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Prescriptive Analytics in Procurement: Reducing Process Costs

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Prescriptive Analytics in Procurement: Reducing Process Costs

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Abstract. In obtaining low-cost goods, the indirect expenses associated with sourcing suppliers can be substantial compared to the potential advantages of lower direct purchase costs. We addressed this problem as an "exploration" vs. "exploitation" trade-off. The proposed methodology uses a Bayesian technique to learn a stochastically optimal sourcing strategy from quotation data directly. We illustrate our approach using real quotation data for the procurement of electronic resistors (n=201,187). Rather than making optimal predictions, we concentrate on making optimal decisions. In doing so, we offered a significant improvement in purchase and procurement process costs. Our model is also more robust to prediction errors.

Keywords: prescriptive analytics, procurement, process costs.

1 Introduction

Employees in organizations often spend a considerable amount of time on tasks with uncertain outcomes. A particular context where such a problem exists is supplier search in procurement. In procurement, a purchasing agent must search for the best supplier source for the company. To find the best supplier, the purchasing agent must first survey the supplier market and obtain a price quotation from each supplier for the specific purchase. However, the problem for the purchasing manager is that procurement prices are unknown before identifying, approaching, and negotiating with a supplier. In addition, the cost of acquiring a price quotation is spent ex-ante. On the other hand, the potential cost reductions associated with receiving a lower-priced quotation are contingent on the unknown price and are only discovered ex-post. To summarize, finding a better supplier quotation is often not guaranteed.

Another significant aspect of supplier search is that identifying a supplier source takes hours of investigation, supplier verification, and evaluation. Hence, procurement done exclusively and extensively by humans makes supplier search time-consuming. While the primary aim of every purchasing manager is to minimize direct purchase costs, any savings from acquiring goods at a lower price therefore must be balanced against increased procurement process costs [3, 4]. Traditionally, purchasing managers utilize a curated list of a few vendors to acquire quotations or limit the number of

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obtained quotations, especially for low-cost items. However, a fixed limit may not be optimal.

The trade-off between learning new information and using the learned information is often called the "exploration" vs. "exploitation" dilemma [6]. This trade-off is the main question of research on optimal stopping, reinforcement learning, and bandit algorithms [6–8]. Ideas from this type of research have been successfully adapted to business problems such as optimal pricing experiments [9, 10], order release decisions [11], production scheduling [12, 13], or inventory management [14, 15] – each area developing unique solutions for the specific settings in these applications.

The "exploration" vs. "exploitation" dilemma is also present in procurement. In addition, there is the problem of the relatively high exploration cost of obtaining price quotations from the supplier. Supplier search in procurement can therefore be reframed as a problem of optimal stopping. An analytics solution that solves this problem can help purchasing managers decide how many resources (e.g., person-hours) should be allocated to a specific procurement task. By doing so, we recognize that much of procurement involves certain work steps that cannot be further automated and that targeted resource allocation is required. Such analytics problems can be seen as prescriptive analytics problems [16, 17]. To the best of our knowledge, no previous study has considered procurement automation a problem of optimal stopping. The purpose of this study is to address this problem. Therefore, we ask the following research question: *How can we help procurement managers to balance direct purchase and overall procurement process costs?*

To answer this research question, we investigated a practice-motivated problem in procurement. More specifically, we examined the problem of obtaining low-cost goods electronic resistors, where the indirect costs related to selecting suppliers (procurement process costs) are often substantial in proportion to the benefits of lower direct purchasing costs. Electronic resistors can be found in every electronic device (e.g., washing machines, lighting systems). With prices typically ranging between a few cents and up to a few euros, resistors are relatively cheap compared to the devices they are used in. Resistors come in various materials (e.g., carbon, ceramic), types (e.g., axial, surface mounted), and sizes. Purchase departments must therefore manage a sizeable quantity of different items, often from separate suppliers. The study grew out of a continuing collaboration with a German SME (small and medium-sized businesses) whose management identified the need to improve management and control of sourcing and procurement processes.

We investigated a significant issue within supply chain automation, a classic research problem [2, 18–20]. We were particularly interested in algorithmic characteristics that balance decreasing direct purchase costs with increasing process expenses. For this, we calculated the expected discount of searching for a lower-cost supplier offer based on the current best available offer. We also studied a Bayesian strategy for improving machine-learning estimates based on actual supplier price quotations. Our proposed technique considers model uncertainty and its impact on decision-making to generate sound prescriptive predictions. Our study contributes to the information systems literature by proposing a novel prescriptive machine learning method with impactful implications for supply chain practitioners.

2 Related Literature

To date, several studies have investigated procurement automation. The first step that can be automated is supplier discovery (e.g., by mining online news documents) and the collection of price offers [21, 22]. After suppliers have been identified, the best supplier has to be selected among a pool of candidates, for which different multi-criteria decision-making techniques exist, when selection criteria can be explicitly stated ([23–25], [26, 27], [28], [29]). Alternatively, historical data could be used to infer those selection criteria automatically [30, 31]. Another body of research helped purchasing managers determine the optimal ordering frequency/quantity ([32, 33], [29]). Automation in supplier negotiation is also a topic ([34], [35], [36], [22]).

Table 1. Related literature

Author	**Step being automated**				**Findings**
	Identification	Selection	Negotiation	Spent optimization	
[21]	X				Text and link mining techniques can be effectively used for discovering suppliers from online news documents.
[22]	X				If chatbots collect supplier offers, they must also signal the usage of AI for screening; otherwise, chatbots achieve more expensive purchase prices than humans.
[23]		X			Use selection criteria of purchasing managers in a Fuzzy analytic hierarchy process.
[24]		X			Extensive list of 14 supplier selection criteria. Develop MS Excel macro for fuzzy AHP.
[25]		X			For supplier selection on electronic markets, online mined supplier judgments can be used.
[26]		X		X	Considering dependence between selection criteria by combining ANP, TOPSIS and LP.
[27]		X			Long-term supplier selection. Considering dependence between selection criteria and linguistic uncertainty in judgment.
[28]		X			A visualization of the Pareto front can be used to reduce the number of manual supplier comparisons to be made.
[29]		X		X	Combine supplier selection and optimal order dispatching.

Table 1. Related literature

Author	Step being automated				Findings
	Identification	Selection	Negotiation	Spent optimization	
[30]		X			Machine learn selection criteria from past data.
[31]		X			Hybrid approach. Machine learn selection criteria from past data and efficiency analysis.
[32]				X	Stochastic inventory problem with capital constraints
[33]				X	Purchasing seasonal products with capital constraints.
[37]				X	How to use Bayesian updating for ordering quantity decisions where the provider's future output is stochastic with unknown parameters (i.e., supply stock uncertainty)
[38]			X		Automate supplier negotiation by learning acceptable thresholds for accepting offers
[35]		X	X		Predict the supplier's counteroffer reaction to the purchaser's offer in a selection/negotiation process.
[36]			X		Pairwise prediction of supplier's counteroffer and delivery/return/payment policy

Overall, these studies highlight successful applications of automation in procurement. However, such studies remain narrow in focus, dealing only with replacing tasks typically done by humans. Surprisingly, the question of determining how much supplier search should be optimally conducted has not been addressed before. This is problematic because, currently, supplier quotations can only be evaluated after an exhaustive examination of the procurement market. Our contribution is therefore directed at a data-driven predictive evaluation of supplier quotations.

3 Theoretical Background

3.1 Problem Setup

A purchasing manager seeks to purchase K different goods $k \in 1, \dots, K$. The problem is now to find among a set of S_k different suppliers the cheapest offer $p_{s,k}$ with $s \in S_k$ that provide the good k. However, for new products, suppliers are unknown and difficult to discover. Getting a quotation from a supplier is time-consuming due to explaining product characteristics and negotiating prices. Hence, the purchase manager must determine how many suppliers S_k', $S_k' \coloneqq \{s, s \in 1, \dots, s^*: i \in S_k\}$, to contact and at which index s^* to stop. This is a multiobjective problem: $\min_{S_k'} [\min_{s \in S_k'} p_{s,k}, |S_k'|]$. We study data-driven approaches supporting purchase managers in determining an optimal stopping point s^*.

3.2 Static Stopping Rule: Estimating Reference Price

A simple approach to the above-described problem is the estimation of a reference price $\hat{\mu}_k$, i.e., a preferred buying price, for example, the average market price. This is an approximate version of the ε-constraint method [39] to multiobjective optimization and can be written as $\min_{S_k'} |S_k'|\ s.t. p_{s,k} \leq \hat{\mu}_k$. The reference price for new items can be estimated using historic quotation data by linking product characteristics with the average of all quotation data. This linkage can be found using machine learning. Machine-learning methods are special cases of optimization problems, which are optimized according to a cost function. Hence, an initial design challenge is quantifying a suitable cost function. To find a suitable cost function, we have chosen to examine the economic consequences of a possibly erroneous forecast. Based on the predicted reference price $\hat{\mu}_k$ and the supplier's offer $p_{s,k}$ the purchasing manager can make three decisions. S/he may, firstly, buy directly, or, secondly, reduce/increase negation efforts, or thirdly, temporarily defer the offer in order to search for a lower quotation from another supplier. We can then assess the decision's impact on various market states, analyzing the economic consequences of prediction errors. We assume there will always be suppliers that provide prices above and below the reference price. Using this setup, three possible cases of prediction errors ($\hat{\mu} \neq \mu$) exist:

1. $\hat{\mu} \leq \mu,\ p_s \leq \mu$: Some attractive suppliers will be wrongly rejected $WR \coloneqq \bigcup_k^K \min_s \{p_{s,k}, s \in S_k : p_{s,k} > \hat{\mu}_k\}$. Increases process cost proportional to $|WR|$, lowers purchase cost. If the estimate is too low, no suppliers are discovered.
2. $p_s > \mu,\ \hat{\mu} \leq \mu$: These suppliers are correctly rejected
3. $p_s > \mu$, $\hat{\mu} > \mu$: Some suppliers will be wrongly accepted $WA \coloneqq \bigcup_k^K \min_s \{p_{s,k}, s \in S_k : p_{s,k} < \hat{\mu}_k \,\&\, p_{s,k} > \mu_k\}$. Decreases process costs, increases purchase cost.

The analysis shows that if purchase costs are an issue, the purchaser should choose a prediction technology that undervalues the market price (case 1.). On the other hand, overestimating the purchase price (case 3.) can increase the purchase but decreases the process cost. Therefore, a purchase manager must determine which performance indicator best balances the competing goals of exploration (finding a better deal) and process efficiency (reducing process costs and higher procurement speed). Sections 3.3 and 3.4 discuss a possible solution.

3.3 Dynamic Stopping Rule: without Updating

The primary difference between a static method and a dynamic approach is that the static approach is more likely to inadvertently stop searching even when it is advantageous or not stop searching even when the expected value of the search is low. To achieve a more targeted resource allocation, the dynamic stopping rule changes the stopping point depending on the probability of sourcing a lower price. The reasoning behind algorithm 1 is quite intuitive. The algorithm computes in line 3) the expected value from searching for lower prices than the current best price. That is, it computes for every possible future p_{s+1} price the probability $\tilde{f}(p_{s+1})$ of obtaining this price from the next supplier. If that price is higher than $p_{best,s}$ the purchaser prefers not to buy; otherwise, the saving is calculated.

Algorithm 1.

Initialize s=1

1. Obtain p_s
2. Set $p_{best,s} = min\{p_j | j = 1, \dots, s\}$
3. If $\sum_{p_{s+1}} |min(p_{s+1} - p_{best,s}, 0)| \tilde{f}(p_{s+1}) > c$:
   set s= $s + 1$ and iterate from 1. Else stop and choose offer $p_{best,s}$.

However, the algorithm does not incorporate new information in its current form.

3.4 Dynamic Stopping Rule: with Updating

Now we address the problem of updating the learning algorithm with new data. Updating is important because prediction errors can impair economic outcomes, and algorithm 1 does not update the recommendations in such cases. This also may not be a good use of available data since, regardless of how accurate the prediction algorithm is, on average, the purchase manager needs to source at least one offer before s/he can make any purchase. The sourced offer could contain valuable information that is otherwise unaccounted for. In addition, individual data series for specific items might be relatively brief, making prediction harder. The static approach's prediction accuracy now hinges on how much predictive power comparable items in the data set provided. On the other hand, the Bayesian approach that we suggest also incorporates new data obtained during supplier search, thus potentially resolving the previously stated issue. In concrete, Bayesian updating allows one to sequentially learn from new quotation data as supplier offers are collected. Our second proposed algorithm uses updating:

Algorithm 2.

Initialize s=1

1. Obtain p_s
2. Update $\tilde{f}(p_{s+1} | p_s, p_{s-1}, \dots, p_1)$
3. Set $p_{best,s} = \min\{p_j | j = 1, \dots, s\}$
4. If $\sum_{p_{s+1}} |min(p_{s+1} - p_{best,s}, 0)| \tilde{f}(p_{s+1} | p_s, p_{s-1}, \dots, p_1) > c$:
   set $s = s + 1$ and iterate from 1. Else stop and choose offer $p_{best,s}$.

A particular feature of our approach is that $\tilde{f}(p_{s+1}|p_s, p_{s-1}, \dots, p_1)$ is conditioned on the quotation history at every step, which means that all available information is considered. That also means that an initially deficient estimate could be corrected. The core of our approach is the calculation of the density forecast that incorporates parameter uncertainty using prior knowledge regarding the parameter and is updated sequentially: $\tilde{f}(p_{s+1}|p_s, \dots, p_1) = \int f(p_{s+1}|\theta, p_s, \dots, p_1)\pi(\theta|p_s, \dots, p_1)$. The so-called posterior can be calculated using the Bayes theorem $\pi(\theta|p_s, \dots, p_1) = \frac{f(p_s, \dots, p_1|\theta)\pi(\theta)}{\int f(p_s, \dots, p_1|\theta)\pi(\theta)}$. All that is needed is a likelihood function $f(p_s, \dots, p_1|\theta)$ and a prior function $\pi(\theta)$. For background on Bayesian methods, see [40, 41]. Our concrete implementation is described in Section 4.4.

4 Empirical Application

We evaluated five different approaches to determine the stopping point, namely:

- **Heuristic I**. Only control the process cost by limiting the number of requests for quotation. We set $s^* = 3$, a value typically found at public institutions.
- **Static**. Control the purchase cost by estimating $\hat{\mu}_k$ (see Section 3.2). Stop if at the first quote that undercuts the reference price $\hat{\mu}_k$.
- **Dynamic w/o updating**. Calculate the expected gain from searching for a lower price given the current best offer without learning from supplier quotes (see Section 3.3).
- **Dynamic with updating.** As w/o updating**,** includes supplier quotes in subsequent calculations of expected gain from searching (see Section 3.4).
- **Heuristic II.** Controlling purchase costs by considering many suppliers.

The approaches "heuristic I" and "heuristic II" serve as benchmark cases for controlling process and direct purchase costs.

For the empirical application, we used two data sets. A simulated data set, in which we introduce various kinds of biases in the prediction, to study the robustness of the different approaches. Finally, we employ the algorithm on the real-world data set that motivated our research.

4.1 Simulated Data and Scenarios

The simulated data set is generated by randomly drawing μ_k and σ_k^2 from a uniform distribution. Both parameters constitute the true population parameters. We then simulate supplier offers by randomly drawing from a Gamma distribution parametrized with the true parameters. We then compared several scenarios with the prediction technology. For these, we draw the $\hat{\mu}_k \sim Gamma(\frac{(\mu_k\tau)^2}{\varepsilon}, \frac{\varepsilon}{\mu_k\tau})$ and $\widehat{\sigma_k^2} \sim Gamma(\frac{(\sigma_k^2\tau)^2}{\varepsilon}, \frac{\varepsilon}{\sigma_k^2\tau})$. That means we assume that the prediction technology is of the same quality for both predicted variables. Because of the properties of the gamma distribution $E(\hat{\mu}_k) = \mu_k\tau$ and $Var(\hat{\mu}_k) = \varepsilon$. The results are for $\widehat{\sigma_k^2}$ analogous. The parameter ε controls the accuracy, or noise, of the prediction technology. The parameter τ controls the systematic direction of bias of the prediction technology. We then specify the following scenarios:

- Low error: ε=0.05, $\tau = 1$
- High error: ε=0.20, $\tau = 1$
- Overestimation: ε=0.05, $\tau = 1.2$
- Underestimation: ε=0.05, $\tau = 0.8$

4.2 Real Data Case Study

The case study is from an industrial procurement setting. In concrete, we study procurement of electrical resistors for a large producer of domestic electrical equipment. The data was extracted from suppliers' quotations using text mining. Resistors are inexpensive, costing from a few cents to about 3-5€. Specialized resistors might cost up to €15. Resistors are characterized by different attributes, such as nominal resistance, size, and product quality characteristics. We leverage these attributes to learn the resistor price from its characteristics. The raw data set comprises 201,187 price quotes from suppliers for about 2,400 resistors. Regarding the number of supplier quotations for a specific resistor: the 25th percentile is 18, while the 50th percentile is 53. The study spans the years 2014 through 2019. We improved the comparability of the quotes by adjusting the pricing for 2019. We calculated the average and variance of supplier prices for each resistor type. Using this information, we built two random forests on the training data to forecast each resistor type's average market price and variance. The testing data set includes resistor properties and a collection of offers from numerous vendors. In concrete, we evaluate using 800 unique new resistors.

4.3 Evaluation Strategy

For evaluation, we replicate the purchase process. For each resistor $k \in 1, \ldots, K$ in the testing data, we predict $\hat{\mu}_k$ and $\widehat{\sigma_k^2}$. This information is utilized to evaluate sequentially each of the S_k offers from simulated (4.1) and real (4.2) suppliers. Each approach for determining a stopping point is tested using identical pricing quotations. Therefore, the entire solution space is spanned by a $K \times S$ grid. Each approach is assessed on its ability to efficiently explore the solution space in terms of achieved purchase costs and procurement process costs. Procurement process costs are approximated by the total number of examined quotes and requests made.

4.4 Implementation and Software Used

We now describe the details of how Bayesian updating was implemented. For modeling purchase prices, the gamma distribution is often used [42–44]. The Gamma distribution is flexible and can take many forms depending on the parameter values [43]. Hence, in the case of our application, we assume that prices p_{ik} follow a Gamma-distribution. In particular, we assume that each type of item, indexed k, has its own price distribution, not necessarily unique, parametrized by s_k and a_k. To model the heterogeneity of prices for different items that may be quite different shaped and scaled, we reparametrize $a_k = \frac{\mu_k^2}{\sigma_k^2}$ and $s_k = \frac{\mu_k}{\sigma_k^2}$. This allows modeling parameter uncertainty in terms of expected value μ_k and variance σ_k^2. We estimate these two parameters for each resistor type. Consistent with the Bayesian paradigm, we assume that the purchase manager can encode prior information about the likely values of the parameters. We define the priors $\pi_1(\mu_k)$ and $\pi_2(\sigma_k^2)$ in such a way that their modes correspond to $\widehat{\mu_k}$ and $\widehat{\sigma_k^2}$. We prefer this specification, as it puts much weight on the initial estimates. The prior on σ_k^2 is assumed to be $Gamma(\frac{\widehat{\sigma_k^2}}{\omega-1}, \omega)$. We view ω as an additional hyper parameter that governs the weight of the prior. We settled for $\omega = 3$ using a manual search. The prior on μ_k is assumed to follow a PERT distribution [45]. The PERT is a flexible distribution as it is based on a reparametrized beta model. In addition, the PERT distribution has the advantage that its domain is bounded on the positive scale, in contrast, e.g., to a normal distribution. We prefer PERT for the price distribution because its domain can be bounded on a closed interval. This interval is set to $(0,15]$ according to the typical range of quotes. In principle, other forms of priors are also possible. For example, we could have modeled the prior directly using a Beta distribution. Yet, we settled on the PERT distribution because it can be easily parameterized using only the minimum, maximum, and most likely value. The typical domain of resistor prices defines the minimum and maximum. The most likely value is set to the estimate of the average price $\widehat{\mu_k}$. On the other hand, for the variance, we restrict the domain on values larger than zero and put a higher probability mass on $\widehat{\sigma_k^2}$. Regarding the upper bound on the domain of the prior on σ_k^2, we have more uncertainty. Hence, we chose Gamma distribution as prior for σ_k^2.

All computer code was written in R. For computing the posterior, we used 300×100 Monte Carlo grid approximation for μ and σ^2. The PERT distribution we took from the mc2d package [46], machine learning was done with mlr and ranger [47, 48], and the future package for parallel computations [49]. The stopping threshold c was set to a percentage value of five percent of the estimated product price (relative threshold).

5 Results

The results regarding purchase and process costs are depicted in Table 2 and Table 3. We also tested if the differences between the approaches are significant. For this, we used a paired t-test because all approaches are evaluated on identical simulated/real records and are thus dependent. We find that the average purchase cost for the Bayesian method is significantly higher than for the method w/o (without) updating in both noise scenarios, $t(999) \geq 6.87$, p<0.01. Also, in the case of overestimation, the Bayesian method is significantly more costly than the method w/o updating, $t(999) \geq 17.55$, $p \leq 0.01$, whereas in the case of underestimation, the Bayesian method is significantly less costly, $|t(999)| \geq 6.4, p \leq 0.01$. For all the first three scenarios, the Bayesian method yields significantly fewer requests than the distributional method, $|t(999)| \geq 24, \mathrm{p} < 0.01$, but for the case of overestimation, the Bayesian method needs more number of requests $t(999) = 15.5, \mathrm{p} < 0.01$. Between high error and the underestimation scenarios, there is a significant difference in terms of costs for the Bayesian method, $t(999) \geq 2.46,\ p < 0.05$. There is no significant difference in costs for the Bayesian method across the remaining simulated scenarios, $t(999) \leq 1.5,\ p > 0.1$, except that the low error scenario is significantly higher than the high error scenario $|t(999)| \geq 2.33,\ p < 0.05$.

Table 2. Average purchase cost (K_simulated=1,000, K_real_data=800)

Dataset & Scenario	Heuristic I	Static	Dynamic	Dynamic with updating	Heuristic II
Simulated					
Low error	1.957	1.977 (101%)	1.894 (96%)	1.894 (100%)	1.548 (82%)
High error	1.957	1.962 (100%)	1.796 (92%)	1.912 (106%)	1.548 (81%)
Underestimate	1.957	1.773 (91%)	1.621 (91%)	1.894 (117%)	1.548 (82%)
Overestimate	1.957	2.184 (112%)	1.992 (91%)	1.904 (96%)	1.548 (81%)
Real data					
Random Forest	2.840	2.518 (89%)	2.520 (100%)	2.736 (109%)	2.421 (88%)

Table 3. Average number of requests (K_simulated=1,000, K_real_data=800)

Dataset & Scenario	Heuristic I	Static	Dynamic	Dynamic with updating	Heuristic II
Simulated					
Low error	3	2.171 (72%)	3.494 (116%)	3.378 (113%)	10
High error	3	2.950 (98%)	4.193 (140%)	3.250 (108%)	10
Underestimate	3	4.342 (145%)	6.311 (210%)	3.403 (113%)	10
Overestimate	3	1.405 (47%)	2.204 (73%)	3.277 (109%)	10
Real data					
Random Forest	3	11.20 (373%)	10.98 (366%)	3.887 (130%)	17.186 (573%)

For the number of requests comparing the Bayesian method, there is a statistically significant difference, $|t(999)| \geq 4.22,\ p < 0.05$, except for high error vs. overestimate, $|t(999)| \leq 0.77,\ p > 0.1$. We also calculated the mean percentage error

(MAPE) on all studied settings for reference: For low error 10%, for high error 21%, for underestimate 22%, for overestimate 20%, for random forest 36%. We also tried but did not report other random forests and a neural network whose hyperparameters were tuned on a validation set using MAPE, absolute error, and loss functions that penalize for under-/overestimation. However, predictions turned out to be similar.

6 Discussion

6.1 Results

We found empirically that the static technique has lower purchase costs but higher process costs. The reason is that the static method terminates earlier than heuristic I, hence the purchase price is higher. Process costs are also higher for the real data case, presumably because the random forest underestimated the price average. The simulated results for the underestimating scenario support this. The dynamic rule outperforms the static rule in terms of purchasing costs, not process costs. The dynamic rule without updating has lower procurement costs but slightly higher process costs than heuristic I. So, the dynamic rule keeps searching when there are large expected savings.

Four scenarios of introducing noise and bias in simulation predictions were utilized to assess the dynamic method's ability to correct for forecast errors. The rule with updating reduces process costs in all circumstances except overestimation. In the case of overestimating dynamic without updating is too pessimistic about potential savings, while in the case of underestimation, no updating is too optimistic, similarly to the static rule. The rule with updating is more robust, suggesting that Bayesian updating corrected the initial faulty forecast. That presumably explains why the rule with updating works better in the real data case. The dynamic rule with updating appears to be robust to any prediction bias in the simulated data for purchase costs, as indicated by the non-significant t-tests. This observation suggests that the direction of bias is unimportant for the dynamic approach with updating, although it appears essential for the static and dynamic rule without updating. We find it expected that overall differences between the scenarios for the Bayesian method are non-significant for purchase costs but significantly different in terms of process costs. It shows that the Bayesian method is robust towards deficient predictions that enter as an argument; such deficient forecasts are then corrected by exploring more supplier offers. The method w/o updating has lower purchase costs in the case of underestimation, although this comes at higher process costs. That finding implies that the dynamic stopping rule w/o updating is not recommendable. In the simulated scenario, the distribution of received quotes belongs precisely to the same family of statistical distributions used to calculate the dynamic stopping rule. In contrast, in the real data application, we used the Gamma distribution to approximate the real distribution of prices. Despite being an approximation, our approach also extends to the real data case. Estimating distribution parameters using machine learning works, despite low predictive accuracy, as indicated by the high MAPE for the random forest. Nevertheless, the dynamic stopping rule with updating benefits from information included in obtained supplier quotes.

6.2 Limitations

Our method applies to many procurement situations but is based on explicit assumptions: a) Obtaining a new request for quotation is costly, and b) an offer can be deferred at no additional cost. In concrete, a) is plausible because of all the search-related costs incurred from scouring the market for the best alternative [50]. Assumption b) requires supplier quotations to be valid for a certain period (e.g., if suppliers submit a binding price quotation). This may not apply to some types of products: e.g., seasonal products, temporary discounts, commodities. A workaround is to gradually increase the termination criterion to reflect the effect of delaying.

In sum, these assumptions put weak limits on the applicability of our approach. Even so, some reservations should be made. The supplier's strategic behavior is currently being disregarded (e.g., concerning supplied price offers). This study assumed that the supplier's final best offer is the decision input, ignoring any bargaining premium. However, in practice, a purchase manager should consider negotiation strategies [34, 35, 51]. We did not model price changes, which are essential for real-time spot market purchases (e.g., energy), but can be neglected if prices are temporarily stable. Also, purchasing for immediate production needs limits the ability to delay purchases. Purchasing can also be subjected to additional objectives when considering supplier properties (e.g., lead times, quality). Scalarizing [52] and constructing a joint probability function of these properties may be a way to address this issue. Finally, we did not investigate purchase costs (delivery, logistic, and storage costs) as they are conceptually different from the general procurement process.

6.3 Implications for Practice and Research

The findings are significant for purchasing managers since both the w/o updating and the Bayesian method offer several advantages. First, these techniques can be used to increase average procurement speed while also reducing average costs. As a result, the strategy keeps control over both purchase and process costs. Second, the techniques justify prioritizing specific procurement projects. In concrete, it provides managers with a tool for communicating when procurement efforts should be expanded or when they can be halted or reallocated between projects depending on the expected value of further searches. Third, procurement managers can make more precise statements about the value their department contributes to the organization's bottom line using the proposed technique. Finally, the approach can also be used to track and direct the efforts of the procurement department and the efforts of individual staff members. Purchasing managers can use our algorithms as a self-service-analytics solution (SSA) [53] within standard procurement software solutions [2]. Future research could focus on optimally incorporating our proposed solution in an SSA concerning socio-technic design characteristics. For instance, it is unknown whether purchasing managers view the algorithmic solution positively or whether they would follow the algorithmic recommendations at all.

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