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A new approach to reduce the effects of omitted minor variables on food engineering experiments: Transforming the variable-result interaction into image

Selahaddin Batuhan Akben

Osmaniye Korkut Ata University, Bahce Vocational School, Osmaniye, Turkey

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ABSTRACT

In food engineering experiments aiming the optimization, only the combinations of major variables are tested. Moreover, only the constant optimal value (single value) is suggested to each independent variable in these experiments. However, the suggested values may not always be optimal in future studies due to minor variables that not considered in the experiments. Therefore, it is more accurate to suggest the range of variable values that produce the almost same optimal results rather than a constant optimal value. So that the effect of the minor variables can be minimized. For this reason, in this study, the values of variables obtained by polynomial model were transformed to images then an image processing method was performed to represent the relevant values of the variables as a single colour shade. Thus, the optimal ranges represented by single shade of color were determined. The limits of these ranges were the variable values corresponding to the values of maximum or minimum color shade and very close to the maximum or minimum constant value. The proposed method was tested in an experiment aiming the nisin production optimization depending on three independent variables. Since the same optimization experiment that has been tried with another method is also available in the literature the findings of this study were also compared with the previously suggested constant optimal values. As a result, the superiorities and availabilities of method proposed in this study were discussed.

1. Introduction

Optimization experiments are implemented to save time and cost in food processes. In these experiments, some combinations of independent variable values are tested to produce the desired result. According to obtained response, the model equations are established to represent interaction between the variables and results. Then, all the variable values are tried using the model equations and the variable values that should be used to obtain the optimal experimental result are determined. Finally, the optimal results are predicted depending on the variable values determined in experiments [1–4].

However, only the combinations of major variables are tested in the optimization experiments. Whereas, there are also some other variables (temperature, pressure, etc. ambient conditions) that their effects to experimental results are minor. In future processes, these minor variables may shift the optimal experimental results predicted by the previous optimization experiments, since the values of these minor variables at the experiment time may change in future processes. [5–7]. Especially, if there are sudden changes in the response of experimental result to the variable value (If there are shoulder in the mathematical model curve), the effect of these minor variables may increase the shifting even more. This possible case can be seen in Fig. 1.

In food process to solve this problem, variable values are tested near the constant optimal variable values suggested by previous optimization experiments. However, it is also uncertain that how the current optimal values should far from the previous suggested constant optimal values. So, this solution is like an implementation of optimization experiments again [8]. Also, there are also some leveling proposals for experimental results in the literature. However, there is no algorithm to determine the level limits in these proposals. Even the most commonly used response surface methodology (RSM) in food engineering optimization experiments does not solve this problem since offers only the curve corresponding to the variable / result combinations. As a result, there is no fully statistical or logical method to reduce the effect of minor variables on the optimal results in future processes [9–11].

The reason of this optimal experimental result shifting problem is that the optimal variable values proposed in the optimization experiments are constant [12,13]. If the optimal variable value ranges that produce the same optimal experimental results are suggested instead of the optimal constant variable values, this problem can be minimized.

E-mail address: batuhanakben@osmaniye.edu.tr.

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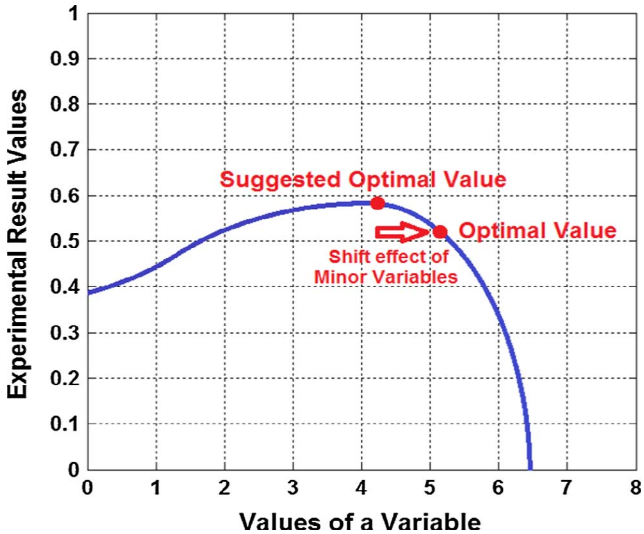

Fig. 1. A sample of the shift effect of minor variables.

Because, it can be avoided from the sudden changes caused by omitted variables as much as possible by choosing the centres of these optimal variable value ranges. In fact, the simple way to determine the optimal range is to select the values that are close to the maximum or minimum. However, a mathematical or statistical method is needed to determine the limits of this closeness. Otherwise the limits of the selection will vary depending on preference and it will lead to error. There are some image processing methods that can reduce similar color tones to single tone. So, the solution may be the to obtain image from the interaction between experimental result and variable value variation. By means of this solution, the variable values that are closely related to the optimal can be determined using image processing methods.

For this reason, the interactions between the variable value variations and experimental results are first transformed to images in this study. Then, close values were transformed to colour tones (levels) using histogram equalization algorithm. Finally, variable values corresponding to white colour tones were determined as the ranges providing the optimality and the centres of these ranges were proposed the optimal variable values farthest away from sudden changes. The usefulness (superiorities and disadvantages) of the proposed method can also be determined by comparing the findings obtained with previous studies.

2. Materials

The experiment in which the method of this study was tested is the optimization of Hemin, Glucose and Dissolved Oxygen Concentration in the fed-batch fermentation system for optimal nisin production of *Lactococcus lactis* N8. Same experiment was previously performed using response surface methodology also is available in the literature. Some informations about this experiment is as follows. More detailed information about the same experiment is already available in the literature [14,15].

Both the *Lactococcus lactis* N8[18] and the sensitive indicator microorganism *Micrococcus luteus* NCIB 8166 (ATCC10240) strain were obtained from the Food Engineering Department of Pamukkale University in Turkey. The *Lactococcus lactis* N8 was cultivated in M17. Broth (M17G, Merck, Germany) contained 0.5% glucose at 30 °C and the *Micrococcus luteus* NCIB 8166 (ATCC10240) was grown in Luria Bertani (LB, FLUKA, Germany) medium at 30 °C with 200 rpm agitation. Tried variable values and the results obtained are also shown in Table 1 [14,15].

Table 1
Variable value variations used in the experiment and the obtained nisin.

Combinations of variable values	Glucose (g $L^{-1} h^{-1}$)	Hemin (μg mL^{-1})	Dissolved oxygen (%)	Nisin (IU mg^{-1})
1	1	1,5	50	1225,33
2	5,5	1,5	50	1153,64
3	1	2,5	20	1138,3
4	1	2,5	80	762,48
5	5,5	2,5	50	1662,53
6	5,5	1,5	50	1101,16
7	10	0,5	20	464,56
8	1	1,5	50	1268,76
9	5,5	1,5	80	314,63
10	10	2,5	80	1271,82
11	10	0,5	80	1346,87
12	1	0,5	20	1212,78
13	5,5	0,5	50	1231,74
14	5,5	1,5	50	1095,84
15	5,5	1,5	50	1073,39
16	5,5	1,5	50	1077,05
17	1	0,5	80	733,13
18	10	2,5	20	1670,88
19	5,5	1,5	20	1191,11
20	5,5	1,5	50	1118,07
21	15	4,5	20	384,4
22	15	4,5	80	491,87
23	5,5	4,5	20	910,42
24	5,5	4,5	80	428,43
25	10	4,5	20	1168,44
26	10	4,5	80	680

3. Methods

3.1. Digital grayscale image

Grayscale images are more convenient to process than color images. Therefore, the proposed method of this study is based on the processing of digital grayscale images. Digital grayscale image is the samples of original image that represented numerically in the cells of a matrix. Digital grayscale image can also be called as grayscale image matrix or only grayscale image. Each image sample is represented numerically between 0 and $(2^{bit\ depth}-1)$ in a cell of image matrix and each numeric value corresponds to a shade (tone) of gray [16,17].

Theoretically the bit depth may be between 1 and ∞. However, it is often 8 in practice since the human eye is sensitive to about 256 different color shades (8-bit image). In addition, the higher *bit depth* means that the digital image is more identical to the original data [18].

Also, higher number of original image samples (pixels) means that the larger size of image matrix. So, the original image represented by more samples creates the more detailed digital grayscale image [19]. Fig. 2 shows a sample 4-bit digital grayscale image and its image matrix.

Bit depth of sample image in Fig. 2 is 4. So, the colours in each cell of matrix were sho[1]wn in gray shades represented between 0 and 15 (15 is white, 0 is black, others are gray tones). Note that some gray shades were not used in the sample image.

3.2. Transformation of experimental model data to image

Experiments in the field of food engineering are aimed to measure the experimental results corresponding to value variations of independent variables. Let's assume that the independent variables in a food experiment are $x_{n,m}$ and the measured experimental result values corresponding to the combination of these variables are y_n. Accordingly, the equation $P(x_{n,m}) \approx y_n$ represents the model of experimental design.

[1] For interpretation of color in Fig. 2,5,6, the reader is referred to the web version of this article.