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Review

Food processing optimization using evolutionary algorithms

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Evolutionary algorithms are widely used in single and multi-objective optimization. They are easy to use and provide solution(s) in one simulation run. They are used in food processing industries for decision making. Food processing presents constrained and unconstrained optimization problems. This paper reviews the development of evolutionary algorithm techniques as used in the food processing industries. Some evolutionary algorithms like genetic algorithm, differential evolution, artificial neural networks and fuzzy logic were studied with reference to their applications in food processing. Several processes involved in food processing which include thermal processing, food quality, process design, drying, fermentation and hydrogenation processes are discussed with reference to evolutionary optimization techniques. We compared the performances of different types of evolutionary algorithm techniques and suggested further areas of application of the techniques in food processing optimization.

Key words: Evolutionary algorithms, optimization, food processing, multi-objective, constrained and unconstrained.

INTRODUCTION

Evolutionary algorithms (EAs) are computational-based biological-inspired optimization algorithms. They are stochastic searching methods, commonly used for solving non-differentiable, non-continuous and multi-modal optimization problems based on Darwin's natural selection principle. They imitate the process of natural evolution and are becoming important optimization tools for finding the global optimum solutions in several real world applications. EAs operate on a population of potential solutions, applying the principle of survival of the fittest to produce successful and better solution by means of evolutionary resembling operations (selection, reproduction and mutation), which are applied on individuals in a population (Ronen et al., 2002). EAs are widely used for single and multi-objective optimization in food processing. Modern day food processing involves a lot of decision making resulting in many objective functions and constraints. EAs can generate Pareto optimal solutions for these models.

Most manufacturing industries are in a continuous effort to increase their profits and reduce their production costs due to the strong competition that exists among them. Food processing as an aspect of biotechnology is recently facing remarkable challenges revolving around maximizing profit in a dynamic and an uncertain environment, while satisfying a variety of constraints such as quality of final product, financial, environmental, safety and human constraints. In response to such challenges, food industries are trying to improve process operations by using better technology. Processing optimization includes a performance evaluation function, control variables, constraints and a mathematical model (Evans, 1982).

Capitalizing on newly available technologies, the food industries have recently started using sophisticated technologies to improve, monitor, optimize and control food processing parameters such as moisture content,

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temperature, concentration of microorganisms and nutrients (Rodríguez-Fernández et al., 2007). These techniques use expert knowledge to achieve a superior performance. In a situation where problem specific technique is not applicable due to unknown system parameters, the multiple local minima, or non-differentiable evolutionary algorithms (EAs) have the potential to overcome these limitations (Price, 1999), by using mathematical model based techniques to make decisions about optimal production scenarios. In standard practice, simulation of multiple future production scenarios using numerical model in solving a related optimization problem in food processing have been discussed (Boillereaux et al., 2003; Mariani et al., 2008).

Many real-world problems have multiple often competing objectives. The optimization of food processing operations may not be an easy task due to complexities and variations in the raw materials (Vradis and Floros, 1994). EAs as a class of direct search algorithms have proved to be an important tool for difficult search and optimization problems and have received increased interest during the last decade due to the ease way of handling multiple objective problems. A constrained optimization problem or an unconstrained multi-objective problem may in principle be two different ways to pose the same underlying problem and can be solved by EAs (Karaboga, 2004; Saputelli et al., 2004). EAs are of interest to finding solution to real world problems because they are proving robust in delivering global optimal solutions which help in resolving limitations encountered in traditional methods. Among the optimization techniques that have been applied to solving complex problems, which includes; linear programming (LP), non-linear programme (NLP), dynamic programming (DP), stochastic dynamic programming (SPD) and heuristic programming such as genetic algorithm (GA), differential evolution (DE), shuffled complex evolution, fuzzy logic (FL), simulated annealing (SA), ant colony optimization (ACO), particle swarm optimization(PSO) and artificial neural networks (ANNs) (Sarker and Ray, 2009; Adeyemo, 2011; Matijasevic et al., 2010; Kennedy and Eberhart, 1995).

DESCRIPTION OF SOME EVOLUTIONARY ALGORITHMS

GAs are evolutionary search and optimization algorithms based on the mechanics of natural genetics and natural selection. They mimic natural evolution to making a search process in which solution is encoded as a string of binary digits. However, new GAs that use real numbers for encoding are now common. Genetic operators, such as selection, mutation and crossover are used to generate new solutions until a stopping criterion is satisfied (Babu and Munawar, 2007; Mohebbi et al., 2008). GA has been successfully used in science and engineering application to reach near-optimum solutions to a variety of problems (Gen and Cheng, 1996) since its introduction by Holland (1975). GA requires long processsing time for a near-optimum solution to evolve.

In an attempt to reduce the processing time and improve the quality of solutions, differential evolution (DE) was introduced by Storn and Price (Storn and Price, 1995). DE is a population based algorithm like genetic algorithm using similar operators; crossover, mutation and selection for optimization problems. Unlike conventional GA that uses a binary coding for representing problem parameters, DE algorithm represents each variable in the chromosome by a real number. The principal difference between GA and DE is that GA relies on crossover, a mechanism of probabilistic and useful exchange of information among solutions to locate better solutions, while evolutionary strategies use mutation as the primary search mechanism (Godfrey and Babu, 2004). DE selection process and its mutation scheme make DE self-adaptive. DE uses non-uniform crossover and tournament selection operators to create new solution strings. All solutions in DE have the same chance of being selected as parents without dependence on their fitness value. DE employs a greedy selection process (Karaboga, 2004). Some advantages of DE include its robustness, simple structure, ease of use, speed, quite selective in nonlinear constraint optimization including penalty functions, easily adaptable for integer and discrete optimization, and usefulness in optimizing multi-modal search spaces (Abbass et al., 2001; Strens and Moore, 2002). DE algorithm is a stochastic optimization method, which minimizes an objective function that can model the problem's objectives while incorporating constraints. It can be used for optimizing functions with real variables and many local optima (Pierreval et al., 2003). The performance of DE algorithm to that of some other well-known versions of genetic algorithm was compared and the simulation results showed that the convergence speed of DE is significantly better than genetic algorithms (Abbass et al., 2001; Strens and Moore, 2002; Karaboga, 2004).

An artificial neural network (ANN) is a collection of interconnecting computational elements which simulates like neurons in biological systems. ANNs allow researchers to build mathematical models of neurons and mimic neural behaviour of complex real systems in a relatively simple manner. ANNs are trained in an efficient way and a model is developed to deal with the system's intrinsic nonlinearities. It has the ability of relating the input and output parameters without any prior knowledge of the relationship between them (Chen and Ramaswamy, 2002; Goni et al., 2008). ANNs may be used to estimate or predict process behaviour without the need of a mathematical model, or a prediction equation associated to the physical problem (Ramesh et al., 1996). The complexity of the problem determines the number of neurons in a model. ANNs are widely used in pattern recognition and pattern classification, diagnosis and control as well as function approximation and optimization (Bose and Liang, 1996).

The introduction of fuzzy set theory by Zadeh (1975) to deal with problems in which a source of vagueness is involved has been reported. Fuzzy modeling is a powerful method, taking advantages of both scientific and heuristic modelling approaches. Fuzzy modelling utilizes the past data and expert knowledge convincingly than conventional methods. Fuzzy logic (FL) mimics human control logic. It can be built into anything from small, hand-held products to large computerized process control systems. It uses an imprecise but very descriptive language as a human operator to deal with input data (Huang et al., 2010). Although, the ability of fuzzy systems to solve different problems with various applications has been established, and an increasing interest in augmenting them with learning capabilities by soft-computing methods such as genetic fuzzy systems is developing (Liao et al., 2001).

APPLICATION OF EVOLUTIONARY ALGORITHMS IN FOOD PROCESSING

A good food processing model will combine the laws of heat, mass and momentum transfer with prediction equations for the physical properties of food, quality and safety kinetic models to reflect how the relevant state variables change with time and position when the food load is subjected to different processing conditions (Tijskens et al., 2001; Wang and Sun, 2003). Moreover, shortage and surplus of goods can lead to loss of income for many companies due to the short shelf-life of their products. Therefore, optimization techniques are necessary in food processing to incorporate the economic values for the processing and marketing of food.

There is a need to maintain high product quality considering the uncertainties and fluctuations in consumer demands. This made food companies to be more concerned in improving very important parts of food processing operations. For example, an improved technique for drying, wetting, heating, cooling and freezing of foods are necessary (Doganis et al., 2006). Hence, model-based optimization is of extreme importance in modern food processing. Computer aided-engineering have significantly helped during the last decades in optimal control problems of food processing. Thermal processing function is an important food preservation method to inactivate bacterial spores of public health significance as well as food spoilage microorganisms in sealed containers of food, using heat treatments at temperatures well above the ambient boiling point of water in pressurized steam retorts (autoclaves) that are not detrimental to food quality and underutilize plant capacity (Simpson et al., 2003; Holdsworth and Simpson, 2007; Abakarov et al., 2009).

The ability of GA to solve multi-objective problems makes them valuable tools for application in food processing systems. The various applications of GAs are computer-aided molecular design (Shunmugam et al., 2000), optimal design of xylitol synthesis reactor (Baishan et al., 2003), on-line optimization of culture temperature for yeast fermentation (Yüzgeç et al., 2009), optimization of ethanol production (Rivera et al., 2006; Guo et al., 2010) synthesis and optimization of non-ideal distillation system (Fraga and Senos, 1996) and estimation of heat transfer parameters in trickle bed reactors (González-Sáiz et al., 2008). Some other applications of genetic algorithm include determining the thermal deterioration of vitamin C in bioproduct processing such as concentration, drying and sterilization, semi-real-time optimization and control of fed-batch fermentation system (Koc et al., 1999; Maria et al., 2000; Zuo and Wu, 2000).

Optimization of process variables using genetic algorithm during single screw extrusion cooking of a fish and rice flour blend was investigated by Shankar and Bandyopadhyay (2004). The objective was to optimize the process variables for each and all extrudate properties during cooking of a fish and rice flour blend. Second-degree regression equations were developed by response surfaces methodology (RSM) for screw speed, expansion ratio, water solubility index, bulk density, hardness, barrel temperature, feed moisture content and fish content as process variables, and optimized using genetic algorithm. The results showed that under individual optimum process conditions, minimum bulk density and maximum water solubility index required high fish content of 41 to 45% and medium moisture content of about 40%, respectively and maximum expansion ratio and minimum hardness required a low fish content of 5% and feed moisture contents of 60 and 40%, respectively. Under common optimum process conditions, all four extrudate properties were optimized at a high fish content of 41 to 45% and medium moisture content of 40%. The study concluded that the common optimum process conditions predicted the properties of the end product more closely than the individual optimum conditions determined for each extrudate property.

The efficiency of a nonlinear predictive control genetic algorithm was developed by Yuzgec et al. (2006) to determine the optimal drying profile for a biomass drying process by using a model of a batch fluidized bed drying process of the baker's yeast that had been developed by Yüzgeç et al. (2004). The objective of this work was to develop a control procedure for a nonlinear drying process in order to increase the quality of product at the end of the process, decrease the energy consumption during drying and reduce the cost of the process. The simulation results showed that the performance of the drying process is an important factor in the food industry to enhance the manufacturing quality and decrease the energy consumption. The drying time and sometimes, the cost of the process can be reduced. Similar works that incorporate genetic algorithm-based optimization for the predictive control have been reported in the literature (Quirijns et al., 2000; Na et al., 2002; Potocnik and Grabec, 2002; Haber et al., 2004). Mankar et al. (2002) studied an on-line optimization control of bulk polymerization of methyl methacrylate using GA to compute temperature in real time for a period of 2 min.

Artificial neural networks (ANNs) and genetic algorithm (GA) mimic different aspects of biological information processing for data modelling and media optimization. The evaluation of ANN supported GA for optimization problems in food science, environmental biotechnology, and bioprocess engineering have been well established (Baishan et al., 2003). ANN–GA based approach was used for simultaneous maximization of biomass and conversion of pentafluoroacetophenon with *Synechococcus* PCC 7942 (Franco-Lara et al., 2006) and optimization of fermentation medium for the production of xylitol from *Candida mogii* (Baishan et al., 2003; Desai et al., 2006). A hybrid methodology comprising the Plackett-Burman (PB) design method, ANN based modelling and GA was developed to enhance the optimization of media and inoculums volume for the exopolysaccharides production by *Lactobacillus plantarum* isolated from the fermented *Eleusine coracan*. PB was used to identify the most three influential media components. ANN was generated for approximating the non-linear relationship between the fermentation operating variables and the yield. Then the input parameters of ANN model was optimized using the GA based process optimization to obtain the maximum exopolysaccharides yield in the batch fermentation (Desai et al., 2006). The optimization of hydantoinase production from *Agrobacterium radiobacter,* production of lipase from a mixed culture and glucansucrase production from *Leuconostoc dextranicum* NRRL B-1146 by ANN–GA model using RSM based data was carried out by Nagata and Chu (2003), Haider et al. (2008) and Singh et al. (2008) respectively. Optimization results as shown in the literature, review the effectiveness of using hybrid algorithms.

Kovarova-Kovar et al. (2000) studied the optimization of fed-batch process for the riboflavin production. Later, thermal inactivation of glucoamylase and optimization of catalytic reaction of pancreas lipase was studied by Bryjak et al. (2004), Manohar and Divakar (2005), respectively. Chen and Ramaswamy (2002) developed an algorithm that combines the mathematical model with the optimization of variable retort temperature thermal processing for conduction-heated foods using ANNs-GA hybrid. A year later, Morimoto et al. (2003) presented the dynamic optimization of a heat treatment for minimizing water losses in tomatoes during storage. An artificial neural network and genetic algorithm were used to determine the optimal processing conditions for spray-dried whole milk powder processing by Koc et al. (2007). The researchers developed a general regression neural network model to predict the responses of lactose crystallinity and free fat content from the processor screw speed, process temperature, milk powder feed rate and lecithin addition rate during the evaluation of fitness function of a genetic algorithm optimization using response surfaces experimental design methodology. The genetic algorithm was used to determine both the individual and common optimal operating conditions for the whole milk powder process. It was demonstrated that the optimal conditions for spray-dried whole milk powder processing variables to produce maximum free fat content, maximum lactose crystallinity and minimum average particle size by using genetic algorithms and neural networks are obtainable. Izadifar and Jahromi (2007) used the experimental data set from a vegetable oil pilot plant reactor to develop a neural network model for a vegetable oil hydrogenation process. The neural network was used as a predictor to evaluate a combination of reaction conditions during the genetic algorithm optimization for the minimum isomer and maximum cis-oleic acid. The same year, Erenturk and Erenturk (2007) studied the drying kinetics of carrot using genetic algorithm and ANNs hybridization.

Applications of ANNs in food process modelling, control and quality evaluation of food products have been surfacing since 1990. Artificial neural networks have been applied in the twin-screw extrusion cooker control (Linko et al., 1992), prediction of dough rheological properties (Ruan et al., 1997) and meat quality prediction (Yan et al., 1998). More recently, ANNs have been receiving greater attention in drying technologies (Kaminski et al., 1998; Sreekanth et al., 1998; Chen et al., 2000), fermentation (Aires-De-Sousa, 1996), food rheology (Ruan et al., 1995) and thermal processing (Sablani et al., 1997a, b). Other applications of ANNs in food processing report include baking (Cho and Kim, 1998) and post harvesting (Morimoto et al., 1997a, b),

Boillereaux et al. (2003) determine the thermal properties of the gelatin gel during thawing using artificial neural networks. Mittal and Zhang (2000) developed a feed forward neural network to predict the freezing and thawing time of food products with simple regular shapes. In a similar study by Goni et al. (2008), they optimized the trial and error definition of the net parameters. The objective of their work was to develop and to validate three neural networks techniques; one for the prediction of freezing times, another one for the prediction of thawing times and a third one for both freezing and thawing times of foods of any shape and composition based exclusively on reported experimental data. The results showed that the developed ANNs were efficient for the estimation of freezing and thawing times of foods of all types, shapes, sizes and compositions and the developed genetic algorithm was also useful for improving the generalization ability of the neural networks.

Rodríguez-Fernández et al. (2007) proposed an integrated two-step identification model for air-drying of food. Structural identifiability analysis for model methods was carried out to improve the efficiency and robustness of model parameters. Drying of tomato using artificial neural network modelling was presented by Movagharnejad and Nikzad (2007). It was reported that the ANN model describes the drying behaviour of tomato more accurately than empirical correlations.

Considerable work on the variable retort tempera-tures (VRT) to improve the quality of canned food and significantly reduce processing times in comparison to traditional constant retort temperature (CRT) processing has been reported in the literature (Teixeira et al., 1969, 1975; Babu and Chaurasia, 2003; Banga et al., 2003). Chen and Ramaswamy (2002) searched the optimal variable retort temperature (VRT) thermal processing using coupled neural networks and genetic algorithm model for heated foods to identify optimal processing conditions that will reduce surface cook value and the process time to maximize the final nutrient retention of a conduction-heated canned food.

Olmos et al. (2002) studied the compromise between the final product quality and total process drying time of rice. Erdogdu and Balaban (2003) studied the optimization of thermal processing of canned foods using several objective functions. On the other hand, very little attempts have been made to solve the multi-objective optimization problem of nutrient destruction by the action of heat during the thermal sterilization of foods, although it is generally accepted that microbiological safety must be the primary objective but foods are sometimes over-processed especially canned foods (Fryer and Robbins, 2005). To this effect, Sendín et al. (2006) and (2010) recently proposed and successfully applied novel multi-criteria optimization method to the thermal processing of foods, where the minimization of total process time and the maximization of the retention of several nutrients and quality factors were simultaneous considered. The new strategy has proved to be efficient and robust when applied to the non-linear dynamic model considered. Ainscough and Aronson (1999) compared ANNs to linear regression for studying the same effects on yogurt. ANNs have been applied successfully to problems concerning sales of food products (peanut butter and ketchup), such as predicting the impact of promotional activities and consumer choice on the sales volumes at retail store (Doganis et al., 2006). They were found to perform better than linear models.

Since the development of differential evolution (DE) algorithm, it has been successfully applied to solve several optimization problems of chemical and biological processes (Chiou and Wang, 2001; Lu and Wang, 2001; Cheng and Wang, 2004; Liu and Wang, 2010). Other applications include; the fuzzy-decision making problems of fuel ethanol production (Wang et al., 1998), fermentation process (Chiou and Wang, 1999; Wang and Cheng 2001), other engineering applications by Babu and Angira, 2002; Babu and Jehan, 2003; Babu, 2004, 2007; Angira and Babu, 2006). These studies concluded that DE takes less computational time to converge compared to the existing techniques without compromising the accuracy of the parameters being estimated.

Sarimveis and Bafas (2003) proposed fuzzy model predictive control of non-linear processes using GA. Peroni et al. (2005) improved the simulation-based approximate dynamic programming method for optimal control of a fed-batch process and the optimal feed rate profile under varying initial conditions by a simulated-based control strategy. A recurrent neurofuzzy network based modeling and optimal control for a fed-batch process was presented by Zhang (2005). Perrot et al. (1998) combined fuzzy and genetic methods for optimal control of the microfiltration of sugar products. In this study, validation of the controller was carried out through simulation using a neural network model of the process and parameters of fuzzy controller were optimized off-line by GA. Petermeier et al. (2002) proposed a hybrid structure for modeling of the fouling process in a tubular heat exchanger for the dairy industry based on a combination of expert knowledge and parameterized equations in a fuzzy model. The ability of a fuzzy inference system to modeling and simulation of the cross ultra-filtration process of milk and to predict permeate flux and total hydraulic resistance under different hydro-dynamics parameters and operating time was studied by Sargolzaei et al. (2008).

The optimization of multiproduct batch plants design problem for protein production using fuzzy multiobjective algorithm concepts was carried out by Dietz et al. (2008). The developed model provided a set of scenarios that constituted a very promising framework for taking imprecision into account in new product development stage and in making decision. Kiranoudis and Markatos (2000) considered the multi-objective design of food dryers using a static mathematical model. The authors minimized simultaneously an economic measure and the colour deviation of the final product. A similar work was presented by Koc et al. (1999). Fuzzy logic was used in the real–time control of a spray–drying of whole milk powder processing. The objective was to increase the free fat content of the whole milk product and consistent colour. The algorithm used controlled the process at the desired power consumption and provided whole milk products with the desired colour values within 3.0 unit deviations. Also, the free fat content was over 95%, and lactose was in crystalline form in the final dry milk product.

CONCLUSION

This paper reviews the computational-based optimization technique algorithms that are becoming promising global optimization tools for major real world applications in finding global optimum solutions to food technology problems. New hybrid optimizers have been successfully developed to solve various constrained and unconstrained multi-objective optimization problems for modern food processing optimization. The paper reviewed some of the successful applications of optimization algorithms in the food processing industry. The successful applications of EAs suggested that EAs will have increasing and encouraging impact for solving real world problems in the manufacturing industry in the future. Therefore, to increase the ability of EAs for solving food processing problems, further research interest to exploit the abundant expert knowledge and deal with high dimensionality common to real world problems are needed.

The final quality and marketing of food products depend on their thermal treatment history. Due to this fact, application of new techniques for food treatment processes especially for the optimal treatment policies for the control of food products and processes regarding microbiological safety and final quality of food is very important. Therefore, fundamental research on the design, modelling, simulation and evaluation of different thermal food process scenarios and heating strategies is crucial. Recent interests are directed towards the simultaneous estimation of the thermal conductivity and heat capacity by means of single or dual heat probe methods to measure the temperature response in the food products.

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