in applying stochastic methods to food engineering problems is the necessity for effective and reliable tools capable of handling constrained multiobjective problems. It is very common that maximizing the quality of food products conflicts with minimizing process costs. In this way, the optimization of processes should always consider all the objectives and restrictions that lead to the real interest of the market, which culminates in the generation of profit. Research brings more practical results when considering multiple objectives, better representing real-world scenarios.

The development and testing of novel stochastic optimizers for solving both global and multiobjective optimization problems are fundamental for food engineering and further research should be performed in this direction.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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