MULTI-OBJECTIVE OPTIMIZATION OF DEEP-FAT FRYING OF OSTRICH MEAT PLATES USING MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION (MOPSO)

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ABSTRACT

Deep-fat frying (DFF) is a very old process that has grown exponentially over the last years. The attainment to a high and constant quality of fried products with appropriate oil content is of considerable interest to food industry and consumers; however, the theoretical aspects of the frying process are highly complex and difficult to understand. Many efforts were done in order to optimize and control the frying process. The majority of the authors have considered the use of single-objective for the optimization. However, the simultaneous optimization of several objectives is much more realistic and desirable. In this study a multi-objective optimization for DFF of ostrich meat plates was performed. Multi-objective particle swarm optimization is used to obtain the best solutions. This problem has three objective functions that must be satisfied simultaneously. Results show a Pareto that all the points on this Pareto are the best possible solutions.

PRACTICAL APPLICATIONS

Moisture content and fat content are very important quality indicators for fried foods in terms of health concerns and palatability of the products. Many efforts were done in order to optimize and control the frying process. The majority of the authors have considered the use of single-objective for the optimization. However, the simultaneous optimization of several objectives is much more realistic and desirable. In this study a multi-objective optimization for deep-fat frying of ostrich meat plates was performed.

INTRODUCTION

Deep-fat frying (DFF) is a fast, common and highly versatile process, which has been used from antiquity to prepare a wide range of foodstuffs. DFF can be defined as the process of drying and cooking through contact with hot oil. Fried food products are so popular, because the consumers prefer their taste, appearance and texture (Oztop *et al.* 2007). The unit operation of frying is basically a dehydration process. When a food is fried, water and any material within that water is pumped out of the food into the surrounding oil. Although frying is an operation that is thousands of years old, it is still being studied from an engineering standpoint and scientists are still trying to get a better understanding of how and why food fries (Stier 2000).

Moisture loss is an important factor in the frying process. It plays a determining role not only in heat transfer, but also in oil uptake because of its ability to create pores. During frying, a partial vapor pressure difference between the product and the frying oil causes the water to evaporate (Costa *et al.* 1999).

During DFF, oil affects the flavor and texture of the fried food. However, oil uptake in food during frying needs to be reduced for health reasons, and this is a major concern in the food industry. The main challenge therefore is to improve the frying process by controlling the quality aspects and lowering the final oil content of the fried product (Ziaiifar *et al.* 2008).

Optimization

To optimize the frying condition, the effects of the process parameters on the product quality have to be clearly understood (Kahyaoglu and Kaya 2006).

Solving optimization problems usually consists of two steps: (i) the development of models for the objective function; and (ii) the identification of optimal conditions that are searched. With the rapid development of computer technology and software, artificial intelligence technologies such as neural networks have been found to offer advantages over conventional methods to deal with system modeling, especially for those involving nonlinear and complex mathematical approaches. Optimization is finding the best solution for the objective function. In the real world, decisions have to be made based on more than one objective, and it may not be possible or satisfactory to reduce the objectives into a single objective. Multi-objective optimization (MOO) is the process of simultaneously optimizing two or more conflicting objectives subjected to certain constraints. These problems involve maximization or minimization of objectives, or a combination of both. Although there can be many objectives, most MOO problems in food engineering consider two or three objectives at the same time. MOO implies a decision-making process concerning a large number of optimal alternatives. From a practical point-of-view, the user is only interested in one final solution. The decision maker is the one responsible for selecting such a solution, who will assign preferences to the objectives using some additional information that quite often is subjective and/or difficult to express in mathematical terms (Seng and Rangaiah 2009; Sendín *et al.* 2010).

A wide range of approaches have been proposed in the last decades to solve multi-objective problems. Reviews of these methods can be found in the book section by Seng and Rangaiah (2009) and the references cited therein.

Therdthai *et al.* (2002) optimized the bread oven temperature to minimize the weight loss during baking for several values of baking times. Obviously, it is desirable to reduce the baking time, which is thus the second objective, but was considered as a constraint in their study. Olmos *et al.* (2002) studied the compromise between the final product quality and processing time by using the so-called e-constraint approach, i.e., the final product quality is maximized repeatedly subject to a constraint on the allowed total drying time, which is varied in each optimization.

Particle Swarm Optimization

In optimization problems, population methods are usually used to find solution(s) for the problem. In this article, a population method named standard particle swarm optimization (PSO) algorithm (Kennedy and Eberhart 1995) is fundamentally considered. PSO is a swarm intelligence algorithm, which is used very often in different engineering problems. In this algorithm, there are some interacting particles that try to optimize a global objective through searching a space of possible solutions.

In order to establish a common terminology, in the following part, we provide some definitions of several technical terms commonly used:

(1) *Swarm*: population of the optimization algorithm.
(2) *Particle*: individual of the swarm. Each particle represents a potential solution to the problem being solved. The position of a particle is determined by the solution it currently represents. Particles fly in the feasible space to find the best solution.
(3) *pbest* (personal best): personal best position of each particle, so far. That is, the position of the particle that has provided the greatest success (measured in terms of a scalar value analogous to the fitness adopted in evolutionary algorithms).
(4) *gbest* (global best): position of the best particle of the entire swarm.
(5) *Leader*: particle that is used to guide another particle towards better regions of the search space.
(6) *Velocity* (vector): this vector drives the optimization process, that is, it determines the direction in which a particle needs to "fly" (move), and its speed of flight, in order to improve its current position.
(7) *Inertia weight*: Denoted by w, the inertia weight is employed to control the impact of the previous history of velocities on the current velocity of a given particle.
(8) *Learning factor*: Represents the attraction that a particle has toward either its own success or that of its neighbors. Two are the learning factors used: c_1 and c_2. c_1 is the cognitive learning factor and represents the attraction that a particle has toward its own success. c_2 is the social learning factor and represents the attraction that a particle has toward the success of its neighbors. Both, c_1 and c_2, are usually defined as constants.

Based on the terminologies mentioned earlier, particles randomly move in the space to finally converge to the optimum solution. In the PSO algorithm, each particle i has its own position (X_i) and velocity (V_i), which are initialized randomly. During the iterative process, each particle memorizes its best visited location (P_{bi}) and the global best location (G_b) among all particles. Each iteration of the algorithm includes updating both location and velocity of each particle as follows:

$$V_i(t+1) = w.V_i(t) + \varphi_1.c_1[P_{bi} - X_i(t)] + \varphi_2.c_2[G_b - X_i(t)] \quad (1)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (2)$$

Where w is the inertia weight, and φ_1, φ_2 are two numerical variables usually set to 2. In single-objective problems, our goal is the minimization of sum of squared error of the objective function, but when there are two or more objective functions, another method is deployed and the method is called multi objective PSO.

The main intention of this research was describing a novel MOO method using PSO algorithm to optimize DFF process for ostrich meat plates.

MATERIALS AND METHODS

Sample Preparation

Ostrich fillet obtained from the leg muscle of 1 year old blue neck (*Struthio camelus australis*) ostriches was purchased from an abattoir in Mashhad, Iran. Frozen meat was cut in plates of about 25 × 20 × 13 mm using an industrial dicer (Food logistic, MF 84, Germany) and covered with plastic film to avoid surface dehydration.

Ostrich meat plates were kept at frozen temperature (−18C) before the experiments. The samples were thawed by refrigeration (at 4C) for 24 h prior to processing. Thawed meat plates were precooked in a calibrated kitchen microwave oven (2,450 MHz, S4821, Boutan, Iran) at three microwave power densities, 5.23, 10.47 and 15.70 W/g for 30 s. Three samples were placed in the system for each batch. Frying was carried out in a deep-fat fryer (Delonghi, F17233) with a capacity for 2 L. 100% pure sunflower oil (Shadgol, Nishapur, Iran) was employed as frying medium. A batch size of 80 g of meat plates in 2 L of oil was selected for further processing. Samples were placed in a wire basket, to ensure good contact between samples and the oil. The unprecooked and precooked meat plates were fried at nine intervals between 0 and 135 s at three temperatures (135, 150 and 160C). The oil was preheated for an hour at these temperatures prior to frying. Meat plates immediately were blotted with paper towel after frying to remove surface oil. After each frying test, oil level was checked and replenished; oil was changed after 1 h of frying time (Amiryousefi *et al.* 2012).

Mass Transfer Kinetic Analysis

Moisture content (MC) was determined by drying the fried samples in an oven (Beschickung-loading, model 100–800, Memmert, Germany) at 105C for 24 h (AOAC 1990) and was reported on dry weight basis. For fat determination, the dried samples were ground in a mortar. About 2 g of the samples were weighed into thimbles for solvent extraction.

Fat extraction was carried out with petroleum ether (b.p. 40–60C) using a Soxhlet extractor following the protocol recommended by AOAC Method 960.39 (AOAC 1990) and the fat content (FC) was reported on dry weight basis.

Shrinkage Measurement

Shrinkage is a common phenomenon during DFF of meat plates, which occurs as the result of water loss and denaturalization of fibers. Imbalanced pressure between the inner and outer of the product took place because of water transfers into outer environment from its surface (Mayor and Sereno 2004).

For studying the shrinkage of ostrich meat plates during frying, displacement method was used. The displacement method consists of the measurement of the sample weight immersed and not immersed in fluid. For that purpose, at the beginning and at the end of the frying process, the weight of the samples was measured immersed and not immersed in toluene. Due to the fact that the weight of the samples immersed in toluene is the difference of the forces that are acting on them, the equation for volume determination could be concluded (Zielinska and Markowski 2007; Clemente *et al.* 2009):

$$V = \frac{m - m_i}{\rho_0} \tag{3}$$

Where V is volume (m^3), m is weight of the sample (kg), m_i is weight of the sample immersed in toluene (kg) and ρ_0 is density of toluene (kg/m^3). Shrinkage is expressed in terms of the percentage change of the sample's volume as compared with its original volume (Kerdpiboon *et al.* 2007).

$$\%Sh = \left(\frac{V_i - V_f}{V_i}\right) \times 100 \tag{4}$$

Where V_i and V_f are the volumes of the sample at the beginning and at the end of each frying run, respectively. All measurements were performed in triplicate and the average values were reported as percentage of shrinkage.

Neural Network Modeling

Models are necessary for optimization and to enable the scientific process design and minimization of energy cost while considering a quality-based control strategy. In this article, a multi-layer perceptron network (MLP) based on back propagation learning rule was used to model mass transfer kinetics and shrinkage percentage. Figure 1 shows the detailed architecture of applied MLP.

A neural network is a collection of interconnecting computational elements, which are simulated like neurons in biological systems. It is a flexible structure, capable of making a nonlinear mapping between input and output

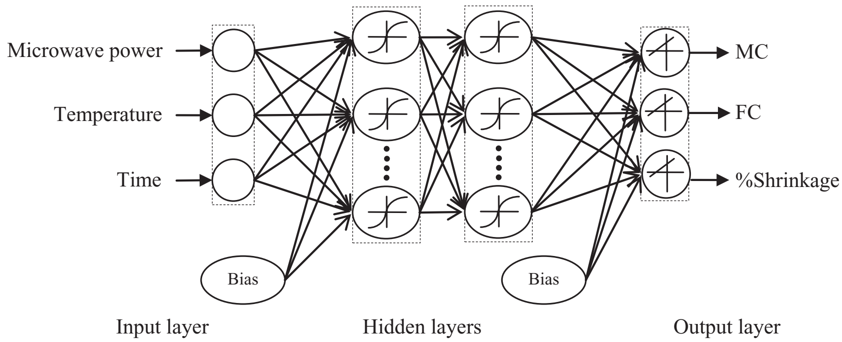

FIG. 1. MULTI-LAYER PERCEPTRON NETWORK NEURAL NETWORK ARCHITECTURE WITH TWO HIDDEN LAYERS FOR PREDICTION MOISTURE CONTENT (MC), FAT CONTENT (FC) AND SHRINKAGE PERCENTAGE OF DEEP-FAT FRIED OSTRICH MEAT PLATES

spaces, without any prior knowledge of the relationship between them (Chen and Ramaswamy 2002).

The MLP network is probably the most popular neural network in engineering problems in the case of nonlinear mapping and is called "Universal Approximator." It consists of an input layer, one or more hidden layers, and an output layer. The input nodes receive the data values and pass them to the first hidden layer nodes. Each one sums the inputs from all input nodes after multiplying each input value by a weight, attaches a bias to this sum, and passes on the results through a nonlinear transformation function. This forms the input either for the second hidden layer or the output layer that operates identically to the hidden layer. The resulting transformed output from each output node is the network output. The network needs to be trained using a training algorithm such as back propagation. Basically the objective of training patterns is to reduce the global error. The goal of every training algorithm is to reduce this global error by adjusting the weights and biases (Kashaninejad *et al.* 2009).

The working variables of DFF of ostrich meat plates (microwave power, temperature and frying time) were used as inputs, whereas MC, FC and also percentage of shrinkage were considered as the outputs. Hyperbolic tangent activation function (Eq. 5) was selected to be used in hidden layers, while using linear function in the output layer.

$$\tanh = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{5}$$

First, the data were divided into three partitions. Sixty percent of data were used to perform training of the network. To evaluate the prediction quality of the network during the training, 20% of data were considered as cross-validation data. Finally, in order to estimate the performance of the trained network on new data, the surplus data, which never were seen by the neural network during the training and cross-validation process, were used for testing. The applied learning algorithm was Levenberg–Marquardt, which is an iterative technique that locates the minimum of a function expressed as the sum of squares of nonlinear functions. It is a standard technique for nonlinear least-squares problems and is a combination of steepest descent and the Gauss–Newton method (Fine 1999). In this study, the artificial neural network (ANN) models were constructed by Matlab release 2008a.

The optimum number of neurons in each hidden layer was determined by trial/error procedure based on minimizing the difference between estimated ANN outputs and experimental values.

Therefore, mean-squared error (MSE), normalized MSE (NMSE), and mean absolute error (MAE) for each output were calculated by using Eqs. (6)–(8) (Amiryousefi and Mohebbi 2010) based on testing data.

$$\text{MSE} = \frac{\sum_{i=1}^{N} (O_i - T_i)^2}{N} \tag{6}$$

$$\text{NMSE} = \frac{1}{\sigma^2} \frac{1}{N} \sum_{i=1}^{N} (O_i - T_i)^2 \tag{7}$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |O_i - T_i| \tag{8}$$

Where O_{i} is the i^{th} actual value, T_{i} is the i^{th} predicted value, N is the number of data and σ^2 is the variance.

Multi Objective PSO

We are interested in solving problems of the type:

Minimize:

$$\vec{f}(\vec{x}) := [f_1(\vec{x}), f_2(\vec{x}), \ldots, f_{\mathrm{k}}(\vec{x})] \tag{9}$$

Subject to:

$$g_{\mathrm{i}}(\vec{x}) \le 0 \quad i = 1, 2, \ldots, m \tag{10}$$

$$h_{\mathrm{i}}(\vec{x}) \le 0 \quad i = 1, 2, \ldots, p \tag{11}$$

Where $\vec{x} = [x_1, x_2, \ldots, x_n]^T$ is the vector of decision variables, $f_i : \mathbb{R}^n \to \mathbb{R}, \ i = 1, \ldots, k$ are the objective functions and $g_i, h_j : \mathbb{R}^n \to \mathbb{R}, i = 1, \ldots, m, j = 1, \ldots, p$ are the constraint functions of the problem.

To describe the concept of optimality in which we are interested, we will introduce next a few definitions:

Definition 1. Given two vectors $\vec{x}, \vec{y} \in \mathbb{R}^k$, we say that $\vec{x} \le \vec{y}$ if $x_i \le y_j$ for $i = 1, \ldots, k$, and that $\vec{x}$ *dominates* $\vec{y}$ (denoted by $\vec{x} \prec \vec{y}$) if $\vec{x} \le \vec{y}$ and $\vec{x} \ne \vec{y}$.

Definition 2. We say that a vector of decision variables $\vec{x} \in X \subset \mathbb{R}^n$ is *nondominated* with respect to X, if there does not exist another $\vec{x}' \in X$ such that $\vec{f}(\vec{x}') \prec \vec{f}(\vec{x})$.

Definition 3. We say that a vector of decision variables $\vec{x}^* \in F \subset \mathbb{R}^n$ (F is the feasible region) is *Pareto-optimal* if it is nondominated with respect to F.

Definition 4. The *Pareto Optimal Set* P^* is defined by:

$$P^* = \{\vec{x} \in F \mid \vec{x} \text{ is Pareto-optimal}\} \tag{12}$$

Definition 5. The Pareto Front PF* is defined by:

$$PF^* = \{\vec{f}(\vec{x}) \in \mathbb{R}^k \mid \vec{x} \in P^*\} \tag{13}$$

In Fig. 2, dominance relation in a bi-objective space is shown. Figure 3 shows a particular case of the *Pareto front* in the presence of two objective functions. Thus, we wish to determine the Pareto optimal set from the set F of all the decision variable vectors that satisfy Eqs. (10) and (11). Note, however, that in practice, not all the Pareto optimal set is normally desirable (e.g., it may not be desirable to have different solutions that map to the same values in objective function space) or achievable.

In order to apply the PSO strategy for solving MOO problems, it is obvious that the original scheme has to be modified. The solution set of a problem with multiple objectives does not consist of a single solution (as in global optimization). Instead, in MOO, we aim to find a set of different solutions (the so-called Pareto optimal set). In general, when solving a multi-objective problem, three are the main goals to achieve (Zitzler *et al.* 2000):

(1) Maximize the number of elements of the Pareto optimal set found.
(2) Minimize the distance of the Pareto front produced by our algorithm with respect to the true (global) Pareto front (assuming we know its location).
(3) Maximize the spread of solutions found, so that we can have a distribution of vectors as smooth and uniform as possible.

Schematic of the applied algorithm is shown in Fig. 4.

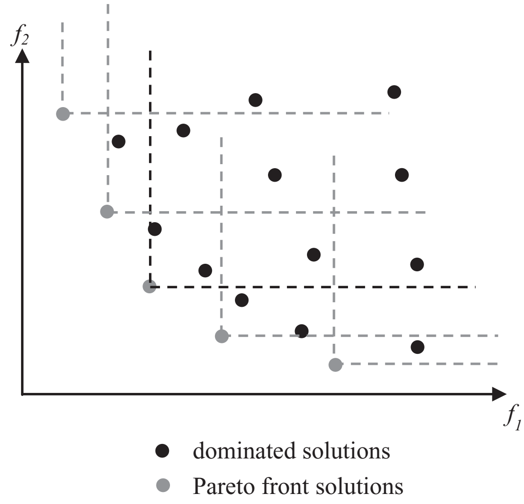

FIG. 3. THE PARETO FRONT OF A SET OF SOLUTIONS IN A TWO OBJECTIVE SPACE

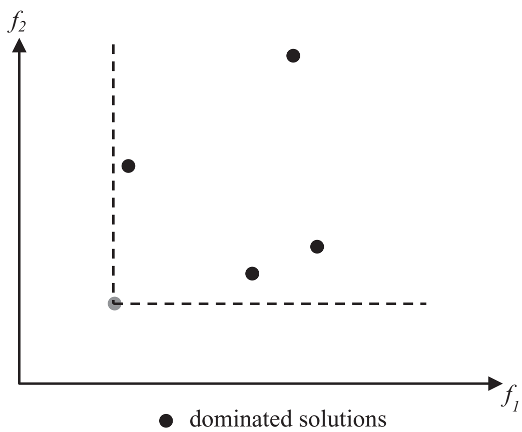

FIG. 2. DOMINANCE RELATION IN A BI-OBJECTIVE SPACE

RESULTS AND DISCUSSION

In this article, a neural network is trained to model the DFF of ostrich meat plates. ANN with eight neurons in the first hidden layer and 10 neurons in the second one was the best.

The matrixes of weights (F matrix of 3×8 between input and first hidden layer, G matrix of 8×10 between first and second hidden layer and H matrix of 10×3 between second hidden layer and output layer) and bias values (B_{1th} matrix of 8×1 for first hidden layer, B_{2th} matrix of 10×1 for second hidden layer and B_{out} matrix of 3×1 for output layer) of the selected network are as follows:

$$F = \begin{bmatrix} 0.0795 & -1.9491 & -0.6490 & -0.0336 & -0.1541 & 0.7373 & 0.6650 & -2.3570 \\ -1.8641 & 1.2541 & 1.5277 & -2.6901 & 2.6195 & -0.7734 & -2.4065 & 0.5213 \\ -1.2984 & 1.5231 & -2.1783 & 1.2432 & -0.4048 & 2.7147 & -1.7959 & -1.1051 \end{bmatrix}$$

$$G=\begin{bmatrix} -0.9205 & -0.8193 & 0.1133 & 0.7989 & -0.0263 & -0.5270 & 0.5285 & -1.0842 & -1.3625 & -0.2778 \\ 1.0549 & 0.7670 & -1.0008 & 0.4825 & 0.1588 & -1.5102 & -0.7692 & -0.9357 & 0.8043 & 0.5712 \\ -1.7283 & -0.7533 & -0.9243 & 0.0365 & 0.1334 & 1.5447 & 0.0041 & -1.0114 & 0.2089 & -0.2130 \\ -0.5257 & 0.3166 & 1.1365 & 1.0504 & 0.8331 & 1.8470 & 0.9871 & -0.8581 & 0.0356 & -1.6679 \\ 0.0864 & -0.6517 & -0.6650 & -1.4871 & -0.6701 & -0.6051 & -1.4048 & -0.3534 & -0.0236 & -0.4920 \\ 1.4827 & -0.6278 & 0.6209 & -0.5464 & 0.7232 & 0.4013 & 0.0971 & 0.9739 & 0.0796 & 0.7010 \\ -0.0187 & -0.5260 & 0.0627 & -0.5993 & 0.6707 & -0.8107 & -0.5309 & 0.9065 & 0.0131 & 1.4586 \\ -0.1913 & -0.3660 & -0.1556 & -1.1923 & 1.0737 & 0.5501 & -0.2392 & -1.4891 & 1.0276 & -0.6680 \end{bmatrix}$$

$$H=\begin{bmatrix} 0.6250 & -0.5936 & -0.9366 \\ -0.4244 & -0.0442 & -0.4784 \\ -0.6345 & -0.1365 & -0.1480 \\ 0.6993 & 0.3776 & -0.2430 \\ 0.4741 & 0.2547 & -0.6597 \\ -0.6025 & 0.1807 & 0.0563 \\ -0.7318 & -0.3739 & -0.2626 \\ 0.8360 & -0.2008 & -0.7711 \\ 0.5934 & 0.4262 & -0.4194 \\ -1.0335 & 0.0898 & -0.5441 \end{bmatrix}$$

$$B_{1th}=\begin{bmatrix} 3.2118 \\ 1.9785 \\ 1.7065 \\ -0.8348 \\ -0.6850 \\ 1.5856 \\ 1.2910 \\ -3.1671 \end{bmatrix} \quad B_{2th}=\begin{bmatrix} 2.5325 \\ 1.3414 \\ -1.3419 \\ -0.3618 \\ 0.5955 \\ -0.6510 \\ 0.6652 \\ -0.6171 \\ -1.2463 \\ -2.3966 \end{bmatrix} \quad B_{out}=\begin{bmatrix} -0.6629 \\ 0.7291 \\ 0.5085 \end{bmatrix}$$

The error measures for estimation of MC, FC and shrinkage percentage during the testing processes of the best architecture of ANN are shown in Table 1.

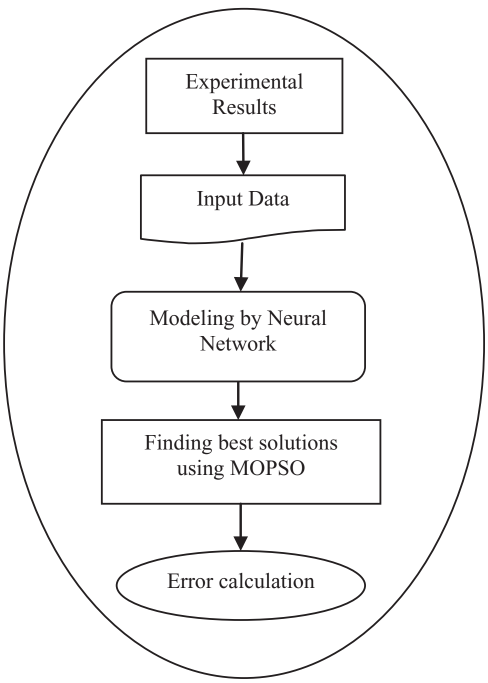

FIG. 4. SCHEMATIC OF THE APPLIED ALGORITHM

TABLE 1. PERFORMANCE OF ANN FOR MODELING OF MC, FC AND SHRINKAGE PERCENTAGE, IN DEEP-FAT FRYING OF OSTRICH MEAT PLATES

	MC	FC	%Shrinkage
MSE	0.060	0.009	1.704
NMSE	0.334	1.200	0.017
MAE	0.198	0.080	0.032

ANN, artificial neural network; FC, fat content; MAE, mean absolute error; MC, moisture content; MSE, mean-squared error; NMSE, normalized mean-squared error.

TABLE 2. PARAMETERS' VALUES

Parameters	Number of particles	*w*	φ_1	φ_2
Values	500	0.6	0.2	0.5

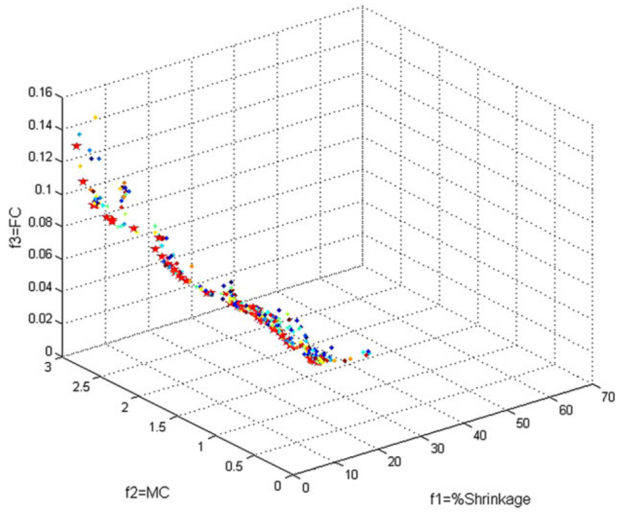

FIG. 5. THE PARETO FRONT OBTAINED FOR DEEP-FAT FRYING OF OSTRICH MEAT PLATES USING MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION

Then, finding acceptable solutions for the neural network model is obtained using multi-objective PSO (MOPSO) algorithm described earlier. Our goal is to minimize two objectives, namely, shrinkage percentage and FC of DFF ostrich meat plates and keeping their MC in a legal range. In next section the results can be viewed.

In the optimization of the neural network model, MOPSO with the parameters in Table 2 was used.

The Pareto front for particles, selected in the last generation, is depicted in Fig. 5. Star points are the Pareto front solutions and circles are the particles' values in the solution space in last generation which converged to the Pareto front.

In Table 3 fitness of particles that include the Pareto front is brought.

TABLE 3. FITNESS OF PARTICLES (NEURAL NETWORK OUTPUT) THAT INCLUDE THE PARETO FRONT

f_1 data	f_2 data	f_3 data	f_1 data	f_2 data	f_3 data	f_1 data	f_2 data	f_3 data
20.32	2.24	0.04	26.33	2.18	0.03	15.57	2.31	0.05
13.30	2.36	0.06	31.26	2.12	0.01	29.75	2.13	0.03
34.35	2.05	0.01	26.49	2.18	0.03	35.68	1.74	1.07
31.03	2.13	0.02	27.04	2.17	0.03	34.08	2.08	0.01
25.08	2.20	0.03	8.00	2.51	0.08	30.21	2.13	0.02
34.91	2.02	0.01	14.45	2.33	0.06	2.04	2.53	0.10
29.18	2.15	0.03	0.33	2.59	0.10	8.01	2.81	0.13
12.42	2.39	0.07	35.75	1.70	0.27	30.23	2.13	0.02
26.31	2.19	0.03	31.40	2.11	0.02	30.60	2.12	0.02
35.44	2.00	0.00	29.98	2.13	0.03	36.01	1.67	0.54
32.97	2.08	0.01	27.42	2.18	0.03	21.22	2.25	0.04
35.56	1.74	0.47	2.50	2.48	0.09	35.64	1.72	0.45
10.91	2.35	0.08	6.35	2.59	0.10	30.11	2.12	0.03
35.57	1.75	0.58	34.10	2.03	0.01	31.11	2.13	0.02
26.06	2.19	0.03	26.89	2.18	0.03	7.72	2.60	0.10
9.02	2.72	0.11	35.52	2.00	0.00	11.29	2.41	0.07
35.66	1.71	1.12	2.50	2.49	0.09	16.38	2.30	0.05
14.90	2.31	0.06	14.26	2.33	0.06	13.72	2.35	0.06

CONCLUSION

MOO applications in food engineering have centered mainly on finding Pareto-optimal solutions for product quality and cost objectives with many of them using MOO methods that generate multiple solutions. These methods are popular, probably because they are readily available and effective at generating Pareto-optimal solutions. An increasing number of food engineering processes are modeled using first principles. Coupled with the conflicting objectives often present in the food industry and the availability of computational power, MOO is becoming increasingly attractive. Therefore, we used MOPSO to find the best solutions. We gathered the best possible solutions in a figure as Pareto front.

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