Chapter 1

Introduction

1.1 Motivation

The global transportation service industry grew by 4.3% in 2006. However, the cargo logistics provider industry could not translate this growth into profitability. Due to high energy and maintenance costs, the average return-on-sales of cargo logistics providers in Europe reaches just 3% (cf. DataMonitor (2003, 2005, 2007) and Ferrulli (2007)). Reducing costs by 1% would lead to an increase of return-on-sales by 32%. Thus, tight control of costs becomes a key factor for success. This is particularly important for fleet ownership costs, which typically make up a large part of total costs of cargo logistics providers.

At the same time, the cargo logistics industry experiences a phase of market concentration, such as we observe in the container shipping industry, where the market share of the 10 largest providers grew from 49% to 60% between 2000 and 2006. As a consequence, the providers and with them their vehicle fleets grow. Large rental companies accumulate hundreds of thousands of vehicles. For example, the largest European container rental company, Sea Containers Ltd., owns about $700,000$ containers. The largest European rail cargo company, Railion AG, plans to invest $1,700$ mio. Euros into new rail cars during the next years (cf. BRS (2006), IICL (2006), Krummheuer (2007), and Sea Containers Ltd. (2005)).

Therefore, fleet management is becoming increasingly complex. While in the past fleet planning could be performed manually, the new vast size of the planning problem necessitates the use of advanced planning tools. These tools do currently not exist and existing research results in the field of operations research do not yet cover the new dimension of this problem.

The substantial effect of fleet planning on company profit and the size of the planning problem have inspired us to develop stochastic models of rental systems. In this thesis, we describe research that contributes to the body of known research on these systems and that can improve decision making in rental fleet planning.

In the remaining sections of this chapter, we first describe the industry of vehicle rental businesses (Section 1.2). Then, we demonstrate how we model rental businesses as stochastic models and we define a common modeling framework (Section 1.3). Finally, we describe the overall structure of the thesis and provide a short outlook into each of the following chapters (Section 1.4).

1.2 Vehicle Rental Businesses

In this section, we introduce vehicle rental businesses. Firstly, we explain the business model of rental services. We provide an answer to the questions of what a rental service is and why customers rent instead of buying vehicles. Secondly, we describe the vehicle rental industry for commercial customers by delimiting this industry from other rental industries and by analyzing the sizes of the container rental industry, the cargo rail car rental industry, and the truck rental industry, which are typical B2B vehicle rental industries.

The Business Model of Rental Services Renting a piece of equipment means that a rental company allows the customer to use its equipment for a certain period of time and the customer compensates the rental company for the service by paying a rental fee. The rental business is therefore a service industry. Services have the characteristics that they are intangible, perishable, and that their production and their consumption are not separable (cf. Van Looy et al. (2003)).

This also applies to rental services, because they are not tangible products and they have to be produced and consumed at the same time as well as in the same place. As a consequence, rental services cannot be produced to stock. The rental company is forced to maintain sufficient capacity to "produce" the rental service whenever the customer needs it. Without sufficient capacity the rental company may loose business.

The customer, on the other hand, does not own the equipment she needs but orders it from the rental company when it is needed. But why do customers of rental companies prefer to rent equipment instead of buying it? The European Rental Association (2007) states several reasons why renting equipment is useful. We describe the ones that apply best to the rental systems we consider in this thesis:

1. **Renting equipment reduces ownership costs** Fleet equipment is often better utilized if it is rented out by a rental company than if it is owned by the company which uses it. The higher utilization of rental equipment compared to other equipment leads to less ownership costs per usage, because cost of capital and depreciation are independent of the utilization.

2. **Renting equipment reduces fixed assets** If a company purchases its own equipment, the investment becomes a fixed asset and the amount of fixed assets in the balance sheet of the company increases by the purchase price. The purchase has to be financed in some way, leading to either more debt or more shareholder equity.

3. **Renting equipment provides more flexibility** Typically, B2B equipment such as cargo vehicles or machines have long life times. If a company purchases its own equipment, it has to utilize it for a long period of time before the investment becomes profitable and, therefore, the company is less flexible with its own equipment than with rented equipment if its demand for equipment changes over time.

Industry	**Market Value** [mio. Euro]	**Fleet Size** [vehicles]
Container Rental	125	800,000
Rail Car Rental	1,750	600,000
Truck Rental	2,500	100,000
Total	4,375	1,500,000

Source: DataMonitor (2006), European Commission (2007), Krummheuer (2007),UNCTAD (1999), Sea Containers Ltd. (2005), VTG AG (2007)

Table 1.1: Annual market value and fleet size in 2005 of the main B2B vehicle rental industries in Europe

4. **Renting equipment reduces risk** Safety issues and maintenance of the rental equipment typically remains the task of the rental company. Thus, the customer does not have to worry about compliance of the equipment with legal regulations or safety standards. Since in most situations, the rental company is specialized in providing a certain type of equipment, it usually has specific knowledge about current regulations.

A major disadvantage of rental equipment is availability. While someone's own equipment is always available, rented equipment might not be available when it is needed.

The B2B Vehicle Rental Industry In this thesis, we consider B2B vehicle rental businesses. In these businesses, commercial customers need to transport cargo and for this reason they order vehicles from a cargo logistics company. The vehicles are e.g. trucks, containers, or rail cars. The logistics rental company provides the vehicles and the customer uses them to store and transport the cargo. Some rental companies only provide the rental service and the transportation service is performed by other companies. This is, for example, the case in the container rental industry. Other rental companies, such as some rail cargo companies, also provide the transportation services. In this case, the company rents out the vehicles and the customer specifies when and where the vehicle should be transported after the cargo has been loaded.

The market value and the market size of the B2B vehicle rental industry is

Figure 1.1: Typical rental process for cargo vehicles

large. The total annual market value of the container rental, the rail car rental, and the truck rental industry in Europe in 2005 was about 4,375 mio. Euros. Their total fleet size exceeded 1.5 million vehicles. The detailed numbers per industry are given in Table 1.1.

The operations of vehicle rental companies differ from operations of other transportation service providers, such as airlines or package delivery companies. The distinguishing feature of vehicle rental businesses is that customers of these businesses rent whole vehicles instead of some space in a transportation vehicle.

In this thesis, we focus on rental systems that serve commercial customers. We specialize on rental systems that serve commercial customers, because commercial customers and private customers behave differently and the customer behavior affects the rental system. One example for a difference between commercial and private customers is that private customers typically order only one vehicle while commercial customers often request multiple vehicles in one order.

A typical rental process begins with the customer order and ends when the vehicle becomes available for other customers (we do not consider secondary activities such as billing). When a customer order arrives, the rental company decides what vehicles it will use to fill the order. The empty vehicles are transported from their current location to the customer destination. After the customer has received the vehicles, she loads the cargo into the vehicles and the transportation to the destination location begins. At the destination, the vehicles are unloaded. In some scenarios, the vehicles are loaded again at the same location and are sent to another destination. After the final unloading, the customer informs the rental company, which picks up the vehicles from the customer site. If the vehicles are defect or need to be cleaned, they are brought to a service facility for repair or cleaning. Afterwards, the vehicles become available for subsequent rental services. This generic rental process is summarized in Figure 1.1.

1.3 Modeling Rental Systems as Stochastic Systems

The models analyzed in Chapters 2, 3, 4, and 5 share some common characteristics. In this section, we first define a generic modeling framework for describing and comparing rental models. Afterwards, we introduce rental systems by applying one of the most basic stochastic loss models, the Erlang Loss Model (ELM), to rental systems. In Section 1.4, we use the framework and the ELM to compare the different models presented in this thesis.

The Modeling Framework The rental company possesses a number of vehicles with which it performs the rental services. Vehicles of the same type are grouped into fleets, and the grouping of vehicles into different fleets is known as the *fleet structure*. The number of vehicles in one fleet is referred to as the *fleet size*. In most models, the vehicles are assumed to be *homogeneous*, i.e., they all have identical operating characteristics and the customer has no preference what vehicle of the fleet she receives. However, some approaches allow for *heterogeneous vehicles*, e.g. models with vehicles that have different processing times. For owning and maintaining a car, it is commonly assumed that the rental company has fixed holding costs per time unit and car. These costs may comprise cost of capital, depreciation, and maintenance cost.

Customers may come from *one customer class* or *multiple customer classes*. Customers place orders for rental services at individual times on a continuous time axis. The arrival times of orders are stochastic and so they are not known to the rental company in advance. The rental company only knows the *distribution of order arrivals*. In most rental models, Poisson distributed orders are assumed. However, there are also models in which no distribution assumption is made for the demand. A customer order may require one or more cars for service. When more than one car is required, the number of cars used for one order is referred to as a *batch* and models that allow customer orders with more than one vehicle are *batch-arrival models*. If customer orders of size one are assumed, the model is referred to as a *single-arrival model*. A typical assumption is that customers need the vehicles right away, although we discuss a model in Part 5 where customers place orders a certain time before their actual demand. This is referred to as *advance demand information* (ADI).

For each customer order, the rental company has to decide how many of the ordered vehicles it allocates to the order. The rental company is free to allocate fewer vehicles than required. The policy with which the rental company allocates vehicles to customers is the *admission policy*. If demand is rejected, we assume that it is lost, i.e., it does neither wait nor return at a later time. The quality of the rental service is measured as the fraction of demand filled, which we refer to as the *service level*. There are two possible scenarios concerning customer behavior: Customers may require that their complete order is served (*entire batch blocking (EBB)*) or they may accept partial service (*partial batch blocking (PBB)*). For each rented vehicle, the customer pays a certain price, and this price may depend on the customer class. In some models, customers receive a compensation for each ordered vehicle that is not served.

If a vehicle is assigned to a customer order, the customer receives the car and uses it for a certain period of time, the *rental time*. One main characteristic of our models is that we do not model the rental process itself. We neither explicitly model what the customer is doing with the vehicle during the rental time nor how the transportation service is performed. For our purposes, it is only relevant how long the customer uses the vehicle and when she returns it. Rental times are, as well as customer arrival times, stochastic. Thus, they are not known in advance to the rental company. Some models assume exponential *rental time distributions*, while other models allow for general service time distributions. If customer orders comprise multiple vehicles, the question arises whether the rental times of vehicles

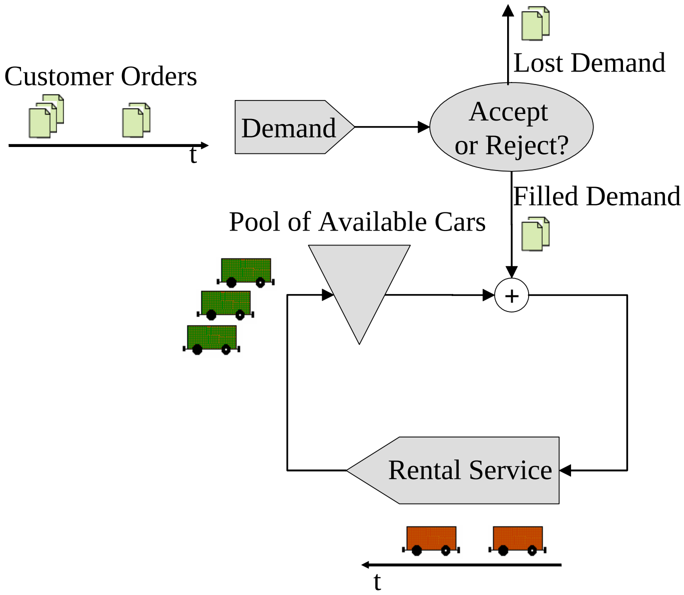

Figure 1.2: Basic rental model

from the same order are *independent* or *dependent*. After a customer has returned the vehicle, it becomes available again and may be used for other customers.

We also distinguish between *stationary* and *non-stationary* models. Stationary models assume that interarrival times and rental times always have the same distribution. In non-stationary models, inter-arrival times and rental times might have different distributions at different times. One common non-stationary model is one that uses demand affected by seasonality. A generic rental model as described above is visualized in Figure 1.2.

The objective function of rental models could be, among others, maximization of expected profit or achieving a certain service level with minimal expected cost. Profit consists of the holding costs, the revenues, and the compensations paid for unfilled demand. In this thesis, we use the fleet size, the fleet structure, and the admission policy in models with multiple customer classes as decision variables.

A Basic Stochastic Rental Model Planning a rental system like the one that we have introduced in this section is not trivial. Since both, customer arrival times and rental times, are stochastic, deterministic planning is not adequate. The stochastic distributions and the decisions that depend on the state of the rental system have to be taken into account simultaneously. We illustrate this complexity by describing one of the most basic stochastic models, the Erlang Loss Model. The model itself has been developed by Erlang (1918). Tainiter (1964) has first applied it to the analysis of rental systems. In the ELM, the rental company has a fleet of c homogeneous vehicles. Each vehicle has holding costs h per time unit. Customers from one common class arrive according to a single-arrival Poisson process with mean λ per time unit. Orders have to be filled as soon as the demand is known, i.e., there are no ADI. Filled orders lead to revenue r, unfilled orders cost penalty p. Rental times are assumed to be independent with an arbitrary distribution. The average rental time is denoted by $\overline{S}$.

The model can be analyzed with Markov Chain Theory (for details see Wolff (1989)). It can be shown that the service level SL of such a system is given by the formula

$$SL = 1 - \frac{\frac{(\lambda\overline{S})^c}{c!}}{\sum_{i=0}^{c} \frac{(\lambda\overline{S})^i}{i!}}. \tag{1.1}$$

Expected profit Π consists of expected revenues $r\lambda SL$, penalties $p\lambda(1-SL)$, and holding costs hc. In total, expected profit is

$$\Pi = r\lambda SL - p\lambda(1-SL) - hc. \tag{1.2}$$

If we want to optimize the fleet size, we can vary it until we find the fleet size that brings the most expected profit. Consider an example with $\lambda = 10$ cars/day, $\overline{S} = 7$ days, $r = 150$ Euros per rental, $p = 250$ Euros per loss, and $h = 3,500$ Euros per year. Figure 1.3 shows how expected daily profit depends on the fleet size. The optimal fleet size, based on the figure, would be 82 vehicles with an expected daily profit of 646 Euros. If we had ignored stochasticity and used deterministic planning, we would probably have found a fleet size of $\lceil \lambda\overline{S} \rceil = 70$ to be optimal,

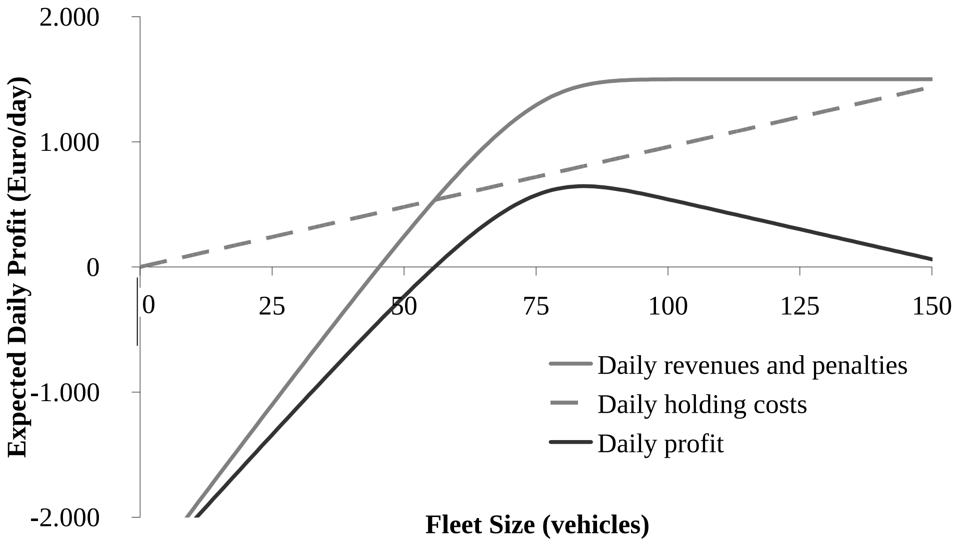

Figure 1.3: Expected daily profit by fleet size for ELM with sample data

which satisfies all demands in a deterministic setting. Expected profit with $c = 70$ is 470 Euros per day, which is 27% below optimality.

The ELM demonstrates that analysis of stochastic rental systems is complex and that ignoring stochasticity in rental systems planning leads to results which are far from optimality.

1.4 Outline

In this section, we describe the structure of the thesis. We explain why there are different, mostly independent research parts, and we give a short outlook into every part. Finally, we compare the four parts by highlighting the differences in the decision variables, the objective functions, and the model assumptions by using the framework defined in Section 1.3.

The remainder of this thesis consists of four separate parts. Each part represents a separate piece of research and is presented in the form of a separate essay. The parts share a general structure. Firstly, there is an introduction which motivates the problem, describes the situation, and outlines the subsequent research. Secondly, each part contains a literature review which provides an in-depth review of the corresponding literature on which the research builds. Thirdly, the model with its assumptions, its decision variables, and its objective function is described. Afterwards, in the main body of each part, the corresponding model is analyzed and optimized. Each analysis and optimization is followed by a short conclusion. The last section of each part contains the mathematical proofs of the analytic results derived in the previous sections.

Finally, after the four main chapters, we conclude the thesis in Chapter 6. In the conclusion, we summarize the key results, give a critical review of the modeling framework that we use for the analysis, and provide an outlook into further research.

We have decided to use such a structure for the thesis, because it facilitates publication of the individual chapters as separate articles in research journals. In addition, it allows the reader to jump directly to one chapter and to read it independently from the others. A disadvantage of this structure is that the literature review sections and the sections containing the model descriptions might overlap at some points.

Next, we give a short outlook into the contents and results of each of the four main chapters.

Chapter 2 Chapter 2 has been motivated by the problem of fleet optimization, which is faced by the rail cargo company that motivated our research. The company operates a fleet of more than $100,000$ rail cars and it invests annually significant amounts of money into new cars. Therefore, planning such a fleet is an important activity at the company. In this chapter, we develop and solve analytical models for fleet planning. We first describe the corresponding rental model. We then develop a profit function and derive several structural results, such as the concavity of the profit function in the fleet size. Building on these structural results we show how the fleet size, the fleet structure (i.e., the types of cars being used), and a joint fleet of owned and leased cars can be optimized. Since some of the optimal methods are difficult to implement, we also develop and test an approximation that is easy to implement. To illustrate our findings and to validate our approach, we provide numerical results that are based on real company data.

Chapter 3 In Chapter 3, we consider a fairly general stochastic rental system with arbitrary batch arrival processes, arbitrary service time distributions, and an arbitrary dependence within orders. In the first part of the analysis, we analytically prove convexity of the loss probability in the fleet size for the case with PBB and we show by counterexample that convexity fails when EBB is assumed. In the second part of the analysis, we extend the model to heterogeneous servers. We extend the convexity proof to this model, and we show that the intuitive idea of ordering the servers by decreasing speed is not necessarily optimal under our model assumptions.

Chapter 4 In Chapter 4, we analyze service differentiation. Service differentiation is an emerging method to improve profit and to better serve high-priority customers. It has recently been introduced by the rail cargo company. Customers of this company can choose between classic and premium service. Premium service is priced above classic service and premium customers receive a service guarantee which classic customers do not receive. The company has to decide under which conditions it will ration its fleet capacity to classic customers in order to increase service of premium customers. We model such a situation as a batch-arrival queuing loss system. We describe the model, solve it optimally, and further analyze it by performing numerical experiments based on real company data. We show that the potential of capacity rationing can be substantial in situations like the one we analyzed. We also derive conditions under which rationing is especially beneficial, such as under high unit fleet holding costs or in the presence of batch arrivals compared to single arrivals.

Chapter 5 In Chapter 5 we analyze service differentiation under advance demand information (ADI). We present a stochastic model of a rental system with

	ELM	Ch. 2	Ch. 3	Ch. 4	Ch. 5
Model features					
Allows for heterogeneous cars			✓		
Number of customer classes	1	1	1	2	2
Order arrival distribution	*Poi.*	*Poi.*	*Arb.*	*Poi.*	*Poi.*
Allows for batch arrivals		✓	✓	✓	
Allows for ADI					✓
EBB or PBB	*n/a*	*PBB*	*both*	*PBB*	*n/a*
Rental time distribution	*Arb.*	*Arb.*	*Arb.*	*Ex.*	*Ex.*
Dependent rental times	*n/a*	✓	✓		*n/a*
Allows for non-stationarity		✓			
Objective function					
Expected profit	✓	✓		✓	✓
Service level			✓		
Decision variables					
Fleet size	✓	✓	✓	✓	
Fleet structure		✓			
Admission policy				✓	✓

Arb. = Arbitrary, Ex. = Exponential, n/a = not applicable, Poi. = Poisson

Table 1.2: Characteristics of the ELM and the models of the four main chapters

two customer classes. As in Chapter 4, customers can choose between premium and classic service. However, under premium service, customers also provide ADI by reserving cars ahead of the time when they need them. The company must again decide which demands to fill and which to reject. We model the system and prove that the optimal admission policy is a threshold policy. Since computing the parameters of the policy is computationally intractable, we propose an ADI policy that can be implemented and executed with moderate effort. We analyze the performance of our ADI policy by analytically deriving upper and lower bounds on the optimal expected profit and by performing numerical experiments using company data. The numerical experiments indicate that the potential benefit of using ADI is significant and that our ADI policy performs close to optimal.

The models analyzed in the four chapters all differ at some points in the decision variables, the objective functions, or the model assumptions. Next, we describe the models with the general modeling framework that we have developed in Section 1.3. This allows an easy comparison of the model characteristics. We also contrast the models to the ELM introduced in Section 1.3. The characteristics of the four models and the ELM are given in Table 1.2. It can be seen that all four models extend the ELM in some respects. However, the models among themselves are not necessarily related. The first two models assume one customer class, while the last two models assume two customer classes. Therefore, the first two models could have more general assumptions about the underlying operations, such as dependent rental times within orders. Each model has a different focus, and with each model we have tried to make only the most essential assumptions with which the models become analytically tractable. The model assumptions are described in detail in each of the four main chapters.

Quelle:
Felix Papier: *Optimization of Rental Systems. Queuing Loss Theory for the Optimization of Cargo Vehicle Rental Systems*,
Kölner Wissenschaftsverlag, Köln, 2008.