Towards a Dynamic Model of Supply Chain Regimes for Complex Multi-Agent Markets

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***Abstract*—Information systems are crucial for effective supply chain management in today's complex supply chains for durable goods. Complex decision making processes on strategic, tactical, and operational level require substantial support in order to contribute to the agility of organizations. Supply chain regimes, i.e., regimes encompassing both the sales and the procurement market in a complex supply chain, provide a way of intuitively and meaningfully characterizing and modeling supply chain market conditions without a need for explicit modeling of individual aspects of the market. This paper makes a first explorative step towards a model incorporating such regimes, while maintaining the dynamics which enable the model to be utilized in the sales process, e.g., for dynamic product pricing. Initial results show that supply chain regimes have feasible characteristics, based on both sales and procurement market indicators. Taking into consideration these regimes enables a more deliberate sales model.**

***Index Terms*—Supply chain regimes, supply chain management, TAC SCM, trading agent**

I. Introduction

Today's supply chain markets for durable goods are typically complex logistics systems which can encompass many interrelated entities that convert raw materials into products and distribute these products to final users [1]. As the relations between supply chain entities tend to get increasingly more flexible and dynamic, effective Supply Chain Management (SCM) is vital to the competitiveness of manufacturers within the chain. Effective SCM enables manufacturers to respond to changing market circumstances in a timely and cost effective manner [2] and can thus improve their agility.

Supply chain entities make decisions on strategic, tactical, and operational level. For instance, manufacturers have to decide on their product mix, product pricing, inventory strategy, procurement, etcetera. The increasing importance of agility in complex supply chains stimulates an increasing dependency on timely, useful information on market circumstances, possibly provided by information systems. The design of such systems becomes more and more challenging as their complexity is steadily growing with the complexity and interactions of the decision making processes they are designed to support.

A major challenge for manufacturers in a complex supply chain lies in the sales process. Manufacturers are faced with decisions regarding which customers to serve and at which price, yet such decisions are inevitably connected to – if not constrained by – decisions with respect to, e.g., inventory management, allocation of production resources, and procurement. Moreover, in complex market environments, decision makers need to take into account numerous external factors, such as competitors' strategies or market conditions [3], [4], [5], [6], [7]. Information systems can provide valuable inputs for such complex sales-related decisions as they can encompass a large variety of data. However, in real-time applications, relevant information may not be (fully) available, as for instance competitors' strategies may not be directly observable.

Economic regimes [8], [9], [10] provide a way of intuitively and meaningfully characterizing and modeling market conditions, without a need for explicit modeling of individual aspects of the market. The original economic regime model as proposed by Ketter et al. uses scarce observations of realized prices as signal for a latent variable in which demand-side market characteristics are quantified. Our recent research endeavors focused on introducing real-time adaptivity to this model in order for it to be useful for dynamic product pricing decisions in a highly competitive setting [11].

Yet, the economic regimes as modeled in previous work are essentially market conditions in one part of the supply chain, irrespective of related conditions in other parts of the supply chain. Hence, the focus of this economic regime model has been on the demand side of the market (sales from manufacturers to consumers), whereas decisions within the sales and procurement process are interrelated. In this paper, we aim to make a first explorative step towards a model of regimes capturing a more comprehensive part of market circumstances in a complex supply chain, while maintaining the dynamics which enable the model to be utilized in the sales process, e.g., for dynamic product pricing.

In our current research, we consider a specific complex supply chain: a supply chain for personal computers (PCs), simulated in the highly competitive Trading Agent Competition for Supply Chain Management (TAC SCM) [12]. This competition has been organized since 2003 in order 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 as well as in a sales market where the assembled products are sold through reverse auctions in response to requests for quotes (RFQs). The market is only partially observable.

The remainder of the paper is organized as follows. In Section II, we briefly discuss related work on regimes, TAC SCM, and the main sales strategies proposed and tested in that context. Our recently proposed dynamic sales model based on economic regimes is briefly discussed and evaluated in Section III. Based on this evaluation, we explore possibilities of extending the economic regime concept to supply chain regimes in Section IV. Our findings are discussed in Section V and we conclude in Section VI.

II. Regimes and TAC SCM

Regimes are sets of conditions of a system or process and provide an intuitive way of conditioning behavior in different scenarios. In an economic context, regimes may also be referred to as business cycle phases, which are most commonly used in macro-economic environments (as is the case in, e.g., [13]). Numerous approaches to regime identification and prediction have been proposed in different contexts, ranging from macro-economics [14] and electricity markets [15], [16] to using real-time signals for determining the state of the plasma used in a nuclear fusion reactor [17].

Over the past decades, research has not only focused on identifying and predicting regimes; regime shifts have been subject to research as well. In 1989, Hamilton published a paper about modeling macro-economic regime changes using postwar U.S. real GNP as input [14]. In his approach, Hamilton uses Markov matrices to observe these regime shifts, by drawing probabilistic inference about whether and when they may have occurred based on the observed behavior of series. Since its publication, this Markov switching approach has inspired many approaches to modeling regime shifts. Whereas the original Hamilton model considers two regimes, three regimes are considered in [18]. In other approaches, the Hamilton model is modified in order to support transition probabilities varying over time [15], [16].

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 [19]. This observation inspired Ketter et al. to develop a model of economic regimes, which can guide tactical (e.g., product pricing) and strategic sales decisions (e.g., product mix and production planning) [8], [9], [10]. This model, as well as its application in dynamic product pricing [11], has been extensively evaluated in TAC SCM.

In the TAC SCM scenario, a one-year product life-cycle is simulated over 220 daily cycles of 15 seconds of real time each. The main focus here is on a supply chain for PCs, consisting of customers, manufacturers, and suppliers. The complexity in this chain is in that PC manufacturers compete in both a sales market and a procurement market where relations between manufacturers and customers, as well as between manufacturers and suppliers, are flexible and dynamic. 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 they procure from suppliers. Manufacturers are software trading agents developed by competing teams and try to maximize their profit over a game. Major challenges in the TAC SCM scenario 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 include an agent's own orders, information about received RFQs, the preceding day's realized minimum and maximum order prices per PC type, and aggregate market statistics issued every 20 days.

World's leading TAC SCM trading agents apply various strategies in their sales processes. TacTex [20] predicts demand using a Bayesian approach. Bids on RFQs (if any) depend on the probabilities of these bids to be accepted, which TacTex predicts using linear regression and adapts to the behavior of opponents. CMieux [21] uses a similar, yet somewhat less complex approach. CMieux predicts demand as well as selling prices using a Poisson distribution. Subsequently, decisions on which RFQs to target are based on distributions of acceptance probabilities of their bids. These probabilities are estimated by means of a probability distribution learned off-line, which is used as an input in a continuous knapsack problem. DeepMaize [22] on the other hand has a relatively simple sales model, as it uses a gradient descent algorithm to find a set of offered prices in order to optimize the expected value of the resulting orders. PhantAgent [23] and the CrocodileAgent [24] use simple heuristics for determining what to sell for what price. Mertacor [25] 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. MinneTAC utilizes a sales model based on economic regimes, as further detailed in Section III.

III. A Dynamic Sales Model Based on Economic Regimes

Manufacturers of durable goods typically sell their products in oligopolistic markets with differentiated customer demand. Competitors' procurement, production and pricing decisions are generally not directly observable and 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 typically varies over time with respect to volume as well as quality.

Yet, accurate predictions of the price at which customers are willing to accept offered products are essential to maintain sustainable market positions. Therefore, the endeavors related to MinneTAC's sales model reported in [11] focus on developing a model for the probability that customers accept offers, given a specific price. The key assumption here is that past information about product sales and prices can be used to infer the (parametric) distribution of order prices in the market. The cumulative density of order prices yields the fraction of order prices realized at or below a specific value, which is similar to the probability that an order is placed with another trader offering a similar or better deal. Consequently, the reverse of this cumulative density is used to approximate the probability for an agent to offer a better deal than other competitors: the customer offer acceptance probabilities.

The parameters of the order price distributions considered in this approach are estimated in real-time, based on available information. Price distributions are subject to market circumstances, which can be characterized using economic regimes. Therefore, the relation between available data and parameters is dynamically modeled using economic regimes (characterizing sales market conditions) and residual error terms (accounting for structural errors in the estimated acceptance probabilities using customer feedback to offered prices).

Radial Basis Function Networks (RBFNs) are used to estimate price distributions, given each dominant economic regime (while accounting for customer feedback on previous estimations). Subsequently, these distribution estimations are used in the sales process, e.g., in order to determine the optimal sales prices expected to move a desired sales quota. The found optimal prices are then weighted for their associated regime probabilities in order to determine an optimal price, while accounting for market circumstances.

More details on the statistical underpinning of the framework, the methods and techniques used in order to realize the framework within the sales model of MinneTAC, and a performance analysis of the framework are provided in [11]. The simulation results presented in [11] show that – compared to a relatively straightforward price-following sales model – in a highly competitive setting, the number of orders obtained when using the dynamic sales model based on economic regimes significantly decreases with over 21%, whereas the obtained orders yield a significant increase in overall profit of about 133%. The results indicate that products are better priced.

Indeed, when we now perform some additional analyses on the simulation results, prices turn out to have significantly increased with approximately 5%. Yet further analysis offers some novel perspectives on the effects of the introduction of the dynamic product pricing mechanism on other sales-related decision making processes. The experimental data show that the increase in sales price and the decrease in sales volume induced by the newly introduced adaptivity is associated with an over 20% increase in storage costs because of higher stock levels. This clearly influences the factory utilization, which drops with approximately 20%. Consequently, procurement volume exhibits a similar decrease. All observed effects are statistically significant according to the paired, two-sided Wilcoxon signed-rank test [26], [27] (with a threshold significance level of 0.05), which is an appropriate test in this case as the distribution of the performance differences between both sales models is unknown.

The simulation results thus show that through the complexity of interconnections between decision processes, completely different behavior emerges in the complete set of sales-related decisions, driven by a single change in the product pricing process. These observations demonstrate that in complex decision making processes, changes in one subset of decisions may indirectly affect other decisions. In this light, we propose to reconsider the regime model driving the sales decisions in order for it to better relate to the full set of sales-related decisions, by capturing market circumstances in both the sales market and the procurement market.

IV. Supply Chain Regime Model

The previous section demonstrates the need to take into account procurement information when modeling regimes in complex markets. This section continues by determining valuable procurement information in Section IV-A. Subsequently, Section IV-B discusses the variables used for determining regimes, and supply chain regimes are elaborated on in Section IV-C.

A. Procurement Information

In order to determine which procurement-related information adds most value to the sales regime model introduced by Ketter et al. [8], [9], [10], we apply the information gain metric [28]. For this, we utilize a data set containing procurement information on prices, quantities, etcetera. gathered from historical TAC SCM game data[1]. We define nine variables that describe the most recent procurement characteristics, i.e., yesterday's values. In our analysis, we distinguish between 1) offer prices, 2) order prices, 3) RFQ lead times, 4) RFQ reserve prices, 5) ratios of orders to offers, 6) order quantities, 7) RFQ quantities, 8) demands, and 9) offer quantities.

The information gain measures the prediction performance improvement of a specific target by knowing certain features, and is a metric based on entropies (i.e., it characterizes the purities of arbitrary collections of examples). In our analysis, the previously mentioned procurement variables represent features, whereas the target is defined as the dominant regime. For a collection of game results W, numW represents the number of possible values of W (i.e., the number of regimes) and $P(w)$ indicates the probability that W takes on value w. Assuming a uniform probability distribution, $P(w)$ is equal to the proportion of W belonging to class w. We can define the entropy of W, $E(W)$, as

$$E(W) = \sum_{w=1}^{\mathrm{numW}} -P(w)\log_2 P(w) \ . \tag{1}$$

Subsequently, numV denotes the number of possible values of feature V. Furthermore, $P(v)$ defines the probability that V takes on value v, and $P(w|v)$ the probability that W takes

[1] Data set contains 2007 Semi-Finals games played on the SICS tac5 server (IDs: 9321–9328), 2007 Finals games played on the SICS tac3 server (IDs: 7306–7313), 2008 Semi-Finals games played on the University of Minnesota's (UMN) tac02 server (IDs: 761–769), and 2008 Finals games played on the UMN tac01 server (IDs: 792–800).

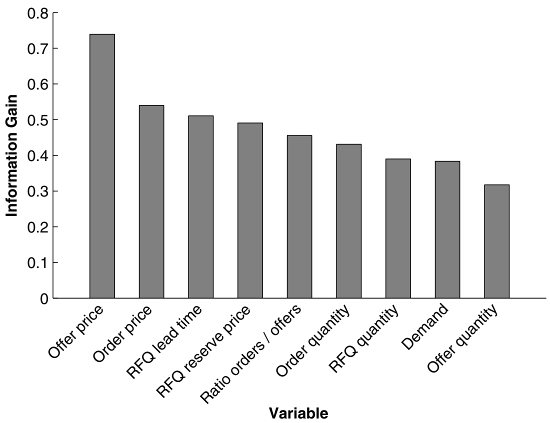


Fig. 1. Information gain per considered variable.

on value w (given v). Thus, we can define the conditional entropy $E(W|V)$ given feature V, as

$$E(W|V) = \sum_{v=1}^{\text{numV}} P(v) \left(\sum_{w=1}^{\text{numW}} -P(w|v) \log_2 P(w|v) \right) . \quad (2)$$

Using (1) and (2), $\text{gain}(W,V)$, i.e., the amount of information gained on outcome W from feature V, can be calculated as

$$\text{gain}(W,V) = E(W) - E(W|V) . \quad (3)$$

Here, the entropy of a collection of game results W given an attribute V is subtracted from the entropy of W.

Calculating the information gain for each procurement variable results in Fig. 1. Component offer prices (recalculated on a per-product basis) are thus most likely to improve the predictive capabilities of the regime model, as the related information gain supersedes all others.

B. Regime Model Variables

Based on the results discussed earlier, we extend the regime model so that it is based on both sales and component offer prices, i.e., np and nc, respectively. For a specific product g, the associated normalized sales price on day d, $\text{np}_{d,g}$ is calculated as

$$\text{np}_{d,g} = \frac{\text{price}_{d,g}}{\text{asmCost}_g + \sum_{j=1}^{\text{numParts}_g} \text{nomPartCost}_{g,j}} , \quad (4)$$

where $\text{price}_{d,g}$ denotes the price of product g on an arbitrary day d, and the product assembly costs are represented by asmCost_g. Furthermore, nominal manufacturing costs for each of the components j associated with product g are denoted as $\text{nomPartCost}_{g,j}$.

To guard for volatility in the estimated normalized mean price, exponential smoothing is applied, resulting in yesterday's exponentially smoothed normalized minimum and maximum prices for product g, i.e., $\widetilde{\text{np}}_{d-1,g}^{\min}$ and $\widetilde{\text{np}}_{d-1,g}^{\max}$. Note that for each day d, data on the previous day $(d-1)$ are considered to be the most recent data. We distinguish between minimum and maximum prices in order to be able to capture changes in means and trends more accurately. Equations (5) through (7) show how a Brown linear (double) exponential smoother is applied to the normalized minimum sales prices, where α is a smoothing factor that is optimized by means of a hill-climbing procedure. Smoothing is done by linearly combining two components as described in (7), the first of which – defined in (5) – is a linear combination of yesterday's normalized price that is calculated in analogy with (4) and the previous first component. The second component, defined in (6), is a linear combination of the first component and the previous second component.

$$\widetilde{\text{np}}_{d-1,g}^{\min'} = \alpha \cdot \text{np}_{d-1,g}^{\min} + (1-\alpha) \cdot \widetilde{\text{np}}_{d-2,g}^{\min'} , \quad (5)$$
$$\widetilde{\text{np}}_{d-1,g}^{\min''} = \alpha \cdot \widetilde{\text{np}}_{d-1,g}^{\min'} + (1-\alpha) \cdot \widetilde{\text{np}}_{d-2,g}^{\min''} , \quad (6)$$
$$\widetilde{\text{np}}_{d-1,g}^{\min} = 2 \cdot \widetilde{\text{np}}_{d-1,g}^{\min'} - \widetilde{\text{np}}_{d-1,g}^{\min''} . \quad (7)$$

Maximum sales prices are smoothed by applying the same Brown linear exponential smoothing technique as is used for minimum prices, and thus we obtain $\widetilde{\text{np}}_{d-1,g}^{\max}$.

$$\widetilde{\text{np}}_{d-1,g}^{\max'} = \alpha \cdot \text{np}_{d-1,g}^{\max} + (1-\alpha) \cdot \widetilde{\text{np}}_{d-2,g}^{\max'} , \quad (8)$$
$$\widetilde{\text{np}}_{d-1,g}^{\max''} = \alpha \cdot \widetilde{\text{np}}_{d-1,g}^{\max'} + (1-\alpha) \cdot \widetilde{\text{np}}_{d-2,g}^{\max''} , \quad (9)$$
$$\widetilde{\text{np}}_{d-1,g}^{\max} = 2 \cdot \widetilde{\text{np}}_{d-1,g}^{\max'} - \widetilde{\text{np}}_{d-1,g}^{\max''} . \quad (10)$$

Using the previously introduced equations, yesterday's exponentially smoothed normalized price for product g on an arbitrary day d can be calculated by averaging smoothed normalized minimum and maximum prices, i.e.,

$$\widetilde{\text{np}}_{d-1,g} = \frac{\widetilde{\text{np}}_{d-1,g}^{\min} + \widetilde{\text{np}}_{d-1,g}^{\max}}{2} . \quad (11)$$

Component offer prices, to which we will refer to as nc, result from all requests for quotation in TAC SCM games. For a specific product g, the offer prices on day d, i.e., $\text{nc}_{d,g}$, are calculated by taking a weighted average of the offer prices of all components associated with g, based on offer quantities qty. These prices and quantities are gathered from requests for quotations to all suppliers that are active in an arbitrary TAC SCM game. Finally, prices are normalized by means of their cost basis. Thus, we obtain

$$\text{nc}_{d,g} = \frac{\frac{\sum_{s=1}^{\text{numSup}_g} \sum_{j=1}^{\text{numParts}_g} \text{nc}_{d,g,s,j} \cdot \text{qty}_{d,g,s,j}}{\text{qty}_{d,g}}}{\sum_{j=1}^{\text{numParts}_g} \text{nomPartCost}_{g,j}} , \quad (12)$$

where numSup_g refers to the number of suppliers that are associated with product g, and numParts_g refers to the number of components for product g.

Again, information is only available up until day $d-1$, and thus for our regime model, we make use of $\text{nc}_{d-1,g}$. Smoothing yesterday's normalized procurement offer prices using Brown linear exponential smoothing, with β representing a

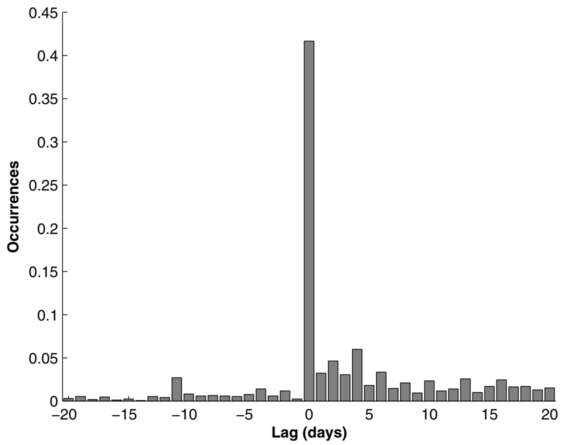


Fig. 2. Calculated lag between np and nc.

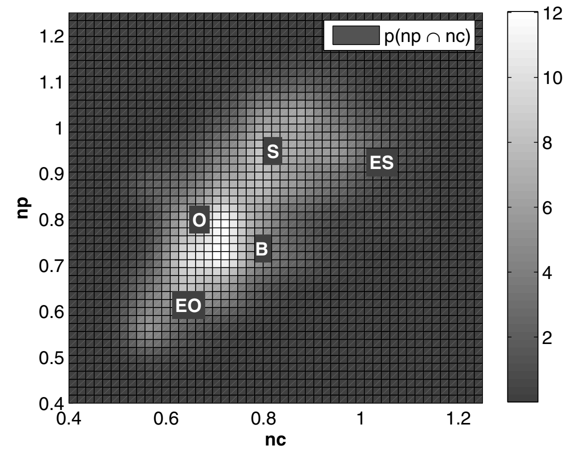


Fig. 3. Supply chain regimes mapped on a joint price density distribution.

smoothing factor determined by a hill-climbing procedure, results in

$$\widetilde{\mathrm{nc}}'_{d-1,g} = \beta \cdot \mathrm{nc}_{d-1,g} + (1-\beta) \cdot \widetilde{\mathrm{nc}}'_{d-2,g} \ , \tag{13}$$

$$\widetilde{\mathrm{nc}}''_{d-1,g} = \beta \cdot \widetilde{\mathrm{nc}}'_{d-1,g} + (1-\beta) \cdot \widetilde{\mathrm{nc}}''_{d-2,g} \ , \tag{14}$$

$$\widetilde{\mathrm{nc}}_{d-1,g} = 2 \cdot \widetilde{\mathrm{nc}}'_{d-1,g} - \widetilde{\mathrm{nc}}''_{d-1,g} \ . \tag{15}$$

To ensure that the correct procurement information is utilized, we evaluate the lagging and leading effects between sales and procurement prices by means of cross correlation studies. Fig. 2 illustrates that there are minor lags (i.e., negative values of lag) of sales prices with respect to procurement prices, as well as leading effects (positive lags) between sales and procurement prices, i.e., future procurement prices are correlated with yesterday's sales prices. However, in general, both variables are aligned properly, as most of our observations indicate a lag of zero days. Thus, we combine $\widetilde{\mathrm{np}}_{d-1,g}$ and $\widetilde{\mathrm{nc}}_{d-1,g}$ for determining regimes in complex supply chains.

C. Supply Chain Regimes

Having defined our sales and procurement variables, we can apply clustering techniques to find similarities and regularities in the data. Clusters contain data points where the in-group similarity is higher than the out-group similarity. As each cluster describes certain conditions and characteristics, ideally, these clusters correspond to economic regimes, or more specifically, supply chain regimes. Clustering into five clusters – representing extreme scarcity (ES), scarcity (S), balanced (B), oversupply (O), and extreme oversupply (EO) situations – is done using the `kmeans` clustering. We tested different clustering algorithms, such as spectral clustering, which resulted in similar clusters.

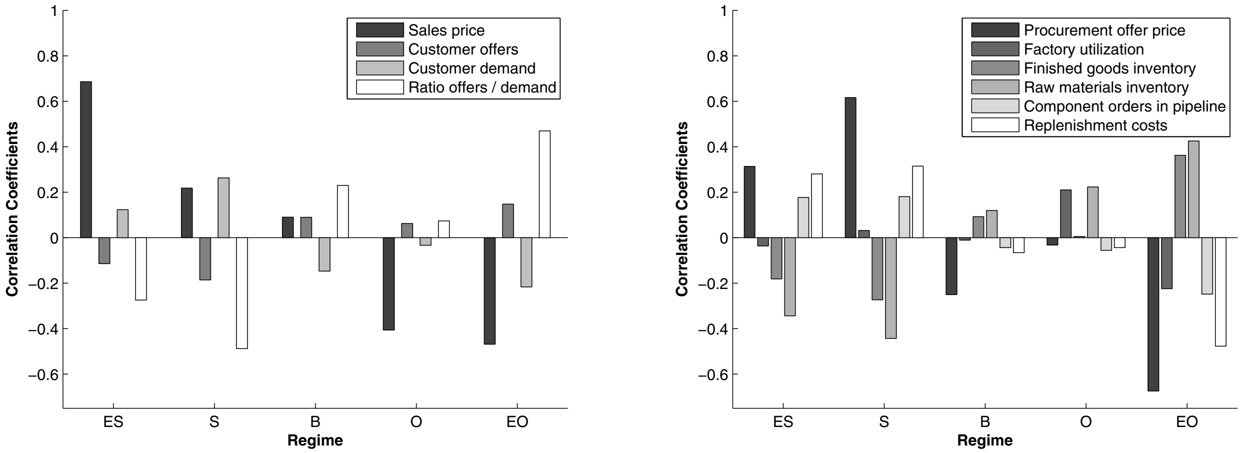
Clustering is done in fifteen replicates, using a maximum of one thousand iterations. Experiments show that this allows the algorithm to converge nicely on our data set. The squared Euclidean distance measure is used to measure distances to the cluster centers for each data point. Fig. 3 shows the results of applying the clustering algorithm to data of an arbitrary product. When mapped on the joint price density distribution of the sales and procurement prices $p(\mathrm{np} \cap \mathrm{nc})$, it becomes clear that cluster centers are located at high-density points, and also roughly describe the bounds of the density peak. In general, scarcity regimes are associated with high prices on both the sales and the procurement market, while prices are much lower in times of oversupply. Judging from the densities, balanced situations occur most often and are linked to mediocre prices.

Correlation studies have been performed on the identified regime clusters and market characteristics, in order to obtain insights into the relation between the regimes and the sales and procurement markets. Fig. 4 gives an overview of the correlations between regimes and sales-related market indicators (e.g., sales prices, customer demand) and procurement-related indicators (e.g., inventories, factory utilization) of an arbitrary product. The product and clusters are the same ones that are used in Fig. 3. The correlations are discussed in further detail in the next section.

On a side note, one could easily extend the model presented to a regime prediction model. When assuming the degree to which data points (a combination of np and nc) belong to a specific regime cluster is representative to determine the dominant economic (supply chain) regime, future regimes can be predicted by means of exponential smoothing (i.e., estimating future prices and classifying them using the clusters), Markov processes, etcetera.

V. Discussion

Figure 4 shows correlation plots, based on data extracted from simulations of a highly competitive supply chain environment. It provides insights into the quality of the identified regimes. From a sales perspective, the regimes have plausible correlations. In times of scarcity, a positive correlation with the sales prices is measured, which implies either rising or high prices. In balanced situations, market prices stabilize and in case of oversupply we see prices dropping again. Furthermore, in general, the balanced situation shows moderate correlations



(a) Sales

(b) Procurement

Fig. 4. Correlation coefficients of identified regime clusters with market indicators.

with all sales-related market indicators. Subsequently, it is clear from the plots that the amount of offers to customers decreases (is low) in times of scarcity, while customer demand increases. This effect diminishes when heading towards a balanced situation, and inverses as oversupply emerges. Lastly, the ratio of customer offers to customer demand (i.e., the manufacturers' tendency of selling to customers) is low in scarcity regimes. This implies that manufacturers are less inclined to sell to customers, either because their stocks are running low, or they deliberately do not want to sell to customers (i.e., they are creating scarcity while aiming for higher prices and/or revenues). In times of oversupply, correlations with the ratio of offers to demand are high, as markets are flooded by manufacturers.

Also the identified regimes are meaningful from a procurement point of view. In general, one could state that in times of oversupply, component offer prices are low, whereas prices tend to be higher in times of scarcity. This also holds for the related replenishment costs. Factory utilization on the other hand, is a rather unpredictable economic indicator, as the various regimes each show weak positive or negative correlations. This could be caused by the fact that some manufacturers envisage strategies such as keeping factories running in times of oversupply (and thus cheap components), in order to stock up on cheap raw materials and finished goods that can be sold in periods of scarcity. Other manufacturers have different strategies, or do not even consider this kind of strategic decision making. Continuing, we observe a negative correlation with scarcity regimes and finished goods and raw materials inventories. Inventories are either very limited or shrinking. In case of an onset of oversupply, the inverse is usually the case. Similarly to the correlations measured with respect to sales-related market indicators, balanced situations show mainly weak correlations with procurement-related market indicators. Finally, we observe little component orders in the pipeline in times of oversupply (thus, manufacturers experience fast deliveries of components), whereas many orders are in the pipeline in case of scarcity.

The supply chain regimes thus defined are more robust with respect to the original economic regimes, as they capture characteristics of the sales market as well as of the procurement market, rather than sales market characteristics only. Signals from both parts of the supply chain are used in order to generate a better-informed perspective on the supply chain market. Such regimes can be utilized in a dynamic sales process in a way similar to the approach presented in [11], which is briefly discussed in Section III. The relation between real-time available data and price distribution parameters can be dynamically modeled using supply chain regimes rather than economic regimes. Optimal prices generated using acceptance probability estimations derived from price distributions thus estimated take into account market conditions in the supply chain as a whole and hence contribute to a more deliberate sales model.

VI. Conclusions

Economic regimes provide a means for guiding sales decisions, as they can capture unobservable, yet crucial market characteristics in the sales market. However, sales-related decisions, ranging from procurement to meeting customer demand, are interrelated. In this paper, we therefore emphasize that the dynamics of the complete sales process should hence be considered when making sales-related decisions. This is supported by findings from simulation results of a previously proposed dynamic sales model based on economic regimes; through the complexity of interconnections between decision processes, completely different behavior can emerge in the complete set of sales-related decisions, driven by a single change in the product pricing process.

Therefore, we argue that a regime model driving sales decision making processes in a complex supply chain should relate to the full set of sales-related decisions, by capturing supply chain market circumstances, i.e., in both the sales market and the procurement market, and not merely the sales market. The main contribution of this paper consists of addressing this need for supply chain regimes, in order to make way for a better-informed sales model. Our data analysis shows that the proposed supply chain regimes have feasible characteristics that are based on both sales and procurement market indicators.

For future work, we aim to implement the supply chain regime model into the MinneTAC trading agent, and to test it thoroughly by evaluating prediction performances as well as the effects of this model on agent performance (e.g., in terms of profit) and on the supply chain as a whole. Furthermore, it is worthwhile investigating applications of supply chain regimes within the procurement market, i.e., taking into consideration these regimes for procurement-related decision making.

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