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On complex adaptive systems and agent-based modelling for improving decision-making in manufacturing and logistics settings

Experiences from a packaging company

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Abstract

Purpose – This paper aims to contribute to the tactical and operational decision making of manufacturing and logistics operations by providing novel insights into modelling and simulation, based on complex adaptive systems (CAS).

Design/methodology/approach – The research approach is theoretically based on CAS with agent-based modelling (ABM) as the implementation method. A case study is presented where an agent-based model has contributed to increased understanding and precision in decision making at a packaging company in the UK.

Findings – The results suggest that ABM provides decision-makers with robust and accurate "what-if" scenarios of the dynamic interplay among several business functions. These scenarios can guide managers in the process of moving from policy space to performance space, i.e. concerning priorities of improvement efforts and choices of production/manufacturing policies, warehouse policies, customer service policies and logistics policies. Furthermore, it is found that ABM can include and pay attention to several aspects of CAS and thus provide understanding of, and explanation for, the patterns and effects which emerge in manufacturing and logistics settings.

Practical implications – Aided by agent-based models and simulations, practitioners' levels of intuition can be enhanced since patterns on the macro level emerge from agents' interactive behaviour. Together with insights from CAS these emergent patterns can be explained and understood, and are thus beneficial for the improvement of decision making in companies.

Originality/value – The case presented distinguishes this paper from what has been written in previous articles on the application of ABM, since such articles have not produced any empirically verified results after implementation of ABM.

Keywords Modelling, Adaptive system theory, Decision making, Logistics data processing, Manufacturing systems, Simulation

Paper type Case study

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Introduction

In an increasingly complex world, managers are confronted with more data and information, which means they need to be able to consider holistic perspectives as specific details in their decision-making processes. Thus, the search for models and methods which assist managers in the process of decision-making is never-ending for all types of management, and is also the case in manufacturing and logistics (Schroeder, 1993; Svensson, 2003). Owing to just-in-time implementations and other lean approaches, the focus on lowering inventory levels in several cases has led to increased vulnerability in terms of disturbances in operational activities (Svensson, 2003). With emerging business concepts, such as agile manufacturing and responsive logistics, the ability to react, and even be proactive, to changing demands and disruptions, will be increasingly important (Brown and Bessant, 2003; Gerwin, 1993). In the development towards agile and responsive enterprises, novel approaches and methods which can assist managers in manufacturing and logistics in the decision-making process are needed.

Even though several models and methods exist to support managers in the decision-making process within the manufacturing and logistics disciplines, their usability needs to be investigated as it depends on situation and context. There are, for example, several reports of successful modelling efforts regarding specific functions or processes, e.g. inventory, production, transport (Axsäter, 2003; Campbell and Hardin, 2005). However, what seem to be missing in the managers' toolboxes are methods and tools when models need to include several company functions or processes which are interconnected and interdependent. In their analysis of business process modelling and simulation, Barber *et al.* (2003) conclude that existing software tools are still limited in breadth and depth. When business processes involving manufacturing, logistics, operations planning, sales, inventory, etc. are considered simultaneously, the complexity of the situation increases. In such wider contexts, over-simplified models often fall short since they are based on assumptions which scarcely reflect reality. As Leombruni and Richiardi (2005, p. 104) state "the traditional approach of simplifying [complex systems] may often 'throw the baby out with the water'". The fact is that there are several simplifying assumptions which are being taken for granted in many existing models and methods and these do not exist in real-life contexts. For example, Vidal and Goetschalckx (2000) describe assumptions in mathematical programming (MP) and mathematical integer programming when these methods are applied to logistics and supply chain management:

- customer demand satisfaction is included in most MP formulations by assuming deterministic demand;
- transport and production costs are assumed to be linear for most of the formulations; and
- the calculation of inventory costs in distribution centres, if included at all, usually assumes deterministic demands and deterministic lead times.

The patterns and behaviours which can be identified in manufacturing and logistics contexts do not match such assumptions. Rather, they can be regarded as being of a complex and adaptive character based on perceptions of ongoing events in the local context (Nilsson, 2005). Complex adaptive systems (CAS) are by definition difficult, and often impossible, to compress into parsimonious descriptions or simplifications

(Anderson, 1999) since they are characterised by self-organising properties causing emergent system-wide effects (Darley, 1999; Gell-Mann, 1994; Holland, 1998; Kauffman, 1995). CAS are better described and understood by assumptions of non-linearity, self-organisation, change, heterogeneity, bounded rationality and emergence. In other words, if manufacturing and logistics operations are regarded as being complex, it is inappropriate to consider models developed under paradigms based on beliefs of linearity, stability, homogeneity, and perfect rationality as producing the best possible explanations and understanding of turbulent contexts.

With the use of agent-based modelling (ABM) and simulation, together with insights derived from complex adaptive systems, this paper illustrates that ABM provides a suitable platform for the creation of robust and accurate "what-if" scenarios within manufacturing and logistics settings. This approach can, in turn, be used to improve the tactical and operational decision-making of manufacturing and logistics operations. The applicability and value of ABM are illustrated in this paper by a case and simulation study from a packaging company in the UK where an agent-based model has been developed and used at the company. The case distinguishes this paper from what has been written in previous articles on the application of ABM since these articles have not shown any empirically verified results after implementation of ABM.

The remainder of this paper is organised as follows. The next section provides an introductory description of CAS. ABM is then introduced as a method and technique to operationalise the CAS perspective in manufacturing and logistics. In the subsequent section, a case is described which illustrates the application of ABM at a packaging company in the UK, showing insights into how CAS and ABM can be applied to improve decision-making. Finally, a concluding discussion of ABM is provided and further research suggested.

Complex adaptive systems

The complexity paradigm is a new approach and a useful perspective for understanding manufacturing and logistics phenomena (Choi *et al.*, 2001; McCarthy, 2004). Recent research has shown that phenomena consisting of many constraints and conflicting demands, i.e. complex systems, can be studied and evaluated by models and methods derived from a complexity perspective (Nilsson, 2003). Insights from the complexity paradigm have been reported before (see, for example, MacIntosh and MacLean's (2001) work on conditioned emergence, MacBeth's (2002) work on emergent strategy and McCarthy's (2004) work on manufacturing strategy). The complexity paradigm has been used to facilitate understanding of other phenomena such as knowledge management (McElroy, 2000; Stacey, 2001), organisation science (Anderson, 1999; Lewin, 1999; Lewin and Regine, 1999), strategy (Beinhocker, 1999; Pascale *et al.*, 2000; Tasaka, 1999), to mention but a few. MacIntosh and MacLean (2001, p. 1345) state that "complexity theory . . . is regarded by some as signalling the arrival of a new scientific paradigm in the Kuhnian sense".

A complex adaptive system is a special kind of complex system since it has the property of adaptation, meaning that it has the "ability to consciously alter its system configuration and influence its current and future survival" (McCarthy, 2003 p. 730). In a manufacturing and logistics context this means that the entities in the system are responsive, flexible, reactive and often deliberately proactive to inputs from other entities which affect them. In the subsequent discussion, we will present and discuss four properties which characterise CAS:

(1) CAS is represented by open dynamic systems which continually exchange information and energy with the surrounding environment (Beinhocker, 1997; Gell-Mann, 1994).
(2) A CAS consists of several agents which dynamically act in correlation and interdependence with each other (Bar-Yam, 1997). The agents act according to certain policies which influence their behaviour and at the same time, that of the other agents, creating non-linearity in the system (Beinhocker, 1997; Pascale, 1999; Stacey *et al.*, 2000).
(3) The type of systems which CAS represents has a common feature; the systems exhibit emergence (Beinhocker, 1997; Choi *et al.*, 2001; Stacey, 2000). Emergence could be described as the outcome of collective behaviour, i.e. interactions among agents (elements, individuals, etc.) performing something individually, or together, which creates some kind of pattern or behaviour which the agents themselves cannot produce (Bar-Yam, 1997; Gell-Mann, 1994; Goodwin, 2000; Kauffman, 1995; Lissack, 1999). Epstein (1999, p. 54) gives an illustrative example of emergent properties; "people can have happy memories of childhood while, presumably, individual neurons cannot". This means that the behaviour of a CAS is unpredictable and often counter-intuitive (Bonabeau, 2002) and contributes to a co-evolutionary process among the agents. It also means that new opportunities are always being created by the system. Moreover, as Bonabeau (2002) claims, the only way to analyse and understand emergent phenomena is to model them from the bottom up.
(4) It is through interaction between the entities that emergence occurs in the process of self-organisation. This process of self-organisation can only be successful in open systems because of the need for energy (Prigogine, 1997). However, even though CAS never reach states of equilibrium, order still emerges. Anderson (1999) describes this as "order arises in complex adaptive systems because their components are partially, not fully, connected". Systems in which every element is connected to each other in a feedback loop are hopelessly unstable (Simon, 2002).

When the scope of business issues is widened, the characteristics of business processes and phenomena become increasingly non-linear, self-organising, changing and rationally bounded. This happens when the interplay among different business functions and processes is to be considered and even more apparent when customers as well as suppliers are to be included in the analysis and understanding. Hence, the characteristics of CAS become evident in a business context. As Sutherland and van den Heuvel (2002 p. 3) state: "business entities are good examples of complex adaptive systems".

However, while insights from CAS provide increased understanding of manufacturing and logistics processes and a helpful framework for modelling, some kind of method is needed in order to transform such an approach into tangible and understandable results, particularly from a management perspective. The rationale behind such a method is that our research has brought out that managers need to be able to test and evaluate different "what-if" scenarios, simulate policy changes or changes in behaviour in order for them to understand and evaluate new ways of thinking and approaches to manufacturing and logistics issues. In this regard, one modelling and simulation approach influenced by the complexity paradigm is ABM, derived partly from object-oriented programming and distributed artificial intelligence (Jennings *et al.*, 1998), and partly from insights from the science of complexity (Axelrod, 1997b; Holland, 1998; Kauffman, 1995). ABM provides a modelling and simulation approach which can be beneficial for a complex adaptive system approach and is useful in creating tangible, understandable results for managers.

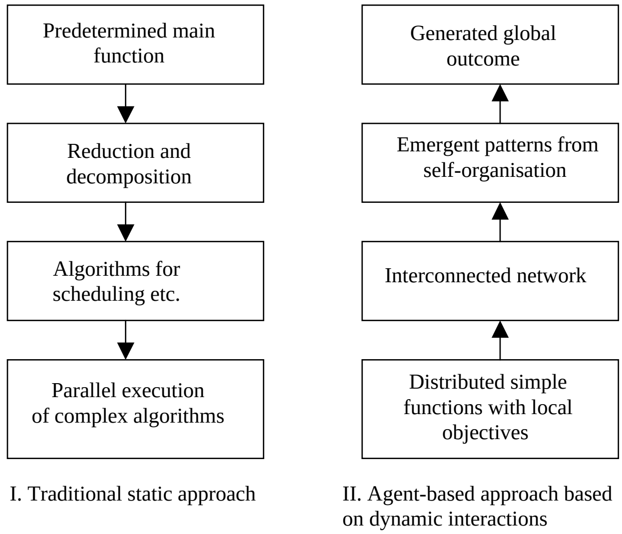
Agent-based modelling

ABM represents a new paradigm in modelling and simulation of dynamic systems distributed in time and space (Jennings *et al.*, 1998; Lim and Zhang, 2003) and ABM "allows the use of CAS approaches [. . .] that can address the behaviour of each of the participants within complex systems" (North *et al.*, 2005, p. 1197). Since manufacturing and logistics operations are characterised by distributed activities as well as decision-making, in both time and in space, and can be regarded as complex, the ABM approach is highly appropriate for these types of systems (Lim and Zhang, 2003; Nilsson, 2005; Wakeland *et al.*, 2004). There is a growing interest in using ABM in several business-related areas, such as manufacturing (Chun *et al.*, 2003; Kotak *et al.*, 2003; Lim and Zhang, 2003; Zhou *et al.*, 2003) and logistics and supply chain management (Gerber *et al.*, 2003; Kaihara, 2003; Knirsch and Timm, 1999; Santos *et al.*, 2003; Schieritz and Grossler, 2003). ABM is considered important for developing industrial systems (Davidsson and Wernstedt, 2002; Fox *et al.*, 2000; Karageorgos *et al.*, 2003) and it provides a pragmatic approach for the evaluation of management alternatives (Swaminathan *et al.*, 1998).

In ABM the focus is on agents and their relationships with other agents or entities (Axelrod, 1997a; Cicirello and Smith, 2004; d'Inverno and Luck, 2001; Jennings *et al.*, 1998). Since the field of ABM is fairly new, no general agreement on the term agent has yet been established (Tripathi *et al.*, 2005). Parunak *et al.* (1998) define an agent as being a software entity with its own thread of control able to execute operations without being externally invoked, while Jennings *et al.* (1998) define an agent as a self-contained, problem-solving entity. In this paper the agents are defined as real-life components identified in the context of interest, characterised with varying degrees of autonomy (i.e. execution ability and self-control), and characteristics based on policies, behaviours, states and constraints. In the manufacturing and logistics context an agent might represent a machine, the order-handling process, inventory handling, trucks, etc.; parts of manufacturing and logistics operations which to some degree are autonomous.

The bottom-up approach

A central feature of ABM is the bottom-up methodology by which an ABM model is constructed. Reaidy *et al.* (2003) provide a comparison of conventional top-down-oriented methodologies and agent-based bottom-up ones (Figure 1). The top-down methodologies are based on the assumption that knowledge is outside the "system" and someone can measure and analyse the observable phenomenon of interest and from that decompose it correctly to different sub-units where the



Source: Derived and modified from Reaidy *et al*. (2003 p.151)

Figure 1. Comparison between traditional modelling methodologies and bottom-up methodologies

sub-problems are solved separately. Then, as Kreipl and Pinedo (2004, p. 83) state, "at the end, the partial solutions are put together in a single overall solution". While this "divide and conquer" approach enables manufacturing and logistics operations to be translated into mathematical equations for correct analytic solutions, it de-emphasises the relationships and dynamics which in reality exist among different manufacturing and logistics entities (Parunak *et al.*, 1998). This is especially the case when the targeted modelling context is widened to include several dispersed functions or processes within a company. Models which are constructed by global performance measures (also called observables (Parunak *et al.*, 1998)), cannot cope with the dynamics of their constituent parts, since the observables are constructed of the aggregated behaviours of the whole system (Swaminathan *et al.*, 1998). Paradigmatically, this top-down assumption is inherited from the positivistic paradigm, hence built on mechanistic assumptions and reductionism. In this regard, Kauffman (1995, p. VII) states that "the past three centuries of science have been predominantly reductionist, attempting to break complex systems into simple parts, and those parts, in turn, into simpler parts".

Bottom-up methodologies are instead based on a synthesising philosophy, where the user presumes that he/she cannot understand the whole phenomenon of interest but can observe, on a micro level, specific activities and processes, and tries to understand their behaviour and their objectives. These agents interact and communicate with other agents and they join to form a coherent whole on a macro level (d'Inverno and Luck, 2001). Each agent's ability to make decisions based on information-processing rules creates the internal dynamics which form the behaviour of the system; often emergent behaviours which cannot be predicted in advance (Axelrod, 1997a). In this regard, Bonabeau (2002, p. 110) states that in order to understand ABM "you first need to understand the concept of emergent phenomena". Emergent phenomena are fundamental in complex adaptive systems. Global patterns emerge from the interacting and interrelated networks of agents. In the words of Parunak *et al.* (1998, p. 10) "direct relationships among the observables are an output of the process, not its input". Jennings *et al.* (1998, p. 9) state that ABMs "are ideally suited to representing problems that have multiple problem solving methods, multiple perspectives and/or multiple problem solving entities". The motivation for this is based on the fact that the agents interactively negotiate different goals, and co-operate and/or even compete in order to reach emergent solutions that solve the problem in question. Jennings *et al.* (1998, p. 9) state that:

> . . . it is the flexibility and high-level nature of these interactions (cooperation, coordination, negotiation) which distinguishes multi-agent systems from other forms of software and which provides the underlying power of the paradigm.

In pragmatic research, with empirical bounding, a bottom-up approach might seem to be advantageous, since the quest for the researcher or practitioner developing the model will entail directly assessing activities, machines, and operations on their most concrete level. This means that when it comes to modelling and simulation there is no need to consider the whole phenomenon at once. Instead, it should be constructed and developed in the process of building the model. Focus can therefore be placed on the local and distributed parts since they may have their own working principles, behaviours, states, and constraints, i.e. natural heterogeneity. Furthermore, with the use of simulations, emergent behaviour can often be identified and understood, and sometimes even predicted (Darley, 1999).

Agents vs objects

It might seem to the reader that agents and objects are similar in nature, however, there are differences in both their construction and execution. Jennings *et al.* (1998) provide a number of differences between them. The first relates to autonomy, where an agent embodies a stronger notion of autonomy than objects (Wooldridge, 2002). Jennings *et al.* (1998) explain autonomy as "objects do it for free; agents do it for money". Another distinction between object and agent systems is with respect to the notion of flexible, (reactive, pro-active, social) autonomous behaviour. In general, objects are passive, i.e. they need to receive a message or something similar in order to become active; agents have their internal mechanism for that (Jennings and Bussmann, 2003). A third distinction lies on the model level, where the agents in agent-based models are each considered to have their own thread of control whereas in the standard object model, there is a single thread of control (Jennings *et al.*, 1998).

While ABM shares several of the characteristics of other types of bottom-up modelling and simulation methodologies (e.g. discrete-event based (DES)), i.e. it represents dynamic, stochastic and discrete settings, there are some differences that could be reflected on. Firstly, the execution of the agents is based on internal rules not on external and global policies. Secondly, the focus is on the agent and its adaptiveness within the system being studied (Garcia, 2005). As stated by Garcia (2005, p. 381) "in an agent-based model, the programmer only models the behaviour of an individual". Finally, compared to event-driven DES models, agent-based models are mostly time driven.

Identified advantages

Increases realism (Jennings et al.*, 1998)*. In ABM the parameters are set to characterise an authentic situation of interest (Bonabeau, 2002). The individual agents can be made directly comparable to machines, vehicles, products or groups of such, found in a real-life context which easily facilitates validation of simulation runs. This makes the models easy to understand for the people involved and there is no requirement for them to understand ABM (Valluri and Croson, 2003) which makes ABM a powerful empirical method (Epstein, 1999).

Includes heterogeneity. In ABM there is no need to aggregate different agents' behaviour into average variables. In reality, manufacturing and logistics activities are not homogeneous at the operational level, which makes ABM a powerful tool for including the heterogeneity in these systems. The results often provide novel insights which are sometimes counter-intuitive (Bonabeau, 2002).

Includes bounded rationality. As is often the case in organisations, the individuals involved lack perfect information, have their own goals, and sometimes their own policies, i.e. they are heterogeneous and have bounded rationality. Valluri and Croson (2003, p. 3) state that in agent-based models "bounded rationality can be built explicitly into agent design rather than either imprecisely modelled or assumed away entirely". The agents do not possess global information, and they do not have infinite computational power (Epstein, 1999).

Promotes scalability and flexibility (Tripathi et al.*, 2005)*. In the development of the models the agents can be developed separately and systems can be built up in several stages until the system one wishes to investigate is covered. Adding another sub-system, i.e. an agent or a set of agents, is fairly easy.

Low costs. Another pragmatic advantage is represented by the low financial costs associated with ABM compared to the costs of other modelling and simulation tools like discrete-event simulation (DES). The latter require licence agreements which are often a significant expense. The ABM software needed is based on open source which can be downloaded free of charge. Examples are JAVA, JADE, Repast, Swarm, Netlogo, Starlogo.

Identified disadvantages

As there will never be any one method or tool without flaws or the best to use in all cases, ABM has its drawbacks. One drawback is that, due to the finer granularity of information, there are relatively high costs in both time and effort compared to equation-based models (Swaminathan *et al.*, 1998). Furthermore, ABM models tend to require more data than many other approaches (Bonabeau, 2002; Garcia, 2005). As a consequence, of the finer granularity and the great amount of data it is often extremely difficult to detect whether the results produced are the cause of a programming error or a groundbreaking insight. Hence, troubleshooting activities can sometimes be very resource demanding. In addition, simulating agent-based models demands knowledge of programming languages (Garcia, 2005). Another disadvantage is that customised models are often specific to the modelled context and therefore have limited re-use (Swaminathan *et al.*, 1998) so that the generalisability of the results is difficult (Leombruni and Richiardi, 2005, p. 104). One way to overcome this though is by making theoretical or assumptive generalisations (Meredith, 1998; Yin, 2003). One should bear in mind that benefiting the most from ABM means understanding the characteristics of the phenomena under investigation at the lowest appropriate level of description. Furthermore, in the context of manufacturing and logistics, the models need to be updated on a regular basis with policies, rules, states and other types of data in order to provide enough similarities with the modelled reality to be valuable and useful. This may be a costly step. Finally, as in any modelling and simulation effort, it is important to establish that an agent-based model will only be as accurate as the assumptions and data which went into it. Stacey *et al.* (2000) particularly address the issue of transferring human behaviour to rules and procedures in a computer and point out that the rich texture of emotional and embodied relating to each other is lost, as is any creative action. In addition, Richardson (2003, p. 8) issues a word of warning that "models are tools that can be used and abused – the best models are worthless in linear hands". A final comment is that it must be noted that ABM and other methods and tools are complements to each other, not rivals.

The packaging company case description

In the following section, a case study which illustrates and exemplifies the use of ABM in an industrial context will be provided. For reasons of brevity and confidentiality, some details have been left out, and focus has instead been placed on the explanation of the modelling context, and the result of the simulation model which has been developed. Consequently, the actual figures presented have been modified.

The case is based on a simulation of a packaging company in the UK where a CAS perspective was used on a plant and its customer relations. The packaging company was facing increased turbulence since customer demands were changing rapidly, at the same time as the costs (particularly warehousing costs) of keeping high service levels were increasing. Furthermore, there was no genuine understanding of the relationships between customer order patterns, factory capacity, factory flexibility, production robustness, machine speeds, set-up times, order batching, warehouse size and on-time deliveries. What the managers in the plant were looking for was a "virtual factory" to test the impacts different policy changes would have on their customer service levels, on their internal logistics, on production and related costs. The key strategy of the company, as described by the plant manager, was one which he and other colleagues believe has made the packaging firm market leader in the northern parts of the UK; to offer the best customer service possible. This differentiation strategy meant that the firm had to be flexible in production, inventory stocking and deliveries to its customers, and most importantly of all, had to give the customers consistency in delivering high-quality products, on time and in full. Offering the customers this high service without the assessment methods for finding the optimal balance, where both the customers' demands and the company's profitability were considered and maximised, made the evaluation of the strategy in this challenging situation difficult. The customer service strategy of the packaging company was not, under any circumstances, to be changed since it had set the company apart for several years, making it profitable.

In order to gain insights concerning the different problems and requirements the managers in the company brought up, a CAS perspective was used, and an agent-based model was developed. In this case there were several reasons for this combination:

- The situation was characterised by several different entities which had access to limited information and which had varying degrees of influence on company operations, i.e. heterogeneity and bounded rationality existed.
- Parallel activities were taking place and decisions were made by several people in different parts of the company, i.e. discrete activities and decentralised decision-making were evident.
- The situation was resource-constrained, i.e. there were limited resources in terms of money, space and time.
- Different performance measurements were used in different parts of the company, which on a company level were in conflict, since some of these constrained each other. In other words, no global target function was to be found and instead, the model needed to incorporate different measurements and aims.

Thus, the situation was characterised by conditions and characteristics similar to what can be defined as a complex adaptive system. Furthermore, in this specific case the packaging company had particular requirements for the modelling process:

- The company wanted a customised model, similar to its operations, i.e. not a general model derived from common computer programs. In this regard, it was easier to build a model which fitted into the company's operations than to tailor the company's operations to an existing model.
- The company wanted a flexible and scalable model which could be easily extended to other functionalities and entities later.

This led to the development of an agent-based model which would represent a virtual factory. This would in turn aid the managers in their decision-making processes.

Agent-based modelling of the packaging company

The project was separated into three phases where the initial phase covered ten interviews and two workshops with staff and involved process mapping of flows and interactions, in order to create the "virtual factory" requested. In this phase, a great deal of time was spent on identifying the type of data that was available and establishing how it could be used. The managers and others involved had considerable experience of running the plant and this made them very suited to providing input to the model and evaluating outcomes from the model. Several of them had been working there for more than 15 years and were useful sources of information. As a final part of the first phase, a preliminary model was built to cover the major features of the plant.

The second phase covered the development of a more detailed model, and involved its calibration. The model could be developed based on real data from 2001 due to the accurate data provided by the packaging company. A total of approximately 20,000 orders was put into the model and the number of products used was close to 2,500. The plant had a total of more than 100 different customers. There was no need to average or simplify any of these orders, products or customers since each entity was included and considered in the model.

After verification and validation the third phase involved the actual modelling and simulation of different scenarios. One of these simulations aided the management in deciding how to handle a particular situation which arose during the second development phase. The result of this simulation will be presented below.

The agents

The agents identified ranged from orders, machinery and shift plans to decision-making rules. In order to identify appropriate agents, process maps were made of the flow through the factory; both the physical flow and the order/information flow (see Figures 2 and 3 for process maps for order and physical flows).

Agents were identified in the plant based on their impact on the value-adding process. The agents were created based on the recognisable characteristics for each identified agent, i.e. the policies, the behaviours, the constraints and their states.

Plant agent = (agentid, policies, behaviours, constraints, states)

The following major agents were identified and incorporated into the model:

- machines (nine in total);
- sales;
- operations planning;
- warehouse; and
- customers.

The agents themselves are fairly simple in design, i.e. they are represented by fairly simple mathematical representations and logical "if-then" rules. The complexity matching the reality to be modelled is found in the emergent outcome as these agents interact during simulation runs.

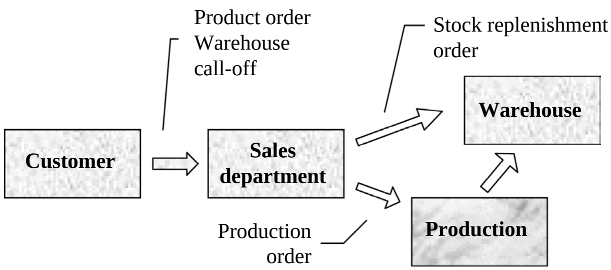


Figure 2.
Process map of order flow at the plant

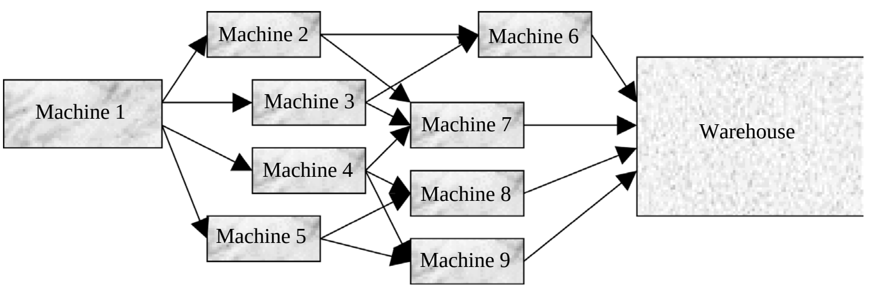


Figure 3.
Process map of the physical flow at the plant

Machine agent. Each machine in the production was considered an agent since its characteristics were significant to the value-adding process. The machines have capacity constraints, e.g. maximum operating speed, and operational behaviours, e.g. mean time between failure rates, mean set-up times, etc. Furthermore, as the model runs, the states of the machines change, e.g. they are occupied, damaged, available, etc. All nine machines were included in the model and modelled as autonomous but interconnected agents.

Sales agent. Within the sales department another value-adding process identified was the incoming order handling process which was regarded as the sales agent. The order handling process had several policies. Dealing with incoming orders means first of all checking if products are in stock or need to be produced, and whether a particular customer is one served by keeping stock or by only "making to order". This leads to behaviours which in the former case, i.e. keeping stock, means that the warehouse agent should be notified and in the latter case, i.e. making to order, a production order is created to provide the operations planning agent with up-to-date orders for scheduling.

Operations planning agent. The operations planning agent's behaviour is set to first produce a rough plan and, based on late changes due to changes in orders or late incoming but prioritised orders, a final production plan. Policies identified for the operations planning were:

- latest possible day;
- earliest possible day; and
- minimum workload day.

The last policy (minimum workload day) was of a more complicated character since it meant considering machine and man-hour utilisation. A final policy used was to include the priority of certain customers in production scheduling. The operations planning agent is constrained by the capacity of both the machines and the warehouse. Only by interaction with these agents can the decisions concerning when to produce and store an order be made. This planning happens each day.

Warehouse agent. The warehouse agent incorporates several aspects and policies for keeping products in stock. The agent is limited by the capacity constraints concerning the number of products which can be stored. Furthermore, there are important aspects concerning the costs of storing and handling the products in stock which affect the policies used. Two policies which it is possible to change are whether a product should be a stock product or non-stock (make-to-order) product. Such a change in policy affects the rest of the agents and consequently the performance of the whole plant, i.e. in customer service terms.

Customer agent. There is a high level of unpredictability in customer behaviour, i.e. when orders are set, which products are ordered, in what quantities, and when and where the products should be delivered. The products themselves are characterised by size, design/colour, quality, number of products per delivery, stock-keeping agreements, lead time agreements. Another influential factor is the seasonality of products some customers experience. Consequently, an agent is created in the model to represent this highly variable set of characteristics from over a hundred customers.

Output

The output of the model was designed to mirror the service levels of the company, i.e. to measure the effects different policy changes had on successful customer service strategy. More explicitly, output parameters were missed dispatches, warehouse levels in terms of pallets (stock and non-stock items), machine utilisation, number of rearranged orders, number of renegotiated orders, storage costs and total costs. Figure 4 shows the computer interface of a simulation run where the data for each machine for each day of a year has been simulated and the results in terms of potential missed dispatches and warehouse levels are graphically illustrated in the two diagrams.

Each simulation run produces a dataset which can be viewed, analysed, compared and saved for future use. This allows different runs with different parameter settings to be compared directly, i.e. the runs can be compared on warehouse levels, by cost, by service quality, by machine utilisation, depending on the parameter settings. One way to analyse the result of simulation runs is in data summary plots showing the various metrics on time scales ranging from daily data to yearly averages.

Model verification and validation

The reliability of the model was crucial for the whole management team. Consequently, it was a qualifying requirement that the model could reproduce what was going on in the plant in a manner which was easy to understand. This meant that verification and validation of the model were conducted on several occasions during the development process. This was done by means of workshops with staff from the packaging company where the previous year was modelled and compared to the real performance in the factory. This calibration of the model was done through several parameters such as actual warehouse levels, actual missed dispatches, hours worked on each machine, etc. After some fine-tuning the model represented and showed the operations done during 2001. The plant manager stated that:

> . . . based on the fact that there are several experienced managers operating, and that their business is quite stable, they have found it quite easy to check the reliability of the model compared to the experience and the figures they have concerning the operations.

One of the advantages of ABM was realised here, namely, that model validation could be done on both micro and macro levels, i.e. each agent's behaviour could be validated and verified quantitatively, with real data, and qualitatively, through discussions of its behaviour and policies. At the same time, macro behaviour, i.e. the behaviour of the whole plant, could be validated and verified with real data representing service level aspects and warehouse levels.

Editing the model and building scenarios

In order to provide the managers at the plant with a virtual factory the model was designed to be easily edited, i.e. customers, products, machines, and other specific parameters can be changed. For each run the customers can be changed, deleted or new customers added. For example, it is possible to include errors in customer orders such as day errors, i.e. predicted delivery date and actual delivery date of the final order, and quantity errors, i.e. the percentage error in the quantity of the predicted order. For each customer, specific products may also be changed. These changes can be choice of

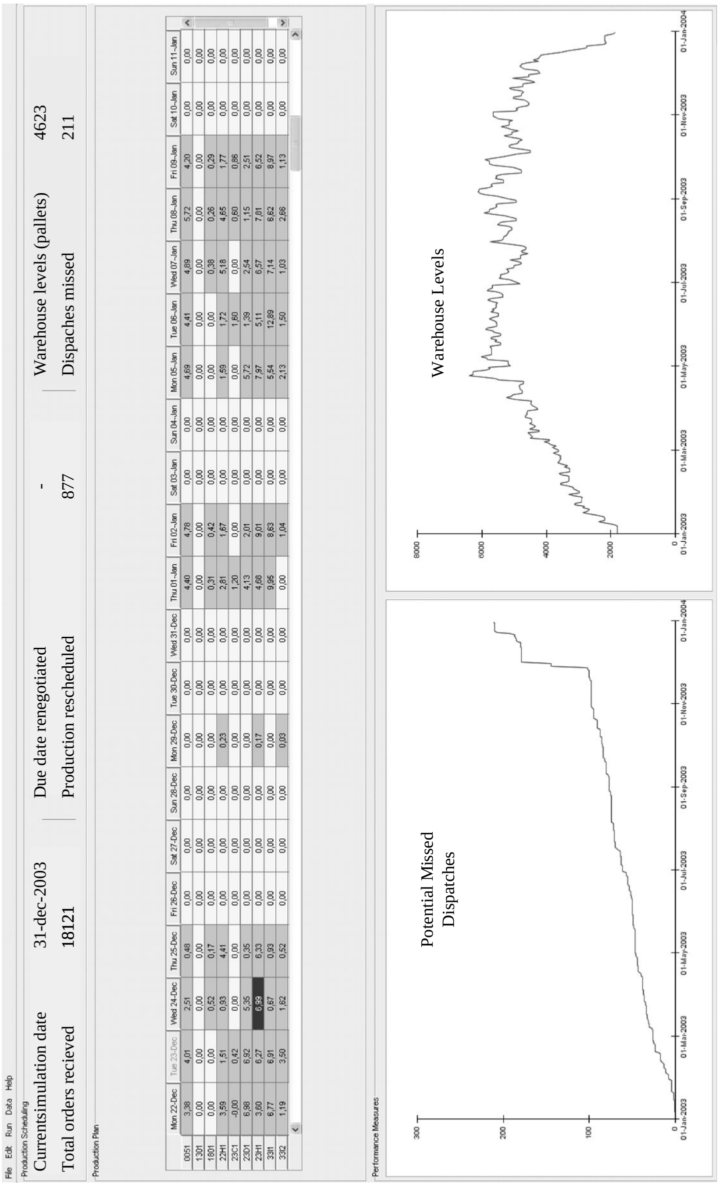


Figure 4.
Simulation interface showing potential missed dispatches and warehouse levels graphically illustrated in two diagrams for one year of production

material, number of products per pallet, whether the products are stock or non-stock products, concerning lead time requirements or withdrawal of some products. The machines can be edited concerning set-up times, speed, associated costs and handling costs. They can also be edited for specific parameters, which involve the use of initial stock, i.e. in order to start with correct historical levels. Furthermore, general production policies can be edited, such as crash orders, i.e. policies which allow orders to be produced the same day as they are received (the normal policy is the following day), and an extra speed factor, which means that a general increase of machine speed is set. In addition, machine shifts can be changed based on a daily utilisation threshold and a weekend utilisation threshold (i.e. a 5-day 3-shift and a 7-day 2-shift working pattern). By default, the model automatically chooses the necessary number of shifts based on the threshold of whether additional shifts are necessary for each and every day. The shift decisions can also be specified manually. The running speed of the model is quite fast - a simulation run over one year of production takes less than a minute on a standard PC, making it possible to generate several scenarios in short periods of time.

Based on the above-mentioned possible parameter changes, several scenarios can be generated. The following section will present a specific scenario which took place at the plant, and it will provide insights into how the model can be used. For this specific scenario the actual outcome compared to the simulations made has been evaluated.

The strategic challenge

At the end of the development phase, two major strategic challenges arose and the model was also used to create accurate simulation scenarios for these challenges. Three months prior to the actual decisions concerning the challenges were implemented a simulation scenario was created. These two challenges were:

(1) The packaging company's largest customer (customer A) was expanding its business and this would significantly increase orders and thereby production. The caveat here was that the current production at that time was close to its maximum and there were different opinions within the firm as to whether it was possible to add any more orders at this point. Any investment in additional capacity was not possible in the foreseeable future and this placed extra constraints on the company.

(2) The contracts with the packaging company's second largest customer (customer B) at that time were supposed to be renegotiated during the fourth quarter of the year. The packaging firm was holding considerable amounts of finished goods inventories (in fact more than for customer A), and there had been a history of problems in the relationship with this customer concerning the costs the flexibility these high inventory levels provided. The customer demanded high levels of flexibility but was only willing to pay for it up to a point. Some people in the organisation questioned the value of having this customer; however, no-one knew the exact cost of the flexible service provided or the consequences of turning the customer down. The obvious profit margins on customer B were larger than on customer A, but these did not take into account the costs of accommodating these customers.

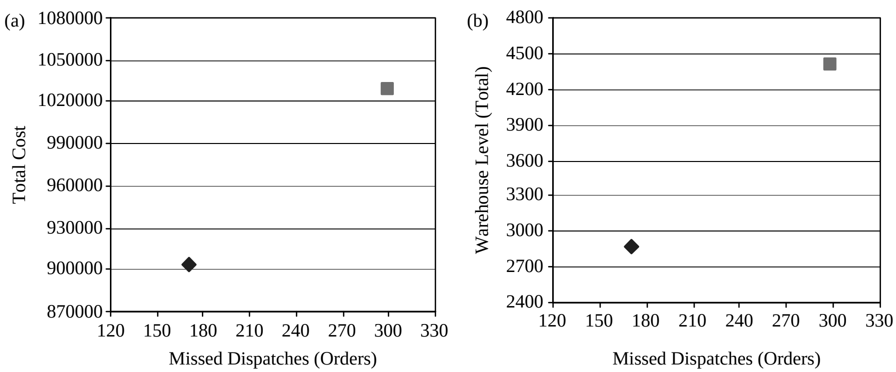
Simulations of the strategic challenge

Based on the model, several scenarios were created and evaluated by management. One of the scenarios tested was actually a combination of the two challenges; namely increasing production for customer A, i.e. by adding products and quantity, at the same time as customer B was removed from the model. Using the model to support its decision the company decided to turn down customer B since both intuition and results of the model indicated that the flexibility provided for this customer was at too high a cost. Moreover, the model was able to clearly show that, even though there would now be more overall work, the factory could just handle the new situation – there would be no negative impact on customer service levels. Consequently, a contract with customer A with its planned increase of products could be agreed on without any major investments in new capacity. This "what-if" scenario was simulated at the beginning of the third quarter and the results of the simulation model for the fourth quarter indicated that such a decision would have an impact on profitability. The model estimated a reduction in warehouse levels of 35 per cent and a decline in missed dispatches of 15 per cent, which would result in a total decrease in costs of £120,000. These figures are shown in the data summary plots in Figure 5(a) and (b) below.

All in all, this meant that, during the busiest month of the year, the company produced 10 per cent more compared to the same month the preceding year at the same time as its costs were lowered by 13 per cent (Table I). Added to this was a decrease in distribution and stock-keeping costs of almost 30 per cent. In total, this meant that the result for that month was increased by more than £100,000 (Richardson, 2003, p. 8). While it is a fact that some of these decisions concerning the customer and production changes would have been made without the input from the model, several of the decision-makers expressed their opinion that "the model provided us with understanding and indicators of what could happen which made the decisions much easier to make".

Case conclusions and discussion

While the model provided guidance for the managers in the change of customers described above, the model was also able to create other "what-if" scenarios. For



Note: The square in the right-hand corner shows the current situation and the square in the lower left-hand corner shows the simulated result of turning down Customer B and increasing production for Customer A. The diagrams show missed dispatches compared to, (1a) total cost in the left-hand diagram, and (1b) total warehouse levels in the right-hand diagram

Figure 5.
Dataset summary plots from simulation runs of the two challenges facing the company

example, it has proved itself very useful in showing how to reduce finished stocks of goods without compromising on-time, in-full delivery. Another result of the modelling and simulation process was that managers started to examine, as the plant manager expressed it, "sacred cows". For example, one issue the management was interested in ascertaining was the number of shifts that would be most beneficial for business. Several scenarios were tested showing what impact different shift alternatives had on inventory levels, missed dispatches and machine utilisation.

Conclusions and discussion

In this paper, novel insights into modelling and simulation improving the decision-making process in manufacturing and logistics have been demonstrated. These insights are theoretically based on CAS and applied through ABM and simulation. It has been shown in this paper that the characteristics of CAS can be modelled and simulated by ABM. Hence, the applicability of ABM is especially great when phenomena of interest are:

- dynamic systems distributed in time and space;
- made up of many interacting and autonomous parts, i.e. agents;
- where several objectives and often conflicting constraints exist; and
- where emergent phenomena could be exhibited.

These characteristics are suitable for manufacturing and logistics operations, since both manufacturing and logistics involve many interacting parts, e.g. machines, vehicles, actors, facilities, etc. which are distributed in both time and space and where the properties of these change over time. Furthermore, manufacturing and logistics operations often have several objectives and constraints which are frequently in conflict with each other, e.g. service levels vs costs, smooth production vs low inventory levels. The advantage of ABM here is that simulations promote simultaneous analysis of manufacturing and logistics operations from several management and organisational perspectives, i.e. perspectives can be widened. Finally, the ability to encompass emergent phenomena makes ABM applicable to, and useful for, modelling and simulating manufacturing and logistics operations. As repeatedly demonstrated in complexity-related research, systems consisting of interacting agents/parts exhibit behaviours on the aggregated level which are often impossible to predict and which are sometimes counter-intuitive. Since emergent phenomena are the collective or aggregated pattern of interacting agents, such phenomena must be modelled from the bottom-up, and ABM exemplifies this.

	Model predictions (three months in advance) (per cent)	Actual outcomes
Missed dispatches	−15	n.a.
Warehouse levels	−34	n.a.
Overall costs	−12	−13 per cent
Distribution and stock-keeping costs	−49 (stock-keeping costs)	−30 per cent
Improved result for simulated month	£120,000	> £100,000

Table I.
Result of model predictions and actual outcome

Based on the identified advantages of ABM found in literature, it can be concluded that insights from the packaging company case show that the advantages in general were verified.

- *Increased realism*. The great advantage of the model, as expressed by the managers at the plant, was that it was directly comparable to the actual activities carried out in the factory. The managers quickly understood what was happening in the model and could easily contribute with more suggestions for fine-tuning at the same time as they were given some insights into the emergent behaviours the model provided in several different "what-if" scenarios.
- *Included heterogeneity*. One year's production data was put into the model. This means that input data such as actual orders, actual customers, etc. was incorporated and not replaced by constant, average or random values. Furthermore, each machine was treated as a single unit with its own characteristics. This heterogeneity applies to customers and their order patterns as well, since some of them have seasonal patterns and others make late changes in both quantity and type of products.
- *Included bounded rationality*. In the model both the sales and planning agents made decisions based on unknown changes in orders and machine breakdowns, i.e. without complete information. In other words, decision-making dispersed both in time and in space and without assumptions of full rationality was considered and used in the model. To put emphasis on perfect rationality in the manufacturing and logistics field misleads decision-makers. The fact is that rationality is convenient in mathematical terms and is consequently an assumption to make in the creation of models mainly based on mathematical equations.
- *Scalability and flexibility*. As a result of the successful implementation and usage of the model at this plant the packaging company decided to expand the model and to include other plants in the latest version. This was possible since ABM designs allow developers to add or remove agents or systems of agents without needing to start from scratch. Each plant model could be developed separately and calibrated to incorporate specific behaviours and data for each and every machine, warehouse, sales department, production planning function, etc. However, while several benefits of ABM have been identified the case confirms the relatively high development costs in time and effort as well as in the in the calibration of the model developed.

Implications for management

Aided by agent-based models and simulations, decision-makers can benefit in several ways. Firstly, they acquire increased understanding of the impact of unscheduled factors often found in reality, such as breakdowns, accidents and changes of demands. Such aspects are reduced, and even ignored, when transferred to most traditional models. Thus, the optimised solutions from these models mislead managers into believing in future scenarios which scarcely reflect reality. Secondly, simulation scenarios can guide practitioners' intuition since patterns on the macro level emerge out of agents' interactive behaviour. Together, with insights from CAS these emergent outcomes can be explained and understood and are thus beneficial for the improvement of decision-making in companies. Thirdly, ABM can also help managers to find where most leverage is to be gained in improvement efforts. This is based on the fact that ABM allows models to encompass several business functions and how they affect each other. Finally, as the case presented in this paper shows, there are sometimes even opportunities to improve predictability based on the scenarios generated.

A concluding observation is that one of the major reasons for using ABM is that its relevance for industry will increase, since models and simulations will be developed for a chosen system, i.e. models and simulations will be context-dependent. In addition, the ABM approach will make research results comprehensible to people in industry and organisations since they can identify themselves more directly with the agents. This is because the agents in the models and the simulations often represent tangible parts in the system being studied (e.g. machines, processes, etc.). Consequently, the ABM approach narrows the gap between managers who are supposed to understand and believe the results derived from models, and the modellers who construct them. This usefulness has been identified in the case provided in this paper. Furthermore, decision-makers aided by agent-based models can directly experiment with, and test, policy changes. They can also create scenarios as to what outcomes such changes would have on their organisations. In essence, ABM and simulation provide several opportunities in improving decision-making.

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