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SELECTING THE BEST SUPPLIER BASED ON A MULTI-CRITERIA TAGUCHI LOSS FUNCTION: A SIMULATION OPTIMIZATION APPROACH

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ABSTRACT

Minimum price is not the only objective that companies pursue when sourcing their materials. Selecting the best supplier entails looking for the best quality as well as the most reliable delivery. This work suggests a Multi-Criteria objective function that linearly aggregates a number of Taguchi loss functions, which represent the criteria of price, quality, and delivery. We initially recommend a framework to represent the market and then generate test data to represent the different market scenarios. We introduce randomness into this framework in order to achieve a highly realistic assumption. This study then employs the Optimal Computation Budget Allocation (OCBA) algorithm to choose the best supplier. OCBA solutions are benchmarked against the deterministic solution to check OCBA's ability to find the optimal solution. OCBA solutions are also compared to an Equal Allocation (EA) algorithm to verify their effectiveness in terms of minimizing the costs of sampling.

1 INTRODUCTION

Selecting appropriate suppliers is an important decision for any supply chain. Price is not the only criterion that purchasers consider when they choose a supplier. In contrast, the supplier selection process is a multiple criteria decision-making (MCDM) problem (William, Xiaowei, and Prasanta 2010). Therefore, this work evaluates the performance of the suppliers with respect to price, quality, and delivery by using a Taguchi loss function (Pi and Low 2005), and it then aggregates these measurements into a single performance measure, giving different weights to the different criteria as required by the purchaser.

To imitate real life behavior, suppliers' performances are assumed stochastic. Intuitively speaking, it is almost impossible to expect the same quality or service levels by any of the suppliers. For example, delivery routes can encounter events that have different probabilities of taking place. In addition, different delaying effects might affect the delivery schedule between a supplier and a purchaser. Literature regarding the MCDM problem is abundant (William, Xiaowei, and Prasanta 2010); however, the literature has yet to address thoroughly the stochastic nature of supply.

Finally, this study does not merely present a market model and the combinations that might arise from such a model; it also presents a solution to this problem by suggesting an Optimal Computation Budget Allocation Algorithm (OCBA) (Chen et al. 1997) to find the best supplier. We generate a test bed of 81 problems and solve them using OCBA. Afterwards, we compare the solutions to the deterministic solutions found through full enumeration and the Equal Allocation budget algorithm (Chen and Yucesan 2005).

2 LITERATURE REVIEW

To cover all the literature related to this subject, this review must cover different topics in detail, mainly: supply chain management focusing on procurement, quality control focusing on Taguchi loss function, and finally, simulation optimization. For this reason, we will only offer a brief review of the first two, and refer the reader to different papers that reviewed simulation optimization techniques in the Winter Simulation Conference, such as Fu, Glover, and April (2005).

2.1 Supplier Selection Problem

Supplier selection involves evaluating a number of suppliers according to a set of common criteria to meet business needs. A number of suggestions have been proposed for choosing among suppliers. Evans (1980) suggests that price, quality and delivery are the most important criteria for evaluating suppliers in the industrial market, while Ellram (1990) suggests that the firm needs to consider the product quality, offering price, delivery time, and service quality in supplier selection.

The cost-ratio method (Timmerman 1986; Dobler, Lee, and Burt 1990) combines quality, delivery, and service costs and compares these costs to the firm's total purchase price. Similarly, Monczka and Trecha (1988) compare suppliers based on an aggregated cost of price, service, and performance. Instead of using quantitative measures, Willis and Houston (1990) use categorial measures: good, fair, and bad. The supplier who gets the largest number of "good" ratings is selected as the best supplier.

Other researchers who numerically combined the different attributes had to devise a system of weights to assign to the different attributes. The weight-point model (Monczka and Trecha 1988), the supplier profit method (Thompson 1990), and the dimensional analysis technique (Youssef, Zairi, and Mohanty 1996) are examples of such weighted methods. The differences among these techniques stems from the weights used and attributes selected for analysis.

The present work's reason for adding quality and delivery criteria to price in selecting the best supplier stems from the literature review paper of William, Xiaowei, and Prasanta (2010). In their work, they reviewed 78 journal papers published in the period from 2000 to 2008. Out of these 78 papers, 68 papers considered quality and 64 papers considered delivery.

2.2 Taguchi Loss Functions

In traditional systems, quality losses occur when the product deviates beyond the specification limits, thereby becoming unacceptable (Pi and Low 2005). Taguchi proposed a narrower view of characteristic acceptability to indicate that any deviation from a characteristic's target value results in a loss and that a higher quality measurement will result in minimal variation from the target value. This means that the loss is zero only when the characteristic's measurement is the same as the target value. Otherwise, the loss can be measured with quadratic functions, which companies can use to study and to reduce systematically the variation from the target value (Kethley and Waller 2002).

Taguchi loss functions have been recently used for non-manufacturing applications. Quigley and McNamara (1992) implemented them to evaluate product quality as an aid to the selection of suppliers. Kethley and Waller (2002) applied them to improve customer service in the real estate industry. Li (2003) used Taguchi loss functions for the measurement of service quality.

3 TAGUCHI-BASED SUPPLIER SELECTION MODEL

The supplier selection process is a multiple criteria decision-making (MCDM) problem, as shown by most researchers as well as by intuition. This paper selects the three mentioned criteria (price, quality, and timely delivery) for the purpose of evaluating suppliers' performances. A Taguchi loss function evaluation model is adopted in this work for the following advantages:

- As stated earlier, if a product measurement falls within the specification limit, the product is accepted, otherwise the product is rejected. Taguchi goes beyond and indicates that any deviation from the characteristic's target value results in a loss, which is more intuitive. Simply speaking, if an item of raw material is delivered late, the purchaser might, in turn, deliver a manufactured part late to the customer. One can propose a similar argument with respect to price and quality.
- It provides a supplier comparison based on the "higher is better" attributes (e.g., service satisfaction and warranty degree) and the "lower is better" attributes (e.g., price and delivery delay).

In this work, we calculate the Taguchi loss value for each criteria i: $L(y_{i=criteria})$. We then aggregate these different measurements using a single loss function, as shown by Equation 1.

$$Weighted\ Loss = \sum_{i=1}^{3} W_i\, L(y_i)\ , \tag{1}$$

where W_i are the weights given to the different criteria. As we will show later, different purchasers will have different priorities regarding these measures. Ranking the suppliers from the smallest to the largest loss can then be done and the supplier with the minimum weighed Taguchi loss can be determined (Pi and Low 2005).

In this work, we use a one-sided minimum (smaller-is-better) loss function of the form

$$L(y) = ky^2\ . \tag{2}$$

4 STOCHASTIC MARKET FRAMEWORK

Realistically, performance measures are not deterministic and it is better to model them as stochastic. The stochastic nature requires a special optimization technique to select the best supplier. In the real world, companies progressively gather information about suppliers with each transaction. For this reason, we have developed a framework to model the real market; then, we show how to use the OCBA method to select the best supplier. Before adding numbers to the models, we start this section with a qualitative description of the different models.

4.1 Qualitative Framework

To be as realistic as possible while portraying a real world situation, we tried to develop a generic purchasing model. In this model, we assume that the purchaser only knows the prices that might have different impacts on product quality and delivery. Additionally, the purchaser might have different priorities regarding these three criteria. For instance, one purchaser might be interested in high quality materials, while another one might be keener for on-time delivery.

For this reason, we developed 81 models, as shown in Figure 1. The models start with three price dispersions. This measure reflects the variance among prices. The second level of detail that we consider is the purchaser's priority, or which criterion is the most important to that company. The third and fourth levels of the tree in Figure 1 reflect how the quality and delivery characteristics are affected by price. For ease of presentation, we will use the following abbreviations to refer to the purchaser's different orientations: Price Oriented, PO; Quality Oriented, QO; Delivery Oriented, DO. To denote the effects of prices on quality and delivery, we will use the letters L, M, and H to show low effect, medium effect, and high effect, respectively. For instance, QM denotes a medium effect of price on quality.

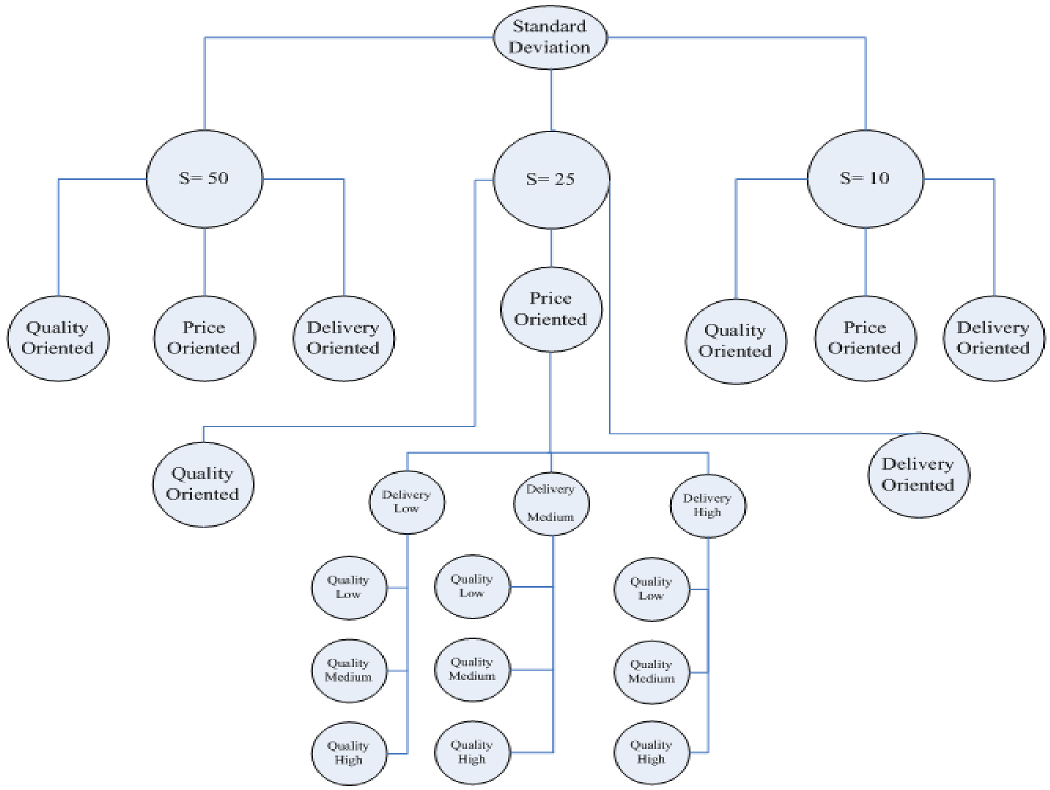

Figure 1: The different possible market scenarios

4.2 Quantitative Framework

In the experiments section, we assumed the following values:

- The average price of the market models is 100.
- The maximum acceptable quality loss is 3%.
- The maximum acceptable delivery delay is 3 days.

For price dispersion, we generated prices from normal distributions that have standard deviations of 10, 25, and 50 to reflect different spectrums of prices. The prices used are as shown in Table 1.

Table 1: Prices used in the different experiments

Supplier	S=10	S=25	S=50
1	89	70	43
2	93	82	64
3	100	102	97
4	105	117	130
5	113	132	168

The other numerical measure that we needed to model is how prices affect quality and delivery characteristics. This effect is assumed to be low, medium, or high. It is modeled using an exponential function for the different markets, as shown in Table 2. As mentioned earlier, a loss of 100% will take place if an item is delivered 3 days late or if the percentage of defects is 3%. The $\Delta\, price$ term shows the difference between the supplier price and the minimum price offered in the market.

Table 2: Decay functions used to describe the effects of price on quality and delivery

Effect	S=10	S=25	S=50
Low	$3e^{(\Delta price)/-100}$	$3e^{(\Delta price)/-200}$	$3e^{(\Delta price)/-400}$
Medium	$3e^{(\Delta price)/-30}$	$3e^{(\Delta price)/-80}$	$3e^{(\Delta price)/-200}$
High	$3e^{(\Delta price)/-10}$	$3e^{(\Delta price)/-40}$	$3e^{(\Delta price)/-80}$

The above-generated values represent the independent variable y in Equation 2. In the stochastic experiments tested later, the values of y are assumed random, except for price. The randomness is added to these systems by generating a new y value from a normal distribution function having a mean of y, and a standard deviation equal to $0.1y$, where the y values are found using the equations presented in Table 2.

To get the values of k, we need first to specify the upper specification limit for each measure. As stated earlier, the upper limits for quality is 3% and 3 days late for delivery. On the other hand, the prices' upper specification limits are assumed 30%, 90%, and 300% for the markets having $S = 10$, $S = 25$, and $S = 50$, respectively. Substituting these values in Equation 2 obtains the following loss coefficient values: k, as shown in Table 3.

Table 3: Loss coefficients: k values

	Price	Quality	Delivery
$S = 10$	1111.11	111111.11	11.11
$S = 25$	123.46	111111.11	11.11
$S = 50$	11.11	111111.11	11.11

Lastly, to reflect the purchaser's orientation towards certain criteria, we used a weight of 0.6 for the most important criterion and 0.2 for the other two. In their work, (Pi and Low 2005) used an Analytic Hierarchy Process (AHP) to define these weights.

4.3 Illustrative Example

To illustrate our market framework without a stochastic nature, we choose a market having $S = 25$ with a price-oriented purchaser, a high effect of price on quality, and a medium effect of price on delivery. By using the equations shown in Table 2, the following values are obtained for the different measures and suppliers. The weights given for the different loss functions are: 0.6, 0.2, and 0.2 for price, quality, and delivery, respectively. Table 4 shows the value of y for each criterion while Table 5 shows the values of the loss function for each criterion and total weighted loss. The last column of Table 5 ranks the suppliers: it shows that the second supplier is the best one.

Table 4: The values of prices, quality measurements, and delivery measurements for a market having S=25, PO, QM, and DM.

Supplier	Price	Quality	Delivery
1	70	3.00	3.00
2	82	2.22	2.58
3	102	1.35	2.01
4	117	0.93	1.67
5	132	0.64	1.38

Table 5: Deterministic solution for the market case as described in Table 4.

Supplier	Price	y_{price}	$L(y_{price})$	$y_{Quality}$	$L(y_{Quality})$	$y_{Delivery}$	$L(y_{Delivery})$	Weighted Loss	Rank
1	70	0.00	0.00	3.0	100.00	3.00	100.00	40.00	3
2	82	17.14	3.63	2.22	54.88	2.58	74.07	27.97	1
3	102	45.71	25.8	1.35	20.19	2.01	44.93	28.50	2
4	117	67.14	55.66	0.93	9.54	1.67	30.88	41.48	4
5	132	88.57	96.85	0.64	4.5	1.38	21.22	63.26	5

5 SIMULATION OPTIMIZATION

Given this framework and its stochastic nature, the purchasing company might be interested in dealing with one supplier, or it might not care if there is a slight difference between the suppliers. To deal with the latter situation, an indifference zone can be assumed and more than one supplier can be selected (Goldsman et al. 1999). On the other hand, a purchaser might be interested in single sourcing, whereby the company needs to choose one supplier. In this case, we suggest the use of a Ranking and Selection Optimization technique. The algorithm we choose for this purpose is Optimal Computation Budget Allocation (OCBA).

In our model, we formulate OCBA to minimize the simulation budget with a guarantee on a specified Approximate Probability of Correct Selection (APCS). In our model, if N_i is the number of samples taken from supplier i, the objective of the algorithm is to minimize the number of samples taken from all the suppliers: $\min N_1 + N_2 + N_3 + N_4 + N_5$, while at the same time guaranteeing that the APCS is satisfied.

More details about OCBA can be found in Chen and Yucesan (2005). We used the following parameters in the algorithm described: $n_o = 10$, $\Delta_i = 10$ and APCS = 90%, where n_o represents the initial budget allocated to each supplier, and Δ_i is the incremental number of samples.

The samples represent transactions in real life. The purchasing manager might choose the supplier based on this algorithm and then wait for feedback from the production and sales departments to assess the total loss function. The system can also be implemented by Exchange Markets to recommend suppliers, as long as purchasers provide the feedback.

6 EXPERIMENTS

In this section, we study OCBA's capabilities in finding the best supplier in addition to the costs entailed in searching for this supplier. We check OCBA's capabilities in finding the best supplier by comparing its results to the deterministic model. The costs entailed in finding the best supplier are benchmarked against an Equal Allocation (EA) algorithm (Chen and Yucesan 2005). In our EA, we allocate 10 samples for each choice until we fulfill the constraint of APCS.

In all 81 scenarios, OCBA was able to find the best supplier as shown by solving the deterministic model. We report here the results we obtained for a quality oriented purchaser and a market having $S = 10$. For this generic scenario, we generate nine different scenarios, as shown in Table 6 below. The table also shows the best supplier based on a deterministic setting; then, it compares the OCBA and the EA in terms of number of replications needed to find the best suppliers, and the extra loss for which the purchaser needs to pay until she discovers the best supplier. By extra loss, we mean the difference between the sum of $eighted\ Loss$, as shown by Equation 1 and the sum of $Weighted\ Loss$ if the best supplier is chosen in all replications.

As Table 6 makes apparent, both algorithms were capable of finding the best supplier in two cases, and they needed only 50 replications to find the best supplier, which means that neither algorithm presented any need to obtain more samples. For these cases, EA showed the same number of replications. It needs to be noted that in all these cases, the relation between quality and price is high. On the other hand, the function of the $Weighted\ Loss$ is flatter if the quality and price relation is low. Such a case makes more replications necessary to find the best supplier in both OCBA and EA.

Table 6: A comparison between OCBA and EA for a market case having $S = 10$

Scenario	Deterministic Model				OCBA		EA	
	Price-Delivery relation	Price-Quality relation	Best supplier	Loss	Number of replications	Extra loss	Number of replications	Extra loss
1	DL	QL	4	65.3	258	639	840	5020
2	DL	QM	5	40.6	70	884	280	4184
3	DL	QH	4	24.1	60	874	100	1720
4	DM	QL	5	57.3	81	537	190	1931
5	DM	QM	5	32.3	60	921	60	1005
6	DM	QH	4	16.5	50	1000	50	1004
7	DH	QL	4	51.6	117	585	660	6380
8	DH	QM	5	28.4	70	887	160	2698
9	DH	QH	4	10.4	50	1008	50	1124

Figure 2 below shows a box-plot of the number of replications needed until the OCBA or the EA locates the best supplier. OCBA clearly shows its superiority, since it has a median of 69 compared to 100 for EA. The arithmetic mean of the number of samples needed to find the best supplier is 104 in the case of OCBA and 177 in case of EA. The maximum number of replications needed for OCBA was 505 compared to 960 for EA. In these cases, the total weight function was flat with respect to price, and the purchaser might be indifferent toward the two suppliers (Evans 1980) for a certain percentage range.

The superiority of OCBA with respect to EA also appears when looking at the extra loss that the purchaser needs to compensate until she finds the best supplier (Figure 3). For OCBA, the median of this loss is 715 and its mean is 750. On the other hand, the median of EA is 1,170 and its mean is 2,055.

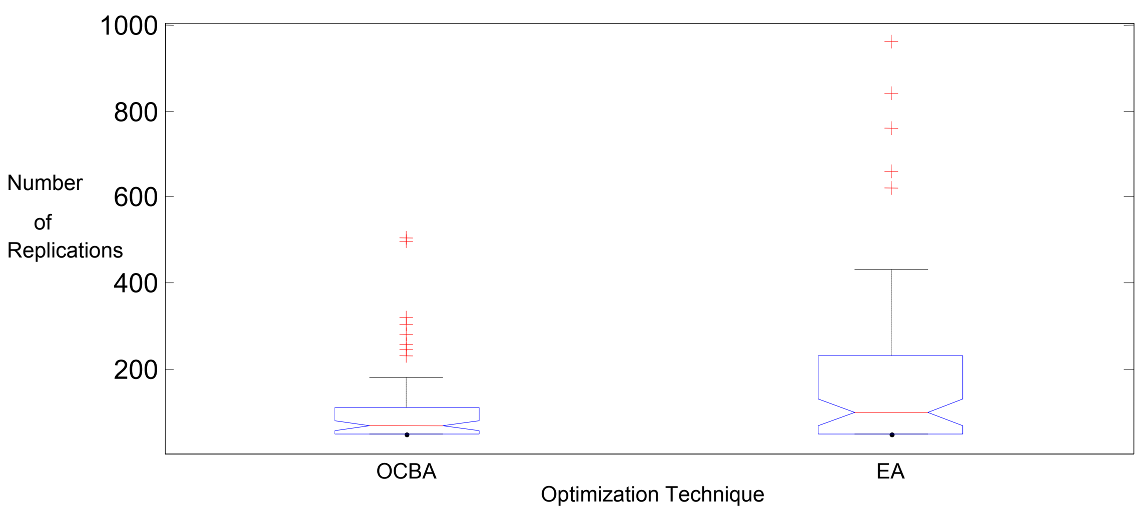

Figure 2: A comparison between OCBA and EA with respect to the number of replications

7 FUTURE WORK

Later studies do not need to aggregate the different performance measures through a weighted loss function; instead, they can obtain multiple solutions. They might be able to obtain these solutions by allowing an acceptable difference among the performances, as in the indifference zone methods, or by using Pareto Optimal Solutions. Future research also needs to address Data Envelopment Analysis (DEA) (William, Xiaowei, and Prasanta 2010) within a stochastic environment.

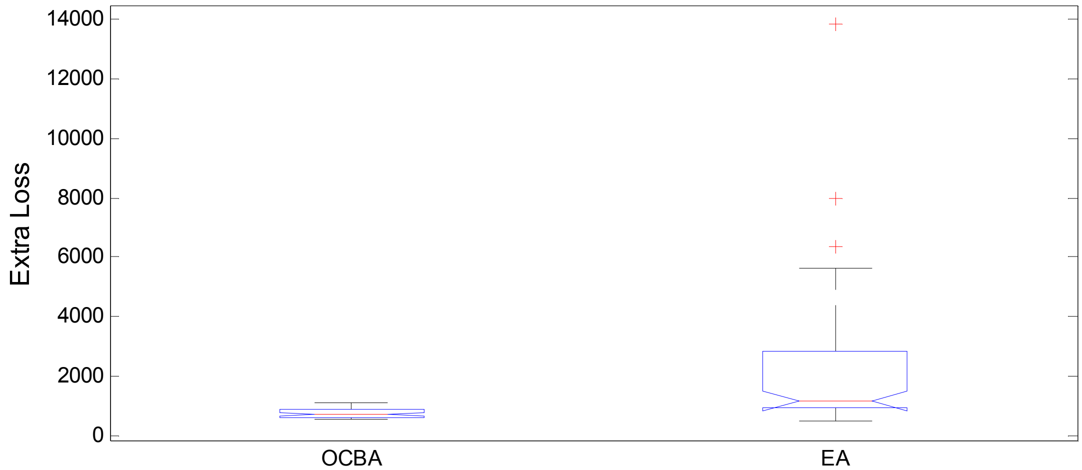

Figure 3: A comparison between OCBA and EA with respect to the extra loss paid to find the best supplier

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