AN AGENT-BASED MODEL OF A CORRUGATED BOX FACTORY: THE TRADEOFF BETWEEN FINISHED-GOODS-STOCK AND ON-TIME-IN-FULL DELIVERY

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KEYWORDS
Agent-Based Modelling, Simulation, Manufacturing

ABSTRACT

Strong competition and the high demands of consumer-goods companies for just-in-time delivery together with high standards of product and service quality are turning the top end of the corrugated-board box market into a very tough place to be. Customers order a large variety of different boxes, each with its own colour scheme and product specific printing, and expect them to be delivered at very short notice. These demands combined with the complexity of a multi-stage production process and the unpredictability of customer behaviour and machine failures lead to larger and larger inventories of finished goods stock at corrugated box factories, all to be able to guarantee “on time and in full” deliveries to the clients. In this paper we show how an agent-based model of a corrugated box plant was used to evaluate different strategies to reduce this level of stock without compromising on-time-in-full delivery, and lead to a much improved factory understanding. The software model is in use as a strategic and operational tool by a world-leading corrugated box manufacturer.

INTRODUCTION

Only to the uninitiated might a corrugated box factory seem like one of the simpler manufacturing environments. But the fact that each box has to be produced to exact customer specifications and the inherent tendency of customers to make last-minute order changes turns the manufacturing of corrugated boxes (at least in the high value end of the business, where customers demand just-in-time delivery on very short notice) into one of the prime examples of a complex dynamic system. The fact that in a reasonably sized plant the production of even very large and complex runs would hardly take more than a couple of minutes on each machine is not much comfort to a seasoned plant manager. Fixed machine set-times between each new run and the necessity of permanently high machine utilisation due to the capital and labour intensity of manufacturing makes the detailed scheduling of all production jobs very necessary. But with the efficiency such detailed scheduling brings to the shop floor comes a high sensitivity to disturbances (like machine failures or last minute orders and order changes).

Such tradeoffs between efficiency and robustness and the interaction of a large number of independent entities are hallmarks of complex systems. Such systems cannot be studied just by looking at the individual parts but the interactions among these parts and the consequences of these interactions are of equal significance. A clear illustration of this is the fact that just adding up the time it takes to run a single production-job on each machine does not give the plant manager any answer to the question of how long before the products have to leave dispatch she should start production. The result is that there was no genuine understanding of the relationships between customer order patterns, factory capacity, factory flexibility, robustness, machine speeds, order batching, warehouse size and on-time deliveries. The problems arising in the management of a corrugated box factory can only be understood in detail using sophisticated simulation technology. A quite similar manufacturing problem has been studied in Moench, Stehli and Schulz (2002), who used an agent-based model to solve the dynamic resource allocation problem in a semi-conductor factory. Our focus here is to be more specific rather than general, and ensure the resulting model is not only accurate, but has a fast run-time for the given class of factories.

A combination of agent-based modelling, where each interacting part is modelled as an individual entity with certain behavioural rules and decision making capabilities, and discrete-event simulation, where the simulation of an entire process is represented by single events that might occur concurrently or consecutively over time, has turned out to be the most reliable approach to modelling such systems. Eurobios has been in the forefront of the development of such practical models in the area of manufacturing and supply chain optimisation for leading companies such as Unilever (Darley et al. 2000) and Procter & Gamble. In fact detailed research has shown this to be the most effective modelling approach in these areas – see van Dyke Parunak, Savit and Riolo (1998). But agent-

Proceedings 5th Workshop on Agent-Based Simulation
H. Coelho, B. Espinasse, eds. (c) SCS Europe BVBA, 2004
ISBN 3-936150-31-1 (book) / 3-936150-32-X (CD)

based modelling has not been restricted to industrial problems. Axelrod (1997) has shown some very interesting applications of agent-based models in the social sciences.

In this article we give a detailed account of an agent-based model build by Eurobios for SCA Packaging, one of the leading international players in the corrugated cardboard industry. The model has been successfully implemented at multiple production sites in the United Kingdom. While the main purpose of the model is the detailed understanding that possible changes in the customer base or the running on the company have on a various number of measures, it has proved itself very useful in showing how to reduce finished goods stocks without compromising on-time-in-full delivery. This will be the focus of this paper.

We note that this is a genuinely *practical* model, which incorporates enough realism to yield results which have proven to be of direct value to factory managers. This differentiates it from many idealised and simplified simulation models in the academic literature, and from the spreadsheet models (with their assumptions of stationarity, and homogeneity) used in industry.

AGENT-BASED MODEL OF A CORRUGATED-BOX FACTORY

One of the key agent types in the model is the customer. Each customer has a number of unique products from which to order various amounts over the year. The characteristics of these orders are:

- product ordered
- quantity ordered
- delivery location
- delivery date (and time)

The products themselves have a number of different attributes:

- box size
- unique print design/colour-scheme
- number of boxes per pallet shipped
- agreement to keep a certain stock
- guaranteeing a certain lead-time

The avenue by which the customers interact with the factory is through the sales-department agent. Here an incoming order (telephoned) order is dealt with: such an order might be a call-off from pre-agreed warehouse stock, then these stock levels have to be checked, the requested amount has to be shipped and a stock-replenishment order might be triggered. Where no stock is kept, a production order must be triggered directly. These production orders then have to be slotted into the current production-plan according to different order handling policies and in case of any existing lead-time agreements in accordance to those as well.

Within the factory itself, we find another important group of agents in the model: the machines, which range from the classic corrugated board machine (turning three or more sheets of paper into a corrugated board) to the converters (cutting and printing the board) to gluers, stitchers and palletising machines. Some plants also have machines to pre-print paper before it is fed into the corrugator, which results in higher quality of printing.

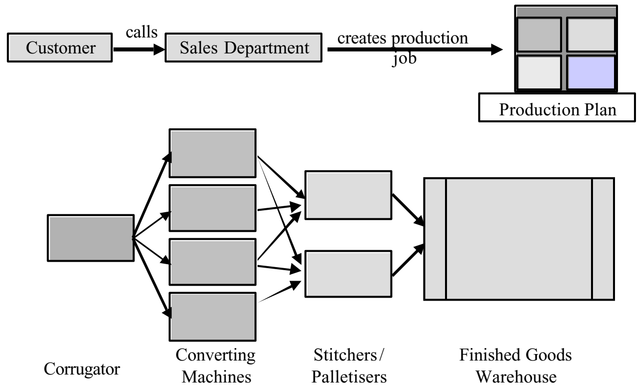

Figure 1: From the Customer Call to the Warehouse

The last agent of major importance is the dispatch area itself where finished goods are waiting to be loaded on the trucks (or other forms of transport) in order to be shipped to the customer. Those goods which are not shipped immediately are stored in the adjoining warehouse.

ORDER-DRIVEN PRODUCTION PROCESS

The ultimate drivers of all activity in such a corrugated box factory and thereby also in our model are the individual customer calls placing orders each day. Such an order contains the customer's name, the name of the product ordered, a call date t_c, a delivery date t_d, and a quantity q. Note that, for simplicity, we use 'date' to refer to a specific date and time. The sales department deals with these orders in the aforementioned ways, leading to the creation of production orders which are slotted into the production plan. The way in which this slotting is done is quite significant and can range from a simple strategy of slotting an order into the production plan as close as possible to t_c ("earliest possible"); as close as possible to t_d ("latest possible") or in more complex ways designed to even-out measures like machine utilisation or the optimisation of the transportation schedule to certain customers. All this happens each day.

Simulation time is obviously faster than real time (the time that represents an entire day in a simulation run might, depending on workload and the used computer equipment, only take a couple of milliseconds) so that an entire year of production can be run in less than a minute. But as simulation-time progresses the planned production for each day, the number of production jobs slotted in for that day has to be checked for its feasibility, some decision has to be taken in what to do with unfeasibly full days and ultimately production has to be commenced so that the products end up in dispatch at the end of the day. The production plan slotting mechanism (in reality a simple IT system used by the sales team) is sufficiently intelligent that gross misallocations are minimised. However, due to the combination of the unpredictability of client behaviour, the occasional unreliability of production machines, the imperfection of the original plan and the peaks and troughs of orders, there are almost always some late changes to the production plan before production can go ahead (there is an 11am meeting where such changes are decided). These changes usually make it impossible for the plant to adhere to all client demands, implying that there will either be some late dispatches or some dispatches that are not of the full quantity ordered (and the missing boxes have to be supplied at a later time). This would have a negative effect on one of the main measures for a corrugated box factory the "on time in full" ratio. This is one example of the kind of intricate chain of cause and effect our model must reproduce.

Once the feasibility of all booked orders is established (by rearranging the production of the less urgent ones to a later date) they are produced by running through the machines according to each product's route, ending up in dispatch where they await delivery to the customers premises.

The other major measure of a corrugated box factory's management quality is the warehouse level, which is a combination of the finished goods stock (that is kept for certain customers in accordance with agreements) and the products that are waiting in despatch in order to be shipped to the customer according to the ordered due date ("work in progress").

Even though the trade-off between the warehouse level and on-time-in-full deliveries is one of the important factors to consider, and we will concentrate our investigations in this paper on this subject, it is only a small part of the whole picture. One simple example might illustrate the complexity of the problem and make it clear why it will always be too simplistic to look just at these two values: if the plant is able to increase the speed of machines the simplistic result should be an increase in finished goods stock and a decrease of missed dispatches, simply because things can be produced faster than before. However, this is not what would typically happen in reality and also not happens in our model. The capacity to run production-jobs faster makes it possible to crew some (or all) machines for fewer shifts which significantly saves on costs, but the

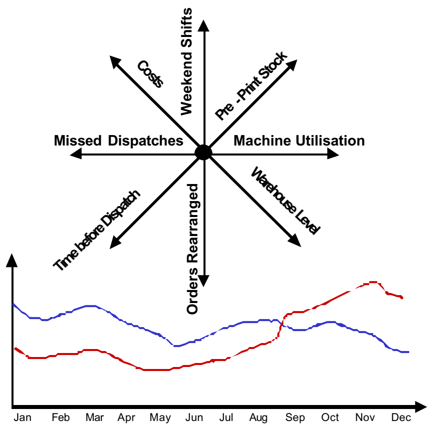

Figure 2: Multi-dimensional problem including time

result of reduced crewing is often a small increase in missed dispatches and decrease in warehouse level. Therefore, when many variables are involved, one must be very careful not to focus too strongly just on the two factors of finished goods stock and "on-time-in-full" deliveries, since this will always be a simplification. However, for the sake of simplicity in this paper we will stick to these two issues.

MODELLING THE EXPERIENCE OF A HUMAN SALES PERSON

Stock-keeping policy is a very delicate part of a corrugated box factory's customer relationship management. Customers always demand a high security buffer of stock on the factory's premises (coincidentally also on the factory's books) but the factory management has an interest to keep the level of stock as small as possible not only for reasons of working capital tie-up but also to reduce storage costs as much as possible. Therefore the sales personnel are employed not only to handle customers orders but also to be in charge of the stock kept for their customers. These sales-people have an intuitive knowledge of the customer's demand and usual ordering patterns, including sensitivity to seasonality and the economy. In order to replicate this knowledge in the model's agents we allowed the sales-agents to perform a single pre-calculation of each customer's seasonality and necessary stock level using information from the year's orders *in advance.* This happens as follows:

In principle, the optimal stock level is a function of all individual orders and the time between them. However, since these individual orders are not known in advance (definitely not to the corrugated box factory, but in most cases also only in very vague terms to the customer placing them over the course of the year) only a very experienced sales person can try to guess this value. In the model we use the average order size as a proxy for the optimal stock level s_i for customer i:

$$s_i = \frac{1}{N}\sum_{j=1}^{N} q_j$$

Even though this might not be the optimal stock level it should be very similar to the value an experienced sales person can deduce from the past ordering history of a single client, assuming orders are quite regularly spaced and sized, which tends to be true.

Seasonality is an important factor in some clients' order patterns. An experienced sales person, knowing that a client is going to order a large amount of boxes in a short time span will ramp-up production of these boxes before the first order arrives and will ramp-down production towards the end of the season. We model this by creating a seasonality ratio σ_i by dividing the total order volume of a product by the time-span between the first and the last order date:

$$\sigma_i = \frac{1}{t_d - t_c}\sum_{j=1}^{N} q_i$$

The higher the seasonality ratio σ_i the more important it is to ramp up production for this client. The percentage of clients that will be ramped-up is one of the parameters that has to be calibrated in order to replicate reality (and can later be used as a parameter to try out in different scenarios in order to find the optimum trade-off between on-time-in-full and finished goods stock). The other two parameters that have to be chosen are the ramp-up ratio specifying how much of a product's overall order volume should be produced before the first order arrives and the ramp-up-time-span specifying how much time before the first order arrives that the process should start.

Minimum stock levels and seasonality are the only two examples where we have to replace the knowledge of an experienced sales person with the knowledge of all future orders but without giving the sales agent implausible foresight which would compromise the validity of the model. Without building such an approach into the model, it's result do not accurately reflect reality.

DATABASE CONNECTIVITY AND SCENARIO CREATION

The main data needed to run the simulation, besides the detailed information about the machines with run-speeds and set-times, are all the customer calls with detailed specifications of the products ordered. The software tool built by Eurobios uses a standard JDBC bridge to read in such data from the factory's relational database (there is a relatively standard database used in the packaging industry). The most sensible way of doing this is to read-in an entire years worth of customer calls, so that any possible seasonality effects are included in the analysis and subsequent scenario generation. Once the data has been read in, multiple calibration runs have to be performed in order to make sure that the model is a sufficiently accurate representation of reality. This calibration process turned out to be quite subtle the first time, but we are now able to quickly and accurately calibrate the model against any given factory, which is a testament to its robustness.

Of course, the main interest in the tool is not the simple re-running of past orders, but rather to change some of the parameters of the factory setup or some of the main characteristics of the customer calls in order to gain an understanding of the effect such changes have on the running of the factory. As already mentioned, the main focus of this paper is the trade-off between finished goods stock and missed dispatches but there are many issues that can be studied using the scenario creation capabilities of the tool: shift-patterns (e.g. three shifts for five days, two shifts for seven days etc.); planning strategies such as just-in-time manufacture; batching and ramping-up of orders; more drastic changes such as removing a machine from the factory (and redirecting all orders that used to go through this machine to the remaining converters), or adding a new machine. Finally, other scenarios that can be generated with this tool concern the customers and the orders placed by them: new customers and new products may be added (with all the details concerning size, machine-route and seasonal order pattern); existing order volumes can be adjusted on a quarterly basis.

One issue which is particularly relevant to the warehouse versus missed-dispatch trade-off is that of production-planning strategy. Typically, jobs can be slotted into the production plan in three different ways: as early as possible after the order arrives; as close as possible to the due-date; or in such a fashion that the workload is equalized as much as possible between the call-date and the due-date. We will show an example of all three strategies in the following section. Such different planning strategies can be explored separately for stock and non-stock orders.

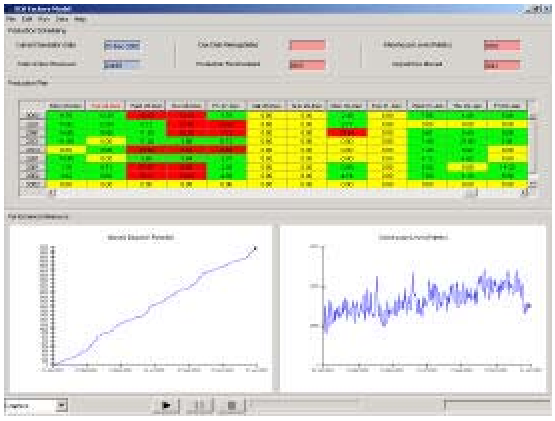

Figure 3: Model Run Screen

SOPHISTICATION OF THE AGENTS

How sophisticated should the agents be in making their decisions in the factory? Most agents modelled are deterministic machines who behaviour is fully described by speed, set-time, and a number of similar parameters (including reliability in more recent versions of this tool). The interactions between most agents are simply the physical movement of product, again deterministic. The only remaining behaviours are those of the sales people and factory planners. While sophisticated dynamic optimisation techniques could be applied, that was not our purpose: the goal of the model was to apply relatively simple rules of thumb to these behaviours, since that is what the humans

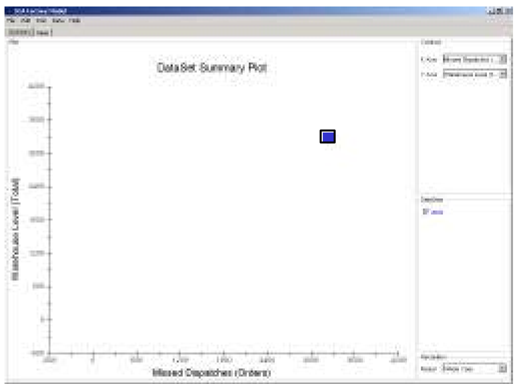

Figure 4: Model run of 2002 data (x-axis: missed dispatches, y-axis: warehouse level)

involved actually do. Any benefits can only be achieved in the short-term by modifying discrete parameters (e.g., "do we stock this customer or not?"), or modifying the behavioural rules of thumb in relatively simple ways (adjusting their priorities, for example, or shifting between the three different planning strategies).

Hence all behaviours were constructed as parametrised 'if-then' rules encoding the behaviours observed in the factory (which were then validated through qualitative and quantitative analysis of the model's results).

Of course in the long term, one could ask questions about the benefit of replacing such rules of thumb with automated optimisation (which would require new IT systems in reality). Such comparatively expensive longer-term plans are not within the scope of the current paper.

THE TRADE-OFF

Once the entire model is up and running and calibrated with data so that the model is a close replication of reality over the given time-span, scenario analysis can begin. Figure 3 shows the model's run screen with the production plan and each machine's booked hours for each day of the year in the centre. The number of missed dispatches (cumulative) and the daily warehouse level are shown in the two graphs at the bottom. The yearly values for these two variables can also be viewed in one of many summary plots, which makes comparisons between different scenarios much easier, see figure 4.

In the following discussion of the trade-off between warehouse level and missed dispatches we will concentrate on this summary plot showing these two variables' yearly values. We will analyse different scenarios in order to find out how we might be able to 'move' as much as possible to the lower left corner of the graph. We should point out here that due to the fact we run each strategy for a full year, the statistical variation between the results for different instances of the same run (due to randomness) is very small.

One of the obvious changes in strategy that will have a direct effect on warehouse level and missed dispatches is a change to the way production orders are put into the plan. We already mentioned the three different possibilities to put them in either as close as possible to the call date, as close as possible to the delivery date or somewhere between those two dates so that each day between these two dates has roughly the same hours of machine capacity booked. Obviously the case where the production jobs are put in as soon as possible will result in the highest warehouse level but the smallest number of missed dispatches. And for the putting in of these production jobs as close as possible to the due date the converse will be true. If they are put in somewhere in between these two extremes than also warehouse levels and missed dispatches will take on some values in between the two extremes. Figure 4 shows exactly this but it is interesting to notice that there is not much of a difference between putting the jobs as close as possible to the due date or equalizing the workload, which hints to a quite busy schedule for each of the machines – something which is easy to verify by looking at the machine utilisation graphs (but we will not do so in this paper for reasons of space).

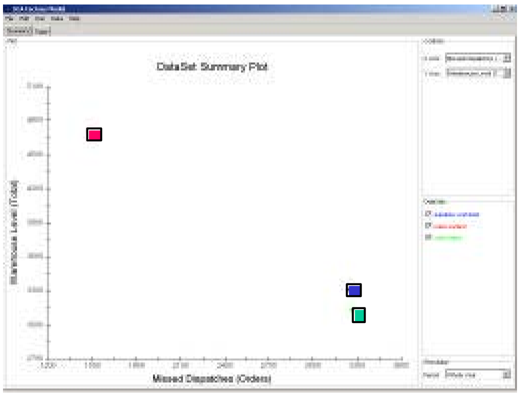

Figure 5: Different Planning Scenarios, blue: equalize workload, red: make earliest, green: make latest

The other very interesting question is if all the stock-keeping agreements are actually necessary or if it might not be possible to produce an order as soon as it is placed by some customers instead of keeping stock (i.e. serving the order from stock and then replenishing the stock over the following days). The complexity of the order pattern of single customers and the different utilisation of the machines these orders go through prevent us (and the factory managers) from making any a priori predictions for the effects of such a change. Using the model we can answer this question immediately: Figure 5 shows that by turning two different customers from stock to non-stock we can get completely different results in terms of the impact on our two metrics!

This is a prime example of how only an agent-based simulation is able to model the factory with sufficient realism to be able to find the optimal stock policy for the wide range of different customers, and to accomplish that modelling task with limited time and resources.

Why is this? ABM and the rules-driven approach to discrete-event simulation form a very direct match with this problem: sufficiently complex, non-linear and 'lumpy'

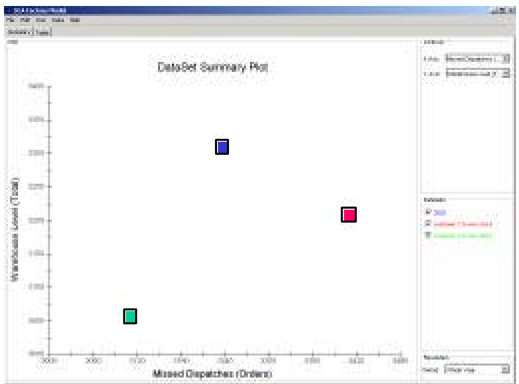

Figure 6: Stock versus non-stock (blue: both stock, red: customer 1 to non-stock, customer 2 to non-stock)

factory dynamics that 'stock and flow' models are not appropriate; totally heterogeneous order data driving the model making statistical approaches largely meaningless; a reality in which rules of thumb drive most actions, making pure optimisation irrelevant today.

SUMMARY

In this paper we presented an agent-based model of a corrugated box plant. The complexity of such a manufacturing plant, caused by a large number of different products, tight deadlines and a multi-pass production process, makes it impossible to predict the consequences of any changes to the way the plant is run without a detailed model of all the elements involved in this process. Using this agent-based model, SCA Packaging was put in a position to have a clear and reliable understanding of the consequence of possible changes to its customer base or the way the plants are run. This confidence made it possible for the plant management to take certain decisions that led to a reduction in warehouse levels by over 35% without compromising their on-time-in-full delivery commitments.

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