Michael Becher

Integrated Capacity and Price Control in Revenue Management

A Fuzzy System Approach

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With a foreword by Prof. Dr. Axel Tuma

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Foreword

Analyzing the basic conditions of modern service and production processes, the strengthened competition constraints and unpredictable demand fluctuations are obvious factors which create an intense pressure, on the one hand, to reduce costs through an efficient process control and, on the other hand, to optimize revenue through an adequate capacity and price control (demand-side revenue optimization). Two points can be recognized when analyzing the research on this basic profit maximization problem: Firstly, much of the research focuses on the cost-reduction problem. This is characterized, for instance, by the operational control of production schedules or the logistics planning. Direct customer interaction is not the main point addressed here. Secondly, the research field underlying the capacity and price control problem during the customer transaction mostly focuses only on one of these two control components of a profit-enhancing Revenue Management. Within the implementation of a Revenue Management approach, it is the real-world applicability which should be focused on. With respect to unexpected fluctuations in demand and unknown behavior of the customers in respect of prices, a solution must be provided that considers these uncertainties in a way which will ensure that the necessary information can be obtained in practice.

Against this background, Mr. Becher develops a concept for an integrated capacity and price control in Revenue Management based on Fuzzy Expert Controllers. It is able to solve the outlined revenue objective under a practicable consideration of the underlying uncertainties. Remarkable is that Mr. Becher not only establishes a comprehensive and consistent theoretical concept but also evaluates his outstanding approach on the basis of three very interesting application cases. The results are important with respect to the adequate development of an integrated capacity and price control in Revenue Management and contribute to the further development of the economic research.

I wish Mr. Becher that this contribution will be successful and have an impact on the further development of Revenue Management in research and practice.

Prof. Dr. Axel Tuma

Preface

This contribution was developed during my time as a Research Assistant at the Department of Production and Environmental Economics of the University of Augsburg. As this book would not have been possible without the tremendous help of many people, I would like take this opportunity here, by means of these acknowledgements, to thank them all.

I would first like to express my gratitude to Prof. Dr. Axel Tuma who offered me a very interesting and informative time at his department. He supported me in all the concerns of my research and provided very worthwhile assistance in the solution of all the problems I faced when writing this dissertation. I would also like to thank Prof. Dr. Hans Ulrich Buhl for his appraisal of this work, and Prof. Dr. Marco Meier for his chairmanship in the disputation. Special thanks also go to the department team which supported me not only with helpful discussions of my research project but also with a great working atmosphere. I am especially indebted to my colleague and friend Dominik Böhnlein who gave me many helpful tips and support during the research, and who thus contributed considerably to this work. Those who supported me with proof-reading should please accept my thanks, too.

My exceptional gratitude must also be expressed to all the people who supported me not only with respect to the work itself but who made it always possible to handle all the related expenditures and releases. First of all, I would like to thank my parents, Ingeborg Becher and Günter Hofmann, for their help throughout all the phases of my life. Without their sacrificial help my education would not have been possible. My thanks also go to my brother, Christian, as well as my friends on whom I can always rely. Last but not least, I am very grateful for the support of my girlfriend, Kerstin. I appreciate very much her patience during the last few years, which cannot have been easy for her, and I am very grateful for her love and constant moral support.

Michael Becher

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List of Abbreviations

AI	Artificial Intelligence
CAB	U.S. Civil Aeronautics Board
CC	Capacity Control
COA	Center Of Area
COM	Center Of Maximum
CPC	Capacity and Price Control
CS	Consumer Surplus
CRM	Customer Relationship Management
CV	Coefficient of variance
CVRP	Capacitated Vehicle Routing Problem
DW	Data Warehouse
e.g.	exempli gratia
EMSR	Expected Marginal Seat Revenue
FCFS	First-Come, First-Served
FECC	Fuzzy Expert Capacity Control
FEPC	Fuzzy Expert Price Control
FESCPC	Fuzzy Expert Capacity and Price Control
IT	Information Technology
km	Kilometers
LOM	Left Of Maximum
MDVRP	Multi-Depot Vehicle Routing Problem
MOM	Mean Of Maximum
OLAP	Online Analytical Processing
PC	Price Control
pm	post meridiem
PS	Supplier Surplus
PVRP	Periodic Vehicle Routing Problem
RM	Revenue Management
ROM	Right Of Maximum
SCM	Supply Chain Management
SCPC	Simultaneous Capacity and Price Control

SDVRP	Split Delivery Vehicle Routing Problem
SVRP	Stochastic Vehicle Routing Problem
sqm.	Square meters
VRP	Vehicle Routing Problem
VRPB	Vehicle Routing Problem with Backhauls
VRPPD	Vehicle Routing Problem with Pick-ups and Delivery
VRPTW	Vehicle Routing Problem with Time Windows
vs.	Versus

1 Introduction

1.1 Motivation

When analyzing the basic conditions of modern service and production processes, the intense competition constraints become evident at first. Secondly, more complex customer relations can be observed.

The **increased competition among companies** is due to the present globalization[1] in all economic sectors. The reduced trade barriers, not only through technical innovations (e.g. the World Wide Web, information technologies[2]) but also through political unions (e.g. the European Union and its current eastern enlargements), have lead to a higher (vertical and horizontal)[3] cooperation potential amongst different companies and a higher level of competition (e.g. in the German freight traffic, almost 56,000 companies competed for 1.7 billion tons of freight in 2005[4]). The deregulation of markets (e.g. the Airline Deregulation Act in the USA in 1978) has added to a strengthened competition through the entering of (low-cost) companies. This enlargement of (international) competitors is currently affecting a lot of supply-side oriented strategies. Companies most frequently follow the intense pressure to reduce costs by optimizing their supply chains in order to meet the cost pressure caused by the higher competition. The success of **Supply Chain Management (SCM)**[5] as a relevant management approach to **supply-side oriented problems** is indisputable. Its concepts have gained importance not only in research but also in practice, mainly due to their successful applications in companies like Hewlett Packard (25% cost reduction by a company-wide inventory planning)

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[1] *Globalization*, in its economic sense, was first mentioned in literature in 1983 [see Levitt 1983].

[2] Especially in the finance sector, information and communication technologies like the Internet were responsible for an intense change in the transaction process [see for example Buhl/Kundisch 2003, p. 3].

[3] *Vertical network partners* are companies along the value chain, whereas *horizontal network partners* are on the same production stage [Friedl 2006, pp. 2].

[4] Source: Bundesverband Güterkraftverkehr und Logistik und Entsorgung (BGL) e.V.

[5] SCM was first literarily mentioned in 1982 [see Oliver/Webber 1992].

[Corsten/Gabriel 2002; Lee/Bellington 1995] or BASF (up to a 100% fill rate of the customers' inventory by a vendor managed inventory)[6] [Grupp 1998].

Furthermore, not only does the higher competition lead to a **growing customer orientation of the companies**, but also the customer relations itself. The main influences result from the continuously changing customer needs, having the consequence of varying customer relationships. Analyses of purchasing behaviors (e.g. reasons for variety seeking instead of brand loyalty[7] [Gierl 1995, p. 274; Berné/Múgica/Yagüe 2001]), the development of the price consciousness (e.g. price-quality irradiation[8] over time [Gierl 1995, pp.587; Rao/Monroe 1989]) and lifestyle analyses (concerning the connection of self- and product-images [Gierl 1995, pp. 323; see also the "VerbraucherAnalyse 2006" or earlier German consumer studies of the Axel Springer Verlag]) show a higher variation in consumer structures. This is enforced by reduced information asymmetries[9] [Arrow 1963; Eisenhardt 1989] with respect to the prices and the availability of goods and services as well as the competing firms in a market. Associated by a higher mechanization of market relations (e.g. through the World Wide Web), the need for a stronger customer orientation becomes evident (e.g. large carriers provide a customer-oriented portfolio of a vehicle fleet corresponding to all customer needs, connected to a freely definable logistic process and a differentiated pricing system).

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[6] In a *vendor managed inventory*, the producer is responsible for the inventory management of the sub-supplier. He has access to the inventory data and generates the orders by himself [see Christopher 1998, pp. 195].

[7] *Variety seeking* is one of the commonly stated specifications of the loyalty construct. It means the addiction to diversification without any correlation to a product's attributes or quality. Reasons for variety seeking can be the ambition for individualism, fast oversaturation or the satisfaction not obtained through the product itself but rather through the opportunity to change. Other forms of loyalty in this context are mono-loyalty, multi-loyalty, hybrid loyalty and zero-order behavior.

[8] *Price-quality irradiation* is when a product's price is connected to the impression of its quality (besides the intrinsic and other extrinsic attributes that are not causal for the product quality). High prices are thereby perceived as an indicator for a high quality.

[9] *Information asymmetry* is the effect that at least one party in an interaction (transaction) has relevant information while the other parties do not. Some asymmetric information models can also be used in situations where at least one party can enforce certain parts of an agreement. In adverse selection models, the ignorant party lacks information when negotiating a contract about the transaction, whereas in moral hazard, the ignorant party lacks information about the performance of the negotiated transaction.

While, thereby, supply-side oriented methods like mass customization[10] and demand fulfillment[11] are frequently used, also demand-side oriented concepts can be adopted in order to meet the increased variability of customer interactions. The success of **Revenue Management (RM)**[12] as the relevant management approach to **demand-side oriented problems** is also indisputable. Its position of importance in research resulted from first successful implementations of Revenue Management systems in practice. There is no single definition of RM that can be seen as a comprehensive understanding of the whole concept [see Corsten/Stuhlmann 1998, pp. 5]. The main idea of thought is that it is an approach to a dynamic and **simultaneous**[13] **capacity and price control (SCPC)**, in which - with the help of IT systems[14] and under consideration of a broad data basis - a limited capacity is distributed to different market segments with different prices in order to optimize revenue [Tscheulin/Lindenmeier 2003, p. 630]. Referring to Klein [2001, p. 248], RM is a compilation of quantitative methods used when deciding about the acceptance or rejection of an uncertain, temporally distributed demand for classes of different worthiness. Thereby, the objective is to efficiently use the inflexible capacity within a timeframe. Closely connected to this objective is the determination of differentiated prices for this capacity. In a broader sense, RM pursues the provision of the right product at the right time (and at each time point) for the right customer at the right price [Cross 2001, p. 61; Kimes 2000, p. 348].

The result of more competition and a higher variability of customer-supplier interactions is that the companies face more **uncertainties**, concerning the demand size and structure, as

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[10] *Mass customization* denotes the production of goods and services corresponding to the individual customer needs combined with an efficient mass production of standardized goods and services [Tseng/Jiao 2001]. Four types of mass customization can be distinguished: Collaborative customization, adaptive customization, transparent customization and cosmetic customization [Pine 1993].

[11] *Demand fulfillment* addresses the receipt and processing of customer orders with the two sub-tasks order promising (delivery time promise) and demand-supply matching (material stock allocation) [Fleischmann/Meyr 2001].

[12] RM (frequently called Yield Management [Weatherford 1997, p. 69]) - as thoroughly explained in the following - is first literarily mentioned in the late 1950's [see Beckman 1958]. Its role as an integrative approach to price and capacity control began in the late 1970's, mostly through practical applications [Tscheulin/Lindenmeier 2003]. This role will be the subject matter of this work.

[13] The term *simultaneous* often expresses the solution of the two control problems at the same time. In practice, this simultaneity often leads to an increased complexity of the planning problem. With the understanding of the problem emerging from this complexity, an adequate way to comprehend the term simultaneous can be to use an integrated solution of the different control parts. This understanding will be followed in this work and it will be explained in more detail in chapter 2.

[14] *Information technology (IT)* is a genus for information and data processing in connection to the required hardware.

well as the price-sensitiveness and the willingness to pay of the consumers. The consequence is that they must adjust to fluctuating demand and unpredictable price changes over time by using dynamic **adaptive methods**[15]**,** in order to reach the required **flexibility in the entrepreneurial action**.

Both management approaches to be considered are directed towards the **over-all profit**[16] **maximization objective** of each company in this world of growing competition and customer orientation. The two main components of profit from a microeconomic point of view are **revenue**[17] **and costs**[18] [Hanusch/Kuhn 1994, p. 405]. Figure 1-1 shows the relationship between these components. In order to maximize profits, revenue can be maximized or costs can be minimized, respectively.

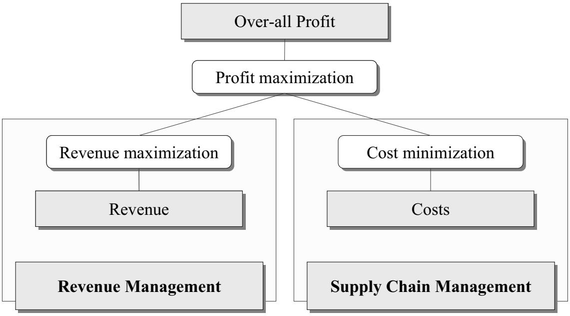

Figure 1-1: The over-all profit maximization problem

In accordance with the over-all profit maximization problem, a concept for the solution should be found that preferably leads to an optimal specification for the resulting **objective**

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[15] *Adaptive methods* in this context indicate the use of methods that change the decision factor corresponding to changing influence factors.

[16] *Profit* (Lat. profectus “progress, growth, benefit”) is the added value realized at the market and is - after Karl Marx - the objective of a capitalistic production process. Here, in this sense, profit is used as a synonym for gains. In business analyses, often the profit margin (amount of coverage) is used to express profits. So, the problem maximization problem in this work implies also the maximization of profit margins.

[17] *Revenue*, as used in this work, means the sum of accounts receivable through the sales of goods and services over a certain time horizon. The term revenue in its broad sense is each event that leads to an increase of the net assets (e.g. including incomes from interests) [Wöhe/Kußmaul 1996, p. 17].

[18] *Costs* here are the part of the wear and tear accumulating in the production of the goods and services over a period (in the sense of production and transportation costs).

system[19], consisting of the revenue maximization and cost minimization objectives. In the described scenario of modern entrepreneurial action, these two objective criteria contain several aspects with respect to the increased competition and customer orientation that have to be addressed. **Central aspects assigned to the RM** part of the profit maximization problem are[20]:

- Allocation of fixed over-all capacities to (product or customer) classes of different worthiness (e.g. the distribution of an assembling line's daily processing time to a premium or standard product with a different unit profit margin).
- Sale of the class capacities to the customers (at a preferable high price).
- Reaching a high workload in all classes (by adjusting the right capacity to a class and selling it at an accepted price).

Central **aspects assigned to the SCM** part are (for instance):

- Inventory management (to avoid an inefficiently high material stock).
- Reduction of the lead time (for a certain lot size of the different products).
- Handling of short-term order fluctuations (to avoid an inefficient operation of the production facility).

The central solution of the total **objective system of a profit-maximizing supplier** seems to be the consequence of the statements above. This, however, would lead to several problems, which result in the failure of a simultaneous solution of all sub-problems [see Fleischmann/Meyr 2003, p. 15]:

- The uncertainty of the required data (e.g. demand forecasts, estimation of the willingness to pay, lead time forecasts, delivery schedule of the sub-suppliers) increases with the complexity of the problem solution and the length of the planning horizon.

---

[19] In this context, initially, *targets* (e.g. profit enhancement) have to be defined. Per an adequate operationalization, corresponding objective functions on the basis of according *objective criteria* (e.g. revenue, costs) result. These are denoted in connection to a *decision criterion* (e.g. building of an extremum like maximization and minimization (or, formulated more abstractly and interchangeable in this work, optimization), satisfication, fixation [see Kosiol 1968]). More objective criteria are combined to an *objective system*.

[20] Thereby, despite the impact of strategic and tactical decisions on the operative RM, this work addresses, in particular, the operative conduction of CPC.

- A simultaneous solution of all appearing sub-problems involves different planning frequencies, corresponding to larger planning horizons. Long-term (e.g. site selection, capacity expansions) as well as short-term decisions (e.g. capacity distribution, price increases) would have to be made by using the same solution concept.
- These decisions result in a need for different aggregation levels for the required data (e.g. time by year, month or day; company-wide or section-wide data).
- Central solutions require more involvement of leading decision-makers.

The conclusion is to divide the over-all problem into sub-tasks[21]. As far as these tasks can be seen as independent, this step is called decomposition [Kistner/Steven 2001, pp. 211]. For this work, a clear demand orientation of the problem solution results from both basic problems, the strengthened competition among companies and the growing customer orientation. When contextualizing the over-all profit maximization problem for the supplier of goods and services and its necessary decomposition, there is a **clear indication for the use of demand-side oriented management approaches**. In the following, thus, the concept of RM forms the basis for the design of a solution concept for the **revenue maximization** part of the underlying problem.

The **beginning of RM** in its new form has been literarily concretized through the Airline Deregulation Act of 1978. Previously, the U.S. Civil Aeronautics Board (CAB) tightly controlled schedules and fares to provide a stable and safe return on investments. All regulations of the CAB were removed over a period of four years until December 31st, 1983 [Phillips 2005, p. 121]. The objective to welcome the entry of new airlines into the market was first fulfilled by PeopleExpress, a low-coast company with lower labor costs, simpler (point-to-point) operations and no extra services (like on-board service). Through its business concept, PeopleExpress was able to provide the main service (a flight to a certain destination) at a significantly lower price (up to 70% lower than the major airlines). Price-conscious travelers (who make a much higher percentage of leisure passengers in comparison to business passengers) switched not only from the car to the airplane but also from more expensive airlines to PeopleExpress.

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[21] In the literature, the conclusion is often to fix one of the two objectives and optimize the other. In this work, maximizing the revenue under the given costs implicitly does this.

The result was a revenue of $1 billion and a profit of $60 million in 1984 (three years after the market entry) [Talluri/van Ryzin 2004, p. 7]. The reaction from the major carriers in the industry was to also implement new strategies, except from supply-sided cost reduction policies (e.g. sale of airplanes, dismissal of employees). Robert Crandall, Vice President of American Airline, is widely acknowledged as the initiator of RM strategies. He recognized that his company (and all major airlines) was able to compete in terms of marginal costs for one seat (which were near zero). He established data analyses to identify the most profitable routes and seats of American Airlines (especially the Monday and Friday flights of business customers). In addition, he established a combination of purchase restrictions[22] and capacity-controlled fares[23]. After the implementation of this new RM system in January 1985, American Airlines increased its revenue by $500 million until the end of the year. In contrast, PeopleExpress struggled and was bought up in the same year for less than 10% of its market value [Phillips 2005, p. 122].

After the successful start of this new management approach, other airlines adopted similar methods. Delta Airlines, for instance, increased sales by $300 million. Lufthansa has calculated its revenue enhancement to $1.4 billion [Kimms/Klein 2005]. Additionally, the **concepts of RM also spread out to other industries**. The hotel sector (e.g. $100 million more revenue at Marriot per year) and the car rental industry (20% revenue rise of National Car Rental) are only a few examples for the fast growth of RM [Cross 2001, p. 15]. Currently, revenue optimization methods are implemented in almost each and every service industry. Furthermore, also the production sector has started using these methods for their revenue maximization problem (e.g. iron and steel industry)[24] (see Harris/Pinder [1995]; Kimms/Müller-Bungart [2003] and Spengler/Rehkopf [2005] for the applicability of RM to manufacturing). This various amount of application areas, the advanced research on the topic and its different aspects, and the potential for the profit maximization lying in this approach is a clear indicator

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[22] These purchase restrictions were implemented as nonrefundable tickets that had to be bought 30 days in advance of the departure. This should prevent late-booking business customers from using those discount fares.

[23] The capacity-controlled fares were reached by limiting the number of discount seats. So, full-fare seats were still available for passengers booking late.

[24] Spengler/Rehkopf/Volling [2007] formulate a multi-dimensional knapsack problem for the reproduction of the order uniqueness and the capacity demand in make-to-order manufacturing. The acceptance or rejection of the orders is implemented in two bid-price calculation schemes (see Klein [2007] on bid-pricing).

for the **business relevance of further research** on the topic [McGill/van Ryzin 1999, pp. 244; Klein 2001, p. 257; Kimms/Klein 2005, pp. 2].

Despite its business relevance, RM itself is not a currently developed management approach. Instead, the idea of it can be found in each kind of economic behavior since the beginnings of trade. The new point nowadays is the method of decision-making. The intuitively clear objective of reaching a high workload over time, together with producing the most profitable goods and services, as well as selling them at the best price is recently supported and enhanced by two main sources [Talluri/van Ryzin 2004, pp.5]. Firstly, research on economics, statistics and operations research have lead to various methods used for the capture of all influences and uncertainties related to revenue optimization (e.g. demand modeling). Secondly, technological developments, especially in IT, have enabled the use of a large data basis and complex algorithms for all kinds of analyses in real-world problems (e.g. data analyses for demand forecasts).

Within this RM context, there are **three main categories of demand-management decisions** to be considered [Talluri/van Ryzin 2004, p. 3]:

- **Structural decisions** concern, for instance, the scale of the planning horizon in that the **capacity and price control (CPC)** has to be taken out. Thereby, the beginning of the planning period is, for example, the opening of the booking cycle or the first order of a customer, whereas the end of the planning period is defined by events like the departure of an airplane, the end of the booking day in a hotel, or the start of the goods delivery in a cargo company. Other structural decisions in this context address the already outlined amount of product or customer classes of different worthiness, the determination of the underlying fixed over-all capacity or the (sub-) markets[25] to be considered in the solution of the revenue maximization problem.
- **Price decisions** concentrate on all questions related to the price setting. These exemplarily concern the degree of possible price adjustments (e.g. free negotiations vs. prices

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[25] An example for sub-markets is the different distribution sectors of an internationally operating company with a network of production sites and depots. By taking out one depot and the market mainly satisfied by this depot, a sub-market is extracted from the whole distribution market.

fixed by law), the determination of the reservation prices[26] (e.g. using forecasts or distribution assumptions vs. no orientation on specific reservation prices), the level of price adjustments (high price changes without possible customer irritations vs. decreasing consumer satisfaction) and the frequency of price changes over time.

- **Capacity decisions** focus on the acceptance or rejection of customer requests for certain products with respect to the probability of losing capacity for a more profitable class (e.g. selling too many standard products early in the planning period may lead to a too low capacity for requests of premium products). The main decision, thus, concerns the suitable allocation of the fixed over-all capacity to the classes of different worthiness. The central issues regard the expected demand in the classes and the degree (and amount) of adjustments of initial allocations over time.

In research and practice, one important decision for the CPC remains. This concerns the separate conduction of **CPC or an integration of both control options (SCPC)** in order to maximize revenue. The main decision criteria here are the degree of flexibility and the costs of changing quantities or prices [Talluri/van Ryzin 2004, p. 176]. Most authors in research thereby claim the integration of price and capacity decisions. Many, however, also state that the resulting complexity has not been met so far, in order to obtain practical and applicable solutions [see McGill/van Ryzin 1999; Tscheulin/Lindenmeier 2003].

Based on the use of RM as the adequate approach to the revenue part of the profit maximization problem, the question emerges to what extent a concept can be developed that contains all abstractly described decision categories in connection to the adequate implementation in the research with respect to the initial practice orientation of methods for RM. In order to answer this question, the subject of SCPC has to be analyzed.

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[26] *Reservation price*, in this context, means the willingness to pay of each single customer. Lies the price above this reservation price, the customer rejects the price offer and no goods and services will be sold to him (with the potential of idle capacities in the case of structurally too high prices). When the price is below the reservation price, the customer gets a consumer surplus and the supplier loses potential revenue. By setting the price equal to the reservation price of each customer, the supplier skims this consumer surplus [see Varian 1999, pp. 236].

1.2 Problem formulation

The subject of this work is the development of a **solution concept for the simultaneous capacity and price control SCPC**. As stated in section 1.1, the three basic decision categories can be combined to this integrated CPC (as it is claimed in literature). The over-all hypothesis of this contribution to SCPC is, therefore, that SCPC is always an adequate execution of RM. However, an important influential factor for the execution of SCPC is the degree of flexibility (also influenced by the changing costs) for changing the capacity distribution over the classes of different worthiness and in adjusting prices within the classes over time. **A comprehensive concept for SCPC and its separate parts** should also be able to capture cases where only one of the two control options can be adopted.

The relationship of the capacity and price decisions as part of the SCPC can be formulated as illustrated in figure 1-2.

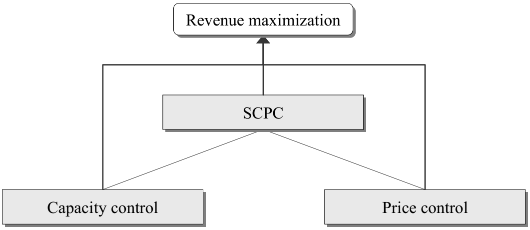

Figure 1-2: The integration of CPC to SCPC

Through the given revenue maximization objective, the use of SCPC instead of the separate use of **capacity control (CC)** or **price control (PC)** may be automatically indicated. However, in order to understand the specifics of SCPC, its components have to be initially understood. The problem, hereby, is to firstly prove that the solution concept works in cases where only one of the two control options can be executed. Only if the solution is proven in its different components, it is clear that all parts of the concept work as intended. In the case that the SCPC does not work adequately, problems in the solution of the components can be excluded from the analysis. The problem then has to relate to the integration itself[27] and is easier to solve.

As already stated in section 1.1, the two main components are the CC and PC. **CC** means mainly the **allocation of the over-all capacity to the different classes** of worthiness (over time) [Talluri/van Ryzin 2004, p. 27]. A typical application case for a single CC is the German health sector. For all hospital services, prices are fixed by law[28]. The two classes are represented by the types of insurances of the patients (private vs. state insurances). The hospital allocates its capacity (labor time per day) to the two classes (in favor of the more profitable private patients)[29]. **PC** is the **price setting within these classes** (over time). An example for pricing as the only feasible instrument for RM is the hospitality industry. Because of constructional limitations, the over-all capacity and its distribution (economy or first-class rooms) cannot be expanded in the short-term. Revenue can only be increased by a profitable price setting. The **integration of both control options** leads to an even higher revenue increase in cases where there is a high flexibility for changing capacities and prices. A typical example is the Cargo Revenue Management [Billings/Diener/Yuen 2003]. Taking the example of a truck with a fixed over-all capacity and its delivery of two goods (premium and standard), the capacity control concerns the distribution of the loading capacity in favor of the demand for the premium product. The price control is the sale of a class capacity to customers who are most willing to pay.

The main contribution of this work is the realization of a comprehensive solution concept that solves the various **problems related to the SCPC and its components**. Exemplarily, the **various uncertainties** resulting from the capacity and price control (e.g. demand fluctuations, unrevealed reservation prices) and the **dynamic character** of the solution context (capacity and price adjustments over time) can be stated here. Additionally, **feasible data analysis**

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[27] This procedure can be referred to as a *bottom-up approach* where first the single components of a system are analyzed before the whole system is examined. A procedure, in which the reverse applies, is called a top-down approach [Sternberg 2005].

[28] §301 SGB V (OPS-301).

[29] As observed in this example, some applications of RM do not only have to be analyzed with respect to the effects on the purchasing behavior of customers [Talluri/van Ryzin 2004, pp. 614; Campbell 1999; Kahneman/Knetsch/Thaler 1986] but also with respect to moral considerations (especially in the health sector). The same counts for other management approaches (like capacity reductions in SCM leading to dismissals).

techniques have to be executed on the basis of real data (with all implications on the data quality). Besides the appropriate expression of the various interdependent relationships between the influence parameters of the CC, PC and SCPC, the **applicability of the solution** in practice also has to be assured. The whole problem context, thereby, obviously seems not optimally solvable. The result can be the design of a solution that is based on a **heuristic concept** [Silver 2004]. In detail, **knowledge- based (expert) systems** are intended to be appropriate for the implementation of SCPC. The reason is that it does not seem possible to formulate exact rules for the expansion or reduction of capacities for profitable classes and rules for the increase or decrease of prices in order to maximize revenue (especially concerning the expression of the relationship of all input parameters)[30].

Moreover, the integration to a SCPC makes the decision problem more complex and vague through all its influences. This **vagueness** is especially represented by the degree of the capacity and price adjustments. It can be addressed by expert systems in connection to knowledge-based methods that are able to process implicit knowledge about the relationship between all strategic parameters. One opportunity is to develop **Fuzzy Expert Systems**[31]. So far, sufficient knowledge about the applicability of these methods in the context of RM (and SCPC) and about application constraints as well as necessary modifications does not exist as Fuzzy Expert Systems have not yet been applied in RM.

Recapitulating, a solution for SCPC as the approach to RM, which seems to have the **highest potential with respects to revenue maximization,** has to be developed based on several application constraints and problems resulting from the components and its integration. In addition, the solution must be flexible enough to also work in applications were only parts of the SCPC can be executed. Knowledge-based expert systems with the ability to process vague information seem, thereby, to be appropriate for the solution.

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[30] See Puppe [1988] for an introduction in expert systems.

[31] The *fuzzy set theory* was invented by Zadeh [1965] and takes into account the fuzziness of an item's membership to two different sets (examples are subjective values like "tall", "high" or "fast"). Biewer [1997] and Zimmermann [1991] give a good introduction to the concept of the fuzzy set theory. Fuzzy approaches are used in many applications in all kinds of industries (e.g. textile industry [Tuma 1994], ecological production control [Tuma/Müller 2000], medical diagnosis [Adlassnig/Kolarz 1982] or weather forecasts and Robotics (see Bothe [1993] for an overview over existing applications)).

1.3 Course of action

The process of this work can be principally divided into two parts. First, models and methods for the execution of a SCPC or CC and PC, respectively, are developed. Subsequently, these methods are evaluated using real applications concerning all three possible constellations.

The first part of the work is dedicated to the theoretical **design phase**, which contains the following steps:

- Design of a concept to SCPC.
- Specification of the concept on the basis of decision models.
- Discussion of the concept's strategic parameters on the basis of their realization in the operational design of the solution.

The **design** contains in a first step the **specification of the requirements for a SCPC**. By the formulation of the planning tasks in RM and the formulation of the problems resulting from the SCPC, the conceptual framework for the solution concept becomes clear. The following **analysis of the objective system** provides an understanding of the appropriate **basic procedure of a SCPC**, as well as the framework for the performance analysis of the provided solution. In addition to the basic procedure of SCPC, the specification of the solution concept is illustrated.

This **specification** starts with the presentation of solutions for the different problems explained in the design phase. On the basis of a **decision model** that reproduces this solution, the strategic parameters influencing the decision process become obvious. The operational design of the solution concept is the consequence of the whole design phase and the specification of the concept. Hereby, **Fuzzy Expert Systems** play a central role (as described in section 1.2).

The strategic parameters and the performance of the different components of the solution are analyzed on the basis of different **application cases** in the second (practical) part of the work. Thereby, all possible application constellations in the context of CC, PC and SCPC are analyzed. The **first application** contains the application of the **CC in the waste incineration industry**, including the corresponding decision model. Thereby, a two-class case for the CC is considered based on the determination of two classes of different worthiness. A CC is conducted because of the fixed prices that are annually negotiated in a consortium. From the fixed kiln capacity, a portion has to be reserved for long-term contracts and regional corporations. The rest can be traded freely and the capacity distribution is flexible. The central questions, that have to be answered with respect to the objectives of this work, are:

- Does the CC component lead to significant improvements of the profit margin in the considered application case?
- Is the developed solution an adequate approach to revenue maximization under fixed prices?
- Does the developed solution concept outperform standard Revenue Management approaches to the CC?

A **further practice case** is dedicated to the **PC** part of the decision model. In the **hospitality application**, three classes of different worthiness are controlled through prices as the capacity distribution is set constant because of constructional limitations. Question to clarify thereby are:

- Does the PC outperform the current price setting in the hospitality application?
- Is there a high variability of the developed solution with respect to variations in the reservation prices?
- Is the solution concept also an adequate approach to the revenue maximization under fixed capacity allocations?

The predominance of the **integrated solution (SCPC)** over the CC and PC is illustrated in an application case to **Transportation Management**. Thereby, the distribution of glass films of an internationally operating company is controlled. One of the distribution markets with a depot located nearby, from which the glass films are transported to the customers, is considered. In addition to the revenue maximization of the resulting delivery lists resulting each day, also the effect of the different control options (CC, PC and SCPC) on transportation costs (vehicle routing problem) is analyzed, in order to find out if the positive revenue effects are consumed by higher delivery costs. The following topics are addressed:

- Is the developed solution concept a feasible approach to the integrated CPC?
- Does the integrated CPC outperform the sole PC and CC?
- Has the revenue-optimization offsetting effects on the cost side of the profit maximization?

The objective of this **evaluation phase** is to transfer, adapt and estimate the potentials of the developed solution concepts in all facets resulting from the different application cases and its implications.

2 Conception for a simultaneous capacity and price control

The design of a concept for SCPC needs, firstly, the specification of the requirements for SCPC as a method for RM in the context of the revenue maximization problem. This includes the description of the addressed planning levels, which have to be considered in the SCPC and the planning tasks that have to be executed. Following the central planning tasks of RM, its underlying application constraints are outlined. The formulation of the objective system of SCPC leads to several problems influencing the operational design of the solution concept. The development of the solution and its first areas of application indicate the appropriate implementation of SCPC.

2.1 Specification of the requirements for a SCPC

After the description of the planning levels of a SCPC and its definition in the context of this work, the RM process and its different tasks are described. The basic application constraints of a SCPC underlie the solution concept and have to be also formulated.

2.1.1 Planning levels of a SCPC

According to the common understanding in literature, three typical main planning levels with a different planning horizon exist[32] [Antony 1965; Domschke 1997; Zäpfel 2001; Klein/Scholl 2004; Fleischmann/Meyr/Wagner 2005] that can also be assigned to RM [Kimms/Klein 2005]:

2.1.1.1 Strategic planning

Strategic planning (or long-term planning) in SCM involves planning tasks with a range of two to ten years[33], that serve as targets for the other planning levels. Typical examples in SCM

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[32] In literature, different criteria (except from the time scale) can be used to distinguish the different planning levels [see Bronner 1999; Schweitzer 2001].

[33] Concerning the time ranges, there are differing statements existing in the literature [Schweitzer 2001].

concern the design and structure of supply chains with effects on the company structure (site planning, new production lines, new software systems) and company culture (emission reduction, more customer orientation, better conditions for employees) [Killich/Luczak 2003].

Rather strategic decisions within the RM concern mostly structural decisions relating to the production mix and the basic capacity planning [Kimms/Klein 2005, p. 11]. Examples are the segmentation and bundling of products and customers in order to get the classes of different worthiness. Also, the determination of the degree of flexibility in terms of prices and quantities can be stated here.

2.1.1.2 Tactical planning

More tactical decisions (mid-term planning) have a range from several months to two years and include targets for the short-term planning. In the production process, the Master Planning is especially done, here[34].

In RM, the tactical decisions concern the precise definition of the production mix and the capacity planning. Examples are the flight schedule of airlines, where the type of aircraft (determining the number and potential size of classes), the specific route and the number of stopovers have to be determined. Additionally, in the case of CC or PC, the setting for the fixed control option has to be determined (prices for the served classes in the case of CC, the fixed capacity distribution in the PC).

2.1.1.3 Operational planning

At the operational (short-term) planning level, typical tasks concern all activities for the immediate execution and control of all points in the production system. Examples in SCM are the allocation of a production order or machine scheduling.

The solution for SCPC in the work here handles the short-term activities of RM. In this context, the operational CPC has to be especially mentioned. If possible, both control options are

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[34] Master Planning is used for the design and coordination of the local production program for the single production lines, under the consideration of the available capacity [see Fleischmann/Meyr/Wagner 2005].

executed for each customer request, leading to a real-time SCPC[35]. The matching of the capacity allocation (due to the demand in a class) and the price setting (due to the willingness to pay) are the main operational decisions here.

Recapitulating, this work concerns **mainly the operational planning level**. However, tactical subjects also have to be analyzed in the context of SCPC, especially when it comes to adjusting a SCPC solution for an applied case (e.g. the identification of the classes and the over-all capacity). Altogether, these **planning levels are strongly connected** and cannot be exactly separated in a feasible solution.

2.1.2 Planning tasks in the RM process

In connection with the definition of RM and the central decision categories formulated in chapter 1, as well as the classification of the underlying planning levels, an overview of the **central planning tasks** within the (operational) RM process (see figure 2-1) helps to understand the specifics of this approach. Its different parts (information flows and control steps) are subsequently explained.

2.1.2.1 Data Collection

The data collection in modern RM systems consists of **computer-aided management information systems**[36] that gather data from three important sources of information: **Market and product information** contains data about customers (e.g. purchasing behavior, customer segments), competitors (e.g. amount and potential of other companies in the market), market trends (e.g. chances of new products, preferred innovation cycles), common seasonal effects (e.g. weather sensitive branches), product life-cycles, production costs for all products, and so on.

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[35] The amount of control steps in practice very much depends on the underlying aggregation level of the data and its quality, as well as the degree of adjustment flexiblity.

[36] A *management information system* is an information system that supports decision making by delivering information helping companies to control their business.

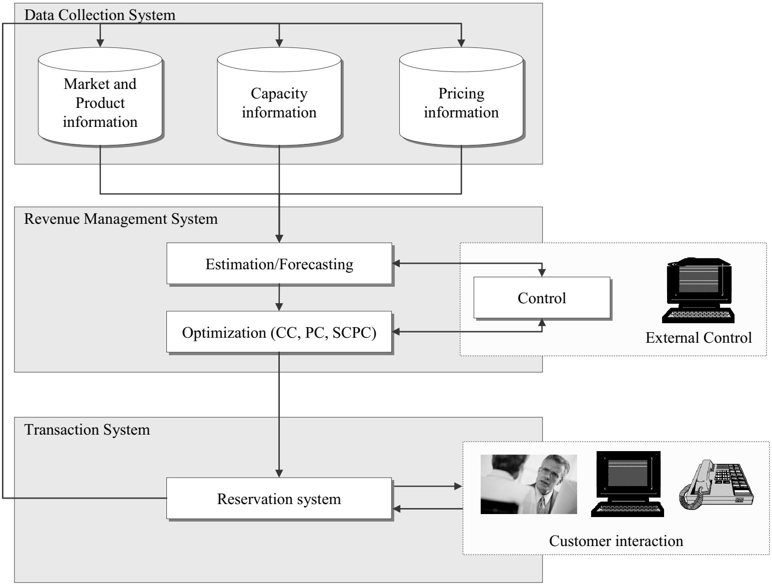

Figure 2-1: Schematic overview of a RM process flow
(according to Simon [1992]; Talluri/van Ryzin [2004, p. 19]; Phillips [2005, p. 134])

This information is exemplarily used for the building of classes of different worthiness and the determination of the over-all capacity for the relevant markets. **Capacity information** contains all information connected to the capacity allocation to the classes and the resulting workload in these classes. An example is the determination of the capacity distribution to the premium class that has been insufficient over the last period (100% workload in class already in the first half of the planning period) and should be increased. **Pricing information** is basically the sales data (based on the capacity allocation). Interesting here, for example, is the case that many requests from customers are not satisfied with the price offer given by the supplier, clearly indicating that prices are often set above the reservation prices of the customers (implying a lower price level for the next planning period).

2.1.2.2 RM system

The RM system uses the gathered information for the **determination of the right capacity and pricing policy**. As already stated, the data implies certain changes in the capacity allocation and price setting. These implications are analyzed within this step of the RM process (see figure 2-2). A common method is to use the collected data for the estimation, forecast, or the determination of the relevant strategic parameters needed for the CPC or its integrated conduction.

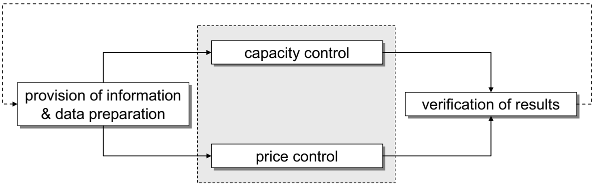

Figure 2-2: Components of a Revenue Management System

For **CC**, the main information is the expected demand of the different classes in the next planning period. It is used for the capacity allocation to the classes (building of so-called contingents) and for the determination of overbooking[37]. The expected demand is often estimated by specific forecasting techniques[38]. The main problem is thereby the high fluctuation of the demand due to the reasons explained at the beginning of this work. These fluctuations have central implications for the solution concept for SCPC.

The main strategic parameter for the **price control (PC)** is the reservation price (structure) of the customers. The difficulty occurs when the consumers intentionally do not reveal their willingness to pay in order to receive a consumer surplus. Besides the knowledge that the res-

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[37] The *overbooking* concept results from the problem of no-shows and cancellations. This problem would lead to idle capacity and to revenue losses that cannot be balanced completely by cancellation fees. The solution in practice is to sell more capacity units than available. For this, a certain percentage of the class capacity is calculated (from previous cancellation data). The overbooking concept is not central for the work here and, thus, not considered any more.

[38] *Forecasting* is the prediction of an event, a state or a development over time. Qualitative and quantitative forecasting techniques can be distinguished. In this context, especially quantitative methods are relevant. Examples are exponential smoothing, regressions or various autoregressive and moving-average methods [Lancaster/Salkauskas 1986; Schlittgen/Streitberg 1987; Bamberg/Baur 1998, pp. 217; Tempelmeier 2005].

ervation price structure is usually higher in premium classes, the information regarding the differing willingness to pay among the customers also has to be determined.

This problem has central implications for the solution for **SCPC**. In this integrated CPC, the effects of one control option on the other have to be additionally captured (adding to the complexity of this concept). Within the optimization part of the RM system, the strategic parameters are used to provide an appropriate control of capacities and prices. By assuring the best capacity allocation and price setting over time, the revenue maximization objective is fulfilled.

2.1.2.3 Performance control

Within the central RM part of the process, a control instance supervises not only the **technical process of the forecasting and optimization,** but also the **performance of the SCPC within the running system** over time. The accuracy of the forecasts, as well as the SCPC have to be analyzed at each time point. The performance control over time assures that structural variations are recognized and the optimization algorithms, in particular, are adapted to changes, leading to a **need for adaptive systems for the SCPC** that capture all kinds of short-term and long-term changes. Besides the automatic performance control that is implemented in the system, an external control (by specialists) is also important for the recognition of bad performance.

2.1.2.4 Transaction system

The transaction system stands for the **interaction with the customer over different channels** (e.g. personal contact or contact per telephone, internet). In almost all cases, the transaction process is executed with a computer-aided reservation (booking, order) system, where all requests, bookings, and reservations of customers are saved and controlled. The transaction data is introduced to the RM system by storing it in the database. Thus, current data can be used for the whole process in time, depending on the intervals, in which the process is executed[39].

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[39] These control intervals are usually very frequent. In some cases, even an immediate capacity and/or price control is executed for each customer request.

2.1.3 Application constraints of a SCPC

A set of **application constraints** can be formulated that clarifies the context, in which RM techniques are applied [e.g. Kimes 1989; Friege 1996; Weatherford 1997; Bertsch/Wendt 1989; Corsten/Stuhlmann 1998; Tscheulin/Lindenmeier 2003b; Klein 2001; Kimms/Klein 2005]. A distinction can thereby be made between typically formulated constraints and further constraints (often characterized by an adduction or even a relaxation of the typical constraints).

2.1.3.1 Typical application constraints

Firstly, the constraints that are typically presented in literature have to be considered in the execution of RM:

- **Relatively fixed capacity**
  The opportunity to quickly increase the over-all capacity in order to fulfill the over-all demand would lead to a complete flexibility in the provision of goods and services. As an effect, a revenue-optimal allocation of the over-all capacity to the product and customer classes would not be necessary. In reality, at least in the short-term, no capacity extension is possible in many applications (e.g. the change of the number of hotel rooms, the change of an airplane size, the building of a new production line).
- **Perishable capacity**
  Service industries are characterized by a perishable inventory because of the existence of a clearly defined end of the planning period (e.g. the start of an airplane, the end of a booking day in a hotel). After this point in time, idle capacities cannot be sold anymore and have negative effects on the revenue maximization.
- **High costs of capacity increases, low marginal sales costs**
  The problem of high capacity costs in change is strongly related to the requirement of fixed capacities. In the short-run, the extension of the capacity would cause high costs (e.g. because of the potential need for technological innovations for a significant growth in capacity). In contrast, especially in the service industries, the marginal sales costs of

the capacity units are very low (e.g. the costs of one additionally sold airplane seat). As a consequence, each demand can be fulfilled (with preference for profitable customers).

- **Fluctuating demand**
  Besides the need for a revenue enhancing adjustment of capacities among classes of different worthiness based on the demand for a specific class (especially premium classes), the adjustments of prices per unit of capacity within a class can also be changed due to the fraction of customers who have a high or low willingness to pay. The process of CPC would not lead to the challenges of implementing a feasible solution if the demand and the reservation prices of the consumers were exactly known[40]. Due to the fast-changing needs of the consumers and the increasing competition (as formulated in section 1.1), demand is highly fluctuating. Methods for CPC have to be established that capture these fluctuations.

- **Product sale in advance**
  If all orders or bookings arrived at the last time point in the planning period, the most profitable customer could be simply chosen until the whole capacity is sold or the demand is satisfied. Only by having the opportunity to reserve or use units of capacities for a certain time point before the end of the planning period, the problem of accepting the current requesting customer or waiting for more profitable orders arises.

- **Ability of market segmentation**
  The segmentation of markets is closely related to the decision about the underlying classes of different worthiness (based on products or customers). Different customer classes can be built based on assumptions about their price (e.g. leisure or business customers) or time sensitiveness (early or late bookers). In addition to the possibility of obtaining classes with different revenue potentials, product specifications and strategic considerations also influence the worthiness of a class (e.g. premium products with a high, standard products with a low unit profit margin).

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[40] These demand fluctuations lead to a high uncertainty concerning the whole decision process in RM. Together with other uncertainties (like the unrevealed reservation prices of the customers), the fundament of all methods concerning pricing and capacity control, as it is considered in the research on RM, is provided.

2.1.3.2 Expansion and relaxation of the application constraints

Secondly, several further constraints that pick up and expand or relax the basic constraints have to be taken into account:

- **The perishability of capacity in the production sector**
  RM is frequently acknowledged as a concept suitable for the service industry (distinguished from the production sector by the need for an external factor[41]). The perishability of the capacity is, in the service industry, determined by a defined end of the planning period (e.g. departure of an airplane, end of the day). In addition, even in the production sector (especially in the make-to-order or assemble-to-order manufacturing), the problem of perishable fixed capacities can be identified (e.g. non-reducible line capacities in make-to-order manufacturing are idle if not enough orders are received). RM is not an adequate approach in cases, where the provision of the product may take place in advance of the sale (e.g. production of storable goods for an anonymous market) [Günther/Tempelmeier 2005].

- **Limited operational flexibility**
  An expansion of the basic fixed capacity constraint is the construct of a limited operational flexibility (see especially Kimms/Klein [2005, pp. 6]). Reason for the expansion is the problem of an exact understanding of the term "relatively fixed capacity". Examples (e.g. short-term seat adjustments in an airplane) show that this term may be misinterpreted as a fixed capacity distribution over time. In this sense, here, the fixed over-all capacity is the right interpretation. The degree of flexibility aspects in the expansion or reduction of the over-all capacity introduces the definition of the critical factors concerning the capacity change (e.g. time or monetary constraints).

- **Clearly defined product mix**
  The main decision categories "price decisions" and "capacity decisions" (see section 1.1) lead to a need for a stable product mix in order to provide the adequate data basis for the necessary decisions (demand estimation/forecast, reservation price determination). The uncertainties underlying these decisions would increase even more if the

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[41] Corsten/Stuhlmann [1998] and especially Fandel/Blaga [2004] discuss the external factor as a difference criterion between the service and production industries.

product mix were changed in the short-term (e.g. stable routes of an airline over at least a year)[42].

- **Marginal costs**
  One additional basic constraint, which has to be relaxed in the work here and is not addressed in literature, is the existence of low (zero) marginal costs. Also in the case of significant marginal costs, RM methods can be implemented. The change especially concerns the building of classes of different worthiness and the PC part. Classes have to be built now with respect to unit profit margins and not only to prices (both indicators for worthiness). In the PC, a minimum price has to be introduced, which prevents the prices going below short-term bottom values (e.g. variable costs).

2.2 Specification of an objective system for a SCPC

The objective system of a SCPC can be formulated as illustrated in figure 2-3. For each control option, two objectives can be formulated that have to be reached simultaneously in a comprehensive revenue-maximizing solution for SCPC. Thereby, these objectives can basically have three kinds of relationships [Zwehl 1993; Laux 2003; Bamberg/Coenenberg 2006]: Complementary[43], indifferent[44] and competing[45]. The **capacity and price control objectives at hand can be classified as competing**.

For the CC, a pure **maximization of the sales in the most profitable class** implies that the capacity of the class is set equal to the over-all capacity in order to avoid any rejection as a result of its limited capacity. The result would be a revenue loss if the demand for the profitable class was below the capacity. A sole **minimization of idle capacities** would lead to a favored distribution of the over-all capacity to the class with the highest demand. As this is usually not

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[42] If the definition of a product mix is not possible (e.g. in make-to-order manufacturing with completely individual products), the implementation of an adequate project management was found to be more reasonable [Kleinaltenkamp/Plinke 1998; Kimms 2001].

[43] In the case of *complementary objective* relationships, an increase in the satisfaction level of one goal has the same effect on the other goal.

[44] *Indifferent objectives* have no influence on each other.

[45] *Competing objectives* imply that an improved satisfaction level of one goal worsens the performance in the other objective.

the most profitable class, this objective also causes revenue losses. The exclusive **maximization of the price per capacity unit** in the PC implies very high prices, which can be expected to be far above the reservation prices of the customers (especially in standard classes).

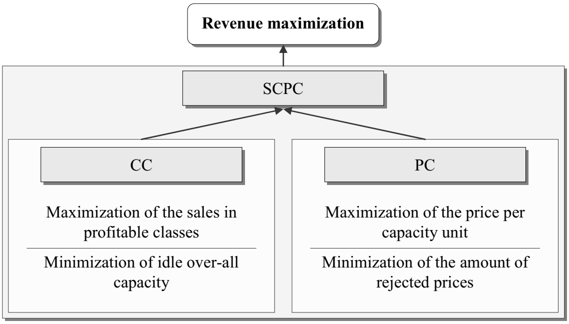

Figure 2-3: Objectives of a SCPC

In addition to this potential for revenue losses, the sole **minimization of the amount of rejected prices** (which is equivalent to the objective of little idle capacity) causes very low prices and, thus, lowers revenue. In the case of SCPC, all four (actually three, as the two minimization objectives concern both the prevention of idle capacities at the end of the planning period) have to be reached together, indicating again the higher complexity of the integrated solution[46].

Altogether, a way has to be found for each control option to fulfill both objectives. The challenge, thereby, is the existence of more than one efficient alternative. Common approaches to this **problem of multi-criteria decision-making**[47] can be found in literature. Examples are the lexicographical order, the setting of aspiration levels and the objective weighting. In the lexicographical order, the evaluation of the action alternatives is carried out on the basis of the most important objective (e.g. maximization of sales of profitable goods). If this does not lead

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[46] Here, the same problem as in chapter 1 results (ending in the choice of RM as the relevant management approach). However, the solution here does not need an explicit division of the decision problem to sub tasks. A central solution for SCPC seems reachable.

[47] In *multi-criteria decision-making*, a decision has consequences for multiple objectives. As far as all consequences and the preferred satisfaction levels are known, an objective system can be formulated.

to a definite decision, the next important objective is used [Adam 1993][48]. The setting of aspiration levels concerns the transformation of one of the objective functions into a constraint, such that a certain level of satisfaction is reached for this objective (e.g. maximization of sales of profitable goods under the constraint that not more than 10% idle capacity is left at the end of the period)[49]. Objective weighting results in a weight for two objectives, which expresses the decision maker's preference for the objectives. This concept solves the deficit of the aspiration levels that results from the probability of a goal being pushed to its lower or upper boundaries by an optimized objective (e.g. assuring only maximum (allowed) pollution levels or minimum profit margins).

In RM, a large amount of approaches have emerged that address this fulfillment of the competing control objectives. In the following, these approaches are explained for the CC, PC and the SCPC[50]. Thereby, many approaches address these objective problems only implicitly in the provided solutions.

2.2.1 Competing objectives of the CC

The control of the capacity of the classes of different worthiness contains two objectives:

- **Maximization of the sales in profitable classes**
  The classes with a higher worthiness (premium products) are defined by a higher value proposition to the revenue maximization problem (e.g. through a higher unit profit margin). If, in the CC process, too little capacity is allocated to the profitable classes, customer requests have to be rejected with the consequence of revenue losses. The objective, thus, is to maximize sales in the premium classes.

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[48] As this decision rule may lead to no consideration of less important objectives (e.g. environmental in comparison to economic objectives), it cannot meet the requirements of current entrepreneurial decision-making.

[49] A classical example for the setting of aspiration levels is the conduction of offensive or defensive environmental protection in companies. With the given competing objectives "profit margin maximization" and "pollution minimization", an offensive protection strategy would be to minimize pollution under the constraint of a minimum profit margin. The defensive alternative is to maximize the profit margin under consideration of maximum pollution levels [see Wagner 1990, p.14].

[50] A comprehensive overview over capacity and price control methods (and the state-of-the-arts) is given in various contributions to RM (see for example Tscheulin/Lindenmeier [2003]; Talluri/van Ryzin [2004]; Phillips [2005]).

- **Minimization of idle over-all capacity**
  The first objective may imply the complete allocation of the over-all capacity to the most profitable class. If the demand for this class in the planning period, however, is below the over-all capacity, idle capacities result with the consequence of revenue losses. In order to avoid this, only the capacity equivalent to the expected demand should be allocated to the profitable classes.

The solution for the capacity part of the revenue maximization problem is the subject of various research on RM. Beginning with its practical applications in the airline industry, a lot of approaches to the control of capacities have emerged.

2.2.1.1 Practical solutions for CC

The first developed methods for CC focus more on practical considerations than on theoretical concepts [Bertsch/Wendt 1999]. Examples are the establishment of partitioned or nested booking limits, protection levels and the use of bid prices (figure 2-4 gives an overview of the relationship between these methods).

The setting of **booking limits**[51] restricts the amount of capacity that can be allocated to a specific class. A booking limit of $K_2^P = 50$ units of the over-all capacity k = 100 for class 2, for example, means that at most 50 units of k can be sold to customers of class 2[52]. Beyond this limit, the class is closed to the concerned customers. Thereby, instead of **partitioned booking limits** K_s^P (with s = 1,…,S as class s) with fixed capacity allocations to the classes over time (also called contingent in the sense of the class capacity K_s with $\sum_{s=1}^{S} K_s = k$), also **nested booking limits** K_s^N can be set. The difference is that nesting provides the possibility of overlapping class capacities over time, giving a preference to more profitable classes[53].

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[51] Because of the airline context in the beginnings of RM, this method is also called seat inventory control.

[52] In the work here (and in most research), it is assumed that a customer request is connected to one specific class (e.g. a business seat in an airplane).

[53] A further distinction can be made between standard nesting (additional capacity for the more valuable class comes only from the class below) and theft nesting (additional capacity comes from all classes below) [Talluri/van Ryzin 2004, pp. 30].

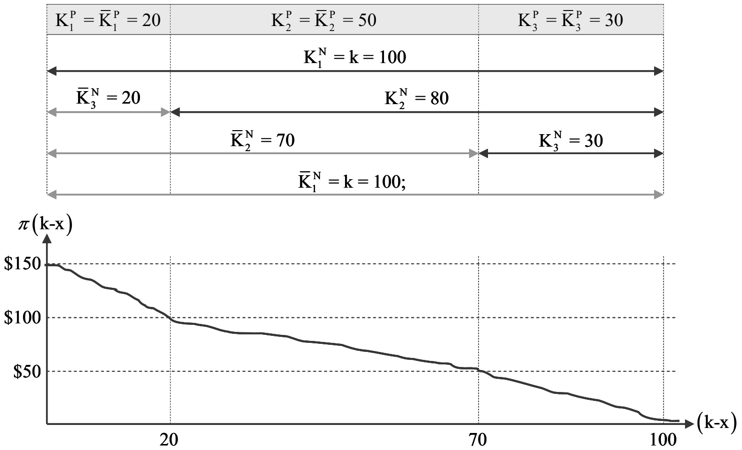

Figure 2-4: Relationship between booking limits (K_s^P, K_s^N), protection levels ($\bar{K}_s^P$, $\bar{K}_s^N$) and bid-prices ($\pi(k\text{-}x)$) (according to Talluri/van Ryzin [2004])

This hierarchical approach assures that a demand for premium classes, which exceeds the booking limit, is satisfied by enlarging the class capacity (corresponding to the objective of maximizing sales in more valuable classes). Thereby, the capacity of the class with the lowest profitability cannot profit from this nesting as it serves as a kind of reservoir for capacity that is not sold in the other classes (corresponding to the objective of minimized idle capacity). So, as seen in figure 2-4, instead of the fixed contingents ($K_1^P = 20$, $K_2^P = 50$ and $K_3^P = 30$), flexible contingents ($K_1^N = k = 100$, $K_2^N = 80$ and $K_3^N = K_3^P = 30$) have been established, indicating that class 1 can get the whole over-all capacity k, whereas class 2 only gets the rest capacity ($k - K_1^N$) and class 3 gets $k - K_1^N - K_2^N = K_3^P$.

Protection levels are the amount of capacity reserved for the classes. In its **partitioned case** ($\bar{K}_s^P$), it is equivalent to the booking limits ($K_s^P = \bar{K}_s^P$). **Nested protection levels** ($\bar{K}_s^N$) are also defined hierarchically. Assuming that s also indicates the order of the classes (s = 1 as the premium class), $\bar{K}_s^N$ is defined as the amount of capacity that has to be protected for the classes s, s-1, …, 1 combined (for class s and higher). In the figure, $\bar{K}_2^N = 70$ indicates the protected capacity for class 1 and 2. The relationship of protection levels and booking limits can be formulated as follows: $K_s^P = k - \bar{K}_{s-1}^P; s = 1,...,S$.

Bid-prices, in contrast to class-based booking limits and protection levels, are **revenue-based**. In this method, threshold prices are set that determine the acceptance or rejection of a customer request, depending on whether the revenue is over or under the bid-price. Bid-prices often depend on the remaining capacity or the rest time until the end of the planning period, as they are updated after each sale. They are used for the nested variant of CC. In figure 2-4, the bid-price π(k-x) is solely dependent on the demanded capacity units x. For the total capacity remaining, the bid-price lies below the receivable revenue of all classes (class1 \$150, class 2 \$100 and class 3 \$50). As a result, the requests for all classes are accepted. Between a rest capacity of 70 and 20 units, the receivable revenue for class 1 is below the bid-price. Therefore, no requests from class 3 are accepted. Finally, with a rest capacity of 20 and lower, only the requests for class 1 are satisfied.

Several **disadvantages of these practical methods** can be stated. Firstly, for all partitioned solutions it becomes problematic if the demand forecasts, forming the basis for the building of the contingents, do not hold because of unexpected fluctuations. The fixed contingents lead then to sub-optimal solutions and resultantly, to a loss in revenue maximization. In the nested cases, one problematic assumption concerns the class determination and the initial contingents. The initial allocations and the class settings require a complete coverage of the potential demand, otherwise the methods do not lead to a maximized revenue [Hornick 1991]. For bid-prices, which do not depend on the rest time or capacity, the fixed thresholds may lead to the acceptance of any requests as long as the revenue is above the bid-price. This would also be sub-optimal. These disadvantages are tried to be abolished by various other approaches to CC.

2.2.1.2 Examples for basic solution categories

Basic solution categories concern the division of CC methods into **static and dynamic, as well as exact (optimal) and heuristic approaches**. Static models for CC neglect the time between the CC and the end of the planning period. This means that it is implicitly assumed that the expected amount and structure of requests (demand) does not change over time. The CC is not updated over time but the initial settings are kept. As far as the CC is a **dynamic and sto-**

chastic[54] **problem** [Tscheulin/Lindenmeier 2003], static models only provide feasible results in cases where the assumption holds. In other cases, dynamic methods have to be considered, instead. They update the initial capacity settings based on the current value of the decision parameters. In both cases, exact and **heuristic**[55] **approaches** are known. Following the description of the two most known approaches to CC, examples for research in a dynamic context (as considered in modern research on CC) are given.

Littlewood [1972] implemented a concept called the **Marginal-Seat-Revenue** for a single-resource, two-class model, which can be considered as a static exact model. With the demand for class s denoted as D_s and its price per unit p_s, under the assumption that the demand for class 2 arrives completely before the demand for class 1, the decision is to sell now to customers requesting capacity units for class 2 or to sell later to the profitable class 1. The reserved capacity k-x (remaining or marginal capacity after the sale to class 2) for class 1 can be only sold if $D_1 \geq \text{k-x}$. As a result, class 2 requests are only accepted, if $p_2 \geq p_1 P\left(D_1 \geq \text{k-x}\right)$.

Connected to the protection level method, an optimal protection level $\overline{K}_1^*$ for class 1 can be established, whereby capacity is only sold to class 2 if the remaining capacity exceeds $\overline{K}_1^*$. Through a continuous distribution of the demand $F_1\left(\text{k-x}\right)$, the so-called **Littlewood's rule** can be used to find the optimal protection level, which determines the class capacities in the two-class case[56]: $p_2 = p_1 P\left(D_1 > \overline{K}_1^*\right)$ or, equivalently $\overline{K}_1^* = F_1^{-1}\left(1-\frac{p_2}{p_1}\right)$.

In contrast to this exact solution, also heuristic models can be used for the solution of the CC. The origins of heuristics in RM can be found in the practical execution of an airline's CC, due to the missing theoretical (and exact) approaches in the research in the early stages of RM [Talluri/van Ryzin 2004]. For the practical execution of CC, heuristics are intended to be simpler and faster to code and to implement. In addition, exact solutions are often based on non-

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[54] *Stochastic* (Greek: stochos "goal") means "characterized by conjecture and randomness". A stochastic process is non-deterministic in the sense that the next state of an environment is not (fully) determined by the previous state.

[55] Heuristic approaches were already mentioned in chapter 1. Silver [2004] explains the basic understanding of and the reason for heuristics.

[56] In the multiple class case, a dynamic programming approach [Bellman 1957] is basically used to find the same solutions based on the same assumptions.

realistic assumptions in order to be able to cope with the complexity of the solution. Thus, heuristics can often be based on more realistic models and lead to faster solutions that are, at least, close the optimal results [Silver 2004, p. 937]. Based on Littlewood, Belobaba [1987a; 1987b; 1989] has developed the widely known and used **Expected-Marginal-Seat-Revenue (EMSR)**. The **EMSR-a**, the first version of EMSR, is based on the idea that the protection levels resulting from Littlewood's rule are added to successive pairs of classes (multiple-class approach). With the demand again arriving corresponding to the revenue value of the class (as already assumed in the approach above), the current demand for a specific class j+1 leads to a protection level $\overline{\mathrm{K}}_{\mathrm{j}}$ for classes j or higher (meaning the class j, j-1, …, 1). This is reached by first computing the isolated protection levels for a single class s, and by then adding up the corresponding levels for this and each higher class. This main idea of the EMSR-a is formulated as follows:

$$\mathrm{P}\left(D_s > \overline{\mathrm{K}}_{\mathrm{s}}^{j+1}\right) = \left(\frac{\mathrm{p}_{\mathrm{j+1}}}{\mathrm{p}_{\mathrm{s}}}\right) \text{ and } \overline{\mathrm{K}}_{\mathrm{j}} = \sum_{s=1}^{j} \overline{\mathrm{K}}_{\mathrm{s}}^{j+1} .$$

The main problem of the EMSR-a was the so-called **pooling effect**, which resulted from the potential production of protection levels being too large due to the statistical averaging effect. As an extension of the EMSR-a, the **EMSR-b** was developed to rid this pooling effect. The EMSR-b aggregates the demand for the classes instead of the aggregation of the protection levels and builds a weighted average for the class revenue. An additional assumption, thereby, is an independent and normally distributed demand for each class s.

In the dynamic context of CC, most research is done on the development of dynamic stochastic programs, being under consideration of one of the described basic approaches. Other approaches transformed the explained methods into the stochastic and dynamic context. Klein [2007] developed a current example for CC using self-adapting bid-prices. Thereby, bid-prices are calculated based on their functional dependence of the amount of capacity already sold, and the expected future demand. The calibration of the bid-prices in this dynamic context is done by a simulation-based[57] optimization (scatter search). Other authors like

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[57] *Simulation* is the reproduction of time-related processes in a model, in order to draw conclusions about the behavior of a real system [see VDI 1993]. Conventional simulation methods can be found in Fujimoto [1999].

Spengler/Rehkopf/Volling [2007] formulated a multi-dimensional knapsack problem[58] for the decision problem (here RM in make-to-order manufacturing) and implemented a bid-price approach. Zhao/Zeng [2001], van Slyke/Young [2000] and Liang [1999] used stochastic dynamic programs for their solution, giving partial consideration to no-shows and cancellations in an overbooking context. The first successful CC application of the fuzzy expert system developed in this work is described in Becher [2007] (see also chapter 4). Various other contributions in this context represent the diversity of the tremendous research carried out in CC (see Tscheulin/Lindenmeier [2003, pp.633] for relevant literature references). All these contributions also mark the **state-of-the-art CC methods**. Also typical questions of overbooking (in order to prevent idle capacities because of so-called no-shows) [Vickrey 1972, Rothstein 1985] as well as multi-leg inventory control (to address origin-destination control problems) [Glover et al. 1982, Talluri/van Ryzin 1999] were more and more addressed. Many other related problems like demand forecasting and demand uncensoring [see Talluri/van Ryzin 2004] were also discussed extensively in the literature.

2.2.2 Competing objectives of the PC

The control of the prices in each class also contains two objectives:

- **Maximization of the price per capacity unit**
  The revenue maximization objective implies that prices have to be set in each class, such that the revenue per capacity unit is maximized. This leads to prices that are as high as possible.
- **Minimization of the amount of rejected prices**
  The first objective may imply the setting of (infinitely) high prices in order to fulfill the objective. However, the reservation price and, thus, the willingness to pay of the customers has to be considered in order to avoid the rejection of all prices by the customers. The higher the price, the lower the portion of potential customers who are willing to buy

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[58] A *knapsack problem* is a problem in combinatorial optimization. Given a set of items with a specific cost and value, the problem is to determine the number of each item that is, for instance, allocated as efficient as possible with respect to a limiting factor (e.g. capacity) [see Martello/Toth 1990].

the goods or services. Again, in order to avoid idle capacities, prices should only be as high as the expected reservation prices.

The solution for the price part of the revenue maximization problem has also been the subject of various research conducted on RM. Beginning with practical applications in pricing, many other approaches to the control of prices have emerged.

2.2.2.1 Practical solutions for PC

All developed PC methods focus mainly on the **relationship between the price and the demand**. Thereby, the following functional relationship is commonly considered:

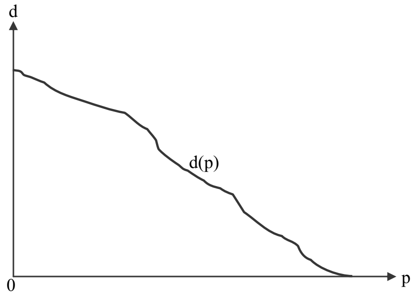

Figure 2-5: Typical price-response curve

The functional relationship d(p) is commonly known as the **price-response function** [Phillips 2005, p. 41] or demand function [Varian 1999, pp. 3]. It shows the demand that is connected to a specific price. Formulated as p(d), it shows the price setting of the supplier with respect to the demand for a specific class[59].

The beginnings of PC are strongly connected to the idea of **price differentiation** [Varian 1999, pp. 411]. Thereby, the objective of the supplier is to reduce the consumer surplus[60] resulting in a market equilibrium (with the assumption of perfect competition in most work to

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[59] Thereby, the functional specifics are non-negativity, continuity, differentiability and the downward slope [Phillips 2005, pp. 40].

[60] *Consumer surplus* is the consumer's benefit occurring in a transaction, which results from the difference between the prices that consumers are willing to pay and the supplier price.

PC). In figure 2-6, the basic idea is presented. With the given linear price-response function d(p), the setting of one supplier price p^* leads to a demand of d^*. Under the assumption that the supplier can produce this amount of goods, he gets the revenue $PS = d^* \cdot p^*$. **PS**, thereby, indicates the **supplier surplus** resulting from the transaction. **CS**, instead, is the **consumer surplus** resulting from the transaction. In an aggregate view, some consumers were able to make the transaction at the price p^* despite their willingness to pay more (indicated by the demand curve lying above). A price differentiation[61] (setting two or more different price levels) results in a higher producer surplus ($PS{+}PS^{add}$) and a lower consumer surplus ($CS - PS^{add}$).

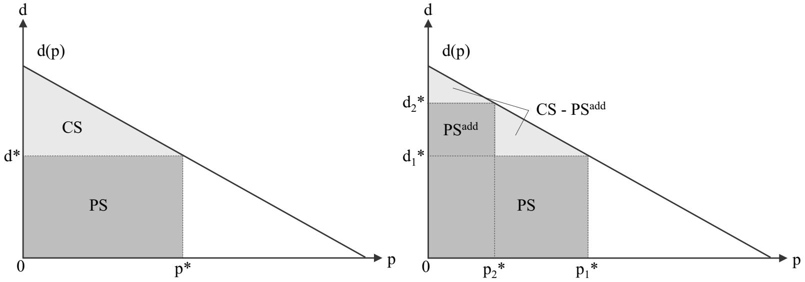

Figure 2-6: Skimming consumer surplus by price differentiation

Practical solutions for PC based on this concept of price differentiation use several tactics for pricing:

- **Group pricing**
  By segmenting customers according to their willingness to pay, grouped prices result that are able to provide differentiated prices. Examples are student discounts, pensioner discounts, or family prices. Four criteria must be satisfied for group pricing: Membership evidence (e.g. student ID cards), a strong correlation between membership and price sensitivity (senior citizens compared to middle-aged people with a high income), no arbitrage, and, finally, the acceptance of segmentation (legally and culturally).

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[61] Certain limitations to price differentiation can be stated: Imperfect segmentation (missing knowledge of the willingness to pay of each customer), cannibalization (customers with high reservation prices trying to get lower prices, e.g. discount prices of airlines) and arbitrage actions (third parties buying at low prices and selling the good at a higher price to people with higher reservation prices) [Phillips 2005, p. 77].

- **Channel pricing**
  Here, different distribution channels lead to different prices (e.g. discount book prices for the on-line orders of a book shop). This pricing type is often connected to different transaction costs[62].
- **Time-based pricing**
  Examples for time-based price differentiation are discount fares for early bookers or night electricity.
- **Regional pricing**
  This is often connected to the price sensitivity for the same good in different regions (countries). Examples are different prices for Aspirin (much higher in Germany compared to Spain).
- **Couponing**
  By offering discount prices over coupons (e.g. in journals or newspapers), customers may self-select their favorite price segments (depending on their flexibility, time and effort to get the lower price).
- **Product versioning**
  This approach to price differentiation is one of the most used approaches to price differentiation in its basic form. By establishing different versions of a good (e.g. through the use of different brands), a good with, at most, minor differences can be distributed to different customer types[63].
- **Volume discounts**
  Setting different prices for different volumes of goods or services is also a very popular pricing tactic (e.g. paper copies, electricity).

Besides these various examples for the practical access to pricing in RM, various methods for PC have emerged in this research field.

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[62] *Transaction costs* are costs incurred in making an economic exchange. Examples for cost components are search and information costs (e.g. for the determination of the availability and the lowest price), bargaining costs (required for the agreement) and policing and enforcement costs (to assure the compliance with the contract).

[63] One specific is that the customers belonging to the higher price segment feel that they buy a higher quality if the relationship between the different product versions is not recognized.

2.2.2.2 Examples for basic PC solutions

While in CC, static and dynamic approaches as well as exact (optimal) and heuristic approaches are distinguished, especially **dynamic models** are used in PC research in contrast to the above illustrated practical methods where one fixed pricing schedule is developed. On the basis of price-response models[64], three specific examples of dynamic pricing can be outlined:

Style- and seasonal-goods markdown pricing is most prevalent in apparel, high-tech and foods retailing where the deterioration of goods due to style or seasonal reasons plays an important role. The main reason for this markdown pricing is to sell the goods before the season ends or before they are perished. However, other reasons for markdown pricing can also be found. With a given uncertainty about the popularity of new goods, suppliers have an incentive to set higher prices initially. Popular products are bought at the higher price, unpopular stay in the stock and have to be priced on a lower level [Lazear 1986]. Additionally, markdowns can be used to segment customers with respect to their purchase behavior. People who like to be first movers in owning new products have a higher reservation price. Therefore, at the beginning of a product lifecycle, the price level is higher [Pashigan/Bowen 1991].

The specific of **discount airline fares** is that prices increase over time and are not lowered. Based on the capacity and demand for a certain flight, prices vary over time. With the workload going up, prices increase. The main reason is that leisure passengers are intended to book earlier and are more price sensitive than business passengers. Lowering the price would dissatisfy leisure customers. In addition, business customers also fly for a higher price that is satisfied with respect to their late booking.

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[64] Criteria for the differentiation of dynamic pricing models, besides the price-response functions, are the customers' purchasing behaviors and the size of the population. The first criterion distinguishes two forms of customer behavior: Myopic customers (who buy as soon as the price is at most as high as their reservation price) and strategic customers (who adjust their purchasing behavior to the pricing strategy of the firms). The second criterion distinguishes infinite- and finite-population models. Infinite-population models consider a non-durable-goods assumption (a replacement approach is adopted where the number and type of customers does not change over time, depending on past transactions). Finite-population models orient on a durable-goods assumption, where the structure of customers matters for the decisions (different customer types are assumed with a limited number of consumers per type).

Consumer-packaged goods promotions are short-term price reductions in the consumer-packaged goods industry (e.g. soap, coffee). With underlying reference prices (the feeling of the customers about fair prices), the effects of promotions have to be analyzed carefully to avoid habituation or stockpiling [Talluri/van Ryzin 2004, pp. 181].

In the tremendous research conducted on PC, **exact and heuristic methods** can be found. The development of research on pricing strategies started out with single-period pricing models [Whitin 1955; Mills 1959; Hempenius 1970]. After considering multi-period, finite-horizon models [Zabel 1972; Thowsen 1975], first continuous-time models were adopted [Li 1988, Gallego/van Ryzin 1994]. Examples of exact solution methods for PC were realized by Badinelli/Olson [1990], Feng/Gallego [1995] and Feng/Xiao [2000]. Badinelli/Oslon [1990] considered hotel RM with the problem of hidden reservation prices. The fact that customers have no incentive to reveal their willingness to pay implies an approach for pricing based on diverging reservation prices. Feng/Gallego [1995] abstracted from the reservation price problem and developed an optimal method for the provision of time-based thresholds for price variations in the context of a sales deal. Optimal price levels have been dynamically set in different application cases researched by Feng/Xiao [2000]. Heuristic solutions were exemplarily provided by Gallego/van Ryzin [1994] and Gallego/van Ryzin [1997]. In 1994, Gallego and van Ryzin developed a fixed-price heuristic for the case of an interval of continuously variable prices. For the case of discrete sets of prices, they developed a heuristic method that provides critical time points for the price setting. In 1997, the same authors expanded their research to the multiple product case and to network effects of RM. In addition, solutions based on integer programming were provided by other authors [Garcia-Diaz and Kuyumcu 2000]. A special case of dynamic pricing is the use of auction[65] algorithms for the price setting [Krishna 2002; De Vries 2003; Cramton 2006]. This method assures that customers reveal their willingness to pay. It has the advantage that this information does not have to be introduced in the transaction process.

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[65] Thereby, for instance, English (open ascending), Dutch (open descending), Sealed-bid first-price and Vickrey (sealed-bid second-price) auctions can be distinguished [Klemperer 2004; Vickrey 1961].

Research on pricing has also been extended to other application fields, like the non-profit sector (Metters and Vargas 1999), logistics (Kleywegt and Papastavrou 2001) and the assemble-to-order manufacturing (Harris and Pinder (1995).

2.2.3 Integration of the objectives to a SCPC

As voluminous the research on CC and PC is, as sporadic are the contributions to SCPC. Despite the claim of many researchers to integrate the CPC problem because of its higher revenue potential [see Tscheulin/Lindenmeier 2003; Weatherford 1997; McGill/van Ryzin 1999], only little work has been done on SCPC. Therefore, the distinction between practical methods and examples for state-of-the-art methods cannot be made here. In addition, the concerning contributions often use parts of the already described methods and combine them by adding the PC or CC component. So, an outline of the current work on SCPC should be sufficient.

Simultaneous, in the sense used here, means that CC and PC are integrated. This integration can be executed in different ways. Weatherford [1997] included the class prices as decision variables in the CC of a capacity-limited company, even though he found out that the integration of CC and PC is very problematic due to the complexity of the decision model. Weatherford/Bodily [1992] proposed perishable-asset RM to combine CC, overbooking and pricing. They provided a 14-point taxonomy for the resulting decision problem. The article of Garcia-Diaz/Kuyumcu [2000] illustrated a new analytical procedure for joint pricing and seat allocation considering demand forecasts, the number of fare classes and the capacity. The proposed theoretical approach of polyhedral graphs utilizes split graphs and cutting planes for the solution of the integer program[66] for the SCPC. Feng/Xiao [2006] developed a method for SCPC in the case of a fixed over-all capacity, finite sales horizons (planning periods), and multiple customer classes of different worthiness (all assumptions also forming the basis for this work) that are served with the same product. Thereby, a served request is connected to a certain price of a given price set. One problem faced by all researchers so far is the practical application of the developed approaches. For research purposes, Kimms and Müller-Bungart

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[66] *Integer programming* is a special case of linear programming with the unknown variables being integer [Schrijver 1998.]

(2006) provided a data generator for Network Revenue Management in order to bridge the gap between research and practice. However, this does not assure the feasibility of the solution methods in practical decision-making.

There are several important conclusions that can be drawn from the existing literature on SCPC. These conclusions are based on the solution of different problems resulting from a SCPC, which have to be solved in order to get a comprehensive and applicable solution concept. It can be already stated here that the existing solutions, so far, are not able to solve all problems of SCPC, even though they indicate the potential of an integration of CC and PC.

A basic example illustrates that the integrated solution for the revenue maximization problem offers the exhaustion of the whole revenue potential in many application cases:

class	contingents [units]	price [€]	demand [units]	reservation price [€]
1	20	20	30	25
2	80	5	80	10

Table 2-1: Skimming consumer surplus by price differentiation

Based on former demand forecasts, the over-all capacity of 100 units is distributed to two identified classes with a different price level (class 1 is the more profitable class) as given by the so-called contingents. The current scenario with fixed contingents and prices leads to a revenue of €800. Considering the capacity control option CC, it can be seen that the workload in both classes is 100%. However, as far as class 1 is more profitable, an increase in the contingent of class 1 (due to the higher real demand of 30 units, which may result from demand fluctuations) could lead to a higher revenue. This implies an increase of the contingent of this class (an increase by 10 units in the example). The new capacity distribution leads, then, to a revenue of €950 (18.75% increase). Considering the price control option PC, it is assumed that the average reservation price for both classes is higher than the offered price. This means that the consumers are willing to pay more than the current price for one unit of capacity of both classes. In order to skim this consumer surplus, prices can be increased up to the level of the reservation price. With the new prices, a revenue of €1,300 can be achieved (62.5% increase). Consistent with the proposed SCPC approach, the result of the integrated conduction of CPC is a revenue of € 1,450, meaning an even larger revenue than achievable by the separate conduction (81.25% increase).

Despite this example, which shows the basic advantage of a SCPC, some difficulties in the context of a SCPC have to be considered in order to be able to reach the full revenue potential in a practice application.

2.3 Problems resulting from a SCPC and its components

While all the described methods for CC, PC and SCPC contain the main fields of the revenue maximization problem, various **problems emerge that have to be solved by a feasible solution concept for SCPC** (see section 1.2). These problems are at most only partially solved by the existing methods [Tscheulin/Lindenmeier 2003, p. 654]. The six central problems, which have been discovered in this research on SCPC, are described in detail as follows.

2.3.1 Problems concerning the decision context

The following problems emerge that have to be sold in the basic decision context:

- **Dynamic context of the SCPC**
  The dynamic context of the SCPC refers to the general predominance of dynamic over static solutions [Hornick 1991]. In addition, the dynamic context seems to be more appropriate for the SCPC as **short-term fluctuations of demand** and **unexpected customer behavior** show a clear need for an **adaptive system** that can adjust the capacity allocation and price setting over time. Therefore, a comprehensive approach to SCPC must fulfill the requirement of a dynamic method.
- **Flexibility in the decision categories**
  Not only the flexibility concerning the **uncertainties** (unknown demand and reservation prices) faced when developing a solution for SCPC but also the necessary flexibility

with respect to the application constraints has to be considered in an adequate solution. As already stated in chapter 1, not all applications need an integrated solution of CC and PC. In the German health sector, for instance, prices for hospital services are fixed by law. In the hotel sector, capacities are fixed due to constructional limitations. By contrast, capacities, as well as prices, can be adjusted over time in Transport Management. An applicable solution for SCPC must **combine the CC and PC component in a way that allows the fixing of one of the two control parts** due to the underlying application case[67].

- **Underlying data basis for the data analysis**
  For the capacity and price adjustments due to the demand (or workload), but also for the determination of the classes of different worthiness, the underlying variable costs, the time horizon, the customer structure and the current practice of RM etc., several data analysis techniques have to be adopted. These are required in order to get all the relevant information for the SCPC. Not only the adequate choice of data analysis methods and the use of appropriate software for the efficient execution are of concern in the context of SCPC, but also the data basis itself. A whole **data analysis process** (containing all steps starting at the data extraction, followed by its preparation and modeling and, finally, the evaluation and deployment) has to be executed to obtain the information relevant for a SCPC. The better the data basis, thereby, is, the more valid the results of the data analysis are[68].

- **Applicability of the solution concept**
  The necessary applicability of the solution concept cannot only be derived from the **missing applications** of the literarily provided solutions of SCPC (often result of the missing solution of one of the above problems). It is a **requirement formulated by many researchers in RM** [see Talluri/van Ryzin 2004, p. 654]. Besides the claiming to also assure the separate conduction in an SCPC approach, also the reduction of the large

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[67] Thereby, a continuum of possible capacity and price adjustments exists depending on the flexibility and the costs of changing [Talluri/van Ryzin 2004, p. 176].

[68] A central problem in the context of RM is thereby the presence of censored (constrained) data where only the accepted requests of customers are stored in the data basis. Rejected offers (from the supplier or consumer side) are not saved. Thus, not the real demand and transaction structure is reproduced in the data. Several techniques are available for the unconstraining of data [Talluri/van Ryzin, pp. 473].

amount of influences to a few central decision variables and parameters is crucial for the applicability in practice.

2.3.2 Problems concerning the influence factors

Concerning the execution and implementation of the solution system with respect to the decision context and the objectives, the following problems have to be solved:

- **Demand estimation for the CC**
  Many approaches to CC, PC and SCPC work are based on demand forecasts or assumptions about the demand structure and its distribution over time. In contrast, many researchers criticize the use and the **feasibility of demand forecasts** in the context of a fluctuating demand [Kuhlmann 2004]. Documented in literature on forecasting, many authors also address the limited applicability of many forecasting methods in the context of short time series and fluctuations [Schlittgen/Streitberg 1987; Lancaster/Salkauskas 1986]. A comprehensive solution also tries to avoid these kinds of demand estimation problems by looking for **reliable indicators of demand** in the applied context of a real data basis.
- **Reservation price determination**
  The determination of the customers' reservation prices leads to a similar problem as that of the demand estimation. Customers have **no incentives to reveal their willingness to pay** in order to receive consumer surplus. Techniques for the **SCPC without the need for unreliable reservation price estimations** have to be found in order to provide a comprehensive solution without a lack of validity arising from estimation mistakes.
- **Consideration of time aspects**
  Besides the two main influences on the capacity allocation among classes and the price setting within each class, i.e. the workload (as an indicator for demand) and the reservation price, there are also other parameters influencing the SCPC decision problem. Especially **time aspects** play an important role in the SCPC. For example, at the beginning of a planning period, the workload is commonly very low. However, this does not necessarily imply that the demand in a class during this planning period is low. If the work-

load stays very low in the period, demand is too low and, as a result, capacities as well as prices have to be accordingly adjusted.

- **Consideration of the customer value**

  A further example of the influence variables is the **value of the customer currently requesting**. Regular (and, thus, high-valued) customers with a very low acceptance of price changes may be irritated by price variations, having negative effects on their purchasing behavior. This diversity in the price-sensitiveness and the connected customer reaction on varying prices can be basically explained with the concept of **price elasticity**[69].

  In cases of high price elasticity, even low price variations can have significant effects on the demand. Thus, only small price adjustments are possible without having the risk of an underperforming PC. The result is possibly a lower over-all price level. In contrast, price-inelastic demand does not change very much with price changes. The PC must cause clear price adjustments in order to affect customer behavior and to skim consumer surplus. The diverse customer behavior in the context of pricing is also part of various research fields in **Customer Relationship Management (CRM)**. The CRM goals of customer satisfaction and loyalty are very important in the context of pricing, particularly. In general, all CRM activities are based on the **Analytical CRM** as the technical basis for all customer-oriented entrepreneurial action [Bruhn 2007; Bruhn/Homburg 2003; Raab/Lohrbacher 2002]. Based on the underlying database (often in form of Data Warehouses[70], see figure 2-7) [Holthuis 1999]), all important customer and transaction information is given to the decision maker in the **operative CRM**. In the analytical

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[69] The *price elasticity* of demand ε can be explained as the percent change of demand (in our context the amount of requested capacity units, x) with respect to one percent change in the price (p): $\varepsilon = \Delta x / x / \Delta p / p$. The price elasticity can be the reason for significantly different price levels in different markets despite that the same product is sold. If the demand is price-elastic, even small variations of the price lead to a noticeable change in the demand. A price-inelastic demand does not change with price modifications [Varian 1999, pp. 257].

[70] A *data warehouse (DW)* is a “subject-oriented, integrated, time-variant, nonvolatile collection of data in support of the management´s decision-making process“ [Inmon/Hackathorn 1994]. This definition is only one of the various attempts to describe the complex structure of a data warehouse with its typical components of data input (with the important data extraction and transformation process [Bauer/ Günzel 2000]), data management (with the meta-database, the central data base and data marts, as well as the storage system), and the data deployment (use of the data base for the analyses relevant for the operative and communicative CRM) [Devlin 1997].

CRM, several data analysis techniques, Data Mining[71], and reporting systems (like OLAP[72]) provide the information needed for the precise customer analysis (e.g. customer value determination, customer segmentation, cross-selling[73] analysis) in the operative CRM. The individual customer interaction in the **communicative CRM** (e.g. via call centers, WWW, other e-commerce techniques or face-to-face communication) is the result of a narrow interaction between the analytical and the operative CRM[74]. In this work, the customer value is the main information entering the decision model to address the described problem of customer reactions on the pricing. Here, it is intended to forgo facing regular customers with extreme price fluctuations in order to avoid irritations. Many other approaches for the incorporation of customer information into RM can be found in literature [e.g. Dickinson 2001; Breffni/Kimes/Renaghan 2003].It has to considered in order to avoid the circumstance of a regular customer becoming irritated by extensive price variations [Breffni/Kimes/Renaghan 2003; Reichheld/Teal 1996; Link 1995; Bruhn/Homburg 2003].

- **Short-term costs or seasonal effects**
  These have to be included in the price setting in order to avoid prices being below variable costs or to avoid the wrong pricing in sectors having seasonal effects. Additionally, strategic rather than cost reasons imply the pricing at a certain level.

It has to be assured that all kinds of influences are addressed in the solution concept for a SCPC. In addition, the following basic assumptions have to be made.

---

[71] *Data Mining* is the automatic knowledge discovery in large databases in order to find complex or complicated patterns with the help of specific data mining techniques (e.g. rule induction, decision trees) [Witten/Frank 1999; Tan/ Steinbach/Kumar 2005; Hippner et al. 2001].

[72] *On-line Analytical Processing (OLAP)* is an approach to the repeated and automatic provision of company-related information. In contrast to Data Mining (discovery system), the analyzed relationships in the data are clear and well-known. In this context, OLAP is commonly named a verification system.

[73] *Cross-selling* refers to the offer of additional products related to a product recently bought by a customer. The objective is to increase the shopping cart by additional products and to avoid that the customer buys the additional products from the competitor.

[74] One CRM component also named in this context is the collaborative CRM that concerns a customer-oriented process over the whole value-added process, including not only the different divisions within a company but also the interactions to other companies (e.g. sub-contractors).

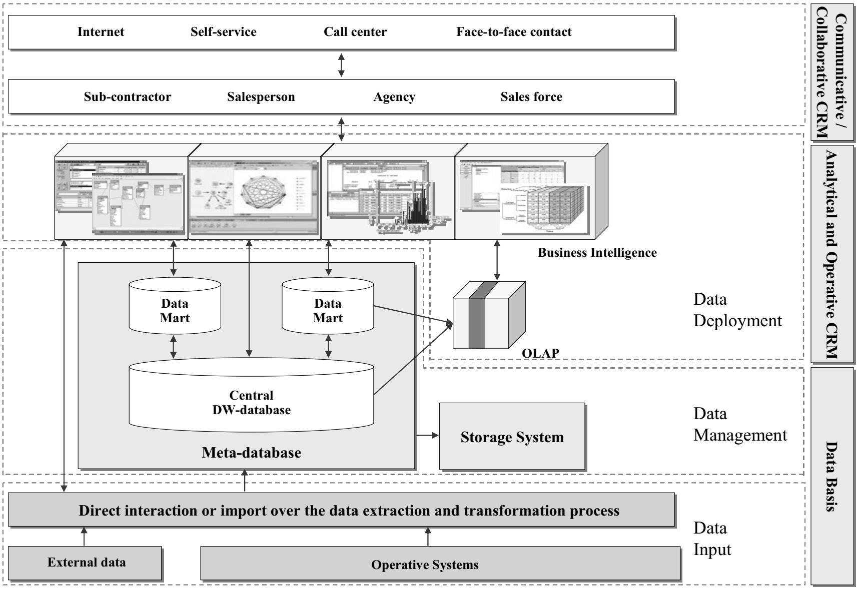

Figure 2-7: Data Warehouse for the analytical CRM

2.4 Derivation of the solution concept

Summarizing the illustrations to the concept for a SCPC, the following underlying basic assumptions for the solution concept can be formulated:

- **Fixed over-all capacity**
  In this work, the basic assumption of a fixed over-all capacity as a prerequisite for RM-focused approaches is also made. In cases, where the over-all capacity is adjustable in the short-run because of a high flexibility and low costs, the capacity allocation is no decision problem.
- **Finite planning period**
  The assumption of a finite planning period implies that the problem of idle capacities at

the end of the period basically exists. Thus, an end point of the planning period has to be defined.

- **Multiple customer or product classes**
  The CC problem is only present in the case of a multiple class case. In the single class case, no capacity allocation problem exists. The pricing problem also has to be considered in a single class case.
- **Dynamic capacity allocations and price adjustments within a period**
  The dynamic context as the appropriate solution approach is addressed also in the provided solution.
- **Customers demand only for one specific class capacity**
  Customers only demand a certain amount of capacity of a specific class and do not switch to another class in the case of no availability. Thus, a rejection of a customer in the demanded class is final and the opportunity of offering another class is not given.
- **No overbooking, no-shows and cancellations**
  The fixed over-all capacity cannot be expanded by overbooking policies that try to capture the possible no-shows and cancellations and, thus, minimizing idle capacities. The addressing of the overbooking and cancellation context would afford to have access to the concerning data. In many practical cases, this information is not available.

The discussed problem setting is the basis for the implementation of this solution concept for SCPC. The concretization of the concept will be illustrated in the following.

3 Concretization of the concept for the simultaneous capacity and price control

The concretization of the basic concept for SCPC, as well as its components CC and PC, provided in chapter 3, concerns particularly the solution of the described problems in the context of CC, PC and SCPC founded on the basic understanding of their dynamic execution. In addition to this, the mathematical framework of the provided solution has to be formulated. The resulting decision model bases the implementation of a CC, PC and SCPC.

3.1 The decision context of SCPC

The decision context of a SCPC becomes clear by looking at the basic understanding of the decision process and the specifics that result from this basic SCPC procedure.

3.1.1 The basic procedure of SCPC

For the execution of SCPC, the following connection of the different decision variables and parameters has to be considered. The underlying variables are consistent with the influences described in the conception part of this work:

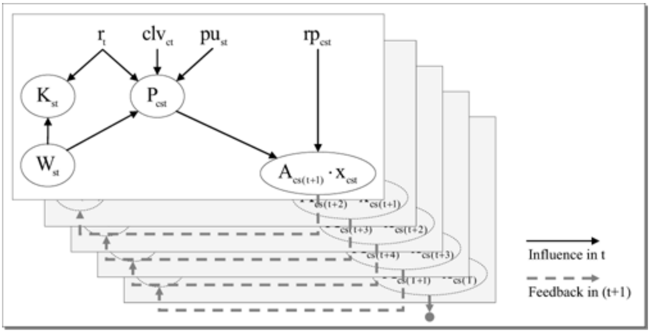

Figure 3-1: The basic procedure of SCPC

For t = 1, initial sets of prices and capacities (and, thus, workload) are set based on the expected demand and information on former prices for the different classes s (s = 1, …, S). The decision process, hence, starts in t = 2. The capacity or contingent K_{st} for each class is allocated at each point in time t (t = 1, ..., T), based on the current workload W_{st} and the remaining time until the end of the period, r_t. The result of this decision is the degree of capacity adjustment κ_{st} for the capacity allocation in the next time point.

In the continuing process, a customer c (c = 1, …, C) demands a specific amount of capacity in a certain class x_{cst}. Based on the current workload W_{st}, with the remaining time r_t, the customer value clv_{ct} and the short-term bottom price pu_{st}, the supplier price P_{cst} for the demanded amount is set by the supplier. The result of this decision is the degree of price adjustment ψ_{cst} for the price setting in the next time point. On the basis of the final price, the consumer decides whether to accept that price and buy the demanded amount of capacity or to reject the offer. The responsible parameter for the decision of accepting or rejecting is the reservation price of the customer, rp_{cst}. The consumer accepts the offered price only if it is at most equal to this willingness to pay. In addition, the supplier decides whether to accept the customer request based on the available capacity. He accepts the request only if enough capacity is free to satisfy the request. These two decisions are represented by the variable $A_{cs(t+1)}$. This decision influences the variables in the next time point as illustrated in figure 3-1. $A_{cs(t+1)} \cdot x_{cst}$ means that the workload is increased by the portion of accepted units of capacities, inducing a new capacity allocation step, which is followed by the price setting.

Within a dynamic decision process, this operative procedure of SCPC leads to the difficulties outlined in section 2.3. However, by formulating this basic procedure, certain conclusions for the solution of the formulated problems of section 2.3 can be automatically drawn.

3.1.2 Specifics of the solution concept

The implications of the basic understanding of the SCPC process can be used to solve the underlying problems adequately.

3.1.2.1 Specifics concerning the decision context

The solution of the problems formulated in section 2.3.1 is as follows:

- **The dynamic context** in its narrow sense (as a continuous problem) would lead to circular reasoning as the CC immediately influences the PC and vice versa. Dynamic in this context, however, means that the initial solutions for the CPC can be adjusted over time. The time parameter hereby is not the dynamic factor. It only divides the planning horizon in different parts. The result is that the course of time is not seen as continuous but event-driven (each time point, so, can be also represented by a customer request). An **iterative on-line procedure** (see figure 3-2), in which firstly the CC is taken out followed by the PC, assures the absence of immediate feedbacks that lead to circular reasoning (the PC has influences on the CC only in the next point of time).

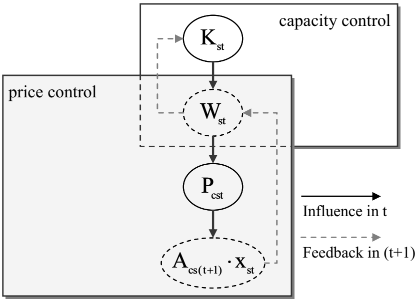

Figure 3-2: Iterative SCPC

- The **flexibility in the decision categories** is also reached by this iterative procedure. By separating the CPC and having the **workload as the only connection** (see figure 3-2), the opportunity to omit one of the control options is reached.
- The **underlying data basis** contains a large potential for errors when determining all influences and the whole decision framework (e.g. class definition). In the solution concept, **adequate data analysis techniques, based on current software** (see figure 3-3 and 3-4), are used to prepare the data basis for the CC. The same techniques are used in all cases of CC, PC and SCPC.

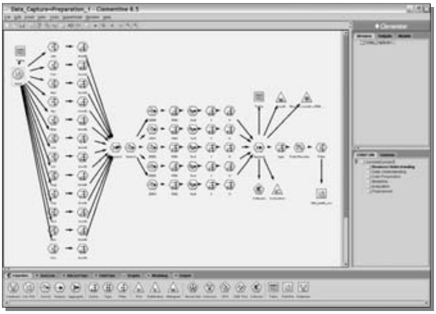

Figure 3-3: Data capture and data preparation with SPSS Clementine®

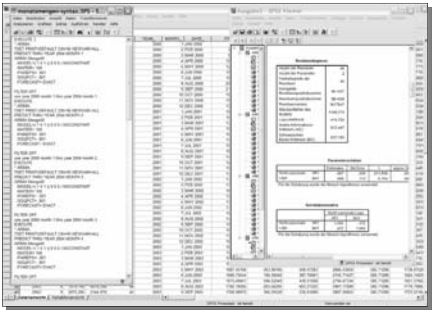

Figure 3-4: Demand forecasting with SPSS®

- The **applicability of the solution concept** is, on the one hand, assured by the **use of real data** for the conduction of the SCPC. This also leads to an implicit test of the solution in a running system. Additionally, the influence factors for the CC and PC are reduced to **three central factors**: The **workload in the class** and the **rest time in the planning period**, as well as the **customer value** for the PC. The workload could thereby serve as an indicator for the demand in a class in the understanding of it as the amount of (already) sold capacity units in the planning period divided by the class capacity (see figure 3-5). A high workload, for instance, indicates that the (cumulative) demand for a class is higher than expected because of the high percentage of the sold capacity units. The demand is thereby seen as a value that consists of all bookings over the planning period. In this case, either the price can be increased because of the high probability of customers with a high willingness to pay (the capacity is “reserved” for customers with a high reservation price), or the capacity can be increased in order to provide more capacity (independent from the customers’ willingness to pay). A combination of both implications can be also thought of. A low workload, instead, implies a low demand for the class, leading to lower prices or a capacity decrease (or a combination of both).

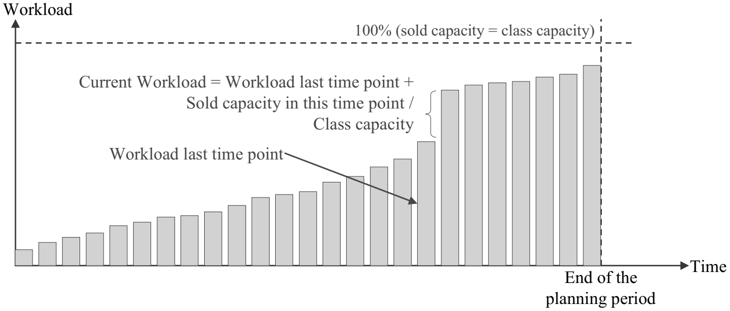

Figure 3-5: Workload illustration

3.1.2.2 Specifics concerning the influence factors

The introduction of the influence factors into the decision model takes place as follows:

- The **workload is an indicator for the whole demand** in a class, as it tends to be high or low if the demand in a class is high or low, respectively. As the workload is, per definition, low at the beginning of the planning period (first requests for the goods provision at the set end of the period, e.g. the departure of an airplane) and high at the end of the period, the **rest time in the planning period** plays an important role for the control. A low workload, for example, implies the decrease of the corresponding class capacity and price because of the potentially low demand in this class. With a high rest time, however, no decreases are undertaken because of the commonly low workload at the beginning of the period. If the workload stays low, capacities and prices are more and more lowered because of the lower than expected demand. A high workload at the beginning of a period implies a high demand with the result of an increasing capacity and price. At the end of the period, a high workload simply means that the CC and PC have worked well, so no increases are necessary. Capacities and prices can now be adjusted over time based on the fulfillment of the demand expectations, starting with an initial solution that expresses the expectations (initial class sizes and prices corresponding to the demand expectations).

- One **additional factor in the PC** is the **customer value**. Regular customers are not intended to suffer from large variations in prices. Therefore, price adjustments take place in a narrower range compared to non-regular customers (on the importance of integrating CRM and RM strategies, see Dickinson [2001] and Belobaba [2002]).
- Also **short-term bottom prices** have to be considered, that are built based on cost or strategic decisions (see chapter 3 for a detailed description of the customer value and the short-term bottom price).

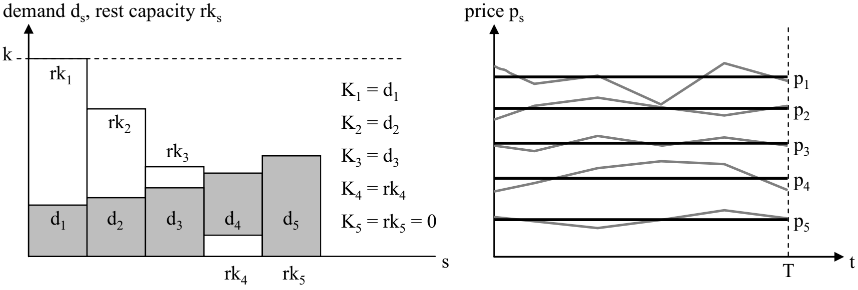

Figure 3-6: Building of initial sets of capacities (left fig.) and prices (right fig.)

- **Demand estimation** in a dynamic CC is not necessary and the problems and practical limitations of demand forecasts do not need to be regarded in the solution concept. Forecasting is only conducted to build **initial solutions for the CC and PC** (figure 3-6). Because of the high variability of the CC, it is common to only take the average capacity sales in the classes into account[75]. Prices are highly fluctuant due to different reservation prices and workloads. The proposed SCPC will help to solve this problem by incor-

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[75] In application case I (sole capacity control), the practice case is controlled on the basis of initial capacity distributions as the result of demand forecasts assuming an ARMA (1, 1) process [Schlittgen/Streitberg 1987]. In terms of forecasting quality, this process had the best results. In terms of the capacity setting itself, just taking the average of the last periods would have led to the same results.

porating the demand and price problem into the SCPC through the building of initial sets of capacities and prices for the classes of different worthiness only at the beginning of the planning period (no need for demand forecasts for each time point) and adjusting them over the planning period based on the described parameters. For the capacity control (see left figure 3-6), the initial sets are built by distributing the over-all capacity to the classes of different worthiness[76] with respect to the expected (or forecasted or average) demand and in favor of more profitable classes. Figure 3-6 shows that, for the most profitable class, the rest capacity (rk) is equal to the over-all capacity. With the expected demand (d) lower than the capacity, the rest can be distributed to the next class. For the fourth class, the demand is higher than the rest capacity. Therefore, it only gets this rest. No capacity is left for the least profitable class before the beginning of the capacity adjustment over time. The initial set of prices (see right figure 3-6) is built by determining the expected price, too[77]. This set, again, is adjusted during the planning period like explained before.

- In fact, **no reservation price estimation** is necessary in the solution concept itself. As the workload and the rest time in a period are the central influential factors, supplier prices above the reservation prices are indicated by a low workload. Thus, a clear indication for a price decrease is given. The reservation prices, however, determine the acceptance or rejection of the supplier price and, therefore, the sold units of capacity. So, not the reservation price of each customer is estimated but the prices are adjusted based on the reservation price level of the consumers. The distribution of the reservation prices among customers is considered by selling at a higher price level in times of high demand (high workload) and at a lower price in times of low demand (low workload). In the first case, the remaining capacity is only demanded by consumers with a higher willingness to pay. In the second case, the classes are opened also for customers with a low reservation price. However, in order to analyze the performance of the PC or SCPC, reservation price estimations have to be executed. With different assumptions about the distribution of the reservation price among customers, the variation of the performance of the SCPC can be analyzed. The objective is to get a solution that is not sensitive to

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[76] In the figure, s = 1 is the most profitable class whereas s = 5 is the least profitable.

[77] In contrast to the capacity control, it could be adequate in practice to undertake no forecasts and to take the mean prices of the last period, simply because of the high volatility of (reservation) prices over time.

reservation price variations. As a result, in contrast to other research, reservation prices are not estimated for the solution in the running system itself but **only for the performance analysis**.

These illustrations are the background for the formulation of a decision model for SCPC. By introducing this decision model, the remaining crucial restrictions for the implementation of a solution concept become obvious and determine the use of appropriate methods.

3.2 Formulation of a decision model for SCPC

The decision problem of a SCPC explained in the previous section leads to the mathematical formulation presented below:

Indices:

$c = 1,...,C$	$\in \mathbb{N}$	Customers
$s = 1,...,S$	$\in \mathbb{N}$	Classes
$t = 1,...,T$	$\in \mathbb{N}$	Time

Parameters:

r_t	Rest time in the planning period
clv_{ct}	Customer value
rp_{cst}	Reservation price of the customer
pu_{st}	Short-term bottom price
x_{cst}	Capacity units demanded by the customer
k	Fixed over-all capacity
K_{s1}^{0}	Initial capacity for the classes
P_{cs1}^{0}	Initial prices
W_{s1}^{0}	Initial workload
κ_{min}	Minimum degree of capacity change
ψ_{min}	Minimum degree of price change
κ_{max}	Maximum degree of capacity change
ψ_{max}	Maximum degree of price change

Decision variables:

κ_{st}	Degree of capacity change

ψ_{cst}	Degree of price change
K_{st}	Class capacity
P_{cst}	Supplier price
W_{st}	Workload
A_{cst}	Acceptance decision

Objective function:

$$\max \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{c=1}^{C} A_{cs(t+1)} \cdot x_{cst} \cdot P_{cst} \tag{3-1}$$

Constraints:

$$K_{st} = \kappa_{st}(W_{st}, r_t) \cdot K_{s(t-1)} \qquad \forall s,t \geq 2 \tag{3-2}$$

$$P_{cst} = \psi_{cst}(W_{st}, r_t, clv_{ct}) \cdot P_{cs(t-1)} \qquad \forall c,s,t \geq 2 \tag{3-3}$$

$$K_{st} \geq \sum_{t'=1}^{t-1}\sum_{c'=1}^{c} A_{c's(t'+1)} \cdot x_{c'st'} \qquad \forall s,t \geq 2 \tag{3-4}$$

$$\sum_{s=1}^{S} K_{st} = k \qquad \forall t \tag{3-5}$$

$$W_{st} = \begin{cases} 1, \text{ if } K_{st} = 0 \\ \dfrac{\sum_{t'=1}^{t-1}\sum_{c'=1}^{c} A_{c's(t'+1)} \cdot x_{c'st'}}{K_{st}}, \text{ else} \end{cases} \qquad \forall s,t \geq 2 \tag{3-6}$$

$$A_{cs(t+1)} = \begin{cases} 1, \text{ if } P_{cst} \leq rp_{cst} \wedge K_{st} \geq \sum_{t'=1}^{t-1}\sum_{c'=1}^{c} A_{c's(t'+1)} \cdot x_{c'st'} + x_{cst} \\ 0, \text{ else} \end{cases} \qquad \forall c,s,t \tag{3-7}$$

$$\kappa_{\min} \leq \kappa_{st}(W_{st}, r_t) \leq \kappa_{\max} \qquad \forall c,s,t \geq 2 \tag{3-8}$$

$$\psi_{\min} \leq \psi_{cst}(W_{st}, r_t, clv_{ct}) \leq \psi_{\max} \qquad \forall c,s,t \geq 2 \tag{3-9}$$

$$P_{cst} \geq pu_{st} \qquad \forall c,s,t \tag{3-10}$$

$$K_{s1} = K_{s1}^{0} \qquad \forall s \tag{3-11}$$

$$P_{cs1} = P_{cs1}^{0} \qquad \forall c,s \tag{3-12}$$

$$W_{s1} = W_{s1}^{0} \qquad \forall s \tag{3-13}$$

$$K_{st}, P_{cst}, W_{st}, \kappa_{st}, \psi_{cst} \in \mathbb{R}_0^+,\ A_{cs(t+1)} \in \{0,1\} \tag{3-14}$$

The constraints of the optimization problem have to be interpreted as follows:

- 3-2

  The capacity of each class is adjusted over time by the degree of capacity change $\kappa_{st}(W_{st}, r_t)$.

- 3-3

  The price in each class is adjusted over time by the degree of price change $\psi_{cst}(W_{st}, r_t, clv_{ct})$.

- 3-4

  The capacity of a class has to be at least equal to the already sold units in this class.

- 3-5

  The whole over-all capacity has to be allocated to the classes at each time point.

- 3-6

  This constraint is the workload definition.

- 3-7

  This binary variable expresses the decision of the acceptance or rejection of the supplier's price offer by the customer as well as the acceptance or rejection of the customer's request by the supplier. The price is only accepted by the customer if it is at most equal to his reservation price. The request is only accepted by the supplier if enough capacity is available in the concerned class.

- 3-8 and 3-9

  The degree of capacity and price changes is at least equal to a defined minimum value and at most equal to a defined maximum value. Depending on the application case, this minimum and maximum degree can be changed.

- 3-10

  The price has to be at least equal to the determined short-term bottom price.

- 3-11, 3-12, 3-13

  The initial sets of capacities, prices and work load are determined within the data analysis part for the SCPC. The capacity and price control starts in $t = 2$.

The decision model for the SCPC also contains the relevant equations for its components, the CC and PC (see figure 3-7):

Decision model for CC	**Decision model for PC**
Objective function:	**Objective function:**
$\max \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{c=1}^{C} A_{cs(t+1)} \cdot x_{cst} \cdot p_s$	$\max \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{c=1}^{C} A_{cs(t+1)} \cdot x_{cst} \cdot P_{cst}$
Constraints:	**Constraints:**
$K_{st} = \kappa_{st}(W_{st}, r_t) \cdot K_{s(t-1)} \quad \forall s, t \geq 2$	$P_{cst} = \psi_{cst}(W_{st}, r_t, clv_{ct}) \cdot P_{cs(t-1)} \quad \forall c, s, t \geq 2$
$K_{st} \geq \sum_{t'=1}^{t-1}\sum_{c'=1}^{c} A_{c's(t'+1)} x_{c'st'} \quad \forall s, t \geq 2$	$P_{cst} \geq pu_{st} \quad \forall c, s, t$
$\sum_{s=1}^{S} K_{st} = k \quad \forall t$	
$W_{st} = \begin{cases} 1, \text{ if } K_{st} = 0 \\ \dfrac{\sum_{t'=1}^{t-1}\sum_{c'=1}^{c} A_{c's(t'+1)} \cdot x_{c'st'}}{K_{st}}, \text{ else} \end{cases} \quad \forall s, t \geq 2$	$W_{st} = \begin{cases} 1, \text{ if } k_s = 0 \\ \dfrac{\sum_{t'=1}^{t-1}\sum_{c'=1}^{c} A_{c's(t'+1)} \cdot x_{c'st'}}{k_s}, \text{ else} \end{cases} \quad \forall s, t \geq 2$
$A_{cs(t+1)} = \begin{cases} 1, \text{ if } K_{st} \geq \sum_{t'=1}^{t-1}\sum_{c'=1}^{c} A_{c's(t'+1)} \cdot x_{c'st'} + x_{cst} \\ 0, \text{ else} \end{cases} \quad \forall c, s, t$	$A_{cs(t+1)} = \begin{cases} 1, \text{ if } P_{cst} \leq rp_{cst} \\ 0, \text{ else} \end{cases} \quad \forall c, s, t$
$\kappa_{\min} \leq \kappa_{st}(W_{st}, r_t) \leq \kappa_{\max} \quad \forall s, t \geq 2$	$\psi_{\min} \leq \psi_{cst}(W_{st}, r_t, clv_{ct}) \leq \psi_{\max} \quad \forall c, s, t \geq 2$
$K_{s1} = K_{s1}^{0} \quad \forall s$	$P_{cs1} = P_{cs1}^{0} \quad \forall c, s$
$W_{s1} = W_{s1}^{0} \quad \forall s$	$W_{s1} = W_{s1}^{0} \quad \forall s$
$K_{st}, W_{st}, \kappa_{st} \in \mathbb{R}_0^+, \ A_{cs(t+1)} \in \{0,1\}$	$P_{cst}, W_{st}, \psi_{cst} \in \mathbb{R}_0^+, \ A_{cs(t+1)} \in \{0,1\}$

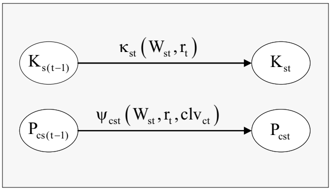
Figure 3-7: Decision models for CC and PC

The differences between the two decision models for CC and PC result from the fixed price setting (use of the parameter p_s instead of the variable P_{cst}, no equations for the price changes) and the fixed capacity distribution (fixed capacity setting for each class k_s instead of variable contingents K_{st}, no capacity constraints).

These decision models contain the objective system of the SCPC implicitly. The focusing on the objectives plays an important role within the operative execution of SCPC. However, this execution is limited by further difficulties described in the next section. The problem concerns the **vague information about the concrete degrees of adjustments** which are dependent on certain combinations of the workload and the rest time.

3.3 The Fuzzy Expert SCPC

Two kinds of imprecise functional relationships have to be solved in the SCPC, based on the workload and the rest time of the planning period, as well as the customer value. The first relationship concerns the CC part, the second the PC part of SCPC (see figure 3-8).



K_{st} = capacity in class s at time point t
P_{cst} = price for customer c in class s at time point t
W_{st} = work load in class s at time point t
r_t = period rest time at time point t
clv_{ct} = value of customer c at time point t
$\kappa_{st}(W_{st}, r_t)$ = degree of capacity change
$\psi_{cst}(W_{st}, r_t, clv_{ct})$ = degree of price change

Figure 3-8: Imprecise functional relationships in SCPC

In the **capacity adjustments over time**, the capacity in class s at time point t-1 (with T equivalent to the length of the planning period), $K_{s(t-1)}$, is reduced or increased by the degree $\kappa_{st}(W_{st}, r_t) \in [0,2]$ to K_{st}. **Prices are adjusted** by the degree $\psi_{cst}(W_{st}, r_t, clv_{ct}) \in [0,2]$. These two degrees of change basically depend on the workload in the class W_{st} and the rest time r_t (as well as the customer value clv_{ct} in the PC). This dependence, however, cannot be expressed explicitly in terms of concrete functional interdependencies (no deterministic solution).

Obviously, the decision model is non-linear and continuous. In combination with the large amount of variables, an optimal solution of the decision problem seems very unlikely despite the appropriate handling of the stochastic effects. By using appropriate approaches for solving the described difficulties, this automatically leads to a **heuristic solution**. With the decision context becoming more complex, heuristic approaches perform better and better, as the decision problem is not solvable with a justifiable (computation- and resource-) expense [Domschke 1997, p. 234, Gietz 1994, Silver 2004]. Thus, heuristic methods seem to be appropriate in many cases despite having the possibility of not reaching or recognizing an optimal solution. In heuristic approaches, the optimization problem is often divided into sub-problems that allow an easier solution of the decision problem [Silver 2004, p. 949]. Domschke/Drexl [2005] determined the distinction of the sub-problems into construction heuristics (for the determination of a first feasible solution) and improvement heuristics (for the improvement of the initial solution).

The recommended solution here is to use **expert knowledge** in order to determine the influences on the capacity and price settings as precise as possible. The main advantage is that this expert knowledge is problem-oriented. It is founded on experiences in the daily business of the SCPC and its parts. As the solution for the SCPC is very dependent from the application context, the determination of the correct relationships and the building of the rule basis would be too laborious without the help of experts. By employing this expert knowledge, a **rule-based system** able to execute the SCPC can be derived, based on the rules and the different sets of values for the input and output factors, which are also formulated by experts.

3.3.1 Rule-based systems for the SCPC

Rule-based systems are the result of the **representation of expert knowledge**. The impossible comprehensive[78] formulation of explicit deterministic interdependencies concerning the degree of capacity and price change (e.g. 60% workload and a rest time of 12 hours in first class hotel rooms lead to a price decrease of 5% for non-regular customers) requires an approach that allows the processing of **implicit knowledge** resulting from the experience or expertise of the decision makers (e.g. experience like “if the workload in the first class is low after 5.00 pm, prices have to be slightly decreased”, or discrete knowledge like “a workload below 50% after 5.00 pm leads always to a price increase of 5%” as well as “10% workload is certainly low”). In its broad sense, such formulations can be determined as knowledge-

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[78] Comprehensive, in this context, refers to the ability to formulate exact rules for all possible combinations of workload and rest time (both continuous variables), as well as the customer value (in some cases also discrete, e.g. regular vs. non-regular customers).

based[79]. **Knowledge-based systems**, as a sub-field of Artificial Intelligence[80], are understood as systems that contain domain knowledge presented explicitly in a symbolic character, in a program, or as a data set [Blumberg 1991, p. 18; Kurbel 1992, p. 16]. In the case that decisions are made using or supported by the experts' domain knowledge, these systems are called **expert systems** [Harmon/King 1986; Feigenbaum/McCorduck 1984][81]. The knowledge representation in expert systems can be executed in different ways (see figure 3-9):

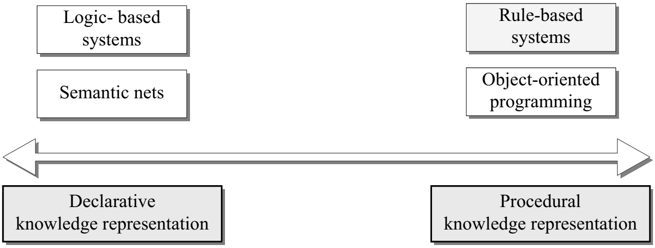

Figure 3-9: Examples for knowledge-representation formalisms [see Kurbel 1992, p. 37]

Given the two basic patterns for the knowledge representation (declarative[82] and procedural[83]), **rule-based systems** seem to be adequate for the representation of expert knowledge in the context of SCPC that allow to transform the implicit knowledge of the experts into explicit rules.

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[79] The implicit knowledge is transformed into explicit knowledge by its rule-based representation. This, however, is discrete, leading to further implications described in this section.

[80] *Artificial Intelligence (AI)* is characterized by Minsky [1966] as the "science of making machines do things that would require intelligence if done by men." This leads to the understanding of "intelligent" computer systems having abilities that would be considered by men as intelligent behavior (e.g. problem solving, learning) [Kurbel 1992, p.1].

[81] Examples for applications of expert systems are presented in Hoff [1990], Mertens [1986; 1987; 1988] and Bullinger/Kornwachs [1990].

[82] *Declarative knowledge* representation is the pure description of facts without any statements regarding the processing of information for a problem solution. Examples are logic-based systems and semantic nets.

[83] In *procedural knowledge* representations, the active use of knowledge for a problem solution is also described. Examples are rule-based systems and object-oriented programming.

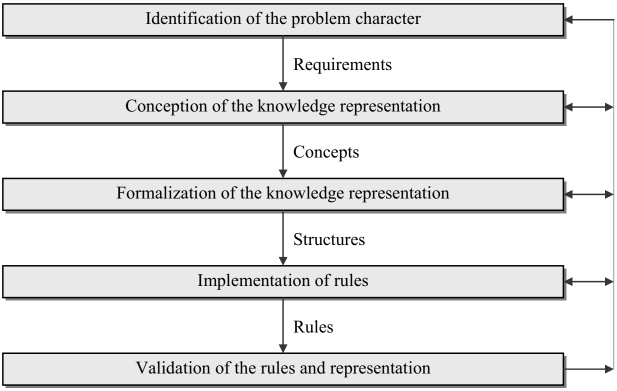

Figure 3-10: Standard steps for the incremental knowledge development for rule-based systems [Puppe 1988]

Altogether, rule-based systems allow for an incremental development of a knowledge basis (see figure 3-10), which is helpful in complex decision situations with continuous combinations of LHS (left hand side) variables (antecedents) and continuous RHS (right hand side) consequences [Blumberg 1991, p. 33].

Reasons for the choice of rule-based systems in the given context are the following [Tuma 1994, p. 37; Kurbel 1992, p. 47; Blumberg 1991, p. 34]:

- **Non-deterministic description of problem solutions**
  The expert knowledge underlying the rule sets is discrete and implicit. Therefore, this knowledge cannot be transformed into functional equations that explicitly express the interdependencies of the input and output variables (e.g. the experts may know that a 100% workload is very high and prices should be increased; they, however, may not know what a workload of 65% means and which is the adequate consequence for the price).
- **Practice orientation**
  As one of the requirements for the SCPC, an adequate approach must be practice-oriented and easy to implement. Because of the problem-specific knowledge of experts,

the feasible consideration and connection of certain inputs and outputs is a prerequisite, automatically leading to a practical solution.

- **Managing a large amount of quantitative parameters and decision variables**
  As the experience of the experts allows them to use a large pool of information for their decision of capacity and price adjustments, they are able to formulate rules also in cases where the decision context is very extensive.
- **Handling of interdependencies**
  One of the most prevailing arguments for the use of a rule-based system is that it automatically clarifies the interdependencies of the input and output variables.
- **Intuitively clear rule basis**
  As the rule set is built with the help of information of experts in the considered application context, it is intuitively clear for all users that are familiar with the application field.
- **Easy to understand**
  Not only is the rule set intuitively clear, the representation of the implicit expert knowledge in form of “if-then” connections makes it easy to understand and to use for solutions.
- **Handling of fuzzy knowledge and information**
  The discreteness of the expert knowledge has another implication. Not only cannot all values and possible combinations of inputs be considered by experts (e.g. 67.4% workload). Often do the rule sets represent only vague information of the experts (e.g. meaning of a high workload). This discreteness can be handled with the help of the developed rule basis by processing them in an adequate manner.

Especially the possibility of a non-deterministic description of the relationships concerning the SCPC (no information about the specific functional relations), the practice orientation (intuitive formulation of rules through experts and adequate use of accessible information) and the handling of fuzzy information (meaning of a “high” workload or “low” customer value) are the main reasons for using a rule-based approach to SCPC. The result of this development is the rule bases for the CC and PC components[84] (see figure 3-11). These two exemplary rule sets differ by the amount of input variables, but are similar given the fact that both the CC and PC are based on the same inputs and the same conclusions given a certain combination of these inputs. For example, a very high workload and rest time implies in both cases a very high increase of the class capacity and the class price. This similarity, however, depends on the application context. In the incremental development of the rule basis, the two control options are addressed independently.

W	r	κ
Very high	Very high	Very high
Very high	High	High
Very high	Medium	Less high
Very high	Low	Zero
Very high	Very low	Zero
High	Very high	Very high
High	High	High
High	Medium	Less high
High	Low	Zero
High	Very low	Zero
Medium	Very high	High
Medium	High	High
Medium	Medium	Zero
Medium	Low	Less low
Medium	Very low	Less low
Low	Very high	Less high
Low	High	Less high
Low	Medium	Zero
Low	Low	Less low
Low	Very low	Negative
Very low	Very high	Zero
Very low	High	Zero
Very low	Medium	Less low
Very low	Low	Low
Very low	Very low	Very low

W	r	clv	ψ	W	r	clv	ψ
very_high	very_high	high	high	very_high	very_high	low	very_high
high	very_high	high	less_high	high	very_high	low	high
medium	very_high	high	zero	medium	very_high	low	less_high
low	very_high	high	zero	low	very_high	low	less_high
very_low	very_high	high	zero	very_low	very_high	low	zero
very_high	high	high	high	very_high	high	low	very_high
high	high	high	less_high	high	high	low	high
medium	high	high	zero	medium	high	low	less_high
low	high	high	zero	low	high	low	less_high
very_low	high	high	zero	very_low	high	low	zero
very_high	medium	high	less_high	very_high	medium	low	high
high	medium	high	zero	high	medium	low	less_high
medium	medium	high	zero	medium	medium	low	less_high
low	medium	high	zero	low	medium	low	zero
very_low	medium	high	zero	very_low	medium	low	less_low
very_high	low	high	zero	very_high	low	low	less_high
high	low	high	zero	high	low	low	less_high
medium	low	high	zero	medium	low	low	zero
low	low	high	zero	low	low	low	less_low
very_low	low	high	less_low	very_low	low	low	low
very_high	very_low	high	zero	very_high	very_low	low	less_high
high	very_low	high	zero	high	very_low	low	zero
medium	very_low	high	zero	medium	very_low	low	less_low
low	very_low	high	less_low	low	very_low	low	low
very_low	very_low	high	low_low	very_low	very_low	low	very_low

Figure 3-11: Rule sets for the CC and PC

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[84] The illustrated rule set (figure 3-11) is only fictive. The rule sets underlying the application cases are given in the practice part of this work.

For the SCPC, the two rule sets are simply used to find the right values for the degree of capacity and price change. The iterative character of the solution requires no fusion of the rule sets.

One problem, however, cannot be solved by the sole implementation of rule-based systems. The basic question is **how the expert rules can be processed in order to solve the SCPC problem**. The rule basis is the result of the implicit knowledge of the experts in the practical SCPC, having certain implications for the solution concept:

- This experience-based knowledge (past capacity and price decisions) cannot be formulated explicitly[85] [Tuma 1994, p. 18] (e.g. only: 70% workload is clearly high, 10% is clearly low).
- The implicit knowledge describes the decision problem only in a discrete way because not all possible combinations of the inputs (LHS) and outputs (RHS) can be considered by the experts in complex models.
- The different values of the LHS and RHS parameters are commonly connected to subjective opinions (e.g. a high workload is considered by a hotel manager to be at least 30%, by manager in the chemical industry to be at least 70%).

As already stated, especially the opportunity of **processing discrete implicit knowledge** by developing continuous interpretations of the rules and the ability of **processing vague information** (e.g. the degree of membership of explicit values of workload ($W_{st} = 0.63$) and rest time ($r_t = 24$ [hours]) to the exemplary terms “high workload” or “low rest time”) are the main advantages of **fuzzy expert controllers**[86].

The resulting comprehensive solution concept with all its parts is illustrated in figure 3-12.

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[85] Explicit knowledge would have a broader validity and increase the transparency and acceptance of systems and methods for the practical use [Tuma 1994, p. 18].

[86] While, for example, in production processes a workload close to 100% is often essential for the success of the company, in the hospitality industry, also a workload of 70% could be regarded as high.

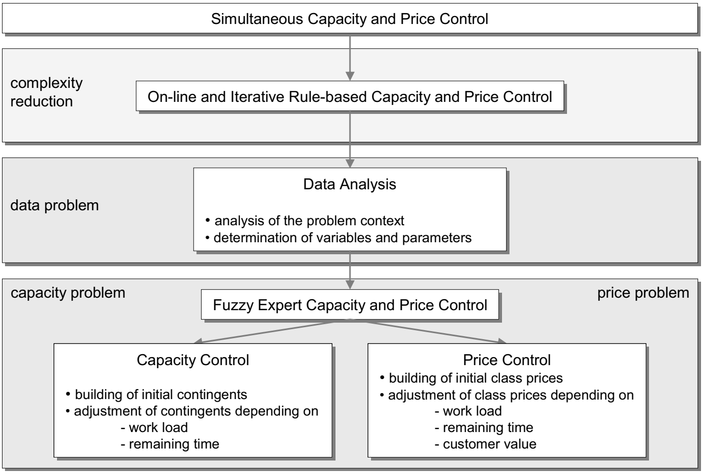

Figure 3-12: The solution concept

The rule-based SCPC is executed on the basis of an on-line and iterative procedure as result of the outlined specifics of the SCPC (see section 3.1.2). After the data analysis part (determination of the classes and initial settings for the capacity and prices), a **Fuzzy Expert Simultaneous Capacity and Price Control (FESCPC)** is conducted. For each adjustment step (e.g. for each customer request), first the capacity control is taken out, followed by the price control.

3.3.2 Applying fuzzy expert controllers

The Fuzzy Set Theory (introduced by Zadeh [1965]) enables the processing of all available expert information regarding the two imprecise functional relationships $\psi_{cst}(W_{st}, r_t, clv_{ct})$ and $\kappa_{st}(W_{st}, r_t)$. The understanding of vagueness automatically leads to the conclusion to implement a fuzzy expert controller [Tuma 1994, p. 38]. This vagueness of information is observable in many real-world problems with the consequence that this central approach is used in all kinds of industries, e.g. entertainment industry (cameras), production sector (skim regulation) and transport industry (autopilots) [Biewer 1997, pp. 35].

The following typical cycle for the execution of a fuzzy inference process is used to conduct the resulting **fuzzy expert SCPC (FESCPC)**, the separate **fuzzy expert capacity control (FECC)**, or the **fuzzy expert price control (FEPC)** (for the development of fuzzy controllers, see - for example - Zimmermann [1991], Biewer [1997]):

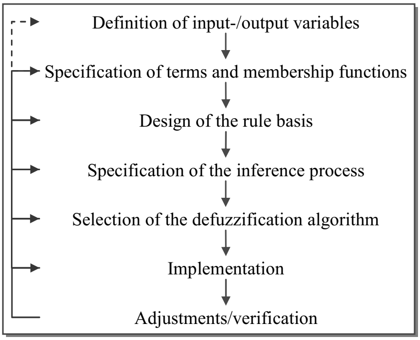

Figure 3-13: A typical process cycle of a fuzzy expert controller [Biewer 1997]

3.3.2.1 Definition of input and output variables

In most cases, the input and output variables[87] are determined by the underlying problem. Here, the imprecise relationships stated above lead to the inputs **workload W_{st}**, **rest time r_t** and **customer value clv_{ct}** (for the PC), as well as the output **degree of capacity change κ_{st}** (CC) and **degree of price change ψ_{cst}** (for the pricing). Expert information plays already an important role as, firstly, the input factors themselves have to be determined. Hereby, the practical requirements are also important, as significant revenue effects have to be achieved under the constraint not to use too many inputs and factors that are too laborious to determine. Secondly, expert knowledge was necessary to identify the impreciseness concerning this relationship.

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[87] The term "variables", here, has to be understood as factor, not as variables in its meaning in the decision modeling formalism.

3.3.2.2 Specification of terms and membership functions

Membership functions represent the degree of membership of real input values to so-called linguistic terms that have to be configured based on considerations regarding the effectiveness and the promptness of response [Mamdanis and Assilian 1975; Biewer 1997]. This **linguistic representation** of the real input values helps to decide about the corresponding output value based on the underlying rule-based expert knowledge representation. As this knowledge is often also limited to linguistic output values, the output variables have to be represented by membership functions, too. In the case of fuzzy expert systems, the specification of those membership functions is carried out with the help of the experts.

Firstly, the **amount and structure of linguistic terms** has to be set for each input and output. In this work, the inputs workload and rest time are linguistically represented by five terms (W_{st}, r_t → {very_low, low, medium, high, very_high}). The customer value is transformed to two terms, which corresponds to the common understanding of regular or non-regular customers (clv_{ct} → {low, high}). For the degree of capacity change and the degree of price change, the choice of seven terms (κ_{st}, ψ_{cst} → {very_low, low, less_low, zero, less_high, high, very_high}) seems adequate. Hereby, values below zero mean a decrease, values above zero an increase of the capacity or price (see figure 3-14).

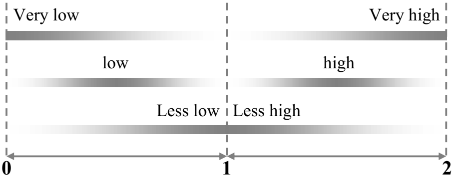

Figure 3-14: Correlation of the terms for the linguistic variables κ_{st} and ψ_{cst} and their exemplary co-domain $[0,2]$

Secondly, the **connection of real and linguistic values** has to be determined with the help of the experts. They have to identify the boundaries for each term by identifying the real values that have a 0% or 100% **degree of membership μ** to a certain term. Examples for the resulting membership functions are illustrated in figure 3-15[88]. The horizontal axis, thereby, shows the underlying co-domain of the variables (e.g. $0 \leq W_{st} \leq 1$). The vertical axis represents the degree of membership. The intersection of both axes gives the degree of membership of a real value to the different terms (e.g. $\mu_{medium}(W_{st} = 0.5) = 1$, $\mu_{high}(W_{st} = 0.5) = 0$).

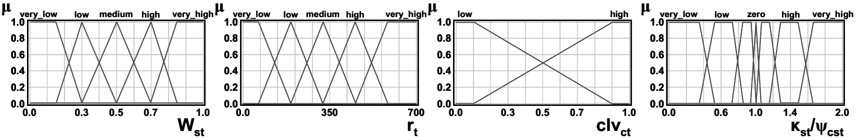

Figure 3-15: Membership functions for the inputs and outputs of FESCPC

Taking as an example the definition of the workload membership functions, the experts are asked to set the level of the real workload that does belong to the term " medium" with a degree of zero ($\mu_{medium}(W_{st}) = 0$) or a degree of one ($\mu_{medium}(W_{st}) = 1$), respectively. In figure 3-15, $\mu_{medium}(W_{st}) = 0$ is valid for $0 \leq W_{st} \leq 0.3$ and $0.7 \leq W_{st} \leq 1$. $\mu_{medium}(W_{st}) = 1$ is assumed by the experts at $W_{st} = 0.5$. The other linguistic terms are specified by the experts in the same way, leading to the membership functions illustrated in figure 3-15. The result, therefore, is a continuous representation of the expert knowledge concerning the inputs and outputs for the FESCPC. This is reached by connecting the different points identified by the experts. This connection can be both L-shaped and S-shaped, as well as individually formed[89].

3.3.2.3 Design of the rule basis

A central step within the design of the fuzzy controller is the construction of the rule basis. In expert-based solutions, **expert knowledge is extracted and combined to rules** like outlined in figure 3-11. The term "fuzzy expert controller", thereby, refers also to this expert knowledge. The main advantage lies in the formulation of such rules instead of the explicit formula-

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[88] The illustrated membership functions are examples from one of the application cases in this work. The shape, boundaries and the structure is part of the development process of the fuzzy expert controller and has to be incrementally designed based on the expert information.

[89] The choice of the adequate shape of membership function is still object of research and discussion on fuzzy systems (see, for example, Biewer [1997]).

tion of the relationships presented. Important for the rule basis is the combination of all important linguistic terms of the input variables[90].

The objective of the fuzzy control is to **translate real values of input variables** (W_{st} and r_t for the CC and PC as well as clv_{ct} for the PC) **into real values of output variables** (κ_{st} and ψ_{cst}), based on expert information, the resulting membership functions, and the rule basis. This translation is executed using diverse **inference methods** [e.g. Dubois/Prade 1988; Zimmermann 1988 and 1991] and **defuzzification algorithms** [e.g. Bandemer/Gottwald [1992]; v. Altrock et al. 1990; v. Altrock/Zimmermann 1991]. Against the background of the development of an **applicable solution for SCPC**, also the chosen algorithms should be practically applicable and easy-to-understand. Thus, the algorithms illustrated here are of basic nature, despite the voluminous research carried out on algorithms for fuzzy control (see, for instance, Sala/Guerra/Babuška [2005]).

3.3.2.4 Specification of the inference process

Fuzzy inference methods[91] relate the linguistic terms of the input variables (e.g. W_{st} = "high", r_t = "medium") for the rules addressed by a certain combination of real values (e.g. $W_{st} = 0.8, r_t = 100$) to the linguistic terms of the output variables (e.g. κ_{st} = "less_high", ψ_{cst} = "less_high"). The inference methods consist of an aggregation operator, a result aggregation operator (often not explicitly mentioned) and a composition operator. Mamdani and Assilian [1975] provided the most common fuzzy inference method, entitled the **max-min-inference**. Based on the notion that the related input and output variables in a rule ($\text{IF } x = A_i \text{ THEN } y = B_i;\ x \in \Omega_A,\ y \in \Omega_B$ with A_i and B_i as fuzzy subsets of Ω_A and Ω_B) are related by the Cartesian product of the involved fuzzy sets, this rule describes a fuzzy relation $R_i = A_i \times B_i$. In relations to the degrees of membership of the real input values to the linguistic terms $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$, the following central relation can be determined:

$\mu_{R_i}(x,y) = \min\left(\mu_{A_i}(x),\mu_{B_i}(y)\right)$ or

$\mu_{B_i^*}(y) = \min\left\{\mu_{A_i}(x),\mu_{B_i}(y)\right\}$ (if x is a real-valued input for the current output B_i^*).

---

[90] In a strict sense, the rule basis illustrated in figure 3-11 is a fuzzy rule basis. There basically exist other representation forms of this rule basis.

[91] Fuzzy inference methods are often just called fuzzy operators.

This relation has to be built for each rule addressed by the input combinations (**fuzzy aggregation**). In case that more than one rule is addressed, these have to be aggregated. Mamdani and Assilian [1975] chose the conjunction over a set union and come up with:
$\mu_{B^*}(y) = \max\left(\mu_{B_1^*}(y),...,\mu_{B_n^*}(y)\right)$ with $B^* = \bigcup_{i=1}^{n} B_i^*$ (**fuzzy composition**).

By adding so-called grades of fulfillments to the rule basis, Holmblad and Østergaard [1982] provide the **max-prod-inference**[92]. This method allows weighting the influence of one specific rule on the determination of the actuating variable. Currently, various other inference methods can be found in literature and practice. They are mostly developed for special applications. Examples for such methods that entered also the research are the **gamma-inference** and the **avg-min-inference**. Both compromise the degree of maximization or minimization in the inference process[93]. Further inference operators are the **NOT-operator** (negation), the **Hamacher sum or product**, as well as the **Einstein sum or product**. Another possibility instead of aggregating two rules with the same conclusion (**fuzzy result aggregation**) by the maximum is to build **bounded sums (BSum)**, which sum up the membership degrees until one. Like illustrated in table 3-1, the **main decision criteria** for the use of a certain fuzzy operator is whether to use a **conjunction** (AND-connection), **disjunction** (OR-connection), **compensatory operators** as well as **negations** (NOT-operator). Thereby, the conjunction reflects an extreme pessimistic or cautious position because a rule becomes only activated if all inputs have a membership degree greater zero. The disjunction is very optimistic, as rules become activated if at least one input has a membership degree greater zero. The formulas of the mentioned fuzzy operators are given in table 3-1. All operators can be used for the three steps of the fuzzy inference process:

---

[92] The max-prod-inference is also called max-dot-inference.

[93] In practice, mostly the max-min-inference is used because its implementation is easier and more efficient [Biewer 1997]. However, arguments against this inference method can also be found [Rommelfanger 1994].

AND-operators (conjunction)		**OR-operators (disjunction)**	
Minimum	$\min(\mu_1, \mu_2)$	Maximum	$\max(\mu_1, \mu_2)$
Algebraic product	$\mu_1 \cdot \mu_2$	Algebraic sum	$\mu_1 + \mu_2 - \mu_1 \cdot \mu_2$
Bounded difference	$\max(0, \mu_1 + \mu_2 - 1)$	Bounded sum	$\min(1, \mu_1 + \mu_2)$
Einstein product	$\frac{\mu_1 \cdot \mu_2}{2 - (\mu_1 + \mu_2 - \mu_1 \cdot \mu_2)}$	Einstein sum	$\frac{\mu_1 + \mu_2}{1 + \mu_1 \cdot \mu_2}$
Hamacher product	$\frac{\mu_1 \cdot \mu_2}{\mu_1 + \mu_2 - \mu_1 \cdot \mu_2}$	Hamacher sum	$\frac{\mu_1 + \mu_2 - 2 \cdot \mu_1 \cdot \mu_2}{1 - \mu_1 \cdot \mu_2}$
Gamma-operator (compensation)	$(\mu_1 \cdot \mu_2)^{1-\gamma} \cdot ((1-\mu_1) \cdot (1-\mu_2))^{\gamma}$ $\gamma = 0$: Conjunction (product) $\gamma = 1$: Disjunction (sum) $0 < \gamma < 1$: Compromise between AND and OR		
NOT-operator	$1 - \mu_1$		
μ_1, μ_2 : membership degrees			

Table 3-1**:** Main fuzzy operators

Figure 3-16 shows an example for a fuzzy inference process (CC component). The real values (workload of 80%, 550 hours before the end of the planning period) are translated into linguistic variables[94] by using the developed membership functions. For the work load, two degrees of membership greater zero can be identified, leading to two addressed rules. In the fuzzy inference process, firstly the **inference aggregation** has to be taken out. In the example of a max-min-inference, this means that the minimum value of each input combination is processed. In the example of figure 3-16, $\mu_{high}(W_{st})$ and $\mu_{very\_high}(W_{st})$ are both below $\mu_{very\_high}(r_t)$, so these two membership degrees are processed. As the two addressed rules have the same conclusions, these have to be aggregated before the composition step. By using a BSum result aggregation, a membership degree of 1 results from the two inputs, leading to the grey-shaded area in figure 3-16[95].

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[94] This step is also called fuzzification.

[95] The composition step is not necessary here as only one rule remains after the result aggregation.

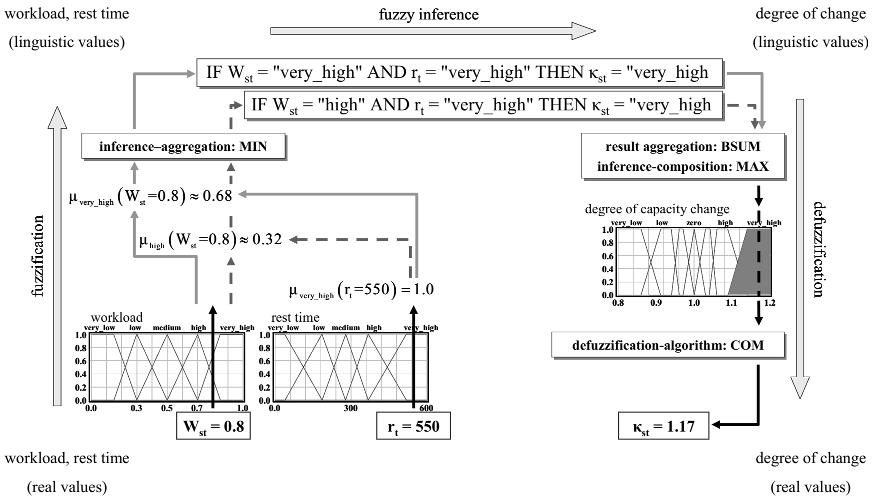

Figure 3-16: Example for a fuzzy inference

3.3.2.5 *Selection of the defuzzification algorithm*

The result of the inference process is a fuzzy set of the output variable. In most applications (e.g. in the control of production processes), however, real control values have to be determined for the control process. For this **defuzzification**, various algorithms can be applied [Biewer 1997, pp. 388]. Derived from the two **dominating main methods**, the maximum method and the center-of-area method, several defuzzification algorithms can be found (see figure 3-17). Based on the possible set of values $M = \left\{ y \in \Omega_Y \middle| y = \max\left(\mu_{B^*}(y_1),\ldots,\mu_{B^*}(y_n)\right)\right\}$ (with n as the number of addressed rules), the **mean-of-maximum defuzzification** leads to the real output values (y_0) by setting it equal to the mean of the extreme values belonging to the fuzzy set with the highest membership degree ($y_0 = (y_{min} + y_{max})/2$). By only taking the extreme values, the **left-of-maximum** ($y_0 = y_{min}$) and the **right-of-maximum defuzzification** ($y_0 = y_{max}$) result. The **center-of-area defuzzification** uses the abscissa of the center of area of the fuzzy set B^*. Because of the difficulties in numerical integrations, a **modified-center-of-area method** is often used that, firstly, computes the abscissas of each term's center and then builds the weighted average. By taking simply the means of the centers, the **center-of-maximum defuzzification** results.

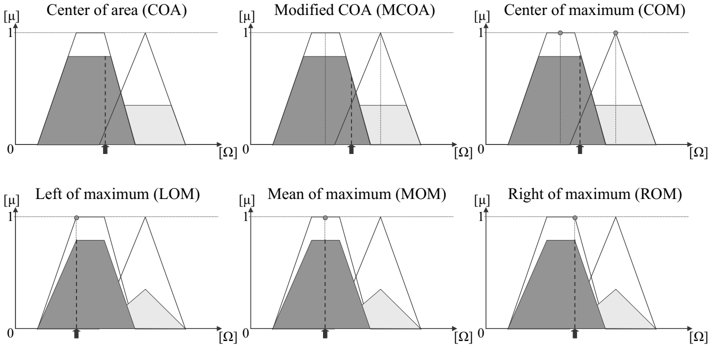

Figure 3-17: Standard defuzzification methods [Biewer 1997, p. 391]

For the two main methods, the maximum and the COA, as well as the COM defuzzification as a method often used in practice (and in this work), the formulas are given in table 3-2:

<table>
<tr><td>Maximum defuzzification</td><td>y_D with $\mu(y_D)=\max_{y}\mu(y)$
LOM, MOM or ROM possible, if more than one y_D satisfy the constraint</td></tr>
<tr><td>COA defuzzification</td><td>y_D with $\int_{-\infty}^{y_D}\mu(y)\cdot dy=\int_{y_D}^{+\infty}\mu(y)\cdot dy$</td></tr>
<tr><td>COM defuzzification</td><td>$y_D=\frac{\sum_{i=1}^{n} y_i\cdot\mu(y_i)}{\sum_{i=1}^{n}\mu(y_i)}$
y_i: local maximum</td></tr>
<tr><td colspan="2">i: membership functions of the output
y: output
y_D: Result of the defuzzification
$\mu(y)$: result of the inference process</td></tr>
</table>

Table 3-2**:** Main defuzzification algorithms

In the example illustrated in figure 3-16, the COM defuzzification is used to determine the real degree of capacity change. The result is an increase of the capacity by 17% ($\kappa_{st} = 1.17$).

3.3.2.6 Adjustments and Verification

An important part of the implementation process marks the **verification of the fuzzy controller**[96]. In the case of fuzzy expert controllers, the established fuzzy system should already provide reasonable results, as experts would base their decision on the same information framework. Due to better results, the fuzzy expert controller has to be improved by addressing the various degrees of freedom within the system. Not only the membership functions can be varied but also the inference and defuzzification methods as well as the so-called degrees of support (indicating the weight of single rules within the control process). The rule basis itself should be almost fixed due to the expert information. Especially the **robustness of the fuzzy control system** is a central requirement within the development of fuzzy expert controllers (Zadeh 1968a). This requirement can be addressed within the verification process, too. Not only is the highest revenue a reasonable solution of the FESCPC. The solution must also be preferably unaffected by random, especially concerning the set of reservation prices. Therefore, the variability of the solution should be low despite changes in reservation prices. A sensitivity analysis has to be executed in order to analyze the robustness. The **plausibility of the system** can be stated here, too. The reaction of the system on the inputs has to be consistent with the objectives and the expected system behavior. This has to be also a part of the system analysis.

The verification process, thus, has the objective of an **incremental improvement** of the basic setting for the fuzzy expert controller. While the development of one single fuzzy system can be executed based on available standard software (see figure 3-18), for this verification, a large amount of resulting fuzzy systems requires the use of specific software that automatically builds the systems and explores them on the basis of the underlying data. Such software was implemented in the computational part of the research to SCPC. Per application case (see

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[96] Especially here, the feedbacks illustrated in figure 3-13 are very obvious. The implementation and verification process are interchangeable and conducted together in practice as it involves the test of the system in the test data and in the running system.

part II of this work), a large amount of variations of each fuzzy expert controllers was calculated in order to get the best results concerning the revenue effect and the robustness of the system.

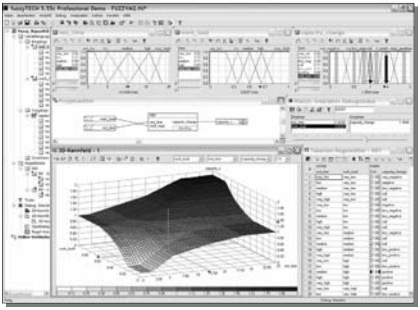

Figure 3-18: Fuzzy system building and execution with FuzzyTech®

3.3.2.7 *Implementation*

The development and the implementation of a fuzzy system are very dependent from the practical context. After the design of the fuzzy expert controller by using test data, the solution has to be tested on the basis of the **running system**[97] in order to avoid a low performance in the practical decision making (see, for instance, Meyer-Gramann/Jüngst [1993]). The main reason for this second test is the potential of structural errors in the test data, which is only a cutout of the real decision context. In addition, it is often constrained in the sense that only satisfied requests and bookings are stored in the data base. Besides those structural difficulties, also the pricing decisions may vary in the practice setting compared to the test setting. Though the sensitivity analysis concerning the reservation prices is done carefully, the real context may differ.

On the one hand, the differences between the test and real application should be only marginal because of the following reasons:

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[97] *Running system* is the real decision environment of the application case.

- The test data is taken from a representative decision period in order to avoid the consideration of strong seasonal effects.
- The design of the fuzzy expert controllers is not only executed with respect to the revenue effects but also to the plausibility of the system behavior.
- Sensitivity analyses are executed concerning the problematic influence factors (reservation prices). The variation of these factors is carried out on the basis of representative assumptions (e.g. mean prices in the considered periods).
- The constrained data has only implications on the existence of customers with low reservation prices as their request is not satisfied. Besides the short-term bottom price, that prohibits the acceptance of too low prices, also the fuzzy expert controller would reject a lot of low-price requests.

On the other hand, the implementation of the solution concept in the running system (daily business) should follow common **project management** standards (see, for instance, Burghardt [2006]; Zimmermann/Stark/Rieck [2006]). Besides the coordination of all technical aspects (e.g. software development), the mentioned second test in the running system has to be planned and executed before the fuzzy expert controllers can be used for the capacity and price decisions.

3.3.3 Limits of the fuzzy expert control

Much research is done on the development and application of fuzzy (expert) controllers in cases where the structure of the problem and the availability of information prohibits the development of common control systems like the feed-forward control (no feedbacks of the control process), or the control with feedbacks (see figure 3-19)[98]. Thereby, the main difference between fuzzy control systems and control systems is not the potential functionality but the

---

[98] In the context of SCPC, two connected control systems result. Within the CC part, the command variable is the (maximal) workload, the control unit is the fuzzy controller (with the additional influence rest time), and the controlled system is the capacity distribution with the actuating variable κ. In the PC part, the command variable is the supplier price. Based on the workload, the rest time and the customer value, the fuzzy control leads to the actuating variable ψ for the price system (controlled system). The feedback for the PC is the current price (after the negotiation with the customer). For the CC, the feedback is the current workload after the PC, which is also the central connection between both control systems (for the transition from CC to PC).

design of the decision model. Instead of the development of a mathematical model as the basis for the control system, a cognitive or operational model is developed [Biewer 1997, p. 405].

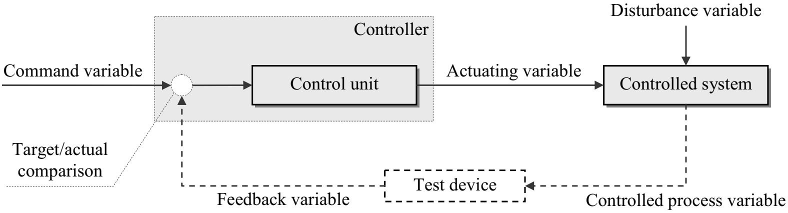

Figure 3-19: Basic control process (with feedbacks)

Possible applications in the context of fuzzy control are tremendous. Besides the classical fuzzy control systems in subways, container terminals and robotics as well as in the medical and camera industry [e.g. Terano/Asai/Sugeno 1994; Ralescu 1994], fuzzy set models are also implemented in operations research as the main research field in the context of RM. Examples of such implementations are the use of fuzzy set models for transportation problems [Chanas et al. 1984], for production control and scheduling [v. Altrock 1990], for job-shop scheduling [Bensana et al. 1988], and inventory control [Kacprzyk/Staniewski 1982]. In RM, no fuzzy control approaches seem to have been developed so far.

While these examples also prove its basic relevance for business applications in a wide sense, the execution of fuzzy (expert) control in those cases (and, thus, also in RM) faces certain limitations: One of the most talked about disadvantages of fuzzy controllers is the little opportunity they provide to prove the **stability of the system**. However, besides the ability to analyze the numerical stability, especially the **robustness** is estimated better for fuzzy controllers as they are more robust against parameter variations and unexpected disturbances (as needed in the context of this work) [Kahlert/Frank 1993]. Also the **verification and adjustment process** is often described as a simple trial and error with respect to the real-world requirements, and without any benchmarks for the resulting system. The incremental process when building the fuzzy control system, however, is very similar to many heuristic approaches and also to the common control theory, where **fine-tuning and tests** are also essential. Therefore, a software-based incremental adjustment process has been developed to provide an automatically improved fuzzy control system for each application case. In the case of the fuzzy expert control, especially the **experience and the implicit knowledge of the experts** can be used to provide promising start solutions for fuzzy systems. In practice, however, the **reliability of the experts** is often questioned. The use of well-founded expert knowledge is a common approach to many problem analyses, formulations and solutions. Misinformation or other **problems in the determination of the expert knowledge** would, thereby, lead to under-performing solutions. In contrast, fuzzy expert controllers even lead to satisfying solutions in cases where information or input was incomplete or wrong[99]. In business applications and in the context of this work on SCPC, practitioners often criticize that they would have to **rely on the outputs** of a “black box” without making their own decisions, which, in terms of capacity distributions and price settings in the customer interaction, could result in serious problems concerning the profitability of a company. The outputs, however, are provided based on their inputs (expert knowledge) and the system has to be well **tested, also in the context of a running system**. With these prerequisites, the output should be reliable. Closely connected to this argument against fuzzy controllers is the questionable **acceptance and use of the outputs** by the users. This problem, however, is also not specific to the fuzzy control and has to be solved in the whole RM decision context. The necessary **fine-tuning of the fuzzy expert controller** in practice (e.g. choice and parameterization of the composition operators), however, is often problematic. Besides the opportunity to combine certain modeling methods (e.g. expansion of the fuzzy expert controller by adaptive elements like neural nets [Tuma 1994, p. 47][100], a **software-based fine-tuning** of the initial fuzzy system that allows a large number of small variations in inputs and outputs (e.g. characteristics of the membership functions, rule basis, degrees of fulfillment) seems also to be adequate.

Altogether, the use of fuzzy expert controllers for the SCPC problem is based on the potential problems of optimal solutions for RM in this context and the resulting difficult applications.

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[99] One famous example of good performances of fuzzy controllers despite missing system components is the fuzzy-computer of Yamakawa, which also worked after the removal of a blank [Yamakawa 1989].

[100] Especially in data-based solutions, so-called neuro-fuzzy approaches are used for the determination of the rule basis.

With the limitation that the heuristics FECC, FEPC and the FESCPC may provide non-optimal solutions, the use of this solution seems adequate. The missing step is to analyze the performance in all three possible constellations of CPC. The developed solution concept for FESCPC has thereby to be tested bottom-up by first analyzing the FECC and the FEPC as sub-tasks of the FESCPC. Problems in the integrated solution can be limited to the integration method itself if the sub-tasks are proven to provide adequate solutions.

4 Analysis of the capacity control option: FECC

Corresponding to the postulation of firstly evaluating the components CC and PC before the analysis of the whole concept for SCPC, the following chapter considers the CC component performed in the waste incineration industry.

The main questions that emerge when analyzing the FECC are the following:

- Does the FECC lead to significant improvements of the profit margin in the considered application case?
- Is the FECC an adequate method for revenue maximization under fixed prices?
- Does the developed solution concept outperform standard Revenue Management approaches to the CC?

4.1 Application constraints of the FECC

Given a low flexibility of adjusting prices within the decision process of SCPC, only the CC component can be considered when executing the FESCPC in the revenue maximization problem. As the advantages of the FESCPC also hold in its partial conduction, a FECC is executed.

In the context of CC, a few specifics have to be considered in its conduction:

- **Deduction of price effects**
  The prices are assumed to be fixed in the CC because of the inflexibilities in and the high costs of variations in the pricing (e.g. long-term pricing agreements). Therefore, only the objectives of the CC have to be considered here. The capacity allocation must provide enough contingents for the profitable classes. Additionally, idle capacities must be avoided.
- **Determination of the initial solutions for the capacity allocation**
  As the solution concept is based on a heuristic approach that starts in $t = 2$ based on the

described influential parameters, initial solutions for the class capacities have to be found. As stated in chapter 3, in many cases forecasts are not feasible in the context of fluctuating demand and variable customer behavior. In this application case, it is reasonable to use forecasts at least for the initial settings. The profitable class initially gets an amount of capacity that is equal to the forecasted demand. The rest of the over-all capacity is distributed to the other class (two class scenario).

- **Diverse customer reactions on the capacity allocation**
  As already stated, the customer reactions on the capacity allocation are assumed to be not as central as in the PC. The reason is that the consumers only have the information that the class is "sold out" at the moment. This has not the irritation consequences that may result from price variations.
- **Use of an iterative approach also in CC and PC**
  One more specific can be stated, which has to be relevant for PC and CC as well: As stated in the description of the solution concept (see chapter 3), the feedbacks from the PC on the CC have to be assured in order to only effect the decision process during the next time point. In the sole conduction of the CC and PC, these effects can also occur. So, this requirement also has to be fulfilled here.

4.2 Description of the waste incineration application

A waste incineration plant with a typical operational structure is considered in the following (see figure 4-1):

In the waste delivery process, the waste is weighted before emptying it into the storage silo. Cranes fill the funnel tube at the beginning of the incineration facilities. The waste is transported over conveyance grates that transport and rotate the waste. The resulting autonomous incineration leads to mineral slag and rejected heat as the only remainders. The energetic use refers to the use of the rejected heat for the extraction of electricity, power-heat coupling and district heat. Power-heat coupling is thereby especially used by companies demanding process heat. Combined with the energetic use is the cleaning of the process remainders through baghouse filters, stack gas cleaning facilities and catalyzers.

Given this three basic steps of the waste incineration process, the waste delivery, in particular, is potentially qualified for RM. From the annual kiln capacity of 230,000 tons, 67,660.68 tons (assuming no technical disturbances) are free for market trade in the considered year 2004[101]. The rest is limited to the operation of regional corporations and long-term contractual partners. This fixed capacity has to be distributed to two classes of different worthiness: Sort A (shredder fractions) and sort B (plastics and residual waste). Coinciding with the problem of not knowing the above stated demand for these two classes in advance, the CC problem emerges. Depending on the development of the workload during the planning period, the **over-all kiln capacity has to be distributed to the two classes in favor of the more profitable sort B, depending on the demand for kiln capacity**.

The plant currently conducts “first-come, first-served” (FCFS), meaning that waste is accepted until the annual capacity of the kilns is reached, not considering the profitability of different classes of waste. One planning period consists of one month. Within this month, a certain amount of capacity is demanded by firms and private actors that are not in long-term contracts with the waste incineration plant. The following application takes place in 2004. For each month, the capacity control is taken out. The results will be compared on an annual level, as this is the normal planning procedure in this plant.

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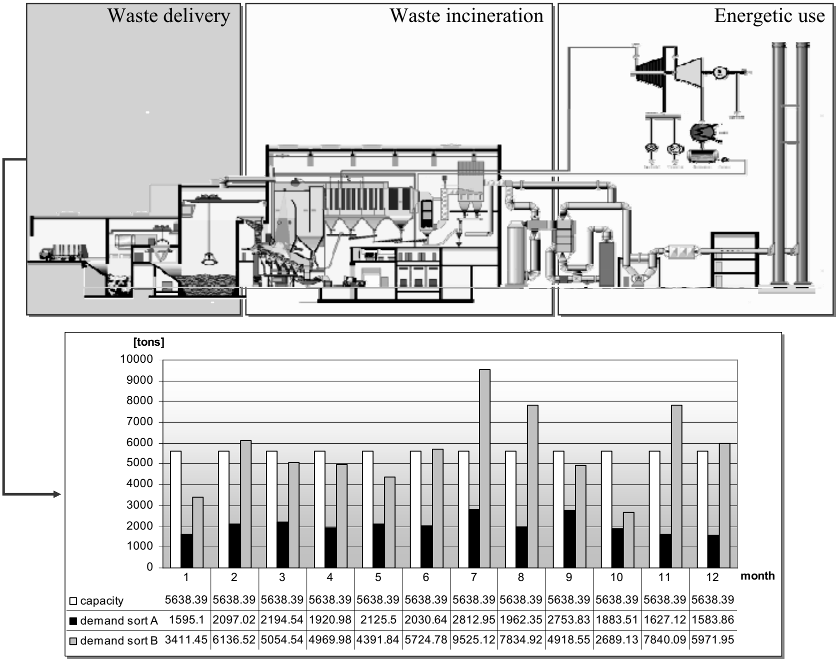
[101] From 2005 on, the intermediate storage of waste was forbidden by law in Germany (see the “Technische Anleitung Siedlungsabfall” (TASi), the “Kreislaufwirtschafts- und Abfallgesetz” (KrWG/AbfG) and the “Deponieverordnung” (DepV) in Germany), leading to a RM problem with limited capacities also in this sector.



month	1	2	3	4	5	6	7	8	9	10	11	12
☐ capacity	5638.39	5638.39	5638.39	5638.39	5638.39	5638.39	5638.39	5638.39	5638.39	5638.39	5638.39	5638.39
■ demand sort A	1595.1	2097.02	2194.54	1920.98	2125.5	2030.64	2812.95	1962.35	2753.83	1883.51	1627.12	1583.86
▨ demand sort B	3411.45	6136.52	5054.54	4969.98	4391.84	5724.78	9525.12	7834.92	4918.55	2689.13	7840.09	5971.95

Figure 4-1: The basic waste incineration process

4.3 Execution of the FECC

Corresponding to the illustrated solution concept (see figure 3-12), the following tasks have to be executed for the FESCPC, and therefore also for the FECC:

- Identification of the problem context
- Determination of all variables and parameters
- Building of the initial capacity distribution
- Adjustment of the capacity distribution

4.3.1 Identification of the problem context

The function of the analysis of the problem context is to **determine the potential of the revenue maximization** in the considered application and the **analysis of the fulfillment of the constraints for RM** in the practice case (see chapter 2). The result of the problem analysis shows that the FECC in the waste incineration plant meets the constraints:

- **Relatively fixed capacity**
  As stated in section 4.2, the over-all capacity available for the FECC refers to the kiln capacity. As the kilns incinerate waste in a constant process, not only the annual capacity is fixed but also the monthly capacity (as the basis for the FECC).
- **Perishable capacity**
  Unused kiln capacity cannot be stored for future demand and, thus, is perishable in the described sense.
- **High costs of capacity increases**
  A capacity increase can only be accomplished by the building of new kilns, associated by high costs.
- **Marginal costs**
  The marginal costs can be calculated and introduced into the decision process.
- **Fluctuating demand**
  The demand for the two classes fluctuates as illustrated in figure 4.1.
- **Product sale in advance**
  Accepted waste cannot be rejected anymore. So, bookings of incineration capacity have to be processed as negotiated.
- **Ability of market segmentation**
  The result of the analysis of the plant is that the rest capacity for FECC can be distributed to two classes, sort A (shredder fractions) and sort B (plastics and residual waste). The higher worthiness of sort B becomes obvious by looking at the average unit profit margins from 2000 to 2004:

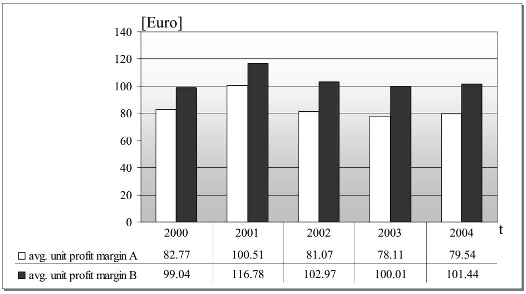


Figure 4-2: Profitability of the FECC classes

4.3.2 Determination of all variables and parameters

With respect to the described influences in the FESCPC, for the FECC, only the capacity distribution has to be adjusted over time, due to the development of the class workload until the end of the planning period.

The following factors have to be determined:

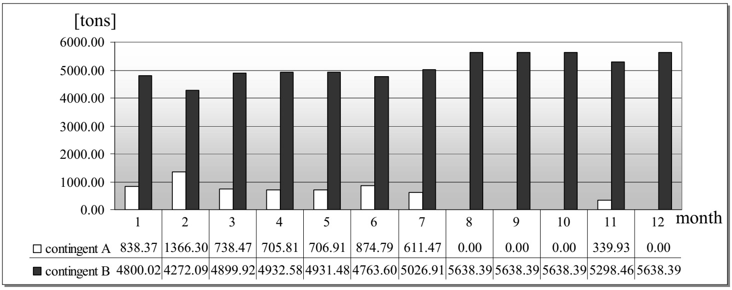
- **Over-all capacity k**
  As stated before, from the kiln capacity, the reserved amount for regional corporations and long-term contracts has to be abstracted. 67,660.68 tons (assuming no technical disturbances) are free for market trade in the considered year 2004. On a monthly level, k = 5,638.39 tons.

- **Workload W_{st}**
  As defined in chapter 3, W_{st} is calculated as a cumulative variable, depending on the accepted requests of capacity units within the planning period. For each adjustment step (in this case once per day), the workload is computed and the FECC is executed.

- **Rest time r_t**
  The monthly planning period consists of 25 days (incineration prohibited by law on Sundays). So, $r_0 = 25$, and $r_t = r_{t-1} - 1$. The scale of the rest time is set based on the flexi-

bility of capacity adjustments and the availability of data. Here, the requests arrive for a certain day for delivery and are stored in the data basis on a daily level.

- **Definition of the adjustment steps**
  Depending on the flexibility in and the costs of adjusting the capacity, as well as on the available data basis and tactical considerations, the time between two planning steps is defined. Here, a daily adjustment is the result. In many cases, a request-based modification is executed, meaning that a new capacity distribution is taken out for each customer request.
- **Building of initial contingents**
  As the FECC is executed here, firstly an initial capacity distribution has to be found. This is carried out based on past data. As described in chapter 3, depending on the past demand, the expected demand for the most profitable class is satisfied, followed by the distribution of the rest capacity to the other classes. The waste incineration case is controlled on the basis of initial capacity distributions as the result of demand forecasts assuming an ARMA (1, 1) process [Schlittgen/Streitberg 1987]. In terms of forecasting quality, this process had the best results. In terms of the capacity setting itself, just taking the average of the last periods would have led to the same results.



	1	2	3	4	5	6	7	8	9	10	11	12
□ contingent A	838.37	1366.30	738.47	705.81	706.91	874.79	611.47	0.00	0.00	0.00	339.93	0.00
■ contingent B	4800.02	4272.09	4899.92	4932.58	4931.48	4763.60	5026.91	5638.39	5638.39	5638.39	5298.46	5638.39

Figure 4-3: Initial contingents in each planning period

4.3.3 *Adjustment of the capacity distribution: FECC*

The most important part of the solution concept is the choice of fuzzy expert control as an adequate method for the solution of the SCPC. For illustration, the resulting fuzzy expert system for the CC in the waste incineration application is shown in figure 4-4. As this is a two-class scenario, only the lucrative sort B has to be controlled, the remaining capacity automatically represents the contingent for sort A.

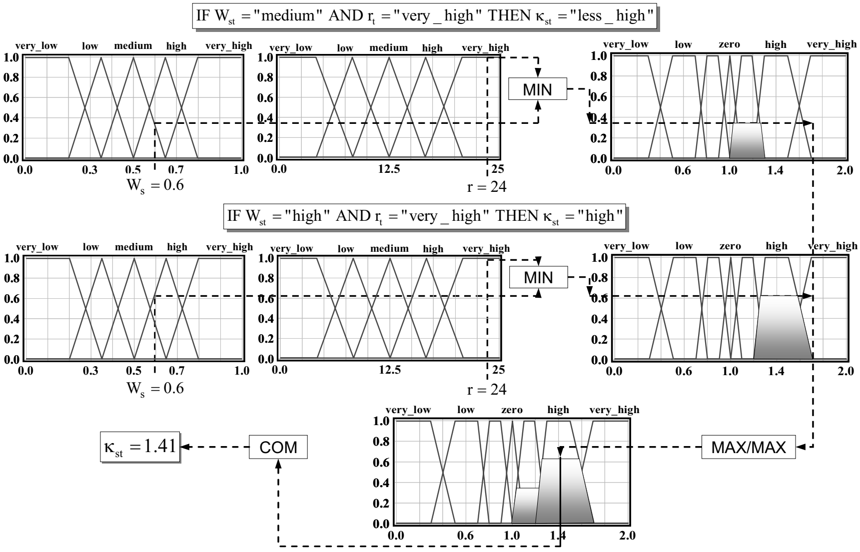


Figure 4-4: Example for a capacity adjustment with FECC

According to the described development of fuzzy expert controllers (section 3.3.2), the in- and output variables are transformed into linguistic variables in the fuzzification step. For two real-valued inputs ($W_{st} = 0.6$ and $r_t = 24$), two rules out of the rule set illustrated in figure 4-5 are addressed by these inputs. The inference process is executed on the basis of a max-min-inference with a maximum result aggregation. The membership degrees $\mu_{medium}(W_{st} = 0.6) \approx 0.35$ and $\mu_{high}(W_{st} = 0.6) \approx 0.65$ are combined with $\mu_{very\_high}(r_t = 24) = 1.0$ over a minimum conjunction:

$$\mu_{very\_low}(\kappa_{st}) = 0$$
$$\mu_{low}(\kappa_{st}) = 0$$
$$\mu_{less\_low}(\kappa_{st}) = 0$$
$$\mu_{zero}(\kappa_{st}) = 0$$
$$\mu_{less\_high}(\kappa_{st}) = \min\left(\mu_{medium}(W_{st} = 0.6), \mu_{high}(r_t = 24)\right) \approx 0.35$$
$$\mu_{high}(\kappa_{st}) = \min\left(\mu_{high}(W_{st} = 0.6), \mu_{high}(r_t = 24)\right) \approx 0.65$$
$$\mu_{very\_high}(\kappa_{st}) = 0$$

The inference composition is based on a maximum operator, meaning that for each point in the co-domain of the output variable, the maximum membership degree is taken, leading to the grey-shaded area as a result for the linguistic output variable:

$$\mu(\kappa_{st}) = \max\left(\mu_i(\kappa_{st})\right) \; \forall i \; (i: \text{Membership function})$$

A COM defuzzification translates the linguistic output value into the real value $\kappa_{st} = 1.41$, meaning a 41% increase of the capacity of sort B. For this, the corresponding values are calculated from the fuzzy system (compare to figure 4-4). Thereby the membership degrees can change because of the maximum composition of the inputs in the fuzzy inference:

$$\kappa_{st} = \frac{\sum_{i=1}^{n} y_i \cdot \mu(y_i)}{\sum_{i=1}^{n} \mu(y_i)} \approx \frac{1.23 \cdot 0.50 + 1.55 \cdot 0.65}{0.50 + 0.65} = 1.41$$

This clear increase seems reasonable, as after the first day, already over the half of the contingent of the lucrative waste sort is reserved. It is very probable that the initial contingent is chosen too small and would lead to rejections of profitable demand.

Over the whole planning period, all arising combinations of workload and rest time are used to determine the best distribution of the over-all capacity. Figure 4-5 indicates the possible constellations and the consequences for sort B's capacity[102]. A degree of capacity change

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[102] The figure 4-5 illustrates also the argument that the expert knowledge is made continuous by using fuzzy systems for the decision-making.

greater 1 indicates an increase of the capacity (e.g. $\kappa_{st} = 1.41$ means 41% increase), a degree below 1 indicates a decrease (e.g. $\kappa_{st} = 0.91$ means 9% decrease).

W_{st}	r_t	κ_{st}
Very high	Very high	Very high
High	Very high	High
Medium	Very high	Less high
Low	Very high	Zero
Very low	Very high	Zero
Very high	High	Very high
High	High	High
Medium	High	Less high
Low	High	Zero
Very low	High	Zero
Very high	Medium	High
High	Medium	High
Medium	Medium	Zero
Low	Medium	Less low
Very low	Medium	Less low
Very high	Low	Less high
High	Low	Less high
Medium	Low	Zero
Low	Low	Less low
Very low	Low	Negative
Very high	Very low	Zero
High	Very low	Zero
Medium	Very low	Less low
Low	Very low	Low
Very low	Very low	Very low

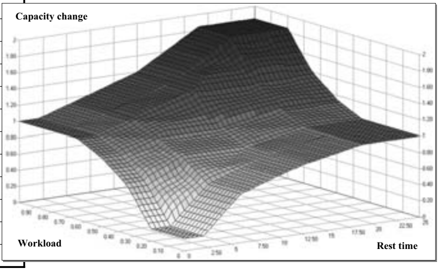

Figure 4-5: Input/output relation in the FECC

As stated in section 3.3, especially the **robustness of the fuzzy control system** is a central requirement within the development of fuzzy expert controllers [Zadeh 1968a, p. 101]. In this case, it is assured by developing a fuzzy system based on 35,000 tested settings. Thereby, the best performing and robust, as well as plausible in terms of the reaction on the system inputs, system was determined.

4.4 Results for the FECC

The plausible and correct operation mode of the FECC can be illustrated by looking at the development of the capacity of sort B compared to the demand (cumulated for each month) of 2004 (see figure 4-6):

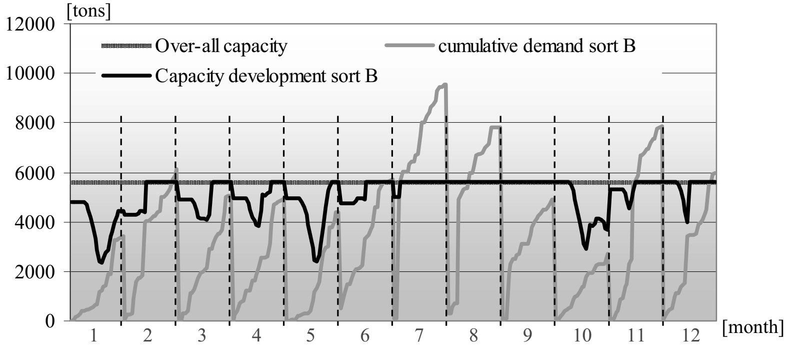

Figure 4-6: Capacity development in the FECC

It can be observed that the capacity of sort B, starting on an initial level at each month, is often firstly reduced, due to the demand arriving relatively late. When the workload in the class becomes higher, the capacity is increased again, indicating the adaptive behavior of the fuzzy system, due to unexpected demand developments. In months where the cumulative demand is already high at the beginning of the period, the capacity is increased up to the over-all capacity. Except from month 9, the fuzzy system clearly orients on the workload and the rest time of the period as the two core factors influencing the capacity setting in the profitable class. In month 1 and month 10, the demand for the profitable class is not high enough to consume the whole capacity. The result is that the rest capacity is allocated to sort A, in order to avoid idle capacities[103]. The figure clearly indicates that the **FECC behaves corresponding to the central objectives and corresponding to the expected actions in order to reach the objectives**.

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[103] In the capacity illustration, the already satisfied capacity units of sort B are not considered. In the calculation of the results and in the system setting itself, these accepted reservations are subtracted and the rest capacity is used. Figure 4-6, thus, only serves as an illustration of the system behavior.

The described process is executed at each month in 2004. The performance is compared over this year:

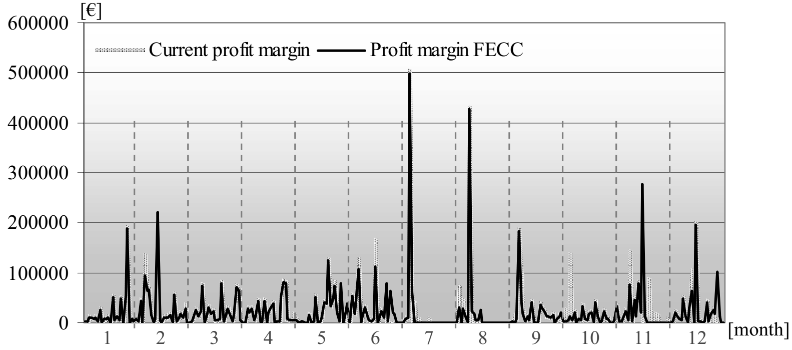

Figure 4-7: Profit effects of the FECC

Method		Sort A	Sort B	Total
FCFS	**amount [tons]**	15,044.34	49,957.41	65,001.75
	profit margin [€]	1,196,626.80	5,067,679.67	6,264,306.47
FECC	**amount [tons]**	7,672.46	58,961.95	66,634.41
	profit margin [€]	610,267.19	5,981,100.09	6,591,367.28

Table 4-1**:** Results of the FECC

In the over-all performance, the FECC shows to lead in most cases at least to the same profit margins than the current practice in the waste incineration company (see figure 4-7). The similarity of the profits on a daily basis results from the high demand for the profitable class. Therefore, also the FCFS approach already leads to good results.

The results show a predominance of the capacity control part of the FESCPC. The resulting profit margin is €327,060.56 higher than the one resulting from the currently used FCFS approach. Therefore, the conduction of the proposed FECC leads to a **significant increase of the profit margin by 5.22%**. The proposed concept provides a **capacity control only 0.21% worse than the optimal solution** (that can be calculated in this case from the given data).

All together, the advantage of the FECC approach is shown clearly. Additionally, a stable and robust fuzzy system is established, meaning that, firstly, for other years, the results with the FECC approach dominate, too. Secondly, even small changes in the fuzzy control system (e.g. adjustment of the boundaries of membership functions) do not change the solution significantly. The developed FECC is the result of an extensive test and verification process, as claimed in the literature on fuzzy system development.

In addition to the comparison of the FECC to the current situation, the solution concept is also compared to two basic RM methods (see section 2.2.1), the building of fixed contingents and the explained EMSR approach (see table 4-2).

Method		**Sort A**	**Sort B**	**Total**
Contingents	**amount [tons]**	6,182.04	55,881.28	62,063.33
	profit margin [€]	491,719.46	5,668,597.04	6,160,316.50
EMSR	**amount [tons]**	0	59,265.79	59,265.79
	profit margin [€]	0	6,011,921.84	6,011,921.84

Table 4-2: Results for the standard RM methods in the waste incineration application

Compared to these standard methods, the FECC leads to a revenue of €6,591,367.28 and, thus, to a profit margin increase of 9.6% over the EMSR and 7.0% over the contingent building. Thus, it can also be shown **that the FECC also outperforms standard RM methods for the capacity control**.

4.5 Conclusions to the FECC

Three main questions were addressed by the application of the FECC in the waste incineration industry. They will be answered in the following.

- Does the FECC lead to significant improvements of the profit margin in the considered application case?

The underlying RM problem in the waste incineration process concerns the revenue-optimal distribution of the available kiln capacity to two classes. The current practice in the company is first-come-first-serve, which means that the delivery in the profitable class (plastics and residual waste) and in the other class (shredder fractions) is allowed until the over-all incineration capacity is reached. The resulting profit margin was €6,264,306.47 in the considered year 2004. With the execution of FECC, a profit margin of €6,591,367.28 results. Thus, the question of significant improvements is clearly answered. The **FECC leads to an increase in the revenue by €327,060.56 or 5.22%**.

- Is the FECC an adequate method for revenue maximization under fixed prices?

The FECC was developed under consideration of all important influences on and requirements for the design of a fuzzy expert system. The extensive verification process (over 35,000 control steps in the incremental improvement of the system) and the long-term execution (FECC over one year) indicate that the capacity control part in the FESCPC **corresponds to all objectives and requirements** formulated in chapter 2 and 3. The significant revenue effects implicate the predominance of the solution concept. Therefore, not only **is the FECC an adequate method for revenue maximization under fixed prices**. It is also proven that **an underperforming integrated solution is not structurally caused by the capacity control part**.

- Does the developed solution concept outperform standard Revenue Management approaches to the CC?

Two basic approaches were discussed in chapter 2, which basically qualify for the application in the waste incineration industry, especially against the background of the requirement of a practical approach to the CC: The first one is the building of fixed contingents for the two classes based on the expected demand in the planning period. The second is the use of the EMSR approach as an accepted solution for the CC problem and the basis for many developed RM methods. Both approaches are outperformed by the FECC. With a resulting profit margin of €6,011,921.84 with EMSR and €6,160,316.50 with the fixed contingents, the FECC leads to an improvement of the profit margin by 9.6% and 7.0%, respectively. So, the **FECC**

also meets the requirement of a better performance in comparison to standard RM methods.

However, so far, only the capacity control option is proven to provide promising and stable results in simple cases. The remaining work will mainly concern practical applications that also include the price control option and the integrated approach.

5 Analysis of the price control option: FEPC

The next step in the bottom-up analysis of the SCPC is to apply the PC option. Based on the specific application constraints of PC in the context of the hospitality industry, the general solution concept has to be transferred to the PC part, followed by the analysis of the performance in the context of a real application case.

The general objective of this part of the work is to answer the following questions:

- Does the FEPC outperform the current price setting in the hospitality application?
- Is there a high variability of the developed solution with respect to variations in the reservation prices?
- Is the FEPC an adequate method for the revenue maximization under fixed capacity allocations?

5.1 Application constraints of a PC

On the one hand, the adaptation of the SCPC solution is easy to conduct because of the iterative on-line approach that allows omitting the control option that is currently not needed. On the other hand, in the context of PC, a few specifics have to be considered in the conduction:

- **Deduction of capacity effects**
  The capacity distribution is assumed to be fixed in the PC because of the inflexibilities in and high costs of variations in the capacity setting (e.g. modifications in a hotel with the need of temporarily closing the hotel) Therefore, the PC can only effect that the given capacity is sold at the highest possible price together with a high workload. In cases, however, where the capacity of a class is structurally too high (e.g. too many second-class rooms), even an optimal PC would not reach a high workload. Thus, prices

are set low not because of an unexpected low demand but because of the **structural**[104] **under-utilization**. In such cases, the fuzzy expert system has to be adjusted adequately (e.g. changing the membership functions for the workload).

- **Determination of initial solutions for the price**
  As the solution concept is based on a heuristic approach that starts in t = 2 based on the described influential parameters, initial solutions for the price in each class have to be found. As stated in chapter 3, in many cases, forecasts are not feasible in the context of fluctuating demand and variable customer behavior. In some cases, it might be reasonable to use forecasts at least for the initial settings. Often, however, the prices are determined using simply the average prices of the last planning period.
- **Diverse customer reactions on pricing**
  Customers basically understand if they are told that there is no capacity left to process their request. However, the customer reaction on different prices for the same good or service over time is diverse. Very price-sensitive customers who act as bargain hunters understand the search for the best deal as a challenge, and may look for variable prices. Customers with a very low acceptance of price changes may, instead, be irritated by price variations, having negative effects on their purchasing behavior. The customer value, therefore, has to be considered in order to avoid the circumstance of a regular customer becoming irritated by extensive price variations [Breffni/Kimes/ Renaghan 2003; Reichheld/Teal 1996; Link 1995; Bruhn/Homburg 2003]. Customers with a high value are intended to be faced with less price variations than customers with a low value.
- **Determination of the short-term-bottom price**
  As defined in chapter 2, the short-term bottom price is the minimum price that results from the FEPC (and FESCPC). In its basic definition, the short-term bottom price equals the variable costs, which need to be at least covered by the price in order for the supplier to stay in the market [Varian 1999, pp. 339]. In an extension, planning calcula-

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[104] *Structural*, in this context, means that the workload in a class is not low because of an under-performance of the PC, but rather because of the given capacity distribution that is not consistent with the demand structure. In the practice of hotel RM, such effects are reduced in the short-run by adding different service levels and, as a result, increasing or decreasing the “value” of the capacity unit (e.g. two hotel rooms with different equipment).

tions may also play an important role in the determination of the bottom price. Seasonal events (e.g. fairs, sport championships in the hotel case) give the decision maker the opportunity to increase the price level because of the temporarily high demand. As an alternative, price levels in different classes of different worthiness may be significantly different. Also strategic decisions may induce the setting of a certain bottom price (e.g. marketing or promotion actions). All such effects on the price level have to be captured by an adequate analysis and considered in the PC.

- **Definition of the planning periods**
  In the context of RM in hotels, but also in other PC and CC applications, the length of the planning periods varies amongst the different classes (with the potential of multiple parallel planning horizons for different classes). Leisure guests in a hotel, for example, often plan their holiday weeks and months before their arrival. Business guests, however, often book within the last one or two days. As the rest time of the planning period is an important influence factor, this has to be captured in the solution.

The consequence of these specific conditions for PC is that, in most cases, one single fuzzy expert control system is not sufficient enough to perform well in all identified classes. Also, in the hotel application case that follows, one FEPC results for each class as a consequence of the described incremental (and software-based) improvement of the initial fuzzy system with respect to the considered application case[105].

5.2 Description of the hotel application

The general advantage of the proposed solution concept will now be explicitly illustrated with an example of the hospitality industry as an application case for fuzzy expert price control (FEPC) as the counterpart of the fuzzy expert capacity control (FECC) presented in chapter 4 and Becher [2007].

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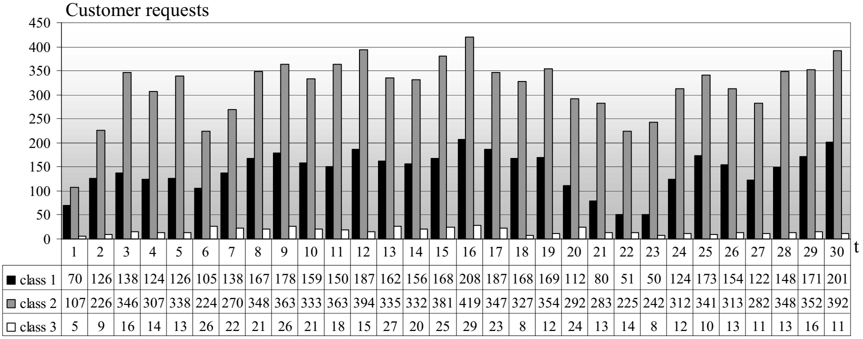
[105] This conclusion also holds for the FECC in general. In the waste incineration application, only two classes were considered.

A hotel with a typical operational structure is considered. The hotel's over-all capacity is 350 rooms. Three classes of rooms can be determined: The first category rooms ($k_1 = 100$), the second category rooms ($k_2 = 240$) and the third category rooms ($k_3 = 10$). While, thereby, the first two categories are comparable to common categories in hotels, the third category is a special concept of the hotel due to the geographical closeness to an airport. This legitimates the supply of rooms that are only used within a day for the preparation for business meetings or similar things. One planning period consists of one day, where the booking policy is to accept bookings within the whole day. The over-all period under consideration is one representative month in 2000. The demand for the different room classes is illustrated in figure 5-1. The unknown demand and the unknown reservation price leads to the problem of **determining the right price level in the classes, depending on the current workload and the reservation price level of the customers**.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
■ class 1	70	126	138	124	126	105	138	167	178	159	150	187	162	156	168	208	187	168	169	112	80	51	50	124	173	154	122	148	171	201
▨ class 2	107	226	346	307	338	224	270	348	363	333	363	394	335	332	381	419	347	327	354	292	283	225	242	312	341	313	282	348	352	392
□ class 3	5	9	16	14	13	26	22	21	26	21	18	15	27	20	25	29	23	8	12	24	13	14	8	12	10	13	11	13	16	11

Figure 5-1: Demand in each hotel class

The current pricing strategy of the considered hotel is unknown. The pricing solution depends on RM techniques that are described in chapter 2. The comparison of the current solution with the FEPC, thus, already implies the analysis of the performance against RM techniques used in practice.

5.3 Execution of the FEPC

Corresponding to the illustrated solution concept (see figure 3-12), the following tasks have to be executed also for the FEPC: Identification of the problem context, determination of all variables and parameters, calculation of the initial price levels, and adjustment of the price levels in the classes.

5.3.1 Identification of the problem context

Like in the FECC, also in the FEPC the **potential of the revenue maximization** in the hospitality industry has to be analyzed under consideration **of the constraints for RM** (see chapter 2). As RM in the hotel sector is one of the most common research and application fields (besides the airline industry), the constraints are clearly met here:

- **Relatively fixed capacity**
  The over-all capacity available for the FEPC refers to the hotel capacity. Due to constructional limitations, this capacity can only be increased by long-term investments of the hotel company.
- **Perishable capacity**
  Unused hotel capacity cannot be stored for future demand and, thus, is perishable in the described sense. The latest bookings for a certain class and day mostly arrive at the mid of this day, so often the rest capacity is not sold anymore.
- **High costs of capacity increases**
  A capacity increase can only be accomplished by the building of hotel rooms, associated by high investment costs and costs for the daily business (e.g. cancelled bookings because of constructions, need for closed areas in the hotel).
- **Marginal costs**
  The variable costs of the hotel are not known here, so the decisions are based on prices, not on unit profit margins. They are anyway assumed to be low compared to the room prices.

- **Fluctuating demand and reservation price level**
  The demand for the three classes fluctuates as illustrated in figure 5.1. Additionally, the reservation prices fluctuate, and are additionally unknown.
- **Product sale in advance**
  Accepted booking cannot be rejected anymore without high costs. So, bookings of a class capacity are assumed to be processed as negotiated.
- **Ability of market segmentation**
  The analysis of the hotel shows three clearly separable classes of different worthiness, class 1 (comparable to first class), class 2 (economy class) and class 3 (dressing and lounge rooms for business people with single day stays)[106]. The different worthiness becomes obvious by looking at the average unit prices (per room per day) from the month before the considered period in 2000:

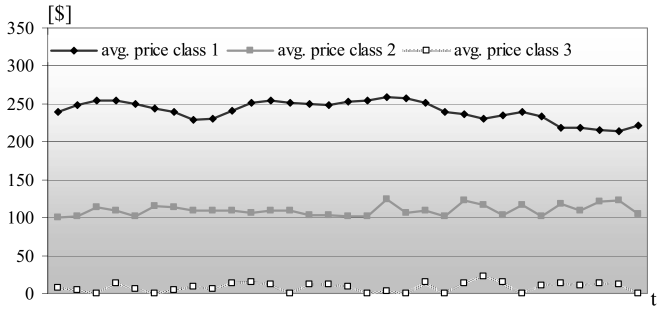


Figure 5-2: Variation of the daily hotel prices

5.3.2 Determination of all variables and parameters

For the FEPC, only the price level has to be adjusted over time, depending on the development of the class workload until the end of the planning period and the reservation prices of the customers, as well as the customer value.

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[106] In reality, many different classes are determined by the decision makers in hotels. For simplicity, these are reduced to three clearly separable categories with significantly differing prices. This is most consistent with the objective of controlling classes with a different worthiness.

The following factors have to be determined:

- **Over-all capacity k and fixed capacity distribution k_s**
  As stated before, the fixed over-all capacity consists of 350 rooms. The capacity distribution is fixed to k_1 = 100 rooms, k_2 = 240 rooms and k_3 = 10 rooms.
- **Workload W_{st}**
  As defined in chapter 3, W_{st} is calculated as a cumulative variable, depending on the accepted requests of hotel rooms within the planning period (one day). For each adjustment step (in this case for each customer request), the workload is computed and the FEPC is executed.
- **Rest time r_t**
  The monthly planning period is measured in hours, starting with the first request for a specific day, ending at 12:00 pm of the considered day.
- **Reservation price rp_{cst}**
  Corresponding to the difficulties in determining the (correct) reservation prices of the customers, their willingness to pay is not considered directly in the solution concept. However, as long as the FEPC is not implemented in a running system, its performance has to be analyzed also with respect to this important influence factor. For this, the reservation price is estimated for each customer with the assumption of an underlying normal distribution [Fahrmeir et al. 2004, pp. 90]. In order to minimize estimation errors, the reservation prices are varied around the mean prices of the accepted bookings. For each variation, the FEPC is executed. Thus, a sensitivity analysis of the behavior of the FEPC with respect to reservation price variations can be conducted. The variation of the solution should be by far beneath the variation of the reservation price, which would indicate the robustness of the solution system and the correctness of the approach to omit the reservation price as a direct influence in the solution concept[107].

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[107] The indirect influence of the reservation price is given in the acceptance decision of the consumer. So, again a low workload indicates the (in)correct price level, as it was already the indicator for a too high and too low capacity.

- **Customer value clv_{ct}**
  The need for the consideration of the customer value is described in chapter 2. In practice, the determination of this value is part of much research [e.g. Link 1995; Mani et al. 1999; Rosset et al. 2003; Breffni and Kimes and Renaghan 2003; McKim 2003]. In the data of the hospitality application, no long-term consumer data is available. However, regular customers can be identified, leading to the conclusion to determine this influence factor by their status as a regular customer (high value) or non-regular customer (low value).

- **Short-term bottom prices pu_{st}**
  Here, cost-based bottom prices are used to build lower limits for the FEPC, in order to avoid that prices are too low to receive at least the variable costs. These lower limits were set by the company (no access to cost data) at \$144.36 in class 1, \$79.77 in class 2, and \$10.02 in class 3. These bottom prices do not have to be implemented in the FEPC. They are considered in the adjustment of the prices in the form that resulting prices below the limit are set equal to the bottom price.

- **Definition of the adjustment steps**
  Depending on the flexibility in and the costs of adjusting the prices, as well as on the available data basis and tactical considerations, the time between two planning steps is defined. Here, a request-based adjustment is the result. The fuzzy system for the FEPC has to capture more than one specific day. Reason is that requests may arrive for more than one day simultaneously. In addition, one request may refer to a multiple day stay, which means that the customer plans to stay at the hotel for more than one night. So, more than one FEPC is executed, depending on the current request.

- **Building of initial price levels**
  The high variations in and the high range of the daily price level leads to the conclusion to simply take the mean prices of the previous month in 2000 as initial values. These mean values are \$240.60, \$113.96 and \$12.53 for class 1, 2 and 3.

5.3.3 Adjustment of the price setting: FEPC

For the FEPC, each class has to be controlled in contrast to the FECC. As this is a three-class scenario, three fuzzy expert systems result, which makes sense because of a different booking behavior in the different classes (e.g. business people book later than many leisure customers) and the resulting differences in the FEPC (despite a high structural similarity of the systems). Thus, for each day and for each class, a FEPC is executed, with possible differences between the classes. Such an execution is exemplarily discussed for one input constellation in class 1 in the following.

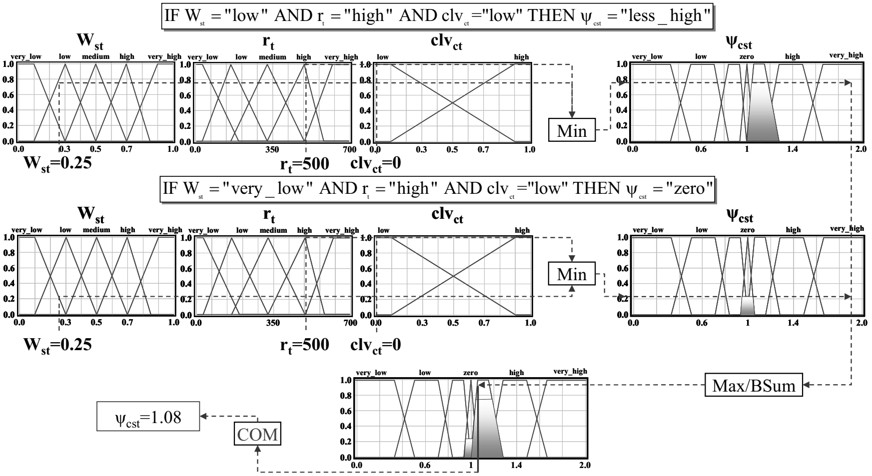

Figure 5-3: Exemplary FEPC step for the first hotel class

For the exemplary real-valued inputs ($W_{st} = 0.25$, $r_t = 500$, $clv_{ct} = 0$, meaning 25% workload, 500 hours rest time and a request of a non-regular customer), two rules out of the rule set illustrated in figure 5-4 are addressed. The inference process is executed on the basis of a max-min-inference with a BSum result aggregation. The membership degrees $\mu_{very\_low}(W_{st} = 0.25) \approx 0.25$ and $\mu_{low}(W_{st} = 0.25) \approx 0.75$ are combined with $\mu_{high}(r_t = 500) = 1.0$ and $\mu_{low}(clv_{ct} = 0) = 1.0$ over a minimum conjunction:

$$\mu_{very\_low}(\psi_{cst}) = 0$$
$$\mu_{low}(\psi_{cst}) = 0$$
$$\mu_{less\_low}(\psi_{cst}) = 0$$
$$\mu_{zero}(\psi_{cst}) = \min\left(\mu_{very\_low}(W_{st} = 0.25), \mu_{high}(r_t = 550), \mu_{low}(clv_{ct} = 0)\right) \approx 0.25$$
$$\mu_{less\_high}(\psi_{cst}) = \min\left(\mu_{low}(W_{st} = 0.25), \mu_{high}(r_t = 550), \mu_{low}(clv_{ct} = 0)\right) \approx 0.75$$
$$\mu_{high}(\psi_{cst}) = 0$$
$$\mu_{very\_high}(\psi_{cst}) = 0$$

The inference composition is based on a maximum operator, meaning that for each point in the co-domain of the output variable, the maximum membership degree is taken, leading to the grey-shaded area as a result for the linguistic output variable[108]:

$$\mu(\psi_{cst}) = \max\left(\mu_i(\psi_{cst})\right) \ \forall i \ \left(\text{i: Membership function}\right)$$

A COM defuzzification translates the linguistic output value into the real value $\psi_{cst} = 1.08$, meaning a 8% increase of the capacity of sort B. For this, the corresponding values are calculated from the fuzzy system (compare to figure 5-3):

$$\psi_{cst} = \frac{\sum_{i=1}^{n} y_i \cdot \mu(y_i)}{\sum_{i=1}^{n} \mu(y_i)} \approx \frac{1.01 \cdot 0.50 + 1.18 \cdot 0.75}{0.50 + 0.75} = 1.08$$

This increase seems reasonable, as already over the half of the contingent of class 1 rooms are booked at an early time point in the period. It is very probable that the (rest-)contingent can be sold also at a higher price level.

Over the whole planning period, all arising combinations of workload, rest time and customer value are used to determine the best price level for each class. Figure 5-4 indicates the possi-

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[108] No result aggregation has to be executed in the example above. As described in chapter 3, the membership values are summed up until 1 (see also table 3-1).

ble constellations and the consequences for the class 1[109]. A degree of price change greater 1 indicates an increase of the price level (e.g. $\psi_{cst} = 1.08$ means 8% increase), a degree below 1 indicates a decrease (e.g. $\psi_{cst} = 0.9$ means 10% decrease).

W	r	clv	ψ	W	r	clv	ψ
very_high	very_high	high	high	very_high	very_high	low	very_high
high	very_high	high	less_high	high	very_high	low	high
medium	very_high	high	zero	medium	very_high	low	less_high
low	very_high	high	zero	low	very_high	low	less_high
very_low	very_high	high	zero	very_low	very_high	low	zero
very_high	high	high	high	very_high	high	low	very_high
high	high	high	less_high	high	high	low	high
medium	high	high	zero	medium	high	low	less_high
low	high	high	zero	low	high	low	less_high
very_low	high	high	zero	very_low	high	low	zero
very_high	medium	high	less_high	very_high	medium	low	high
high	medium	high	zero	high	medium	low	less_high
medium	medium	high	zero	medium	medium	low	less_high
low	medium	high	zero	low	medium	low	zero
very_low	medium	high	zero	very_low	medium	low	less_low
very_high	low	high	zero	very_high	low	low	less_high
high	low	high	zero	high	low	low	less_high
medium	low	high	zero	medium	low	low	zero
low	low	high	zero	low	low	low	less_low
very_low	low	high	less_low	very_low	low	low	low
very_high	very_low	high	zero	very_high	very_low	low	less_high
high	very_low	high	zero	high	very_low	low	zero
medium	very_low	high	zero	medium	very_low	low	less_low
low	very_low	high	less_low	low	very_low	low	low
very_low	very_low	high	low_low	very_low	very_low	low	very_low

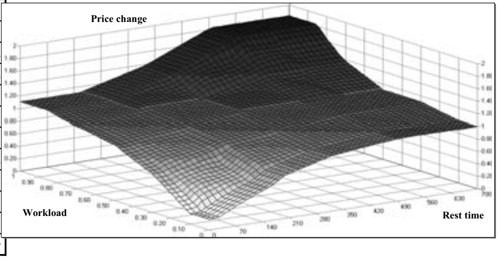

Figure 5-4: Input/output relation in the FEPC

For the FEPC, the **robustness of the fuzzy control system** is also a central requirement. In this case, it is assured by developing a fuzzy system based on over 15,000 tested settings. Thereby, the best performing and robust, as well as plausible in terms of the reaction on the system inputs, system was determined.

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[109] Figure 5-4 also illustrates the argument that the expert knowledge is made continuous by using fuzzy systems for the decision-making. Thereby, only the case of non-regular customers is explicitly shown in the right figure.

5.4 Results for the FEPC

As already stated, the described process is executed for one representative month. Thereby, the advantage of the developed concept is proven on the basis of 30 days per class and, altogether, with over 15,000 control steps. Thus, the results equal a performance analysis for a running Revenue Management system in a hotel and can be considered as representative. In addition, the performance of the FEPC is compared to a currently applied RM approach for pricing (in the following denoted with "Current"). Therefore, the comparison also indirectly occurs against the current RM practice. The results can be observed in table 5-1 and figure 5-5.

Method		**1st class**	**2nd class**	**3rd class**	**Total**
Current	Workload (%)	67.81	65.24	77.00	66.31
	Revenue ($)	309,441.40	372,923.43	2,887.56	685,252.39
FEPC	Workload (%)	59.88	61.96	74.07	61.71
	Revenue ($)	315,420.52	425,571.74	3,002.73	743,994.99
percent change	Workload (%)	-11.69	-5.04	-3.81	-6.95
	Revenue (%)	1.93	14.12	3.99	8.57

Table 5-1**:** Results of the FEPC

Because of the executed sensitivity analysis, these results are all average values (weighted with the class size in the case of workload), subject to the five reservation prices that are randomly built for each customer request at each day.

The workload in all classes is slightly lower when using the FEPC in contrast to the current price setting. The main reason is the missing cost data and the given bottom prices, as well as constrained data. Additionally, the fuzzy expert system is developed based on past test data. The system has to be tested and implemented in the running system in order to receive the best performing constellation. However, also the current situation shows clearly that the hotel suffered from a structural under-utilization in 2000.

Even with a lower workload in the classes, the **over-all revenue increased by 8.57%**. With a similar workload, it can be assumed that also the profit margin increased similarly, despite the missing comprehensive cost data. The most considerable increase is recorded for class 2. In the most profitable class, despite the lower workload, still 1.93% revenue increase results.

By looking at the results of the FEPC compared to the current situation on a daily basis (figure 5-5), especially the negative impact of the FEPC on the workload in class 1 becomes obvious. From the middle of the month on, the workload is significantly below the current workload. In the other two classes, the workload is by far closer to the current situation, leading to even higher revenue gains. Figure 5-5 illustrates these revenue improvements. Especially in the second class, the revenue is higher at most days of the month.

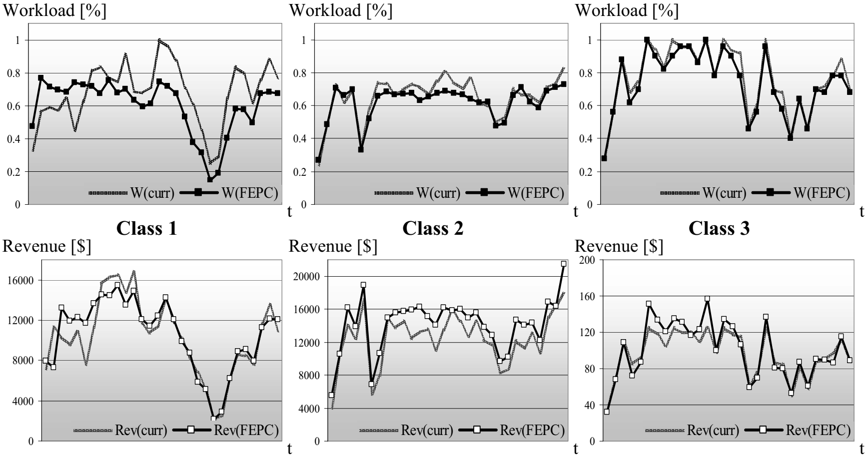

Figure 5-5: Daily revenue and workload in each class

In order to show that the results of the FEPC do not depend on the reservation price estimation in the test setting, a sensitivity analysis is conducted for the considered month (see table 5-2 and figure 5-6). The conducted sensitivity analysis shows the low variability of the results due to random changes in the reservation prices. The low values compared to the coefficient of variance for the reservation prices of about 40% justify the averaging of the results.

Method	Coefficient of Variance (CV)		Setting	
Current	CV (Workload) (%)	6.71	Best Case (%)	66.78
			Worst Case (%)	65.88
	CV (Revenue) (%)	9.25	Best Case ($)	693,006.26
			Worst Case ($)	679,627.17
FEPC	CV (Workload) (%)	6.58	Best Case (%)	62.25
			Worst Case (%)	60.87
	CV (Revenue) (%)	8.47	Best Case ($)	754,061.35
			Worst Case ($)	734,658.04

Table 5-2**:** Sensitivity analysis

The sensitivity analysis is conducted based on the calculated coefficient of variance (CV) that expresses the variability of the workload and the revenue due to the changing reservation prices. Thereby, it is assumed that the average of the reservation price in each class is equal to the mean of the accepted prices of the last planning period (last month).

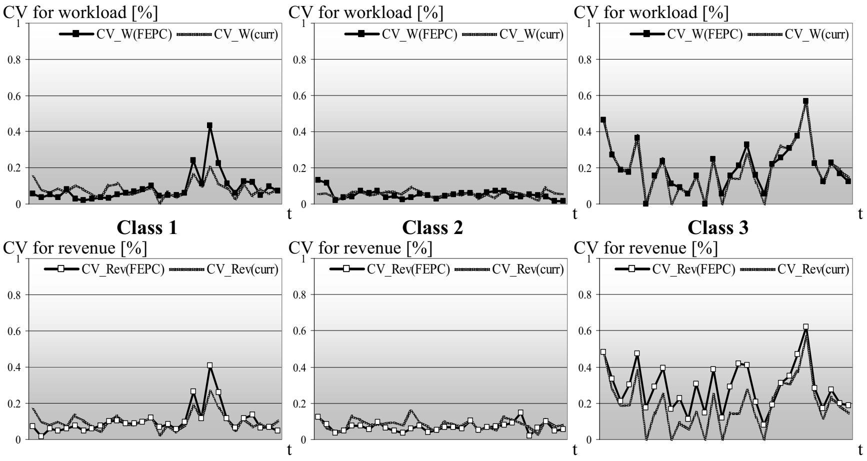

Figure 5-6: Daily variability of revenue and workload in each class

It can be observed that the **variance coefficients for the FEPC are 6.58% for the workload and 8.47% for the revenue** (weighted average in each class at each day). These values can be understood as very low as even the CV for the revenue is low compared to the absolute values and the variability of the reservation prices. Therefore, the fuzzy expert controller is proven to be robust. In comparison to the current situation, the CV for the workload and the revenue is almost the same. The variability of revenue and workload in the FEPC is at most days lower than the variability of the current approach (see figure 5-6). Only for the third class, the CV is higher, due to the low booking rate which leads to greater fluctuations in the price control. Together with the absolute values, this comparison implies a clear advantage of the use of FEPC.

Even in the over-all worst case scenario (which is indicated by the worst case for FEPC and the best case for RM with respect to the reservation prices), a decrease in the workload of 8.86% and an increase in the revenue of 6.01% results. In the over-all best case scenario (best case for FEPC and worst case for RM), the workload drops by 5.51% and revenue rises by 10.95%. Therefore, the average results presented in table 5-1 are significant and show a predominance of the price control part of the FESCPC approach. On average (weighted with the class capacity), the workload decreases only by 6.95% while the **revenue rises by $ 58,742.60 (8.57%) within only one month**. Profit margins are increased by a similar factor because of a similar workload. Thereby, the current workload of 66.31% can be seen as average in the hospitality industry as it can be expected in the context of the underlying application of the price setting in an airport hotel.

5.5 Conclusions to the FEPC

Three questions are of interest when conducting the price control option of the FESCPC. These are answered in the following:

- Does the FEPC outperform the current price setting in the hospitality application?

The FESCPC approach is also the basis for application cases where only one of the two possible control options in a demand-oriented revenue optimization scenario can be addressed. In the presented case of the hotel industry, prices have to be adjusted due to the workload in a class and the rest time in the planning period as well as the customer value (FEPC). The proposed solution concept leads to **significant increases in the revenue of the concerned hotel**. The resulting revenue is $58,742.60 higher than the current revenue in only one considered representative month (monthly increase of 8.57%). Altogether, the proposed approach improves the profitability despite the reduction of the influence parameters to workload, rest time of the planning period and customer value, implying a **solution that is easy to apply in practice**. Thereby, the FEPC implicitly **outperforms also standard RM approaches to PC**, as such an approach is used in the current hotel pricing.

- Is there a high variability of the developed solution with respect to variations in the reservation prices?

The developed fuzzy expert controller was shown to be **robust in comparison to the reservation price variations**. Given a reservation price variation of about 40% around the accepted mean prices of the previous month, the workload shows a coefficient of variance of only 6.58%, the revenue of only 8.47%. Therefore, no significant sensibility of the fuzzy expert system with respect to reservation price changes in the test setting can be observed. The system should be implemented in a running system in order to test the revenue effects in the practical decision-making context.

- Is the FEPC an adequate method for the revenue maximization under fixed capacity allocations?

The PC case in the hospitality industry clearly identifies the potential of the partial SCPC approach also in the context of pricing. Thereby, a strong argument for the applicability of the solution is that the adjustment process of the SCPC to the CC and PC case is only marginal compared to approaches that only work in one context. The FEPC is developed under consideration of all important influences on and requirements for the design of a fuzzy expert system. The extensive verification process (over 15,000 control steps in the design and fine-tuning of the system) and the sensitivity analysis indicate that the price control part in the FESCPC **corresponds to all objectives and requirements** formulated in chapter 2 and 3. While at days with a high workload at an early time point the controller increases the price level significantly (in order to reach the objectives of a high price level for each capacity unit), low workload at the end of the planning period leads to decreasing prices (for the objective of avoiding idle capacities in the classes). Even a combination of both objectives, depending on the combination of workload and rest time is observable. The customer value leads to less extensive price changes in order to avoid customer dissatisfaction. The significant revenue effects implicate the predominance of the solution concept. Therefore, not only **is the FEPC an adequate method for revenue maximization under fixed capacities**. It is also proven that **an underperforming integrated solution is not structurally caused by the price control part**.

The decrease of the workload in the FEPC is due to the underlying data basis that does not contain all relevant information about unprocessed customer requests (constrained data) and costs. By testing the FEPC in a running system, all customer requests can be taken into account and the workload may not decrease. Three concerns of the pricing option in the SCPC still remain. Firstly, practitioners argue that difficulties may result from the automatic price setting without the final decision being made by the decision maker. The effect is that the **acceptance of the FEPC** could be low in the running system. In contrast, even if the PC would lead to significant improvements in the revenue, the users of the system often tend to override the recommended price because of their decision behavior or informal customer relations. Closely connected to this kind of incentive to differ from the recommendations is the use of **pricing as a marketing strategy** (e.g. low prices because of an anniversary despite of a currently high workload). All of these effects only occur in a running system and cannot be tested in advance. Secondly, the **irradiation effects of the PC on the customer behavior** have to be analyzed intensively. In the cases of lower price levels perhaps the price-quality-irradiation effect (see chapter 1) may result, as customers perceive the quality as lower if the price decreases. On the other side, too high prices may lead to the migration of the customers to the competitors. The customers’ impression of highly variable prices may also lead to arbitrage behavior (buying at a low price and selling at a higher price that is still below the current supplier price), or dissatisfaction (e.g. if the price variations are recognized during the service provision). Third, the results show that, in some cases, the **PC focuses on the price maximization objective** and neglects the objective to minimize idle capacities (indicated by the workload decrease of 6.95% compared to the revenue increase of 8.57%). On the one hand, this is because of the underlying data basis being incomplete. On the other hand, this is a clear indication for the **potential of the integration of CC and PC**. The integration to the SCPC in cases where this is possible could result in a simultaneous and equal persecution of the maximization objectives (high prices and much capacity for the premium classes), and the minimization goals (no idle capacities). Therefore, both central factors, high workload and high prices, add to the solution of the revenue maximization problem. In the following, this integration will be executed in the context of Transportation Management.

6 Analysis of the integrated capacity and price control: FESCPC

The remaining task in this work is to apply the SCPC. Based on the specific application constraints of SCPC in the context of the transport industry, the general solution concept has to be conducted based on a real application case, followed by the analysis of the solution performance in the context of the **distribution of goods**.

This application marks the last step in the determination of the advantage of a SCPC. The following three remaining questions to the work on the SCPC:

- Is the FESCPC a feasible approach to the integrated CPC?
- Does the FESCPC outperform the FECC and the FEPC?
- Has the revenue-optimization of delivery lists substantial effects on the transportation costs?

6.1 Application constraints of the SCPC

The results of the FECC (higher workload, higher revenue) are based on the adjustment of the capacity allocation to the different classes. The main focus, thus, is on the harmonization of the supply and demand of the class capacity with direct implications on the over-all workload. As the results of the FEPC show (lower workload, higher revenue), this control option focuses more on the determination of the highest possible price level. Apart from the underlying data basis, the nature of the FEPC is not to force the minimization objective with respect to the idle capacity. The conclusion, that is consistent to the literature, is to combine both control options to the FESCPC. Thereby, two special constraints have to be considered. Firstly, the flexibility of the capacity and price adjustments has to be regarded. Secondly, the effects of the FESCPC on the cost side have to be analyzed, in order to find out if the potential positive revenue effects are offset by higher distribution costs.

6.1.1 Flexibility in the adjustment of capacities and prices

Besides the requirements and objectives of an FESCPC discussed in chapter 2 and 3, especially the **flexibility in adjusting capacities as well as prices** has to be considered in the application of the FESCPC [Talluri/van Ryzin 2004, p. 176] (see figure 6-1):

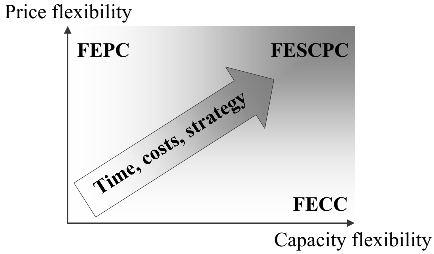

Figure 6-1: Influences on the flexibility of price and capacity adjustments

Three main influences on the flexibility of price and capacity adjustments can be discovered:

- **Time aspects**
  The dynamic context of the FESCPC approach and its parts refers to the opportunity of setting prices and capacities not only at the beginning of the planning period but also within the period. Time aspects in this context refer to the amount of the possible adjustment steps. In the South-German waste incineration industry, prices are adjusted once per year in a kind of consortium. Thus, prices are fixed within the planning periods. The result is the sole FECC that is conducted on a daily basis. In a hotel application, the capacity distribution can only be changed by reconstructing the hotel building. Therefore, only a FEPC is available for each customer request. The question, then, not only regards the possibility of FEPC or FECC, it also raises queries in regards to which interval it is applicable in. If the intervals are too large to fit into the corresponding planning period, the concerned control option cannot be reasonably conducted.
- **Cost aspects**
  Related to the time aspects is the consideration of costs for the price and capacity adjustments. In the case of price adjustments, it is mainly the transaction costs, which can

be stated. First, the information costs on the supplier side increase in cases when the prices have to be made available for customer requests. Each PC step has to be communicated to the consumer in the transaction process. Second, bargaining costs rise because of having to explain the price changes to (regular) customers who do not accept the new prices without a comprehensive explanation and negotiation. In the case of CC, all costs related to the capacity allocation can be stated. Thereby, not only the time costs of the system updates are relevant. In the production industry, for instance, the material costs for testing an adjusted production line and the labor costs (all connected by the term setup costs) are also often significant.

- **Strategic aspects**
  In the last consequence, strategic and tactical aspects may arrange for the flexibility of CC and PC, apart from their principle applicability. Examples for strategic interventions in the PC process are all kinds of price-related marketing actions (e.g. special price actions), and price negotiations with special customers (e.g. long-term contracts). Strategic decisions influencing the capacity flexibility are, for instance, the change of the capacity settings (e.g. introduction of new classes with a fixed contingent) or the overall capacity (e.g. closing of a production line that was able to process all product classes).

6.1.2 Consideration of cost effects of the FESCPC

The second important application constraint is the **consideration of the cost effects of the FESCPC**. In many application cases, costs are not only responsible for the applicability of different parts of the SCPC. They also influence the execution of the SCPC as a whole. As stated in chapter 2, the common RM **assumption of zero/low marginal costs** cannot be held in practice and must be relaxed. The result is the **consideration of the short-term bottom price**, which is at least equal to the variable production costs or costs of providing a service. However, it is not only the costs directly related to the FESCPC, which have to be analyzed in order to see the performance of the solution in the running system. **Irradiation effects** on other tasks within the service provision may result from the revenue maximization. While, in this work, the cost side (as the main focus of SCM) is set constant in the direct profit maximization, the effects, which RM applications have on it, have to be analyzed in order to avoid the disruption of the positive effects on the revenue side by the negative effects on the cost side. In the application presented, the FESCPC is conducted in the context of Transportation Management. The main influenced cost factor (besides the vehicle fleet itself) is, thereby, the **vehicle routing costs, resulting from the revenue-optimized delivery lists**. Hereby, the basic **supply chain flexibility** plays an important role and has to be described before the illustration of the **vehicle routing problem (VRP)**.

6.1.2.1 Supply chain flexibility

The flexibility idea with respect to Supply Chain Management (SCM) reflects - according to its broad definition - “the ability of a system to properly and rapidly respond to changes, coming from inside as well as outside the system” [Garavelli 2003]. By looking at the different aspects of flexibility (functional, hierarchical, measurement, strategic, time horizon and object-oriented aspects) in the context of the application case, the argument of addressing this important objective as a whole within supply chain management emerges.

In contrast to this, the (central) planning of all sub-tasks of the supply chain planning can - in practice - only be realized by a (hierarchical) decomposition of the over-all problem in sub-problems [Kistner/Steven 2001] because of organizational reasons (in contrast to technical reasons like processor capacity). For instance, increasing effects of uncertainties in complex planning approaches as well as effects of changes in one planning task on other tasks [Fleischmann/Meyr/Wagner 2005] can be stated.

Following the application case, the mentioned aspects of flexibility are reflected: By reducing the flexibility objective to one planning horizon (short-term planning within the time horizon aspect) [Zelenovich 1982], as well as a certain planning task (short-term capacity- and price-oriented transport planning as object-oriented aspect) [Vickery/Calantone/Droge 1999], flexibility improvements with direct implications for the profit-optimization problem can be reached without significant negative effects caused by too many planning tasks. Thus, the flexibility in this context concerns the operational flexibility (on-line control of customer requests as strategic aspect) [Gerwin 1993] in logistics (concerning the distribution as a functional aspect) [Barad/Sapir 2003; Kim 1991], also in terms of applicability of the solution in the practice of the producer [Gupta 1993; Koste/Malhorta 1999] (which can also be regarded as an aspect of flexibility). The solution concept, thereby, directly indicates the **higher flexibility by significant positive revenue effects without higher costs** [Sarker et al. 1994; de Groote 1994].

In this discussion about supply chain flexibility in the context of the application case, the **degree of interaction of the concerned management approaches** has to be determined. As shown in figure 6-2, mainly three management approaches are concerned by the application case: Revenue Management, Production Management and Logistics Management. Thereby, Revenue Management can be seen as directly connected to Production Management, as the delivery capacity (as a fraction of the production for the European market) has to be sold to the different customers located within the distribution area of the depot at the production site of the glass film producer. In this work, the contribution of Revenue Management to the overall profit optimization problem is analyzed under consideration of the effects on the vehicle routing (point 1 in figure 6-2). Further research has to consider the integration of Revenue and Logistics Management (point 2).

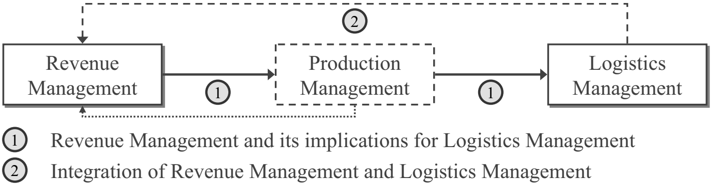

Figure 6-2: Interaction of the concerned management approaches

In the following, the above statements to the profit and flexibility effects in the context of the application case are proven by addressing the two sub-problems revenue optimization of delivery lists and vehicle routing. Therefore, the basic understanding and concepts for the **vehicle routing problem (VRP)** have to be outlined.

6.1.2.2 *Vehicle routing for the revenue-optimized delivery lists*

The VRP is characterized by a class of problems associated with the determination of a set of routes for a fleet of vehicles located in one or more depots for a number of geographically dispersed customers [Domschke 1995; Domschke 1997]. Using the common notation in VRP, a simple example clarifies the basic problem of vehicle routing:

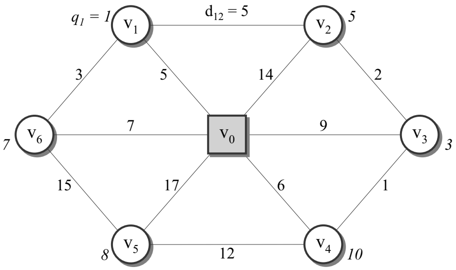

Figure 6-3: Illustration of a vehicle routing problem

Starting at the depot v_0, the amount of n (in figure 6-3 n = 6) nodes of the set $V = \{v_0,...,v_n\}$ has to be served. The nodes are thereby the unloading points with the distances d_{ij} $(i = 0,...,n; j = 0,...,n)$[110] and the demand q_j $(j = 1,...,n)$[111]. In vehicle routing, the number of routes[112] is also determined by the available vehicles in the fleet $F = \{f_1,...,f_m\}$.

Based on this simple example, various VRP specifications are founded on the following **[α|β|γ|δ]-classification** [Domschke 1997, pp. 207; Golden/Assad 1988]:

- **Depot and unloading point characteristic α**

  The determination of the node characteristics (depots and unloading points) includes different aspects:

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[110] In many model descriptions of VRP, the graphs G are presented as G[V,E,d]. E, thereby, is the set of edges between the nodes with the according distances. Often, edge-oriented problems build the basis for a VRP (example: garbage removal).

[111] In the work at hand, the demand q_j equals the accepted capacity units in the FESCPC, $A_{cs(t+1)}x_{cst}$. Thus, it is the basis for the revenue-optimized delivery lists. In figure 6-3, q_j is represented by the italicized numbers.

[112] A tour is defined by the specification of the number of unloading points, the depots, as well as the distances (often given by a distance matrix) between the depot(s) (or the edges) and the unloading points, and between the unloading points themselves. A route is the order in which the unloading points are approached [Domschke 1997, p. 206].

  - Number of depots (single vs. multiple depot cases)
  - Demand types (e.g. node-oriented vs. edge-oriented, VRP with pick-up and delivery vs. VRP with backhauls)
  - Possibility of split deliveries
  - Time aspects (e.g. fixed schedule vs. time windows)
  - Order constraints (e.g. fixed vs. flexible order)
  - Operational degrees of freedom (e.g. serving each customer vs. serving only sub-sets of customers, traveling along each edge vs. choice of served edges)

- **Vehicle characteristics β**

  Vehicle characteristics concern the limitations within the vehicle fleet:

  - Size of the vehicle fleet
  - Capacity constraints (identical vs. different capacities of the vehicles)
  - Time limitations (e.g. hours of service)
  - Maximum duration of a tour or route
  - Number of tours or routes in the planning period

- **Problem and additional characteristics γ**

  These aspects concern all specifications of the underlying graph, the service strategies, and the limitations of the vehicle allocation to the depots and unloading points:

  - aspects of the underlying graph (directed vs. undirected graphs or hybrid graphs)
  - Suitability of vehicles for certain depots and unloading points (e.g. vehicle sizes that cannot be processed in an unloading point)
  - Periodicity of the plan (single- vs. multi-period plans)

- **Objectives δ**

  The most important objectives in the VRP are[113]:

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[113] In the execution of vehicle routing, these objectives are often closely connected. Therefore, the transportation expenses very much depend on the covered distances and/or the driving time.

  - Minimization of the covered distances
  - Minimization of the driving time
  - Minimization of the amount of vehicles or tours
  - Minimization of the transportation expenses

Using the basic classification, the following **examples for** the **main standard problem types of vehicle routing** can be distinguished (see Dantzig/Ramser [1959] and Balinski/Quandt [1964] for first descriptions of the VR problem types). Thereby, all combinations of the above illustrated [α|β|γ|δ]-classification can be built:

- **Capacitated VRP (CVRP)**
  A CVRP is a VRP with the constraint of having vehicles with a uniform capacity, which must service the known demand for a single good from one depot. The additional restriction compared to VRP is that the demand on a whole route must not exceed the vehicle capacity [Fleischmann 1994; Kopman et al. 1994]. Examples for CVRP are parcel services and shipping companies.
- **Multiple depot VRP (MDVRP)**
  A MDVRP results if a company has several depots, and the unloading points cannot be clearly assigned to one depot (which would lead to a set of independent VRPs). Each depot thereby has a fleet of vehicles, which depart from and return to the same depot. As examples for MDVRP, the furniture and chemical industry can be stated. Often, the application cases are characterized by the need for reloading or dividing the sales areas [Laporte et al. 1988; Renaud et al. 1996].
- **VRP with time windows (VRPTW)**
  Here, a time window is associated with each unloading point. The unloading point has to be supplied within this time window. In cases where the vehicle arrives the unloading point before the lower bound of the time window, additional waiting time results. Those time windows may also exist for the depot(s). A well-known example of VRPTW is the newspaper logistics, where the latest departure times are determined by the latest delivery time from the delivery boy to the customer [Solomon 1995].

- **Split delivery VRP (SDVRP)**
  The demanded capacity has not to be served by a single vehicle but can be supplied by more vehicles if the over-all costs are reduced [Dror et al. 1994]. An example is cargo transportation with customer demands that are larger than the vehicle capacity.
- **VRP with backhauls (VRPB) and VRP with pick-up and delivery (VRPPD)**
  In both, VRPB and VRPPD, the delivery as well as the backhaul of commodities are possible. In contrast to the VRPB, in VRPPD, the backhaul commodities can be unloaded also at one of the other unloading points and not only at the depot. An example for VRPB is garbage collection or the backhaul of empties. Examples of VRPPD are the delivery of rental items from one customer to the other (e.g. cranes) and shared taxis [Atkinson 1990; Ioachim et al. 1995].
- **Periodic VRP (PVRP)**
  For many VRPs, the planning period is one day. However, in some cases, recurrent VRPs have to be considered. The potential unloading points may not always have to be supplied or the demand may vary. Examples are the disposal of residual or industrial waste, or the supply of gas stations by refineries [Ahrens et al. 1978; Russel/Gribbin 1988; Gaudioso/Paletta 1992].
- **Stochastic VRP (SVRP)**
  The problem of random components within VRP adds to its complexity through three apparent kinds of stochastic influences: Stochastic customers/unloading points (e.g. VRP with a pool of customers who do not order in every planning period), stochastic demands (e.g. customers with varying demands), as well as stochastic service and travel times (e.g. travel times in cities because of traffic jams, accidents, and unexpected weather changes) [Malandraki/Daskin 1992; Gietz 1994].

The mathematical representation [Domschke 1997] of the **[1|$\mathcal{M}$,cap,dur| |L] VRP** [see Domschke 1997, p. 212] standard CVRP, that has to be solved in the goods distribution application, is illustrated in the following. The objective is to find a solution that minimizes the total travel length. The daily logistics management task is to achieve a cost optimized delivery of clear and colored glass films to n different customers with the non-negative demand q_i ($i = 1,\ldots,n$). The customers v_i and the depot v_0 at the production site in central Germany are expressed as a set of vertices $V = \{v_0,\ldots,v_n\}$. Furthermore, a complete distance matrix containing non-negative distances d_{ij} between v_i and v_j is given. Customers specified in the delivery lists are daily supplied with the usage of a homogeneous vehicle fleet $F = \{f_1,\ldots,f_m\}$, whereas the m used vehicles, rented from a sub-company, cause variable costs of € 1.50 per kilometer. Additionally, the vehicle capacities c_{max} (4.0 tons per day) and the maximum tour length restriction l_{max} (900 km per day) have to be kept.

indices:	**variables:**	**parameters:**	
$i = 0,\ldots,n$ = vertex	x_{ijk} = order of delivery	d_{ij} = distance between v_i and v_j	l_{max} = maximum tour length
$j = 0,\ldots,n$ = vertex	y_{ik} = vehicle assignment	q_i = demand of customer v_i	n = number of customers
$k = 1,\ldots,m$ = vehicle		c_{max} = vehicle capacity	m = number of vehicles

Table 6-1: Mathematical formulation of the vehicle routing problem

$$\text{Minimize} \sum_{i=0}^{n}\sum_{j=0}^{n} d_{ij} \sum_{k=1}^{m} x_{ijk} \tag{6-1}$$

subject to

$$y_{ik} = \begin{cases} 1 & \text{if } v_i \text{ is supplied by vehicle } f_k \\ 0 & \text{otherwise} \end{cases} \tag{6-2}$$

$$x_{ijk} = \begin{cases} 1 & \text{if vehicle } f_k \text{ directly supplies } v_j \text{ after } v_i \\ 0 & \text{otherwise} \end{cases} \tag{6-3}$$

$$\sum_{i=1}^{n} q_i y_{ik} \le c_{max} \quad \forall k=1,\ldots,m \qquad \text{(capacity restriction)} \tag{6-4}$$

$$\sum_{i=0}^{n}\sum_{j=0}^{n} d_{ij} x_{ijk} \le l_{max} \forall k=1,\ldots,m \qquad \text{(maximum tour length)} \tag{6-5}$$

$$\sum_{k=1}^{m} y_{ik} = 1 \ \forall i=1,\ldots,n \qquad \text{(each customer served by exactly one vehicle)} \tag{6-6}$$

$$y_{0k} = 1 \ \forall k=1,\ldots,m \qquad \text{(the depot is the only common node for all vehicles)} \tag{6-7}$$

$$\sum_{i=0}^{n} x_{ijk} = y_{jk} \quad \forall j=0,\ldots,n;\ k=1,\ldots,m \qquad \text{(all vertices } v_j \text{ have exactly one incoming edge)} \tag{6-8}$$

$$\sum_{j=0}^{n} x_{ijk} = y_{ik} \quad \forall i=0,\ldots,n;\ k=1,\ldots,m \qquad \text{(all vertices } v_i \text{ have exactly one outgoing edge)} \tag{6-9}$$

$$\sum_{i\in Q}\sum_{j\in Q} x_{ijk} \le |Q|-1 \qquad \text{(no routes with single nodes)} \qquad 6\text{-}10$$
$$\forall Q \subseteq V\backslash\{v_0\} \text{ with } 2 \le |Q| \le n;\ k=1,...,m$$

$$y_{ik} \in \{0,1\}\ \forall i=1,...,n;\ k=1,...,m \qquad 6\text{-}11$$

$$x_{ijk} \in \{0,1\}\ \forall i=0,...,n;\ j=0,...,n;\ k=1,...,m \qquad 6\text{-}12$$

The constraints 6-4 and 6-5 represent the capacity restriction and the maximum tour length for a homogeneous vehicle fleet. Every customer is supplied by exactly one vehicle (6-6) and the only common node of all vehicles is the depot (6-7). The side conditions (6-8), (6-9) and (6-10) postulate that every vehicle route has the form of a TSP, whereas (6-10) prohibits routes containing just the depot and one more node.

The transportation problems in practice are often characterized by more than one of the mentioned aspects. Examples for such combinations of VRPs can be found in Bodin et al. [1989], Gietz [1994] or Ioachim [1995]. The solution of these VRPs can be divided into two basic groups: **Exact solutions and heuristic approaches**. As the decision context becomes more complex, heuristic approaches perform better and better [Silver 2004]. In the context of VRP, the specification of the [α|β|γ|δ]-values in practice leads to a NP-hard[114] decision problem that is not solvable with a justifiable (computation- and resource-) expense [Domschke 1997, p. 234, Gietz 1994, Silver 2004]. Thus, heuristic methods seem to be appropriate in many cases despite having the possibility of not reaching or recognizing an optimal solution. In heuristic approaches, the optimization problem is often divided into sub-problems that allow an easier solution of the decision problem [Silver 2004, p. 949]. Domschke/Drexl [2005] determined the distinction of the sub-problems into construction heuristics (for the determination of a first feasible solution) and improvement heuristics (for the improvement of the initial solution)[115]. In figure 6-4, examples of the main solution techniques for VRPs are given. While meta-heuristics already include both sub-problems, specific improvement heuristics are recommended particularly for basic heuristics[116]. Sometimes improvement heuristics, however, seem to be adequate for meta heuristics [e.g. Rochat/Taillard 1995]. Additionally, using one heuris-

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[114] *NP (non-deterministic polynomial time)* is the set of decision problems solvable in polynomial time on a non-deterministic Turing machine.

[115] In the FESCPC, the construction heuristic is the finding of the initial solutions for the price levels and for the capacity distribution. The improvement heuristic is the fuzzy expert control.

[116] Domschke [1997, p. 245], for example, recommends a 2-opt or 3-opt algorithm for the Savings method.

tic as a construction procedure for the other heuristic (which is then used for the improvement), seems to be beneficial in many cases (e.g. using Savings for the initial routes for the Tabu Search). Altogether, all kinds of hybrid heuristics using the basic approaches exemplarily stated in figure 6-4 seem feasible if improvements are reached.

The **application case** that underlies the analysis of the FESCPC predominance over the FECC and FEPC, can be understood as a **[1|$\mathcal{M}$,cap,dur| |L] VRP** [see Domschke 1997, p. 212]. For these cases, the **Ant Colony Optimization** and the **Tabu Search** algorithm are especially stated in the literature as potentially adequate heuristics, all in all against the background of up to 300 unloading points per day. This seems to lead to a decision problem not optimally solvable [Taillard 1993; Osman 1993]. To eliminate errors (distortion effects) in the results, which arose because of the use of an inadequate method, both of the potentially feasible VRP algorithms are analyzed. Following the analysis, the best is used to determine the **effects of the revenue-optimized delivery lists through the FESCPC, FECC and FEPC on the transportation costs**.

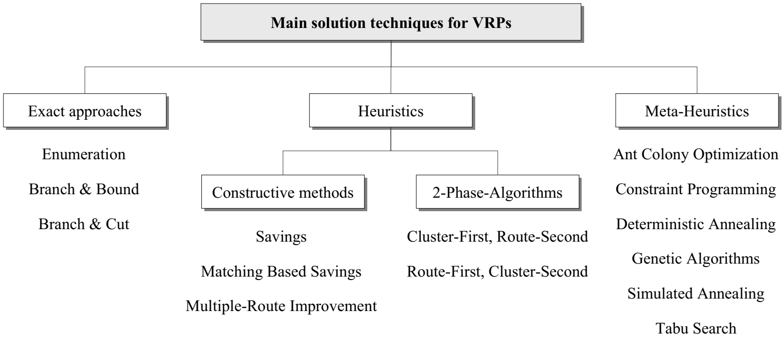

Figure 6-4: Extract of the main solution techniques for VRPs

6.2 Description of the goods distribution application

In the practical execution of a FESCPC, an application in the **goods delivery of a glass film producer** is considered. The company is spread over Europe with several production sites and depots. Requests of the customers (mainly car and airplane, as well as building industry) are preferably satisfied by the depots that are located at the corresponding market. Besides, requests can also be met by other depots or third-party distributors, such that an Europe-wide production and distribution network results. In this work, the distribution of two goods, clear and colored glass films, that meet the needs for specific safety (e.g. sun protection) and convenience (e.g. colors) glass films, is taken into account. As part of the production capacity of the discussed production site in central Germany (extraction of a sub-market), a 20 tons (over 7200 sqm.) daily delivery capacity for the German market has to be distributed daily to a pool of 300 customers, whose demand varies significantly. Thus, the profit optimization problem concerns the revenue-optimization of delivery lists for the vehicle routing (under consideration of its cost effects) of the depot in central Germany. Two sub-problems emerge: First, the **delivery capacity has to be distributed to the two produced goods** (with favor for the premium product colored films with a higher unit profit margin) and the **capacity units have to be delivered to the customers at a price as high as possible**. Thereby, idle capacities have to be avoided[117]. Second, the resulting delivery lists for each day have to be worked off at as low costs as possible. The central problem addressed here, thus, concerns not the production of the glass films (which is adequately scheduled in the company-wide context for 20 tons delivery capacity per day). **The FESCPC considers the revenue-enhancing distribution of the products to the customers**.

In the following, all three possible approaches to the revenue optimization of the delivery capacity are compared to the current situation: Fuzzy Expert Capacity Control (FECC), Fuzzy Expert Price Control (FEPC) and Fuzzy Expert Simultaneous Capacity and Price Control (FESCPC).

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[117] As in reality, also in this application, all requests of the customers are served by the company, either by the central depot of the market, by other depots, or by third-party distributors. For this work, the German market is considered with its associated customers. In the application, rejected customers are not really rejected but only not delivered by the considered depot.

The planning period is one day (24 hours), a time point equals a request of a customer (t = 1, thereby, corresponds to the first request of a customer for the delivery at the next day which arrives - as per the data analysis - up to 25 days before the delivery date). For a delivery date, up to 300 requests may occur for each product. In order to simulate a running system in which the fuzzy expert control is taken out, one month is taken into account, where the capacity and price decisions are made on-line per day, leading to over 150,000 control steps within the month. The current practice in the glass film depot is not known, but it has to be assumed that it is a kind of first-come-first-served approach.

6.3 Execution of the FESCPC

As illustrated in the conception of the solution (see figure 3-12), also for the FESCPC the basic tasks in the fuzzy expert system development have to be met:

- Identification of the problem context
- Determination of all variables and parameters and building of the initial capacity distribution
- Adjustment of the capacity distribution and the price level

6.3.1 Identification of the problem context

The problem analysis shows that the FESCPC in the goods distribution meets the constraints for RM formulated in chapter 2:

- **Relatively fixed capacity**
  The over-all capacity for the FESCPC refers to the delivery capacity of the glass film depot. The 20 tons capacity results from the amount of square meters (sqm.) of glass films that can be distributed. The limiting factors is, besides the fleet capacity itself (20 tons correspond to over 7200 sqm. films, which have to be specially protected and transported cooled), the production quantity in combination with the problematic storage of the glass films.

- **Perishable capacity**

  The start of a distribution cycle is a classical example for the perishable capacity constraint. No more requests can be processed after the fleet left the depot.

- **High costs of capacity increases**

  The increase of the capacity would afford besides the increase of the production and storage facilities also the purchase of additional transport vehicles.

- **Marginal costs**

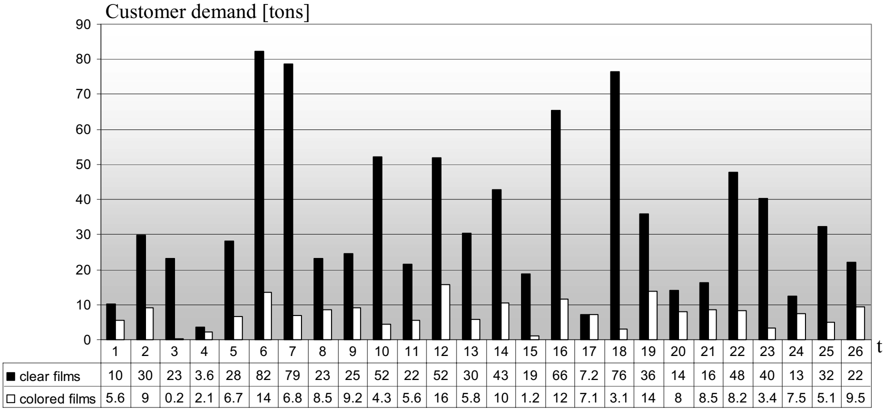
  Two types of marginal costs can be stated in this application. The production costs are assumed to be fixed as no changes in the production process are the result of the illustrated problem. However, these costs are known and introduced in the decision process with the result of calculating in terms of profit margins. The delivery costs are affected by the FESCPC. The costs of the transportation are calculated with €1.50 per kilometer. By adjusting the capacities and prices, different delivery lists result, which have to be processed adequately.

- **Fluctuating demand**

  The demand for the two classes fluctuates as illustrated in figure 6-5. It can be observed that the demand for both glass films is very variable, depending on the demand of the final user. The variations have a lot to do with the poor stocking opportunity of the glass films.

- **Product sale in advance**

  Accepted bookings cannot be rejected anymore because, otherwise, the customers would have to stop production, which has severe implications for the relationship to the glass film producer. Rejected bookings, instead, are processed by other depots or subcontractors of the glass film producer, such that no effects on the production can occur.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
■ clear films	10	30	23	3.6	28	82	79	23	25	52	22	52	30	43	19	66	7.2	76	36	14	16	48	40	13	32	22
□ colored films	5.6	9	0.2	2.1	6.7	14	6.8	8.5	9.2	4.3	5.6	16	5.8	10	1.2	12	7.1	3.1	14	8	8.5	8.2	3.4	7.5	5.1	9.5

Figure 6-5: Demand in each product class

- **Ability of market segmentation**

  The glass film plant produces two goods: Colored films and clear films. With a current average price (inclusive delivery) of €9,661.83 for colored films and €9,389.51 for clear films, and due to strategic considerations, colored films are assumed to be the premium products.

6.3.2 Determination of all variables and parameters

The following factors have to be determined when executing the full solution concept for the FESCPC:

- **Over-all capacity k**

  As stated before, 20 tons distribution capacity has to be controlled on a daily level. Over one year, this corresponds to the delivery of 2,250,000 sqm. glass films.

- **Workload W_{st}**

  As defined in chapter 3, W_{st} is calculated as a cumulative variable, depending on the accepted requests of distribution capacity within the planning period. This acceptance decision has to be made by the supplier (acceptance of the requests based on the available capacity), as well as by the consumer (acceptance of the supplier price based on the willingness to pay). For each adjustment step (in this case, a request-based decision is made like in the hotel FEPC)), the workload is computed and the FESCPC is executed.

- **Rest time r_t**

  The planning period of this month consists of 26 days. The requests for each day arrive already far before the end of the planning period (up to 25 days), which leads to the same implications as in the hotel application (parallel fuzzy expert systems). The rest time is measured in hours until the departure of the fleet.

- **Customer value clv_{ct}**

  In this application, no information about the customer value is available. Therefore, this influence has to be excluded from the fuzzy expert system.

- **Reservation price rp_{cst}**

  The reservation price is estimated for each customer with the assumption of an underlying normal distribution [Fahrmeir et al. 2004, pp. 90]. For the necessary sensitivity analysis of the behavior of the FESCPC with respect to reservation price variations, this estimation is varied, too.

- **Short-term bottom prices pu_{st}**

  The bottom prices for the pricing part in the FESCPC are determined from past data. For the colored films, the bottom price is set at €9,000, for the clear films at €8,500 (due to the higher production costs of the colored films).

- **Definition of the adjustment steps**

  A request-based modification is executed, meaning that a new adjustment step is taken out for each customer request.

- **Building of initial contingents and prices**

  As initial contingents, simply the mean values of the previous period is set (7.157 tons for colored films, 12.843 tons for clear films). Looking at the variability of the demand for the two glass films (see figure 6-5), this procedure seemed reasonable. The price variations implicated also the use of the average prices for the initial price setting (€9,661.83 for colored films and €9,389.51 for clear films).

6.3.3 Adjustment of the capacity distribution and the price level: FESCPC

While in the capacity component, only the colored films are controlled (two class case), the price setting needs a fuzzy expert system for both classes. Besides, the same procedure is used as in the previous applications. In the integrated FESCPC, however, the iterative procedure illustrated in chapter 3 (section 3.1.2) has to be applied. The result is that, for each adjustment step for colored films, firstly the capacity control is executed, followed by the price control. The connection of the two control components is the workload of the considered class.

For the illustration of the integrated control, one adjustment step in the resulting fuzzy expert systems for the colored films is shown in figure 6-6:

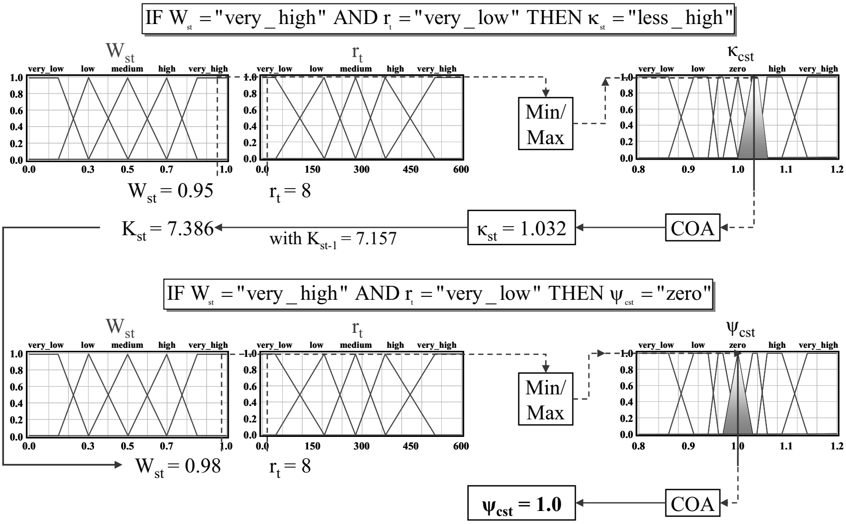


Figure 6-6: Example for a capacity adjustment with FESCPC

The iterative procedure of the FESCPC is realized by firstly executing the CC part:

According to the described development of fuzzy expert controllers (section 3.3.2), the in- and output variables are transformed into linguistic variables in the fuzzification step. For two

real-valued inputs ($W_{st} = 0.95$ and $r_t = 8$ hours), only one rule (see figure 6-6) is addressed. The inference process is executed on the basis of a max-min-inference with a maximum result aggregation. The membership degrees
$\mu_{very\_high}(W_{st} = 0.95) = 1.0$ and $\mu_{very\_low}(r_t = 8) = 1.0$ are combined over a minimum conjunction:

$$\mu_{very\_low}(\kappa_{st}) = 0$$
$$\mu_{low}(\kappa_{st}) = 0$$
$$\mu_{less\_low}(\kappa_{st}) = 0$$
$$\mu_{zero}(\kappa_{st}) = 0$$
$$\mu_{less\_high}(\kappa_{st}) = \min\left(\mu_{very\_high}(W_{st} = 0.95), \mu_{very\_low}(r_t = 8)\right) = 1.0$$
$$\mu_{high}(\kappa_{st}) = 0$$
$$\mu_{very\_high}(\kappa_{st}) = 0$$

For this input constellation, no result aggregation and no composition are necessary, because of one single rule being addressed.

A COA defuzzification translates the linguistic output value into the real value $\kappa_{st} = 1.032$, meaning a 3.2% increase of the capacity of colored films. For this, the corresponding values are calculated from the fuzzy system (compare to figure 6-6):

$$\kappa_{st} \text{ with } \int_{-\infty}^{\kappa_{st}} \mu(\kappa_{st}) \cdot dy = \int_{\kappa_{st}}^{+\infty} \mu(\kappa_{st}) \cdot dy \approx 0.09 \text{ for } \kappa_{st} \approx 1.032$$

This marginal increase seems reasonable, as, despite the very high workload, only 8 hours are left until the departure of the vehicle fleet. It is very unlikely that a significant higher contingent would be sold in the remaining time.

Figure 6-6 explicitly demonstrates the connection between the CC and PC over the workload:

The new workload ($W_{st} = 0.98$ instead of 0.95) has to be combined, again, with $r_t = 8$ hours. On the basis of a max-min-inference with a maximum result aggregation, the membership degrees $\mu_{very\_high}(W_{st} = 0.98) = 1.0$ and $\mu_{very\_low}(r_t = 8) = 1.0$ are combined over a minimum conjunction, too:

$$\mu_{very\_low}(\psi_{cst}) = 0$$
$$\mu_{low}(\psi_{cst}) = 0$$
$$\mu_{less\_low}(\psi_{cst}) = 0$$
$$\mu_{zero}(\psi_{cst}) = 0$$
$$\mu_{less\_high}(\psi_{cst}) = \min\left(\mu_{very\_high}(W_{st} = 0.98), \mu_{very\_low}(r_t = 8)\right) = 1.0$$
$$\mu_{high}(\psi_{cst}) = 0$$
$$\mu_{very\_high}(\psi_{cst}) = 0$$

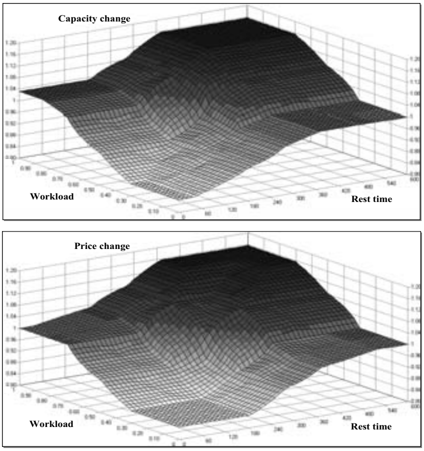
A COA defuzzification is also used for the PC part. The result is $\psi_{cst} = 1.0$, implying no price change for colored films. The corresponding values are calculated from the fuzzy system:

$$\psi_{cst} \text{ with } \int_{-\infty}^{\kappa_{st}} \mu(\psi_{cst}) \cdot dy = \int_{\kappa_{st}}^{+\infty} \mu(\psi_{cst}) \cdot dy = 0.15 \text{ for } \psi_{cst} = 1.0$$

The result of the PC component is, that, despite the very high workload, the price of colored films is not increased. Especially against the background of the slightly raised capacity and only 8 hours are left until the departure of the vehicle fleet, this output seems reasonable. It is very unlikely that the (higher) contingent would be sold also at a higher price in the remaining time.

Figure 6-7 indicates the possible constellations and the consequences for the colored films. It can be observed that there are small differences in the rule bases of the two control options, but all together the two components are very similar. This is one of the additional positive effects of the FESCPC. The practicability is further enhanced by similar control components. The development of this fuzzy expert system was thereby carried out with over 150,000 control steps.

W	r	κ
Very high	Very high	Very high
Very high	High	Very high
Very high	Medium	High
Very high	Low	Less_high
Very high	Very low	Less_high
High	Very high	Very high
High	High	Very high
High	Medium	High
High	Low	Zero
High	Very low	Zero
Medium	Very high	High
Medium	High	High
Medium	Medium	Zero
Medium	Low	Low
Medium	Very low	Low
Low	Very high	Zero
Low	High	Zero
Low	Medium	Less_low
Low	Low	Low
Low	Very low	Very_low
Very low	Very high	Zero
Very low	High	Zero
Very low	Medium	Less_low
Very low	Low	Low
Very low	Very low	Very low



W	r	ψ
Very high	Very high	Very high
Very high	High	Very high
Very high	Medium	High
Very high	Low	Less_high
Very high	Very low	Zero
High	Very high	Very high
High	High	High
High	Medium	High
High	Low	Zero
High	Very low	Zero
Medium	Very high	High
Medium	High	High
Medium	Medium	Zero
Medium	Low	Low
Medium	Very low	Low
Low	Very high	Zero
Low	High	Zero
Low	Medium	Low
Low	Low	Very low
Low	Very low	Very low
Very low	Very high	Zero
Very low	High	Less_low
Very low	Medium	Low
Very low	Low	Very low
Very low	Very low	Very low

Figure 6-7: Input/output relation in the FESCPC

6.4 Results for the FESCPC

For this application, two kinds of results can be stated. Firstly, the results for the conduction of the FESCPC and, secondly, the results for the analysis of the cost effects are presented.

6.4.1 Revenue effects of the FESCPC

The results for the executed FECC, FEPC and FESCPC are outlined in table 6-2 and figure 6-8. The solution concept is proven to significantly raise the revenue in the considered application case. The applicability and the higher flexibility compared to the current situation, thus, is also shown. Especially the claimed management flexibility leads to the exploitation of the whole revenue potential. Table 6-2 shows that all components of the integrated capacity and price control lead to significant revenue improvements. The FECC (sole capacity control) increases revenue by €94,000, the FEPC (sole price control) by €210,000 and the FESCPC by €243,000. As also in the separated analysis of the revenue effects production costs can be considered (marginal cost constraint), these are included. The resulting profit margins are 2.80% (FECC), 6.28% (FEPC), and 7.25% (FESCPC) higher than the profit margin of the current situation. Thereby, the FESCPC profit is only 0.97% higher than the FEPC profit. On the one hand, this is due to the chemical industry application, where typically high lot sizes and high unit prices can be observed. The consequence is that price changes have more effects than capacity adjustments. On the other hand, 0.97% more profit equals €33,000 per month, meaning an increase of up to €400,000 per year. This implies a **significant revenue enhancement when executing the integrated capacity and price control**.

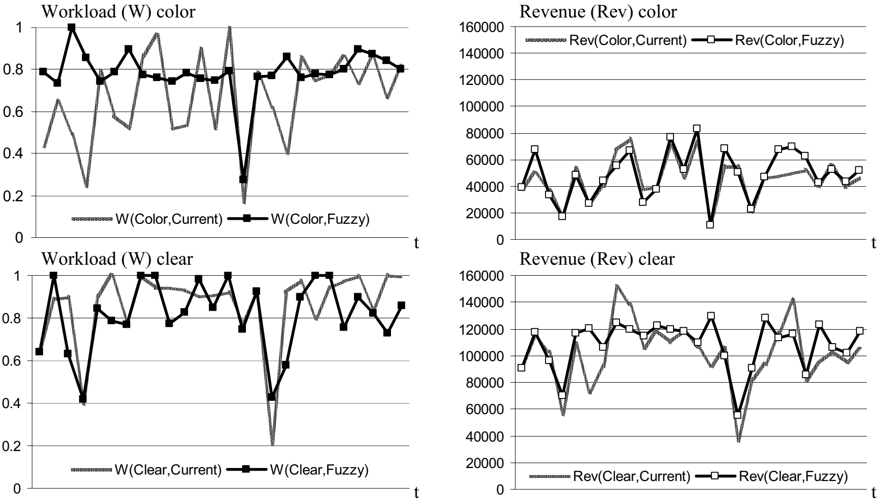


Figure 6-8: Comparison of the fuzzy expert controllers

	W_1	W_2	R_1	R_2	PM_{1+2}	%dW	%dR	%dPM
Current	66.44	86.15	1.188	2.633	3.348	-	-	-
FECC	76.47	81.97	1.223	2.706	3.442	1.15	2.82	2.80
FEPC	66.31	82.58	1.305	2.714	3.558	-2.96	5.18	6.28
FESCPC	78.33	81.39	1.268	2.813	3.591	1.52	6.81	7.25

s = 1 (colored films), 2 (clear films); W_s = workload [%]; R_s = revenue [Mio. €]; PM_s = profit margin [Mio. €]; %dW (R, PM) = percentage change of W (or R, PM), weighted by the sold capacity

Table 6-2: Results for all fuzzy expert control approaches

The analysis of the FESCPC against the current approach shows significant revenue increases in both classes. By looking at figure 6-8, the revenue level being at least as high as the current revenue becomes obvious for almost each day in the concerned month.

One analysis that is missing in consistence with the previous applications is the sensitivity analysis of the PC part. In the goods distribution, also test data is used for the development and evaluation of the FESCPC. Therefore, the same implications result as in the FEPC. This sensitivity analysis is outlined in figure 6-9. It shows that, compared to an average reservation price variation of 46.55% (colored films) and 25.77% (clear films) at each day (four variations), the **CV for the FESCPC is very low for the revenue as well as the workload in both classes**. On average, for colored films, the CV is 6.56% for the revenue and 4.53% for the workload, indicating the robustness in this class. Average values of 3.68% (revenue) and 2.11% (workload) imply the same conclusion for the clear films. In most cases, the CV for the FESCPC is similar to the current situation, due to the price-dominated scenario in the chemical goods delivery (high unit prices). The reason for the few higher values in the FESCPC is the low demand for the concerned classes at these days. This implies the prerequisite of a sufficiently high demand for the FESCPC to perform well with respect to highly varying reservation prices.

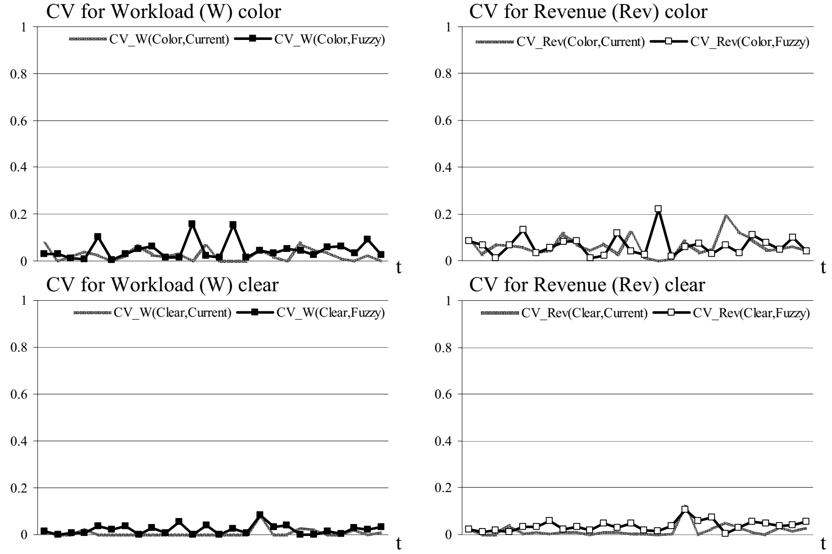


Figure 6-9: FESCPC variability with respect to reservation price changes

While the higher flexibility in terms of demand and price flexibility leads to higher profit margins in all cases of fuzzy expert control, the flexibility increase through the integrated solution can be observed in figure 6-10. FECC focuses on the capacity distribution and increases workload in the lucrative class by far. FEPC, in contrast, focuses more on the price optimization, resulting in an even higher revenue but lower workload. FESCPC focuses on both objectives at the same time. By looking at figure 6-10, it can be seen that, in most cases, FESCPC belongs to the prevailing approaches (indicated by the shaded parts in the figure). In addition, the lines for the integrated solution mostly follow the currently prevailing FECC or FEPC approach, indicating that **FESCPC is more flexible in fulfilling the requirements and objectives of the integrated capacity and price control**.

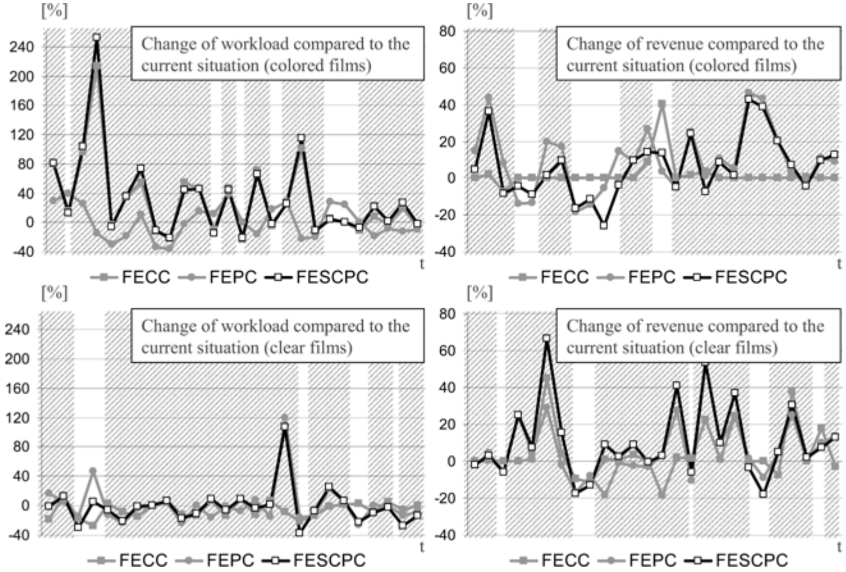


Figure 6-10: Comparison of the fuzzy expert controllers

The conclusion of the revenue effect analysis is that the FESCPC outperforms the current practice in the glass film company. The fuzzy expert system is robust and performs corresponding to the formulated objectives and requirements. However, one step missing is the proof that the positive revenue effects in the distribution case are not offset by negative effects of the vehicle routing costs. The hypothesis, thereby, is that the vehicle routing algorithms are flexible but also stable enough to find prevailing solutions for different delivery lists.

6.4.2 *Cost effects of the FESCPC on the vehicle routing*

As the second sub-problem of this application, the above formulated objective concerning the compensation of positive revenue effects by negative cost effects is analyzed. The delivery lists resulting from the current situation and the FESCPC contain the demand of each customer at a specific day as well as the customer’s location.

The CVRP is solved by the implementation of two heuristics that have reached good results when applied on the literature's instances: A tabu search heuristic and an approach based on ant colony optimization. Both approaches are intended to give good results in the underlying application case. However, in order to avoid effects caused by a specific algorithm, both are executed and the different cost effects are analyzed.

- **Tabu search**
  A standard tabu search heuristic is implemented corresponding to the literature [Taillard 1993]. The initial solution consists of tours with a separate vehicle for each city. As a neighborhood structure λ-interchanges, i.e. an exchange of up to λ customers between two tours with restriction to feasible solutions are disposed [Osman 1993]. Thereby, a neighborhood type of (1,1) is used, i.e. swaps (1,1) as well as moves (1,0) and (0,1) respectively are executed in each iteration. For each iteration, two tours are randomly chosen. The best solution generated through the neighborhood search initializes the next iteration even if it is worse than the current solution. Solutions containing interchanges in the tabu list are forbidden unless a new very best solution is reached. The evaluation of the tours is done by solving a simple TSP as proposed by [32]. Moreover, a post-optimization with the 2-opt heuristic is executed every 200 iterations. The algorithm is stopped after 2500 iterations without finding a new best solution and finished with a post-optimization with 2-opt. As an extension of the standard tabu search, a union of two tours followed by a 2-opt optimization is conducted as it may lead to an improvement of the solution.

- **Ant colony optimization**
  The ant system approach is based on the ideas of the approaches of [Reimann/Doerner/Hartl 2003; Gambardella/Taillard/Agazzi 1999; Bullnheimer/Hartl/ Strauss 1999; Dorigo/Gambardella 1997]. For a given number of iterations (e.g. 20 iterations without finding a new best solution), the construction of vehicle routes, followed by an optimization with 2-opt and a pheromone trail update is repeated. The algorithm starts with a size of 25 ants in randomly chosen vertices. The ants choose the next node according to the random proportional rule of [Bullnheimer/ Hartl/Strauss 1999] and the exploitation factor q0 of [Gambardella/Taillard/Agazzi 1999]. In our case the visibility function $\eta_{ij} = 1/d_{ij}$ performed better than the usage of a savings function as proposed by [Do-

erner et al 2002]. For the application case, the setting of α = 3, β = 2, q0 = 0.85 and ρ = 0.95 performed best, whereas α and β are parameters that determine the influence of the pheromone trail and the visibility, respectively, and ρ is a parameter for the trail persistence. The pheromone trail is updated by 5 elitist ants as recommended by [Bullnheimer/ Hartl/Strauss 1999].

The comparison of the algorithms is based on 10 runs for each day (the tabu search heuristic is analyzed including the union-extension as well as without the extension). To realize a comparison between the heuristics, the four possible routing plans are optimized and evaluated.

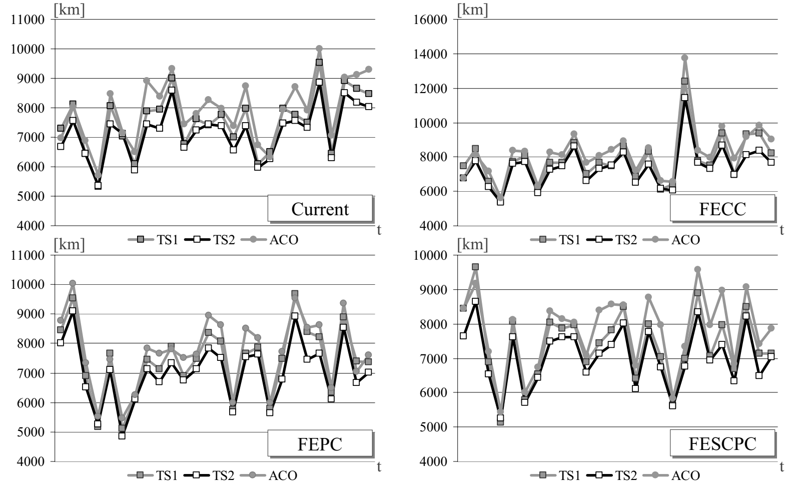


Figure 6-11: Comparison of the VRP solutions

The **tabu search heuristic obtained better results than the Ant Colony heuristic and is used for the evaluation of the cost effects**. It is clearly shown that the extension improves the good results of the standard tabu search with λ-interchanges in our application case. The fact that the tabu search heuristic outperforms competing approaches – as for example the ant colony optimization – is confirmed by independent experiments of many researchers [Cordeau/Laporte 2002].

	Current	**FECC**	**FEPC**	**FESCPC**
Profit margin (RM) [€]	3,348,020.57	3,441,685.25	3,558,320.22	3,590,831.51
%-change profit margin (RM) [%]	0	2.80	6.28	7.25
Costs (VR) [€]	280,410.63	289,426.80	274,370.34	275,030.34
%-change costs (VR) [%] **(compared to current)**	0	3.21	-2.15	-1.92
%-effect VR on profit margin [%]	-8.38	-8.41	-7.71	-7.66

Table 6-3**:** Over-all cost effects

Table 6-3 contains the over-all effects of the different revenue optimization approaches. It can be clearly shown that the **revenue effects are not compensated by higher transportation costs**. Additionally, there is no significant cost increase due to changing delivery lists. Cost variations are within 0.75%.

On a daily basis, however, partially clear effects can be observed. As shown in figure 6-12, cost variations resulting from the different approaches to CPC exist on a few delivery days. The reason for the peak in figure 6-12 as an example, indicating a cost increase of over 50% through the FECC, is due to the fact that 14 tours instead of currently 10 tours resulted from the optimization. This effect indicates that the integration of Revenue and Logistics Management (point 2, figure 6-2) should be considered in further research.

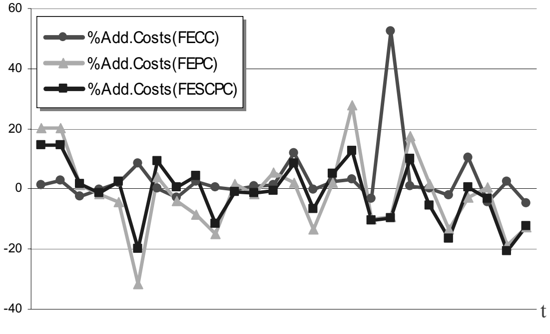


Figure 6-12: Additional transportation costs compared to the current situation

6.5 Conclusions to the FESCPC

The goods distribution application marks the last step in the determination of the advantage of integrating the capacity and price control in RM. The following three questions for the work on SCPC remained before this last practice case and will be answered now:

- Is the FESCPC a feasible approach towards the integrated CPC?

The first question can be clearly answered affirmatively. The **FESCPC leads to a profit margin increase** of €243,000 (7.25%) compared to the current situation. The workload increased by 1.52% (weighted average with respect to the class size). The robustness of the results is shown in figure 6-9. The performance of the FESCPC is below the current situation for only a few days. The robustness is also observable by looking at the variability of the results of FESCPC with changing reservation prices (performance analysis to justify the omitting of reservation price estimations, see chapter 2 and 3). For this, the coefficients of variances (CV) of the revenue and workload are analyzed on a daily level (see figure 6-9). The **solution concept can be considered as inured to reservation price changes**.

- Does the FESCPC outperform the FECC and the FEPC?

The application also justifies the use of the FESCPC instead of the separate conduction of FECC or FEPC in cases where the flexibility in capacity and price adjustments is given. The results show that the FESCPC increases the profit margins by €33,000 in comparison to the FEPC. This relatively small improvement of 0.97% can be explained through the underlying application case. In the context of the chemical industry, unit prices for the capacity are often very high in order to justify the relatively high fixed costs. Therefore, price adjustments have a larger impact on revenue, implying the PC as the dominant control strategy. However, as shown in figure 6-10, the FEPC focuses relatively more on the price maximization objective, leading to a lower workload (decrease by 2.96%). The predominance of the FESCPC over the FECC is more obvious. Here, the profit margin increases by €149,000 (4.45%). However, the workload only increases by 0.37%, showing the focus of the FECC on the capacity objective of revenue maximization (see figure 6-10, which illustrates mostly higher workloads during the whole period in comparison to the FEPC). To summarize, the FESCPC combines both of the separate approaches and, thus, **contributes the most to the revenue maximization problem**. This is a clear statement in favor of the FESCPC.

- Does the revenue-optimization of delivery lists have substantial effects on the transportation costs?

Additionally to the production costs of the glass films (profit margin analysis), and to costs that are only indirectly assignable (concerning the high fixed costs that are partially considered in form of the short-term bottom price in the fuzzy expert control), also the transportation costs (as the crucial cost part in the delivery of the glass films have to be analyzed. The transportation costs of glass films need to be analyzed with respect to the revenue optimization of the delivery lists for vehicle routing. As the practice case indicates, the **positive effects of revenue maximization are not compensated by higher transportation costs**. A variation of only between 7.66% and 8.41% (with the absolute values being low compared to the revenue in chemical industries) shows that also the consideration of all related costs does not cause the FESCPC, FECC and FEPC to lead to a worsening of the results in comparison to the current situation. This applies to cases where the different problem fields (SCPC and VRP) are optimized by adequate methods.

The last statement introduces the summary of the work. Besides the recapitulation of the central concepts and results, the remaining research on and the limitations of the use of fuzzy expert controllers in the context of RM as the management approach to the revenue maximization problem are illustrated. Thereby, the use of integrated methods for the solution of this problem context is especially outlined (e.g. the integrated revenue maximization and vehicle routing in transportation).

7 Summary

The concern of this work is the development of a concept for an integrated capacity and price control under consideration of the underlying multi-criteria objectives with relation to the demand-oriented profit maximization. In addition to the illustrated goals, the specific framework of Revenue Management as the central management approach in this context is considered, as well as the possibility of applications in that only one of the control options (capacity or price control) can be executed.

The **managerial relevance** of the work results from the strengthened competition constraints of a company and the need for an intensified customer orientation that implicates the profit optimization in the form of revenue maximization (under the cost aspects held constant). The short-term demand and price fluctuations related to the underlying problem area often lead to the sub-optimal allocation of the fixed over-all capacity to the existing (customer- or product-) classes of different worthiness (with respect to prices or unit profit margins) or an incorrect pricing. The only possible reaction, from an entrepreneurial point of view, is to dynamically adjust the capacity distribution and the price levels within the classes due to these fluctuations

The **planning concept of Revenue Management**, in this context, raises a complex problem because of its different influences (especially demand and willingness to pay) and the underlying conditions (development of an applicable practice-oriented concept under consideration of the flexibility with respect to the capacity and price control). The underlying objective system has to be fulfilled in regards to this problem context.

The **basic objective system** consists of three primary goals:

- **Maximization of the capacities of premium classes**
  Given the classes of different worthiness, one objective is to maximize the capacity of the classes with the highest price or unit profit margin. The result is that the customer requests for these classes are not rejected because of the capacities being too low, which would lead to sub-optimal revenue.

- **Maximization of the prices per capacity unit**
  For each class, the price per unit has to be maximized in order to receive the highest possible revenue.
- **Minimization of idle capacity**
  With respect to the above formulated objectives, one competing goal results. The sole maximization of the capacity may lead to an excess supply of premium goods or services. In cases where the demand is below the resulting capacity, this stays idle, despite that it may be otherwise sold in the other classes. In addition, setting the prices over the reservation prices of the customers also leads to unsold capacities in each class. As idle capacities lead to sub-optimal revenue, these cases must be considered.

The arising multi-criteria objective system is realized in this work with regard to the following **problems of and influences on the solution concept**:

- **Dynamic context of the solution concept**
  Because of the need for and the advantage of the capacity and price adjustments within a planning period, a dynamic approach towards the integrated capacity and price control in the form of an adaptive system has to be designed. As the formulation of the dynamic decision problem reveals the potential of circular reasoning in this context, an iterative on-line approach towards an integrated capacity and price control updates the information needed for the decision process in each time point, and assures that one planning step effects the system not until the next time point.
- **Flexibility in the decision categories**
  In order to provide a comprehensive solution for the revenue maximization problem, a solution concept should not only provide a feasible method for integrated capacity and price control. All possible application cases have to be covered, depending on their degree of flexibility in and the costs of adjusting capacities and prices.
- **Analyzing the underlying data basis**
  A practice-oriented approach has to be developed and tested based on real data in order to simulate the execution of the solution concept in the running system as realistically as possible. There is a large error potential that lies in the determination of all influences

and information needed for the execution (e.g. identification of the classes, prices and costs, customer value determination). Adequate data analysis techniques, under employment of appropriate software, are essential for the avoidance of this error potential.

- **Applicability of the solution concept**

  The use of real data for the analysis of the solution concept is not the only component assuring its applicability. By reducing the influences to three central terms, being workload, rest time in the planning period and customer value, the decision process becomes more intuitive and clear. In complex applications, the expansion of the influence parameters is possible.

- **Demand estimation**

  Based on the technical and conceptual difficulties experienced when estimating the demand for the different classes in the concerned planning period, a way has to be found to get demand information. This is despite the high fluctuations, which occur due to tougher competition and unpredictable customer behavior. One adequate way is to pass on the forecast of the demand, and to use a reliable indicator for the demand for a certain class within the planning period. The workload in the class serves as this indicator. However, without the incorporation of time aspects into the workload, misinterpretations may result. By adding the rest time of the planning period to the influential factors, this potential for such misinterpretations is lowered. The combination of both terms provides a good interpretation of the demand, either behaving in an expected way (e.g. a low workload at the beginning of the planning period, a high workload at the end of the planning period) or an unexpected way (e.g. a high workload at the beginning of the period, a low workload at the end). Capacities and prices can now be adjusted over time based on the fulfillment of the demand expectations. This is achieved by starting with an initial solution that expresses the expectations (initial class sizes and prices corresponding to the demand expectations).

- **Reservation price determination**

  The uncertainties connected to the demand estimation can be also stated for the reservation price identification. The customers have no incentive to reveal their willingness to pay in the transaction process. Thus, a way must be found to set the prices as high as the reservation prices (which generally maximizes revenue and minimizes idle capacity), without needing to determine the willingness to pay of each customer. One possibility is to factor out the reservation price from the central solution concept. By setting prices according to the workload and rest time (as well as the customer value), the workload indicates a too high of or too low of a price level. Therefore, not the reservation price of each customer is estimated but the prices are adjusted based on the reservation price level of the consumers. The distribution of the reservation prices among customers is addressed by selling at a higher price level in times of high demand (high workload) and at a lower price in times of low demand (low workload). In the first case, the remaining capacity is only demanded by people with a higher willingness to pay. In the second case, the classes are also opened for customers with a low reservation price. For the performance analysis in a test setting, reservation prices have to be estimated. However, thereby, not the right estimation is essential, but the variation of the solution in comparison to variations of the reservation prices (conduction of a sensitivity analysis).

- **Imprecise functional relationships**
  The design of the solution concept is characterized by many information and relationships between the influence factors and the capacity and price adjustments. The adequate procedure is to use expert knowledge for the development of a solution. Founded on the rule-based representation of this implicit and vague knowledge, fuzzy expert controllers can be designed that allow for the dynamic decision-making based on this knowledge.

The resulting decision context for a simultaneous capacity and price control can be realized using the following steps:

- Illustration of the concerned object in form of the **basic procedure needed for a simultaneous capacity and price control**, which regards to the objective system, the influences on the objectives, and the resulting problems.
- **Design of the decision models** for the capacity and the price control, as well as the model for the integrated capacity and price control.

- **Exposure of the problems connected** with the relevant dynamic capacity and price adjustments in the context of an adaptive system (degree of capacity change $\kappa_{st}\left(W_{st},r_t\right)$ and degree of price change $\psi_{cst}\left(W_{st},r_t,clv_{ct}\right)$).
- Development of a comprehensive solution concept, based on a **heuristic solution system** founded on a rule-based expert system and conducted in the form of a **fuzzy expert controller** that executes the determination of $\kappa_{st}\left(W_{st},r_t\right)$ and $\psi_{cst}\left(W_{st},r_t,clv_{ct}\right)$. So far, sufficient knowledge about the applicability of the chosen solution concept in the context of RM (and SCPC) and about application constraints as well as necessary modifications does not exist as Fuzzy Expert Systems have not yet been applied in RM.
- **Evaluation of the solution concept** in the context of the **three possible application case constellations**: Capacity control, price control and integrated capacity and price control, resulting in three fuzzy expert controllers: **Fuzzy Expert Capacity Control, Fuzzy Expert Price Control and Fuzzy Expert Simultaneous Capacity and Price Control**.

The initial setting of the fuzzy expert controllers depends on the framework of the application case as well as on the quality of the rule basis and has to be incrementally improved by variations in the basic parameter configuration. This stepwise adjustment of the shape of the membership terms, the rule consequences as well as the inference methods and defuzzification algorithms, is responsible for the **different developed fuzzy expert systems** for the application cases and, in addition, for the different classes in each application (depending on the requirements for the influence parameters, e.g. different short-term bottom prices because of structural higher reservation prices in premium classes).

The first application case considered is the **capacity control of the waste incineration industry**. The fixed prices over one year result in the capacity distribution as the only flexible factor for revenue maximization. The two identified classes result in the use of the max-min-inference with a maximum result aggregation, together with a COM-defuzzification. The input values of “workload” and “rest time” are represented by five linguistic membership terms. The output “degree of capacity change” ($\kappa_{st}\left(W_{st},r_t\right)$) is represented by seven membership functions. The resulting rule basis contains 25 rules. Given this solution setting, the Fuzzy Expert Capacity Control leads to an increase of profit margins by 5.22% per year.

The second application case concerns the **price control in the hospitality industry**, where only prices can be adjusted dynamically due to constructional limitations. While the basic form of the main inputs is the same as in the capacity control case (except from the real values that are adopted from the application context), one additional input is included: The "customer value", represented by two membership functions (indicating a regular or non-regular customer), leads to 50 rules in the rule basis. Besides the changed shape of the input membership functions (e.g. a different course of the rest time because of other planning periods), also another output has to be considered: The "degree of prices change" ($\psi_{cst}\left(W_{st}, r_t, clv_{ct}\right)$). In contrast to the capacity control, where only S-1 classes have to be controlled (the least worthy class gets automatically the capacity not distributed to the other classes), here, all classes have to be controlled. While the first and second class are controlled with a max-min-inference (BSum aggregation) and a COM defuzzification, a max-avg-inference is used for the third class (as a result of the incremental system adjustment). Also, the shape of the membership functions is adapted according to the class specifics (e.g. the linguistic terms "high rest time" and "very high rest time" start earlier in the planning period for the first class as business people, as the main customers of the first class book, later in the planning period). With this solution, the application of the Fuzzy Expert Price Control results in a revenue increase of 8.57% per month.

The third application addresses the **simultaneous capacity and price control in the transportation industry**. Apart from the same inference (max-min) and defuzzification (COA), the rule bases varied over the two classes. In addition, the two fuzzy expert controllers have to be connected in this case. The main connection point is the workload that resulted from the capacity or price control, respectively. The execution of the Fuzzy Expert Simultaneous Capacity and Price Control resulted in a 7.25% profit margin increase per month.

The **evaluation** of the best settings for the fuzzy expert control is carried out for each application case and the possible control option(s). The measures of evaluation are mainly the resulting workload and the resulting profit margin (or revenue in cases where the cost data was only rudimental). Besides the evaluation of the improvements of the current situation, also other important aspects are analyzed:

- The sole capacity flexibility in the waste incineration industry leads to the use of a **Fuzzy Expert Capacity Control**. The results show its clear predominance over the current situation (first-come, first-served). In addition, the concept is compared to the building of contingents and the expected-marginal-seat-revenue method, both common Revenue Management approaches for capacity control. Here, also better results can be obtained. It can be thereby observed that the fuzzy expert capacity control focuses on the determination of the right capacity distribution over time in favor of the premium classes. An increase of workload in all classes is obtained.
- The sole price flexibility in the hotel sector asks for the implementation of a **Fuzzy Expert Price Control**. The results, again, show that the fuzzy expert approach outperforms the current RM technique applied at the hotel in question. Hereby, also the robustness of the fuzzy expert price controller with respect to significant variations of the reservation prices is proven in a performance analysis, illustrating the potential of the solution concept in a running system (without reservation price estimations). The fuzzy expert price controller focuses on the price maximization objective, leading to a revenue gain, but also to a lower workload for the three classes.
- The transport application marks the last step in the evaluation of the **Fuzzy Expert Simultaneous Capacity and Price Control**. Here, not only the predominance of the simultaneous fuzzy expert control itself over the current situation can be proven. The results show that all three fuzzy expert controllers outperform the initial solutions, with the largest increase reached by the integrated solution. In addition, the cost effects in the context of transportation are analyzed. The advantage of the fuzzy expert control is not consumed by higher transportation costs, an aspect that is particularly important in the context of the integration of Revenue Management and Supply Chain Management methods. The over-all effect of the Fuzzy Expert Simultaneous and Price Control in this application case is an 8.09% profit margin gain per month.
- In all applications, thereby, the system behavior is consistent with the formulated objectives and the expected performance.

With regard to the transferability and to the further potentials of the developed concept, the following statements can be made:

- In principal, the presented concept can be transferred to every application case that shows flexibility in or low costs of the capacity or price adjustments[118]. In cases where no flexibility is given to at least one of the control options, the Revenue Management as an approach to revenue maximization does not work. In such cases, either cost reduction strategies through Supply Chain Management approaches, or time and cost reductions through an adequate Project Management have to be pursued in order to add to the overall profit maximization objective. Cost aspects in the analysis of the applicability of capacity and price controls are relevant as, despite the principal flexibility in the adjustments, the resulting costs may cause the adjustments to be inefficient (e.g. high setup costs in the production industry).
- Especially in applications where the demand is in principal higher than the supply in each class, the (simultaneous) capacity and price control works particularly well. The reason is that the capacity and price adjustments can affect customer behavior to the same extent as intended through the degree of adjustment. However, also in cases where the demand was less than the supply, the applications indicated the advantages of the solution concept.
- With respect to the three analyzed practical cases, the relatively straight-forward application of the concept has to be mentioned. Within the context of two or three class sizes, well definable planning periods, and a data basis suitable for Revenue Management applications, the solution concept itself can be well implemented. In more complex cases, the adaptation would be more time and resource intensive.

Restricting aspects of the developed solution concept for the simultaneous capacity and price control are the following:

- The determination and preparation of the relevant data for the capacity control and the price control as well as the integrated capacity and price control may prove difficult.

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[118] Thereby, the formulated underlying application constraints of Revenue Management must hold.

This especially concerns the detection of the real demand for the different classes, and the determination of the underlying costs.

- The developed fuzzy expert controller has to be implemented in a running system for the analysis of the customer's reaction upon the capacity and/or price changes, and for the examination of the user acceptance. The described limitations of the fuzzy expert control may thereby play a role.
- Particular to the transportation case (and in similar applications) is the expansion of the analysis to the whole (delivery) network. This is necessary to determine the over-all advantage of the solution concept.
- The integration of the concepts developed for Revenue and Supply Chain Management seems to provide a promising further extension up to the limitations resulting from a centralization of the decision-making process.

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