Adaptive Pricing in Multi-Agent Supply Chain Markets using Economic Regimes

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Abstract

In today's complex supply chain markets, information systems are crucial for effective supply chain management, supporting complex decision processes that can improve the agility of organizations. The highly competitive nature of today's complex supply chain markets requires sophisticated dynamic product pricing that can adapt quickly to dynamic market conditions, competitors' strategies, etcetera. We propose a product pricing approach which estimates the parameters of the distribution of all prices offered by suppliers in real-time, based on available information. The relations between price distributions and available information are dynamically modeled by accounting for customer feedback and by characterizing different market conditions using economic regimes. Given the parametric approximations of price distributions, offer acceptance probabilities are estimated using a closed-form mathematical expression, which is used to determine the price that is expected to yield a desired sales quota. We validate

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our methods by presenting experimental results from a testbed derived from the Trading Agent Competition for Supply Chain Management (TAC SCM). When competing against world's leading TAC SCM agents, performance significantly improves; bid efficiency increases and profits more than double.

1 Introduction

Supply chain markets are ubiquitous in today's global economy. In a supply chain, raw materials are converted into products and distributed to final users [11]. As today's supply chains are complex logistics systems which can encompass many interrelated entities, effective Supply Chain Management (SCM), focused flexible and dynamic relationships among entities in the supply chain, is vital to the competitiveness of manufacturers within this chain. Effective SCM enables manufacturers to respond to changing market demands in a timely and cost effective manner [5] and can thus improve the agility of supply chain entities. A challenge in this context is dynamic product pricing. When flexible and dynamic relationships between supply chain entities stimulate manufacturers to compete for customer orders, optimal product prices must account for numerous factors, such as competitors' strategies or market conditions [9, 22, 23, 34, 37]. This requires a sophisticated dynamic product pricing approach, possibly facilitated by automated decision support systems that rely on data retrieved from information systems.

Information systems can provide valuable inputs for the product pricing process as they can encompass a large variety of data. However, in real-time applications, information relevant to product pricing may not be (fully) available, as for instance competitors' strategies may not be observable. Despite the limited visibility of market characteristics, real-time adaptation to changing market circumstances is desired in today's complex supply chain markets. This suggests a need for information systems to be used in a more creative way in order to augment their utility in supporting decision making processes. Therefore, we investigate how dynamic pricing decisions using estimations of economic regimes – characterizations of market conditions [16, 17, 20] – can contribute to profit maximization. We validate our approach in a highly competitive setting in the Trading Agent Competition for Supply Chain Management (TAC SCM) [7], which has been organized since 2003 to promote high quality research into trading agents in supply chain environments. In TAC SCM, several manufacturers (autonomous software trading agents) compete in a component procurement market and in a sales market where assembled products are sold through reverse auctions in response to requests for quotes (RFQs). The market is only partially observable.

The paper is organized as follows. In Section 2, we discuss related work on dynamic product pricing. Our own product pricing approach is introduced in Section 3. In Section 4, adaptivity is introduced to this approach. We evaluate the novel approach in the TAC SCM in Section 5 and we conclude in Section 6.

2 Related Work

A common and intuitive approach for effective dynamic product pricing accounts for the probability that a customer actually accepts the offer and hence proceeds to buy the product for the offered price. A good approximation of this probability can help a seller assess how sales targets can be met. Recent research suggests viability of this approach. For instance, in [9], products are priced using a dynamic pricing algorithm which considers an estimated distribution of the buyer reservation price for products of a seller. Reversing the cumulative form of this distribution yields a function expressing the proportion of buyers willing to pay the seller a specified price, which can also be interpreted as the probability that a customer accepts an offered price. This function can subsequently be used to determine the price expected to yield a specified sales quota. In [42], estimated distributions of buyer's private values are used in a similar way.

Another way of modeling acceptance probabilities is by using linear regression on data points representing recent offer prices and their resulting acceptance rate [32]. Acceptance probability distributions could also be trained off-line [2]. Another option is to try to model the decision function of the accepting entities, based on their decision histories, e.g., using Chebychev polynomials [34].

Related work suggests that other aspects besides acceptance probabilities are relevant in the product pricing process. For instance, in case of known demand and uncertain supply, a responsive pricing policy, in which the retail price is determined after observing the realized supply, results in a higher expected profit than a pricing policy in which the realized supply is not taken into account [39]. Consequently, modeling expected or observed supply-side behavior in the product pricing process could contribute to profit maximization. Furthermore, current and future offers of competitors (outside options) could be considered [22, 23]. In [37], outside options are considered as well by quantifying both the price change of a product itself and the relative price of competing products in a price elasticity. Using scenario analysis for distinguishing between various situations of price elasticity (i.e., market conditions), the optimal pricing policy is selected.

Market conditions can also be accounted for using economic regimes [16, 17, 20]. Regimes are sets of conditions of a system or process and provide an intuitive way of conditioning behavior in different scenarios. Several approaches to regime identification and prediction have been proposed in different contexts [1, 13, 14, 29]. In an economic context, the ability of decision makers to correctly identify the current regime and predict the onset of a new regime is crucial in order to prevent over- or underreaction to market conditions [25]. Economic regimes can guide tactical (e.g., product pricing) and strategic sales decisions (e.g., product mix and production planning) [16, 17, 20].

Past research describes several aspects in the product pricing process. Using expected or observed supply-side behavior, current and future offers of competitors (or competitors' pricing strategies), along with perceived market conditions (characterized using economic regimes) to estimate the probability that a customer accepts a price appears to be a viable strategy in dynamically determining the optimal product prices. However, a dynamic product pricing approach that takes all these findings into account, and is thus able to adapt to ever-changing market circumstances such as those in highly competitive complex supply chains, is yet to be proposed.

3 Product Pricing based on Offer Price Distributions

Manufacturers of durable goods typically sell their products in oligopolistic markets with differentiated customer demand. Knowledge about competitors' procurement, production and pricing decisions is generally not available. Such knowledge can at most indirectly be inferred from unexpected increases or decreases of the volume or profitability of one's own sales. Customers may be expected to simply purchase the lowest priced product from any offer of equally preferred product specifications, but aggregate demand will vary over time with respect to volume as well as quality. Accurate predictions of the price at which customers are willing to accept offered products are essential to maintain sustainable market positions.

In this section, we develop a model for the probability that offers are accepted given a certain price. The model is based on the idea that past information about product sales and prices can be used to infer the distribution of offered prices in the market. Real-time application of this model requires flexible updating of the parameters involved, for which we propose Artificial Neural Networks (ANNs).

3.1 General Framework

Given the considerations presented in Section 2, we propose to approximate customer offer acceptance probabilities by taking into account the distribution of all offered prices, because we can thus model the unobservable decision making processes of all traders and obtain a complete estimation of customer acceptance probabilities. Using, e.g., linear regression on recent offer prices as proposed in [32] would imply a less accurate model of supply-side behavior and competitors' pricing strategies. Furthermore, modeling offer price distributions rather than individual – potentially non-occurring – offer prices (as proposed in [22]) yields a more robust approach.

Assuming that customers only consider bids at or below their reservation price and always select the trader offering their requested product for the lowest price, the distribution of realized order prices can be derived from the distribution of valid offer prices. Modeling order price distributions using offer price distributions is intuitive, as this captures the market dynamics and facilitates the representation of relevant information on supply-side behavior. Now, let for product g on day d a mean number of $\overline{n}_{dg}$ randomly sampled valid offer prices p_{dg} for each out of m_{dg} RFQs be identically and independently distributed in accordance with a distribution $f\left(p_{dg};\theta\right)$ and a cumulative distribution $F\left(p_{dg};\theta\right)$, with $0 < p_{dg} < u$ (i.e., prices are non-negative and have an upper bound u) and θ a vector of unknown parameters. For such a distribution, the cumulative distribution of the minimum valid offer prices (and thus the order prices) $\underline{p}_{dg}$ over all m_{dg} RFQs can be derived as

$$F_{\underline{p}}\left(\underline{p}_{dg};\theta\right) = \left(1-\left(1-F\left(\underline{p}_{dg};\theta\right)\right)^{\overline{n}_{dg}}\right)^{m_{dg}}, \quad 0 < \underline{p}_{dg} < u, \quad \overline{n}_{dg}, m_{dg} > 0. \tag{1}$$

The cumulative density of order prices, $F_{\underline{p}}\left(\underline{p}_{dg};\theta\right)$, yields the fraction of order prices realized at or below a value. Consequently, the reverse cumulative density approximates the probability for an agent to offer a better deal than other competitors. Hence, the reverse cumulative density of order prices associated with product g on day d is an estimation of the probability that a customer will place an order o with an agent, given its offer price p_{dg}, $P\left(o|p_{dg}\right)$. Acceptance probabilities can therefore be estimated as

$$P\left(o|p_{dg}\right) = 1-\left(1-\left(1-F\left(p_{dg};\theta\right)\right)^{\overline{n}_{dg}}\right)^{m_{dg}}, \quad 0 < p_{dg} < u, \quad \overline{n}_{dg}, m_{dg} > 0. \tag{2}$$

Equation (2) can be used to estimate the share of received orders with respect to the total number of RFQs for product g on day d, generated by a price offered on all these RFQs.

Now, let q^*_{dg} be the sales quota for product g on day d, with m_{dg} associated RFQs, for each of which $\overline{n}_{dg}$ prices are offered. Hence, $P\left(o|p^*_{dg}\right)$ is required to be q^*_{dg}. Solving the equation to p^*_{dg} yields the optimal offer price p^*_{dg} expected to yield the desired quota.

When pricing products, θ and $\overline{n}_{dg}$ in (2) must be estimated. When all data is available, $\overline{n}_{dg}$ can be determined by a counting process and θ can be estimated by maximum likelihood as follows. Let us assume that all prices in the sample of prices $\vec{p}_{dg}$ offered for all m_{dg} RFQs issued for product g on day d are identically and independently distributed in accordance with the offer price distribution $f\left(p_{dgri};\theta\right)$. Then, the joint distribution of all valid offer prices equals

$$f\left(\vec{p}_{dg};\theta\right) = \prod_{r=1}^{m_{dg}} \prod_{i=1}^{n_{dgr}} f\left(p_{dgri};\theta\right), \quad 0 < p_{dgri} < u, \tag{3}$$

where p_{dgri} is the ith of n_{dgr} prices offered on day d for RFQ r for product g. Following (4), parameters θ can be estimated by minimizing their negative log-likelihood function for observed offer prices $\vec{p}_{dg}$ (e.g., using the Newton-Raphson method described in [6]).

$$L\left(\theta;\vec{p}_{dg}\right) = \sum_{r=1}^{m_{dg}} \sum_{i=1}^{n_{dgr}} - \ln\left(f\left(p_{dgri};\theta\right)\right), \quad 0 < p_{dgri} < u. \tag{4}$$

However, data on offer prices may not be available due to limited visibility of the real-time environment. This suggests the need for a mapping of real-time available information to target distribution parameter values.

3.2 Real-Time Parameter Estimation

The distribution parameters θ and $\overline{n}_{dg}$ can be estimated using a vector of real-time available information, $\vec{x}$. The relations between available information and distribution parameters, $h_\theta\left(\vec{x}\right)$ and $h_{\overline{n}_{dg}}\left(\vec{x}\right)$, can be modeled using Artificial Neural Networks (ANNs), yielding approximations of these relations: $\hat{h}_\theta\left(\vec{x}\right)$ and $\hat{h}_{\overline{n}_{dg}}\left(\vec{x}\right)$. An ANN is a mathematical model inspired by biological neural networks, which provides a general, practical method for learning real-valued, discrete-valued, and vector-valued functions over continuous and discrete-valued attributes from examples in order to facilitate regression or classification [27]. The model consists of interconnecting artificial neurons (nodes), ordered into an input layer, hidden layers, and an output layer.

Due to the ability of an ANN to capture complex nonlinear relations, we can replace parameter estimation using (4) with such a model, albeit with different inputs (i.e., real-time available data). Representing the unknown relations between distribution parameters and real-time available data using ANNs also brings the attractive feature of fast evaluation of these functions, which is crucial for real-time product pricing. Other advantages include robustness to noise in the training data [27], the possibility to introduce adaptivity by adjusting the weights of each node's inputs on-the-fly using newly obtained examples (if any), and the fact that ANNs have proven to be useful for economic forecasts in various domains [22]. Moreover, our experimental results regarding TAC SCM show that ANNs better capture the relation between data and distribution parameters than, e.g., linear regression.

We propose to use a specific type of ANN: a radial basis function network (RBFN), because this type of ANN can be designed and trained in a fraction of the time it takes to train standard feed-forward back-propagation ANNs [27]. A RBFN is a two-layer ANN consisting of a hidden layer and an output layer. The activation function in each hidden unit h is a local function $K_h\left(d\left(\vec{x}_h, \vec{x}\right)\right)$, where $\vec{x}$ is a vector of features, $\vec{x}_h$ is the center of $\vec{x}$, and $d\left(\vec{x}_h, \vec{x}\right)$ is the "distance" between $\vec{x}_h$ and $\vec{x}$. $K_h(z)$ is a function whose value is a maximum when $z = 0$, and approaches zero for large values of z. The local functions in the hidden layer typically are Gaussians, centered at $\vec{x}_h$ with variance σ_h^2. The number of Gaussians H is subject to optimization and their centers can be determined by clustering the data, using for example the k-means algorithm [24]. The network's output for an instance $\vec{x}$, $\hat{h}\left(\vec{x}\right)$, is a linear combination of the activation units, weighted for their weights w_h, and a bias w_0 [27]:

$$\hat{h}\left(\vec{x}\right) = w_0 + \sum_{h=1}^{H} w_h K_h\left(d\left(x_h, \vec{x}\right)\right), \tag{5}$$

$$K_h\left(d\left(x_h, \vec{x}\right)\right) = e^{\frac{1}{2\sigma_h^2} d^2\left(x_h, \vec{x}\right)}. \tag{6}$$

Hence, a RBFN is a global approximation $\hat{h}\left(\vec{x}\right)$ of a target function $h\left(\vec{x}\right)$, represented as a linear combination of local functions around their centers. Because of the relatively easy design and training, as well as the robustness, possibilities for introducing adaptivity, and the fast real-time evaluation capabilities, a RBFN would be a good approximator for distribution parameters. By mapping real-time available information to distribution parameter values through a RBFN, our proposed product pricing model is responsive to this observable information in a predefined way. However, the model is essentially static, as it does not adapt the modeled relations between price distributions and observable data to changing market conditions and market responses. Therefore, we propose to introduce true adaptivity to the model using economic regimes [16, 17, 20].

4 Adaptive Product Pricing using Economic Regimes

We are especially interested in market scenarios where changes in bidding behavior of the competitors cannot be directly observed. In previous research [20], we have shown that different market conditions can be identified by using economic principles and machine learning techniques. In that work, historical data were used to compute price distributions that, in turn, were used to compute prices and identify economic regimes. This paper builds on previous work, adding real-time adaptivity using observable market information. Realized order prices and hence order probabilities tend to vary, depending on the distribution of economic regimes [16, 17, 20]. In order to facilitate a truly adaptive, real-time applicable product pricing approach, we dynamically model the relations between available data and price distributions using economic regimes, such that product pricing strategies can be differentiated depending on market characteristics. Per dominant regime k, price distribution parameters θ_k and $\overline{n}_{dgk}$ for product g on day d can be estimated using RBFNs, yielding M separate price distribution estimations when M dominant regimes are considered. The acceptance probabilities $P(o_k|p_{dgk})$ derived from these distributions can subsequently be weighted for the associated regime probabilities for regime R_{dgk}, $P(R_{dgk})$.

The weights in the RBFNs could be updated on-line, but when new samples cannot be presented to the ANNs (due to limited visibility), we can adjust daily acceptance probability estimates by multiplying the probabilities by a factor representing the ratio of the number of actually received orders to the number of predicted orders [31]. This ratio can be used as a residual term δ, through which market responses are fed back to the model, as it can be updated in real-time. A smoothed error term $\widetilde{\delta}$ can prevent over- or undercompensation.

For a dominant regime k, the probability that a customer accepts an offer and hence places an order o_k, given price p_{dgk} for product g on day d, $P(o_k|p_{dgk})$, ranges from 0 to 1. Multiplying this probability with the suggested ratio $\widetilde{\delta}_{(d-1)gk}$ (which depends on regime k and has been updated using performance information up until day $d-1$) yields a corrected probability $P(o_k|p_{dgk})'$ in the range $\left[0, \widetilde{\delta}_{(d-1)gk}\right]$. This implies that no suitable price can be found for $q^*_{dg} \geq \widetilde{\delta}_{(d-1)gk}$, which is an undesirable feature in case $\widetilde{\delta}_{(d-1)gk} < 1$. However, when the corrected customer offer acceptance probability $P(o_k|p_{dgk})'$ is defined as

$$\begin{aligned} P(o_k|p_{dgk})' &= P(o_k|p_{dgk})^{\widetilde{\epsilon}_{(d-1)gk}}, \quad 0 < p_{dgk} < u, \quad \widetilde{\epsilon}_{(d-1)gk} > 0, \\ &= \left(1 - \left(1 - (1 - F(p_{dgk}; \theta_k))^{\overline{n}_{dgk}}\right)^{m_{dg}}\right)^{\widetilde{\epsilon}_{(d-1)gk}}, \\ &\quad 0 < p_{dgk} < u, \quad \overline{n}_{dgk}, m_{dg}, \widetilde{\epsilon}_{(d-1)gk} > 0, \end{aligned} \tag{7}$$

offer acceptance probabilities continue to range from 0 to 1 for $0 < p_{dgk} < u$ after correction through a smoothed error term $\widetilde{\epsilon}_{(d-1)gk}$.

Using (7), the corrected offer price $p^{*'}_{dg}$ expected to yield the desired sales quota q^*_{dg} for product g on day d can be defined for each dominant regime k, by requiring $P\left(o_k|p^{*'}_{dgk}\right)'$ for that product on that day to be q^*_{dg}. Solving the equation to $p^{*'}_{dgk}$ yields the optimal corrected offer price $p^{*'}_{dgk}$ expected to yield the desired quota q^*_{dg} under dominant regime k. When these corrected prices are then weighted for their associated regime probabilities $P\left(R_{dgk}\right)$, the corrected price $p^{*'}_{dg}$ expected to yield the required quota can be obtained.

The error term considered in (7) should be assigned values such that under each dominant regime k, the expected customer offer acceptance probabilities $P\left(o_k|p^{*'}_{(d-1)g}\right)$ associated with an offer price $p^{*'}_{(d-1)g}$ are corrected by the unsmoothed exponential error terms to the proportion of actually received number of orders $q_{(d-1)g}$. The found error terms can subsequently be smoothed. Hence, offer price and customer response should be related as follows:

$$q_{(d-1)g} = P\left(o_k|p^{*'}_{(d-1)g}\right)^{\epsilon_{(d-1)gk}}, \quad 0 < q_{(d-1)g} < 1, \quad 0 < p^{*'}_{(d-1)g} < u, \quad \epsilon_{(d-1)gk} > 0. \tag{8}$$

In an attempt to track the trend in the error terms and thus provide an accurate estimate of the error of the model on day d, given information up until day $d-1$, the error terms can be smoothed using double exponential smoothing [3]. Here, the smoothing factor β is weighted for the associated regime probabilities in order for errors only to be attributed to the models responsible for these errors. Smoothing is done by linearly combining two components (see (12)). The first component (10) is a linear combination of the latest error (9) and the previous first component. The second component (11) is a linear combination of the first component and the previous second component.

$$\epsilon_{(d-1)gk} = \frac{\ln\left(q_{(d-1)g}\right)}{\ln\left(P\left(o_k|p^{*'}_{(d-1)g}\right)\right)}, \quad 0 < q_{(d-1)g} < 1, \quad 0 < P\left(o_k|p^{*'}_{(d-1)g}\right) < 1, \tag{9}$$

$$\widetilde{\epsilon}'_{(d-1)gk} = \beta P\left(R_{(d-1)gk}\right)\epsilon_{(d-1)gk} + \left(1 - \left(\beta P\left(R_{(d-1)gk}\right)\right)\right)\widetilde{\epsilon}'_{(d-2)gk}, \tag{10}$$

$$\widetilde{\epsilon}''_{(d-1)gk} = \beta P\left(R_{(d-1)gk}\right)\widetilde{\epsilon}'_{(d-1)gk} + \left(1 - \left(\beta P\left(R_{(d-1)gk}\right)\right)\right)\widetilde{\epsilon}''_{(d-2)gk}, \tag{11}$$

$$\widetilde{\epsilon}_{(d-1)gk} = 2\widetilde{\epsilon}'_{(d-1)gk} - \epsilon''_{(d-1)gk}. \tag{12}$$

So far, the model assumes offer prices to be distributed in accordance with a distribution the type and parameters of which are undefined. For this purpose, we propose a log-logistic distribution, as this distribution covers a variety of shapes depending on the parameters α and γ and has the attractive feature that an analytical closed form expression exists for the cumulative density function. Moreover, this distribution appears to sufficiently describe the data in TAC SCM in over 60% of the analyzed price samples from historical data[1], according to the Kolmogorov-Smirnov test [26] (when requiring the p-value to be under 0.05). The remaining samples could not sufficiently be described using a simple parametric distribution such as the log-logistic distribution due to the complex form of their true densities. The log-logistic distribution $f(p;\alpha,\gamma)$ and its cumulative form $F(p;\alpha,\gamma)$ [28], truncated such that the distribution is defined on the domain $0 < p < u$ and reparameterized such that α represents the median and γ quantifies the distribution tightness, can be described as

$$f\left(p;\alpha,\gamma\right) = \frac{\left(\alpha^{-\gamma} - u^{-\gamma}\right)\gamma p^{-\gamma-1}}{\left(\alpha^{-\gamma} - 2u^{-\gamma} + p^{-\gamma}\right)^2}, \quad 0 < p < u, \quad \alpha,\gamma > 0, \tag{13}$$

$$F\left(p;\alpha,\gamma\right) = \frac{\alpha^{-\gamma} - u^{-\gamma}}{\alpha^{-\gamma} - 2u^{-\gamma} + p^{-\gamma}}, \quad 0 < p < u, \quad \alpha,\gamma > 0. \tag{14}$$

When $F\left(p_{dgk};\theta_k\right)$ in (7) is substituted for (14), the corrected price $p^{*'}_{dg}$ expected to yield a required sales quota (i.e., acceptance probability [18]) q^*_{dg} can be obtained as shown in (15) through (17) for $1 \le k \le M$, with the number of considered regimes $M = 5$ [16, 17, 20].

$$q^{*'}_{dg} = \sqrt[\overline{n}_{dgk}]{1 - \sqrt[m_{dg}]{1 - \sqrt[\widetilde{\epsilon}_{(d-1)gk}]{q^*_{dg}}}}, \quad 0 < q^*_{dg} < 1, \quad m_{dg}, \overline{n}_{dgk}, \widetilde{\epsilon}_{(d-1)g} > 0, \tag{15}$$

$$p^{*'}_{dgk} = \left(\frac{u^{-\gamma_k}\left(\alpha_k^{-\gamma_k}\left(u^{\gamma_k} - 2\alpha_k^{\gamma_k}\right)q^{*'}_{dg} + 1\right)}{1 - q^{*'}_{dg}}\right)^{-\frac{1}{\gamma_k}}, \quad \alpha_k,\gamma_k > 0, \tag{16}$$

$$p^{*'}_{dg} = \sum_{k=1}^{5} P\left(R_{dgk}\right) p^{*'}_{dgk}, \quad 0 < p^{*'}_{dgk} < u. \tag{17}$$

[1]TAC SCM 2007 Semi-Finals and Finals (9323–9327tac5 and 7308–7312tac3) [35] and TAC SCM 2008 Semi-Finals and Finals (763–768tac02 and 794–799tac01) [41] game data.

Now, the model assumes a double-bounded log-logistic distribution to be underlying offer prices, the parameters of which can be estimated real-time using RBFNs. The relation between available data and parameters is dynamically modeled using economic regimes (characterizing market conditions) and error terms (accounting for customer feedback). The proposed framework can now be evaluated in a highly competitive setting.

5 Testbed: The Trading Agent Competition for Supply Chain Management

The final framework can be evaluated by implementing the approach in the MinneTAC trading agent [8], developed for the Trading Agent Competition for Supply Chain Management (TAC SCM). To this end, product pricing should be done using (9) through (12) and (15) through (17). The α_k, γ_k, and $\overline{n}_{dgk}$ parameters for product g on day d for dominant regime k are to be estimated using RBFNs. In the following sections, we give an overview of our TAC SCM testbed.

5.1 TAC SCM Overview

The TAC SCM scenario models a supply chain for personal computers (PCs) over a simulated one-year product life-cycle. Each of the 220 daily cycles is completed in 15 seconds of real time. This supply chain consists of customers, manufacturers and suppliers (see Figure 1). Every day, customers issue RFQs for 16 different PC types, on which manufacturers can bid. Customers always place an order with the manufacturer offering the requested product for the lowest price (at or below their reservation price). Products are assembled by the manufacturers using components procured from suppliers. Manufacturers are software trading agents developed by competing teams, maximizing their profit over a game. Major challenges include limited visibility of the market, limited time for decision-making, and the need to coordinate decisions across the supply chain. Real-time available data consists of information about received RFQs and agent's own orders, the preceding day's minimum and maximum order price of each PC type, and aggregate market statistics issued every 20 days.

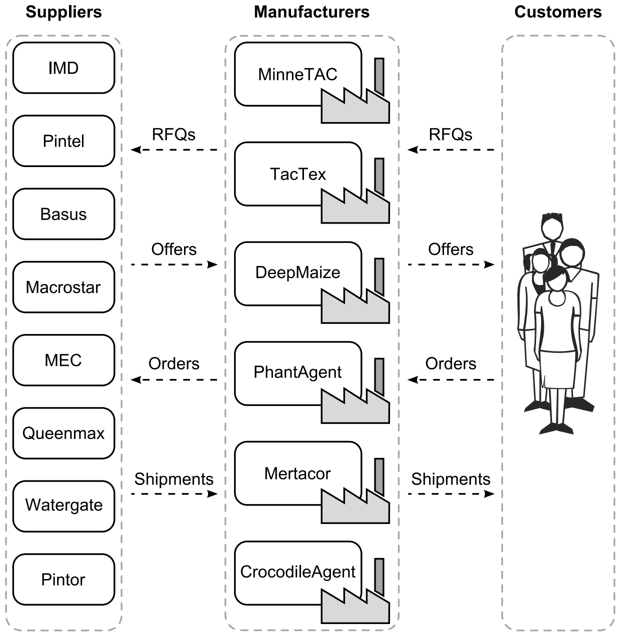

Figure 1: Schematic overview of a typical TAC SCM game scenario.

The distributions of order prices realized in TAC SCM tend to be volatile. First of all, the mean order price changes over time. Furthermore, the order price distributions are often extremely tight, whereas the spread of prices is larger on other days. Also, opportunistic or manipulative agents may inject noise into the price signal. The result of this volatility is that it is difficult to estimate price distributions, making TAC SCM a good testbed for our product pricing approach.

5.2 Implementation in the MinneTAC Agent

The sales decisions made by the MinneTAC agent originate from price predictions based on market observations, and characterized separately for each of the three market segments. These economic regimes can be characterized as extreme scarcity, scarcity, a balanced situation, oversupply, and extreme oversupply. On day d, the regime for good g is identified as the regime having the highest probability, given the estimated normalized mean price for that day. We estimate the normalized mid-range price, $\widetilde{\text{np}}_{dg}$, as the average of the double exponentially smoothed normalized minimum and maximum price observed in the market. The normalized price np_{dg} for good g on day d is the ratio of actual price to nominal production cost, which is the sum of the nominal costs of the parts required to build a product. Normalized prices rarely fall below half of nominal cost, since this is the lowest cost available from suppliers, and never rise above 1.25 of nominal cost, the upper bound on customer reserve price.

A price density function has been modeled on historical normalized order price data using a Gaussian Mixture Model (GMM) [40] with a sufficient number of Gaussians (25 at the moment), reflecting a balance between prediction accuracy and computational overhead. Clustering these price distributions over time periods (using the k-means algorithm) has yielded distinguishable statistical patterns: economic regimes. In TAC SCM, price information is only available up until the preceding day. Hence, the MinneTAC agent estimates the mean price of day d using an exponentially smoothed prediction of $\widetilde{\text{np}}_{dg}$ and then returns the regime probabilities for day d. When such an estimate is supplied to the model, the individual Gaussians in the model are activated differentially, thus generating an expected price distribution. Subsequently normalizing all clusters' price densities enables determination of regime probabilities. Future regime probabilities are determined by using Markov prediction and Markov correction-prediction processes (for short-term and long-term decision making, respectively) [19]. When current or future regime probabilities have been determined, products are priced using offer acceptance probabilities of these prices, such that a sales quota is fulfilled.

In our benchmark sales configuration, price trends are estimated by the regime model. Median product prices are estimated using a price-following approach implementing a double exponential smoother. The trends and medians, along with cost estimates and resource constraints, are inputs to a linear program that computes sales quotas that will maximize profits over a medium-term time horizon. Given these daily sales quotas, optimal offer prices are computed as the price that will sell the quota, given an order acceptance probability curve. The acceptance probability curve is approximated using the estimated median price and the curve's slope in that median, estimated using exponentially smoothed prices. In order to compensate for uncertainty in generated predictions, interval randomization is applied to offer prices, which adds a slight variability to these prices. The estimated median is then corrected using feedback derived from the desired optimized acceptance probability and the associated true acceptance probability observed the next day.

The price distributions estimated by the GMM are updated on-line, but they do not account for factors other than a mean price estimate and lack full adaptivity. In an attempt to improve the product pricing process by combining regime information with real-time available data, we replace the benchmark's sales model with a system designed for Product Pricing using Adaptive Real-time Regime-based Probability of Acceptance Estimations: PPARRPAE. The algorithm (Algorithm 1) involves parameter estimation using RBFNs and subsequent product pricing using (15) through (17) (with $u = 1.25$). An error term is used, following (9) through (12) (with $\beta = 0.5$, as determined by a hill-climbing procedure).

We built an adapter using the RBFNs that transforms price distributions estimated by the regime model into a parameterized acceptance probability function per dominant regime and assigns weights to these functions, equal to their associated regime probabilities. This adapted distribution can then be used for product pricing. Given a quota for a product (specified by the allocation component), the product pricing component uses the adapter to compute the price expected to yield this quota per dominant regime and weights the suggested prices for their associated regime probabilities. The optimized price is then offered on all selected RFQs for the considered product. The market responses to these offers are fed back to the adapter. As opposed to the benchmark approach, interval randomization is not applied to the optimized price. This is because in the MinneTAC agent, market feedback is derived by comparing optimized and realized acceptance probabilities. Interval randomization would yield a bias in this comparison, as randomized prices imply that not

```
foreach d in days do
    foreach g in products do
        // Update error using last feedback, following (9) through (12)
        error = updateError(getFeedback(d − 1, g));
        // Retrieve data from regime model
        regProbs = getRegProbs(d, g);
        regPriceDistr = getRegPriceDistr(d, g);
        trends = getTrends(d, g);
        // Estimate parameters using RBFNs
        priceDistr = estParams(regPriceDistr, getData(d, g));
        // Determine median price using (15) through (17)
        median = priceForProb(0.5, priceDistr, error, regProbs);
        // Retrieve allocated quota
        quota = getQuota(d, g, median, trends);
        // Determine price expected to yield quota using (15) through (17)
        price = priceForProb(quota, priceDistr, error, regProbs);
        // Bid optimized price on selected RFQs
        priceProduct(d, g, price);
    end
end
```

Algorithm 1: The PPARRPAE approach.

every targeted acceptance probability associated with the offered price equals the optimized acceptance probability.

5.3 Radial Basis Function Network Training

For each dominant regime k, a RBFN needs to be trained for estimating α_k, γ_k, and $\overline{n}_{dgk}$ for product g on day d. Therefore, training and test datasets[2] must be split into datasets per dominant regime. These dominant regimes are identified by the current regime model. We attempt to adapt regime-based price distributions done using the GMM implemented in the MinneTAC agent in order for them to be useful in the daily product pricing process. Hence, these regime-based price distributions should be used as RBFN inputs. For now, let these distributions be described by their 10th, 50th, and 90th percentile and the spread of these

[2] TAC SCM 2007 Semi-Finals and Finals (9321–9328tac5 and 7306–7313tac3) [35] and TAC SCM 2008 Semi-Finals and Finals (761–769tac02 and 792–800tac01) [41] game data. The first two games and the last game per server form the test set, the rest forms the training set.

percentiles.

The RBFNs should adapt these distributions using on-line available data. We use data on product type, day, RFQ characteristics, and observable prices. Data on product type and day is incorporated into our model because of the heterogeneity of products and the volatility of their associated prices, mentioned in Section 5.1. RFQ characteristics are incorporated, as (competitors') pricing strategies – which related work discussed in Section 2 suggests to be relevant when pricing products – are likely to depend on these characteristics. For example, a reservation price provides an indication of the maximum price manufacturers will bid. Also, the number of simultaneous similar bidding processes affects the associated revenues due to their (partial) substitutivity [42]. Observable (historical) prices can also provide more insight in competitors' pricing strategies [22, 16, 17, 20]. The relevance of the on-line available data mentioned is supported by initial experimental results on Pearson correlation between the data and target distribution parameter values.

Using historical data, target parameter values can be determined by a counting process (for $\overline{n}_{dgk}$) and by fitting distributions using (4) and (13) (for α_k and γ_k). A typical training dataset thus generated contains over 15,000 samples, a typical test dataset over 8,000. The performance of RBFNs trained on the training set can be evaluated on the test set, as the latter set is sufficiently large and representative [27]. For the resulting optimal values for γ_k, the increment in γ_k needed to tighten the distribution increases as the distribution gets tighter. Hence, as the required accuracy decreases for an increasing γ_k, the networks are trained to predict the natural logarithm of γ_k.

For each regime-specific RBFN, the architecture is subject to optimization. The number of inputs and the number of outputs are fixed. The number of hidden nodes is determined using a hill-climbing procedure, with the objective to minimize the root mean squared deviation (RMSD) on the test set, after training on the training set. The RMSD equals

$$\text{RMSD} = \sqrt{\frac{\sum_{\omega=1}^{\Omega}\left(\hat{x}_\omega - x_\omega\right)^2}{\Omega}}, \tag{18}$$

Dominant regime	Hidden nodes	RMSD α_k	RMSD $\ln(\gamma_k)$	RMSD $\overline{n}_{dgk}$
1	15	0.0449	0.7686	0.9979
2	15	0.0347	0.6975	1.0725
3	19	0.0370	0.6514	1.0152
4	30	0.0386	0.6414	0.9440
5	23	0.0410	0.6805	0.8092

Table 1: Optimized number of clusters for parameter estimating RBFNs and the RMSD of parameter values predicted by the models from their target values per dominant regime k.

where $\hat{x}_\omega$ is an observation in a set of Ω observations (in this case a value predicted by the model), the associated benchmark value in the test set of which is x_ω.

In order to train the RBFNs, data is normalized to zero mean and unity variance. Then, following [30], normalized data is subsequently clustered using the k-means algorithm, with the number of clusters equal to the number of hidden nodes. Gaussians are then fit on the data, with centers (initialized as the cluster centers) subject to optimization, using the expectation maximization algorithm [10]. Gaussian widths equal the maximum squared Euclidian distance between the function centers. Finally, internal weights of the RBFNs are optimized, such that the sum of squared errors is minimized. See Table 1 for the results.

5.4 Performance Evaluation

The performance of the PPARRPAE system, proposed in Section 5.2, can be assessed in real TAC SCM games, as specified in [7]. The randomness incorporated in TAC SCM (e.g., in customer demand) creates a more realistic simulation, but introduces a problem when this simulation is used as a testing environment in which two approaches are to be compared. The randomness in market conditions implies that many experiments should be run in order to obtain results with any statistical significance. The issue of randomness in the testing environment is tackled by a controlled TAC SCM server [36], in which random seeds used for generating market conditions can be re-used. Stochastic behavior of participating agents cannot be controlled, as this behavior is not generated on the server, but research shows that under equal market conditions, such stochastic behavior does not have a significant impact on the agent profit levels [36]. The results presented in [36] also indicate that most significant profit differences between agents can already be detected in approximately 40 games.

The performance of the PPARRPAE system can hence be evaluated in 40 experiment sets on a controlled server. Each experiment set consists of a paired evaluation of the performance of the benchmark and the PPARRPAE system under equal market characteristics. The configurations can be tested in a highly competitive setting, in which MinneTAC competes against world's leading TAC SCM trading agents. TacTex [32] predicts demand using a Bayesian approach and offer acceptance using linear regression, and adapts these offer acceptance estimations to its opponents' behavior. DeepMaize [21] uses a gradient descent algorithm to find a set of offered prices in order to optimize the expected value of the resulting orders. PhantAgent [38] and the CrocodileAgent [33] use simple heuristics for determining what to sell for what price. Mertacor [4] predicts the winning bid per RFQ using a regression model, complemented with a price-following correction mechanism and the acceptance probabilities are subsequently estimated using a k-nearest neighbors algorithm [24].

Performance differences should be assessed with respect to their statistical relevance. This can be done using a paired, two-sided Wilcoxon signed-rank test [12, 15]. This is a non-parametric test, which tests the hypothesis that the differences between paired observations are symmetrically distributed around a median equal to 0. If this null hypothesis is rejected (at a significance level below 0.05), the compared sets of samples can be assumed to be significantly different. This test would be suitable in this experimental setup, as the distribution of the values to be compared is unknown.

Over all experiments, PPARRPAE outperforms the benchmark with respect to final bank account balance, with significantly lower order volume (see Table 2). Generally, when using PPARRPAE, the number of orders significantly decreases with over 21% (with a Wilcoxon p-value of 0.0000), but the obtained orders yield a significant increase in final balances of about 133% (with a p-value of 0.0004 for the Wilcoxon test) with respect to the benchmark. The number of usable acceptance probability estimations significantly increases with approx-

	Final bank account balance				Order volume			
	Benchmark		PPARRPAE		Benchmark		PPARRPAE	
Agent	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
MinneTAC	-0.8945	3.9476	0.3002	4.3534	3.6969	0.5943	2.9127	0.5532
TacTex	7.1728	5.3571	7.9741	5.4748	6.6769	0.4087	6.7296	0.4194
DeepMaize	5.4684	4.1937	6.9568	4.2669	5.4586	0.5381	5.7646	0.5726
PhantAgent	7.6837	5.4520	8.7418	5.4219	6.2407	0.4235	6.3372	0.4208
Mertacor	-1.4308	4.1982	-0.3394	4.5195	6.4888	0.3424	6.5655	0.3831
CrocodileAgent	-4.4767	5.3321	-4.3196	5.3752	5.8434	0.5788	5.9564	0.5038

Table 2: Mean and standard deviation of final bank account balance (in millions) and order volume (in thousands) per agent, calculated over all experiments.

imately 108% (with a Wilcoxon p-value of 0.0000). These observations indicate that orders are better priced. This could be caused by prices of obtained orders to be closer to second-lowest prices, instead of being significantly lower, which results in a reduced margin between customers' reserve prices and realized order prices. Hence, using the PPARRPAE approach improves the quality of acceptance probability estimations and consequently results in better bid efficiency.

6 Conclusions and Future Work

When product pricing strategies are linked to price distribution estimates, taking into account real-time available information, the relation between data and price distribution parameters can be dynamically modeled using economic regimes (characterizing market conditions) and error terms (accounting for market feedback). Thus, in a constrained environment like TAC SCM, economic regime estimates contribute to profit maximization when they are used to differentiate product pricing strategies. Test results indicate that in a highly competitive setting, this novel approach significantly improves the performance of a price-following product pricing approach; bid efficiency increases and profits more than double. Proper statistical methods, combined with effective real-time parameter estimation, produce real results.

Even though the performance of the proposed model already is very promising, some aspects still require more research. First of all, the type and parameterization of models for real-time price distribution and approximation of offer acceptance probability could be further improved. Other possible predictors for acceptance probabilities could be considered as well. Procurement information might be a good candidate here, as costs associated with specific orders could influence the price, depending on the cost allocation applied in the participating trading agents. Another option for future research is trying to use the improved acceptance probability estimations in the setting of sales quotas. Finally, the effects of our novel approach on the supply chain as a whole could be assessed.

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