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IMPROVEMENT OF PROCESS YIELD

Carol Ventresca
George C. Derringer
Battelle
505 King Avenue
Columbus, Ohio

Alan Stephens
Signet Armorlite, Inc.
1001 Armorlite Drive
San Marcos, California

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ABSTRACT

In today's competitive environment, there is constant pressure to improve quality and reduce production costs. Off-shore competition, scarcity of investment capital, the regulatory environment, and other forces continuously drive us to improve process yield and product quality. A modest investment in appropriate statistically designed experiments can solve process problems and produce near-term payback. Experimental design techniques elicit the most information for the least cost, and they are broadly applicable to industrial problems. This paper provides a case study illustrating how these techniques were applied to reduce the occurrence of a particular defect in a polymer casting process. The result was a significant improvement in process yield and a first-year savings of many times the cost of the experiment.

INTRODUCTION

According to an eminent student of the late statistician, Dr. William G. Hunter, "... things left unattended or unimproved will change — for the worse."[1] If this is true, few plants can afford to leave quality unattended. Volumes are written on the definition of quality, and controversy persists on how to improve it. Transcending the semantics and the testimonials for palliative TLAs (three-letter acronyms) is a simple imperative: most companies must continuously improve quality in order to remain competitive for the sake of the business over the long term.

Without debating the essence of quality or the benefits of improving it, the author asserts that every production operation has at least one problem that, if identified and addressed, would further the objectives of that operation, whether they be reduced costs, tighter adherence to specifications, longer service life, etc. This paper is written to explain how one company did just that. The body of knowledge supporting the work described here is vast, and successes are numerous. This case study illustrates how a group of committed people identified and solved their biggest yield problem quickly, cost effectively, and, apparently, permanently. The case study also illustrates the techniques used so that the reader may assess their value in his/her operation and learn how to begin to apply them.

THE PROBLEM

The process is the manufacture of scratch-resistant ophthalmic lenses. An acrylic formulation is mixed and pregelled to a predefined point, then held until needed in the casting area. An intricate monomer handling and filtration system delivers pregelled monomer to pour stations on continuous casting lines. At the pouring stations, molds are filled, closed, and hung on curing racks. A mechanized system conveys the filled racks through the curing process where B-stage cure is effected.

Defective lenses that emerge from B-cure cannot be reworked; thus, they are scrapped after hours of processing. Lenses may be defective in several different ways, but the most frequent defect at the start of this study was the premature opening of the mold, referred to as a "water open." When the mold opens before B-cure is complete, the ophthalmic properties of the lens are compromised, and the lens must be scrapped. The water-open rate on Casting IV ranged from 3.9 percent to 13.8 percent, averaging 6.8 percent for the six months prior to the start of the study, costing the company hundreds of thousands of dollars each year. The magnitude of the problem threatened the very survival of the company.

A cross-functional team was formed to analyze and solve the problem. The team included staff from process engineering, product development, quality control, production, and accounting. Upper management initiated and supported the undertaking. Thus, the resources were mobilized to solve the problem.

APPROACH

To begin a quality improvement program, the best strategy is to select the biggest problem within the purview of the problem solvers, where "biggest" is defined as the most visible and/or that with the largest implications for profitability or other important measure of performance. The Pareto Principle is "the phenomenon whereby, in any population that contributes to a common effect, a relative few of the contributors account for the bulk of the effect."[2] Based on this principle, conventional wisdom asserts that 80 percent of problems result from 20 percent of factors.

The project team convened and quickly agreed that their mission was to reduce the occurrence of water opens to less than 2 percent of production. Following definition of the problem to be studied, the team focused attention on the factors that might cause water opens. The goal of the project was to determine the "optimal set points" for process variables; optimal set points in this context are parameter values that produce the minimum number of water opens. This is essentially the approach recommended in the Taguchi method. The technical knowledge and engineering judgment of plant personnel were captured as part of the fact-finding effort. Sixty-three factors were identified as having the potential to affect the process and, specifically, the water-open rate. These included formulation variables, process variables (e.g., cure cycle parameters, die temperature), environmental conditions, and physical characteristics of the molds.

Each factor was debated to assess the likelihood that it was a significant contributor to the water-open problem. The set of 63 was reduced to a manageable subset of factors that could be controlled in an experiment in the plant. After careful consideration and examination of historical data, 15 factors were chosen and are presented in Table 1.

In a production environment it is important to maximize the information obtained from a minimum amount of experimentation. This was accomplished in two ways: (1) by designing the experiment judiciously and (2) by carefully recording hourly observations of the "noise" variables omitted from the design.

Table I

Design Variables

Variable	Variable Name
X_1	Cure Cycle Profile
X_2	Resin A and Resin B in Coating Solution
X_3	Die Temperature at Coating (°F)
X_4	Rings
X_5	Coating Solution Temperature (°F)
X_6	Release Agent in Monomer
X_7	UV Absorber in Monomer
X_8	Monomer Reclaim
X_9	Coating Solution Reclaim
X_{10}	Release Agent in Coating Solution
X_{11}	Coating Cure: IR Lamps
X_{12}	Coating Cure: UV Dose
X_{13}	Inserts
X_{14}	Relative Humidity at Coating Station
X_{15}	Cooling Tower Temperature

STATISTICAL DESIGN

An experimental design provides a blueprint for each set of conditions or trial. It prescribes the target values for the independent variables. For each set of target values, the system response is observed. A two-level, resolution IV, statistical screening design in 40 trials with 15 variables was used. The levels for each variable were thoughtfully selected based on the need to introduce enough perturbation into the process to provoke a change if, indeed, the factor is capable of causing one but not so much as to generate undue quantities of scrap. One trial was defined as 4 hours of production, and the system response (dependent variable) was the percentage of water opens, based on the number of lenses cast.

These 40 trials included four sets of triplicate trials. Repeated trials permit understanding of the reproducibility of the process and are used to test the adequacy of the model fitted to the data obtained. This specific design was selected because it permits main effects to be estimated uninfluenced by interaction effects. When compared to a full factorial design in which all 32,768 possible combinations of 15 variables would be run, the savings is clear.[3]

The design is presented in Table 2. Each row represents an experimental trial and each column represents a variable (or factor). For example, for trial number 3, variable X_1, Cure Cycle, was to be the normal cure cycle used in production; X_2, a formulation variable, was to be held at its low level; X_3, Die Temperature at the Coating Station, was to be targeted at its low level, 70°F; new rings were to be used (see X_4), etc.

Table II

Experimental Design

Trial No.	X1 Cure	X2 A/B	X3 Die T	X4 Rings	X5 CtgSol	X6 Mon-R	X7 Mon-U	X8 Mon-Recl	X9 Ctg-Recl	X10 Ctg-Rel	X11 IR Dos	X12 UV Dos	X13 Inserts	X14 CtgSta	X15 Towr T
1	Normal	Low	70	Normal	60	Low	Low	Recycle	Recycle	Low	Normal	0.44	Unwash	15%	70
2	Normal	Low	70	Normal	60	Low	Low	Virgin	Virgin	High	Off	0.33	Washed	23%	74
3	Normal	Low	70	New	70	High	High	Recycle	Recycle	Low	Normal	0.33	Washed	23%	74
4	Normal	Low	70	New	70	High	High	Virgin	Virgin	High	Off	0.44	Unwash	15%	70
5	Normal	Low	70	Normal	60	Low	Low	Recycle	Recycle	Low	Normal	0.44	Unwash	15%	70
6	Normal	High	74	Normal	60	High	High	Recycle	Recycle	High	Normal	0.44	Unwash	23%	74
7	Normal	High	74	Normal	60	High	High	Virgin	Virgin	Low	Normal	0.33	Washed	15%	70
8	Normal	High	74	New	70	Low	Low	Recycle	Recycle	High	Off	0.33	Washed	15%	70
9	Normal	High	74	New	70	Low	Low	Virgin	Virgin	Low	Off	0.44	Unwash	23%	74
10	Normal	Low	70	Normal	60	Low	Low	Recycle	Recycle	Low	Normal	0.44	Unwash	15%	70
11	Test	Low	74	Normal	70	Low	High	Recycle	Virgin	Low	Off	0.44	Washed	15%	74
12	Test	Low	74	Normal	70	Low	High	Virgin	Recycle	High	Normal	0.33	Unwash	23%	70
13	Test	Low	74	Normal	70	Low	High	Recycle	Virgin	Low	Off	0.44	Washed	15%	74
14	Test	Low	74	New	60	High	Low	Recycle	Virgin	Low	Off	0.33	Unwash	23%	70
15	Test	Low	74	New	60	High	Low	Virgin	Recycle	High	Normal	0.44	Washed	15%	74
16	Test	High	70	Normal	70	High	Low	Recycle	Virgin	High	Normal	0.44	Washed	23%	70
17	Test	High	70	Normal	70	High	Low	Virgin	Recycle	Low	Off	0.33	Unwash	15%	74
18	Test	High	70	New	60	Low	High	Recycle	Virgin	High	Normal	0.33	Unwash	15%	74
19	Test	High	70	New	60	Low	High	Virgin	Recycle	Low	Off	0.44	Washed	23%	70
20	Test	Low	74	Normal	70	Low	High	Recycle	Virgin	Low	Off	0.44	Washed	15%	74
21	Test	High	74	New	70	High	High	Virgin	Virgin	High	Off	0.33	Washed	23%	74
22	Test	High	74	New	70	High	High	Recycle	Recycle	Low	Normal	0.44	Unwash	15%	70
23	Test	High	74	Normal	60	Low	Low	Virgin	Virgin	High	Off	0.44	Unwash	15%	70
24	Test	High	74	Normal	60	Low	Low	Recycle	Recycle	Low	Normal	0.33	Washed	23%	74
25	Test	High	74	New	70	High	High	Virgin	Virgin	High	Off	0.33	Washed	23%	74
26	Test	Low	70	New	70	Low	Low	Virgin	Virgin	Low	Normal	0.33	Washed	15%	70
27	Test	Low	70	New	70	Low	Low	Recycle	Recycle	High	Off	0.44	Unwash	23%	74
28	Test	Low	70	Normal	60	High	High	Virgin	Virgin	Low	Normal	0.44	Unwash	23%	74
29	Test	Low	70	Normal	60	High	High	Recycle	Recycle	High	Off	0.33	Washed	15%	70
30	Test	High	74	New	70	High	High	Virgin	Virgin	High	Off	0.33	Washed	23%	74
31	Normal	High	70	New	60	High	Low	Virgin	Recycle	High	Normal	0.33	Unwash	23%	70
32	Normal	High	70	New	60	High	Low	Recycle	Virgin	Low	Off	0.44	Washed	15%	74
33	Normal	High	70	New	60	High	Low	Virgin	Recycle	High	Normal	0.33	Unwash	23%	70
34	Normal	High	70	Normal	70	Low	High	Virgin	Recycle	High	Normal	0.44	Washed	15%	74
35	Normal	High	70	Normal	70	Low	High	Recycle	Virgin	Low	Off	0.33	Unwash	23%	70
36	Normal	Low	74	New	60	Low	High	Virgin	Recycle	Low	Off	0.33	Unwash	15%	74
37	Normal	Low	74	New	60	Low	High	Recycle	Virgin	High	Normal	0.44	Washed	23%	70
38	Normal	Low	74	Normal	70	High	Low	Virgin	Recycle	Low	Off	0.44	Washed	23%	70
39	Normal	Low	74	Normal	70	High	Low	Recycle	Virgin	High	Normal	0.33	Unwash	15%	74
40	Normal	High	70	New	60	High	Low	Virgin	Recycle	High	Normal	0.33	Unwash	23%	70

THE EXPERIMENT

The order of the trials within the design was randomized to the extent possible without undue disruption of the production process. This is necessary so that the confidence level at which conclusions are stated is not inadvertently inflated. As is common in industrial situations, complete randomization was not feasible.

Two or more hours were allocated between trials to establish factor levels at the target values for the next trial. Because it is not always possible to achieve the precise value specified for every variable in a design, actual factor levels achieved during the experiment were recorded. Environmental variables were tracked. Ambient relative humidity was so significant that it was included as X_{16} in the final analysis. The weather cooperated by providing a well-behaved range of conditions during the experiment. Because of this fact and the power of the design, it was possible to include ambient relative humidity in the analysis.

The quality of the data was good, thanks to the conscientious effort of plant personnel. An interesting phenomenon occurred during the course of the experiment. In general, the scrap rate was lower than anticipated. This is not uncommon during in-plant trials. It could be a Hawthorne-like effect wherein test subjects perform better than usual simply because they are involved in a special process. However, the effect remained long after the experiment ended. A similar positive and lasting change has occurred following trials in other plants.

RESULTS

The results of the experiment were analyzed using multiple regression analysis to model the response by a least-squares fit of a second-order polynomial to the data.[4] Various models were fit, some including "noise" variables, such as ambient temperature and relative humidity, that were recorded along with the 15 design variables. Interaction effects were entertained when they were considered important.

MAIN EFFECTS

A main effect is the change in the response (value being measured, Y, e.g., water-open percentage) as a function of a factor, independent of the values of other variables. An interaction effect is a change in the effect of one variable based on the value of another.

The best regression equation fitted to the normalized data is as follows:

$$\sqrt{Y} = 2.03 + 0.001X_1 - 0.6056X_8 + 0.30X_{16} + 0.232X_6 + 0.175X_9 - 0.196X_1X_8 + 0.193X_6X_9 - 0.115X_6X_8 \quad (1)$$

where Y = water-open percentage
X_1 = cure profile
X_8 = monomer recycle
X_{16} = ambient relative humidity
X_6 = monomer release agent
X_9 = coating reclaim.

The main effects are presented in Figure 1. Here the effect of each variable on water opens as each variable ranges from its lowest level to its highest level is illustrated. As monomer recycling, which has a significant effect, goes from its lowest to its highest level in the design, the net *change* in water opens can be expected to be

$$0.6056 - (-0.6056) = 1.2112 \text{ percent.}$$

In other words, the use of reclaimed monomer results *on the average* in an increase in the water-open rate of 1.2 percentage points. (Note that this and other conclusions in this paper apply to the conditions during the trials, which, on average, were lower in humidity than usual.) Other effects are interpreted similarly.

The main-effect information is also presented in the form of a Pareto diagram in Figure 2. The vertical axis is percentage of total modeled variation in water-open rate. Variables are listed on the horizontal axis from most important to least important with respect to their effect on water opens. The height of the bar for each variable indicates its contribution to the modeled variability in water-open rate. The curve shows the cumulative contribution of the variables on the horizontal axis. This type of analysis is useful in prioritizing the order in which improvement measures are undertaken. The interpretation is as follows. Of the variable contributions to water opens (which constitute over 88 percent of the total variation), monomer recycling contributes 38 percent, monomer release an additional 13 percent, etc. The order shown here is slightly different from that of Figure 1. The t-statistics were used to construct this plot whereas predictions from extreme variables were used for Figure 1. If no interaction effects were operative, the information in Figure 1 would be suitable for prediction, and, indeed, a prediction equation could be constructed.

INTERACTION EFFECTS

Among the fifteen variables in this study, there are potentially 105 two-factor interaction effects. The relevance of interaction effects is that if, for example, $X_1 X_2$ is a significant interaction, then the concept of the effect of X_1 or X_2 by itself has no meaning. The effect of either can be specified only if the *level* of the other is fixed.

Using the experimental design of Table 2, the 105 interaction effects are estimable in groups of seven. In other words, the design permits the estimation of an effect such as the following:

$$\text{Effect} = (X_1 X_3) + (X_2 X_4) + (X_5 X_7) + \text{three other interactions.}$$

On the surface, this would not appear useful. However, two general principles are of help. First, main effects are generally larger than interactions, and, second, it is unlikely for an interaction to be significant if one of the corresponding main effects is not significant. Thus, the interaction between a Monomer Recycle and Monomer Release Agent can be estimated because both variables exhibit statistical significance as main effects. It should be noted that because the interaction between Cure Profile (X_1) and Monomer Reclaim (X_8) was significant, X_1 was forced into the model for the sake of consistency, even though the coefficient for it was near zero. This is an unusual case.

ISOLATION OF STATISTICALLY SIGNIFICANT EFFECTS

Figures 1 and 2 summarize all effects, regardless of significance. It is a major goal of an experimental design to isolate important effects. In this analysis, the goal was to identify probable causes of water opens—special effects that have a low probability (0-10 percent) of being due to noise (i.e., the inevitable fluctuations of experimental data). Regression analysis indicated that the following variables are significant:

- Monomer Recycle
- Ambient Relative Humidity
- Monomer Release Agent
- Coating Reclaim.

Beyond these, no main effects were demonstrated to be significant.

These variables were then used in a full regression analysis to obtain the many model diagnostics that can lead to the most plausible model. The model included the following interaction terms:

- Cure Profile x Monomer Recycle
- Monomer Release Agent x Coating Reclaim
- Monomer Release Agent x Monomer Recycle.

These interactions were all statistically significant. Furthermore, after their addition to the model, the model was judged to be a good statistical representation of the data, based on fit, variance, and bias criteria.

This model was confirmed by running best subsets regression analyses. The equation with the above terms gave the best C-p statistic. C-p is a measure of both variance and bias. The model accounted for 88 percent of the variability of the system over the period of the test.

The model can be illustrated meaningfully by four 2-dimensional figures. Figure 3 shows the overall effect of relative humidity. The experiment confirmed the team's belief that increasing humidity increased the water-open rate.

Figure 4 illustrates the Monomer Reclaim x Cure Profile interaction. Here it is clear that, for both cure profiles tested, virgin monomer is preferred. The test cure profile, however, was more sensitive to recycled monomer.

Figure 5 illustrates the Monomer Release Agent x Coating Recycle interaction. Here, increasing release agent significantly increased water opens when virgin coating solution was used but not when coating solution was recycled.

Figure 6 illustrates the Mold Release Agent x Monomer Reclaim interaction. It indicates that high monomer release agent exacerbates the detrimental effect of monomer reclaim.

Predicted values of water-open rate were calculated for different scenarios based on the model. The best case modeled produced an expected value of 0.3 percent water opens when virgin monomer is used, when the cure profile is not the normal one, and when the relative humidity is 15 percent or less. Release agent was set at 0.01 percent and coating solution was assumed to be recycled. The 95 percent prediction interval around this value is 0.0 to 1.6 percent. While care must be exercised in extending the model (because extension involves an extrapolation outside the region of the experimental data), this indicates that there is opportunity for improvement in process yield by optimizing the cure cycle.

The company has since implemented improvements in the process based on the results of this study. They minimize the use of reclaim, especially when the humidity is high, control the relative humidity at the pour station, and formulate the coating for improved performance. The water-open rate consistently averages less than 0.5 percent.

CONCLUSION

This approach of using designed experiments to solve a particular problem is mature and powerful. If applied responsibly, it can improve yield, increase product quality, decrease production costs, reduce variability, etc. The authors recommend starting with a small study on a laboratory scale, but the case study shows that an in-plant experiment involving disruption of 2 weeks of production can still be cost effective.

A problem that had existed for years was solved within months, and the payback on the investment was tenfold within the first year. In the year and a half since this work was completed, the problem has remained under control, and every indication is that the problem has been solved permanently.

There is a tendency to maintain the *status quo* until some event makes it impossible to continue with business as usual. Business as usual should be continuous improvement. Continuous process improvement is a "pay-as-it-goes" plan. Once the transition is made to this approach, it is hard to justify having done anything else.

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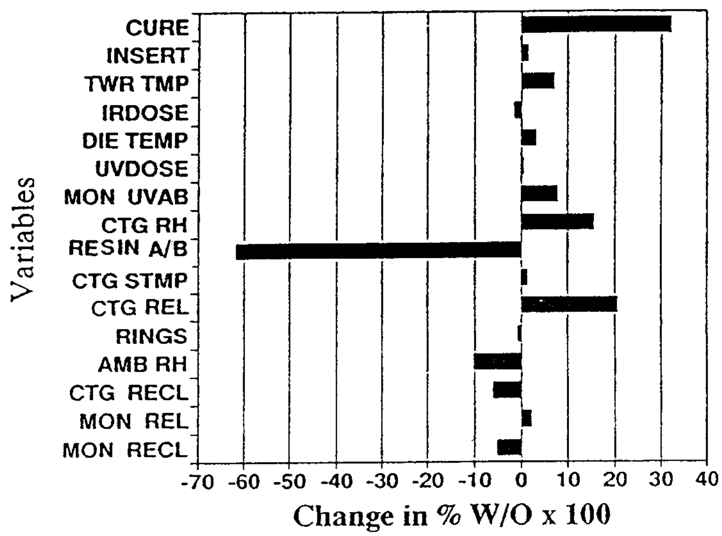

Figure 1. Variable Effects, Ignoring Interactions

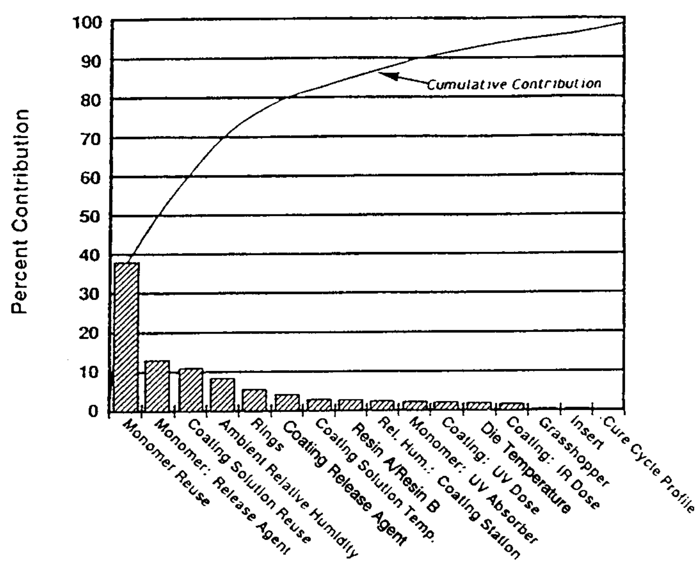

Figure 2. Pareto Diagram of Variable Contributions to Water-Open Rate

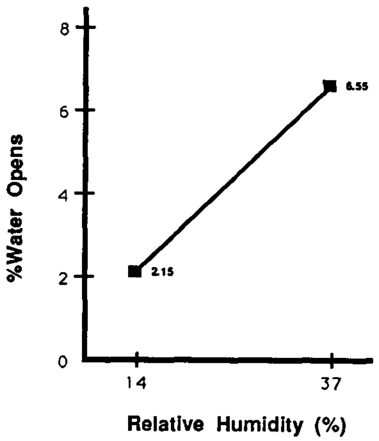

Figure 3. Effect of Ambient Relative Humidity on Water Opens

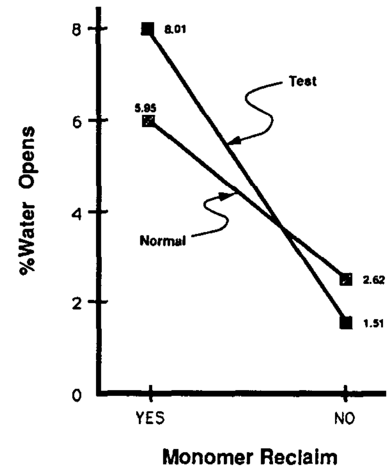

Figure 4. Interaction Effect of Cure Profile and Monomer Reclaim

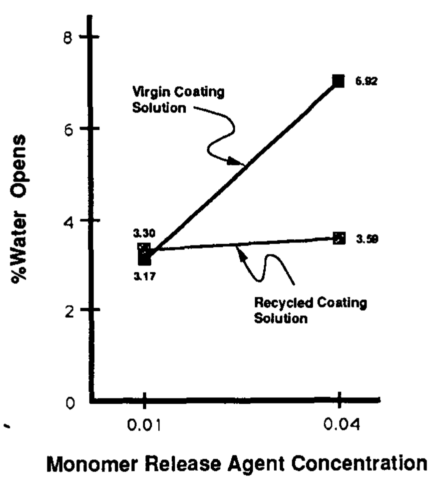

Figure 5. Interaction Effect of Monomer Release Agent and Coating Reclaim

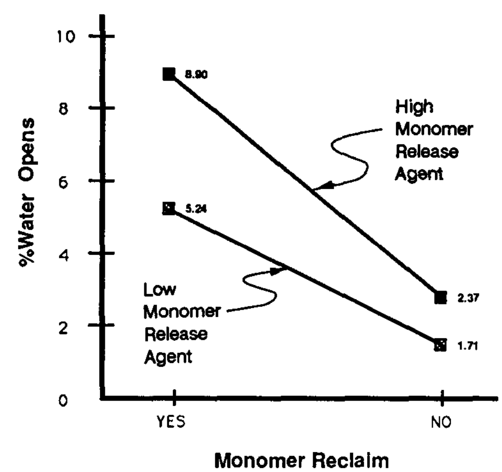

Figure 6. Interaction Effect of Monomer Reclaim and Monomer Release Agent