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# Establishing Optimal Dehydration Process Parameters for Papaya By EmployingA Firefly Algorithm, Goal Programming Approach

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**Abstract**
This study employs a Firefly Algorithm (FA) to determine the optimal osmotic dehydration parameters for papaya. The functional form of the osmotic dehydration model is established via a standard response surface technique. The format of the resulting optimization model to be solved is a non-linear goal programming problem. While various alternate solution approaches are possible, an FA-driven procedure is employed. For optimization purposes, it has been demonstrated that the FA is more computationally efficient than other such commonly-used metaheuristics as genetic algorithms, simulated annealing, and enhanced particle swarm optimization. Hence, the FA approach is a very computationally efficient procedure. It can be shown that the resulting solution determined for the osmotic process parameters is superior to those from all previous approaches.
**Keywords-**Firefly Algorithm, Non-linear Goal Programming, Process Parameter Optimization, Food Dehydration

## I. Introduction

The annual global agricultural production of fruits and vegetables is a multi-trillion dollar enterprise with the production of papayas currently exceeding 12 million tonnes per year [1]. As with many agricultural commodities, the high moisture content of papayas renders them highly perishable and, due to various microbial, enzymatic and chemical reactions, they start to deteriorate immediately upon harvesting. Therefore, it becomes imperative to determine effective preservation methods that maintain the quality of the fruit. This is frequently accomplished through various forms of drying such as heat processing and dehydration. The drying of fruits permits longer storage periods, reduces shipping weights, and minimizes their packaging requirements. However, hot-air dried fruits using conventional vacuum, cabinet or tray dryers have not received popular acceptance due to poor product quality.

Consequently, osmotic dehydration was recently introduced as an alternative preservation technique for producing higher quality fruit products. In the process of osmotic dehydration, fruit is placed into a hypertonic solution where water is drawn out of the produce and into the solution due to the differences in their concentrations. In this fashion, osmotic dehydration removes a proportion of the water content in the fruit leading to a product of intermediate moisture content. Osmotic dehydration of fresh produce can also be used as a pre-treatment to additional supplementary drying processing to improve sensory, functional and even nutritional properties. The quality of the subsequent product is better than one without pre-treatment due to (i) the increase in sugar/acid ratio, (ii) the improvements to fruit texture, and (iii) the stability of the colour pigment during storage. Thus, in conjunction with other drying technologies, osmotic dehydration produces a higher quality, shelf-stable product for both local consumption and export markets.

Water removal in the dehydration process is influenced by many factors such as type and concentration of osmotic agents, temperature, circulation/agitation of solution, solution to sample ratio, thickness of food material, and pre-treatment. The actual osmotic process contributes only minimal thermal degradation to the nutrients due to the relatively low temperature water removal process. Simultaneously a transport of solids takes place between the fruit and the solution.

While an expanding market currently exists for osmo-convective dehydrated papaya in both domestic and world markets, only limited efforts have been undertaken to optimize the osmotic process parameters [2][3]. Specifically, an analysis of the mass transport occurring within the osmosis process measured in terms of water loss and sugar gain is of considerable practical relevance. In this study, the functional form of the osmotic dehydration model is established using a standard response surface technique [4][5][6]. The format of the resulting optimization model to be solved is a non-linear goal programming problem. This study provides a procedure that employs a Firefly Algorithm (FA) [7][8][9] to determine the optimal osmotic dehydration parameters for the papaya case introduced in [2]. It can be shown that the resulting solution for the osmotic process parameters determined by the FA are superior to those from all previous approaches.

## II. Functional Form and Mathematical Model of the Osmotic Dehydration Process

The first component for the study is to determine the appropriate functional representation of the impact of the three main osmotic process parameters – (i) solution temperature, (ii) syrup concentration and (iii) duration of osmosis – on the water loss and sugar gain of the papaya. This model can then be used to predict the water loss and sugar gain responses in the papaya over the requisite experimental ranges of the three parameters. Once the appropriate functional form has been specified, the next step is to optimize this model in order to determine the maximum water loss and the optimum sugar gain during osmotic dehydration. In the subsequent analyses, let *T* represent the syrup temperature in $^{o}$C, *C* be the syrup concentration in $^{o}$Brix, and *D* be the duration of osmosis in hours. In addition, let *WL* correspond to the percentage of water loss and let *SG* be the percentage of sugar gain of the papaya during the osmotic dehydration process.

A response surface procedure is a statistical technique frequently used for optimization in empirical studies [4][5][6]. Response surfaces employ quantitative data in appropriately designed experiments to simultaneously ascertain the various variable relationships within multivariate problems [5]. The equations constructed describe the effect of various test variables on responses, determine interrelationships among the test variables and represent the combined effect of all test variables in any response. Response surfaces enable an experimenter to undertake an efficient exploration of a process or system [5][6]. These approaches have frequently been used in the optimization of food processes [2][10] and will, consequently, be employed in this study to determine the appropriate mathematical representation. The proposed model can then be used to predict the water loss and sugar gain in the dehydration of papaya over the different experimental ranges for the process durations, syrup concentrations and syrup solution temperatures.

For the osmotic dehydration process, it should be noted that the exact mathematical representation for the relationship between the parameters remains unknown. Thus the response surface method enables an empirical approximation to be made using efficient experimental design techniques [5][6]. The specific testing design actually contains the three variables (T, C, D) each set at three levels using the data taken from [2] in order to determine the corresponding water loss (WL) and sugar gain (SG). This experimental design for the various combinations of input variables and levels requires fifteen experiments as shown in Table 1 (see [2]).

**Table 1.**Response Surface Experimental Design Layout for 3 Variables and 3 Levels

| Level for *T* | *T* ($^{o}$C) | Level for *C* | C ($^{o}$Brix) | Level for *D* | D (Hrs) |
|---|---|---|---|---|---|
| 1 | 50 | 1 | 70 | 0 | 5 |
| 1 | 50 | -1 | 50 | 0 | 5 |
| -1 | 30 | 1 | 70 | 0 | 5 |
| -1 | 30 | -1 | 50 | 0 | 5 |
| 1 | 50 | 0 | 60 | 1 | 6 |
| 1 | 50 | 0 | 60 | -1 | 4 |
| -1 | 30 | 0 | 60 | 1 | 6 |
| -1 | 30 | 0 | 60 | -1 | 4 |
| 0 | 40 | 1 | 70 | 1 | 6 |
| 0 | 40 | 1 | 70 | -1 | 4 |
| 0 | 40 | -1 | 50 | 1 | 6 |
| 0 | 40 | -1 | 50 | -1 | 4 |
| 0 | 40 | 0 | 60 | 0 | 5 |
| 0 | 40 | 0 | 60 | 0 | 5 |
| 0 | 40 | 0 | 60 | 0 | 5 |

Based upon the response surface experimental design appropriately applied to the response outputs of Table 2 [4][5][6], the functional equations empirically determined for the water loss and the sugar are, respectively:

$$WL = 63.745 - 1.56275T - 0.6615C - 6.075D + 0.0286T^2 + 0.00925C^2 + 0.79D^2$$

$$SG = 13.90875 - 0.830275T - 0.044875C + 0.51249D + 0.01058T^2 + 0.002825TC.$$

**Table 2.**Experimental Data for Water Loss and Sugar Gain Under Different Treatments

| Temperature ($^oC$) | Concentration ($^o$Brix) | Duration (Hrs) | Water Loss (%) | Sugar Gain (%) |
|---|---|---|---|---|
| 50 | 70 | 5 | 44.5 | 8.1 |
| 50 | 50 | 5 | 35.2 | 5.5 |
| 30 | 70 | 5 | 31.7 | 4.5 |
| 30 | 50 | 5 | 23.6 | 3.0 |
| 50 | 60 | 6 | 44.5 | 8.2 |
| 50 | 60 | 4 | 39.6 | 7.0 |
| 30 | 60 | 6 | 27.2 | 3.9 |
| 30 | 60 | 4 | 23.2 | 2.5 |
| 40 | 70 | 6 | 37.8 | 4.8 |
| 40 | 70 | 4 | 34.8 | 4.3 |
| 40 | 50 | 6 | 28.4 | 4.4 |
| 40 | 50 | 4 | 25.7 | 3.4 |
| 40 | 60 | 5 | 29.7 | 4.3 |
| 40 | 60 | 5 | 30.0 | 4.3 |
| 40 | 60 | 5 | 30.2 | 4.4 |

Organoleptic properties refer to aspects of food as experienced by the senses, including taste, sight, smell, touch, dryness, moisture content, and stale-fresh factors. Jain et al. [2] determined organoleptic ranges for the osmotic dehydration parameters and restricted their search for best parameter settings to values within these ranges. In order to find efficient values for the osmotic dehydration parameters, Jain et al. [2] constructed a number of contour plots by varying the values of the three variables and observed the effect that these had on the response functions that they had calculated for *WL* and *SG*. By superimposing the various contours onto a single figure, they visually determined best values for the temperature, concentration, and duration as those shown in Table 3.

**Table 3.**Experimental Data for Water Loss and Sugar Gain Under Different Treatments

| Temp. ($^oC$) | Conc. ($^o$Brix) | Dur. (Hrs) | Water Loss (%) | Sugar Gain (%) |
|---|---|---|---|---|
| 37 | 60 | 4.25 | 28 | 4.0 |

## III. A Goal Programming Formulation for Setting Osmotic Dehydration Parameters

It can be observed that in the previous section, the determination of the settings for the parameters is, in fact, a multi-response optimization process. Therefore, this task can also be represented by a corresponding mathematical programming formulation. In this section, this will be performed by converting the problem into an equivalent goal programming format.

Based upon the organoleptic ranges established for the parameters and response functionsin [2], the technical constraints for the problem can be specified as:

$$23.02 \le WL \le 44.5$$

$$2.56 \le SG \le 8.1.$$

$$30 \le T \le 50$$

$$50 \le C \le 70$$

$$4 \le D \le 6$$

Furthermore, based upon the desired organoleptic properties for the solution, various desirable attributes can be established for the responses and variables. These attributes are summarized in Table 4. From an economical perspective, several of these criteria can be established as more important to achieve than the others. Namely, from a dehydration perspective, the water loss needs to be as high as possible within the indicated range, while the sugar gain should be as close to 4% as possible. The hierarchy in achieving these targets is indicated in the last column of Table 4. Hence, from a mathematical perspective, each of these desired targets can be specified as a goal and the entire problem can them be solved using conventional goal programming techniques. Clearly an objective function that penalizes deviations from the desired goals needs to be introduced and, in the subsequent mathematical programming formulation, a percentage deviation objective weighted by the relative importance of each goal is employed. Consequently, determining osmotic dehydration parameter values can be transformed into the following non-linear goal programming formulation.

**Table 4.**Ranges for Process Variables and Response Goals in the Osmotic Dehydration

| Parameter | Goal | Aim | Lower Limit | Upper Limit | Relative Importance |
|---|---|---|---|---|---|
| *T* ($^oC$) | 1 | Minimize | 30 | 50 | Important |
| *C* ($^o$Brix) | 2 | Minimize | 50 | 70 | Important |
| *D* (Hrs) | 3 | Minimize | 4 | 6 | Important |
| *WL* (%) | 4 | Maximize | 23.02 | 44.05 | Very Important |
| *SG* (%) | 5 | Target = 4.0 | 2.56 | 8.1 | Extremely Important |

Min $W_1*P_1 + W_2*P_2 + W_3*P_3 + W_4* N_4 + W_5*(P_5 + N_5)$

*s.t.*
$P_1 = T - 30$
$N_1 = 50 - T$
$P_2 = C - 50$
$N_2 = 70 - C$
$P_3 = D - 4$
$N_3 = 6 - D$
$P_4 = WL - 23.02$
$N_4 = 44.05 - WL$
$P_5 = SG - 2.98$
$N_5 = 4.00 - SG$
$P_6 = SG - 2.56$
$N_6 = 8.1 - SG$
$P_i \geq 0, N_i \geq 0 \qquad i = 1, 2, 3, 4, 5, 6$

In order to complete the transformation of the problem into the series of defined goals, several additional deviation variables have been introduced. Namely, for the goal model, define $Pi$ and $Ni$, $i = 1$ to 6, to be the positive and negative deviations, respectively, from the disparate goal targets and constraint limits shown for the variables in Table 4. Let $Wi$ correspond to weighting factors applied to goal $i$, $i = 1$ to 5, to reflect the relative importance in achieving that goal's target. Each $Wi$ also contains the appropriate denominator constant required to transform the deviation variables into the requisite percentage deviation value format. Thus, solving the goal programming model would be equivalent to determining optimal parameter values for the osmotic dehydration process.

## IV. Firefly Algorithm For Function Optimization

Although various alternate solution approaches could have been applied to the resulting optimization problem, the actual approach employed uses the FA-driven procedure of [8] and [9]. For optimization purposes, Yang [8] has demonstrated that the FA is more computationally efficient than such commonly-used metaheuristics as genetic algorithms, simulated annealing, and enhanced particle swarm optimization. Hence, the FA approach is a very computationally efficient procedure. While this section briefly outlines the FA procedure, more detailed specifications can be located in [7] and [8].

The FA is a biologically-inspired, population-based metaheuristic with each firefly in the population representing a potential solution to the problem. An FA procedure employs three idealized rules: (i) All fireflies within a population are unisex, so that one firefly will be attracted to other fireflies irrespective of their sex; (ii) Attractiveness between fireflies is proportional to their brightness, implying that for any two flashing fireflies, the less bright one will move towards the brighter one; and (iii) The brightness of a firefly is determined by the value of its objective function. For a maximization problem, the brightness can simply be considered proportional to the value of the objective function. Yang (2010) demonstrates that the FA approaches the global optima whenever the number of fireflies $n \rightarrow \infty$ and the number of iterations $t$, is set so that $t \gg 1$. In reality, the FA has been shown to converge extremely quickly into both local and global optima [7][8]. The basic operational steps of the FA are summarized in Figure 1 [8].

Objective Function $F(\boldsymbol{X})$, $\boldsymbol{X} = (x_1, x_2, \ldots x_d)$
Generate the initial population of $n$ fireflies, $\boldsymbol{X}_i$, $i = 1, 2, \ldots, n$
Light intensity $I_i$ at $\boldsymbol{X}_i$ is determined by $F(\boldsymbol{X}_i)$
Define the light absorption coefficient $\gamma$
**while** (t < MaxGeneration)
**for** $i = 1: n$ , all $n$ fireflies
**for** $j = 1: n$ ,all $n$ fireflies (inner loop)
    **if** $(I_i < I_j)$, Move firefly i towards j; **end if**
    Vary attractiveness with distance $r$ via $e^{-\gamma r}$
**endfor** $j$
**end for** $i$
Rank the fireflies and find the current global best solution $\boldsymbol{G}^*$
**end while**
Postprocess the results

**Figure 1**: pseudo code of the firefly algorithm

By solving the goal programming problem using the FA-driven procedure, optimal process parameters for the osmotic dehydration of the papaya were determined and these resulting values are displayed in Table 5. In contrast to the solution found in [2], it can be observed that the temperature parameter remains essentially the same, the syrup concentration increases by 10 $^o$Brix, while the duration of dehydration process has been reduced slightly by 0.25 hours. More importantly, in terms of the key responses, while the sugar gain essentially remains at the highly desirable target of 4%, the water loss – which is obviously the key feature of dehydration – has increased by 5%. Consequently, since the water loss response has been increased significantly from that determined in [2], this goal programming solution represents a significant improvement in the osmotic dehydration process.

**Table 5.** Optimal Process Parameters Determined for the Osmotic Dehydration of Papaya

| **Temp. ($^o$C)** | **Conc. ($^o$Brix)** | **Dur. (Hrs)** | **Water Loss (%)** | **Sugar Gain (%)** |
|---|---|---|---|---|
| 37.776 | 70 | 4 | 32.8 | 4.02 |

## V. Conclusions

In this paper, the optimal osmotic drying parameters for papaya were determined using an FA-directed algorithm. In the computational study, the functional form of the osmotic dehydration response surface was established empirically using a response surface experimental technique and the format of the resulting optimization model was a non-linear goal programming problem. The resultant solution found for the osmotic process parameters by the FA-driven approach was superior to all previous approaches. Since FA-directed techniques can be adapted to solve a wide variety of problem types, the practicality of this approach can clearly be extended into numerous other "real world" applications. These extensions will become the focus of future research.

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