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Continuous process improvement through designed experiments and multi-attribute desirability optimization

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Process optimization is a problem with many dimensions. Attributes of interest compete with one another and are affected by a host of variables. It is impossible to achieve the best possible values for all process outputs simultaneously. For this reason, it is important to define what should be achieved from the process. Once the objectives are known, statistically designed experiments can be used effectively to determine the optimal levels of controllable process variables that will produce the desired result and make the process robust to variations in the influential parameters that cannot be controlled. This paper describes an approach to establishing values for process variables to consistently achieve the optimal set of process outputs. It is an iterative process that produces continuous improvement. Principles of statistical experimental design and multi-attribute desirability optimization methodology are employed. The benefits of this approach include better products, less variability, lower costs, and more efficient process definition.

Introduction

Products are made by committee. In a typical organization, many people with different functions take a product from the concept stage to market. Upper management selects the business of the enterprise. With information from Marketing, Management might decree, "We are in the widget-making business". Marketing is then tasked with positioning the organization to sell widgets; Engineering is commissioned to design the best widget it can design; Sales people are sent out to take orders for widgets; and Production is expected to produce widgets that match the type that Marketing promised and, presumably, Engineering designed. Further, Production must make the proper number of them for less than the specified unit cost by the specified time to fill the orders taken by Sales. Each group does its best with the knowledge and experience it has to achieve its objectives.

In an ideal world, Management, Marketing, Sales, Product Engineering, Process Engineering, and Production all work together to specify a product. They agree on the features, cost, and ranges of desired values for measurable characteristics. Communication among these groups sorts out which factors are really important and what tolerances are acceptable around targeted values for outputs that quantify quality. Any trade-offs among competing characteristics are made based on relative importance.

Since the world is not ideal, the scenario of the first paragraph is all too common. What can the process engineer do? Optimize the process. In short, determine what levels of controllable process parameters achieve the best possible results. *One obtains the best results by maximizing the probability that the process will generate an optimal combination of process outputs.* The multi-attribute desirability optimization methodology can provide a framework for achieving the most desirable combination of measurable outcomes. When applied in the product definition phase, it can lead to more efficient process definition. During the production phase, this methodology can help identify causes of quality problems, ways to reduce costs, and ways to eliminate process variability. Because it is based on experience and data, it

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is a flexible tool that can be applied repeatedly for continuous process improvement.

This paper describes the techniques of using statistically designed experiments and the multi-attribute desirability optimization methodology to improve a product and its process. The description is largely theoretical for two reasons: (1) to give a general background for applying these new techniques and (2) to protect the confidentiality of actual work performed for companies whose problems led the author to these conclusions. An example problem has been selected from the literature and used as a case study to illustrate the methodology, with the intent of bridging the gap between abstractions and the reader's reality.

Principles of experimental design

The goal of performing a statistically designed experiment is to obtain information as efficiently as possible. An experiment is a series of planned trials in which factors (independent variables) that are thought to affect the outcome are varied systematically and the outputs (dependent variables, also called responses) are measured and recorded. An experiment provides insight into how a system (e.g., your process) behaves and, perhaps, why it behaves as it does. Barker defines an efficient experiment as one that derives the required information with the least expenditure of resources [1]. There are a number of approaches for designing an experiment.

Traditional experimental approaches involve manipulating one variable at a time and looking at all possible combinations of the system variable levels. This approach becomes extremely costly and time consuming as the number of factors increases. Consider a system with three factors at three levels. The total number of combinations is 27. The inclusion of another three-level factor increases the total to 81. Let k be the number of factors and p the number of levels of each factor. If all k factors are included and each of its p levels is run with all combinations of the other factors at their p levels, p^k trials are required. If three replications or, at a minimum, repetitions of some of these p^k trials are run, the result will be a good understanding of the system.

However, the efficiency of this information-gathering plan is subject to question. The number of combinations increases geometrically as the number of factors grows. Typically, the experimenter lacks the resources to conduct the full factorial design when the number of variables exceeds a handful. One answer to this problem is a "shotgun" approach, wherein the experimenter tries a series of experimental conditions that are expected to work. The results may suggest other conditions worth examining. The total number of trials will no doubt be fewer than with the try-all-combinations approach, but, without a modicum of good luck, the result will be less predictive of the system than the more costly approach.

Another answer is statistical experiment design. Designing the experiment statistically involves selection of the responses to be measured, factors that might influence those responses, and ranges of values over which those factors should be evaluated. According to Barker [1], *experimental design is applicable in two areas that are important to the process engineer: characterizing the process and troubleshooting problems*. The first area is characterized by, among other methods, statistical process control (SPC). SPC separates assignable, or special, causes of variation from common causes [2]. The assignable causes are then the focus of troubleshooting efforts, the second area, whose goal is to remove them. This involves testing hypotheses and implementing results. Reiterating the steps of determining assignable causes and removing them results in continuous process improvement.

Randomization

Once the design is selected, the order of the trials should be randomized to improve the likelihood that each trial is an independent observation of the system. Often it is not practical to fully randomize the trials. For example, process variables with long response lag times, such as furnace temperature, are extremely inconvenient to change. The accepted practice is to arrange the experiment in such a way that frequent changes in such variables are avoided. The price paid for this concession is possible autocorrelation in the data and bias in the result, as well as an underestimate of variability in the response. It also inflates the confidence level of significance and reduces the reliability of the prediction.

The experiment

The process of planning and executing the actual experiment begins with a clear definition of the problem and its scope. The definition is refined through examination of all available information, including in-house data and literature from suppliers, trade journals, and public sources. Establishing the design parameters is accomplished effectively with a cross-functional team of interested parties. They come together with different perceptions of the system and its problems. The result of such interaction is typically a better definition of the problem and a more objective perspective on the potential solutions than that of any single individual.

The primary criterion for choosing a response is that it be *meaningful*, i.e., significant in the context of the objective of the experiment. Thus, the response should relate to the quality or cost or characteristic that is targeted for improvement. It should also be repeatable, quantifiable, and measurable. While it is tempting to select a response simply because it is easy to measure, the meaningfulness criterion should take precedence.

Typically, the ideal levels of all responses are not achievable simultaneously. For example, it is not possible to produce the best quality of shoe at a low cost in the range of that for a shoe of unspecified quality, because the high-quality shoe requires a fine leather, which is more expensive than the standard grade. Similarly, tires that provide good traction often wear faster than tires that hold the road less well. To optimize the product, it may be necessary to trade off some tread wear for traction and vice versa. In some cases, there is no feasible solution within the constraints imposed. Thus it may be necessary to relax the constraints and re-evaluate the trade-offs to achieve a feasible solution. The multi-attribute desirability optimization methodology was developed to solve the problem of analyzing the trade-offs and selecting the combination of process variables that produces an optimized set of product characteristics and process outputs.

Careful planning and reviewing at various check points will improve the quality of the results of the experiment. Selection of the design and analysis of the results are closely related, since an experimental design implies a model for analysis. Once the data are collected, the data analysis, interpretation of results, and implementation of conclusions can be carried out.

Analysis of results

The analysis of results involves the use of multiple regression to fit the model that reflects the hypothesis tested using the design. The typical hypothesis tested is that nothing is going on. In other words, the response varies from its mean due only to random variation and not as a result of an assignable cause. The model to be fitted is a multivariate linear, quadratic, or higher-order polynomial equal to the response value. The linear model, for example, is given by

$$Y = C + \sum_{i=1}^{k} B_i X_i + \varepsilon,$$

where Y is the response, C is the mean value of the response, B_i is the fitted coefficient of X_i (half the effect of X_i), X_i is the ith factor, k is the number of factors, and ε is the error.

The hypothesis, then, is that

$$Y = C + \varepsilon$$

(the response is constant except for random variation) and that coefficients on all other terms are equal to zero. Response-surface methodology involves generating the response surface represented by this polynomial equation and exploring it for an optimal value of the response [3].

The optimization methodology

The multi-attribute desirability optimization methodology provides a rigorous means for incorporating expert judgments into the specification of product characteristics or process outputs and determining the best balance of those outputs. It recognizes the fact that such responses are often competitive in nature and that it may be impossible to achieve the most desirable value of each simultaneously.

The methodology provides a means to translate the various properties onto a single scale (d). This transformation permits comparisons and trade-offs to be performed with regard to responses that typically cannot be measured in common units. After each response is transformed to a desirability scale, the individual desirabilities are combined into a composite desirability function (D), which can then be optimized using mathematical techniques [4]. The ImproveIt® Property Balancing System [1] is a software product that performs this set of transformations and optimization. While ImproveIt® is convenient to use, the technique, published in the open literature, can be performed using custom software or a combination of various statistical and graphics packages.

The following are the steps in the application of desirability of the optimization methodology:

(1) Select the product/process characteristics (responses, i.e., the set of Y_j).
(2) Select parameters (independent variables, i.e., the X_is).
(3) Assign weights to responses to indicate their importance using engineering judgment and expert opinion as well as quality function deployment (QFD) techniques [5].
(4) Decide on the shape of the desirability curve given by $d_i = g(Y_i) = h[f(x_1, x_2, x_3, \ldots x_n)]$, where d_i is a dimensionless quantity ranging from 0.0 to 1.0.
(5) Form the composite desirability function (D) as a weighted geometric mean of the individual desirabilities.
(6) Maximize D over the range of the input variables.
(7) Experiment with the system using the model to evaluate the trade-offs.
(8) Implement the optimal solution.

[1] ImproveIt® is a registered trademark of Battelle.

A case study

This section presents a case study to illustrate the use of statistically designed experiments, response-surface methodology, and the multi-attribute desirability optimization methodology. An example from the literature that illustrates the optimization of noodle processing is Oh et al. [6], who studied the effect of five processing variables on seven characteristics of noodles to determine the optimal values of the five controllable process variables. They used response-surface methodology to model the behavior of the noodle-making process. This methodology conforms to that recommended above. Their modeling effort is summarized here as an illustration of the application of response-surface techniques. They then applied graphical methods to analyze the results and select the optimal values of the process parameters. This paper illustrates an alternative approach, application of the multi-attribute desirability optimization methodology to the results obtained, to illustrate the efficiency with which it leads to an optimal solution.

The problem

The authors were interested in determining the effects of five independent variables on seven responses (see Tables 1 and 2).

The first two responses are properties of uncooked noodles; the last five are characteristics of cooked noodles. The authors carefully specified how each of these seven responses would be measured. Color was measured as percent reflectance in the green mode using an Agtron® reflectance spectrophotometer. Breaking stress was measured using the Inkstrom® universal testing instrument (g/mm^2). Cooked mass was measured as the wet mass after the cooked noodles drained for a period of five minutes at room temperature. Cooking loss was calculated as the percentage change in mass (initial mass less

Table 1
Independent variables

Variable	Variable name
X_1	Water absorption
X_2	Dough pH
X_3	Mixing time
X_4	Roll speed
X_5	Percentage reduction in roll gap

cooked mass) when compared to initial mass. Similarly, the other four responses were measurable in accordance with documented procedures. Thus, the criteria that responses be quantifiable, repeatable, and measurable were fully satisfied. Further, the responses were meaningful in light of the stated objective of the experiment.

In the noodle-making system, a number of variables might have an effect on these responses. These include formulation variables such as the amount of salt, type of flour (soft wheat or durum), amount of flour, amount of water, resting time of the dough before rolling, number of sheeting steps, initial roll gap, and cooking time. Flour type could be further described by particle size, milling time, etc., and each of these factors might affect the noodle characteristics. Available information was evaluated to select levels at which to fix these variables. One or more screening experiments were performed to identify potential causative factors to be studied in this experiment.

The results

Each of the five variables selected was to be run at five levels covering the range of values determined to be of interest. A full factorial design with five variables, each having five levels, constitutes 3,125 trials. The authors chose to use a central composite rotatable design [7], which included 32 trials and a center point replicated six times. They randomized the order of the trials. This design was chosen based upon the assumption that the quadratic model was the best equation to describe this system:

$$Y = C + \sum_{i=1}^{5} B_i X_i + \sum_{j=1}^{5} \sum_{i=1}^{5} B_{ij} X_i X_j.$$

This design provides the power necessary to estimate the 21 parameters of the above equation for each of the seven response variables. The best prediction equations for noodle characteristics as obtained by the authors using stepwise regression are as follows:

Color:

$$Y_1 = 301.7 - 5.59X_1 - 24.40X_2 + 0.64X_2^2 + 0.44X_1X_2;$$

Breaking stress (g/mm^2):

$$Y_2 = -10{,}905.2 + 630.83X_1 + 767.97X_2 - 59.46X_4 - 57.73X_5 - 7.63X_1^2 - 29.40X_2^2 - 14.79X_1X_2 + 1.76X_1X_5 + 9.04X_2X_4;$$

Cutting stress (g/mm^2):

$$Y_3 = 16.7 - 0.21X_1 + 1.93X_2 + 0.16X_3 - 0.027X_5;$$

Resistance to compression (%):

$$Y_4 = 10.4 - 0.50X_1 + 8.77X_2 + 0.27X_3 - 0.45X_2^2;$$

Surface firmness (g/mm):

$$Y_5 = 7.1 + 7.64X_2 - 1.28X_4 + 0.17X_5 - 0.050X_2^2 + 0.04X_4^2;$$

Cooked weight (g):

$$Y_6 = 85.3 - 3.55X_1 - 0.15X_5 + 0.056X_1^2 + 0.003X_5^2;$$

Cooking loss (%):

$$Y_7 = 10.8 - 0.72X_2 - 0.27X_4 + 0.048X_2X_4,$$

Table 2
Responses

Response	Response name
Y_1	Color
Y_2	Breaking stress
Y_3	Cutting stress
Y_4	Resistance to compression
Y_5	Surface firmness
Y_6	Cooked weight
Y_7	Cooking loss of cooked noodles

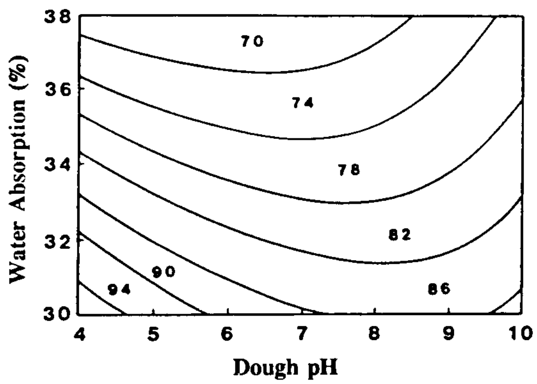

Fig. 1. Color (% reflected light) of uncooked noodles as a function of water absorption and dough pH at the center points for the other independent variables (mixing time 6 min, roll speed 12 rpm, 30% reduction in roll gap).

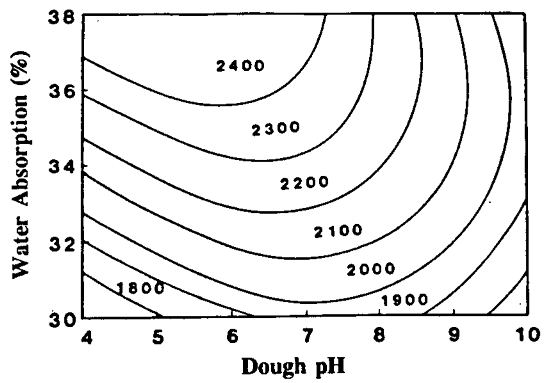

Fig. 2. Breaking stress (g/mm^2) of uncooked noodles as a function of water absorption and dough pH at the center points for the other independent variables (mixing time 6 min, roll speed 12 rpm, 30% reduction in roll gap).

where X_1 is water absorption, X_2 is dough pH, X_3 is mixing time, X_4 is roll speed, and X_5 is reduction percentage.

These prediction equations explain the effect of the factors studied on the responses measured. For example, color is a function of only water absorption and dough pH, and it is not affected by mixing time, roll speed, or reduction percentage. Figure 1 presents isopleths of color as a function of the two variables, water absorption and dough pH. This relationship is fairly easy to visualize from the figure because it is only three-dimensional. Had the coefficients of the other three X variables and their higher-order terms been significant, the result would be a response surface in six-dimensional space, which is harder to interpret visually. This is one shortcoming of graphical techniques for interpretation of response-surface models in n-dimensional space when n is greater than 3. Another is that if a solution is found, it may be adequate, but it is seldom the *best* solution.

Breaking stress (Y_2) illustrates the difficulty. Figure 2 is a plot of breaking stress isopleths as a function of dough pH and water absorption. Water absorption was found to be a function of four of the five independent variables. Therefore, to generate this plot, the surface was collapsed by removing two of the dimensions. This was done by fixing their values at their center points and contour plotting the response as a function of the remaining two. Selecting different values of the omitted variables would produce different plots.

If all seven responses were functions of all five X variables, ten plots would be required for each of the seven responses to examine a contour plot of each response as a function of each pair of independent variables. The problem is simpler in this case because some coefficients were not significant and, therefore, some X terms dropped out of some equations. Table 3 summarizes the seven responses and the significant factors for each. The last column illustrates the number of contour plots required to examine the response as a function of all the possible X_iX_j pairs.

It is seen that 21 plots are required to examine the relationships between the responses and the pairs of independent variables found to be significant. The matter is further complicated by the

Table 3
Number of contour plots

Response		Significant factors	Number of plots
Y_1	Color	X_1, X_2	1
Y_2	Breaking stress	X_1, X_2, X_4, X_5	6
Y_3	Cutting stress	X_1, X_2, X_3, X_5	6
Y_4	Resistance to compression	X_1, X_2, X_3	3
Y_5	Surface firmness	X_2, X_4, X_5	3
Y_6	Cooked weight	X_1, X_5	1
Y_7	Cooking loss	X_2, X_4	1
Total number of plots			21

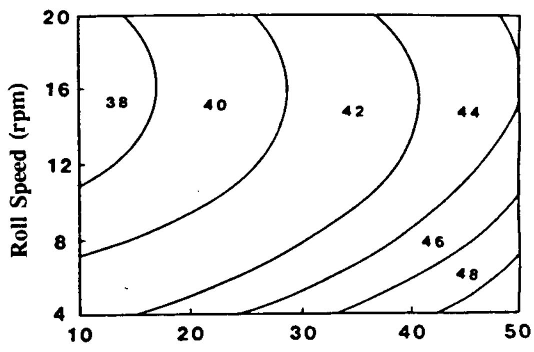

Fig. 3. Surface firmness (g/mm) of uncooked noodles as a function of roll speed and reduction percentage at the center of the other independent variables (mixing time 6 min, 34% water absorption, dough pH 7.0).

fact that the selection of values for the Xs not represented affects the contour plot displayed. Figure 3 presents isopleths of Y_5, surface firmness, as a function of reduction percentage (X_5) and roll speed (X_4). Dough pH is also a factor in surface firmness. Figure 3 is the contour plot obtained when dough pH is fixed at 7.0. But the experimental region for dough pH was 4.0 to 10.0. Any value within this range might have been selected and the resulting contour plot would be different. Thus, there is essentially an infinite number of contour plots for each of the responses that is influenced by more than two X variables.

Figures 4 through 9 present the same kind of information using three-dimensional graphics instead of contour plots wherein the third dimension (the response) is projected onto the plane of the two X_is plotted. Figure 4 presents the same information as Fig. 1, while Fig. 5 corresponds to Fig. 2 and Fig. 7 is like Figure 3. The three-dimensional representation is more informative than contour plots to some readers.

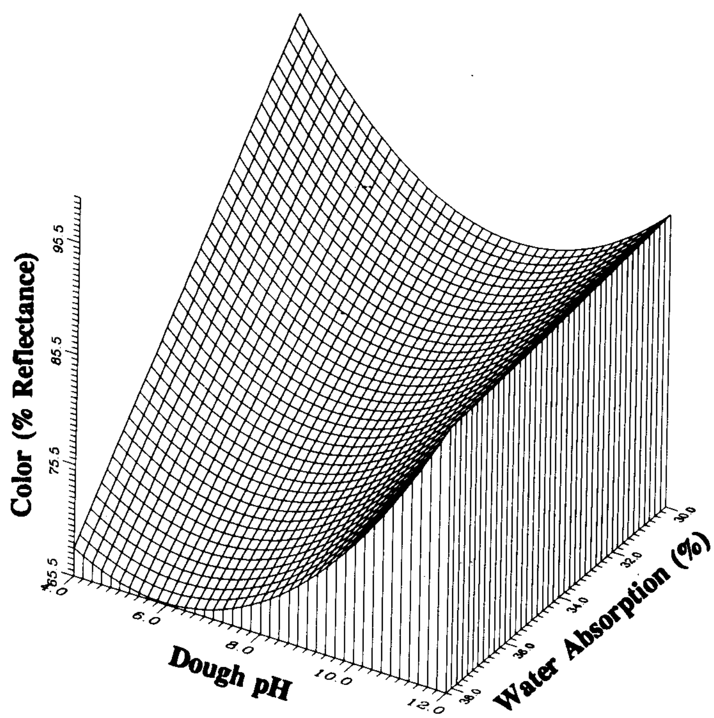

Fig. 4. Response surface of color (% reflected light) of uncooked noodles as a function of water absorption and dough pH at the center points for the other independent variables (mixing time 6 min, roll speed 12 rpm, 30% reduction in roll gap).

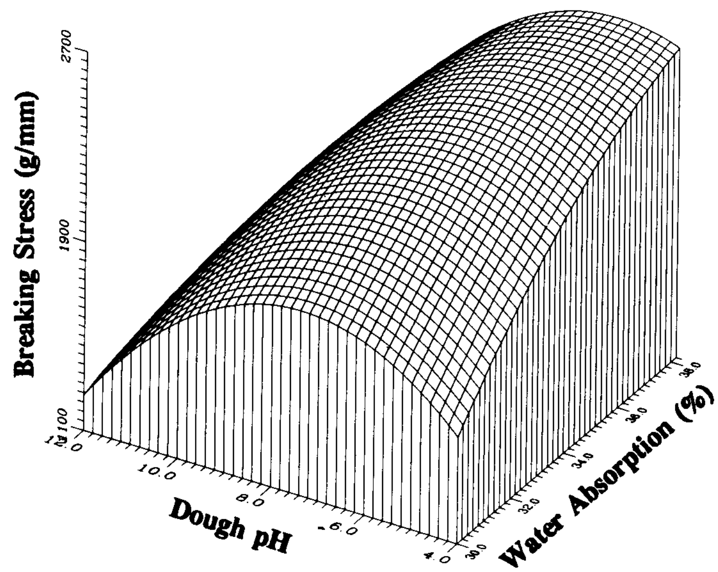

Fig. 5. Response surface of breaking stress (g/mm^2) of uncooked noodles as a function of water absorption and dough pH at the center points for the other independent variables (mixing time 6 min, roll speed 12 rpm, 30% reduction in roll gap).

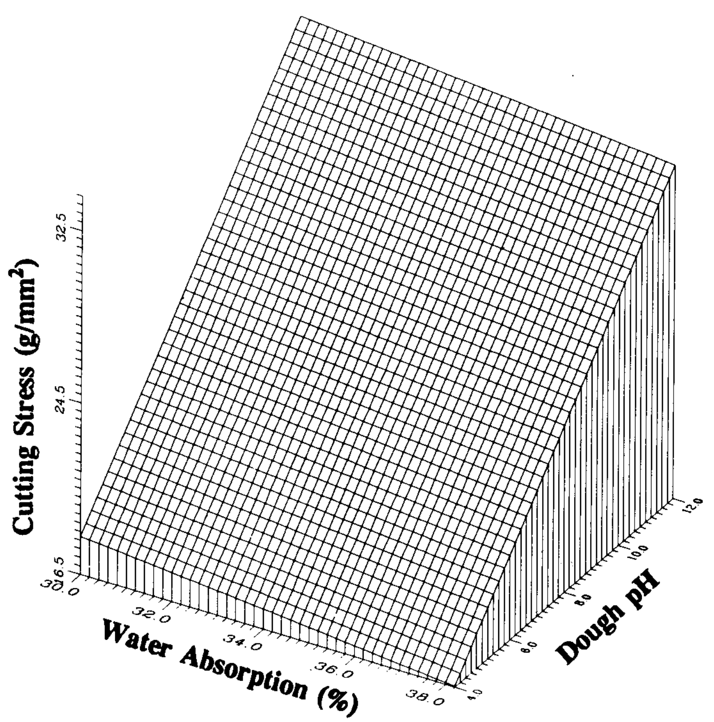

Fig. 6. Response surface of cutting stress (g/mm^2) of cooked noodles as a function of water absorption and dough pH at the center points for the other independent variables (mixing time 6 min, roll speed 12 rpm, 30% reduction in roll gap).

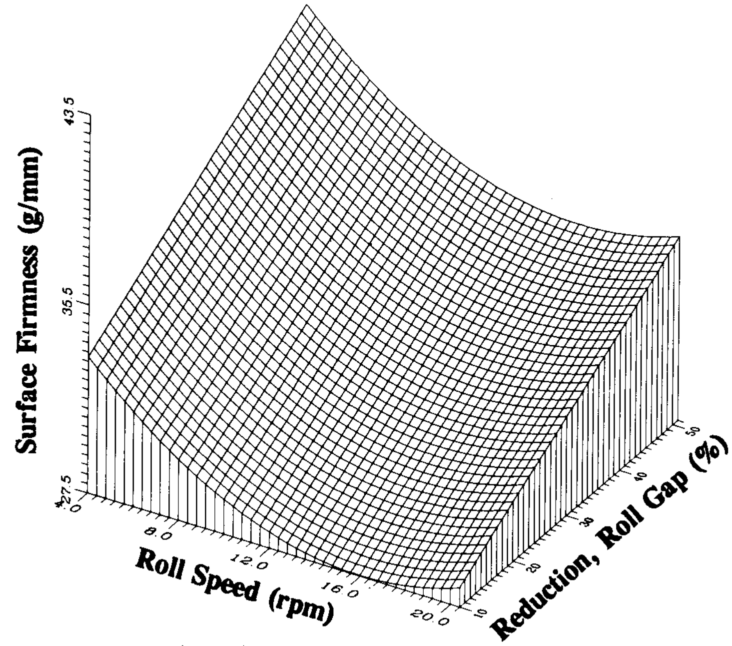

Fig. 7. Response surface of surface firmness (g/mm) of cooked noodles as a function of roll speed and reduction in roll gap at the center points for the other independent variables (34% water absorption, dough pH 7.0, mixing time 6 min).

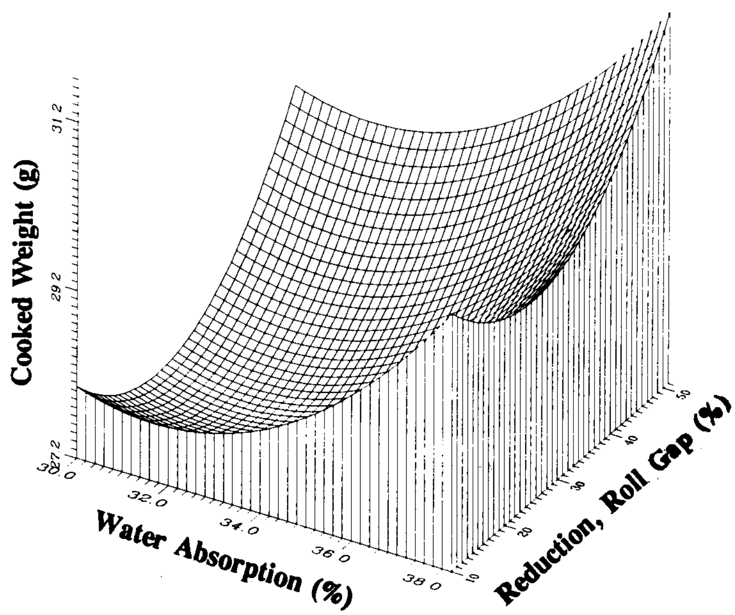

Fig. 8. Response surface of mass (g) of cooked noodles as a function of water absorption and reduction in roll gap at the center of the other independent variables (dough pH 7.0, mixing time 6 min, roll speed 12 rpm).

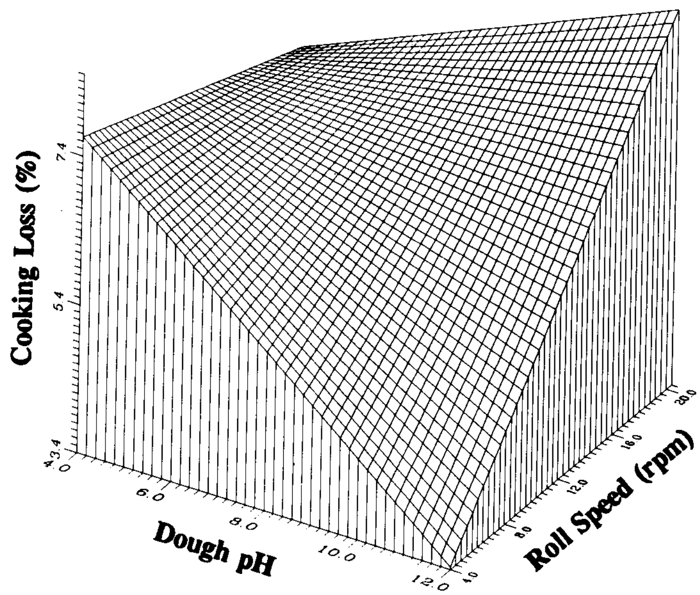

Fig. 9. Response surface of cooking loss (%) as a function of dough pH and roll speed at the center of the other independent variables (34% water absorption, mixing time 6 min, 30% reduction in roll gap).

The authors (Oh et al. [6].) concluded that the process parameters should be set as indicated in Table 4. The selected values for water absorption and dough pH were derived from the graphical technique applied by the authors. However, the analysis yielded no strong recommendation for the other three responses. Therefore, they selected a minimal mixing time, presumably to minimize overall processing time, and they fixed roll speed and roll gap reduction to minimize mechanical wear on the rolls. Although they began with seven responses to be optimized, they completed the analysis and established "optimal" levels for three of the five factors based on two new objective functions.

Table 4
Process parameters

Variable		Optimal value
X_1	Water absorption	32–35%
X_2	Dough pH	6.0–9.0
X_3	Mixing time	3 min
X_4	Roll speed	8 rpm
X_5	Percentage reduction in roll gap	30%

Table 5
Parameters of $d_i = g(Y_i)$

Property		Model	Target value	Range
Y_1	Color	Target	74%	68–94%
Y_2	Breaking stress	Maximize	2,500 g/mm^2	1,800–2,500 g/mm^2
Y_3	Cutting stress	Target	25 g/mm^2	16–25 g/mm^2
Y_4	Resistance to compression	Maximize	50%	30–50%
Y_5	Surface firmness	Maximize	50 g/mm	30–50 g/mm
Y_6	Cooked weight	Target	30 g	28–30 g
Y_7	Cooking loss	Minimize	0%	0–8%

Table 6
Results

Variable		Optimal value
X_1	Water absorption	35.8%
X_2	Dough pH	8.1
X_3	Mixing time	10.0 min
X_4	Roll speed	4.0 rpm
X_5	Percentage reduction in roll gap	50%

Table 7
Property values

Characteristic		Value
Y_1	Color	73.3%
Y_2	Breaking stress	2,241 g/mm^2
Y_3	Cutting stress	24.9 g/mm^2
Y_4	Resistance to compression	36.6%
Y_5	Surface firmness	40.2 g/mm^2
Y_6	Cooked weight	30.0 g
Y_7	Cooking loss of cooked noodles	5.49%

Optimization using the multi-attribute desirability optimization methodology

Applying the Multiattribute desirability optimization methodology to these results solves the problem of trying to visually sort through an infinite number of plots to obtain an acceptable solution. It leads directly to an optimal set of values for the process parameters. Table 5 illustrates the parameters of the mapping of the response values onto the nondimensional desirability scale. For this analysis, each response was given an equal weight, although *the methodology permits unequal weighting of responses if some are judged to be more important than others*. This was an arbitrary choice because no information was available to indicate that a different scheme was appropriate.

The composite desirability function was constructed as follows:

$$D = \left(\prod_{i=1}^{7} d_i \right)^{1/7}$$

and maximized to obtain the following results shown in Table 6. The resulting property values are shown in Table 7.

The composite desirability (D) for this solution is 0.6086, using the zero-to-one desirability scale on which any nonzero value constitutes an acceptable solution. Figures 10 through 13 illustrate D as a function of selected pairs of factors.

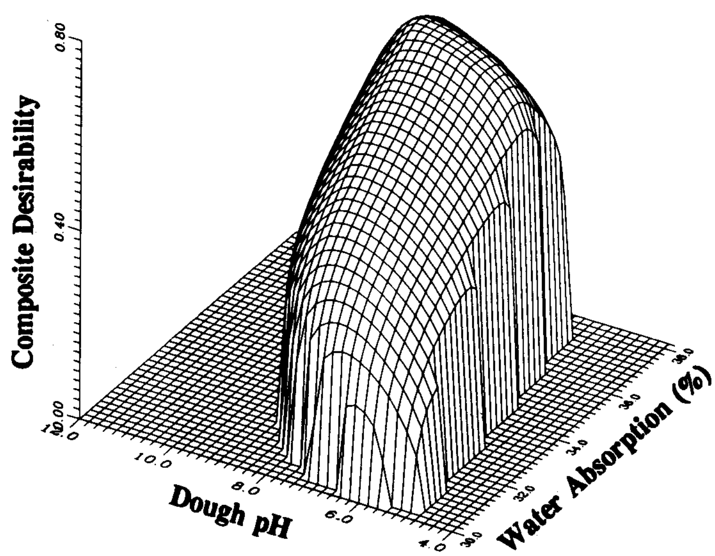

Fig. 10. Composite desirability as a function of water absorption and dough pH at the optimal values of the other independent variables (mixing time 10 min, roll speed 4 rpm, 50% reduction in roll gap).

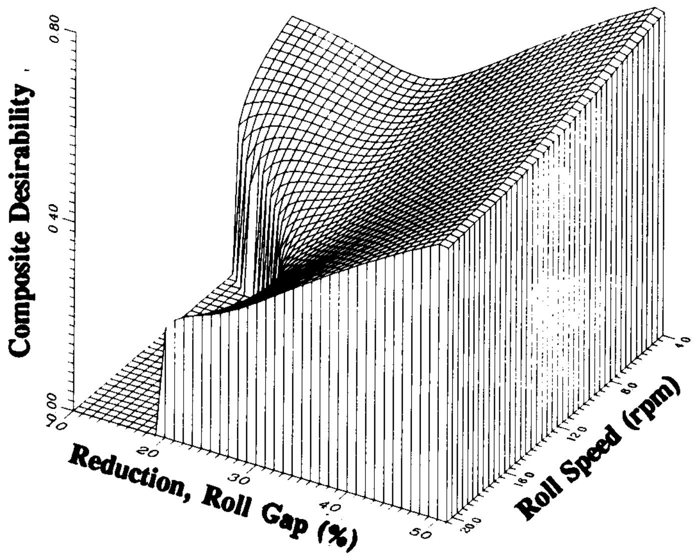

Fig. 11. Composite desirability as a function of roll speed and reduction in roll gap at the optimal values of the other independent variables (35.8% water absorption, dough pH 8.07, mixing time 10 min).

Figure 10 shows the influence of dough pH and water absorption. It is seen that the feasible region is bounded by dough pH in the range of 4.4 to approximately 10. The optimal value is 8.0, which is in the range of 6.0 to 9.0 as determined by the authors. But the optimal value of water absorption is 35.8%, not 32 to 35% as the authors concluded,

Figure 11 shows interesting behavior of composite desirability with respect to roll speed and

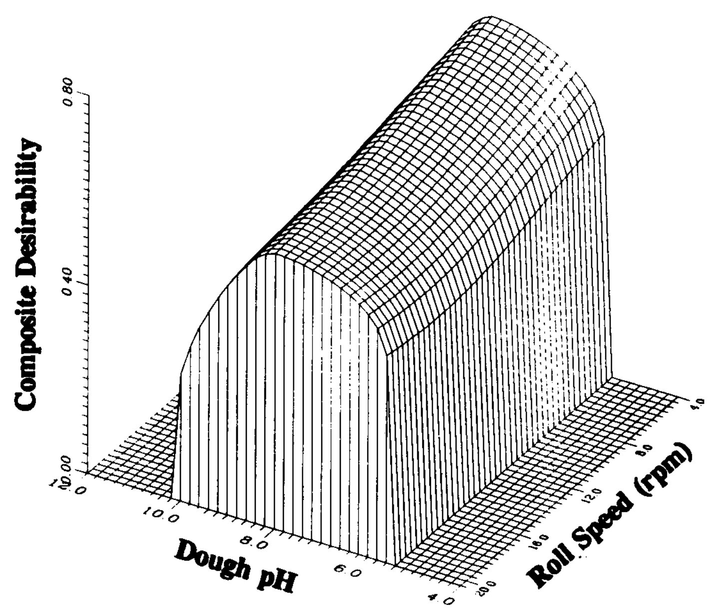

Fig. 12. Composite desirability as a function of dough pH and roll speed at the optimal values of the other independent variables (35.8% water absorption, mixing time 10 min, 50% reduction in roll gap).

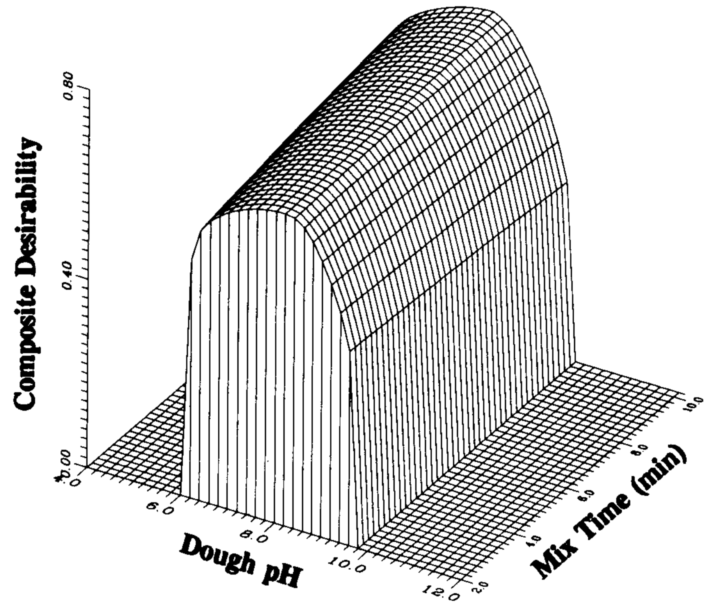

Fig. 13. Composite desirability as a function of dough pH and mixing time at the optimal values of the other independent variables (35.8% water absorption, roll speed 4 rpm, 50% reduction in roll gap).

percent roll gap reduction. While the authors needed to apply extraneous criteria to establish a choice, the multi-attribute desirability optimization methodology illustrates that within the experimental region the system improves as roll gap increases and as roll speed decreases.

Figure 12 shows composite desirability as a function of dough pH and roll speed, while Fig. 13 combines the effects of dough pH and mixing time. It is interesting to view this surface as a function of pairs of factors to gain an understanding of the behavior of the system over the independent-variable ranges modeled and where the feasible region lies.

The multi-attribute desirability optimization methodology is more rigorous and less tedious than the graphical technique. For the two factors with the greatest influence on the responses, the two techniques produced numerically similar results, although the graphical technique provided a range that encompassed most of the feasible solution space, while the multi-attribute desirability optimization methodology produced two values. The authors arbitrarily selected mixing time at 3 minutes as an optimal value, primarily to avoid increasing processing time unnecessarily. Using the desirability optimization methodology, it is a simple matter to include an additional response, processing time, if it is desired to minimize this along with optimizing the other responses. The technique provides greater power to achieve a better result in less time than overlaying contour plots and other graphical techniques that have been used for the simultaneous optimization of multiple responses. All nine responses (including processing time and mechanical wear on rolls) could have been optimized simultaneously.

Conclusion

This paper has presented a rigorous approach to the selection of process parameters based on the simultaneous optimization of multiple responses. It describes a powerful technique that permits the determination of optimal rather than adequate solutions. When applied in the product definition phase, it can lead to more efficient process definition. During production, this methodology can help identify causes of quality problems, ways to reduce costs, and ways to eliminate process variability. And because it is based on experience and data, it is a flexible tool that can be applied for continuous process improvement.

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