Customer Service in Physical Distribution: A Utility-Function Approach\textsuperscript{1}

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Abstract
Decision Analysis in Management Science employs concepts from Economics such as utility functions and indifference curves. In this article, a utility function $U$ will model the "satisfaction" that a customer obtains from logistics service. Here $U$ depends on two attributes (lead time, fill rate) whose values more directly represent customer service. The shipper can, at additional cost, improve either or both of these attributes. Various utility functions $U$ are constructed and maximized, given a total budget $B$ for distribution service. Without increasing the budget, we find that overall logistics service can often be improved from the customer's point of view. Whether $U$ is additive or multiplicative, a customer's utility resulting from the optimal lead time and fill rate is typically 20% higher than when those attribute levels are set intuitively (without reference to customer preferences and tradeoffs expressed by $U$). Some introduction to Decision Analysis (certainty equivalent, risk aversion, ...) is given to aid in understanding the functional forms employed for $U$ and methods of solution, rendering the paper more self contained.

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Introduction

For many manufacturers and wholesalers, the satisfying of customers has become pre-eminent in differentiating the company's products from those of its competitors. This paper examines customer service in logistics, from the point of view of outbound rather than inbound shipments. We concentrate on two elements of physical distribution. Lead time denotes the interval elapsed between order placement and the customer's receipt of that order in good condition. Fill rate is the percentage received of the requested order. For example, 50 cases ordered and 45 received would correspond to a fill rate of 90 per cent.

The business objectives of a firm's distribution activities are to determine appropriate customer service levels, and to manage effectively the cost/service tradeoffs. Rosenfield et al. (1989) consider an "efficient frontier" of industry-wide tradeoffs between lead time and cost. Suppose a customer were satisfied with an 85 per cent fill rate. It would not benefit the company to provide more, if this customer were only willing to pay a price consistent with 85 per cent. Yet Sterling and Lambert (1989) found that, frequently, management subjectively set customer service levels that are too high, not realizing that customers have different needs than the seller. (The firm's predictions of important activities may not be the activities cited by their clients.)

Our research aims to help a shipper decide which one of many service options should be given, considering both costs to the company and satisfaction of the customer. To meet customer requirements, service levels cannot be pre-specified by the shipper. Throughout this article, we employ a single term, "customer", to also represent the "consignee" of a transaction. Similarly, to avoid confusion the term "shipper" is used to denote different entities such as "manufacturer", "supplier", "wholesaler" or "distributor".

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The targeted service to furnish an output of the model is to be maximized for a given budget. Impact of the budget figure can, of course, be studied through sensitivity analysis.

Schrer (1982) has discussed strategic issues when a shipper adapts to longer-term customer requirements. We remark that in a buyer's market, a shipper may have no choice but to meet service standards set by competitors or customers, regardless of cost. The service level would then be predetermined; each a case does not require the present analysis.

The difference between the present paper and earlier work is thus the calculation of optimal service levels. Research in marketing has often concentrated on the most important determinants of service (discussed in the following section). Other research has identified a functional relationship between service levels and several variables. We are unaware of a previous study that has demonstrated what service levels to provide. These should be based on customer tradeoffs and satisfaction, which can be quantified through the concept of utility.

The following section reviews some of the literature on customer service in physical distribution. Many of the articles describe surveys of customer preferences or outline general strategies to improve logistics service. Utility is defined more thoroughly in our third section; decision makers' attitudes towards risk imply analytical relationships between variables involved in utility functions. We next develop the mathematical models and solution methods. Successive sections present results from additive utility models and multiplicative models. Conclusions and suggestions for future research are then offered.

Literature on customer service

Customer service and its influence on sales

It is clear that an excellent product is no longer sufficient, by itself, to retain customer loyalty. Sophisticated consumers expect the "whole package", which includes distribution service (availability of stock, reliable delivery (Kumar and Sharman, 1989), O'Neil and Iveson (1991) suggest a framework to improve that service; La Londe et al. (1988) present a number of case studies.

Li and Lee (1994) find that in modelling competition between two otherwise equal firms, the one furnishing better service enjoys a larger market share and a price premium. A higher-quality service is thus presumed to lead to greater sales revenue. Omermont and Chaud (1986) note, however, that when competing suppliers all offer high fill rates, say, the result may be a statistically significant relationship between fill rate and sales. Additional details are given by Christopher (1994).

A survey of the grocery industry found a strong relationship (Pisharodi and Langley, 1991) between market response (purchase volume) and customers' perceptions of service. It is important (Pisharodi, 1994) to distinguish between the delivered service as perceived by the manufacturer or supplier, and the service perceived by the customer: no relationship was found (Pisharodi and Langley, 1991) when the independent variable was the manufacturer's perception of service. Indeed, a firm's prediction of important activities may not be the service attributes cited by their clients (Pisharodi, 1994; Pisharodi and Langley, 1991).
Relationship between service and satisfaction
It is reasonable to assume a positive relationship between customer utility, or sales, and customer service levels. Tucker (1983) criticizes previous literature for accepting too quickly an additive linear relationship, between customer service attributes and dependent variables (satisfaction, sales or profits). While some theories do support this form, other results suggest a non-linear relationship.

Through an empirical study in the pharmaceutical industry, Levy (1981) found diminishing returns for some customer service attributes, such as lead time. Once a satisfactory service level had been reached, the marginal utility (estimated using conjoint analysis (Green and Srinivasan, 1969)) for better service started to decline. The fill rate, however, did not exhibit diminishing returns. We wish to point out that, whether or not there is diminishing marginal utility for improved customer service, these improvements (Johnston, 1991) probably require increasing costs (Levy, 1981) (in the absence of a re-engineering or the substitution of information for more-expensive assets).

Bookbinder and Usher (1991) optimally allocate a total logistics budget between the functions of purchasing, inventory management, and transportation. In the context of a linear programming model, Bookbinder and Wengin considered the short-term effects of customer service (backorders, lost sales; the present paper studies the utility (Bunn, 1984) of customer service.

Overall assessment of literature
A few results are evident. Assuming (Anderson and Narus, 1985) a company offers a service that is relevant and of value to customers, there is a positive relationship between service furnished and customers’ evaluation of that service. Second, company managers do not necessarily know what service their customers require; their predictions of these needs are often incorrect. The third conclusion is that, when the budget is limited for logistics service, no model exists to help a shipper find the best service package to offer a customer.

This article addresses that third issue. Several models that use utility functions to represent customer preferences for logistics service levels will be developed. Tradeoffs between those service levels and costs to provide the underlying attributes (lead time, fill rate) will be identified. The optimal values of these attributes maximize customer utility, subject to the given budget on distribution service. We begin with properties of utility functions.

Utility, risk attitudes and customer service
Utility (Farquhar, 1984) is the satisfaction a person receives from consuming commodities or services. A utility function \( U(x) \) models this satisfaction by assigning preferences to each level of a selected attribute \( x \). Traditionally, \( 0 \leq U(x) \leq 1 \): utility of zero is given to the least preferred value of the attribute; the most-preferred attribute level has utility of one. Functional form \( U(x) \) is determined by the individual’s perception of risk. A customer’s attitude can be risk-averse or risk-neutral, as follows.

Suppose the attribute is fill rate, and imagine the following fair gamble: there are equal chances of receiving a 60 per cent fill rate or a 100 per cent fill rate. The average fill rate, i.e. expected value \( EY \), is thus 80 per cent. A risk-averse individual would be indifferent between (say) a 75 per cent fill rate for sure, and the 50-50 chance at 60 per cent and 100 per cent fill rates. The difference, relative to the certainty equivalent \( CE \) of 75 per cent, is \( EV-CE = 5 \) per cent. This is termed the "risk premium", the fact that it is positive (rather than zero) means the customer is risk-averse. He/she would prefer definite fill rates less than the expected value, but guaranteed, rather than have possibly only 90 per cent.

Risk aversion is the attitude for most people (Bunn, 1984), typically cautious (risk averse) over prospects with payoffs significant to their wellbeing. However, risk neutrality can pertain to a decision maker considering a choice common in a firm’s daily operations, with modest payoffs/costs (Bunn, 1984). Regardless of the risk attitude, it need not be constant over the attribute’s range. As his/her assets increase, a risk-averse individual may exhibit decreasing risk aversion: The risk premium \( RP \) decreases with increasing \( x \). The attitude is constant risk aversion if \( RP \) is the same for all \( x \), and increasing risk aversion when the risk premium becomes larger with an increase in \( x \).

Again consider receiving an uncertain fill rate \( x \) from the shipper. When the expected value of \( x \) was 80 per cent, \( RP \) was five per cent. If \( EV \) of \( x \) increased to 85 per cent, this same risk-averse decision maker might have \( CE = 85 \) per cent; \( RP \) would now be 2 per cent. In this case, the risk premium decreases as the level of \( x \) (fill rate) increases. This individual, exhibiting decreasing risk aversion, is more willing to "play the odds" as the gamble becomes less significant. For how to determine a client’s level of risk aversion see Bunn (1984), Farquhar (1984) and Huber (1984).

Henceforth, \( x \) (and later \( E_x \) or \( n_x \)) will denote a normalized attribute providing utility, i.e. after scaling, the value of \( x \) ranges from zero to one. A final concept, the risk aversion function \( r(x) \), summarizes attitude towards risk. \( r(x) \) is thus a shorthand description of how a person perceives the risks of everyday business decisions. It is calculated as \( r(x) = -U’(0)/U(0) \), i.e. by dividing the negative of the second derivative by the first derivative of the utility function. For example, the utility function \( U(x) \) of a risk-neutral participant is a straight line. The slope is constant; hence \( U’(x) \) and \( r \) would equal zero. A risk-averse person has a concave utility function (its positive slope is diminishing), meaning \( r(x) > 0 \); \( r \) is constant, independent of \( x \), for the exponential utility function; \( r(x) \) is a decreasing function of \( x \) for the logarithmic or square-root utility functions.

Model development and solution methods
In this paper we study the risk-neutral and risk-averse attitudes. Our model objectives contain the preceding utility functions (Bunn, 1984), \( U(x) \) (Figure 1). They and their risk aversion functions follow. Note always \( U(0) = 0, U(1) = 1 \).

Risk-neutral – linear:
\[ U(x) = x \quad r = 0 \]

Risk-averse, constant risk-aversion – exponential:
\[ U(x) = (1 - e^{-x})(1-e^{-x}) \quad r = 1 \]
have positive scaling constants \( k \). The utility functions \( U_i(v_i) \) and \( U_j(v_j) \) will be chosen from the five examples \( U(v) \) given earlier in equation form. Attribute \( v^* \) in Figure 1 and in those equations can thus be \( v_i \) or \( v_j \).

 Attributes similar to ours have been studied (Christopher, 1983) using conjoint analysis (Green and Srinivasan, 1990), which implicitly assumes utility independence. Although the additive model is also supported by Huber (1984) and by Schoemaker and Waid (1982), there certainly are decision-analysis applications (Bunn, 1984) requiring the more complex form because attributes are not utility independent. We will thus consider both types of utility models; four problems can then be developed.

The first involves an additive utility function and a linear budget constraint: (forms of the budget constraint are discussed in Appendix 2). Maximize
\[ k_1 U_i(v_i) + k_2 U_j(v_j) \text{ subject to } c_1 v_1 + c_2 v_2 = B. \]
A second case has this additive utility with a non-linear budget:
\[ a_1 v_i^2 + a_2 v_j^2 = B. \]
The third problem considers a linear budget constraint, now with multiplicative utility. Multiplicative utility and non-linear budgets define the fourth case:
\[ \max k_1 U_i(v_i) + k_2 U_j(v_j) + (1 - k_1 - k_2) U_i(v_i) U_j(v_j) \]
s.t. \( a_1 v_i^2 + a_2 v_j^2 = B \)

Results for the additive model are followed by those for multiplicative utility in the sequence of Cases 1-4. First we describe the solution methodology.

**Solution approaches**

Except for problems with risk-neutral utilities, the preceding are non-linear optimization models which can be solved by introducing a third variable: a Lagrange multiplier \( \lambda \) for the budget constraint. Partial derivatives of the Lagrangian (original objective – \( \lambda \) (constraint equation)) with respect to \( v_1, v_2 \) and \( \lambda \) are equated to zero and solved simultaneously in the three variables. For simple \( U_i \), those optimal attribute values will be found analytically; equations will be exhibited for the complex cases solved numerically.

**Results from additive models using a linear budget**

**Logarithmic, quadratic, exponential utilities**

The optimal \( v_1 \) and \( v_2 \) values for logarithmic utility are:
\[ v_1 = [k_1 (B + c_1 + c_2) - c_1] / k_1 \]
\[ v_2 = [k_2 (B + c_1 + c_2) - c_2] / k_2 \]

It turns out that for each budget level \( B \), the optimal lead times and fill rates here are identical to those calculated for the case of the linear utility function. When unit costs of both attributes are equal, the customer prefers the attribute \( v_i \) whose scaling constant \( k_i \) is greater. Only when that favoured attribute is at its maximum (1.0), does the second attribute enter the optimal solution as the budget increases. (Further explanation below)

Now consider quadratic utility functions with budgets linear in \( v_1, v_2 \). The optimal value for each attribute \( v_i \) as a function of \( B \) again has two slopes. One
variable is not increased beyond its base value until the other variable reaches a particular level:
\[ v_1 = \frac{c_1 k_1 (B - c_2) + c_2 k_2}{c_1 k_1 + c_2 k_2} \]
\[ v_2 = \frac{c_1 k_1 (B - c_2) + c_2 k_2}{c_1 k_1 + c_2 k_2} \]  \hspace{1cm} (2)

With attribute costs of 20 and 40, for \( v_1 \) and \( v_2 \), respectively and scaling constants \( k_1, k_2 = 0.5 \), Figure 2 shows optimal lead times and fill rates. When \( B < 10 \), it is not worthwhile to introduce \( v_2 \) into the optimal solution. When \( B = 10 \), \( v_2 \) is still zero (fill rate \( x_2 = 60 \) per cent) and \( v_1 = 0.5 \). Eleven (in units of one-

thousand dollars) is the lowest (integer) budget figure, for quadratic utility, where one unit spent for \( v_2 \) yields larger improvement in utility than a unit spent on \( v_1 \). At the optimal values \( v_1, v_2 \) for a given budget (equation (2), Figure 2), it turns out that each attribute has an equal rate of marginal utility to marginal cost (since \( k_1 = k_2 \)).

The exponential utility function has constant risk aversion, and optimal values equal to
\[ v_1 = \left[ B - c_2 \delta \frac{k_1 c_1}{k_1 c_2} \right] \frac{\delta}{c_1 + c_2} \]
\[ v_2 = \left[ B + c_1 \delta \frac{k_2 c_1}{k_2 c_2} \right] \frac{\delta}{c_1 + c_2} \]  \hspace{1cm} (3)

There are three slopes in Figure 3 (optimal attribute values vs budget). Unlike the quadratic case with only two slopes, in the exponential case the favoured attribute reaches its maximum before the entire budget is used. This is due to constant risk aversion.

The reader may have noticed, here and in equations (1) and (2), that certain parameter values can cause \( v_1 \) or \( v_2 \) to exceed 1 or fall below 0. Equations (1)-(3) require no modification when they produce \( v_1 \) in the desired range. Otherwise, an attribute \( v_j \) is replaced by 1 if its calculated value exceeds unity, or replaced by zero if the calculation yields \( v_j < 0 \). This helps explain the "kinks" in most of our graphs of lead time and fill rate, kinks which would not be present according to equations such as (1)-(3).

**Comparison of results to pre-set values**

To put the preceding results in context, we compare the optimal \( v_1 \) and optimal total utilities to cases where attribute levels were decided in advance, intuitively. Budgets were sufficient to meet the reasonable, predetermined lead times and fill rates. Table 1 presents this comparison for a logarithmic utility function, with costs \( c_1 = c_2 = 30 \). The pre-set attributes all had lead times lower than optimal \( v_1 \) values.

For the \( c_1 \) and \( k_1 \) of Table 1, total utility increased by 20.6 per cent when averaged over the five utility functions \( U(\phi) \) of Figure 1. Average improvement was 8.5 per cent with unequal costs (20,40) and scaling constants both 0.5. These gains in overall utility (no budget increase) show the importance of understanding customer preferences and trade-offs expressed by \( U \). It is otherwise unlikely that a shipper would coincidentally set lead time and fill rate at optimal values for a given budget. For some pre-set values, in fact, utility enhancements = 70 per cent were possible for that \( B \), perhaps greatly increasing sales and profits.

**Minimization of budget**

Virtually all examples in this article constrain the budget and choose the lead time \( v_1 \) and fill rate \( v_2 \) to maximize utility \( U(v_1, v_2) \). We now study the complementary problem of minimizing the budget required to attain a specified level of utility.
Square root utility is used for this example, whose problem formulation is thus

\[ \text{min } c_1 v_1 + c_2 v_2 \]

subject to \( k_1 v_1 + k_2 \sqrt{v_2} = S \)

where \( S \) is the service, measured by overall utility. The optimal values of \( v_1 \) and \( v_2 \) are:

\[ v_1 = \left[ \frac{c_2 S k_1}{k_1^2 c_2 + k_2^2 c_1} \right]^2 \]

\[ v_2 = \left[ \frac{c_1 S k_2}{k_1^2 c_2 + k_2^2 c_1} \right]^2 \]

Table 1. Pre-set versus optimal levels for logarithmic utility: optimal \( v_1 \) for budget required by pre-set values \( c_1 = 30, c_2 = 40 \)

<table>
<thead>
<tr>
<th>Pre-set load time</th>
<th>Pre-set fill rate</th>
<th>Total utility for preset values</th>
<th>Optimal load time</th>
<th>Optimal fill rate</th>
<th>Total utility for optimal values</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>70</td>
<td>0.50</td>
<td>9</td>
<td>100</td>
<td>0.75</td>
</tr>
<tr>
<td>3</td>
<td>80</td>
<td>0.48</td>
<td>7</td>
<td>100</td>
<td>0.74</td>
</tr>
<tr>
<td>3</td>
<td>90</td>
<td>0.55</td>
<td>5</td>
<td>100</td>
<td>0.91</td>
</tr>
<tr>
<td>5</td>
<td>70</td>
<td>0.44</td>
<td>10</td>
<td>95</td>
<td>0.63</td>
</tr>
<tr>
<td>5</td>
<td>80</td>
<td>0.54</td>
<td>9</td>
<td>100</td>
<td>0.75</td>
</tr>
<tr>
<td>5</td>
<td>90</td>
<td>0.78</td>
<td>7</td>
<td>100</td>
<td>0.84</td>
</tr>
<tr>
<td>7</td>
<td>70</td>
<td>0.36</td>
<td>10</td>
<td>85</td>
<td>0.69</td>
</tr>
<tr>
<td>7</td>
<td>80</td>
<td>0.55</td>
<td>10</td>
<td>95</td>
<td>0.93</td>
</tr>
<tr>
<td>7</td>
<td>90</td>
<td>0.70</td>
<td>9</td>
<td>100</td>
<td>0.75</td>
</tr>
</tbody>
</table>

Figure 4 shows the optimal attributes for each utility \( S \) when scaling constants are the same and costs differ. As in the utility-maximizing model, both attributes enter the optimal solution from the lowest constraint level (utility or budget).

The optimal budget for each overall-utility value is contained in Figure 5. A shipper can use this graph to determine the lowest possible budget to furnish a specified service. Figure 5 well demonstrates the effect of diminishing returns (Li and Lee, 1994). The additional budget needed to attain a given improvement \( \Delta S \) in customer satisfaction increases with \( \Delta S \).

An interesting remark can also be made concerning the "inverse function" for Figure 5. If that utility were plotted as a function of budget, the result would be the optimal utility achievable for those budget dollars (with same parameters \( k_1, k_2 = 0.5, c_1 = 20, c_2 = 40 \)). For example, just as 30 is the minimum budget that would provide a utility level of 0.75 (from Figure 5), so is 0.75 the maximum utility attainable with a budget of 30. The optimal load time and fill rate values are also identical in the two problems.

**Results from additive models, non-linear budget**

This section presents results for additive utilities under the non-linear budget constraint, \( a_1 v_1^2 + a_2 v_2^2 = B \). Outcomes for both linear and square root utility functions will be shown.

Using a linear utility function, the optimal \( v_1 \) and \( v_2 \) were determined to be

\[ v_1 = \frac{k_1}{2a_1 \lambda} \]

\[ v_2 = \frac{k_2}{2a_2 \lambda} \]

where \( \lambda = \sqrt{\frac{a_1 k_1^2 + a_2 k_2^2}{4a_1 a_2 B}} \)
Initial improvements (fill rate increases from 60 per cent, lead time decreases from ten days) come at very low expense; the cost of each attribute is slowly varying for small attribute values. However, further improvements in overall utility again exhibit diminishing returns.

**Square root utility**

The square root utility function and non-linear budget constraint yielded solutions

\[ u_1 = k_1 \left( \frac{4\lambda a_1}{a_1} \right)^{2/3} \]

\[ u_2 = k_2 \left( \frac{4\lambda a_2}{a_2} \right)^{2/3} \]

where the Lagrange multiplier now has the more complicated form

\[ \lambda = \left( \frac{k_1^{4/3}a_1^{2/3} + k_2^{4/3}a_2^{2/3}}{4(a_1b_1)^{3/4}} \right)^{3/4} \]

Figure 6 shows several indifference curves (combinations of [lead time, fill rate] of the same overall utility to the customer) and budget lines (values of [lead time, fill rate] that can be offered with a budget \( \beta \)). Note that lower utility might result from attribute pairs that cost more [two-day lead time, 83 per cent – fill rate] costs 40 budget units \( (U = 0.84) \), whereas \( \beta = 35 \) permits a customer to receive utility \( = 0.89 \) [5½ days, 96 per cent]. The customer, however, only expresses preferences when he/she does not consider cost to the shipper.

Still, the utility-maximizing combination of lead time and fill rate, given a budget level, is the unique point of tangency of that budget line to an indifference curve. Figure 6 reveals that at highest \( \beta \), budget lines will intersect or be tangent to indifference curves when fill rates are 100 per cent. For example, the line for a budget of 45 is almost tangent to the indifference curve whose utility value is 0.95; such a budget provides optimal utility of 0.952.

This model exhibits diminishing returns (in utility and budget, i.e. non-linear costs) that are more observable here than before. Suppose costs are equal but scaling constants are not (Figure 7). When the budget is expanded by five, from zero, total utility improves by 0.55. When this increase of five occurs at a budget level of 55, total utility grows by only 0.01. Even enlarging \( \beta \) from 10 to 15 only improves utility by 0.07. These findings indicate that offering very high service levels, with an increasing cost function, would not be profitable. Small enhancements in customer utility would not likely stimulate sales enough to offset higher costs. Note that diminishing returns cause both attributes to appear in the optimal solution from the first budget increase (Figure 7).

**Results from multiplicative models**

The multiplicative model, constrained by a linear budget, will be solved for both the linear and square root forms of the individual utility functions. When
Square root utility

The optimal attribute values corresponding to a square root utility function are:

\[ u_1 = \frac{-2\lambda c_1 h_1 + (1 - h_1 - h_2) h_2}{4\lambda^2 c_1^2 (1 - h_1 - h_2)^2} \]

\[ u_2 = \frac{-2\lambda c_2 h_2 + (1 - h_1 - h_2) h_1}{4\lambda^2 c_2^2 (1 - h_1 - h_2)^2} \]

where \( \lambda \) can be determined by solving the budget constraint \( c_1 u_1 + c_2 u_2 = B \).

All three \( c_i, h_i \) combinations have both \( u_1, u_2 \) in the optimal solution, even for lowest \( B \). By contrast to Figure 8, neither attribute stays at its minimum, due to the shape of the square root function. In the case \( e.g. \) of identical scaling.

Linear utility

Optimal values of \( u_1, u_2 \) for the multiplicative linear utility function and linear budget are:

\[ u_1 = B(1 - h_1 - h_2) + c_1 h_1 - c_1 h_2 \]
\[ 2c_1 (1 - h_1 - h_2) \]
\[ u_2 = B(1 - h_1 - h_2) + c_2 h_2 - c_2 h_1 \]
\[ 2c_2 (1 - h_1 - h_2) \]

With identical constants \( h_1 = h_2 = 0.4 \) and different costs \( c_1 = 20, c_2 = 40 \), despite a multiplicative portion of utility, the fill rate has minimum value until lead time increases linearly to its best value. Before fill rate enters the solution, contributions to overall utility come only from the first term in \( U(u_1, u_2) \); both other components are zero.

For equal costs \( c_1 = c_2 = 30 \) but scaling constants \( h_1 = 0.3, h_2 = 0.6 \), values of optimal attributes are identical to those of the additive linear utility case with equal costs and different \( h_i \). These optimal lead times and fill rates follow the preceding pattern regarding delayed entry into the optimal solution of the less-favoured attribute.

The third set of parameters for this model also used identical costs, but \( h_1 = 0.2 \) and \( h_2 = 0.3 \). The low sum of scaling constants makes the multiplicative component more important now, hence two kinks or three slopes in the optimal \( u_i \) (Figure 8).
constants ($k_1 = k_2 = 0.4$) but different costs ($c_1 = 20$, $c_2 = 40$), $v_1$ reaches its best value long before $v_2$ hits its maximum, but each attribute improves from the initial budget increases.

**Non-linear budget**

Multiplicative, linear utilities were used for the non-linear budget. Numerical solution was required because this model is the hardest, as demonstrated by the optimal values:

\[
\begin{align*}
  v_1 &= 2k_1a_1(1-k_2)k_2 - (1-k_1-k_2)k_1k_2 \\
  &= \frac{2k_1a_1(1-k_2)^2 - 4\lambda^2a_1a_2}{(1-k_1-k_2)^2 - 4\lambda^2a_1a_2} \\
  v_2 &= \frac{2k_2a_2(1-k_1-k_2)k_1}{(1-k_1-k_2)^2 - 4\lambda^2a_1a_2} \\
\end{align*}
\]

where $\lambda$ is determined by the budget constraint, $a_1\lambda^2 + a_2\lambda^2 = B$.

With equal costs, and scaling constants $k_1 = 0.3$ and $k_2 = 0.6$, fill rate is obviously the favoured attribute, reaching its maximum value at a budget of 40. However, the multiplicative component and the non-linear budget cause both attributes to be in the optimal solution from the first budget increase. In the case $k_1 = 0.2, k_2 = 0.3$, fill rate is now only slightly favoured, requiring a budget of 55 to attain its best value.

Optimal values of $v_1$ and $v_2$ are compared to pre-set attribute levels in Table II. This again shows the importance of understanding customer trade-offs; improvements in overall utility can be as high as 49 per cent, with a mean increase of 11 per cent. Percentage improvements in utility are generally greater when $B$ is small. As the budget increases, the pre-set lead times and fill rates become closer to optimal.

**Conclusions and future research**

A company may obviously have many customers, yet a utility function is assessed for an individual and not a group. Two assumptions are plausible for the purpose of this article. One is that there are several customers, but the shipper can differentiate the service packages and prices according to the needs of customer groups. (Segmentation of customers by cluster analysis is addressed by Christopher (1994).) Another potential assumption is that the firm has only a few major customers and because of their operational similarities, these customers have the same preference and risk attitudes towards the service attributes discussed.

Knowledge of the resulting form of customers' utility functions, and of the costs to provide logistics service, permits calculation of the best attribute values to maximize overall utility. Those optimal lead times and fill rates are not always intuitive (Tables I and II). However, they can provide significantly higher levels of utility (service perceived by the customer) than using pre-set attribute values; Table I presents details for the logarithmic utility function. Figure 6 shows how utility levels can vary greatly for the identical budget, and how budgets may widely differ but produce the same customer utility.

Greatest improvements in overall utility generally occur at the initial budget increases. Further additions to $B$ bring diminishing marginal improvements in total utility, an effect quite evident for a non-linear budget and square root $U_1$ (Figure 7). It would rarely be worthwhile for a shipper to incur large cost increases in providing extremely high service; customers could receive practically the same utility at considerably reduced costs. (Throughout we assume the utility function is accurately assessed; Jones and Sasser (1995) note difficulties in retaining customers whose satisfaction is overestimated or whose preferences may have changed.)

With additive multi-attribute utility and individual linear or logarithmic $U_i$, the entire budget increase is often spent on one attribute; the second does not enter the optimal solution until the favoured attribute reaches its best value. (This effect, partially present for quadratic (Figure 2) or exponential (Figure 3) utility, is discussed following equation (5).)
Multiplicative models, however, with individual linear (Figure 8) or square root utility functions usually result in optimally improving both attributes right from initial budget increases. While a favoured attribute may reach its maximum sooner, the preferred attribute does not completely dominate. In reality, this situation is most likely to occur, which suggests that the multiplicative form deserves further attention.

A multi-attribute utility function requires such a $U_i U_j$ term in the absence of additivity independence between attributes (Appendix 1). The smaller the sum of the scaling constants ($k_i + k_j$), the stronger will be the effect on overall utility of the multiplicative component. Indeed, that component reduces the calculated total utility, when compared to the additive utility function for the same attribute levels.

The research of this article can be applied to customers in a specific industry, beginning with calculation of cost parameters (Appendix 2). By inviting customers to express opinions, attribute values yielding utility of zero or one can be found. The shape of individual utility functions $U_i$ (Figure 1) can also be determined by querying customers, assessing their relative preferences and tradeoffs for physical distribution attributes. Suppliers to this industry would perhaps learn that, without increasing the budget, overall logistics service could be improved from the customers' point of view. Shippers may also determine the minimum budget (Figure 3) required to furnish a particular service level (total utility), and the lead time and fill rate yielding this utility for that budget (Figure 3).

Many distributors offer two grades of service, say normal and premium quality. How much extra, $\Delta S$, should be spent on premium service? Compared to the normal-service optimal solution, should those extra dollars be invested in lead-time reductions? Fill-rate increases? Or some combination? Our approach can address these questions.
Appendix 1: Additivity Independence of Attributes

A general multi-attribute utility function \( U(x_1, x_2, x_3) \) will contain a term in the product \( U(x_1, x_2, x_3) \). However, the multiplicative form reduces to the additive form when the scaling constants satisfy \( b_1 + b_2 = 1 \). For the less complex additive model to be appropriate, the condition of additivity independence must hold. Additivity (or utility) independence requires that the decision maker be indifferent between the following two options, where \( x_p \) is the best value of attribute \( i \), and \( x_0 \) the worst value of that attribute:

Option 1: \( (x_p - x_0) \) with probability 0.5 or \( (x_p - x_0) \) with probability 0.5

Option 2: \( (x_p - x_0) \) with probability 0.5 or \( (x_p - x_0) \) with probability 0.5

If additivity independence holds, then only one of the scaling constants, say \( k_1 \), need be determined. It can be assessed by having the decision maker estimate the probability \( k_1 \) that makes him/her indifferent between the following options:

Option 1: \( (x_p - x_0) \) with probability 1

Option 2: \( (x_p - x_0) \) with probability \( k_1 \) or \( (x_p - x_0) \) with probability \( (1 - k_1) \)

Schoemaker and Waid (1982) compared five methods to estimate weights for additive utilities. If additivity independence does not hold, then both scaling constants must be determined. \( k_1 \) is obtained as above; \( k_2 \) is assessed by that method with slight modifications (Haber, 1984). Determination of scaling constants was not a concern for our research. For either form of the multi-attribute utility, we took the scaling constants as given, but several different values were employed for the \( k_i \).

Appendix 2: Linear and Non-Linear Budgets

A budget for distribution service must be allocated between lead-time improvements and fill-rate improvements. Whether budgets for these attributes are linear or non-linear, we assume there are minimum cost figures \( k_i \) for the lead time to be ten days, and \( r \) when the fill rate is 60 per cent. (Financial data (budgets, cost parameters) are in thousands of dollars.)

For linear attribute costs, there is a charge \( \alpha \) for each one-day decrease in lead time below ten days, and an amount \( \beta \) for each percentage increase in fill rate above 60 per cent. Converting to the transformed variables of lead time and fill rate, through the original budget equation,

\[
\theta + \alpha (10 - x_1) + \beta (x_2 - 60) = B' \text{(Budget)}
\]

\[
\sigma (10 - x_1) + \beta (x_2 - 60) = B'' - \theta - \rho = B
\]

The transformed variables will thus have a budget equation (where \( c_1 = 80, c_2 = 40\beta\)):

\[
\alpha c_1 + \beta c_2 = B
\]

The second budget relationship considers non-linear costs of each attribute, whereby additional charges are associated with squared values of those attributes. There are costs \( \xi \) for the square of each one-day decrease in lead time below ten days, and \( \tau \) for the squared value of each per cent increase in fill rate over 60 per cent. Using these non-linear relationships, the original budget constraint is:

\[
\theta + \xi (10 - x_1)^2 + \rho + \tau (x_2 - 60)^2 = B' \text{(Budget)}
\]

\[
\sigma (10 - x_1)^2 + \rho + \tau (x_2 - 60)^2 = B'' - \theta - \rho = B
\]

In the variables \( \xi \) (setting \( \alpha = 64\xi, \alpha = 1600\beta \)), the budget constraint becomes

\[
\alpha c_1^2 + \beta c_2^2 = B
\]

Consider the two types of cost functions when each attribute coefficient (\( c_1 \) or \( c_2 \)) is set at an equal amount (50, for us). For given attribute levels \( x_0 \), although total cost is always lower for the non-linear budget than the linear case, incremental charges to improve either attribute grow at an increasing rate for the non-linear function. The non-linear budget, perhaps more plausible for our particular attributes, complicates the search for optimal attribute values. It may also be harder to calibrate in practice.

Resource-based theory and strategic logistics research

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The need for theoretical development in logistics and the strategic repositioning of the discipline have been suggested as major challenges for logistics researchers (Stock, 1990). Despite recent advances made by logistics, the requirement for further theoretical development on the strategic role of logistics remains a key priority (Menzler and Kuhl, 1983; Stock, 1990). Today's turbulent competitive environment mandates that a firm must have agility in the marketplace to survive and succeed. Therefore, logistics has become an increasing area of strategic concern for firms (Bowersox et al., 1989; Bowersox et al., 1995; Michigan State University Global Logistics Research Team, 1998; Stalk et al., 1992). Acknowledging the dramatic changes in the economy, which has become more information-intensive, more global and more dependent on technology, several authors, both inside and outside the logistics discipline, have indicated the importance of logistics as a source of sustainable competitive advantage (SCA) (Achrol, 1991; Day, 1994; Porter, 1985; Stalk et al., 1992; Webster, 1992).

Borrowing and adapting theories from other fields is a beneficial and commonly-used way to rapidly elevate a discipline's level of theoretical development (Stock, 1990). Nevertheless, the influence of strategic management on logistics has been mainly restricted to and constrained by the work of Porter. Consequently, ten to 15 years of research and strategy development in strategy research has been largely neglected in the strategic logistics literature. Surprisingly, despite the call for more theoretical and strategically oriented work in logistics, the resource-based theory (RBT) of the firm and the related capabilities approach — which represent a dominant stream of research in competitive strategy management over the last decade — have not been prominent in the logistics literature.

We believe, that the "capabilities approach to strategy" and the underlying resource-based theory of the firm have, at least, implicitly influenced recent work in strategic logistics (see for instance, the Michigan State University's Global Logistics Research Team's 1995 report). However, no clear exposition of the approach has been provided in the logistics literature.

We propose that the RBT has the potential to be applied to important areas of logistics research (i.e., the relationship between distinctive logistics capability and SCA, the role of logistics in strategic partnerships and outsourcing and the interface of logistics with marketing and other functional areas). The purpose of