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Towards a model for managing uncertainty in logistics operations

– A simulation modeling perspective

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Department of Design Sciences
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Lund University

Thesis for the degree of Licentiate in Engineering

**Towards a model for managing
uncertainty in logistic operations**
– A simulation modeling perspective

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Lund, May 2006

Ola Johansson

Abstract

Uncertainty rules supply chains. Unexpected changes constantly occur on all levels; on strategic levels through globalization, introduction of novel technology, mergers and acquisitions, volatile markets, and on operational levels through demand fluctuations, and events such as late arrival of inbound material, machine equipment breakdown, and quality problems. Uncertainty is becoming an increasing problem as the focus on cost reductions and efficiency in industry tends to stretch supply chains, making them longer and leaner, and thus more vulnerable to disturbances.

The aim of this thesis is to explore strategies for evaluating and managing uncertainties in a logistics context. It has as its objectives; “to propose a method for modeling and analyzing the dynamics of logistics systems with an emphasis on risk management aspects”, and “to explore the impact of dynamic planning and execution in a logistics system”.

Three main strategies for handling uncertainties are discussed; robustness, reliability, and resilience. All three strategies carry an additional cost which must be weighed against the cost and risk of logistical disruptions. As an aid in making this trade-off, a hybrid simulation approach, based on discrete-event simulation and Monte Carlo simulation, is proposed. A combined analytical, and simulation approach is further used to explore the impact of dynamic planning and execution in a solid waste management case.

Finally, a draft framework for how uncertainty can be managed in a logistics context is presented, along with the key reasons explaining why the proposed simulation approach has proven itself useful in the context of logistics systems.

Keywords: supply chain, logistics, simulation, uncertainty, risk

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Paper 1: The effect of dynamic scheduling and routing in a solid waste management system

Paper 2: Managing uncertainty in supply chain operations – a hybrid simulation approach

Paper 3: Notes on the validity and generalizability of empirical simulation studies

1 INTRODUCTION

1.1 Background

The increasing competitive pressure in the global economy has forced companies to reduce costs, expand markets and develop new, innovative products at an ever more rapid pace. Some of the key strategies for supporting this are global sourcing, supplier base reductions, lean manufacturing, outsourcing, and improved IT/IS infrastructure. The overall result has been improved efficiencies in the industrial sector, but also more and more complex and fragile supply chains which require stability and predictability to function. Alas, globalization has also resulted in increasing market turbulence through more volatile demand, shorter product and technology life-cycles, and increased vulnerability to disruptions (Christopher and Lee, 2004). This paradox suggests that supply chain managers must increasingly devote time and energy to handling uncertainties, either through the design of the supply chain, or through increased ability to rapidly respond to changing conditions – or both.

The strategic design of a supply chain has a major impact on its performance when unexpected events occur and there are numerous examples of how companies have encountered severe problems when their supply chains were disrupted. The closure of US airspace after the terrorist event September 11, 2001, for example, forced the car manufacturer Ford to close down five of its plants which led to a 13% reduction in production in the fourth quarter (Martha and Vratimos, 2002). Similarly, the outbreak of Severe Acute Respiratory Syndrome (SARS) challenged supply chain flows from Asia in 2003 (Arminas, 2003), and more recently, hurricane Katrina hit the US Gulf Coast leading to massive disruptions in logistics operations in the area (Levans, 2005).

Traditional models for supply chain design focus on cost efficiencies, and in vogue strategies such as Just-In-Time, are extremely vulnerable to disruptions (Armbruster, 2003). The cost and risk of not obtaining supply can, however be leveraged, to encompass redundancies in inventory and supply base. These considerations will be either to increase reliability, i.e. to minimize the risk that disruptions occur, or to increase robustness, i.e. to ensure high performance despite disturbances. Reliability can be

accomplished through local sourcing versus global sourcing, while robustness can be achieved through dual sourcing instead of single sourcing.

Regardless of the level of built-in risk tolerance in the supply chain design, undesirable events will occur which need to be managed in order for damage to be contained. This translates to a need for responsive behavior to restore the supply performance after being disturbed. This property has been defined as supply chain resilience (Christopher and Rutherford, 2004). To accommodate responsive behavior, the gap between planning and execution must be closed and systems which support dynamic planning, i.e. rapid planning and execution cycles, are needed.

1.2 Research purpose and objectives

The purpose of the thesis is to explore strategies for evaluating and handling uncertainties in a logistics context. Based on this purpose, two more tangible objectives can be defined:

- To propose a method for modeling and analyzing the dynamics of logistics systems with emphasis on risk management aspects.
- To explore the impact of dynamic planning and execution in a logistics system

1.3 Scope and demarcations

The breadth of contemporary research in logistics and supply chain management makes it important to delimit the research area by defining the scope of this thesis work. The thesis has the following focal points and bounds:

Logistics domain: Management of uncertainty on a tactical level in logistics systems. This means that strategically taken decisions, e.g. localizations of plants and warehouses, provide boundaries for decisions on a tactical level.

Simulation domain: Discrete-event simulation, mainly as a method for exploring the dynamics and stochastic behavior of logistics systems.

Performance indicators: Comparisons between different solutions or systems are based on monetary performance indicators.

2 FRAME OF REFERENCE

The frame of reference outlines the theories, models, and definitions used in the thesis work in order to provide a background and knowledge of the researcher's stance within the research field.

2.1 Logistics and supply chain management

2.1.1 Logistics

Logistics has been a research area since the beginning of the 20th century, but the history of logistics dates back much further than that. Throughout the history of mankind, the success, or failure, of armies has been attributed to logistics capabilities. One of the most successful military commanders of all times, Alexander the Great, managed to conquer most of the known world largely due to superior logistics planning; his troop movements were synchronized with harvest cycles and access to sea transportation, flexibility and speed were improved by removing the usual team of servants, spouses and wagons from the marching army, and base camps with supplies were set up prior to the arrival of the marching army (Van Mieghem, 1998). Much of the early developments in the logistics discipline were done based on military needs. The first use of the word *logistics* itself is attributed to the French General Antoine-Henri Jomini, who devised a theory of war based on the trinity of strategy, ground tactics, and logistics. Military logistics has been a source of inspiration for civilian use and still offers many insights into business logistics. The US Air Force defines logistics as:

“The science of planning and carrying out the movement and maintenance of forces. In its most comprehensive sense, those aspects of military operations that deal with: a. design and development, acquisition, storage, movement, distribution, maintenance, evacuation, and disposition of material; b. movement, evacuation, and hospitalization of personnel; c. acquisition or construction, maintenance, operation, and disposition of facilities; and d. acquisition or furnishing of services.” (Air Force Logistics Management Agency, 2002)

The term *logistics* entered business terminology during the 1960s. Prior to that, logistics was referred to as physical distribution. In addition to military logistics, commercial logistics in the early days was also influenced by the

agricultural sector, and later, by many other disciplines such as industrial economics, management science, information technology, management strategy, and marketing (Kent & Flint, 1997). A commonly used commercial definition of logistics has been provided by the Council of Supply Chain Management Professionals (CSCMP):

“Logistics management is that part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services, and related information between the point of origin and the point of consumption in order to meet customers’ requirements...” (CSCMP, 2005)

The major differences between the military and the civilian definitions of logistics are that customer requirements and efficiency aspects are not mentioned in the military version. Military logistics, however, often emphasizes that logistics processes occur in dynamic and unpredictable environments. As a consequence, logistics processes often require “a combination of forecasting ability, the ability to control that which is controllable, and the flexibility to adapt to changing conditions and unexpected events.” (McGinnis, 1992)

2.1.2 Supply chain management

Supply chain management (SCM) is a concept closely related to logistics management. Researchers argue over the exact meaning of SCM. Larson and Halldórsson (2004) have identified four perspectives of the relationship between logistics and SCM; (1) the traditionalist perspective, where SCM is a field within logistics, (2) the re-labeling perspective, where SCM is another name for logistics, (3) the unionist perspective, where SCM is a larger field containing the smaller logistics field, and (4) the intersectionist perspective, where SCM and logistics are equally large fields that to some extent, overlap. The CSCMP has taken the unionist perspective and defined supply chain management in the following way: *“Supply Chain Management encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third-party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across*

companies ...” (CSCMP, 2005). Others confess that they “do not distinguish between logistics and supply chain management.” (Simchi-Levi et al, 2000)

2.2 Uncertainty and risk management

Uncertainty is term which can be used to describe a multitude of phenomena. When faced with a problem, we might be uncertain about our knowledge of the situation, we might be uncertain of our preferences towards different solutions, and we might be uncertain how to solve it. There are many reasons behind uncertainty such as incomplete information, conflicting information, approximations, linguistic imprecision, and variability. Typically, we are even uncertain about our degree of uncertainty.

The most common tool for quantifying uncertainties is the mathematical concept of probability. This concept is, however, not without controversy and two main schools of thought exist. The classical or frequentist view is that probability is the frequency with which an event occurs in a long sequence of similar trials, while the Bayesian or subjectivist view is that probability is the degree of belief a person has that a certain event will occur, given all the relevant information currently known to that person. Since different people may have different information, and people will acquire additional information, there is no one “fixed” probability for an event. The subjectivist view, however, allows for analysis in real-world cases where no relevant population of trials can be identified.

On a fundamental level, two types of uncertainty can be distinguished, aleatory, or stochastic uncertainty and epistemic, or knowledge-based uncertainty. The aleatory uncertainty represents randomness in nature and has been given many different names in literature, e.g. variability, randomness, stochastic or irreducible uncertainty. The epistemic uncertainty on the other hand represents a lack of knowledge about fundamental phenomena, and is thus often referred to as ambiguity, knowledge-based, or reducible uncertainty. From a practical point of view, one distinction between the two types of uncertainty is that knowledge-based uncertainty can be reduced, e.g. by gathering more information, while stochastic uncertainty cannot. Another important difference is that the stochastic uncertainty partially cancels itself out in a risk analysis, but knowledge-based uncertainty does not.

On a less profound level, and more applicable in a modeling context, Parry (1996) discusses three major groups of uncertainty:

- parameter uncertainty
- model uncertainty
- completeness uncertainty

Parameter uncertainty is a consequence of incomplete information about the value of parameters used in a model. Parameter uncertainty can be handled by assigning a probability distribution to the parameter describing the uncertainty in the value, or by conducting a parametric sensitivity analysis to examine the effects of deterministic changes on the output. Parameters which are subject to natural variability are usually treated by the former method, while the latter method is recommended for parameters which represent decision variables, i.e. variables the decision maker can control, e.g. buffer size, or value parameters, i.e. parameters which represent preference aspects, e.g. discount rate (Morgan and Henrion, 1990). Model uncertainty originates from the fact that any model is unavoidably a simplification of reality, and thus is false. This is closely related to epistemic uncertainty. Finally, completeness uncertainty is a consequence of scope limitations, and is as such not an uncertainty in itself. Completeness uncertainty is, however, difficult since it deals with the unanalyzed contribution to the overall uncertainty.

The concept of risk is related to uncertainty as risk by definition is “the possibility of suffering harm or loss.” (The American Heritage® Dictionary of the English Language: Fourth Edition. 2000) Early influential references often distinguish the difference between risk and uncertainty by stating that risk is something which can be assigned a probability, while uncertainty is something unique and whose probabilities are unknowable (Knight, 1921; Luce and Raiffa, 1957). More recent references adopt the Bayesian view (e.g. Covelto and Merkhofer, 1993) and define risk as “A characteristic of a situation or action wherein a number of outcomes are possible, the particularly one that will occur is uncertain, and at least one of the possibilities is undesirable.”, and uncertainty as “a situation where a number of possibilities exist and one does not know which one of them has occurred or will occur.” Others have pointed out that risk is a single value representing the probability that a certain (often negative) event will occur, while uncertainty is a probability distribution function representing a range of possible values (Simpson et. al., 2000).

From a more technical perspective, risk can be defined as the probability of an event multiplied by the (negative) consequences of the event. Kaplan (1997) suggests that risk is defined by the answer to the three fundamental questions: (1) “What can go wrong?”, (2) “How likely is that to happen?”, and (3) “What are the consequences?”. The technical view of risk has, however, been criticized for neglecting important social, psychological, and cultural aspects. What people perceive as undesirable events depends on their values and preferences, the interaction and consequences of human activities are more complex than probability numbers can capture, and the calculation of risk with equal weights for probability and magnitude implies indifference between high-consequence, low-probability- and low-consequence, high-probability events. This has been shown not to be true. Nevertheless, technical risk analyses serve a major purpose in facilitating decision making (Renn, 1998).

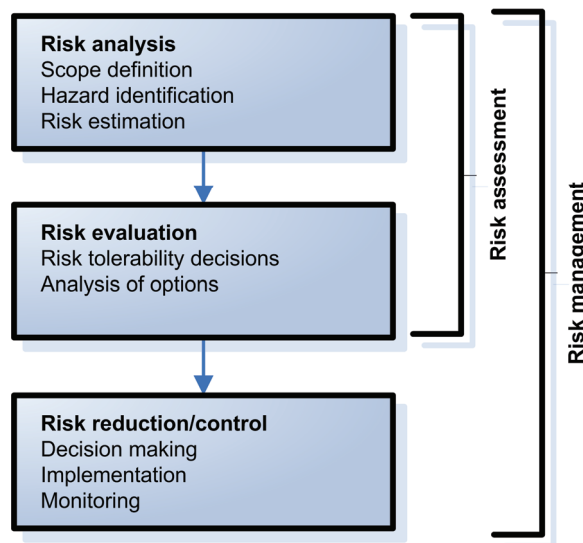


Figure 2.1 Risk Management (IEC, 1995)

2.2.1 Risk management

Risk management is the systematic approach to identifying, analyzing, and acting on risks. It incorporates all steps from the initial identification of risks to the final decision on risk-reducing actions and risk monitoring. The process can be divided into three key steps, see figure 2.1. (IEC, 1995).

2.2.2 Risk analysis

Risk analysis is the structured process of (1) identifying sources of risk and undesirable events, (2) estimating their probabilities, (3) estimating their consequences, and (4) calculating the associated risks. A wide array of methods exists for identifying sources of risk, e.g. comparative methods (e.g. checklists), fundamental methods (e.g. Failure Mode and Effects Analysis (FMEA)), and logical diagram methods (e.g. fault tree analysis). Nevertheless, the identification of risk sources appears to be the least-mentioned risk technique, despite the fact that it is seen as the most important step (Elkington and Smallman, 2002). Once the potential risk sources have been established, their respective probabilities are estimated through the use of historical data or expert opinions, and the resulting consequences, should an unwanted event occur, are assessed. Qualitative methods are generally used for identifying sources of risk, while semiquantitative methods are used for estimating probabilities and consequences. The final step of calculating the risks is normally quantitative and can be either deterministic or stochastic. In the case of stochastic analysis, uncertainties are incorporated by modeling input parameters as probability distributions which are propagated through the analysis to the corresponding uncertainty of the result.

2.2.3 Risk evaluation

During risk evaluation, the decision maker determines whether the identified risks are tolerable, and investigates alternative options. A few guiding principles exist, although in practice it is often impossible to apply them all (Haeflner et al 2000):

- *Reasonableness principle*: An operation should not involve risks if this can be avoided or if the risk level can reasonably be decreased.
- *Proportionality principle*: The risks an operation involves should not be disproportionately large in relation to the benefit the operation results in.
- *Distribution principle*: The risks should be reasonably distributed in a society in relation to the advantage the operation results in.
- *Catastrophe avoidance principle*: The risks should result in accidents, with limited consequences which can be managed by available rescue resource in the society, rather than a large catastrophe.

The tools used during risk evaluation are sensitivity analysis, the study of how the risk quantitatively relates to different risk sources, or scenario analysis, analyzing possible future events by considering alternative possible outcomes. In the case of stochastic risk analysis, the output distribution shape can also be studied.

2.2.4 Risk reduction and control

The basic objectives of the risk reduction and control step are to consider whether a risk is worth accepting, and if so, to develop risk minimization actions which focus on lowering the probability of occurrence and/or lessening the consequence, in order to reduce the overall magnitude of the risk.

It should be mentioned that risk reduction is not the only option available to decision makers. Other risk-handling strategies may be to accept the risk as is, to trade the risk through e.g. an insurance policy, or simply to neglect the risk.

2.3 Supply chain uncertainty

Risk management and contingency planning may be well known and used in many firms on an individual basis. Nevertheless, these firms have often overlooked the critical exposures along their supply chains (Jüttner et al, 2003). In a situation of increasing supply chain vulnerability, this makes adopting a risk and uncertainty perspective to perhaps one of the most important capabilities a firm needs to have today (Barry, 2004).

“Supply chain uncertainty refers to decision making situations in the supply chain in which the decision maker does not know definitely what to decide as he is indistinct about the objectives; lacks information about (or understanding of) the supply chain or its environment; lacks information processing capabilities; is unable to accurately predict the impact of possible control actions on supply chain behaviour; or, lacks effective control actions (non-controllability).” (van der Vorst and Beulens, 2002)

Supply chain uncertainty can be categorized in different ways. One framework for dividing uncertainties based on a framework by Mason-Jones and Towill (1998) has been suggested by Christopher and Peck (2004):

- Uncertainty internal to the focal firm

- Process, i.e. disruptions in internal processes, e.g. machine breakdown
- Control, i.e. rules, systems and procedures for controlling internal processes, e.g. batch sizes, order quantities, stocking policies etc.
- Uncertainty internal to the supply chain (but external to the focal firm)
 - Demand, i.e. disturbances in the flow of products, information or cash between the focal firm and the market
 - Supply, i.e. the upstream equivalent of the above
- Uncertainty external to the supply chain
 - Environmental, e.g. political instability, terrorism, natural disasters, regulatory changes, strikes etc.

A concept closely related to supply chain uncertainty is supply chain vulnerability. It has been defined as “the existence of random disturbances that lead to deviations in the supply chain of components and materials from normal, expected or planned schedules or activities, all of which cause negative effects or consequences”. (Svensson, 2000) In a proposed framework for categorizing supply chain vulnerability, Svensson distinguishes between the sources of disturbance, i.e. atomistic (i.e. direct) and holistic (i.e. indirect), and the categories of disturbance, i.e. quantitative and qualitative.

Uncertainty management in logistics

There are many strategies for managing uncertainty to be found in the logistics literature and a broad vocabulary to describe supply chains which are designed with uncertainty in mind. Three terms, however, seem to be more prevalent than others; reliability, robustness, and resilience. In practice, as well as in literature, the terms are often used interchangeably, and although overlapping areas exist, they can have quite different meanings in the context of supply chains. The terms are briefly described in the sections below.

2.3.1 Reliability

Reliability is the ability of a system to perform its required functions under stated conditions for a specified period of time (IEEE, 1990). Increased

reliability generally means a reduced risk of disruptions occurring. The concept, however, does not cover the system's ability to handle disturbances once they have taken place. One of the most important design techniques to achieve reliability is redundancy. Basically, this means that if one part of the system fails, there is a backup system. Although redundancy significantly increases the reliability of a system, it is expensive and provides no value, except in those rare occasions when disruptions actually occur. Due to the cost, it is often limited to the critical parts of a system. In the context of supply chains, redundancy would equate to having backup suppliers or backup transportation modes. Other design techniques rely on understanding the reasons behind disruptions at a detailed level so the processes can be re-designed in order to minimize risks, or on "derating", i.e. using requirements which significantly exceed the normal specification for the expected need. An illustration of the former technique would be to use local suppliers instead of suppliers located in another continent, and the latter would be to require suppliers to have considerably shorter lead times than what is actually needed.

2.3.2 Robustness

Robustness is the degree to which a system can function correctly in the presence of invalid inputs or stressful environment conditions (IEEE, 1990). Furthermore, "robustness signifies insensitivity against small deviations in the assumptions." (Huber, 2004) Taguchi (1986) is a pioneer in developing methods for designing robust systems. His parameter design methodology is generally used in manufacturing environment to achieve robustness by designing products or processes so that they consistently exhibit a high level of performance and are minimally sensitive to noise. A parameter design generally involves two types of factors: control and noise factors (uncontrollable factors). Parameter design examines how control factors should be set in order to achieve the desired function of the system, while minimizing the negative impact of the noise factors. In terms of logistics system, decision variables such as buffer sizes and inventory policies are control factors, while lead-time variation, machine breakdown, and strikes are examples of noise factors.

2.3.3 Resilience

Resilience is a term often used in materials sciences where it refers to the capacity of a material to absorb energy when it is deformed elastically and then, upon unloading, recovers its shape. In analogy, resilience has been

defined in the context of logistics as “the ability to bounce back from a disruption.” (Sheffi, 2005) Resilience is thus closely linked to the notion of flexibility. Christopher and Peck (2004) have proposed a broader definition where resilience is “the ability of a system to return to its original state or move to a new, more desirable state after being disturbed.” This definition also includes an adaptability aspect.

Resilience can be achieved by either creating redundancy or increasing flexibility. While redundancy represents sheer cost as discussed in the previous section, flexibility not only increases resilience in unstable times but also provides benefits in the normal course of business, e.g. better responsiveness in situations with high demand and supply volatility (Sheffi, 2005).

2.4 Lack of knowledge

Despite the widely acknowledged increase of uncertainty in today’s supply chains, a more structured approach to investigate this area can only be traced back a few years and the area is still largely unexplored (Jüttner et al., 2003; Peck, 2005). Furthermore, researchers have quite different views on how to deal with supply chain uncertainty. Christopher and Lee (2001) argue for visibility as a vital factor for managing supply chain risk. Wilding (1998) takes the position that understanding complexity is the key, while Towill (1999) argues for the removal of complexity in the design. Another approach, supply continuity planning, is proposed by Zsidisin et al. (2005) and still another, early supplier involvement, by Zsidisin and Smith (2005). A large proportion of the research so far uses a soft systems approach. A hard systems approach using predictive simulations is, however, called for as a next step (Peck, 2005).

3 RESEARCH METHODOLOGY

The logistics discipline can be regarded as an interdisciplinary science combining concepts, principles, methodologies, and approaches from other disciplines (Stock, 1997). This chapter will outline the research perspectives and methodologies used in this thesis. As the choice of methodology is not purely a technical question, but rather a reflection of individual beliefs and ideals, a personal motivation will also be included.

3.1 Methodological approach

In the logistics discipline, the basic methodological approach has been the systems approach (Gammelgaard, 1997). “The systems approach is a critical concept in logistics. Logistics is, in itself, a system; it is a network of related activities with the purpose of managing the orderly flow of material and personnel within the logistics channel.” (Lambert, Stock & Ellram, 1998) Although other methodological schools exist, the analytical school and the systems school seem to dominate in logistics research (Gammelgaard, 2004). The approach taken in this thesis is the systems approach.

3.2 Systems approach

Systems theory is an interdisciplinary field which studies groups of connected, associated, or interdependent components forming a complex whole – a system. The systems approach is concerned with viewing systems in a holistic manner. To gain insight into the performance of a system, the linkages and interactions between the components which comprise the whole must be understood, rather than dividing the system into pieces which are analyzed on their own, and assuming that the whole is the sum of its parts. This is essential, since many system changes leads to counterintuitive system responses; a change in one area of a system can adversely affect another area of the system in unexpected ways. The systems approach is fundamental, especially for those who have made organizations, a special type of system, their principal subject of study (Ackoff, 1971).

General systems theory was initially proposed by Ludwig von Bertalanffy as a reaction against reductionism (von Bertalanffy, 1969). General systems theory attempts to formulate general principles valid for all systems in an effort to guide and unify research in several disciplines, by providing a

common framework and terminology. Similar thoughts were developed in cybernetics, the mathematical theory of communication and control of systems through regulatory feedback, which later evolved into control theory (Ashby, 1956, Beer, 1959). Systems theory is also closely related to system dynamics, a method for understanding the dynamic behavior of complex systems. The method recognizes that the structure of the relationships between the components, e.g. feedback loops and time delays, is often just as important in determining the behavior of a system as the individual components themselves (Forrester, 1968).

System sciences were later split in two branches; hard systems and soft systems approaches (Checkland, 1993). The former can be defined as the use of computerized analysis of mathematical models for a better understanding of diverse system phenomena. In the beginning, mathematical methods dominated, while simulation was regarded as a “method of last resort” (Wagner, 1969). With the advances in computer technology, the importance of simulation has grown. The latter, the soft systems approach, was a reaction to the work of hard systems theorists and their failure to solve problems involving human beings. The soft systems approach is thus concerned with systems which cannot easily be quantified, especially those involving people interacting with each other or with systems. It is a useful approach for understanding motivations, viewpoints, and interactions but it cannot provide quantified answers (Checkland, 1993).

Systems can be categorized as either being open, i.e. having interfaces to the surrounding environment where matter, energy or information can be exchanged, or closed, i.e. it is self-contained so that outside events have no influence upon the system. It must be recognized that logistics systems involving humans are open systems, and are therefore affected by the environment in which they exist.

Furthermore, systems can be divided into thermodynamic systems, i.e. based on matter and energy, or conceptual systems made up of ideas and information. The use of the systems approach in this research can be summarized as being the overarching framework for the study of logistics systems, which are thermodynamic systems, with the intent of building conceptual systems modeling the “real thing”.

3.3 Simulation methodology

Simulation has been defined as the “imitation of the operation of a real-world process or a system over time.” (Banks, 1998) It consists of developing a conceptual system model describing the real system in sufficient detail, and translating it into a software model which can be executed by a computer. The purpose is to create a computer model which allows investigations of system performance and behavior over time, when different rules and policies are applied (Shapiro 2001). One of the advantages of simulation is that it allows one to explore different scenarios (Banks et al., 2001).

Generally, a simulation model is a mathematical model that can be classified in three dimensions as being (Anu 1997, Banks 1998, Banks et al. 2001, Law & Kelton 1982):

- Static versus dynamic
A static simulation model represents a system at a specific “frozen” point in time, whereas a dynamic simulation model represents a system which changes over time.
- Deterministic versus stochastic
A deterministic simulation model is completely defined and has a unique output to any set of input parameters. In a stochastic simulation model the behavior of the simulation model is determined by stochastic variables.
- Continuous versus discrete
In a continuous simulation model, variables change continuously over time, whereas in discrete simulation models the variables only change at discrete points in time i.e. when an event occurs and changes the state of the system.

For the chosen research topic, discrete-event simulation has been selected. It is considered an appropriate simulation technique for the modeling of stochastic behavior in logistics operations over time, where the focus is on events in the system, e.g. the arrival of a truck, or the breakdown of machine equipment.

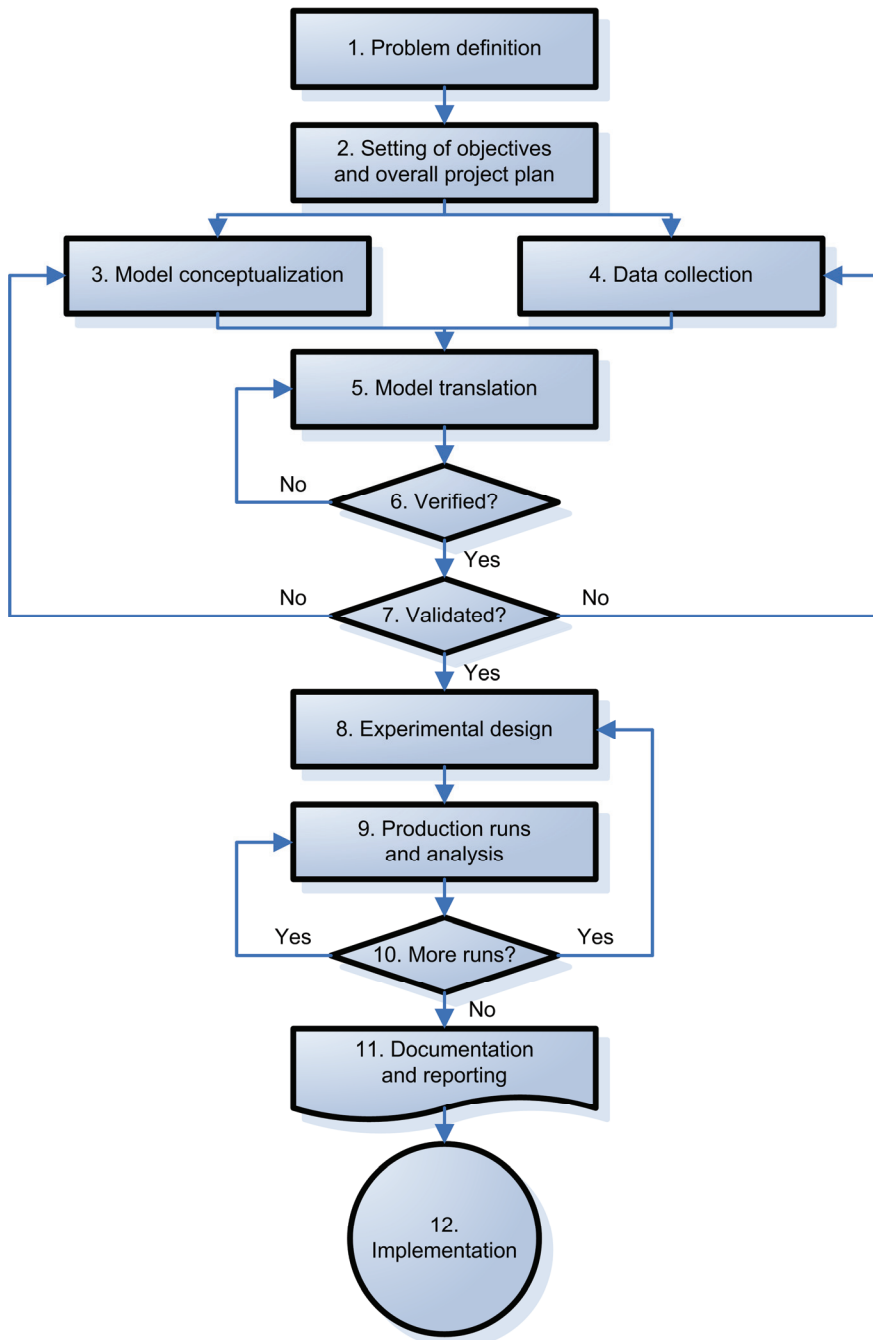


Figure 3.1. Steps in a simulation study (Banks et al., 2001).

3.3.1 Simulation methods

A number of comprehensively described simulation methods exist in literature (e.g. Banks et al., 2001; Robinson, 1994; Musselman, 1998). They are typically structured around a number of project phases or steps which should be performed in a certain sequence. A simple, three-step, model-centric view has been presented by Fishwick (1995): (1) model design, (2) model execution, and (3) model analysis, while a more detailed model has been presented by Banks et al. (2001), see figure 3.1. While not all simulation studies follow this exact sequence, they provide an overarching guideline for how to perform a simulation project (Musselman, 1998).

Although simulation methodology is at the core of this thesis, attempts have been made to construct parallel analytical models in order to triangulate the results and thus reduce methodological shortcomings. The validity of the research is thereby strengthened.

3.4 Personal motivation

The choice of research methodology is not purely a technical question, but also a reflection of personal preferences. Before commencing on my research journey, I worked 10 years in the manufacturing industry. The main theme of what I was doing can be labeled as operational development, i.e. improving business performance by identifying and correcting poorly working processes. My experiences are that operational development is an often unreliable process - considered more of an “art” than a “science”. Consequently, rank and personal beliefs are often the dominant factors which determine the course of action, rather than a sincere attempt to evaluate different options in an objective way. The lack of facts-based management I have experienced is not limited to the companies I have worked for, but seems to be a universal problem. “For the most part, managers looking to cure their organizational ills rely on obsolete knowledge they picked up in school, long-standing but never proven traditions, patterns gleaned from experience, methods they happen to be skilled in applying, and information from vendors.” (Pfeffer and Sutton, 2006) Pfeffer and Sutton (2006) further suggest that “when managers act on better logic and strong evidence, their companies will beat the competition.”

The question then becomes; what constitutes better logic and strong evidence, and how can this be achieved? I believe that both qualitative and quantitative research methodologies can contribute to better logic and strong

evidence in a business context. Furthermore, I am well aware of the fact that “not everything that can be counted counts, and not everything that counts can be counted.” (quote attributed to Albert Einstein) In the context of understanding system behavior, however, I believe that simulation is an indispensable tool. Sterman (2002) has articulated the same view even more forcefully; “Simulation is essential for effective systems thinking, even when the purpose is insight, even when we are faced with a “mess” rather than a well-structured problem.” The reason, Sterman argues, is fundamental limitations in the intellectual capacity of humans; “Indeed, our experimental studies show that people are unable to accurately infer the behavior of even the simplest system, systems far simpler than those emerging from qualitative modeling work.” Simulation models based on data and subject on the other hand to thorough analysis result in more reliable conclusions about dynamic systems and help to reveal errors in our mental simulations (ibid).

From my personal experience in industry, I have also seen many projects fail despite grand visions and perfectly devised strategies, usually not on the basis of single major causes, but rather many, often perceived as insignificant, trifles - the devil is truly in the detail. For these reasons, I have chosen a quantitative approach with a bottom-up perspective, i.e. my focus is on the operational and tactical levels in logistics with the intent of capturing the small, but potentially critical, details which might be overlooked from a more strategic, top-down perspective.

4 RESULTS

There are three appended research papers which are an integral part of this thesis and where the bulk of research can be found. For the reader's convenience, this chapter contains brief summaries of the papers.

Paper One - The effect of dynamic scheduling and routing in a solid waste management system

Solid waste collection and hauling account for the greater part of the total cost in modern solid waste management systems. In a recent initiative, 3,300 Swedish recycling containers have been fitted with level sensors and wireless communication equipment, thereby giving waste collection operators access to real-time information on the status of each container. In this study, analytical modeling and discrete-event simulation have been used to evaluate different scheduling and routing policies utilizing real-time data. In addition to the general models developed, an empirical simulation study has been performed on the downtown recycling station system in Malmö, Sweden. From the study it can be concluded that dynamic scheduling and routing policies exist which have lower operating costs, shorter collection and hauling distances, and reduced labor hours compared to the static policy of fixed routes and predetermined pick-up frequencies employed by many waste collection operators today. The results of the analytical model and the simulation models are coherent, and consistent with experiences of the waste collection operators.

Paper Two - Managing uncertainty in supply chain operations – a hybrid simulation approach

The 'golden standard' for a supply chain simulation is a complete, microscopic, discrete-event simulation replicated over the full parameter space of the model, which would allow for a complete search of solutions and associated risks. Such an endeavor is, however, computationally unfeasible for any complex supply chain model. In this paper, the novel approach of building hybrid simulations in which discrete-event simulation is combined with Monte Carlo simulation through the use of regression meta-models is presented. The meta-models are used in the search for near-optimal values of decision variables considering multiple responses, and to

assess the robustness of the solution. The described hybrid simulation has been used in an empirical simulation study of an assembly-type supply chain through three tiers of suppliers. Hybrid simulation can serve as a tool for exploring the sources and nature of stochastic behavior in supply chains, and the trade-offs in decision making. The approach is computationally efficient and facilitates scaling to large, complex supply chain models. A formal analysis of the accuracy of the hybrid simulation has, however, not been performed and this will be an important challenge for future work.

Paper Three - Notes on the validity and generalizability of empirical simulation studies

Simulation as a research methodology is becoming increasingly important in the study of logistics systems. Empirical simulation studies, however, are often criticized for lacking scientific rigor in terms of the validity and generalizability of the results. This applies in particular to the study of future, “what if”-scenarios. The aim of this paper is to explore and discuss the issue of achieving validity and generalizability of empirical simulation study results based on the experiences from an empirical solid waste simulation study done in Malmö, Sweden. The results of this single case indicate that a combination of analytical model building and simulation model building not only increases the validity of the model, but also enables a better assessment of the generalizability of the model results. No conclusive evidence can, however, be presented from a single case, and although progress seems to have been made, assessing and inferring generalizability of results from empirical simulation results will remain an intricate and perilous activity.

5 DISCUSSION AND CONCLUSIONS

The aim of this thesis has been to explore strategies for evaluating and managing uncertainties in a logistics context – an aim which certainly opens up a wide spectrum of research opportunities. The objectives; “to propose a method for modeling and analyzing the dynamics of logistics systems with an emphasis on risk management aspects”, and “to explore the impact of dynamic planning and execution in a logistics system”, narrow down the scope to a more tangible level. Nevertheless, it is still a challenge to cover the area and bring the results to a coherent unity.

As supply chain complexity increases as a result of globalization, market volatility, the introduction of novel technology, outsourcing, and mergers and acquisitions, so does the level of uncertainty. The focus on cost reductions and efficiency tends to stretch supply chains to become longer and leaner, thus making them more vulnerable to disturbances. While a continued search for cost reductions and efficiency gains is essential in an intensely competitive world, the challenge is to find methods in which uncertainty management is considered concurrently. Three main strategies for handling uncertainties have been discussed; robustness, reliability, and resilience. With traditional accounting, all three strategies usually carry an additional cost, e.g. incurred through additional buffers and safety stock, extra costs related to dual sourcing instead of single sourcing, and operating with free capacity to improve flexibility.

If cost efficiency is supply chain managers’ number one priority, then organizations may arrive at lean, but vulnerable, solutions. The dilemma can be avoided by leveraging the cost and risk of logistical disruptions, i.e. decision makers must make conscious decisions to sacrifice cost efficiency in return for their improved capability to handle uncertainties. Making this trade-off implies that the decision is made with the full comprehension of both the advantage and disadvantage of the particular choice, i.e. the expected cost of risk recovery and the cost of uncertainty management must be assessed and weighed against each other.

The hybrid simulation methodology presented in paper two proposes a method for modeling and analyzing the dynamics of logistics systems with emphasis on risk management aspects. The hybrid simulation approach is based on discrete-event simulation and Monte Carlo simulation which

allows the trade-off between cost on one side, and robustness and reliability on the other side, to be quantified.

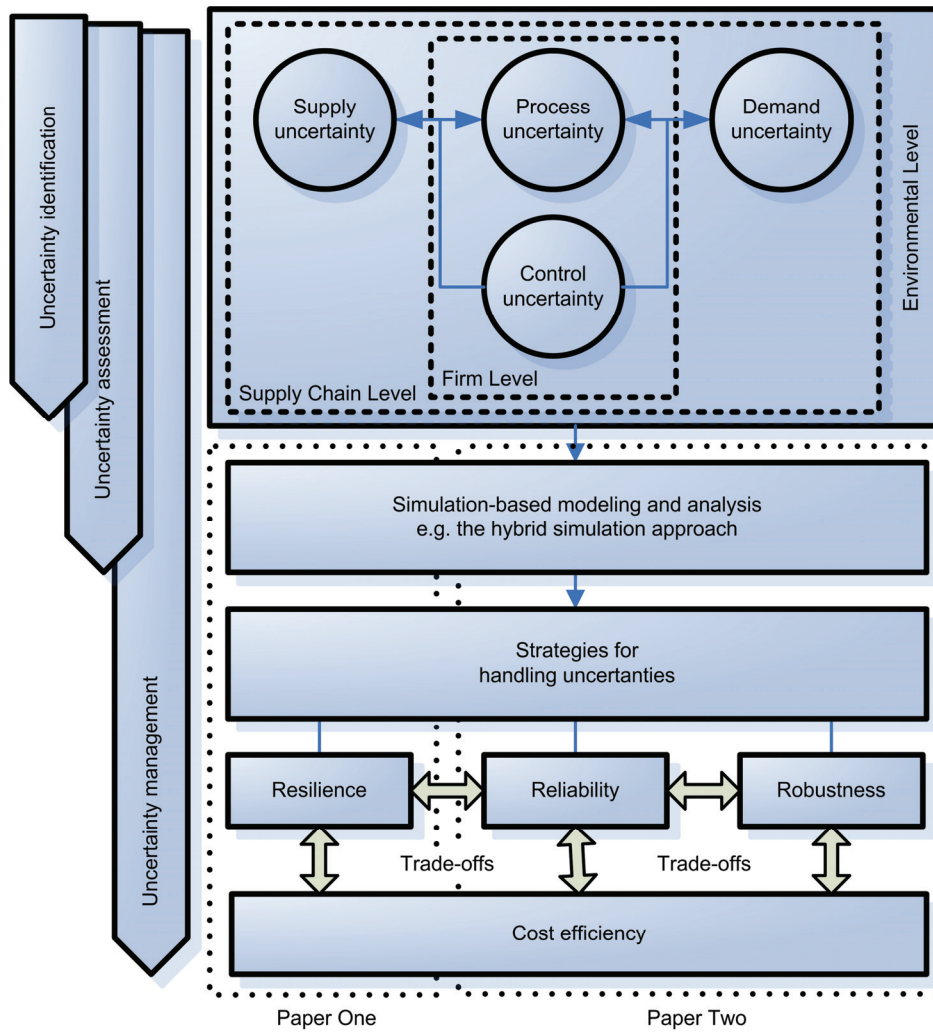


Figure 5.1 The scope of the studies positioned in a draft uncertainty management framework

In the empirical simulation study of a supply chain through three tiers of suppliers, the approach was used to identify and assess risks, locate robust, near-optimal solutions, and assess the impact of uncertainties in so that trade-offs, e.g. between lead time and capital employed, could be quantified. Both atomistic and holistic sources of disruptions were included in the

model, while only quantitative disruptions were analyzed. Qualitative disruptions, e.g., quality problems, were not included due to a scope limitation of the actual study. Furthermore, the empirical simulation study did not explicitly include any resilience aspect. It does, however, not mean that the hybrid simulation approach is not capable of modeling adaptive behavior. On the contrary, as paper one demonstrates, discrete-event simulation is very well suited to studying the effects of dynamic, responsive behavior in logistics systems, i.e. key elements for achieving resilience. In addition, the results from a hybrid simulation study may very well lead to a rethinking of supply policies and development of contingency plans, regardless of whether these actions to improve resilience are part of the simulation model or not.

In the solid waste management case, in paper one, the impact of dynamic planning and execution in a logistics system is explored. In the case, demand uncertainty is partly removed by the introduction of “intelligent” containers with level sensors and telecommunication equipment. Various adaptive planning policies are evaluated against the static planning according to which the system is operated today. The reduction of uncertainty is proven to have an economic value through new scheduling and routing policies, but requires the operator of the system to have a certain level of flexibility. The economic value of the adaptive policies is increasing by increasing volatility in demand. The value and choice of policy are, however, dependent on system properties such as size, density, and demand.

The scopes of the two papers are marked in figure 5.1 and positioned in the wider perspective of uncertainty management. The arrows in the figure indicate different trade-off situations between cost efficiency and uncertainty-handling strategies, and also between different uncertainty-handling strategies. The studies performed indicate that a simulation modeling approach is a suitable method to explore and evaluate the different options. There are five key reasons for why this methodology has proven itself useful in the context of logistics systems.

System complexity

Logistics systems are typically highly complex with many interfaces within and outside a single business entity. There are often many factors linked in a web of feedback loops which affect the performance of the system. As a result, imposed changes in the system often lead to counterintuitive system

responses. Methods which rely on simple input-output models therefore often fail since they cannot capture the complexity of the system. Discrete-event simulation, however, allows these aspects to be modeled and analyzed.

Stochastic behavior

Logistic systems behave stochastically, i.e. the effects of the activities vary randomly over possible outcomes, regardless of the complexity of the system. This property of the system can be modeled using discrete-event simulation, and by running the system several times with the same (or varying) initial conditions, the variability in the response variables can be determined.

Visualization of the system

Many logistics problems concern bottleneck situations, lead time reductions and related issues, where mere statistics such as average delivery time can be misleading. In these cases, simulation approaches have an advantage over steady-state analytical solutions in that they can dynamically display the level of oscillations, effects of transients etc.

Verification of solution

Simulation modeling is by no means the only method which can assist in the design of logistics systems. There are plenty of other qualitative and quantitative methods to aid decision makers. As paper three suggests, however, a multi-method approach, where simulation modeling is one component, can lead to a methodological triangulation where the validity of the results can be examined and the generalizability of the results assessed.

Assessment of sensitivity

Regardless of the methodology used to generate a solution, supply chains are complex systems where small changes in the input assumptions may lead to significant differences in performance. For that reason, the sensitivity of any solution must be assessed in a rigorous manner.

5.1 Contributions

The contributions of the research have been separated into the three categories; practical, theoretical, and methodological contributions.

5.1.1 Practical contributions

The modeling approaches used in this thesis are highly practical and should be applicable in many industrial settings. Hopefully, this research can help practitioners to appreciate simulation modeling and show them how it can be applied to improve processes inside a company and across a supply chain in order to aid decision makers to formulate the necessary trade-offs between cost efficiency and uncertainty hedging.

5.1.2 Theoretical contributions

Some theoretical contribution to the field of logistics is presented in paper one, where the impact of real-time information, i.e. demand visibility, and responsive planning policies in a logistics systems, is quantitatively evaluated.

5.1.3 Methodological contributions

The hybrid simulation approach provides a computer-efficient framework for combining discrete-event simulation with risk management methods where the impact of uncertainties can be assessed in a logistics context.

The methodological triangulation approach, discussed in paper three, outlines the benefits of combining analytical and simulation modeling for both improving the validity of the results and assessing the generalizability of conclusions drawn from a study.

5.2 Future research

The scope of the studies in figure 5.1 provides a draft framework for how uncertainty can be managed in a logistics context. It is, however, by no means a complete picture and needs further development, hence the title of this licentiate thesis. Further research is needed in the following areas:

- Exploring methods and models which can be used to identify, assess, and measure logistics uncertainty

- Exploring how qualitative disruptions can be included in dynamic models for evaluating logistics systems
- Exploring the requirements for implementing dynamic planning and execution in logistics systems
- Exploring the trade-off between resilience versus reliability and robustness
- Conducting a formal analysis of the accuracy of the hybrid simulation approach
- Improving the computing efficiency of the hybrid simulation approach, e.g. through replacing the Monte Carlo simulation with Latin hypercube sampling

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Appended Papers

Paper 1

The effect of dynamic scheduling and routing in a solid waste management system

Accepted for publication in the International Journal of Integrated Waste Management, Science and Technology, September 19, 2005. Available online 9 November 2005. Article in press.

Paper 2

Managing uncertainty in supply chain operations – a hybrid simulation approach

Accepted for a formal oral presentation at the 11th International Symposium on Logistics (ISL), Beijing, PRC., 9-11 July 2006, and for publication in the symposium proceedings.

Paper 3

Notes on the validity and generalizability of empirical simulation studies

Presented at the 17th Annual conference for Nordic Researchers in Logistics, NOFOMA , Copenhagen, Denmark, 9-10 June 2005. Published in the NOFOMA 2005 proceedings.

Paper 1



The effect of dynamic scheduling and routing in a solid waste management system

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Abstract

Solid waste collection and hauling account for the greater part of the total cost in modern solid waste management systems. In a recent initiative, 3300 Swedish recycling containers have been fitted with level sensors and wireless communication equipment, thereby giving waste collection operators access to real-time information on the status of each container. In this study, analytical modeling and discrete-event simulation have been used to evaluate different scheduling and routing policies utilizing the real-time data. In addition to the general models developed, an empirical simulation study has been performed on the downtown recycling station system in Malmoe, Sweden. From the study, it can be concluded that dynamic scheduling and routing policies exist that have lower operating costs, shorter collection and hauling distances, and reduced labor hours compared to the static policy with fixed routes and pre-determined pick-up frequencies employed by many waste collection operators today. The results of the analytical model and the simulation models are coherent, and consistent with experiences of the waste collection operators.

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1. Introduction

Over the last 20 years, car traffic has grown at a rate of 3.3% per annum, and road freight traffic has grown almost at 5% per annum (OECD, 1995). Consequently, freight transportation-related problems are mounting (OECD, 1997). Solid waste collection and hauling are estimated by municipal planners in Malmoe, Sweden, to account for 10–15% of the total freight transportations in the city, but due to the low average speed of vehicles used, and numerous stops during collection, the effect they have on congestion, air pollution, and noise is higher than that of other types of freight transportation.

The most important achievements in reducing traffic-related problems to date have been effected through advances in technology; e.g., developments in engine technology to reduce fuel consumption, noxious emissions and noise; and cleaner fuels. The gains made have in some cases,

however, been offset by changes in behavior, e.g., savings in fuel through engine design has been offset by the trends towards more powerful engines, higher speeds, and increased congestion (OECD, 1995). Policy-makers and scientists alike agree that technology alone cannot solve the problems; habits and behaviors need to change too. This makes telematics technology an interesting topic as it can be used to enable and aid changes in traffic behavior. The word telematics was “originally coined to mean the convergence of telecommunications and information processing, the term later evolved to refer to automation in automobiles. GPS navigation, integrated hands-free cellphones, wireless communications and automatic driving assistance systems all come under the telematics umbrella.” (Definition from TechEncyclopedia; www.techweb.com, 2004-06-28). Recent developments have extended the concept to equipment fitted on the load carrier. Examples of such equipment are the level sensors and alarm systems for recycling containers for corrugated board and cardboard in Sweden.

Since 1994, Sweden has had producer’s responsibility regulations for packaging waste. All companies that

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manufacture, import or sell packaging are responsible for ensuring that packaging waste can be collected and recycled. Together, these companies have formed five material handling companies working together under the name Packaging Collection Service, with the task of organizing and administering this responsibility. In order to collect packaging waste, the Packaging Collection Service has set up recycling stations at more than 7000 locations throughout the country. A typical recycling station has a number of containers where nearby households can discard plastic, paper, cardboard, corrugated board, metal, and glass packaging. The collection, hauling, and sorting of packaging waste is contracted out to local entrepreneurs. The containers are typically collected by front-loading compacting vehicles. Due to heavy congestion, this vehicle type cannot, however, be used in downtown areas and consequently some inner city containers are of a different design and are collected using smaller, less efficient, non-compacting, open-sided vehicles that use a crane for waste collection. Recently, the material handling companies for corrugated board and cardboard, Returwell and Svensk Kartongåtervinning, respectively, fitted their containers with level sensors and wireless communication equipment in order to assess the quality of the service provided, and to give the contracted waste collection operators the opportunity to plan their logistics operations more efficiently. The investment was paid in full by the material handling companies. Approximately 3300 containers of this type have been distributed to recycling stations around the country. The sensor is mounted under the lid of the container. It is activated once an hour and assesses the level of the container by means of four infrared light-emitting diodes. If three of the four beams are broken, an alarm is raised and transmitted through the GSM network, and an automatically generated mail is sent to the waste collection operator. A second alarm is raised when all four beams are broken and a reset signal is sent when a tilt-sensor indicates that the container has been emptied. In order to assure the quality level of the service, the operator is charged a penalty if the time between the second alarm and the reset signal exceeds 24 h on weekdays and 48 h on a weekend.

Studies of solid waste management systems report that waste collection and hauling represent the greater part of the total cost of such systems (Bhat, 1996; Sonesson, 2000). Although the equipment fitted on the recycling containers in Sweden has given waste collection operators access to real-time information on container status, many operators have chosen not to use the data to improve the planning of their operations. Instead, they continue to rely on their traditional static planning approach, employing fixed routes with pre-determined pick-up frequencies. The situation where some waste collection operators have embraced the technology while others have rejected it raises many questions on how real-time data can be used for planning purposes and for what type of systems it is valuable.

The purpose of this paper is, therefore, to evaluate different scheduling and routing policies, and how they relate to some basic characteristics of a solid waste management system. This problem is characterized by the simultaneous presence of three fundamental aspects:

- Scheduling: to specify a time or set of times when a certain route should be executed.
- Routing: to organize the physical movement of goods between different geographical sites.
- Dynamicity: the two aspects above embedded in a framework of constantly changing information, a time horizon, and in situations where earlier decisions influence later decisions.

It should be pointed out that the study is primarily related to waste collection from a relatively small number of discrete points, and does not apply directly to house-to-house curbside collection of residential wastes.

1.1. Vehicle scheduling and routing

Vehicle scheduling and routing problems have been extensively researched during the last three decades. The classic vehicle routing problem (VRP) aims to minimize the total cost of routing a multiple number of vehicles from a depot to service customer nodes and then return. The problem can be further characterized by, for example, type of fleet, number of depots, and type of operations (pure pick-ups, pure deliveries, and mixed). The vehicle scheduling and routing problems (VSRP) are an extension of the VRP with a time horizon, additional time constraints and place requirements on, for example, the order of operations (see Bodin and Golden, 1981; for an overview). Most work in this area has, however, focused on static problem formulations where all information is known to the planner beforehand. Yet many real-world problems are characterized by stochastic and/or dynamic information.

Stochastic vehicle routing and scheduling problems arise when elements of the problem are modeled as random variables, e.g., stochastic travel time and stochastic demand. The typical solution approach to this class of problems is a priori optimization of the probability that the tour(s) can be completed given the constraints of the problem. With advancements in technology that support real-time decision making, such as wireless communication, geographic information systems (GIS), and global positioning systems (GPS), the importance of simultaneously handling the temporal aspects of uncertainty is growing. Dynamic data is characterized by its constantly changing nature and includes, e.g., real-time traffic conditions, customer demands, driver and vehicle statuses. Psaraftis (1988) and Powell et al. (1995) feature comprehensive surveys of stochastic and/or dynamic vehicle routing problems.

The problem domain belongs to a class of optimization problems that are intrinsically hard to solve. Thus, much of the research effort has focused on finding efficient heuristic

computational procedures for different variations of the problem. Little attention has been paid to the underlying characteristics of the studied systems and to how they relate to different planning policies. Nevertheless, Lund et al. (1996) introduced the concept of degree of problem dynamism, measured by the ratio of dynamic distance over static distance, and evaluated its effect on the quality of the solutions. This concept was further explored by Larsen et al. (2002) who also proposed a taxonomy for dynamic routing systems where the ratio between dynamic requests and total number of requests is used as the key determinant of the system's degree of dynamism. In the context of this study, only containers where the sensors have raised alarms and initiated a tour are regarded as dynamic requests. Other containers that might be collected on the same tour are regarded as non-dynamic, planned events, although the planning takes place ad hoc at the time when the tour is initiated. Applications of VRP and VSRP related to waste collection can be found in Bommisetty and Dessouky (1998), Tung and Pinnoi (2000), Shih and Chang (2001), Baptista et al. (2002), Angelelli and Speranza (2002), and Zografos and Androutsopoulos (2004). However, none of the articles deals with dynamic scheduling and routing, nor the underlying system characteristics or how they are connected to different scheduling and routing policies.

2. Methodology

The research methodology used in this study is a blend of analytical and simulation modeling combined with empirical case research. The first approach was to construct analytical models in an attempt to reflect an ideal system, thus isolating vital system characteristics, which determine the effect of dynamic planning in a waste collection context. The second modeling approach, stochastic discrete-event simulation, was used to build more realistic

models of the system. The simulation approach allowed a relaxation of the assumptions made in the analytical models and more advanced geometries, heterogeneous sets of containers, and more complex planning policies could therefore be evaluated. The final simulation case study is built on observations and interviews with planners and drivers operating the downtown recycling stations in Sweden's third largest city, Malmö. Supplementary interviews have also been conducted with two other operators of similar systems in order to investigate their usage of real-time data.

2.1. Analytical model

In order to evaluate the benefits of adopting dynamic scheduling in solid waste collection, an analytical model of a system with N containers was developed using probability theory. It was assumed that the weight of each container's contents after a certain time would follow a normal distribution, based on the central limit theorem which states that the sum of many stochastic variables of arbitrary probability distributions approaches a normal distribution (in this case, the amount of waste deposited by each person is the stochastic variable that is summed). This assumption is supported by the empirical data collected (see Fig. 1). The goal of the static scheduling is to collect all containers before the capacity of any one is expected to exceed its limits. In order to compute the optimal static collection frequency, an acceptable risk-level, α , has to be set. The α -level is the risk that any of the N containers exceeds its capacity. It is assumed that all N containers are emptied on the same tour and that the truck has sufficient capacity to handle all containers on the same tour. Furthermore, it is assumed that the containers are independent of each other, but identical in terms of capacity, mean fill rate, and standard deviation of the fill rate.

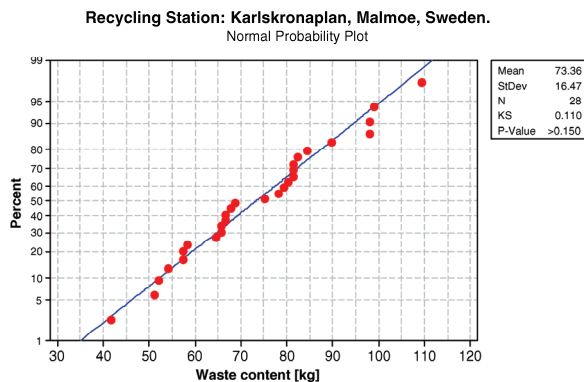


Fig. 1. Normal probability plot of the waste collected from the recycling station at Karlskronaplan, Malmö, Sweden. The mean weight of the waste collected in a week is 73.36 kg with a standard deviation of 16.47 kg, or 10.5 kg/day, with a standard deviation of 6.2 kg/day^{0.5}.

The mean time between collections (MTBC) is then defined by Eq. (1).

$$MTBC = \frac{2 \cdot M \cdot \bar{x}_{day}/Z^2 + s_x^2 - \sqrt{4 \cdot M \cdot \bar{x}_{day} \cdot s_x^2/Z^2 + s_x^4}}{2 \cdot \bar{x}_{day}^2/Z^2}, \quad (1)$$

where $Z = F^{-1}(p | p = (1 - \alpha)^{\frac{1}{N}})$, inverse cumulative standardized normal distribution; α , risk of exceeding any container capacity; \bar{x}_{day} , mean inflow per container and day (kg/day); s_x , standard deviation of inflow per container and day (kg/day^{0.5}); M , container capacity (kg); N , number of containers.

This time should be compared to the MTBC for a dynamic system where the collection occurs when the first container exceeds its capacity and an alarm is raised. It is assumed that the dynamically controlled system has sufficient capacity to respond to the alarm and that the time for collection is negligible. The MTBC for the dynamic system can then be calculated by using Eq. (1) with an α -value of 0.50, which corresponds to a 50% chance (or risk) that at least one of the N containers is 100% full and triggers the alarm (see Fig. 2). A sample calculation of the potential savings for dynamic scheduling is provided as Appendix 1.

Since the real system does not operate 24 h a day, 7 days a week, the equation has to be adapted to operating only in the daytime on weekdays. The optimal MTBC_{static scheduling} value was thus truncated to the closest possible static interval that does not violate the constraints posed by working hours, e.g., an optimal static frequency interval of 7.6 days is truncated to 7 days. For the dynamically controlled system, the probability that an alarm would occur and that the containers would be collected on a certain day was computed and used to calculate a weighted average for the MTBC_{dynamic scheduling} that complied with the constraints posed by working hours. Since the model assumes

that all N containers are emptied on the same tour, regardless of whether the tour is initiated by a static schedule or triggered by a level sensor, the cost of the individual tours is the same, but since the frequency of tours differs, the long-term cost will be different. The ratio between the MTBC_{static scheduling} and the MTBC_{dynamic scheduling} is a measure of the potential cost reduction of adopting dynamic planning.

2.2. Simulation model

The simulation model consists of containers, vehicles, and a recycling facility. The key attributes of the containers are mean waste fill rate (kg/day), standard deviation of fill rate (kg/day^{0.5}), current weight (kg), capacity (125 kg), and location. Each container is fitted with a level sensor that triggers an alarm signal when the container exceeds the 75% level (“yellow alarm”), and when it is 100% full (“red alarm”). The key attributes of the vehicles are the current weight of its load (kg), capacity (2500 kg), average speed (20 km/h), time to perform different actions, e.g., check station and set up vehicle for collection (2.5 min), collect (2.5 min/container), reset vehicle and leave station (2 min), empty vehicle at recycling facility (10 min), distance cost (0.6 EUR/km), and hourly cost (39 EUR/h). The key attribute of the recycling facility is its location. The default values used in the simulations, if nothing else is indicated, are written in italics above. The capacity and cost figures were provided by the operator of the system. All other values were estimated based on empirical observations.

Two different Euclidian geometries were used in the evaluation. The first geometry was a hypothetical city model where the collection points were equidistantly located around a circle with a recycling plant which lies outside the circle. The simulation results reported in this

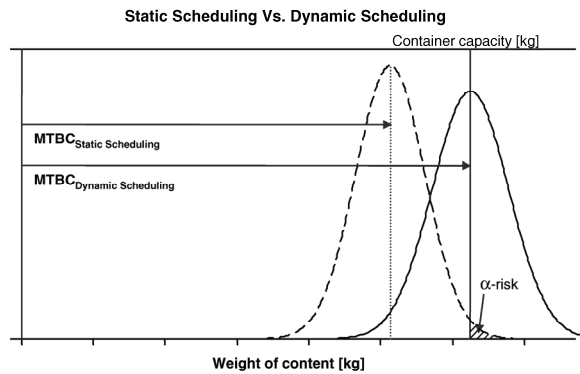


Fig. 2. A theoretical representation of the additional container weight expected when comparing a system with optimal static scheduling for a given risk-level versus a system with event driven, dynamic scheduling and a negligible response time.

article are based on a geometry with a city center radius of 2 km and a distance to the recycling plant of 15 km. The second geometry used in the simulation was a model of the actual system in Malmoe, Sweden, see Fig. 3.

At the beginning of each simulation run for the hypothetical city model, a random system was created, based on input values for system size, in terms of the number of containers and geometry parameters, minimum and maximum values for the waste generation, and standard deviation of fill rate. The mean waste fill rates per container are drawn from a uniform distribution with the minimum and maximum values for the waste generation as parameters. The simulation results reported in this article are based on a waste generation minimum value of 4 kg/day, a maximum value of 20 kg/day, and a standard deviation of 50% of the mean fill rate if nothing else is indicated.

During the simulation, each location generates waste according to a normal distribution and adds it to the containers on an hourly basis. The reason for the time resolution of 1 h is because the level sensors have a sampling frequency of once per hour. It should be pointed out that the inflow model of having a normally distributed amount of waste added to the container once an hour is not a true representation of the variation in inflow to the containers. On an aggregated level, however, the normal distribution appears to adequately resemble the real system over time and in particular in the later stages when the container's

content is approaching the critical levels where the sensor raises alarms.

When the waste quantity exceeds the threshold values of 75% and 100%, alarms are raised and depending on which planning policy is used, vehicles might be scheduled and routed to the recycling point. If a container is full and not collected within a specified time, 24 h on weekdays and 48 h during the weekend, a penalty is charged. As with the real system, collection and hauling are only conducted in the daytime on weekdays. The duration of a simulation run was 104 weeks.

The primary performance indicators used include the total operational cost of the system, penalty cost, labor hours, collection and hauling distance, number of tours, and number of containers collected, all on an annual basis. All simulation runs were replicated five times and the mean values of the performance indicators were computed. The variations in outputs between simulation runs were small, and five replicates appeared sufficient to allow an estimate of the system behavior.

Four different collection policies were used in the evaluation.

2.3. Policy 1: Static scheduling and static routing

This policy mimics the actual operations of the system practiced today with fixed collection days and routes. The

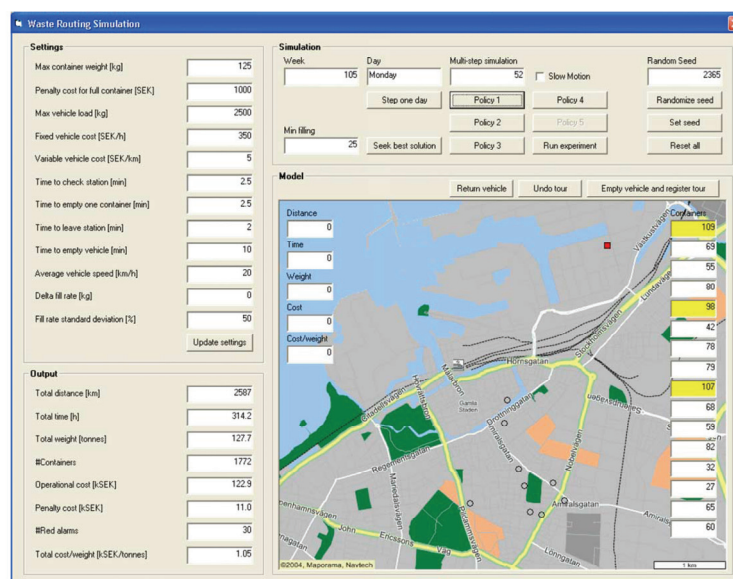


Fig. 3. The Malmoe simulation model.

procedure for solving the static scheduling and routing problem is based on the heuristic algorithm proposed by Christofides and Beasley (1984). Briefly, the method is based on an initial calculation of optimal collection frequency for each container, followed by a grouping of collection days and containers aiming at minimizing the total collection cost for the time period. The mean and standard deviation of the waste generation are assumed to be known to the planner. Since the recycling stations are located around a circle, the problem of finding the most efficient route is straightforward. Once a solution has been obtained, the system is simulated using the static schedules and routes for the duration of the simulation.

2.4. Policy 2: Dynamic scheduling and dynamic routing to full containers

This policy is fully event-driven and initiates a tour to full containers within 24 h from the receipt of a “red alarm”. In order to avoid overfull containers and subsequent penalties during weekends, a special rule for Fridays was introduced so that containers where the “yellow alarm” has been triggered were also collected. An alarm that is received while a vehicle is already collecting waste will not re-route that vehicle, but will instead initiate a new tour within 24 h. As with all dynamic scheduling policies, it is assumed that the system has sufficient vehicles and manpower to handle the collection requests within 24 h.

2.5. Policy 3: Dynamic scheduling and dynamic routing to “almost” full containers

This policy is similar to policy 2, and initiates a tour to full containers within 24 h from the receipt of a “red alarm” or a “yellow alarm” on a Friday. The vehicle is, however, not routed exclusively to full containers, but also to nearby containers which have an estimated level greater than a set threshold value. The level of each container is predicted by the assumed known mean fill rate for the container and is calibrated at the time of the “yellow alarm” (or by the absence of the alarm). As with policy 2, an alarm that is received while a vehicle is already collecting waste will not re-route that vehicle, but will instead initiate a new tour within 24 h. Policy 3 aims to utilize the vehicle more efficiently during the collection day.

2.6. Policy 4: Static scheduling and dynamic routing to “almost” full containers

The static scheduling and routing to “almost” full containers policy is based on a static scheduling using the same collection days as policy 1 has chosen. The routing is, however, done to full and “almost” full containers using the same logic as policy 3. An alarm that is received while a vehicle is already collecting waste will not re-route that vehicle. The policy aims to maintain the benefits of having

a static schedule for the drivers, while using the real-time data for improving the demand prediction and routing.

The second simulation model is built on empirical data from the Malmö downtown recycling system and features a realistic geometry and waste generation. The system consists of 9 recycling stations located in the downtown area and comprises 16 containers for cardboard and corrugated board. Currently, a static approach to scheduling and routing is employed; every Monday, a vehicle is routed to all 16 containers, and on Fridays, a vehicle is routed to 2 of the containers with above-average fill rates. The full Monday tour is 12.5 km long and takes approximately 3 h to complete. The mean fill rates of the containers vary from 4.5 to 21.7 kg/day and the standard deviation is estimated to be between 44% and 59% of the mean fill rate. The demand peak around Christmas has been excluded from the data set. With the exception of policy 1, where the heuristic search for the optimal static schedule has been replaced by the actual static schedule employed by the operator, the other policies remain intact.

2.7. Validation and verification of the simulation model

One of the most challenging parts of a simulation study is the verification and validation of the simulation model. The goal of the verification and validation process is two-fold: (1) to create a model that represents the true system closely enough to be used as a substitute for the purpose of experimenting and predicting system behavior, and (2) to create credibility of the model among users and decision makers (Banks et al., 2001).

One of the most critical data assumptions in the solid waste collection model was related to modeling of waste generation that created the demand for collection. Data on recycling waste per recycling point in the real system was therefore collected over a period of 6 months, from November 2003 until May 2004. In the model, it was assumed that the amount of waste in a container after a certain time would follow a normal distribution. With the exception of the time around Christmas, when the generation of packaging waste is extremely high, this assumption was validated using a Kolmogorov–Smirnov Goodness of Fit test for the Normal Distribution on the collected data. Data on the collection and hauling was collected through observations and time studies done on the drivers. The observations also formed the foundation of the structural assumptions for how the collection and hauling operation was performed. These assumptions were later validated in interviews with the planner and drivers operating the real system. In these meetings, people knowledgeable about the real system acknowledged that the model appeared to be correct and was behaving as expected when input variables were changed.

The hypothetical city simulation model was also quantitatively validated by comparing it to the analytical model. To match the assumptions of the analytical model, the vehicle capacity limitation in the simulation was removed,

the waste generation parameters for all containers were set to be equal, and policy 3 was used with a threshold value of 0% to ensure that all N containers were emptied on the same tour once that tour was initiated. In total 6724 simulation runs of varying system sizes ranging from 5 to 50 containers, mean fill rates ranging from 5 to 25 kg/day, and standard deviations ranging from 0 to 10 kg/day^{0.5} were compared to the analytical model with a mean average percent error (MAPE) of 0.18%, indicating a very good match between the models.

A quantitative validation of the model and the Malmoe system was not done due to the lack of data on individual tours. Instead, aggregated data on a yearly basis was available, allowing the model to be validated (and calibrated) on this level. This validation was only done for the static policy according to which the operation of the real system was performed. To assess the validity of the other policies, changes in the computer representation of the model have to be considered. Although the changes in the system seem huge, i.e., the change of the triggering of a tour from a static schedule to a dynamic alarm from a level sensor, and the change from a static route to a dynamic route, the actual changes in the program code are small: (1) a change in the start condition of a tour from checking the simulation clock to checking alarms, and (2) minor changes in the list of waypoints of the tour. It was also possible to validate the latter change by comparing the simulation output for policies 1 and 4 for different levels of the threshold value for when a container should be considered 'full enough' to be added to the list of waypoints. As expected, policies 1 and 4 produce identical results when the threshold value is set to 0%. Although policies 2 and 3 cannot be quantitatively validated, the minor programming change required for implementing these policies means that a great deal of the validity obtained for policies 1 and 4 can be carried over to these policies as well.

3. Results and discussion

In the analytical model, the savings potential is given by the increased MTBC in the dynamically controlled system versus the system with static planning. This is illustrated in Fig. 4 where the savings potential is plotted as a function of the mean fill rate and the standard deviation of the fill rate for a system that operates 24 h a day, 7 days a week. It is evident that dynamic planning offers the greatest savings potential for systems exhibiting high variation and low mean fill rates, while the potential for systems with low variation is negligible.

Fig. 5 displays the savings potential for a system where operations are allowed on weekdays only. The jagged nature of the surface merits explanation. Due to constraints posed by working hours, the static scheduling policy operates with spare capacity for most combinations of inflows. As the fill rate increases, however, the spare capacity decreases until the system reaches full capacity and an additional tour is scheduled and the system is again operating with spare capacity; the operating cost thus becomes a step function. For the dynamically controlled system, the MTBC is a weighted average of all potential collection days and their associated probabilities. As the fill rate increases, the weighted average decreases and the operating cost increases continuously. Since the savings potential is given by the quotient between the operating cost of a static scheduling system and a dynamically controlled system, a saw-like surface is the result.

The result that variability has a significant impact on the savings potential is also confirmed by the simulation results of the hypothetical city model. Figs. 6 and 7 compare the collection and hauling cost for policy 1 (static scheduling and routing) and policy 2 (dynamic scheduling and routing) for different levels of waste generation variability and system sizes. Systems with sizes ranging from 25 to 1000

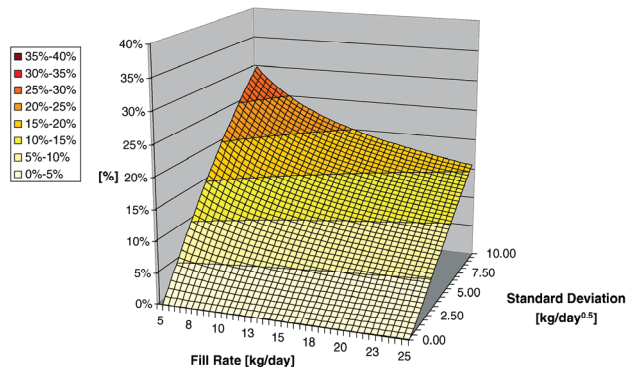


Fig. 4. Savings potential for dynamic scheduling and routing versus static scheduling and routing, for a 10-container system operating 24/7, calculated using the analytical model (%).

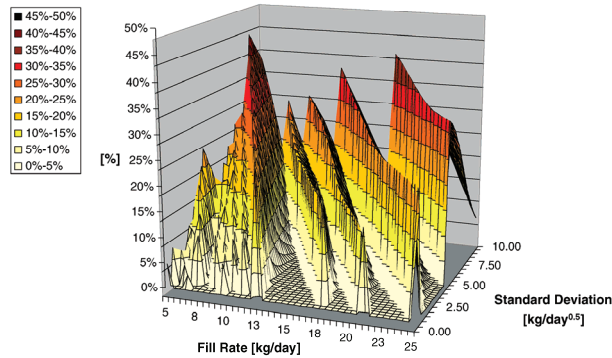


Fig. 5. Savings potential for dynamic scheduling and routing versus static scheduling and routing, for a 10-container system operating on weekdays only, calculated using the analytical model (%).

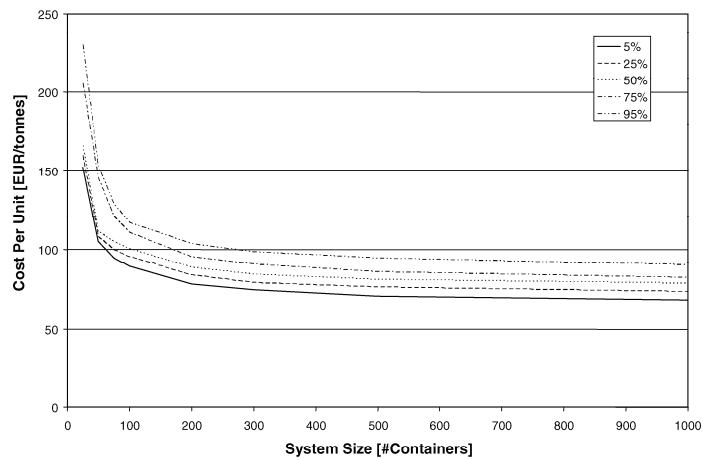


Fig. 6. Simulation results for the operating cost of policy 1 (static scheduling and routing) for different levels of waste generation variability and system size for a hypothetical city (EUR/tonnes).

containers were simulated with standard deviations of the fill rate ranging from 5% to 95% of the mean fill rate value. The resulting operational cost and penalties (if any) per unit of collected waste for the simulation period were then plotted. It is evident from the graphs that increasing variability increases the collection and hauling cost regardless of the policy, but the increasing uncertainty impacts the static scheduling and routing (Fig. 6) to a much greater extent than the dynamic policy (Fig. 7).

In Tables 1–4, the impact on collection and hauling distance, container utilization, truck utilization, and mean time between tours are listed for different policies and sys-

tem sizes. The dynamic policy 2 has the greatest container utilization, but for small systems, the process comes at the expense of frequent tours, long distances, and low utilization of the vehicle. For a larger system, however, this policy proves to be the most cost efficient although the distance is slightly higher than for the other policies. In fact, it can be shown that policy 2 is optimal for large, dense systems, i.e., systems where the distances between the containers are small, thus making the collection cost dominant and the hauling cost small in comparison. For smaller systems, however, policy 1 is superior to policy 2. Since most systems for recycling containers are smaller than 100

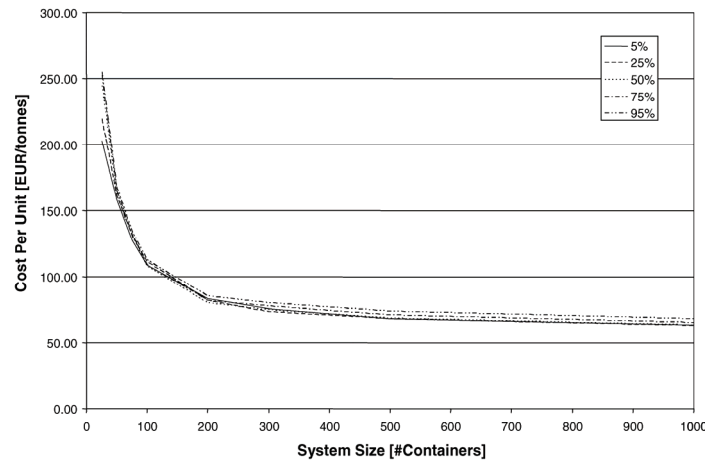


Fig. 7. Simulation results for the operating cost of policy 2 (dynamic scheduling and routing) for different levels of waste generation variability and system size for a hypothetical city (EUR/tonnes).

Table 1
Simulated annual collection and hauling distance per container for different policies and system sizes for a hypothetical city (km/container)

| Policy | System size (number of containers) | | | | |
|--------|------------------------------------|-----|-----|-----|------|
| | 10 | 50 | 100 | 500 | 1000 |
| 1 | 484 | 111 | 95 | 62 | 57 |
| 2 | 619 | 215 | 141 | 73 | 63 |
| 3 | 283 | 103 | 85 | 67 | 60 |
| 4 | 476 | 108 | 94 | 60 | 56 |

Table 2
Simulated average utilization of the container at time of collection for different policies and system sizes for a hypothetical city (%)

| Policy | System size (number of containers) | | | | |
|--------|------------------------------------|------|------|------|------|
| | 10 | 50 | 100 | 500 | 1000 |
| 1 | 56.4 | 57.0 | 55.8 | 55.9 | 56.0 |
| 2 | 99.2 | 99.4 | 99.8 | 99.8 | 99.7 |
| 3 | 71.8 | 64.1 | 61.0 | 89.8 | 89.3 |
| 4 | 58.8 | 58.0 | 58.9 | 96.2 | 96.0 |

Table 3
Simulated average truck utilization for different policies and system sizes for a hypothetical city (%)

| Policy | System size (number of containers) | | | | |
|--------|------------------------------------|------|------|------|------|
| | 10 | 50 | 100 | 500 | 1000 |
| 1 | 17.7 | 71.5 | 76.6 | 96.1 | 98.7 |
| 2 | 10.7 | 32.5 | 56.2 | 89.6 | 95.3 |
| 3 | 31.3 | 70.3 | 83.0 | 93.3 | 96.9 |
| 4 | 17.8 | 74.6 | 81.2 | 96.9 | 99.4 |

Table 4
Simulated mean time between tours for different policies and system sizes for a hypothetical city (days)

| Policy | System size (number of containers) | | | | |
|--------|------------------------------------|-----|-----|-----|------|
| | 10 | 50 | 100 | 500 | 1000 |
| 1 | 3.5 | 3.1 | 1.6 | 0.4 | 0.2 |
| 2 | 2.1 | 1.4 | 1.2 | 0.4 | 0.2 |
| 3 | 6.2 | 3.0 | 1.7 | 0.4 | 0.2 |
| 4 | 3.5 | 3.2 | 1.7 | 0.4 | 0.2 |

containers, this comparison explains the reluctance of waste collection operators to adopt the dynamic policy 2.

For systems smaller than 100 containers; policy 3, and to a lesser degree policy 4, manage to reduce the collection and hauling distance and increase both vehicle and container utilization compared to policy 1. It should be pointed out that the results of operating according to policies 3 and 4 are highly dependent on the threshold value for what should constitute an “almost” full container. A range of simulations with different values and system settings has been evaluated, and it was found that systems with fewer than 100 containers benefit from a small threshold value and larger systems need a higher value to produce satisfactory results. In the simulations reported in this study the threshold values of 40% and 75%, respectively, were used. The relatively low value of 40% for smaller systems indicates the importance of fully utilizing the vehicle once it has been decided that a tour should be initiated.

Operating cost has been used as an aggregated measure of the efficiency of a system. The simulation results from the hypothetical city model reveal that there is a strong link between the system size and the cost of operating the differ-

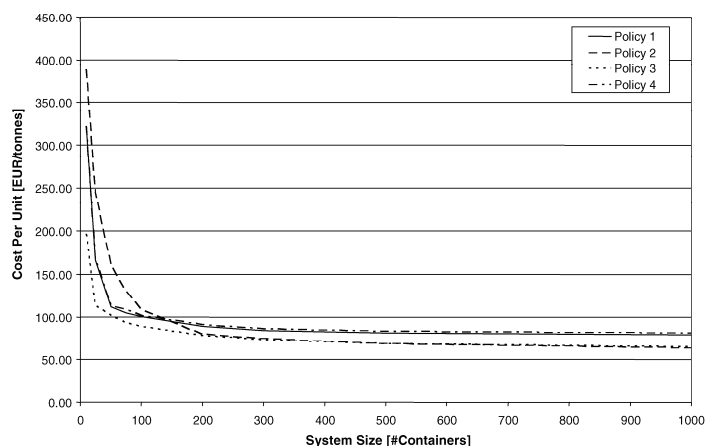


Fig. 8. Operating cost for different policies and system sizes for a hypothetical city (EUR/tonnes).

ent policies. In Fig. 8, the operational costs per unit of waste for the different policies and system sizes ranging from 10 to 1000 containers are compared. It is obvious that policy 3 is superior to the current policy 1 for small and medium-sized systems. Nevertheless, none of the interviewed operators has adopted policy 3. The reasons given are that they lack the IT support needed to manage waste forecasting, and they cannot evaluate how dynamic scheduling would impact their operations as a whole. Further, the results show that policy 4 mirrors the cost of policy 1 closely. This puts the value of the procedure reported by some solid waste collection operators of having fixed schedules and semi-fixed routes, somewhat in doubt.

The results obtained from the hypothetical city model are confirmed by the result from the simulation of the actual system in Malmö. Table 5 shows the simulation results for the different policies in absolute numbers. The result shows that policy 3 reduces collection and hauling distances by 17%, the number of stops to collect containers is decreased by 14% and the operational cost reduced by 15%. As expected, policy 2 is much less efficient due to the small size of the system. In this simulation, the total cost of operating with policy 4 is 17% higher, with 5% of the costs due to penalties for overfilling containers.

Table 5
Results from the simulation of the system in Malmö

| Policy | Distance (km) | Containers (#) | Operational cost (EUR) | Penalty cost (EUR) | Cost per unit (EUR/tonnes) |
|--------|---------------|----------------|------------------------|--------------------|----------------------------|
| 1 | 2604.0 | 1781.4 | 13,744 | 67 | 108 |
| 2 | 4305.2 | 1027.2 | 17,767 | 0 | 139 |
| 3 | 2168.0 | 1533.8 | 11,722 | 0 | 91 |
| 4 | 3040.2 | 1727.2 | 15,344 | 756 | 126 |

4. Conclusions

In this study, the effect of some basic scheduling and routing policies in the collection of solid waste has been examined, both for a hypothetical city model and a model of a real system. From the study, it can be concluded that dynamic scheduling and routing policies exist that have lower operating costs, shorter collection and hauling distances, and which collect fewer containers compared to the static policy employed by many waste collection operators, for all system sizes and realistic levels of variation. Further, dynamic scheduling and routing have the highest potential to decrease cost in the face of irregular demand. For large, dense systems, the dynamic scheduling and routing policy 2 is the optimal solution. When the number of containers is decreased and/or the distance between the containers is increased, this policy rapidly loses its benefits, however. For smaller systems, the dynamic policy 3 is more suited and cost reductions in the range 10–20% can be expected for the type of systems evaluated in this study. The investment cost in sensors, however, has not been considered in this study. The results of the analytical and simulation models are coherent and consistent with experiences of the waste collection operators.

5. Further research

Dynamic scheduling and routing systems cover a wide range of practical applications, and the models and results in this study represent only a first step in analyzing the effect of different planning policies. Although this study shows that there can be significant benefits from introducing an event-triggered dynamic planning approach in the

collection of solid waste, the best way of incorporating and utilizing the sensor data into the planning has not yet been established. Further, the analytical models in this study are simple and not sufficient for characterizing solid waste management systems of realistic size and complexity. In addition, case studies examining companies employing dynamic planning models are needed in order to better understand the practical problems and opportunities that arise as a consequence of introducing new planning policies, e.g., what the prerequisites for introducing dynamic scheduling and routing are, and what (if any) the cost of operating with a higher flexibility is.

Appendix 1. Sample calculation of the difference in MTBC for static and dynamic waste collection using the analytical methods described in this paper.

Assume a 15-container system where the containers have a mean fill rate of 10.5 kg/day with a standard deviation of 6.2 kg/day^{0.5}. The acceptable α -risk is 0.01. Each container has a capacity of 125 kg.

To have a 0.99 probability that not any container in the system exceeds its limit, each individual container should have a 0.9993 probability of not exceeding its limit

$$(1 - \alpha)^{\frac{1}{N}} = (1 - 0.01)^{\frac{1}{15}} \approx 0.9993.$$

The corresponding Z-value is then: $Z = F^{-1}((1 - 0.01)^{\frac{1}{15}}) \approx 3.207$

The MTBC (static scheduling) is then

$$\text{MTBC} = \frac{2 \times 125 \times 10.5/3.207^2 + 6.2^2 - \sqrt{4 \times 125 \times 10.5 \times 6.2^2/3.207^2 + 6.2^4}}{2 \times 10.5^2/3.207^2} \approx 6.9 \text{ days.}$$

For a system with dynamic planning, collection will take place when the first of the N containers is full. The MTBC then corresponds to having a 0.50 probability that not any container in the system exceeds its limit. Then each individual container should have a 0.9548 probability of not exceeding its limit

$$(1 - \alpha)^{\frac{1}{N}} = (1 - 0.50)^{\frac{1}{15}} \approx 0.9548.$$

The corresponding Z-value is then $Z = F^{-1}((1 - 0.50)^{\frac{1}{15}}) \approx 1.694$

The MTBC (dynamic scheduling) is then

$$\text{MTBC} = \frac{2 \times 125 \times 10.5/1.694^2 + 6.2^2 - \sqrt{4 \times 125 \times 10.5 \times 6.2^2/1.694^2 + 6.2^4}}{2 \times 10.5^2/1.694^2} \approx 8.9 \text{ days.}$$

The savings potential by adopting dynamic planning for a system operating 24/7 is: $1 - 6.9/8.9 = 22\%$

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Paper 2

Managing Uncertainty in Supply Chain Operations

- A Hybrid Simulation Approach

Suggested symposium topics:

Design and Organization of Supply Chains
Logistics Planning and Control Models

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ABSTRACT

The 'golden standard' for a supply chain simulation is a complete, microscopic, discrete-event simulation replicated, over the full parameter space of the model, which would allow for a complete search of solutions and associated risks. Such an endeavor is, however, computationally unfeasible for any complex supply chain model. In this paper, a novel approach to building hybrid simulations in which discrete-event simulation is combined with Monte Carlo simulation through the use of regression meta-models is presented. The meta-models are used in the search for near-optimal values of decision variables considering multiple responses, and to assess the robustness of the solution. The described hybrid simulation has been used in an empirical simulation study of an assembly-type supply chain through three tiers of suppliers. Hybrid simulation can serve as a tool for exploring the sources and nature of stochastic behavior in supply chains and the trade-offs in decision making. The approach is computationally efficient and facilitates scaling to large, complex supply chain models. A formal analysis of the accuracy of the hybrid simulation has, however, not been performed and this will be an important challenge for future work.

INTRODUCTION

Uncertainty rules supply chains. Changes constantly occur on all levels; strategically through globalization, introduction of novel technology, mergers and acquisitions, volatile markets, and on an operational level through demand fluctuations, and events such as late arrival of in-bound material, machine equipment breakdown, and quality problems. Because of the unpredictable nature of supply chain performance, supply chain managers try to counter it on an operational level by risk mitigation actions such as adding safety margins to lead times, keeping excess inventory, etc., and a multitude of “fire-fighting” activities once disruptions have occurred. The purpose of supply chain management is to deal effectively with uncertainties in order to drive down overall supply chain cost, and any attempt to design supply chains operations must therefore consider the robustness of the solution, i.e., (1) the level of built-in risk-tolerance, and (2) the availability of mechanisms for containing damage once an undesirable event has occurred (Gaonkar and Viswanadham, 2003). This paper will focus on the first part of the built-in level of robustness, but the results developed using this approach can also be used to enhance risk monitoring and to help build decision support systems for exception management.

LITERATURE REVIEW

Supply chain design has been a challenging problem for many years and the variation inherent in any supply chain is a major complicating factor. A large body of literature deals with analytical modeling and optimization of supply chains under uncertain conditions. Analytical models often employ mathematical programming techniques which typically minimize cost for a given service level by optimizing the strategic design and/or operational policies of a supply chain. Vidal and Goetschalckx (1997) and Beamon (1998) feature reviews of analytical supply chain models. Uncertainty can be handled either directly by stochastic programming (Dupacova, 2002) or robust optimization (Mulvey et al., 1994), or indirectly by *ex poste* sensitivity analysis. Although most researchers agree that inclusion of variability in the problem formulation is preferred to post-optimality studies, at least from a theoretical standpoint, if not from a practical one, issues such as variable transportation and manufacturing lead times, stochastic demand, varying quality, and changing market prices and costs have proven difficult to include in optimization models. Indeed, some stochastic factors may be

included under some assumptions. The problem is, however, that analytical, real-world problems are already hard to solve in their deterministic form, which makes their stochastic formulations close to impossible to achieve, at least for some time (Stadler, 2005). Instead, sensitivity analysis for discovering the impact of data perturbations has been suggested as being the preferred, practical way to analyze system uncertainty (Vidal and Goetschalckx, 2000). Although analytical models can be valuable in solving certain classes of supply chain problems, they are often too simplistic to be of practical use for solving complex supply chain problems (Hung et al., 2006).

Simulation modeling has become a popular alternative when analytical methods do not suffice. This is due to its capability of simulation modeling to capture more realistic supply chain characteristics. In fact, it has been suggested that simulation modeling is the superior method if the intricacy of complicated interactions within a supply chain is to be understood (Hwarng et al., 2005). Simulation, however, is not by itself an optimization tool, nor a risk assessment tool, although it can be extended in these directions. Simulation-based optimization has attracted considerable attention and is an active research field. Literature surveys can be found in Carson and Maria (1997) and Andradottir (1998). The approach of using meta-models for optimization, such as in the hybrid simulation approach, is discussed in Azadivar (1999), Fu et al. (2000) and Cheng and Currie (2004). The works of Dabbas et al. (2001) and Tyan (2004) provide applications of this methodology for multiple response problems. These studies do not, however, address the issue of solution robustness, i.e., the trade-off between optimal parameter setting, and near-optimal parameter settings which stay near-optimal for a wider range of settings to accommodate uncertainties. A combination of simulation modeling, a search for near-optimal solutions, and risk assessment has been presented as a new paradigm for robust planning in supply chains (Van Landeghem and Vanmaele, 2002). The robust planning method bears a great resemblance to the hybrid simulation approach presented in this paper, but differs in that the hybrid simulation approach utilizes meta-models to improve scalability to large supply chain models and to alleviate the search for near-optimal solutions.

THE HYBRID SIMULATION APPROACH

The hybrid simulation approach aims to identify and explore uncertainties inherent in supply chains, allowing supply chain managers to determine

values for critical decision variables, e.g. inventory levels, such that response variables, e.g., service levels and capital employed, become near-optimal and are insensitive to changing conditions. Furthermore, risks should be identified and evaluated *a priori* in order to allow proactive variability-reducing actions. The basic method of the hybrid simulation approach is shown in figure 1 and the steps involved are explained below:

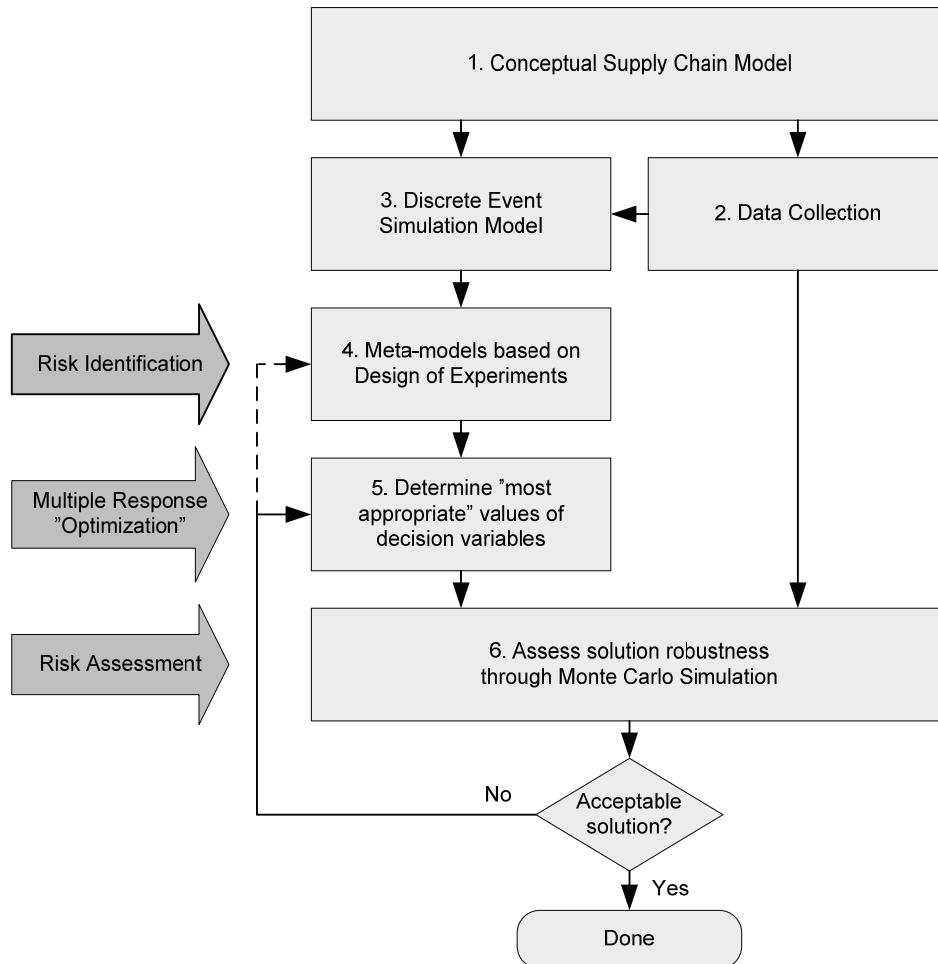


Figure 1. The hybrid simulation approach

1. Build a conceptual model of the supply chain

The conceptual model is an abstract of the real-world system under investigation and defines which part of the system should be modeled, which components and events should be included, and which input/output transformations should take place. The construction of a conceptual model requires, of course, a certain degree of simplification and is thus part science and part art. The goal is to achieve a model which represents the real system in sufficient detail to support decision making and improve managerial insights.

2. Data collection

Gather data of sufficient quality, quantity, and variety to be able to model the stochastic behavior of input variables, e.g., demand, lead times etc., and probabilities of relevant events and the distribution of their magnitude, e.g., mean time between failure (MTBF) and mean time to repair (MTTR). Together with the conceptual model these data will be the foundation for building the simulation model in step 3. There are, however, many cases where no data or only limited data are available, and the analyst has to resort to “guesstimates”. These uncertainties relating to data assumptions are subsequently assessed during step 6.

3. Build a discrete-event simulation model

Translate the conceptual model into a computer model which can be used to generate experimental data. This involves selecting appropriate software and the actual programming and debugging of the code. Before one proceeds to the next step, the model should be verified and validated to ensure that the model represents the true system closely enough to be used as a substitute for the purpose of experimenting and predicting system behavior, and to create credibility of the model among users and decision makers. (Banks et al., 2001)

4. Construct meta-models using design of experiments

Design of experiments is a structured method for determining the input/output relationship of a simulation model (Chung, 2004). It starts by defining the design of experiment, i.e., which factors should be included, which levels should be used, and which response variables should be

measured. It is important to include both controllable decision variables and uncontrollable input variables which might constitute risks. Note that uncontrollable does not mean that the variable cannot be controlled during simulation, only in the real system, e.g., currency exchange rates cannot be controlled in the real system, but the impact of changing exchange rates can be simulated. Once the design has been decided, experimental runs are executed in the discrete-event simulation model and regression meta-models are built on the resulting responses.

5. Determine the “most appropriate” values of decision variables

Decide on the “most appropriate” values of the decision variables. The mathematical technique of steepest ascent, i.e., changing the variables along the gradient of the fitted model, can be used to evaluate the impact on the separate response variables. A formal optimization can be performed if a single, overall criterion function can be formulated by quantifying the trade-offs between the different response variables. However, bear in mind that optimality is not necessarily desired, rather a near-optimal solution which is robust in the face of changing conditions, e.g., for a specific currency exchange rate, sourcing from country A may be the optimal solution. For a different exchange rate, country B might be optimal. In contrast, a robust solution may stipulate that sourcing is carried out in the same currency (country) as the majority of sales, in order to minimize the impact of unpredictable exchange rates.

6. Assess the solution robustness through Monte Carlo simulation

The meta-models are deterministic and calculate the value of the response variables for one precise scenario of the input variables. In reality, however, all input variables are rarely known with full certainty and some may not be controllable, or even measurable. In order to assess the robustness of the solution, a Monte Carlo simulation is executed where the deterministic input variables in the meta-models are replaced with stochastic distributions representing the potential values and associated probabilities the input variables may take. The robustness of the solution can be assessed by reviewing the variability in the response variable, and the associated sensitivity analysis identifies which factors it is most critical to monitor. The

reason for using meta-models instead of the discrete-event simulation model is to reduce computer time and thus improve scalability.

7. Evaluate if the solution is acceptable

The solution has to be judged according to certain criteria particular to the supply chain problem at hand. In general, what is sought after are solutions which are insensitive to varying conditions, in particular to changes in non-controllable or non-measurable variables. If the robustness of the suggested solution is below expectations, a new solution point must be selected and evaluated by iterating back to step 5. In addition, if the suggested solution is outside the region of the experimental design, i.e., the meta-models are used for extrapolating the responses, new meta-models should be constructed by iterating back to step 4.

EMPIRICAL SIMULATION STUDY

To demonstrate the performance of the hybrid simulation approach on a realistic problem, the approach has been applied to a real-world supply chain. The supply chain in the simulation study consists of a large enterprise, one of its first-tier suppliers, a second-tier supplier (which also is a fully owned subsidiary of the enterprise) and seven third-tier suppliers, see figure 2. The enterprise develops, produces, and markets packaging machines for liquid foods. The supply chain can be characterized as a low-volume assembly-type supply chain.

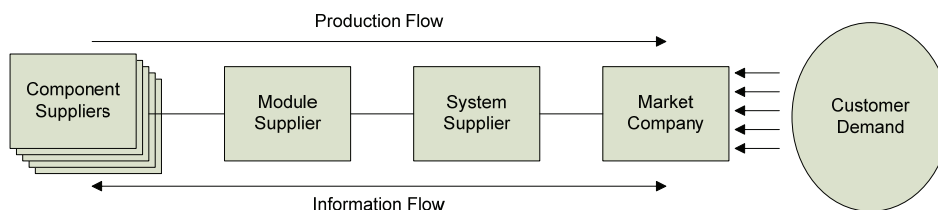


Figure 2. High-level conceptual model of the supply chain

The system operates in two modes from the two ends of the supply chain; the module supplier and downstream sites operate via a pull mode, e.g., material is ordered and assembled when orders are received. In contrast, the upstream component suppliers operate via a push mode according to agreed manufacturing batch quantities using a make-to-stock policy. To facilitate the capacity planning, the market company releases monthly sales forecasts

which are communicated throughout the supply chain. However, the quality of the forecasts is poor, and lumpy demand is one major source of uncertainty in the supply chain. Another source of uncertainty is the frequent design changes which may cause obsolescence at the component suppliers⁷. Although the component suppliers partly obtain obsolescence cost coverage from the enterprise, this risk may affect how the suppliers execute their internal order fulfillment and inventory policies. From the perspective of the enterprise, the decisions taken by the component suppliers might be considered as non-controllable, and even non-measurable, decision variables. A survey of all orders received during 2003 and 2004 for the specific packaging machine studied revealed that more than 50% of the deliveries were delayed compared to the agreed lead times, with a total average delay of 3.5 weeks per order.

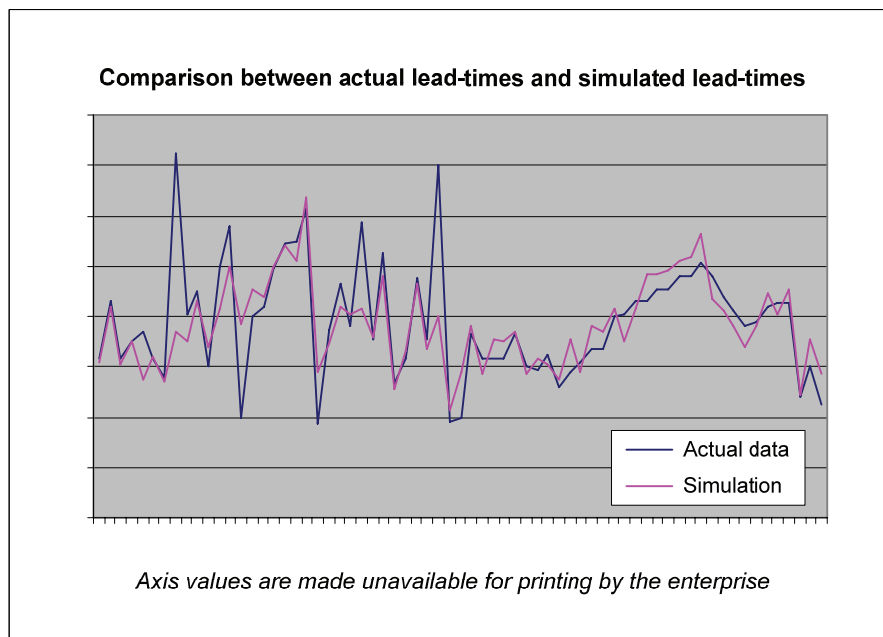


Figure 3. Actual versus simulated total lead times as seen by the market company

Discrete-event simulation model

The simulation model depicts the conceptual model with entities representing orders, work in process, inventory, and material supplied by

external suppliers, and resources representing the suppliers manufacturing and transporting capabilities including policies for controlling manufacturing and stock-keeping. The computer simulation model was built in Visual Basic with a Microsoft® Excel GUI. The choice of platform was specified by the enterprise. The simulation model was verified and validated via the following three techniques: First, the model logic was verified by using debugging tools such as trace and step-wise execution of the program code while variables such as order and inventory status were observed. Second, people who were knowledgeable about the real system confirmed that the simulation model appeared to be correct and behaved as expected when input parameters were changed. Finally, a comparison of input-output transformations was performed for the total lead time, see figure 3. The R-square value is 56% and the residual analysis revealed four orders with a considerable difference between actual lead time and simulated lead time. In discussions with the enterprise, it was concluded that the reasons for these deviations were due to events outside the scope of the simulation model, e.g. rush orders, delays caused by customers or other entities outside the model. If these four data points are removed, the R-square value increases to 82% and the normality assumptions on the residuals can be validated.

Meta-models

In order to build the input-output relationship of the discrete-event simulation mode, a fractional factorial design consisting of 1024 simulation runs with different parameter settings were performed to evaluate the impact of 26 input parameters on five response variables. The input parameters used were the yearly demand, demand variability, manufacturing batch quantity agreements between the suppliers, safety stock levels, and manufacturing and transportation lead times throughout the supply chain. The response variables were the total lead time, capital employed, total stock keeping cost, deliveries out of agreement, and penalty costs. Linear meta-models were built for each response variable. The linearity assumption was verified through the use of center points in the experimental design. The R-squared values were between 90 percent and 95 percent for the lead time, capital employed, and stock keeping cost models, and approximately 70 percent for the out of agreement and penalty cost models. The meta-models allow for conscious decision making when determining near-optimal values for the different decision variables, for example, when making the trade-off between lead time and stock keeping.

Monte Carlo simulation

The software @Risk was used to perform risk assessment through Monte Carlo simulation. The order quantity agreements and safety stock levels were modeled using discrete uniform distributions, while lead times were modeled using exponential distributions, and the yearly demand was modeled using a normal distribution. 10000 iterations were performed on each meta-model and the resulting histogram of the response variable and the sensitivity analysis in the form of a plotted tornado graph, see figure 4. The time required to perform the 10000 iterations is less than a single run of the discrete-event simulation model.

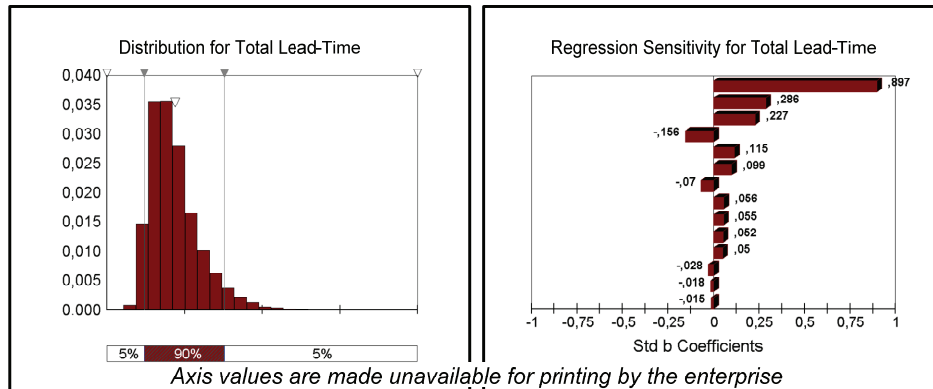


Figure 4. Risk assessment of the total lead time and a sensitivity analysis

Empirical simulation study summary

The main results of the empirical simulation study were; (1) that the trade-off between overall lead time and tied up capital in the supply chain could be quantified, (2) managerial insights into the effect of different decisions made by the third-tier suppliers, e.g., policies for keeping inventory and managing safety stocks, and the negative impact of lumpy demand, which has implications for marketing and sales activities, (3) the pinpointing of risks was such that the enterprise could focus its monitoring actions on the right suppliers and components while paying less attention to other less critical variables, and (4) that a 20% reduction in inventory levels was possible without adversely affecting the overall lead time.

CONCLUSIONS

This paper has presented a hybrid simulation approach to identify risks, locate near-optimal solutions, and assess risks in a supply chain. The practicality of the approach has been tested during the empirical simulation study. Indeed, the concept of building meta-models represents a simplification, but the approach preserves stochastic behavior which allows for a straightforward evaluation of the impact of input variables on multiple responses. Furthermore, the construction of meta-models not only serves the purpose of permitting a calculation of the “most appropriate” values of the different decision variables, but also identifies risk variables. That is to say that if a input variable has a significant effect on a response variable it also serves as a potential risk if the decision variable cannot be determined precisely, or if its value changes for some reason. This risk is assessed during the Monte Carlo simulation on the meta-models and the sensitivity is quantified. This allows supply chain managers to iteratively search for more robust solutions, or to prioritize risk mitigation actions correctly, and define risk monitoring plans accordingly. Finally, the approach is computationally efficient, which enables scaling to very large supply chain models. A formal analysis of the accuracy of the hybrid simulation has not, however, not been performed and this will be an important challenge for future work.

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Paper 3

Notes on the validity and generalizability of empirical simulation studies: Experiences from a Solid Waste Logistics Simulation Study

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ABSTRACT

Simulation as a research methodology is becoming increasingly important in the study of logistics systems. Empirical simulation studies, however, are often criticized for lacking scientific rigor in terms of the validity and generalizability of the results. This applies in particular to the study of future, “what if”, scenarios. The aim of this paper is to explore and discuss the issue of achieving validity and generalizability of empirical simulation study results based on the experiences from an empirical solid waste simulation study done in Malmö, Sweden. The results from this single case indicate that a combination of analytical model building and simulation model building not only increases the validity of the model, but also enables a better assessment of the generalizability of the model results. No conclusive evidence can however be presented from a single case, and although progress seems to have been made, assessing and inferring generalizability of results from empirical simulation results will remain an intricate and perilous activity.

Key Words: Validation, Generalizability, Simulation, Empirical research, Methodology.

INTRODUCTION

The increasing availability of powerful computers and easy-to-use simulation software allow researchers to build ever-more complex empirical simulation models of logistics systems and supply chains. Consequently, methods such as Discrete Event Simulation (DES) and Agent Based Modeling (ABM) are becoming increasingly important in logistics research. This is also reflected in the growing number of articles published on this topic in operations management journals (Shafer and Smunt, 2004).

Empirical simulation studies, as a research methodology are, however, often criticized for lacking scientific rigor in terms of the generalizability and validity of the results. This applies in particular to the study of future, “what if”, scenarios. This critique is unfortunately legitimate. Simulation studies used as a stand-alone method present obvious problems; “There is a very real risk that computational models become ends in themselves, both the subject and object of study.” (Goldspink, 1997) Furthermore, practitioners and researchers in the field of verification and validation seem to agree that one of the major issues concerning simulation studies (both in research and industry) is that “complex simulations are usually not validated at all, or are only subjectively validated; for example, animated output is eyeballed for a short while.” (Joines et al., 2000)

The exact nature of ‘validity’ and ‘generalizability’ in this context is highly debated as no single definition of the terms exists. In this paper, the following definitions will be used:

Validity is the degree of accuracy to which a simulation model describes and explains the phenomena in the real system that it is intended to model. The definition has been inspired by Hammersley, M. (1987).

Generalizability is defined as the “extent to which it is possible to generalize from the data and context of the research study to broader populations and settings” (Hedrick et al., 1993)

The aim of this paper is to explore and discuss the challenge of achieving generalizability and validity of empirical simulation study results through the use of a single case, an empirical simulation study where different

logistical policies for collecting and hauling solid waste were evaluated. The paper begins with a brief section of verification and validation methodology, a section on generalizability of research results. Thereafter follows a presentation of the empirical simulation study, followed by the application of validation and verification methodology in the case. The paper ends with a concluding discussion on how generalizability and validity can be achieved in empirical simulation studies.

VERIFICATION AND VALIDATION OF SIMULATION MODELS

One of the most challenging parts of a simulation study is the process of the verification and validation of the simulation model. The goal of the verification and validation process is twofold; (1) to create a model of reality which represents the true system closely enough to be used as a substitute for the purpose of experimenting and predicting system behavior, and (2) to make the model credible to users and decision makers (Banks et al., 2001). If done correctly, the verification and validation process will ensure the validity of the simulation results. There is, however, no standard theory, nor is there a standard toolbox for verification and validation. There does however exist a large number of software practices, statistical techniques and philosophical theories which can be used for verification and validation (Kleijnen, 1995). In Banks (1998) more than 75 different verification and validation techniques are presented. It is not the purpose of this paper to review all these techniques so that in the section below, only some high-level steps will be presented.

Verification

Verification is the process of building the simulation model correctly, i.e., to ensure that the conceptual model of reality is correctly translated into a computer representation of the model. In a sense, verification aims to create a 'perfect' computer program without any bugs. Verification is also sometimes referred to as 'internal validation'. Several tools and techniques exist for verification purposes.

Good programming practice

Any good programming practice generally used by software engineers is typically also applicable for the development of simulation models; e.g.

object-oriented programming, modular programming, structured code reviews, the use of logic flow diagrams, the use of debug tools for stepping through critical code passages, halting execution and reviewing model variables, conditions, and checking intermediary results, etc.

Comparing simulation output with analytical results

In many situations, the simulation model can be simplified so that an analytical solution can be calculated. The simplified version of the simulation model can then be executed and the result compared to the calculated value. For example; many logistics simulations model reality as complex queuing systems. Consequently, queuing theory can be used to calculate steady state expectations for resource utilization, waiting times etc, for simplified versions of the model, and subject to certain assumption with regards to, for example, the distribution of arrival and service times. In this way, certain parts of the model can be verified analytically.

Computer animation

Most simulation packages enable the user to create animations which display how the simulated system is operating. By reviewing the animations, programming errors may be detected. Classical examples of this type of errors are automate guided vehicles (AGVs) which 'magically' pass through each other, and objects which disappear into or appear out of nowhere due to programming errors.

Validation

Validation is the process of building the right model, i.e., to ensure that the conceptual model is an accurate representation of the real system. Validation, however, does not aim to create a 'perfect' model since the 'perfect' model would be equal to the system itself. Validation rather aims to create a model which is 'good enough' for the intended purpose. What is described here as 'validation' is also sometimes referred to as 'external validation'. One can distinguish three aspects of validation; (1) conceptual model validation, i.e., "to determine that the theories and assumptions underlying the conceptual model are correct and that the model representation of the problem entity is 'reasonable' for the intended purpose", (2) operational validation, i.e., "determining that the model's output behavior has sufficient accuracy for the model's intended purpose over the domain of the model's intended applicability", and (3) data

validation, i.e., “ensuring that the data necessary for model building, evaluation and testing, and conducting the model experiments to solve the problem are adequate and correct” (Sargent, 2003). To perform validation of a simulation model, the following three-step approach, formulated by Naylor and Finger (as referenced in Banks et al., 2001, p. 376), is widely used.

Build a model with high face validity

The first step is to create a model which on the surface appears to be correct to people who are knowledgeable about the real system. This can include qualitative reviews of system outputs, and sensitivity analysis to confirm that the model is behaving as expected when one or many input variables are changed.

Validate model assumptions

Model assumptions can be divided into two classes; structural assumptions and data assumptions. The data assumptions are validated through the collection of reliable and representative sample data from the real system and the use of proper statistical analysis for comparing the real data with the hypothesized distribution in the simulation model. The structural assumption, which involves how the system is operating, is typically validated through observations of the real system and discussions with people who are knowledgeable about the real system.

Comparison of input-output transformations

During this phase of the validation process, the model is validated through the execution of the simulation model using certain input conditions obtained from the real system and comparing the simulation output with data from the real system. Several statistical techniques exist for the purposes of making this comparison. For input-output transformation validation to be conducted, it is a necessary condition that the system exists in reality, and that system data can be collected from it. If the simulation study involves future scenarios, these cannot be validated by comparing input-output transformations. In many cases, however, the future system is a modification of an existing one which can be validated using this methodology. If the modifications are minor (in terms of the computer representation of the system) and the original (unmodified) system can be validated using this methodology, one may also be reasonably confident in the validity of modified system.

It should be noted that the classic article by Naylor and Finger has been criticized on the basis of the underlying philosophical positions, and due to the difficulties which arise in the common situation where the real system does not exist (Kleindorfer et al, 1998).

GENERALIZABILITY OF EMPIRICAL SIMULATION STUDY RESULTS

If validation of an empirical simulation model is difficult, claiming that the results from such a study would apply in another context is even harder. It may, however, be possible to infer generalizability within certain bounds or recognize typical patterns for a system which may apply elsewhere. Nevertheless; “The risk of any one computational model being ‘a mere example’ unfortunately exists” (Kollman et al. 1997 in Goldspink, 1997).

Yin (1994) defines two types of ‘generalization’; (1) ‘statistical generalization’ as the process of generalizing the findings from a sample to the population it represents; and (2) ‘analytical generalization’ as generalizing the findings of a study to create theory. Due to the effort and cost of making empirical simulation studies, such a study can be compared to a single case study, and typically, only ‘analytical generalization’ applies to the study results. Analytical generalization, or ‘theoretical generalization’ as it is sometimes referred to as, is then the extension of insights from the empirical simulation study to other situations or populations.

CASE: THE SOLID WASTE COLLECTION SIMULATION STUDY

Background

Since 1994, Sweden has had a producer’s responsibility for packaging waste. All companies which manufacture, import or sell packaging are responsible for ensuring that the packaging waste can be collected and recycled. Together, these companies have formed five material handling companies working together under the name Packaging Collection Service, with the task of organizing and administering this responsibility. In order to collect the packaging waste, the Packaging Collection Service has set up recycling stations at more than 7,000 locations throughout the country. A

typical recycling station has a number of containers where nearby households can discard plastic, paper, cardboard, corrugated board, metal, and glass packaging. The collection, hauling, and sorting of packaging waste are contracted out to local entrepreneurs. The containers are typically collected by front-loading compacting vehicles. Due to heavy congestion, this vehicle type cannot, however, be used in downtown areas and consequently some inner city containers are of a different design and are collected using smaller, less efficient, non-compacting, open-sided vehicles which use a crane for waste collection.

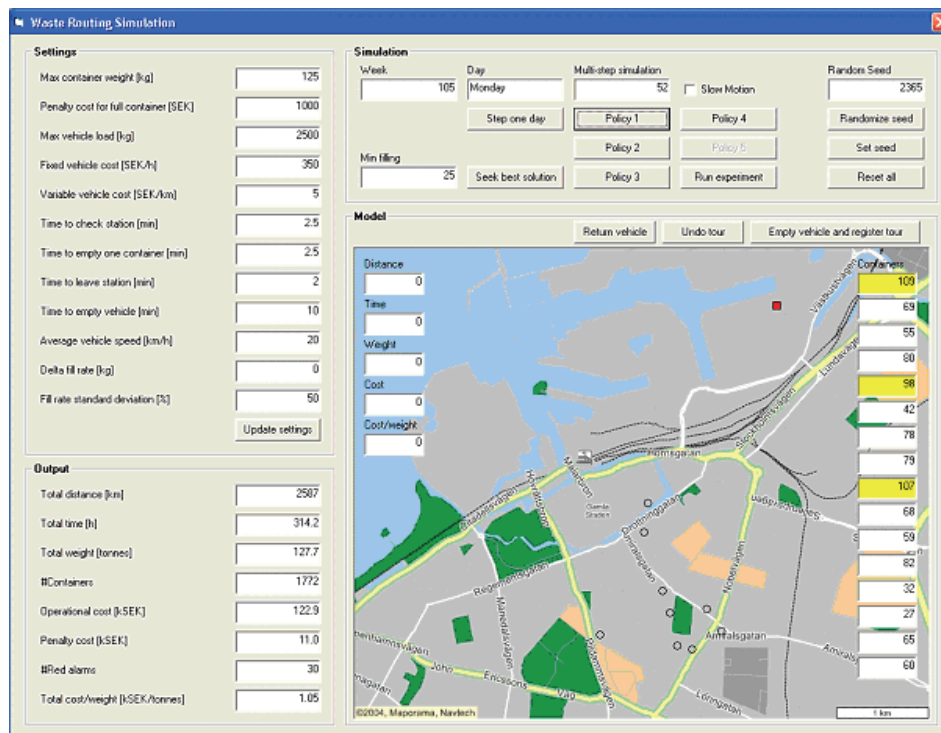
Recently, the material handling companies for corrugated board and cardboard, Returwell and Svensk Kartongåtervinning respectively, fitted their containers with level sensors and wireless communication equipment in order to assess the quality of the service provided by the entrepreneurs, and to give them the opportunity to plan their logistics operation more efficiently. The investment was paid in full by the material handling companies. Approximately 3,300 “smart” containers have been distributed to recycling stations around Sweden. The sensor is mounted under the lid of the container. The sensor is activated once an hour and assesses the level of the container by means of four infrared light emitting diodes. If three of the four beams are broken, a first text message is transmitted through the GSM network to the waste collection operator. A second text message is transmitted when all four beams are broken and a third text message is sent when a tilt sensor indicates that the container has been emptied. In order to assure the quality level of the service, the operator is charged a penalty if the time between the second and third text message exceeds 24 hours on weekdays and 48 hours on a weekend.

The purpose of the simulation study was to evaluate different logistical policies for collecting and hauling solid waste that utilize the real-time demand data, and compare them to the static policy which was used prior to the introduction of level sensors in the system.

Data for the simulation study was collected through observations and interviews with planners and drivers operating the stations in Sweden’s third largest city, Malmö. Demand data from the downtown recycling system was collected over a period of 6 months, from November 2003 until May 2004. Supplementary interviews were conducted with two other operators of similar systems in order to investigate their usage of real-time data.

The simulation model

The simulation model consists of containers, vehicles, and a recycling facility. The key attributes of the containers are mean waste fill rate [kg/day], standard deviation of fill rate [kg/day], current weight [kg], capacity [kg], and location. Each container is fitted with a level sensor which triggers an alarm signal when the container exceeds the 75% level (“yellow alarm”), and when it is 100% full (“red alarm”). The key attributes of the vehicles are the current weight of its load [kg], capacity [kg], average speed [km/h], time to perform different actions, e.g. check station, set up vehicle for collection, collect, reset vehicle, empty vehicle at recycling facility [min], distance cost [SEK/km], and hourly cost [SEK/km]. The key attribute of the recycling facility is its location.



Picture 1. The Malmö Simulation Model

Two different Euclidian geometries were used in the evaluation. The first geometry was a general city model where the collection points were equidistantly located around a circle with a recycling plant which lies

outside the circle. The second geometry used in the simulation was a model of the actual system in Malmö, Sweden, see picture 1.

At the beginning of each simulation run for the first Euclidian geometry, a random system was created, based on input values for system size in terms of the number of containers and geometry parameters, minimum and maximum values for the waste generation, and standard deviation of fill rate. The mean waste fill rates per container are drawn from a uniform distribution with the minimum and maximum values for the waste generation as parameters. The simulation results are based on a waste generation minimum value of 4 kg/day, a maximum value of 20 kg/day and a standard deviation of 50% of the mean fill rate if nothing else is indicated. During the simulation, each location generates waste according to a normal distribution and adds it to the containers. When the waste quantity exceeds the threshold values 75% and 100%, a planning event is triggered and vehicles might be re-scheduled and rerouted to the recycling points according to different planning policies. If a container is full and not collected within a specified time, 24 hours on weekdays and 48 hours during the weekend, a penalty is charged. As with the real system, collection and hauling are only conducted in the daytime on weekdays. The duration of the simulation was 104 weeks and as it is a terminating system, no warm-up period was used.

The primary performance indicators used include the total operational cost of the system, penalty cost, labor hours, collection and hauling distance, number of tours, and number of containers collected, all on an annual basis. All simulation runs were replicated 5 times and the mean values of the performance indicators were computed.

Four different collection policies were used in the evaluation; (1) the static routing and scheduling used today by the waste collection operator; (2) a dynamic policy where vehicles are scheduled and routed based only on information from the level sensor; (3) a dynamic policy where scheduling is controlled by the level sensors, while the routing is based on a heuristic search for full and almost full containers; (4) a policy with fixed scheduling and dynamic routing to full and almost full containers.

Static scheduling and routing [1]

This policy mimics the actual operations of the system practiced today with fixed collection days and routes. The procedure for solving the static scheduling and routing problem is based on the heuristic algorithm proposed by Christofides and Beasley (1984). Briefly, the method is based on an initial choice of the frequency of container collection followed by a grouping of collection days aiming at minimizing the total collection cost for the time period. The mean and standard deviation of the waste generation are assumed to be known to the planner. Once a solution has been obtained, the system is simulated using the static schedules and routes for the duration of the simulation.

Dynamic scheduling and routing to full containers [2]

This policy is fully event-driven and initiates a tour to full containers within 24 hours from the receipt of a “red alarm”. In order to avoid overfull containers and subsequent penalties during weekends, a special rule for Fridays was introduced so that containers where the “yellow alarm” has been triggered were also collected. As with all dynamic scheduling policies, it is assumed that the collection system has sufficient capacity to handle the collection requests regarding the containers within 24 hours.

Dynamic scheduling and routing to almost full containers [3]

This policy is similar to policy 2, and initiates a tour to full containers within 24 hours from the receipt of a “red alarm” or a “yellow alarm” on a Friday. The vehicle is, however, not routed exclusively to full containers, but also to nearby containers which have an estimated level greater than a set threshold value. If the threshold value is set to 100%, this policy becomes equivalent to policy 2. The level of each container is predicted by the assumed known mean fill rate for the container and is calibrated at the time of the “yellow alarm” (or by the absence of the alarm). The rule aims to utilize the vehicle more efficiently during the collection day.

Static scheduling and routing to almost full containers [4]

The static scheduling and routing to almost full containers policy is based on a static scheduling using the same collection days as policy 1 has chosen. The routing is, however, done dynamically to full and almost full containers using the same logic as policy 3.

Simulation results

In the simulation study presented, the effect of some basic scheduling and routing policies in the collection of solid waste has been examined. From the study, it was concluded that dynamic scheduling and routing policies exist which have lower operating costs, shorter collection and hauling distances and which collect fewer containers, compared to the static policy employed by many waste collection operators, for system sizes ranging from a few containers up to 1000 containers, and realistic levels of variation. Further, dynamic scheduling and routing have the highest potential to decrease costs in the face of irregular demand. It was also shown that increasing variability of the inflow increased the collection and hauling costs regardless of the policy, but the increasing uncertainty impacts the static scheduling and routing to a much greater extent than the dynamic policies. Further, for large and dense systems, the dynamic scheduling and routing policy 2 is the optimal solution. However, when the number of containers is decreased and/or the distance between the containers is increased, this policy rapidly loses its benefits. For smaller systems, the dynamic policy 3 is more suitable and cost reductions in the range of 10% to 20% can be expected for the type of systems evaluated in the study.

VALIDITY OF THE SOLID WASTE SIMULATION RESULTS

Verification and validation

One of the most critical data assumptions in the solid waste collection model was related to modeling of waste generation which created the demand for collection. Data on recycling waste per recycling point in the real system was therefore collected over a period of 6 months, from November 2003 until May 2004. In the simulation model, it was assumed that the amount of

waste in a container after a certain time would follow a normal distribution curve. The selection of normal distribution is a consequence of the central limit theorem which states that the sum of many stochastic variables of arbitrary probability distributions approaches a normal distribution curve. With the exception of the time around Christmas, when the generation of packaging waste is extremely high, this assumption was validated using a Kolmogorov-Smirnov Goodness of Fit test for the Normal Distribution on the collected data.

Data on the collection and hauling was collected through observations and time studies done on the drivers. Data on level sensor alarms were retrieved from the operator's mail system. Unfortunately, most of the automatically generated mails concerning alarms had been deleted so only a limited number of alarms was recorded. These alarms were compared to the waste generation data for the specific location to obtain confirmation that the records matched each other. No statistical validation was however conducted.

The observations also formed the foundation of the structural assumptions for how the collection and hauling operation was performed. These assumptions were later validated in interviews with the planner and drivers operating the real system. In these meetings, face validity of the model was also obtained.

A detailed input-output transformation validation of the model and the real system was not done due to the lack of data on tour level. Instead, aggregated data on a yearly basis was available, allowing the model to be validated (and calibrated) on this level. This validation was naturally only done for the static policy according to which the operation of the real system was performed.

To assess the validity of the other policies using real-time data from the level sensors, the changes in the computer representation of the model have to be considered. Although the changes in the system seem huge, i.e. changing the triggering of a tour from a static schedule to a dynamic alarm from a level sensor, and changing from a static route to a dynamic route, the actual changes in the program code are small; (1) a change in the start condition of a tour from checking the simulation clock to checking alarms, and (2) minor changes in the list of waypoints of the tour. The latter change was also possible to validate by comparing the simulation output for policy

1 and policy 4 for different levels of the threshold value for when a container should be considered ‘full enough’ to be added to the list of waypoints. As expected, policy 1 and policy 4 produce identical results when the threshold value is set to 0%. Although policies 2 and 3 cannot be quantitatively validated, the minor programming change required for implementing these policies means that a great deal of the validity obtained for policy 1 and policy 4 carries over to these policies as well.

Development of an analytical model

In order to verify the solid waste simulation model, an analytical model of a system with N containers was also developed using probability theory. It was assumed that the amount of waste in a container after a certain time would follow a normal distribution curve. This assumption was supported by the empirical data collected. Further, it was assumed that all containers are collected during each tour, that the truck has sufficient capacity to empty all containers, and that the containers are equal in terms of capacity, mean fill rate, and standard deviation of the fill rate. For the dynamically controlled system, it was further assumed that the response time for collection was negligible. This dynamically controlled system thus operates according to policy 3 with a threshold value of 0%. In order to compute the static scheduling, an acceptable risk level, α , for exceeding the container capacity has to be set. The mean time between collections [MTBC] is then defined by equations 1.1 and 1.2. Since the real system does not operate 24 hours a day, seven days a week, the system was made time-discrete by truncating the $MTBC_{\text{static scheduling}}$ value and calculating a weighted average value for the $MTBC_{\text{dynamic scheduling}}$, thus allowing the system to operate in the daytime on weekdays only.

$$MTBC_{\text{static scheduling}} = \frac{2 \cdot M \cdot \mu_{\text{day}} / Z_s^2 + \sigma_{\text{day}}^2 - \sqrt{\left(2 \cdot M \cdot \mu_{\text{day}} / Z_s^2 + \sigma_{\text{day}}^2\right)^2 - 4 \cdot M^2 \cdot \mu_{\text{day}}^2 / Z_s^4}}{2 \cdot \mu_{\text{day}}^2 / Z_s^2} \quad [\text{Eq. 1.1}]$$

$$MTBC_{\text{dynamic scheduling}} = \frac{2 \cdot M \cdot \mu_{\text{day}} / Z_d^2 + \sigma_{\text{day}}^2 - \sqrt{\left(2 \cdot M \cdot \mu_{\text{day}} / Z_d^2 + \sigma_{\text{day}}^2\right)^2 - 4 \cdot M^2 \cdot \mu_{\text{day}}^2 / Z_d^4}}{2 \cdot \mu_{\text{day}}^2 / Z_d^2} \quad [\text{Eq. 1.2}]$$

Where:

$Z_s = F^{-1}(p) \left| p = (1 - \alpha)^{\frac{1}{N}} \right.$: inverse cumulative standardized normal distribution

$Z_d = F^{-1}(p) \left| p = 0.5^{\frac{1}{N}} \right.$: inverse cumulative standardized normal distribution

$p = \int_{-\infty}^t \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$: cumulative standardized normal distribution

α : risk of exceeding container capacity

μ_{day} : mean inflow per container and day [kg/day]

σ_{day} : standard deviation of inflow per container and day [kg/day^{0.5}]

M : container capacity [kg]

N : number of containers

The simulation model output was then compared to the analytical model. To match the assumptions of the analytical model, the vehicle capacity limitation in the simulation was removed and the waste generation parameters for all containers were set as equal. In total, 6,724 simulation runs of varying system sizes ranging from 5 to 50 containers, mean fill rates ranging from 5 to 25 kg/day, and standard deviations ranging from 0 to 10 kg/day were compared to the analytical model with an mean average percent error (MAPE) of less than 0.2%. This demonstrated a very good match between the two modeling approaches, and was a strong indicator that the simulation program was indeed correctly coded.

DISCUSSION

In the case presentation, some key steps in achieving validity in the simulation study results have been highlighted. What became apparent during this empirical simulation study was the value of the analytical model, not only for verification purposes, but also for assessing the generalizability of the results. Although, or maybe because, the analytical model is simple and far from sufficient for characterizing a realistic solid waste management system, it can act as a vehicle for thoughts on other situations or populations where the results may apply, e.g. the analytical model may just as well apply in a situation where a manufacturer is considering different policies for

replenishing vendor-managed inventory. This is not readily apparent from the empirical simulation model alone.

Furthermore, the results and conclusions drawn from the simulation study can be compared to the analytical model. While some conclusions from the empirical simulation study are supported by the analytical model, others are not, e.g. the conclusion that “dynamic scheduling and routing have the highest potential to decrease costs in the face of irregular demand” and that dynamic solutions are more robust with respect to increasing volatility are supported by the analytical model, while cost reduction figures and detailed policy comparisons are not. One may then argue that conclusions supported by both the empirical simulation and the analytical model are better candidates for more generalized statements, than statements based on the empirical simulation model alone.

Analytical modeling combined with simulation modeling is, however, rare. Sometimes analytical models are used for verification purposes on a submodule level of a simulation program, but hardly ever on the full model. This is understandable, since one of the key reasons for performing a simulation study in the first place, as opposed to an analytical calculation, is that the problem cannot be formulated as a mathematical problem, or that the mathematical problem is apparently intractable or provably unsolvable. What is often missed is that an analytical solution is sought after for a simplified version of the model, and in the process of simplifying a simulation model, an assessment of what is general and what is specific to the model can be done, thus enabling a more knowledgeable discussion of the generalizability of the empirically simulation results

Although this paper argues that a thorough verification and validation process, with an emphasis on the importance of analytical modeling, not only increases the validity of the model, but enables a better assessment of the generalizability of the results, no conclusive evidence can be presented from a single case, nor can one hope that it is possible to use this methodology in all cases. Assessing and inferring generalizability of results from empirical simulation results will remain an intricate and perilous activity. Nevertheless, the author hopes that the methodology presented will be used and expanded in order to reduce the customary criticism of empirical simulation model results.

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