Modelling Economic and Ecological Aspects of Inventory Management Strategies within a Component-based Material-flow Simulator

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1 Motivation and Goals

Modern society's increased globalization and the growing scarcity and costs of resources require that companies deal effectively with their customers and suppliers. Efficient inventory management strategies, based on optimal ordering policies, play an important role in this process. While profitability is likely to remain the dominant goal, there are many other objectives that must be met, such as reducing the negative impact of economic activities on the environment. By using ordering strategies that improve transportation efficiencies (see [GrHe03]) *ecologically responsible* inventory management must, for example, minimize all environmental burdens attributable to transportation. Such efforts can be further assisted by environmentally friendlier vehicles and shorter delivery routes; see [Wohl et a. 01].

In addition to a set of building blocks for modelling complex inventory strategies, the components discussed in this paper support modelling *environmental* aspects, such as transport emissions, and offer easy embedding of *customized* inventory simulations within a material flow simulator for specific classes of application.

2 Inventory Systems and Simulation

Inventory systems are needed by all types of trading companies and at all levels of industrial production. Their purposes range from ensuring uninterrupted supply of raw materials to the storage of finished products. All inventory systems serve as *buffers* between time-dependent activities. While an inventory's *outputs* are solely determined by external demands, e.g. by customers ordering products, its *inputs* can be controlled by *inventory policies*, whose optimal choice is inventory management's ultimate goal. An effective reordering strategy is one such policy, whose choice must consider relevant tradeoffs between two conflicting goals:

- Minimizing storage costs, by keeping inventory levels as low as possible
- Ensuring a company's capacity to deliver and thereby retain the trust of its customers as well as avoiding any contractual costs associated with failing to do so.

Modern enterprises are complex organizations and optimal reordering strategies must take account of a wide range of factors. Suitable models can therefore become rather complex, particularly if they are to take both economic and *ecological* aspects into account (see [Wohl05]). While *linear optimization* techniques have often been used in the past, their application assumes many simplifications that may lead to incorrect models. Some examples of unrealistic assumptions include:

- Constant and deterministic demands.
- Independence of processes; e.g. supply and demand.
- No consideration of the consequences of an inability to deliver.
- No, or only deterministic and constant procurement and delivery times.
- No consideration of financial and capacity constraints.

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On the positive side, as long as such simplifications can be justified, these models guarantee optimal answers relatively quickly. Unfortunately, however, most practical problems are far too complex to be adequately captured in such closed form solutions and simulations are therefore the only viable alternative.

While good models should always be simple, they should also be valid and accurate with regard to the range of questions they have been designed to answer. This often requires inclusion of details which would make analytical models intractable. Simulation models, on the other hand, can incorporate any level required level of detail and can also include relevant external influences through stochastic components; i.e. probability distributions. On the negative side, simulations are only a tool for model-based *experimentation*, and can not directly derive optimal solutions. Exploring the behaviour of models including stochastic components may also need computationally expensive series of long simulation runs. On balance, however, simulations advantages for studying complex scenarios outweigh their disadvantages.

3 The Material Flow Simulator

The idea of a *material flow simulator* that integrates economic and ecological perspectives is based on a combination of discrete event simulation with classical analysis techniques (see [Wohl99]). Within this context it aims to help answer all ecological *and* economic questions that are relevant for both *tactical* and *strategic* decision making; see [Wohl05], page 177).

Reusability and flexibility have been guiding principles in the material flow simulator's design. This is achieved through a component-based architecture, where application specific components are inserted into a modular framework. Framework implementation was based on *Delphi*, an integrated software development platform that includes *Object Pascal* and a number of class libraries. Component development also has made use of Microsoft's COM architecture.

The resulting software can be deployed in a number of contexts:

- As a *pure simulation system* that supports graphical model construction and the planning, execution and analysis of simulation experiments in many domains; e.g. manufacturing and inventory systems.
- As an *environmental management information system* (EMIS) that integrates discrete event simulation with material flow analysis.
- as an *add-on* to an existing EMIS

By reusing existing components, component-based software aims to increase flexibility and reduce software development time and development costs. The material flow simulator serves these goals by offering core functionalities that can be augmented through plug-in components for various modelling phases; e.g. model construction, experimentation, data analysis and display. It supports both order-based and material-based modelling viewpoints. By using different plug-in components we can, for example, display simulation results in terms of either input-output matrices or standard statistical measures (see [Wohl05], page 180). In this way the material flow simulator integrates economic and ecological system descriptions into a single framework, while its component-based nature significantly reduces model development time.

During a simulation experiment the material flow simulator records all material usage each time a resource consumption or material emission event occurs. This is accomplished by *indicators* which store material and energy consumption for each event or activity; i.e. pairs of start and finish events. Such indicators define which materials are needed as input and output streams for each of the components involved in the event or activity

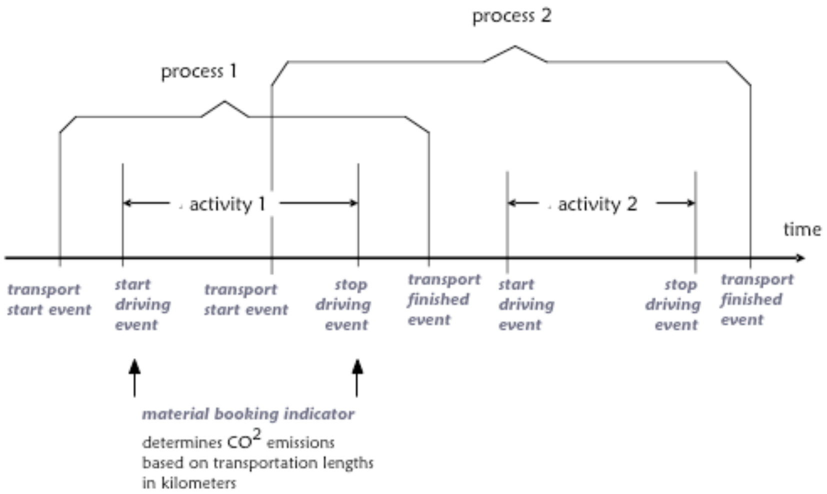

Figure 1: Processes, Activities, Events and Material Booking Indicators

Figure 1 shows how simulation events and material booking indicators are related. There are 8 events, which participate in 4 activities and 2 processes. The two processes describe lifecycles for e.g. two vehicles, each of which is involved in a transportation activity. Driving activities are part of and nested inside transportation activities. They cover a *distance* and occur in between corresponding *start* and *stop* driving events. Vehicle characteristics and driving distance, for example between an inventory depot and a supplier, determine an activity's environmental burden in terms of CO_2 emissions. These are recorded by the relevant material booking indicator.

Indicators are made available to a material flow simulator through plug-ins, whose architecture is based on software engineering's well known *observer* pattern (see [GHJV], page 257). Within this pattern all observers registered at a component will be informed whenever the simulation engine triggers events in which the component will be involved. Relevant *ecological* indicators for transportation activities are mainly CO_2 emissions. These can be directly attributed as environmental burdens to an inventory system, since transportation is needed for orders to reach storage facilities. CO_2 emissions can be reduced by minimizing transport activities, changing vehicle types or by using alternative fuels. Section 5 will briefly discuss the connection between transport activities and inventory policies.

4 Inventory-specific Plug-In Components

The material-flow simulator's component-based plug-in architecture permits easy reusability and extension. Since plug-ins are customized components, the material flow simulator will load them dynamically; i.e. "on demand". This means that the simulator itself becomes simply a framework for managing different processing functions, each of which is provided by a separate plug-in component. Plug-in components interact with this framework on the basis of contracts, which require that a number of pre- and post-conditions must hold after registration; see ([GoHe05], page 83) and ([MaVö03], page 2) for more detail.

A component-based material flow simulator can easily be extended to model complex inventory systems in a convenient manner. For example, we can quickly investigate the effects of multi-product inventories, using multiple suppliers, multiple transportation channels, changing demand patterns and different inventory policies. Economic (e.g. costs and service levels) as well as ecological aspects can be considered. Graphical editor components ease model construction and additional components' functionality supports model execution, data collection and analysis. Models can also be stored in persistent databases and reused on demand.

A command language with graphical features for managing plug-in libraries complements the simulator's tools for graphical model construction. *Figure 2* shows an example, where ovals indicate inventory plug-in commands and components.

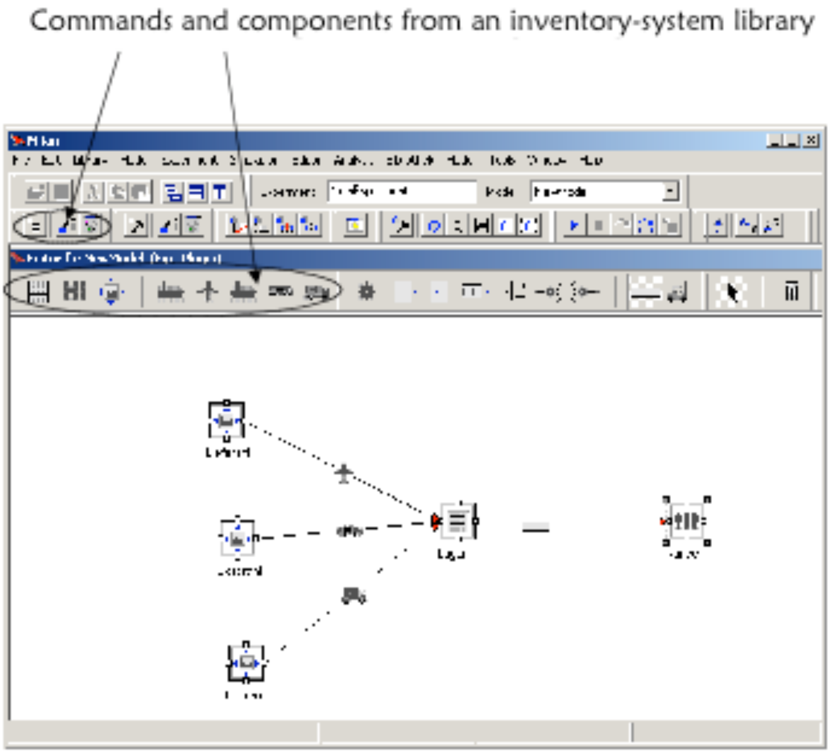

Figure 2: Visualizing Commands and Components

The following list enumerates some of the required components for modelling inventory systems within a material flow simulator:

- *Stationary model components*: inventory component, connection component, supplier component, demand component.
- *Dynamic model components*: products.

Both types of components' functionality is specified through *modules* or building blocks; see [Wohl05], page 253. Dynamic components are often quite simple; i.e. they just move through a model and trigger the stationary components' execution.

5 Example

An example model, which shows how changes to delivery strategies can reduce *both* inventory costs and harmful emissions, will help to make our discussion more concrete. Some data for this example, which includes demand data and model structure, was taken from a co-operation with a medium-sized Hamburg company; see [GoHe03]. Sensitive economic data, such as inventory costs, direct and indirect costs of supply, transportation costs, capital costs and all costs associates with inability to supply, is, however, purely fictional. We have also simplified the scenario to 4 rather than 64 different products.

Let us assume that a company wants to explore the consequences of managing its customers' inventories under a replenishment strategy, and that simulation is used to determine the minimum and maximum inventory levels across all products for a near 100% service level and optimal utilization of inventory capacities and transportation channels. In this context, reducing fuel consumption for trucks, for example, becomes both an economically (i.e. lower expenditure) and ecologically (i.e. lower emissions) desirable goal.

Table 1 shows characteristics of 4 products in terms of their demand distribution, reorder policy, initial inventory and price. Note that empirical data about customer demand has been aggregated into triangular distributions, which the model will sample from. There is also a fixed cost of 20 GE per order, and each inability to supply event costs the company 15 GE per product.

Input Parameters for Simulation Experiments						
product	*demand arrival distri-bution*	*demand volume distri-bution*	*reordering policy*	*minimum and average de-livery volume*	*initial inven-tory*	*price*
rubbish bag *10010*	RealDistNormal (1.0, 0.1)	IntDistTriangular (120, 165, 200)	3000/1600/100	300/300	3000	1.0
rubbish bag *10013*	RealDistNormal (3.0, 1,2)	IntDistTriangular (80, 120, 130)	1680/720/60	240/240	1680	1.2
rubbish bag *92010*	RealDistNormal (8.0, 1.2)	IntDistTriangular (60, 80, a120)	800/390/20	200/200	800	0.8
rubbish bag *11001*	RealDistNormal (2.0, 0.9)	IntDistTriangular (140, 150, 200)	1800/750/80	300/300	1800	1.3

Table 1: Product-specific Model Inputs

Using a "point & click" style for model construction results in a graphical representation of model entities and their connections. This action is followed by entering product details, such as type, name and weight, into separate windows (see *figure 3*). Note that visual representation of inventory, supplier, connections and demand components is mapped into relevant *ActiveX* windows, in which all model attributes can be set or changed later.

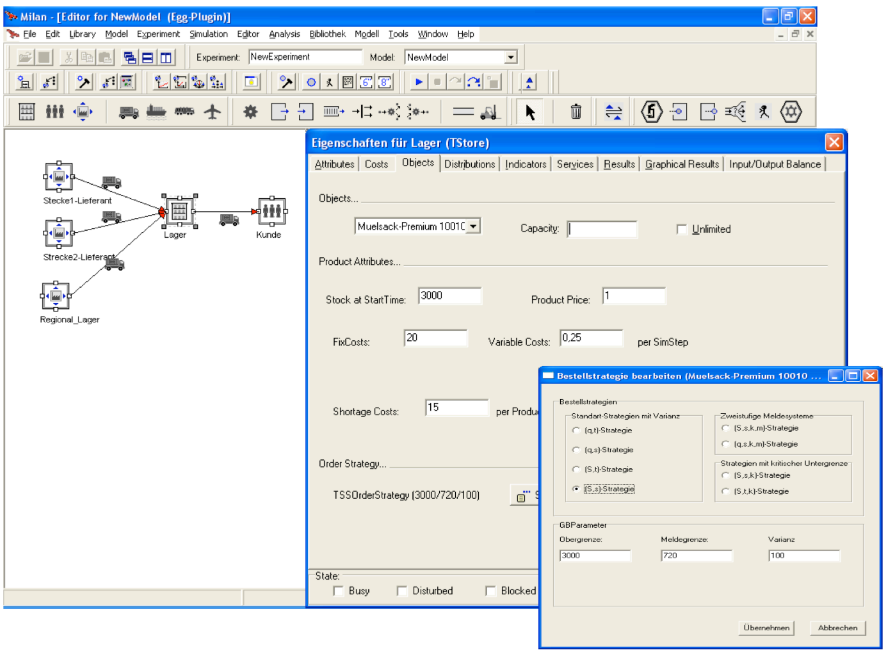

Figure 3: Visual Model Representation with *ActiveX* Windows showing Inventory and Reorder Policy Parameters

Simulation results can be graphically shown as histograms, time series diagrams, or pie charts. Some results of a sample experiment to investigate the relationship between service levels and inventory costs are presented in *figure 4*, where the smaller window summarizes all relevant inventory and product characteristics, such as costs, demand, order and delivery numbers, service levels etc. Note that such numbers will only become meaningful for comparisons across a range of scenarios. Since different inventory strategies and ordering policies may have conflicting goals, each has a different priority level assigned to it. Meeting service demand has the highest priority, together with transportation cost optimization. Minimizing deliveries and achieving high transport vehicle utilization lead to reductions in energy consumption and harmful emissions.

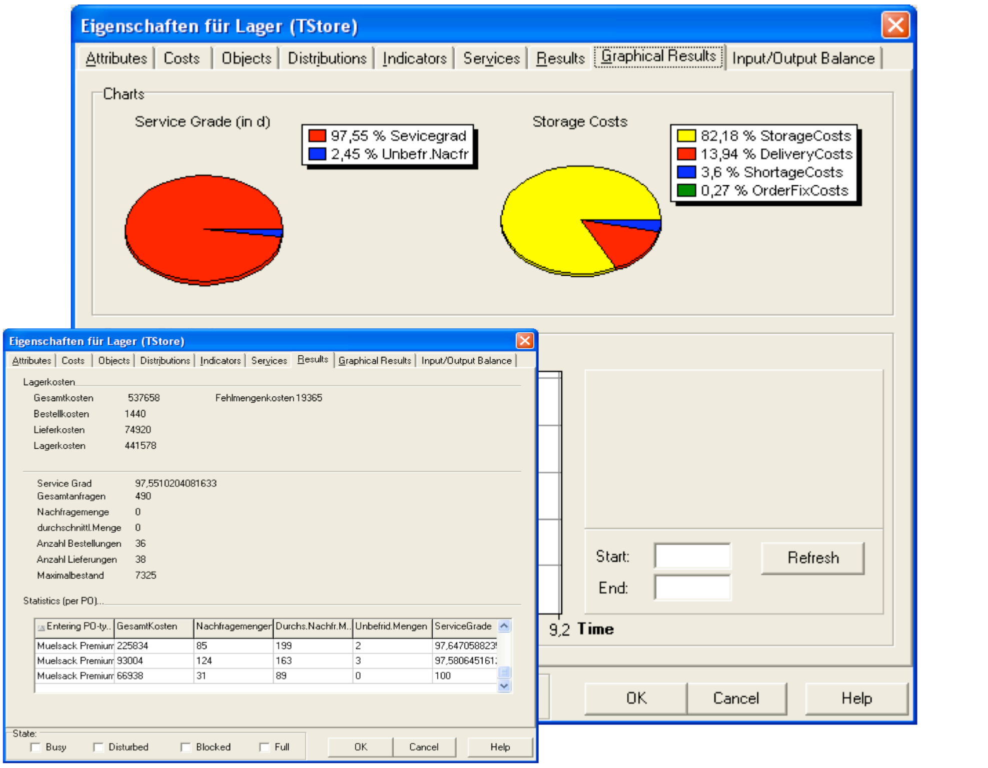

Figure 4: Model Results

Table 2 demonstrates what may happen when inventory policies change. It shows partial results for two different policies; a (S, s) and a (S, t) reorder strategy. Note that a (S, t) reorder strategy uses a constant time interval between orders. t = 30 therefore means that S items will be ordered every 30 time units, regardless of current inventory levels. Our model uses two different t values for different simulation runs (30 and 14). In contrast to this strategy, a threshold of minimum inventory (s) must be crossed in a (S, s) reorder strategy. In that case S is the desired inventory level and a variable number of items (S - s) will be ordered each time inventory falls below level s.

	(S, s) reorder policy	*(S, t) reorder policy with t = 30*	*(S, t) reorder policy with t = 14*
Total costs	537,658	834,636	605,660
Restocking costs	76,360	51,640	76,860
Inventory costs	414,577	*351,536*	528,386
Cost of inability to supply	19,365	431,205	0.00
Orders	36	16	34
Deliveries	38	24	51
Service level	97.55 %	65.40 %	100 %

Table 2: Comparison of Inventory Policies

Table 2 shows the advantages and disadvantages of each strategy clearly. With an (S, t) strategy longer reorder intervals mean fewer deliveries, which means better transport vehicle utilization and fewer emissions. On the negative side, if given service levels must be met, this strategy increases both capital costs and average inventory. The (S, s) strategy, on the other hand, seems to achieve similar benefits at lower overall costs.

6 Summary and Discussion

Simulation can successfully support management decisions related to inventory policy optimization. It allows experimentation with alternative scenarios and highlights errors in assumptions as well as undesirable policy implications, without any negative impact on real systems. In light of these benefits it seems surprising that simulation is not more widely used in industrial practice.

Some of the reasons that are often cited for simulation's lack of popularity refer to factors like costs, length of learning period, a perceived need of programming skills, and inflexible and user-unfriendly software tools. Reducing the effort of model construction and experimentation through better model reusability and transparency can reach a long way towards making simulation a more attractive tool. In addition to these aspects, modern simulation environments also strive to support iterative and exploratory development styles (see [Gruet95], page 204).

By integrating tailored components for modelling inventory management into a generalized simulation framework, the component-based material flow simulator discussed in this paper improves simulation software by applying modular development techniques. In this context a range of plug-ins allow quick and easy model construction, experimentation and analyses, by using a mix of graphical and textual specifications. Tight integration with material flow analysis permits the investigation of economic as well as ecological impacts of different inventory strategies. Modelling ecological consequences such as transport emissions as an integral part of finding an optimal inventory strategy may lead to reduced transportation costs as well as improved good will within the community through ecologically responsible management.

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