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Cooperative Production Networks – Multiagent Modeling and Planning

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Abstract

Consumer goods are mainly produced in multiple steps through a long process. These steps are often done by separate, independent production nodes (enterprises), linked by supply chains. The networks of enterprises—where members have their own objectives and act in an autonomous, rational way to reach their goals—can be naturally modeled by agent-based methodology. The inner structure of each enterprise is similar in the sense that it contains separated planning functions (e.g., production-, inventory-, capacity planning). While the operation inside an enterprise can be controlled centrally, the interaction between the nodes could be synchronized only by negotiation and coordination. Coordination can be based on protocols which regulate information, material and financial flows alike. In this paper we expose an agent-based organizational model of production networks and suggest some planning algorithms which can handle the uncertainty of demand. In addition, we outline the first results of our ongoing research, an analysis of the asymmetric information case and an appropriate coordination mechanism.

Keywords: multiagent modeling, supply chain, inventory planning

1 Introduction

Nowadays, customers of consumer goods are more demanding than ever and manufacturing must fulfill their needs to remain competitive. Naturally, there exist several manufacturing paradigms to answer the existing challenges all with their own advantages and disadvantages [16]. The *craft production*—whose golden age was before the 20th century—allows large variety of products, but requires complicated, time-consuming processes, which are also expensive. *Mass production*—the main paradigm in the 20th century—achieves higher efficiency with standardized products, exploiting economies of scale and (semi-)automated processes, but gives up the wide product scale. In the last few decades the new paradigm of *mass customization* has arisen, which tries to combine the advantages of the previous

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two approaches by offering a larger variety of products made of standardized components with mass production technology and *delayed differentiation*. As it has turned out, while this new paradigm solves some of the problems, it also poses new questions.

Satisfying demand directly from production is impossible, because production and supply lead-times are much larger than the acceptable delivery times for the customers, and, in addition, manufacturers should also exploit the economies of scale. Therefore holding inventories is necessary, which can only be based on fluctuating, uncertain forecasts. Unfortunately, the use of some non-standardizable components (e.g., customized packaging materials) is necessary, which leads to obsolete inventory when the demand for the customized product suddenly ceases. Hence, this phenomenon called *run-out* causes both significant financial losses for the manufacturers and waste of environmental resources.

Consumer goods are mainly produced in a long process of multiple steps, which are often carried out by separate, independent and rational production enterprises, linked by supply chains. This decentralization leads to suboptimal overall system performance called *double marginalization* [19].

The goal of our research is to improve the efficiency of production networks as a whole. In order to do this, we have first developed a multiagent model of the networks and the various planning functions within the enterprises. These functions cover all kinds of decision making that influence and control the future, thus it is substantial to examine and describe them in detail. Then we have analyzed industrial databases and found that component inventory levels have often been inappropriate—either too high or low. These levels are set by the supply processes that connect planning functions of different enterprises. Hence, we have introduced some new models and optimization algorithms which align to the new market conditions. While these models assume a centralized decision maker who possesses all relevant information, in a real network this is not the case. The solutions of these algorithms provide only lower bounds on the total cost in case of a decentralized network with asymmetric information. Hence, our aim is to design and develop such *channel coordination mechanisms* that achieve or approximate the outcome of theoretically optimal decisions even if the partners decide locally, by relying on incomplete (asymmetric) and uncertain information. In the end, we are going to turn our multiagent model into a simulation which will include the implemented planning algorithms in order to verify them on real industrial data.

The goal of this paper is, on one hand, to expose the results of these research steps. On the other hand, we present recent results of our related work in a unified framework that is based on the agent-based design metaphor. As we will show in the sequel, taking the agent-based approach helps a lot in clarifying complex and often blurred organizational relations and constructing an appropriate organizational model. Though the transformation of this model into an agent-based simulation model is far from being straightforward, still it is the best way towards validating and verifying the outcomes of our research.

The motivation of this work comes from a large-scale national industrial-academical R&D project aimed at realizing *real-time, cooperative enterprises*. The participating industrial partners form a complete *focal* network: a central assembly plant with several external and internal suppliers. The assembler produces altogether several million units per week from a mix of thousands of products. The ratio of the customization follows the *80/20 Pareto-principle*: they give 80% of the product spectrum, but only 20% of the volume. The setup costs are significant and since customized products are consumed slower, their smaller lot sizes involve higher average setup costs. Service level requirements are extremely high: some retailers suddenly demand products in large quantities even within 24 hours, and if the request is not fulfilled on time, they cancel the order (i.e., backorders are not possible). This causes not only lost sales, but also decrease of goodwill.

2 Related work

Business process and supply chain modeling research has produced several methodologies in the last decades (e.g., CIMOSA, IDEF0, EPC, SCOR) [22]. These approaches, however, provide tools only for modeling and analyzing the processes and do not support decision making. A uniform model of inter-enterprise planning functions and their hierarchical layout in a matrix is described in [17]. The importance of the role-based modeling approach of collaborative networks is emphasized in [25]. Recently, several efforts have been made towards integrating modeling and optimization, e.g., an object-oriented approach is presented in [1].

From the viewpoint of production networks, there are basically two types of research utilizing agent-based concepts and methods: (i) the general approach handles supply chain management as a problem of designing and operating a multiagent system and (ii) the other kind focuses on specific problems, such as collaborative inventory management, bidding decision, material handling and inventory planning in warehouses. The majority of the literature has been focusing on the general application of agent-based supply chain management. The rich variety of multiagent approaches clearly shows the application potential of agent technology. By now, there is a common understanding that various requirements of networked manufacturing can really be met by autonomous, embodied, communicative and eventually cooperative agents operating in a society.

Still, according to our recent survey, the number of deployed multi-agent systems that are already running in real industrial environments is surprisingly small: even in the "ideal" field of supply chain management, only half a dozen applications can be found that are deployed in everyday use [13]. Other reviews also concluded with the observation that no significant advancement had been made yet in transferring agent technology to industry [12, 15]. This, relatively slow transfer has manifold reasons. First, the introduction of agents, in principle, does not reduce the complexity of problems. Next, interoperability is expensive. Just due to the increased communication overhead, the performance of a multiagent system can degrade and especially rough-grained systems (consisting of sophisticated agents) can hardly be scaled up. Although the agent metaphor is useful in system design, and there are also several methodologies to support agent-oriented software engineering, industrial-strength support is still missing. Finally, in the behavior of a multiagent system there is always an element of emergence which can be a serious barrier to the practical acceptance of agent-based solutions. Industry needs safeguards against unpredictable behavior and guarantee regarding reliability and operational performance.

In order to bridge this gap between theory and practice, we put emphasis on the elaboration of network coordination models that have analytically provable properties and, at the same time, efficient solution techniques. In a production network, it is *logistics* that essentially links the various partners. Hence, our coordination models have been derived from models of logistics and inventory planning.

The history of *inventory planning* is almost hundred years old and the most important models were born in the 1950s. Nevertheless, because of the changing market conditions, the research in this area is still ongoing. The related idea of coordination mechanisms has also attained interest in the recent years [10]. This research can be classified along two dimensions: (i) the nature of the demand is either deterministic or stochastic, and (ii) the decision structure is either centralized or decentralized. From the four possible combinations the decentralized stochastic one is the most complex, hence the literature of this case is scattered. Existing research approaches are mostly based on the results of game theory and economy with asymmetric information. The risk of obsolete inventory and its placement is studied considering different types of contracts in [2].

3 Multiagent organizational model

We have decided to model a production network and the planning functions within an enterprise as a multiagent system and this decision needs explanation, because there already exist widely used methodologies for this purpose [22]. While these modeling tools can describe the high-level structure and processes of enterprises, they cannot be further detailed and do not directly support neither the elaboration of planning algorithms, nor the estimation of their computational complexity, nor the software implementation. On the contrary, agent-oriented methodology offers (i) a design metaphor for complex systems, (ii) technologies for handling interactions and (iii) simulation tools alike [11].

For studying the situation, we have used the Gaia methodology, which is a specification framework for analyzing and designing the organizational model of multiagent systems [24]. This methodology helps to identify and separate different roles in the planning structure of an enterprise, which are in real life sometimes mixed and overlapping.

Gaia deals with two aspects of the modeled system: the *abstract* viewpoint helps to conceptualize and analyze the organization, while the *concrete* viewpoint is used during the design phase to model entities which will be realized in the run-time system. So far we have taken only the high-level analytic approach, but as a future direction, we will continue detailing the model and use it as a basis for multiagent simulation.

The analytic part of Gaia consists of two models: *roles* and *interactions*. Since an organization is considered a collection of roles, the main challenge is to distinguish different roles, describe them and define their interactions. A role can have a set of *permission*s, which are rights associated with the role—typically these are read/create/modify permissions to certain *shared information resource*s. In addition, a role has some *responsibilities*: there are *liveness* properties which declare what the role must do and *safety* properties which are invariants stating situations to be avoided. Liveness properties, which resemble regular expressions, consist of *activities*, which are autonomous computations, and *protocols*, which are interactions between roles. We have extended the roles model with the description of optimization objectives what we have found essential in planning functions.

The evolution of planning functions in production management, and recently in supply chain management, resulted in a planning hierarchy [17] that we adopt to our modeling purpose. This so-called *planning matrix* shows long-term, medium-term and short-term planning functions organized along the main flow of materials. These functions are common at each node of a production network, though, of course, manifest themselves in different forms and complexity. We have described all functions of the matrix as Gaia roles [4]; an example can be seen in Figure 1.

Role Schema: SUPPLYPLANNER
Description: This role ensures the necessary raw materials for the manufacturer by creating medium-term material requirement plan, ordering and maintaining the raw product inventory.
Protocols and Activities: Order, CustomerForecast, Call-off, Transport, Exception, <u>CreateMaterialRequirementPlan</u>
Permissions: `reads` *forecasts* *plannedOrders* *schedule* *technologicalData* `changes` *rawProductInventoryLevels*
Responsibilities Liveness: SUPPLYPLANNER = $(\underline{\text{CreateMaterialRequirementPlan}}\ .\ [\text{Order}]\ .\ [\text{Call-off}]\ .\ ([\text{CustomerForecast}])^{p} \parallel (\text{Exception} \mid \text{Transport})^{\omega}$ Safety: – execution of the schedule must not stop because of material shortage Objectives: – minimal raw product inventory level – minimal obsolete raw product inventory

Figure 1: An example role description in Gaia.

The protocols of the roles can be further detailed in the interaction model of Gaia. While most interactions inside an enterprise are realized via Enterprise Resource Planning (ERP) systems, the inter-enterprise interactions should be precisely regulated according to some protocols. Examples of such interactions—namely forecast sharing and ordering—can be seen in Figure 2, which contains two instances of the planning matrix. In the following, we concentrate on the planning functions directly related to these interactions.

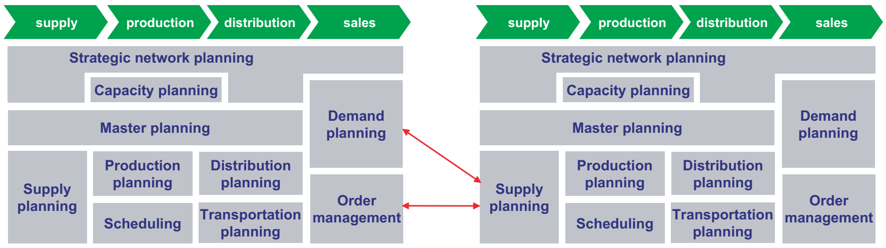

Figure 2: Interactions between enterprises.

4 Uncertainty and planning

While the golden age of inventory research was in the 1950s, the recently changed market conditions have induced paradigm change and the need for new models [3]. In order to remain competitive on global markets, today's production must be *customer-oriented*, which means that customer demand must be satisfied at high service level with short lead-times. These main requirements—which are specified by the long-term *strategic management*—must be achieved on lower levels by the *tactical* and *operational management*, which need new models and tools for optimization.

The strategic decisions are out of the scope of this research; we take their results given. I.e., we depart from an existing network structure and specified high-level goals. The tactical and operational decisions, in turn, can be detached: the medium-term (planning) level is responsible for the cost-efficient production by aggregating production into batches, while the short-term (scheduling) level—where the precise demand is known—cares for the service level requirements. Our models presented below are dealing with planning decisions, but we have also developed a framework for coordinating the two levels [5, 6].

As it was previously mentioned, the production is based on uncertain finished good forecast, which can be prepared using several statistical methods [8] and therefore the uncertainty can be expressed in terms of standard deviation. Unfortunately, this information is usually distorted by human factors [7]. In addition, when the production is planned in medium term, the uncertainty information disappears or is transformed to *safety stock* margins, because most practical planning systems cannot handle stochastic problems. The result of the planning process is a discrete plan of production quantities, respecting the capacity and technological constraints. This is also regarded as the basis of the “component usage forecast” and the economic purchase plan can be determined from this component forecast using appropriate lot-sizing methods. This metamorphosis of demand-related information is illustrated in Figure 3.

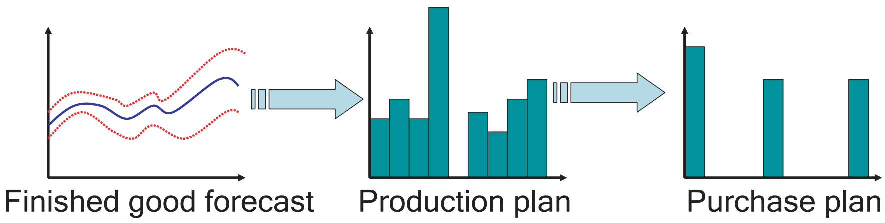

Figure 3: The distortion of demand-related information.

The general inventory planning problem can be briefly characterized in the following way: there exists a medium-term *planning horizon* with an uncertain demand. We regard the component demand derived from the production plan, since supply must be aligned to production instead of the finished good sales. Components should be produced in large batches in order to decrease the setup cost, but this comes together with an increase of inventory levels and of expected obsolete inventory costs. While searching for the optimal trade-off, the constraint of avoiding shortage must be respected.

4.1 Modeling uncertainty

Typically, the operational managers have no models and decision support tools for handling the inventory risk, therefore they usually use ad-hoc rules-of-thumb based on historical statistics—which is sometimes referred to as “driving by the rear-view mirror”.

The stochastic inventory models developed using theoretical approaches are rarely used in the practice because of their complexity and lack of data. Instead, deterministic demand is assumed and reconsidered from time to time, which is called *rolling-horizon planning* [21]. We have extended this practical approach by introducing a single parameter, the weekly *probability of run-out* (p), which reflects the stability of the products and components. It can be assigned either to components or groups, based on market information, as well as on historical data.

Nevertheless, this information about probability cannot be explicitly found in existing enterprise data warehouses and determining it can be costly and time-consuming. Therefore we have proposed to use our planning methods with different run-out parameters in parallel. From these *scenarios* it can be estimated how *robust* is the solution, i.e., how much it depends on the changes of the run-out parameter. If the robustness is low, then the automatically generated plan must be reviewed by human experts or a more precise parameter value is required.

There are two fundamentally different situations according to the information available: (i) the fact of the run-out and its date are known in advance and (ii) run-out can occur with a certain probability, but no further details are known. In the first case, the standard Wagner – Whitin (WW) method [23] can be used, which plans the whole horizon and tells in which periods to produce and how much. Nevertheless, this approach can lead to an inappropriate solution when the horizon is too short: it suggests producing in one lot and disregards the possibility of a larger demand, which causes inefficient additional production. Therefore, if WW proposes producing in one lot, one should switch to a more appropriate method: the so-called *newsvendor model* for one-period. But this first case is exceptional, usually run-out is not known in advance. For this case, we have developed two heuristics and a modified version of WW what we present below.

4.2 One-period model

The inventory systems of perishable goods are usually modeled as *one-period decision problems*: the decision maker has to determine the value of a variable q, then a cost of $c(q, \xi)$ arises, where ξ is a random variable with known distribution. The *risk neutral* decision maker wishes to minimize the expected cost. In the context of inventories, this model is called the newsvendor model, since it describes well the inventory management problems of the daily newspaper markets [8].

In such a case, overplanning leads to obsolete inventory, while underplanning may lead to costly additional setups. The standard model disregards the setup cost. It only considers per unit left over cost—if the demand is below the produced quantity—and per unit shortage cost (it may be interpreted as producing in overtime)—if the demand is above. However, if the inventory is filled by manufacturing instead of ordering, then the setup cost must be included in the calculation.

In our model [6], service level has the highest priority, hence it follows that the manufacturer has to satisfy all demand. If the produced quantity is below the actual demand, it can only be satisfied by an *emergency production* which also involves an additional setup. Thus, our model involves four types of costs: (i) the certain setup cost (c_s), (ii) the production cost for satisfying actual demand (c_p per item), (iii) the expected value of obsolete left over products (with c_p per unit left over cost) and (iv) the expected cost of additional setup. Then the expected total cost becomes:

$$\mathbb{E}[TC(q)] = c_s + c_p\mathbb{E}[\xi] + c_p\mathbb{E}[\max(q - \xi, 0)] + c_s\mathbb{E}[\delta(\xi - q)], \tag{1}$$

where q is the produced quantity, ξ is the random demand and

$$\delta(\xi - q) = \begin{cases} 0 & \text{if } \xi - q \leq 0 \\ 1 & \text{if } \xi - q > 0 \end{cases} \tag{2}$$

In order to minimize the expected total cost, we have to compute the derivative of the cost function, which ought to be zero:

$$\frac{\mathbf{d}\mathbb{E}[TC(q)]}{\mathbf{d}q} = c_p\Phi(q) - c_s\phi(q), \tag{3}$$

where ϕ and Φ are the density and distribution functions of the demand respectively. Here, usually normal distribution is considered, despite of its disadvantages [18].

Since this expression cannot be inverted in the general case as in the standard model, we apply the so-called *logistic distribution* with parameters b and m, which is often used instead of the normal distribution when longer tail is more appropriate. This yields the unique stationary point—which is a minimum—if $b < \frac{c_s}{c_p}$:

$$q^* = m - b \ln\left(\frac{bc_p}{c_s - bc_p}\right) \tag{4}$$

This optimal lot size gives a balance between the risk of obsolete inventory and the additional setup. It can be both more or less than the expectation value, depending on the variance and the cost parameters (see also Section 6).

4.3 Multi-period models

The more remote a forecast is, the more uncertain it is—this reasonable hypothesis was confirmed by our analysis of historical industrial data. Based on this observation, our first idea was to disregard the less trusted remote forecasts and plan only the starting segment of the horizon. Therefore we have developed two heuristic methods, which minimize the expected average cost—both per time unit and per piece—in the first segment of the horizon [20]. As it has turned out, the heuristics have several disadvantages: (i) they cannot estimate the number of setups on the horizon, (ii) disregarding a part of the available information can lead to significant inefficiency and (iii) they sometimes behave unreasonably: increasing the probability of run-out can cause higher lot size, see Figure 4.

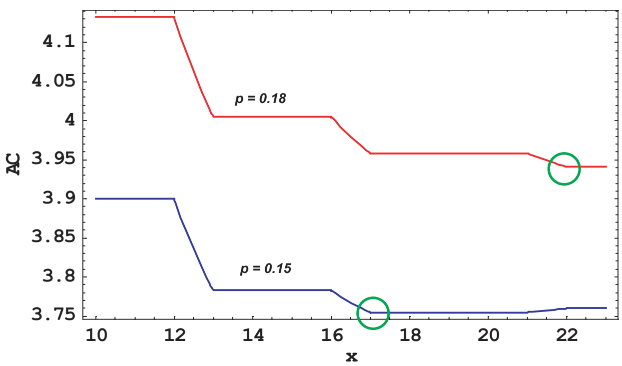

Figure 4: Anomaly of heuristics.

The lines show average costs in case of different run-out probabilities. If $p = 0.15$, producing the demand of 17 time units would minimize the average cost, while the higher p suggests 22 time units. According to our experiments, such anomalies occur rarely, and when run-out probability is relatively high ($p > 0.13$).

Note that such anomalies are known in the field of operations management; see e.g., *nervousness* in the widely used Material Requirements Planning (MRP) method, when a decrease in the demand leads to an infeasible situation [8].

Hence, our conclusion was that planning the whole horizon is necessary, therefore we have decided to use the Wagner – Whitin model ([23]) extended with the probability of run-out, which we abbreviate as WWr [5]. The main elements of this model are as follows: length of the horizon (n), forecasted demand ($F_1, \ldots, F_n$), setup cost (c_s), inventory holding cost per piece per time unit (h), production cost per piece (c_p) and the probability of run-out in an arbitrary time unit (p). The decision variables are the production quantities in the time units throughout the whole horizon ($x_0, \ldots, x_{n-1}$). We assume infinite capacity and introduce a one-period lead-time. In this setting, the Wagner – Whitin property remains valid: it is optimal not to produce, unless the inventory would become empty otherwise. The planned lot sizes can be determined by a dynamic programming algorithm briefly summarized below.

If we produce in time unit t for the period $\{\, t+1, \ldots, t+j \,\}$, this implies that (i) the expected inventory at the beginning of time unit $t+1$ is zero (Wagner – Whitin property) and (ii) the product has not run out until the beginning of time unit t (which has a probability $(1-p)^t$). Then the expected storage cost at time unit $t+i$ is

$$SC(t,j,i) = (1-p)^i h \left(\sum_{k=i+1}^{j} F_{t+k} + \frac{F_{t+i}}{2} \right) \tag{5}$$

and the cost of expected obsolete inventory is

$$OC(t,j,i) = p(1-p)^{i-1} c_p \sum_{k=i}^{j} F_{t+k}, \tag{6}$$

which expresses that with probability $(1-p)^i$ the product is still saleable, therefore storage cost must be paid, and with probability $p(1-p)^{i-1}$ it runs out in the very time unit and the remaining inventory becomes obsolete. The expected total cost of period $\{\, t+1, \ldots, t+j \,\}$ is therefore

$$C_{tj} = c_s + \sum_{i=1}^{j} \left(SC(t,j,i) + OC(t,j,i) \right). \tag{7}$$

The optimal total cost for period $\{\, t, \ldots, n \,\}$ (TC_t) can be computed by the following recursion:

$$TC_n = 0 \tag{8}$$

$$TC_t = \min_{j \in \{\, 1, \ldots\, n-t \,\}} \left\{ C_{tj} + (1-p)^j TC_{t+j} \right\}. \tag{9}$$

Note that $(1-p)^j$ is the probability of the event that the product has not run out and further production is necessary.

With a backward induction, the optimal lot sizes and the expected number of setups can be also obtained from the optimal j values in the recursion. This provides an $\mathcal{O}(n^2)$ algorithm, which is practically acceptable.

5 Asymmetric information

In a real network, no central planner exists with all required information, as it was assumed in Section 4.1. In a two-echelon supply chain system, the supplier is familiar with the production and setup cost for the components, while the end manufacturer can have a good estimate of the finished good demand. In this case, the so-called *first-best solution*s of the presented algorithms provide only lower bounds for the achievable expected total cost.

Our goal is to design a coordination mechanism which helps the partners to reach (or approximate) the results of the first-best solutions. At first, we have concentrated on the one-period newsvendor problem. Extending this research to the multi-period case is part of future work.

In the decentralized newsvendor setting, the production cost (c_p), the setup cost (c_s) are the parameters known by the supplier, while the end manufacturer knows only the demand-related information (m and b). We assume that the lot size decision is made by the supplier—who can schedule its own production—and it also holds the inventory. For being able to do this, the end manufacturer *signal*s the demand information towards the supplier. This information can be distorted—e.g., the mean can be inflated in order to decrease the risk of shortage—therefore we denote these parameters with m' and b'. Note that if there is no distortion (i.e., $m' = m$ and $b' = b$) and this is a common knowledge, supplier is facing the problem presented in Section 4.2 with all required information, therefore its rational lot sizing decision is also optimal on the system level.

This is a conflict of interests: while the optimal network performance requires truthful information sharing, the manufacturer can be better off by distorting the information. This conflict can be resolved by an appropriate payment function which aligns the objective of the manufacturer with that of the supply chain: it guarantees that the expected payment will be minimal, if the end manufacturer signals the truth and does not distort forecast information.

In this situation, the supplier takes all inventory risks, therefore the end manufacturer has to pay for the *service* of flexibility besides paying for the components. Hence, payment consists of (i) the price of the delivered components, (ii) compensation for the deviation from the forecast and (iii) compensation for the forecast uncertainty. Therefore the payment function becomes:

$$P(m', b', \xi) = c_0\xi + \frac{c_1}{b'} d(m', \xi) + c_2(b'), \tag{10}$$

where c_0 and c_1 are constants: the unit prices for required components and inappropriate demand estimation, respectively. The term $d(m', \xi)$ is the difference between the estimated and the realized demand and $c_2(b')$ is the compensation for uncertainty. Note that the payment depends only on commonly known parameters.

A possible choice for measuring the deviation from the forecast is the quadratic difference function: $d(m', \xi) = (m' - \xi)^2$. For this case we have proven that, if the uncertainty compensation is $c_2(b') = c_1 \frac{\pi^2}{3} b'$, the payment function inspires the rational manufacturer to signal the real m and b values to minimize the payment. Since the income depends only on the demand, minimal payment also maximizes the profit of the manufacturer.

6 Experiments

All presented algorithms were implemented—together with the *safety stock* calculation—and tested both on generated and real industrial data in several scenarios. We have studied how the uncertainty influences the optimal lot sizes and the expected costs. We have also simulated the inventory levels according to our models, based on industrial information of past demand. Some of these results are presented below.

An example result of the newsvendor model can be found in Figure 5: the proposed lot sizes vary with the relative deviation of the estimated demand and are compared with the forecast. Note that the solution can be both more or less than the forecast, depending on the uncertainty and cost parameters. Nevertheless, the curve is smooth, i.e., proposed quantities do not fluctuate with high frequency. The intuitive explanation of the shape of the curve is as follows: if there was no uncertainty, optimal lot size would equal to the demand. When the uncertainty increases, it is better to increase the lot size in order to avoid the additional setup. However, when the uncertainty reaches a certain threshold, the expected cost of obsolete inventory equals the expected cost of the additional setup, therefore the optimal lot size starts to decrease.

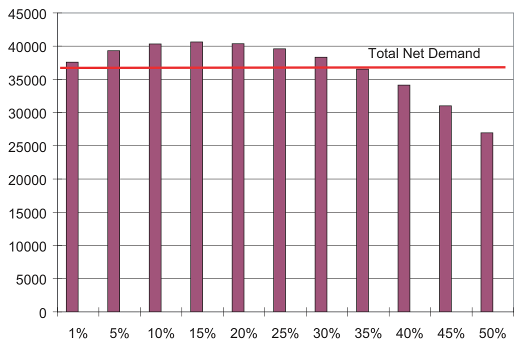

Figure 5: Results of the newsvendor model.

In Figure 6, the results of the two heuristics (AC_x minimizes the average cost for a time unit, while AC_q minimizes the average cost of an item) and the WWr are shown considering different run-out parameters. As mentioned before, WWr can estimate the number of setups on the horizon, therefore these are also indicated. The results were also compared with the lot sizing decision made by human experts. The conclusion of several months of weekly consultations with industrial partners was that, in around 90% of the cases, WWr with probability parameter $p = 0.02$ proposed automatically almost the same lot size as the human planners—apart from the rounding. In the remaining cases the planners had additional information—received via phone or e-mail—which was not stored in the data warehouse, therefore it was not visible to us.

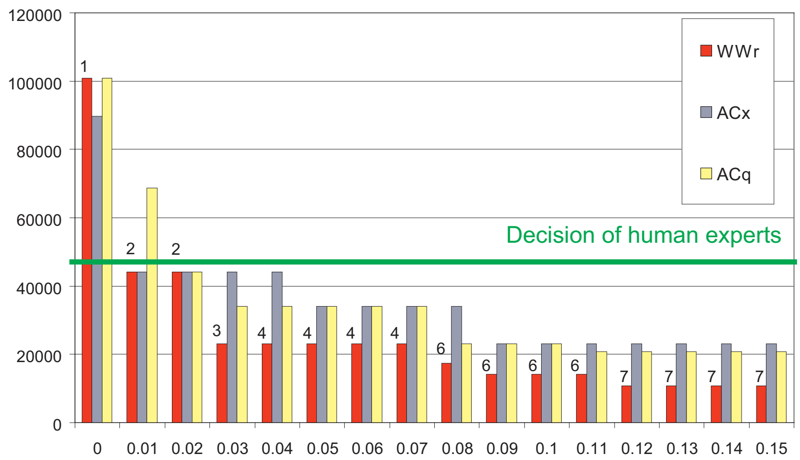

Figure 6: Results of the multi-period models.

The algorithms were also included into a pilot decision support application, which is now under testing in industrial environment.

Finally, we have started to develop a multiagent inventory simulation system in Repast [14]. The structure of the system follows the model presented in Section 3, while the internal decision making of the agents is based on the algorithms of Section 4. The stochastic data can be obtained from two sources:

- for random number generation we use the *Colt* package included in Repast, which was developed for high performance scientific and technical computing by CERN, and

- we can query real forecast and demand data from industrial databases via direct database access (JDBC).

The simulation runs are evaluated using several common indices, such as total cost, number of setups, average inventory level, service level, etc. An example interface of the system can be seen in Figure 7.

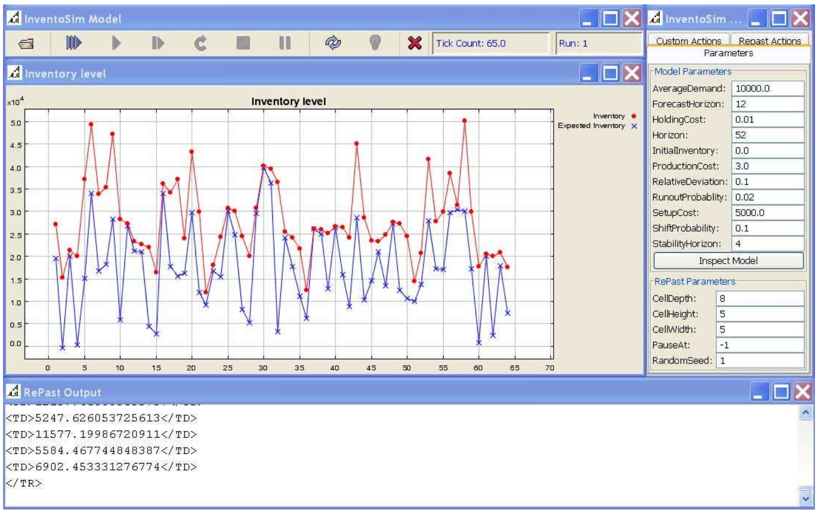

Figure 7: Inventory simulation system in Repast.

7 Future work

The presented multi-period inventory planning models consider infinite capacity and therefore they can be solved efficiently. However, in the real world, capacities are often limited, and in addition, setup costs are not independent of the production sequences. This makes the problem much more difficult: it is proven to be NP-hard. The exact solution of such problems—even with efficient specialized algorithms—is achievable only on relatively small instances [9]. Therefore numerous approximation algorithms and heuristics are applied, which provide quasi-optimal solutions for some special cases. One possible future work is to combine our model with these solution concepts.

So far, we have considered only the one-period case of the asymmetric information. Naturally, we will continue the research in the case of longer horizons. We would also like to improve our agent-based simulation system so that it supports more complex analysis of the problems.

Acknowledgments

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