SIMULATION OF INFORMATION CHOICE

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ABSTRACT

Beginning with the information economics framework and a multi-period decision model [15], this paper considers the use of computer simulation methods within an information system choice environment. Actual decision behavior is replaced by optimal decision rules, and simulation is used to evaluate the effects of parameter changes in the environmental model. Simulation is shown to be functional (1) in estimating the value of alternative information structures within a fifteen period decision model and (2) in providing sensitivity and statistical data which would be useful both for different decision maker utility functions and for a variety of information system design questions.

INTRODUCTION

The problem facing information systems designers is to supply an information system which has benefits that exceed its costs to the users. A key component of this problem is measuring the benefits which would accrue from a proposed information structure. This aspect is complex, especially if the benefits are to be measured in units comparable to those describing the cost of the system. Complicating the problem still further, these benefits must be estimated *ex ante*.

Because of these problems, information system design decisions are often made in terms of a ranking of systems according to their usefulness to the decision makers. Since in most cases, a "better" information system is costly, a rank ordering ignores the cost-benefit trade-offs. The critical question remains: Is an improved information system superior enough to warrant the extra cost?

Information economics proposes a method for estimating the value of information generated by a particular information system in a decision-theoretic context. Because of the computational difficulties inherent in applying the framework in a realistic situation and especially the *ex ante* requirements, a computer simulation approach is proposed as an efficient method of measuring information value.

The information value framework is sufficiently general to be applied in a wide variety of circumstances. In this paper a particular model is chosen which was used in prior research by Mock [15] [16] [17]. This choice is made with two objectives in mind.

1. To demonstrate the application of the information value framework using computer simulation.
2. To obtain measurements of *ex ante* information value in a situation which is interesting in its own right.

The Nature of the Experimental Model

An information structure is an information system specified in terms of its procedures for data collection, measurement, processing, and communication. Information value is generally defined as the difference in expected payoffs when utilizing different information structures. To calculate the expected differences one must construct a framework. The framework must be composed of at least four components—a real-world function, an information function, a decision function, and a payoff function. Figure 1 depicts the interrelationships of these four components.

A dynamic multi-period description of the above may be constructed as follows. Let s_t be the state-of-the-world in time period t. Let a_t be the action taken by the decision-maker in period t. The state-of-the-world in period t+1, then, is $s_{t+1} = f(s_t, a_t, \xi_t)$, where ξ_t is a random noise element. This function f will be called the real-world function. Thus, the state-of-the-world in period t+1 (s_{t+1}) depends upon the initial state-of-the-world (s_t), a random noise factor for period t (ξ_t), and the action taken in period t (a_t).

Let y_t be the signal received from the information structure in period t. Then, $y_{t+1} = \eta(s_{t+1}, y_t, \pi_t)$, where π_t is information noise and η will be called the information function. The signal received in period t+1 depends upon the actual state-of-the-world, information noise, and the prior signal or initial or starting contents of the information structure.

In this paper, the action taken will be assumed to be the same as the decision made. There is no difference between intention and execution. If this simplyfying assumption is made, then $a_t = a(y_t)$, where a is known as the decision function.

One more component of the framework is required if expected payoff differences are to be calculated, *i.e.*, the payoff or utility function $r_t = \omega(s_t)$. The return to the decision maker in period t is a function of the state-of-the-world in period t and will be referred to as the payoff function. (See Figure 2 for a flowchart depicting the time relations among these variables.)

The calculation of the expected payoff for a specific information function and decision involves the conditional probability of state s_t occurring, given information y_{t-1} and the decision function $a(y_{t-1})$. The expected payoff is therefore a derivative of the conditional probabilities and the states-of-the-world. (See [6] and [16] for appropriate calculus.) Solving for the conditional probability and the expected value is not a trivial problem, even with the simplifying assumption made above. In fact, it becomes computationally difficult for most reasonably realistic models with more than one or two variables. Solving the problem for a multi-period model also substantially increases the complexity.

One approach to the utilization of a model of this type is empirical testing using human decision makers as the decision function and employing different information structures. The model developed by Mock [15] [17] [20] has been used extensively in this way and has been tested under several experimental designs.

In contrast, this paper deals with the real world function and its parameters using computer simulation methodology (as opposed to the laboratory methodology)

FIGURE 1

Basic Components of an Information Economics Model

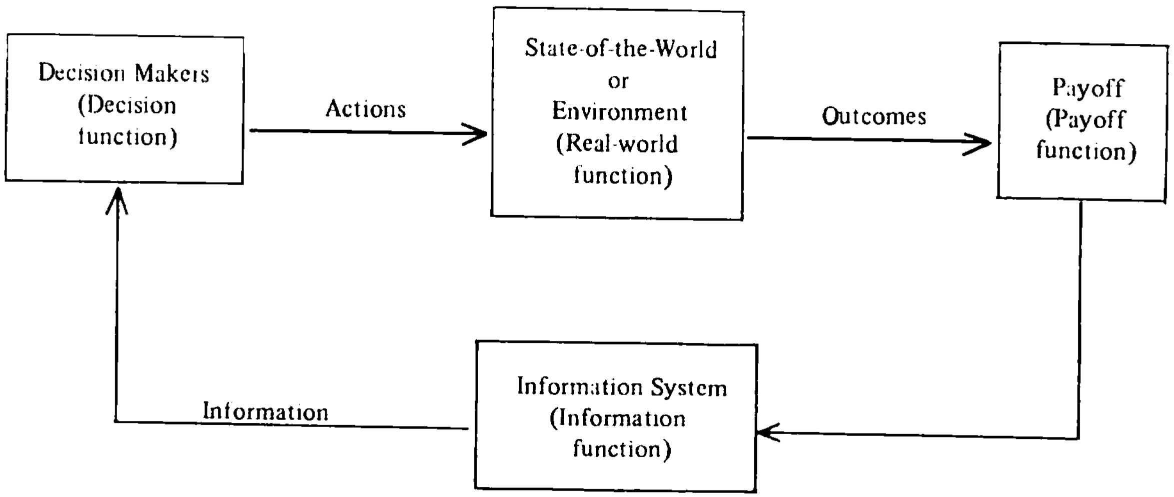
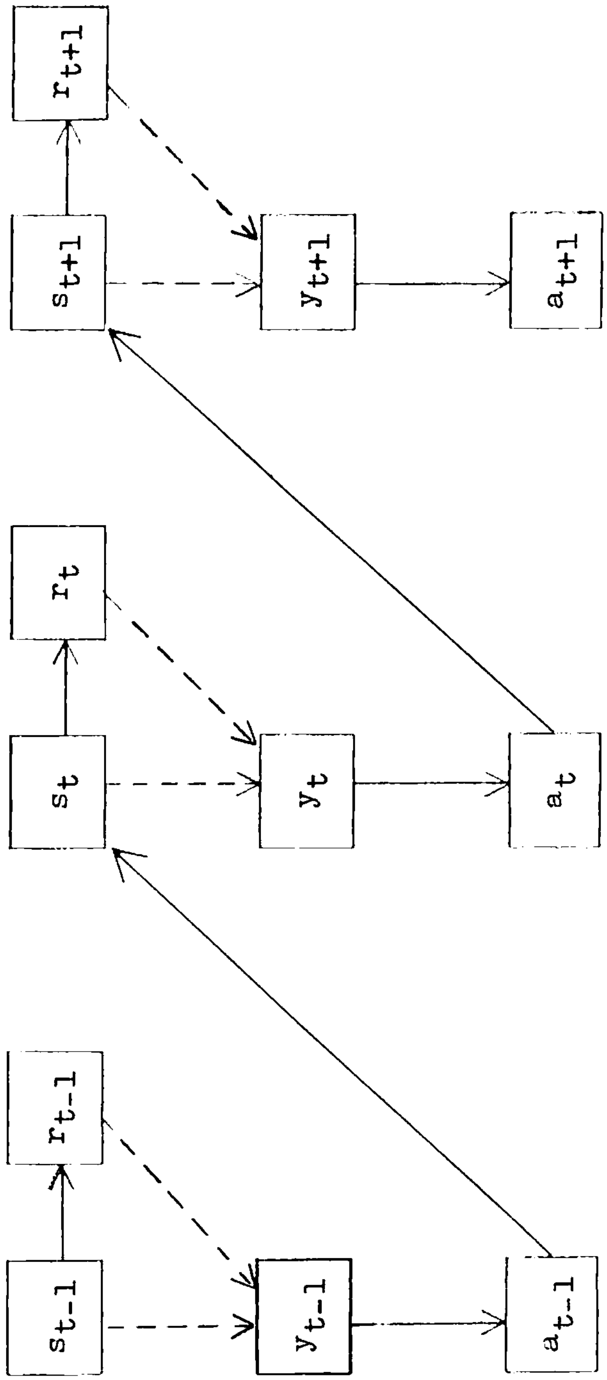


FIGURE 2

Time Relationships Among the Important Variables Within the Information Model



y_t: Information sent in period t.
s_t: State-of-the-world in period t.
a_t: Action taken in period t.
r_{t+1}: Payoff in period t+1.

as an aid to quantitatively estimating the value of alternative information structures for complex decision models. Human decision makers are replaced by an optimal decision function. (See Appendix 1.)

THE SIMULATION MODEL

The chosen model was attractive for several reasons.

1. The model is already part of the information systems literature and is the basis for on-going research inquiry.
2. The question of the *ex ante* value of the information structures involved had not been solved analytically. A simulation solution, then, seemed both appropriate and valuable.
3. The model lent itself to a functional quantitative representation of the four components.

The following sections present the model with a discussion of its components: real-world function, payoff function, decision function, and information function.

The Real-World Function (the decision environment)

The real-world function is defined by the following micro-economic model:

Profit function: $\pi_t = P_tQ_t - C_t.$ (1)

Demand function: $P_t = \beta_t - .03Q_t + 95A_t - A_t^2.$ (2)

Total Cost function: $C_t = \alpha_t + c_t(.0075Q_t^2 - .075Q_t) + 5000A_t.$ (3)

Production function: $1 = 2(M_tL_t)^{½}.$ (4)

Unit Cost function: $c_t = p_{1t}M_t + p_{2t}L_t.$ (5)

where

π_t	=	Profit in Period t.
C_t	=	Total Period Cost.
P_t	=	Selling Price.
Q_t	=	Quantity Produced and Sold.
A_t	=	Advertising Units.
c_t	=	Unit Input Cost (Standard Input Cost).
p_{1t}	=	Material Cost per unit.
p_{2t}	=	Labor Cost per unit.
M_t	=	Material Input per unit.
L_t	=	Labor Input per unit.
α_t	=	Fixed Cost Per Period.
β_t	=	An Exogenous Demand Factor

In this model, Q_t, A_t, and M_t are decision or action variables—results of the decision function. β_t, a_t, p_{1t}, and p_{2t} are events or states-of-the-world not under the control of the decision-maker. They are governed by a random walk so that, for example, $\beta_{t+1} = \beta_t + (\beta_t \times \xi)$, where ξ varies between + 20% and −16 2/3%. If ξ were to vary between ±20%, there would be a downward drift because of the asymmetry of the random walk function. Thus, a correction factor is chosen to eliminate downward drift.

Price, cost, advertising, and, hence, profits are dependent upon the actions of the decision-maker and the values of the state variables during period t. In the general information economics framework, the payoff is a function of actual states and actions. The state variables include demand, fixed costs, price of materials, and price of labor. The set of actions include quantity produced and sold, advertising units purchased, and material input.

The original experiments utilized 15 periods of decisions, and the real-world function was repeated for 15 time periods. The multi-period nature of the model was the main reason that calculation of *ex ante* information value proved to be difficult. Indeed, at the beginning of period 1 when the *ex ante* information value has to be estimated, an infinity of possible environments faced the decision maker.

Payoff Function

In this model, the outcome of the real-world function is profit measured in dollars. Theoretically, a payoff function is required to convert the dollar outcome into utility. Recall that value of information has been defined as the difference in expected utility (or payoff) due to the new information.

One possible assumption is that utility is linear in dollars of the form $r_t = k_1 + k_2 s_t$, where k_1 and k_2 are constants. In this case, estimates of the *expected dollar amount* and *variance or standard deviation* are sufficient to determine individual utility for a classical quadratic utility function. Furthermore, if a normal distribution is assumed, then, all the higher order utility functions can be obtained given an estimate of the mean and variance.[1]

Because of possible differences in personal utility preferences, a payoff function will not be presented. However, the mean and standard deviation[2] of profit figures are reported as well as the shape of the underlying distribution. The ability to define an underlying distribution indicates one of the strong points of simulation as a methodology. The estimation of the mean, variance, and underlying distribution would be more difficult if one used analytic techniques.

[1]One may use the moment generating function for the normal distribution $\psi(t) = e^{tm + \frac{1}{2}t^2}$. See Parzen [22].

[2]The standard deviation is reported rather than the variance because of the intuitive appeal of expressing data in the same units as the mean.

Decision Function

It makes little sense to speak of the relevance or value of information separate from the decision maker who will use that information.[3] If the decision-maker uses a new piece of information to change his decision and if the changed decision yields a change in the expected payoff, then, the information is relevant and has value equal to the change in expected payoff.[4] The value of information, then, depends upon the way the decision-maker translates that information into action, which in turn affect future payoffs.

Since information value is dependent upon the decision function, choice of an appropriate function is an important component of the model. The assumption of a rational decision maker is one which underlies several theories. Rational behavior is an appropriate supposition to make in this research since an optimal solution exists. In addition, diverse types of decision makers could be considered worthwhile but, at this stage, the assumption of a rational decision maker is of the most general research interest. A rational decision maker is one who maximizes expected profit. The derivation of the optimal decision rules is given in Appendix 1.

Some general observations about the decision functions should be made. The materials input decision depends upon the values of the random events p_1 and p_2–the prices of materials and labor. The quantity produced and advertising decisions are dependent upon p_1 and p_2 as well as β–the demand index. None of the decisions is affected by the value of $\tilde{a}_1$ period fixed costs. Thus, this information is irrelevant to the decision maker.

Information Function

There are four signals (of which three are relevant) from the environment which are available to the decision maker–price of materials, price of labor, demand, and fixed cost. All of these are random variates governed by the previous random walk process.

Different information structures would handle these environmental signals in different manners. Some of the original research used the notion of real-time and lagged historical information. A real-time information structure would transmit error-free information on P_{1t}, P_{2t}, β_t for use in decision period t. A lagged information structure would transmit error-free information on p_{1t-1}, p_{2t-1}, β_{t-1}, or any combination of lagged information for use in decision period t. These simulation experiments compare a real-time or perfect information structure with a lagged information structure. Recall that in the previous notation $y_t = \eta(s_t)$. Thus, for the real-time structure $y_t = s_t$, and for the lagged structure $y_t = s_{t-1} = s_t/(1 + e)$, where ϵ is the random walk error term.

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[3] Feltham [6] [7].

[4] In general, payoff is measured in utility, not dollars. Thus, a piece of information may have value *even without changing the decision* if it decreases the riskiness associated with that decision.

Since for a random walk last period's message concerning p_{1t}, p_{2t}, or β_{1t} is the best least-squares predictor of this period's amount, the decision functions remain the same among different information structures. The inputs to the function differ, though, since a decision maker working with a lagged information structure would input p_{1t-1}, p_{2t-1}, β_{1t-1} to calculate the optimal values of the decision variables Q, A, M in period t, while the use of a real-time structure could employ up-to-date or real-time input variables.

In addition, while this arrangement was devised to estimate the value of timely information, it is also dealing with the question of accuracy of information. From the decision maker's point of view, inputting lagged information into the decision function is equivalent to inputting real-time information with an error term. In contrast, accuracy and timeliness of information are often distinct questions for a designer.

POSSIBLE SIMULATION STUDIES

Given a problem characterized by a multi-period, multi-variable, stochastic environment, there are a number of issues to which a simulation study could address itself. All four of the model components are legitimate objects of experimental analysis.

The *decision function* is a particularly fertile area for research. Previous empirical studies [15] [17] [20] indicate that in a time-constrained experimental environment, subjects were not able to make decisions which would maximize profit. In such a situation, a valid inquiry is the analysis of decision rules that most nearly approximate experimental subject behavior. For instance, fixed input decision rules or satisficing rules are possibilities.

Another possible fruitful effort would investigate the value of information for *learning purposes*. If the decision maker is not aware of the configuration of the real-world function, information has value in a feedback or learning sense [16]. Research into these areas, while undeniably interesting, would require hypotheses which are beyond the bounds of this paper. This paper, however, assumes optimal decision-maker behavior.

The value of information to individuals with *different utility* or *preference functions* is another question which could be addressed by a simulation study. This research could be done by formalizing the payoff function and estimating utility for different decision makers.

Another potential area, which is the main emphasis of this paper, is sensitivity analysis of the *real world model*. While the stochastic parameters of the model are kept constant, the starting values of the endogenous variables—fixed cost, price of labor, price of materials, and demand index—are adjusted to test the sensitivity of the model to the starting values.

The final analyzable component is the *information function*. The original research dealt with the idea of accurate information presented either in real-time or lagged for one period. The lagged time information structure presented historical data for two of the variables relevant to the optimal decision maker (P_1 and P_2). For the simulation experiments in this paper, all possible combinations of the three relevant variables are lagged for one period. The value of information is derived by comparing them with real-time error-free information. While this format does not nearly exhaust the possible information structures, a one-period lag sufficiently illuminated the value of timeliness, accuracy, and relevance of information in this complex decision model. It also demonstrated the usefulness of computer simulation in this context.

RESULTS AND STATISTICAL ANALYSIS

The major purpose of these simulation experiments was to estimate the *ex ante* profit difference and the standard deviation of that difference due to different information structures under a variety of starting conditions—initial values of endogenous variables. Also, information about the shape of the distribution of profit differences was desirable, particularly if it could be shown that it approximated the normal distribution.

A simulation of 15 periods was run so that the results could be compared with earlier research efforts. In all the results reported in this paper, there are 40 replications for each set of conditions. The profit figures and the differences for each 15-period replication were averaged and treated as one observation. Blocking the 15 periods into one observation takes advantage of the Central Limit Theorem which states that the distribution of sample means will approach the normal distribution as the number of observations included in the sample increases. In addition to this theoretical reason to assume normality, a chi-square goodness-of-fit test was applied to the distribution of profit differences for the medium starting conditions. The chi-square value was 3.50 with 8 degrees of freedom, well within the range for accepting the hypothesis that the sample was drawn from a normal distribution.

The blocking of the 15 periods into one observation also dealt with the problem of auto-correlation of profit figures. Because of the random walk nature of the model, the profit figures within a 15-period replication were auto-correlated. Treating each 15 periods as one observation insured independence of data points.

To summarize, experiments compared real-time versus lagged, historical information. The main purpose of these experiments was to

(1) estimate the *ex ante* value of real-time information at $t = 0$ and
(2) estimate the effect on information value of different starting values for the environmental variables.

The starting conditions in [15] were taken as a medium level. High and low conditions were obtained by adjusting the medium conditions by plus and minus 20%. The three levels were:

	LOW	MEDIUM	HIGH
Price of Labor	620	775	930
Price of Material	936	1.170	1.404
Demand	9.824	1.228	1.474
Fixed Cost	57.280	71.600	85.920

The simulation results are summarized in Table 1.

TABLE 1

Simulation Estimates of the Effect of Different Starting Conditions on the Value of Real-Time Information

Starting Conditions	Real-Time Information Systems		Lagged (Historical) Information System		Profit Differences	
	Average Expected Profits	Standard Deviation of Profit Estimates	Average Expected Profits	Standard Deviation of Profit Estimates	Value of Real-Time Information (Differences in Average Profits)	Standard Deviation of Information Value
High	152,964	31,022	149,400	30,655	3,564	647
Medium	189,000	28,813	185,327	28,460	3,672	727
Low	229,957	30,499	226,026	30,100	3,926	752

The null hypothesis is that different starting conditions yield results drawn from the same population. This hypothesis was rejected with high confidence for the profit figures, both real-time and historical. The F-value for both information structures was 32.0 with degrees of freedom 2 and 27. Note that the null hypothesis *is not rejected* for the profit *differences* between real-time and historical information structures. The F-value for the profit differences is 1.43.

These results indicate that mean profit difference is not as sensitive to changes in starting conditions as in the actual level of profits. Since the profit difference is the estimate of information value, this is an encouraging result. The mean of $3.672 and standard deviation of $727, then, are reasonably general results which apply over a wide range of starting conditions.

The foregoing results concerned themselves only with the value of real-time information relative to a lagged information structure in which two of the three relevant signals are lagged one period. Also of interest are other information structures which lag other possible combinations of the relevant variables.

The mean profit for each of the seven possible combinations was estimated and the profit difference was calculated by comparing it with the real-time information structure. The results are summarized in Table 2.

These results imply that if a decision maker were interested in a real-time information structure as opposed to one in which all signals were lagged one period, he would be willing to pay $4,560 for such a structure, adjusted by a risk factor as measured in the standard deviation of $912. The comparative values of other structures can be read from the table and a utility transformation function applied if desired.

There appears to be little interaction effect among variables. Addition of real-time demand signals adds approximately $750 to the expected payoff from any information structure. Likewise, the increase in expected profit for real-time materials and labor price information appears to be about $1,800 each.

CONCLUSION

The conclusions to be derived from this research are on two levels. On one level, a rational decision maker faced with an environment approximating that described by the model used in this paper is better prepared to estimate the value of alternative information structures and to compare that value to the cost of obtaining such structures.

The estimates of information value were determined as follows. When using different information structures, the profit differences were determined to be a normally distributed random variable independent of starting conditions over a restricted range. The *ex ante* value of information could then be obtained by examination of the estimated profit differences. For example, if an information structure which transmitted one period lagged information on all three relevant variables was upgraded to a real-time information structure, it would be "worth" $4.500 with a risk-adjustment factor represented by the standard deviation of $912.

TABLE 2

Main Simulation Results

Variables lagged in information structure	Mean Profit	Standard Deviation	Mean profit difference from real-time information structure (e.g., Ex Ante information value)	Standard deviation of profit difference
Real-time (none lagged)	$180.320	$28.118	$–0–	$–0
All delay	175.760	27.574	4.560	912
P_2	178.440	27.857	1.880	487
P_2, β	177.791	27.677	2.529	584
β	179.573	27.926	747	298
P_1, β	177.504	27.808	2.816	651
P_1	178.458	28.042	1.862	332
P_1, P_2	176.614	27.785	3.706	648

The other level of implications concerns the feasibility of computer simulation as a methodology in information systems research. As stated earlier, simulation turned out to be a means for solving this particular research question when other methodologies proved fruitless.

Some programming and analysis problems arose in the course of this project, but were overcome as simulation techniques are fairly sophisticated. Even more complicated and realistic information models may prove to lend themselves to a computer simulation analysis. The models must be limited in one sense, however. The four components of the model—the real-world function, the payoff function, the decision function, and the information function must all be stated in quantitative functional terms. Within these boundaries, however, the computer simulation appears to be a promising methodology in information systems research.

APPENDIX I

Derivation of Optimal Decision Rules

The objective of the rational decision-maker is to maximize profit within each period by choosing appropriate values of *M*, *A*, and *Q*. The equations of the decision model given in the text can be combined and stated in terms of profit:

$$\pi = \beta Q - .03Q^2 + 95AQ - A^2Q - a_1 \quad (p_1 M + \frac{.25p_2}{M}(.0075Q^2 - .075Q)) - 5000A.$$

Take partial derivations with respect to *M*, *A*, and *Q* and set them equal to zero:

$$\frac{\partial \pi}{\partial M} = -(.0075Q^2 - .075Q)(P_1 - \frac{.25P_2}{M^2}) = 0 \qquad (1)$$

$$\frac{\partial \pi}{\partial A} = 95Q - 2AQ - 5000 = 0 \qquad (2)$$

$$\frac{\partial \pi}{\partial Q} = \beta - .06Q + 95A - A^2 - c(.015Q - .075) = 0. \qquad (3)$$

The solution for equation (1) is

$$P_1 = .25P_2/M^2$$

$$M = .5(P_2/P_1)^{1/2}$$

This is the optimal decision function to choose the materials input.

The rules to choose *Q* and *A* are found by solving equations (2) and (3). Substitute (2) into (3) and re-arrange:

$$A^3 - 142.5A^2 + \frac{95^2 - 2\beta - .15c}{2}A + \frac{95\beta - 300 - 67.876c}{2} = 0$$

Let $Z_1 = 142.5$

$$Z_2 = \frac{95^2 - 2\beta - .15c}{2}$$

$$Z_3 = \frac{95\beta - 3000 - 67.875c}{2}.$$

Then, $A^3 + Z_1A^2 + Z_2A + Z_3 = 0.$

Now let $X = A + \frac{Z_1}{3}.$

Then, $X^3 + 1/3(3Z_2 - Z_1^2)X + 1/27(2Z_1^3 - 9Z_1Z_2 + 27Z_3) = 0.$

Let $Y_1 = 1/3(3Z_2 - Z_1^2)$

$Y_2 = 1/27(2Z_1^3 - 9Z_1Z_2 + 27Z_3).$

Then, $X^3 + Y_1X + Y_2 = 0.$

$$\text{If } V = \left[\frac{-Y_2}{2} + \sqrt{\frac{Y_2^2}{4} + \frac{Y_1^3}{27}}\right]^{1/3}$$

$$\text{and } W = \left[-\frac{Y_2}{2} - \sqrt{\frac{Y_2^2}{4} + \frac{Y_1^3}{27}}\right]^{1/3}$$

then three roots are

1. $A = V + W$
2. $A = -\frac{V + W}{2} + \frac{V - W}{2}\sqrt{-3}$
3. $A = -\frac{V + W}{2} - \frac{V - W}{2}\sqrt{-3}.$

If $\frac{Y_2^2}{4} + \frac{Y_1^3}{27} < 0$, then, there are three real, unequal roots. This is the case for the range of values in the simulation model. A trigonometric solution is necessary to calculate the roots. Compute angle ϕ so that

$$\text{Cos } \phi = \frac{Y_2}{2} \div \sqrt{\frac{-Y_1^3}{27}}.$$

Then, the three roots are

$$A = 2\sqrt{\frac{-Y_1}{3}}\,\frac{\text{Cos }\phi}{3} \tag{4}$$

$$A = 2\sqrt{\frac{-Y_1}{3}}\,\text{Cos}\left(\frac{\phi}{3} + 120^\circ\right) \tag{5}$$

$$A = 2\sqrt{\frac{-Y_1}{3}}\,\text{Cos}\left(\frac{\phi}{3} + 240^\circ\right) \tag{6}$$

The value for *A* which maximizes profit for the range of values in this model is the last expression. Substituting back into equation (5),

$$Q = \frac{5000}{95 - 2A}.$$

The three optimal decision functions then are

$$M = .5\left(\frac{P_2^{1/2}}{P_1}\right) \tag{7}$$

$$A = 2\sqrt{\frac{-Y_1}{3}}\,\frac{\text{Cos}(\phi + 240^\circ)}{3} \tag{8}$$

$$Q = \frac{5000}{95 - 2A}. \tag{9}$$

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