DECISION SUPPORT SYSTEM FOR CUSTOMER VALUE-BASED REVENUE MANAGEMENT IN MANUFACTURING

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Abstract

In manufacturing, providers are interested both in a revenue maximizing allocation of their limited production capacity (as goal of revenue management) and the establishment of long-term business relations with their clients (as goal of customer relationship management). Due to long-term contracts and strategic reference customers, users of traditional revenue management systems already account for varying worthiness of clients, and intuitively ignore or override booking control suggestions in order not to endanger customer relations. So in a holistic approach, the integration of both management concepts, each of decisive competitive impact, is suggested. However, a solid scientific foundation of this desirable decision support and an implemented (prototype) IT-system, that provides the revenue analyst with greater insights, higher accuracy, quality and trust in decision process, are still missing for manufacturing industry. Based on a literature review, we believe this paper is the first to define, formalize and analyze the decision-making problem associated with these partly diametric objectives. In particular, the paper introduces a decision support system for a manufacturing provider with limited capacity, supplying analysts with formatted and summarized data to make transparent and comprehensible control decisions, and suggesting specific booking control actions based on simulation results and integrated usage of provided data.

Keywords: Decision Support System, Revenue Management, Customer Relationship Management, Manufacturing.
1 INTRODUCTION

Decision making has been around as long as management and leadership, probably longer (Bennet & Bennet 2008). Decision support systems (DSS) comprise a core subject area of the information systems (IS) discipline, being one of several major expansions that have occurred in the IS field (Burstein & Holsapple 2008). This research area is focused on supporting and improving managerial decision-making, and is about developing and deploying IT-based systems to support decision processes (Arnott & Pervan 2008). As a subject of research and practice, it continues to grow along ever-widening horizons (Burstein & Holsapple 2008). Today’s manufacturing providers are expected to offer, price and deliver material goods in an efficient, standardized but also customized way. So, firms face a non-trivial decision problem about a well-conceived usage of their limited, inflexible and perishable production capacity to provide these products to an uncertain and heterogeneous demand from different market segments (Talluri & van Ryzin 2004). Revenue management (RM) is concerned with the theory and practice underlying this type of problem in order to maximize revenues.

However, the focus of RM on short-term maximization only, may negatively impact customer relationship (Martens & Hilbert 2011). But by strengthening business relations to long-term profitable clients, as goal of customer relationship management (CRM), increasing intensity of competition should be countered. In addition, a relation-oriented perspective is of crucial importance to companies in manufacturing due to long-term contracts and strategic reference customers (Sucky 2009; Spengler et al. 2007). That is why users of the RM system already account for varying worthiness of clients, and intuitively ignore or override booking control suggestions in order not to endanger customer relations (Becher 2008; Martens 2009). In a holistic approach, the integration of both RM and CRM, each of decisive competitive impact, is suggested (Martens & Hilbert 2011). However, a solid scientific foundation of this desirable decision support and an implemented (prototype) IT-system, that provides the revenue analyst with greater insights, higher accuracy, quality and trust in decision process (Holsapple 2008), are still missing for manufacturing industry. So, this paper aims to develop a clearer picture and analysis of the decision-making problem by conducting a comprehensive literature review as an essential approach to conceptualize research domain and synthesize prior research (Webster & Watson 2002). In addition, we want to present our developed prototype DSS to support the sales agents in such a manufacturing environment. For selecting relevant articles, we started our search with the keywords “revenue management”, “decision support” and “manufacturing”, and for the long-term focus we also added “customer relation”. The results found in top IS, management and operations research journals, periodical databases, conference proceedings and dissertations reduced from over a hundred to only a handful of papers that address a combination of at least two research areas, represented by the former keywords. All these articles have been intensively examined to synthesize the literature and grasp a deeper understanding of the identified problem situation in practice.

The remainder of this paper is organized as follows: section 2 will give a literature review about RM in manufacturing, introduce the concept of CRM and its integration with RM, and review characteristics of DSSs and their application in manufacturing. Given the partly diametric objectives of RM and CRM, we then highlight the strategic importance of the integrated DSS and discuss several dimensions to be considered during system development (section 3). Based on the formulated optimization model (section 4), central aspects of the prototype to support the analyst’s decision-making are then examined (section 5). After discussion of results (section 6), the paper ends with a conclusion (section 7).

2 LITERATURE REVIEW

2.1 Revenue Management in Manufacturing

In comparison to services industry, where research gives attention to optimal usage of limited capacity resources since the end of the 70’s, capacity control in manufacturing industry is a relatively young scientific discipline (Chiang et al. 2007). Nevertheless, an increasing number of recent research contri-
butions (Rehkopf 2006; Defregger & Kuhn 2007; Spengler et al. 2008; Wiggershaus 2008) indicate the great topic’s relevance in gaining competitive advantages. Many common characteristics between manufacturing and traditional RM industries (with airline industry as most familiar application), such as uncertain customer demand with heterogeneous worthiness and behaviour, and inflexible and perishable production capacity (Sucky 2009), make manufacturing industries promising environments for RM (Hintsches et al. 2010). So, considerable potential is attested to oil, chemical and pharmaceutical industry, and steel, paper and aluminium industry (Gray 1994; Kolisch & Zatta 2009).

If demand exceeds manufacturing capacity on a regular basis, the provider is faced with the challenge to adequately select the best orders to maximize overall profit (Spengler et al. 2007). The client’s participation implies an uncertain influencing factor for the manufacturer in terms of amount, value and arrival of requests and customer’s reaction if desired material goods are not available. Confronted with the rigidity of available capacity in the short run (Hintsches et al. 2010), the absence of an adequate booking control policy can result in a situation where majority of capacity is reserved for early, but low-class requests, available capacity is overbooked or unutilized (Martens 2009). Although facing uncertain demand, a decision for each incoming booking request whether to accept or deny is needed. The acceptance of lower-value booking requests may prevent sufficient capacity from being available for later requests of higher value (revenue displacement). Conversely, declining too many low-class requests may lead to idle production capacity if such higher-value requests fail to appear (revenue loss). RM governs the proper control and balance between these contrary revenue-relevant effects.

Faced with specific characteristics, such as significant variable costs, heterogeneous capacity consumptions and order delivery dates (Rehkopf 2006), different approaches to cope with the complexity in a manufacturing environment are discussed in literature (Hintsches et al. 2010). Starting in the mid-90’s, initial works of Harris and Pinder (1995), Balakrishnan et al. (1996) and Patterson et al. (1997) investigate the appliance of methods to manufacturing in general (Hintsches et al. 2010). Subsequent works deal with production-pricing problems (see Talluri & van Ryzin (2004) for an overview) and differ in central control parameters. So, approaches for acceptance decision of requests with fixed prices and delivery deadlines (Elimam & Dodin 2001; Kniker & Burman 2001; Spengler et al. 2007), methods to determine delivery dates for orders with fixed prices (Keskinocak et al. 2001) and algorithms to identify product prices and delivery dates (Watanapa & Techanitasawad 2005; Charnsirisakskul et al. 2006) have been developed (Kolisch & Zatta 2009). Hintsches et al. (2010) investigate a possible RM application at ThyssenKrupp, leading to considerable profit improvements.

2.2 Integration of Customer Relationship Management

However, capacity control in manufacturing is mainly transaction-based so far. The order’s acceptance decision is thereby primarily determined by the price of the requested material good (Sucky 2009). By contrast, relationship-based marketing postulates the consideration of value-oriented success indicators to establish long-term relations to profitable customers (Rudolf-Sipötz 2001). By broadening the decision perspective from one transaction to the lifetime value of the customer (Lederer & Yeoman 2003), the provider can reduce the risk to misleadingly decline prospective customers (low current, but high potential future contributions) and reference customers (not necessarily high own but high induced contributions of other customers; Wirtz et al. 2003; Kuhlmann 2004; Martens & Hilbert 2009). In particular, the latter are of strategic importance to companies in manufacturing (Sucky 2009). As the value of a customer for the manufacturer is not limited to the profit from each transaction, but is the total profit the customer may provide over the duration of the relationship with the firm (Kumar & George 2007), customer value is a determining factor for management decisions and is regarded as being closely connected to shareholder value (Berger et al. 2006; Martens & Hilbert 2009). Facing a complexity of customer values causes an adequate differentiation of the provider’s (booking control) actions (Noone et al. 2003) in order to make the limited capacity available for the most valuable customers (Lindenmeier 2005; Martens & Hilbert 2009). The decision to accept short-term higher-paying customers but not necessarily the most loyal ones (Wirtz et al. 2003) should take opportunity costs in terms of lost customer values into account if in return the denied prospective customers will
reduce their future purchases (e.g. buying frequency, product change, amount of cross selling) or even abort the relationship with the provider (Pak 2005; Kim et al. 2006; Wang & Bowie 2009).

In a holistic approach, both RM and CRM should be integrated, Cross et al. (2009) call for a customer-centric RM. So for services industries, Martens (2009) extends transaction-based booking controls for consideration of long-term customer values. Pfeifer and Ovchinnikov (2011) examine the trade-off between acquiring and retaining customer relations for firms with limited capacity. So in general, clients compete for scarce resources of the provider (Mohaupt & Hilbert 2012). The incorporation of value-related revenues into booking controls in manufacturing is desirable, as its importance is pointed out in recent literature, but the elaboration is neither structured nor in necessary detail. Only the works of Rehkopf (2006), Spengler et al. (2007) and Sucky (2009) identify this urgent need for research, but refer only to the subarea of minimum contingents or service levels for clients considered to be served with priority. Even though only one decision period is considered, Buhl et al. (2011) propose a model for a customer lifetime value-oriented capacity control. Based on a numerical example, they illustrate a possible application of the model for an exemplary company in semiconductor industry. Despite the limited preliminary work, an application of customer value-based RM in manufacturing seems very promising. So, Rehkopf (2006) refers to situations in manufacturing with predominant strategic partnerships or limited number of customers and realizes that a DSS solely concentrating on short-term success will not be adequate. Due to high market transparency and long- and medium-term contracts, a relationship orientation does have an even greater importance compared to services industries (Stangl 2005; Silber 2007; Spengler et al. 2007). Strengthening relations to the right clients is vital as only loyal customers are profitable in the long run due to high costs of acquisition. Results of simulation studies in services industries show already that a disregard of long-term contributions of customers can produce counterproductive effects (Martens 2009; Mohaupt & Hilbert 2012). Also an increased attention has to be paid to booking control’s consequences on customer loyalty, e.g. decrease in loyalty as a result of the request’s denial (Wirtz et al. 2003). In addition, there is still a lack of an adequate pricing that incorporates customer’s worthiness when suggesting a bottom price level during common iterative price negotiations in manufacturing (Rehkopf 2006; Becher 2008; Hintsches et al. 2010).

2.3 Characteristics of Decision Support Systems and their Application in Manufacturing

Due to the existence of many approaches in decision-making and wide range of domains in which decisions are made, the concept of DSS is very broad (Ostadzadeh et al. 2010). Turban (1995) defines it as an interactive, flexible and adaptable computer-based IS, developed for supporting the solution of management problems by utilizing data, providing an easy-to-use interface and allowing for decision maker’s own insights. DSS are intended to enhance decision-making effectiveness, improve communication among decision makers, increase their satisfaction and organizational control (Power 2009).

Whereas DSS can be seen as infrastructure that can measure, capture and deliver performance, CRM is primarily a customer-focused strategy. Together, they can generate a knowledge environment that maximizes customer value and measures, monitors and provides intelligence to the firm and customer performance profitability (Jackson 2006). However, CRM applications software may often not correspond well with business objectives (Hart 2006). Stressing the interface between DSS and CRM, Jackson (2006) identifies the core components of an integrated system that can improve decision making in the acquisition, development and retention of customer relations, Noori and Salimi (2005) focus on marketing in business-to-business arena (Hart 2008). CRM/DSSs are systems integrating varied data and applying quantitative techniques that define optimum marketing mix of product features, right price points, best delivery channels and level of service assigned to each client (Jackson 2006).

RM as a promising field of DSS application has received increased attention recently. The revenue maximizing systems have become a competitive necessity (Power & Sharda 2007). Hence, a lot of contributions address how to develop and implement RM systems (Skugge 2002; Okumus 2004). Chiang et al. (2007) highlight the crucial role that revenue analysts can play in RM process by contributing significant incremental revenue. To the best of our knowledge, there are only two works devel-
oping DSS for RM in manufacturing, and understanding the IT-artifacts as comprehensive tools that also offer opportunities to further analyze and initiate scenarios. Embedded in an order acceptance of a manufacturer in iron and steel industry, Rehkopf (2006) develops a simulation tool with interfaces to Excel and optimization software Lingo that informs the analyst about resulting bid-prices, contribution margins, and remaining production capacity, given a constellation of input parameters. Hintsches et al. (2010) present results of a case study of capacity control at ThyssenKrupp in make-to-order steel manufacturing. By means of a developed bid-price control and simulation of different demand scenarios, the sales agent gains further insights and a threshold value to decide whether to accept or decline a request. Unfortunately, both papers only concentrate on short-term profit maximization, long-term value-related revenues and effects of capacity control on customer behavior are not included. Referring to future directions and challenges, Power et al. (2011) point out that analysis capabilities are coming back to forefront, and more time has to be spent on decision analysis and definition. So, future DSS will have to deal with integrating, analyzing, and acting on disparate information on customers. To summarize, a DSS accounting for both short- and long-term revenue potentials in manufacturing is desirable, but still missing. The next section will focus on strategic implications of such endeavor.

3 STRATEGIC DECISION SUPPORT

The definition of an appropriate RM strategy is critical for achieving strategic business objectives of the manufacturer. Whereas the concept of (traditional) RM tries to meet the main objective of short-term revenue maximizing resource allocation, the long-term value of customer base (customer equity) can be affected by the number of (current and potential) customers as well as their individual customer values (Martens & Hilbert 2011; see Figure 1). Potential conflicts of objectives, such as retention of prospective customers and maximization of short-term revenue, require a balancing of goals (Martens & Hilbert 2011). Additionally increasing complexity, various constraints occur (see Figure 1), such as limited capacity and capability of information systems, difficult valuation of clients and estimation of behavioral effects due to booking control decisions (Martens 2009; Mohaupt & Hilbert 2012).

Figure 1  Integration and dimensions of DSS in customer-value based RM

In principle, a DSS has to fit in such a structure of tension with partly diametric objectives and a different view on processes, meaning that the DSS is caught between repeating activities during RM process (cycling forecasting, optimization, transaction control and analysis in every booking period; Martens 2009) and – with ample planning horizon – the customer life cycle (establishment, individualization, actions at the end of relationships; Hippner 2006) with the goal of building a long-term...
profitable customer base (see Figure 1). So, an alignment of DSS’s goals with business strategies is of major importance in order to help the provider to realize its business objectives and compete more effectively (Lederer 2008). That is why RM implementations should be viewed from the perspective of strategic management not as a tactical activity only (Okumus 2004; Eom 2008). In accordance with such a long-term and strategic perspective, the adequate representation of the decision problem has to allow for a consideration of long-term components (see weighting in section 4). Overall and due to these high requisites, the RM system can be considered as intelligent information system. Only an information system with homogeneous data view (McGuire & Pinchuk 2009) will allow for the right information (required and understood by the analyst) at the right time (for taking booking control decisions) in the right quantity (as much as necessary, as little as possible) at the right place (e.g. for calculations during optimization or transaction control, or evaluations in forecasting or analysis, see Figure 1) and in the right quality (sufficiently detailed, valid and directly applicable; Krcmar 1991).

An optimization model is the basis for such decision support function. By definition one or more quantitative models are the dominant components that provide the primary functionality of a model-driven DSS (Power & Sharda 2007). A quantitative model such as decision analytic, optimization, or simulation model, is an abstraction of relationships in a complex situation (Power 2009). By emphasizing access to and manipulation of a quantitative model in RM (see section 4), a model-driven DSS assists in formulating alternatives, planning activities, interpreting and anticipating the effects of specific resource allocations, assessing the consequences of actions and selecting appropriate options (Power 2009; Power et al. 2011). Typically, the model is made accessible to a non-technical specialist such as a revenue manager through an easy to use interface (Power & Sharda 2007).

During development process of the DSS prototype, various dimensions have to be defined in problem analysis to cover decisional requirements, to understand the flow from user input to model calculations to the output and finally to reflect on corresponding aspects of decision support for core problems in the RM process of the manufacturer (Chaudhry et al. 1996; Rhee & Rao 2008). In this paper, we want to differentiate three dimensions (see Figure 1). First, abstractions as a widely accepted dimension in the holistic description of an enterprise (Zachman 2003) are introduced. They are based on six basic interrogatives that are asked to fully understand a specific aspect of DSS (Ostadzadeh et al. 2010). They serve as guide for better comprehension for possible points of decision support (see section 5):

- Motivation / Why do things happen? i.e. integration of objectives from both RM and CRM
- People / Who does what work? i.e. sales agents and revenue managers
- Time / When do things happen? i.e. planning horizon, life cycles, when RM tasks are supported
- Data / What is it made of? i.e. quality, source and presentation of data
- Function / How does it work? i.e. transformations of information used in RM activities
- Network / Where are the elements? i.e. geometry, connectivity of data, mutual interflows of tasks

Used as another dimension, model-based decision support can be divided into three stages: formulation, solution, and analysis (Shim et al. 2002). Formulation relates to the generation of problem and domain models (Viademonte & Burstein 2006). Converting the decision-maker’s specification of the RM decision problem into an algebraic form understandable by a booking control algorithm is a key step in the use of a model (Shim et al. 2002). The solution stage refers to the algorithmic solution of the model, including techniques from operations research (Viademonte & Burstein 2006). The analysis stage relates to the “what-if” analyses and interpretation of model’s solution and outcomes to enhance the sales agent’s ability to analyze and understand the problem and the solution. So given this stage separation, it allows for different focus on specific properties of the prototype and purposeful consideration of corresponding aspects of decision support. So, besides generation of a better solution algorithm, also formulation and analysis functions of the DSS can be pushed (Shim et al. 2002).

Serving as a last distinguishing feature, a DSS is built up of four major components: user interface, database, models and analytical tools, and network (Power & Sharda 2009). These components collectively comprise overall architecture of the decision tool. By means of the user interface, the system can receive input from the sales agents, navigate them through application, and allows for a visualization...
of processed information. It is still prudent to design the user interface in such a way as to foster feelings of perceived usefulness and ease of use (Beemer & Gregg 2008). Improving user interaction is necessary for the system to be trusted, accepted, and to contribute to decision-making process. The database is a collection of data organized for easy access and analysis (Power & Sharda 2009). It may be the case that data from other sources (e.g. pricing, customer transaction history) have to be collected or merged, given adequate interfaces for data import (McGuire & Pinchuk 2009). The model’s formulation and its implementation in the software tool are illustrated in section 4 and 5. The network component refers to how hardware is organized, how software and data are distributed in the system, and how components of the DSS are integrated and physically connected (Rehkopf 2006; Power & Sharda 2009). In section 5, we will refer to different options in software development environment.

4 OPTIMIZATION AND BOOKING CONTROL APPROACH

The DSS prototype should be applied in a manufacturing environment. During financial crisis with low demand, all customer requests could be served (Buhl et al. 2011). In subsequent times of economic boom, demand exceeds capacity on a regular basis. As a result, the provider is confronted with the problem to decide which orders to accept or to reject (Spengler et al. 2007). Given an intense competition, meaning that customers are in a powerful situation, the provider depends on the demand of few customers with whom it predominantly maintain long-term relations (Buhl et al. 2011). In this situation, a twofold consideration of short-term effects (also for reasons of liquidity) and long-term effects of a well-conceived booking control policy is reasonable (Martens & Hilbert 2011).

The manufacturing company offers \(|H|\) types of products \(i \in I\) (e.g. premium and basic product), that are produced by means of \(|H|\) types of machines \(h \in H\) (e.g. front-end and back-end production), each with a total capacity \(g_h\). The element \(a_{hi}\) represents the usage of resource \(h\) by one unit of product type \(i\). Let the capacity consumption matrix be \(A = [a_{hi}]\) and \(r_i\) the revenue for the provider by selling the requested product \(i\) (Hintsches et al. 2010). The provider will grant a discount on \(r_i\) in dependence of the time of requesting. Thereto each booking period is split into \(Y\) arrival periods. The earlier the clients detect their own need for material goods and therefore make a reservation, the greater the discount \(z_i\) offered by the provider. So, clients willing to book early can save money but have to accept a longer lead time until product delivery in the subsequent booking period (Defregger & Kuhn 2007).

Usually, clients directly contact sales department. Their requests thereby often occur ad hoc, following a Poisson process with intensities dependent on product and arrival period (Bertsimas & Popescu 2003; Pak 2005). In this business-to-business market, sales agent can identify clients by customer number (Talluri & van Ryzin 2004, Hintsches et al. 2010). Thus, stored customer history could be used to estimate future buying frequency and average revenue. The customized information is therefore employed to segment customers by two dimensions. The first distinguishing characteristic concerns the average revenue \(\bar{r}_i\) to be expected in future booking periods. Based on historical transaction data, this measure informs about predominantly to be expected future revenue of the customer group \(k \in K\) the requesting client is classified to. It comprises the revenue of the predominantly ordered product type, adjusted for corresponding discount in dependence of predominantly time of requesting, according to customer segment’s preference for product value and lead time. With regard to this segmentation base, high-class customers (with predominantly late arriving requests for predominantly premium products and therefore lower discount but identical resource consumption) are thus more profitable. So, there may be a trade-off between investing in a customer relation (if the client is interested in a product of low-class revenue only at present time, but is predominantly characterized by a high willingness to pay) vs. exploiting short-term revenue \(r_i\) only without consideration of (averaged) client’s revenues \(\bar{r}_i\) to come.

The second dimension for clustering accounts for different effects of the provider’s present availability decisions on the long-term value of the requesting customer (Buhl et al. 2011). Whereas an acceptance can have a positive influence on customer loyalty (e.g. higher repurchase probabilities), a denial can put the customer loyalty at risk (Wirtz et al. 2003; Lindenmeier & Tscheulin 2008). In particular, the non-availability of material goods can lead to negative customer reactions like dissatisfaction, product
change, decrease in buying frequency or even customer churn (Pak 2005; Anderson et al. 2006; Wang & Bowie 2009; Mohaupt & Hilbert 2012). These changes in customer loyalty will have an impact on the amount of future business and cross selling (Noone et al. 2003; Gupta et al. 2006). Defined for $\mathcal{S}$ customer segments $s \in \mathcal{S}$, $c_i^+$ (in case of acceptance) and $c_i^-$ (in case of denial) account for these changes in customer value, representing the expected change of present value of cash flows generated from the customer in all booking periods succeeding the current decision period (Buhl et al. 2011; Mohaupt & Hilbert 2012). For reasons of demonstrating, the customers can be clustered into three exemplary segments. As segment $s = 1$ has only a small share-of-wallet, i.e. this segment orders relevant material goods also from other manufacturers (Venkatesan & Kumar 2004), the change in customer value is not very high for both the acceptance and denial of a request (Buhl et al. 2011; Mohaupt & Hilbert 2012). By further analyzing the customer base, another segment $s = 2$ could be defined. In case of denial of the request, customers of this segment are more likely to abandon the relationship with the manufacturer, i.e. higher churn probability (Rosset et al. 2003; Kim et al. 2006), but in case of accepting their request, they will increase their loyalty (lock-in effect) in return (Buhl et al. 2011). Therefore, the monetary effects on the future cash flows are much higher in contrast to the first segment. Customer segment $s = 3$ has an intermediate level of changes in $c_i^+$ and $c_i^-$ compared to the other segments.

So, the provider will base booking control decisions on value-related revenue (Martens & Hilbert 2011; Mohaupt & Hilbert 2012) representing a combination of short-term revenue, i.e. profit $r_i$ of requested product $i$ adjusted to referring discount $\xi$, and long-term value contributions, including predominantly to be expected revenue $\bar{c}_i$ of the according segment $k$ (based on first segmentation dimension), and the long-term effects on customer value $c_i^+$ and $c_i^-$ (segment $s$, based on second classification dimension) resulting from provider’s availability decisions. A weighting factor $\alpha \in [0;1]$ emphasizes either current or long-term to be expected revenue, see (1). The lower $\alpha$, the greater the extent to which current revenue is modified by long-term value contribution. Another weighting factor $\beta \in [0;1]$ controls the incorporation of expected changes in customer value, see (1). Both $\alpha$ and $\beta$ allow for defining various booking control methods, analyzed and used for decision support in the prototype introduced in section 5.

The efficient allocation of production capacity in each decision period can now be formulated as a Linear Programming Model where $x_{i,y,k,s}$ represents the contingent assigned to a combination of product $i$, arrival period $y$ and customer segment (both dimensions $k$ and $s$), and $b_{i,y,k,s}$ (as element of $B$) is the amount of already reserved product $i$ requested from customers (assigned to segment dimensions $k$ and $s$) in arrival period $y$. The objective function $Z$ maximizes the sum of current revenue, predominantly to be expected future revenue (both adjusted for corresponding discount) and long-term effect in customer values over all segments (both segmentation dimensions), arrival periods and product types and in dependence of $\alpha$ and $\beta$, see (1). Whereas the first of the two terms focuses on accepted requests only, second term is related to all denied requests, i.e. difference between expected demand $D_{i,y,k,s}$ to come in current booking period and provided contingents. Constraint (2) ensures that capacity used to satisfy present bookings and contingents does not exceed total amount of capacity. By introducing measure $R$ in (3), the provider can assure that total short-term attainable profit (by selling all requested products in current period) does not fall below given threshold, e.g. due to liquidity requirements (Buhl et al. 2011). The non-negative contingents must not exceed forecasted demand, see (4).

\[
Z(B) = \max \sum_{i \in I} \sum_{y \in Y} \sum_{k \in K} \sum_{s \in S} \left\{ [\alpha (1 - \xi_y) r_i + (1 - \alpha) \bar{c}_k + \beta c_i^+] x_{i,y,k,s} \right\} 
+ \beta c_i^- (D_{i,y,k,s} - x_{i,y,k,s}) 
\]

\[
\text{s.t. } \sum_{i \in I} \sum_{y \in Y} \sum_{k \in K} \sum_{s \in S} a_{hi} (b_{i,y,k,s} + x_{i,y,k,s}) \leq g_h \quad \forall h \in H 
\]

\[
\sum_{i \in I} \sum_{y \in Y} \sum_{k \in K} \sum_{s \in S} a_{hi} (b_{i,y,k,s} + x_{i,y,k,s}) \geq R 
\]

\[
0 \leq x_{i,y,k,s} \leq D_{i,y,k,s} \quad \forall i \in I, y \in Y, k \in K, s \in S 
\]

In order to obtain the best use of available resources, capacity should be assigned to a request if its total revenue is greater than the value of the capacity required to satisfy it. In this regard, the value of production capacity should be measured by its opportunity cost which is the expected loss in future
revenue from using capacity now instead of reserving it for future use (Deng et al. 2008). It can be calculated by comparing the values $Z$ of the remaining capacity for the rest of the booking period both in case of acceptance and decline of a request (Phillips 2005). An incoming request (represented by matrix $M$) is accepted as long as the sum of short-term profit, predominantly to be expected averaged future revenue and expected effects of changes in long-term lifetime values outweighs opportunity costs (5). In other words, the value of $Z(B+M)$ in case of acceptance plus the sum of $r_i$, $\tilde{c}_k$ and expected increase in customer value $c_r^+$ of client’s classified segment have to be at least as great as the value of $Z(B)$ plus resulting decrease in customer value $c_r^-$ in case of request’s denial, see (6). Accept request if:

\[ ar_i + (1 - \alpha)\tilde{e}_k + \beta(c_r^+ - c_r^-) \geq Z(B) - Z(B + M) \quad (5) \]

\[ \Leftrightarrow Z(B + M) + ar_i + (1 - \alpha)\tilde{e}_k + \beta c_r^+ \geq Z(B) + \beta c_r^- \quad (6) \]

5 DEcision Support System Prototype (DSS-CR²M²)

In practice, sales agents of the manufacturer face a difficult task to master the complexity of the order acceptance decision problem (Hintches et al. 2010). Besides a coordination between often separated departments (Skugge 2002; McGuire & Pinchuk 2009), a consideration of influencing factors (e.g. current capacity utilization, trend in demand, worthiness of incoming request, risk attitude, planning horizon, see goals in section 3) is necessary as well (Defregger & Kuhn 2007; Martens & Hilbert 2011). The authors of this paper provide a software tool to aid such decisions, called Decision Support System for both Customer Relationship and Revenue Management in Manufacturing, abbreviated with DSS-CR²M². The software prototype can take an informative role, supplying analysts with formatted and summarized data to make transparent and comprehensible control decisions (Talluri et al. 2009), and play a deeper role as well, suggesting specific booking control actions based on simulation results and integrated usage of provided data. As this prototype is of high relevance to practice with huge revenue potential, we hope to moderate Arnott and Pervan’s (2008) findings of most research in DSS discipline being disconnected from practice. Following design science paradigm (Hevner et al. 2004; March & Storey 2008), we use Matlab R2012b to construct an IT-artifact as an instantiation of the formulated optimization model and transaction control method (see section 4; March & Smith 1995). Matlab is a high-level language and interactive environment for numerical computation, visualization, and programming (MathWorks 2013). Due to its built-in math functions and easy output analysis (e.g. statistical toolbox), it is already common for complex simulations in RM environment (Bertsimas & Popescu 2003; Perakis & Roels 2007; DeMiguel & Mishra 2008; Van Ryzin & Vulcano 2008; Meissner & Strauss 2010). Not only are we able to take advantage of the strength of Matlab’s numerical computational framework to prepare data and analyze optimization results (Goh & Sim 2011), but Matlab also offers the option to layout, design, and edit custom graphical user interface (GUI) we want to make use of. In the following sections, central aspects of the prototype to support the analyst’s decision-making are discussed. Each one will refer to the corresponding decision support abstractions, stages and components, and corresponding tasks in RM and CRM (see section 3).

5.1 Decision Support in Problem Definition, Parameter Determination and Visualization

In order to make the model-driven DSS accessible to non-technical specialists, the design and capabilities of the GUI are of enormous importance (Power & Sharda 2007). The user interface should allow for inputting and manipulating values and controls how the analyst views and understands results, and hence influences choices. This also includes support in further specifying the decision problem (see section 4) and guaranteeing its conversion into a form understandable by the solution algorithm (see formulation stage in Figure 1, Shim et al. 2002; Power et al. 2011). So, the prototype offers graphical and numerical input modes for certain and uncertain quantities (e.g. total capacity $g_n$, amount of segment’s demand), probability distributions, monetary values and estimates, preferences and priorities, e.g. $\alpha$, $\beta$ or constraints such as minimum total short-term attainable profit $R$ in current decision period (Power & Sharda 2007). As performing “what-if” analysis is of major importance (see sections 5.2 and 5.4), single-model input parameters can be varied over a reasonable range (Power 2009). In
this regard, number of scenarios and probability point estimates can be specified. As an accurate forecast is an essential element of any RM system (Talluri & van Ryzin 2004), sufficient focus on retrieving and defining corresponding measures is necessary. In order to generate a desirable threshold value for order acceptance decision during transaction control (see section 5.3), specific for the forecasted demand scenario and particular request, input information (such as order history) for demand pattern identification is required. That is why the prototype collects general information (e.g. segment of customer, date of order and delivery), production details (e.g. start of production, capacity consumption), and commercial information (e.g. price, costs for sales, transport, material and production) for each order (Hintsches et al. 2010). As true integration is achieved with a system that integrates data from each department and synchronizes analysis (Skagge 2002; McGuire & Pinchuk 2009), the prototype offers data import functions and allows for transfer of values, e.g. customer segmentation patterns identified in data mining. After specifying input parameters, the analyst then can define different booking control methods (in dependence of values of α, β and R) and select which should be considered during scenario simulation (see section 5.2). When displaying results, the sales agent can switch between multiple formats, e.g. value tables, box plots (Power 2009). For ex-post analysis, visual animation of revenue development during booking period is provided. So, the analyst can successively review past period and is sensitized for effects of specific parameter combinations.

5.2 Decision-making under Risk and Uncertainty

Besides high variance in order-specific capacity consumptions and products’ demand (Hintsches et al. 2010), the incorporation of (long-term) future-related revenues, i.e. changes in customer value, is affected by uncertainties as well (Berger et al. 2006). This bunch of volatility leading to varying revenues represents financial risk to the manufacturer. A major step in developing a risk-averse RM tool is to understand the extent of risk and volatility associated with an inventory control policy (Lancaster 2003). Thus, the prototype enables the analyst to consider uncertainty in the decision situation through stochastic programming at the solution stage (see section 3; Shim et al. 2002). One problem with the optimization model formulated in section 4 is that it only considers expected demand and uses a deterministic approach to a highly stochastic problem (Bertsimas & Popescu 2003). To better capture demand variability, we propose a modification that uses Monte Carlo (MC) demand estimation. Given the analyst’s input that demand to come follows a certain distribution, N samples from this distribution are generated: \( D^{(1)}, \ldots, D^{(N)} \). By solving the model for the \( N \) simulated independent scenarios of the demand vector, the comparison value for final acceptance decision is received as mean of the opportunity costs of the different scenarios, see equation (7):

\[
\alpha r_t + (1 - \alpha) \bar{e}_k + \beta(c_s^+ - c_s^-) \geq \frac{1}{N} \sum_{o=1}^{N} \left[ Z(B, D^{(o)}) - Z(B + M, D^{(o)}) \right]
\]  

(7)

Besides demand, segment-specific values \( \bar{e}_k \), \( c_s^+ \) and \( c_s^- \) can be modeled as stochastic factors as well. By increasing the number \( N \) of independent demand scenarios, the quality and complexity of the calculation can be varied allowing to better capture distribution of demand and customer segment-based values in practice (Hintsches et al. 2010). An approach based on multiple samples is more robust regarding forecasting errors and advantageous (Bertsimas & Popescu 2003). Assuming that individual parameters are kept constant, the variety of scenarios generated by MC simulation procedure can then be used for sensitivity analysis (see section 5.4).

As values of short- and long-term revenues will vary in dependence of applied booking control (each with specific values for \( \alpha \) and \( \beta \)), the analyst is offered a direct means of comparing various RM policies. Accounting for expected variation in revenues, risk-adjusted returns are defined that allow the evaluation of opportunities with differing expected returns and risks (Laubsch 1999; Lancaster 2003). Using risk measurements in planning and strategic decision making helps to ensure that production assets are tactically controlled in a more stable manner, lowering exposure to uncertainties. As each booking control policy has its individual response and risk profile, revenue managers do have an opportunity to manipulate policy and strategy to achieve more financially stable results (Lancaster 2003). Following Laubsch (1999), the best-known measure of return on risk is the Sharpe ratio. It
captures the expected improvement of return over a benchmark per unit of risk taken. Various booking control methods can then be compared pair-wise to rank alternatives (Lancaster 2003). In RM, a first-come, first-served rule could serve as a good benchmark, as it requires no control. So, the Sharpe ratio $SR_p$ for a resource allocation policy $p$ can be defined, see (8), where $X^A_p$ is the expected return of policy $p$, $\bar{X}^A$ is the expected return of benchmark policy (both overall revenues adjusted by $\alpha^A$ and $\beta^A$), and $\sigma$ is the predicted standard deviation of $X^A_p - \bar{X}^A$, retrieved from a series of MC-simulations. Please note that each policy controls requests based on value-related revenues, adjusted by $\alpha^C$ and $\beta^C$, whereas $X^A_p$ and $\bar{X}^A$ resulted from a weighting of corresponding revenue components used for analysis purposes by means of factors $\alpha^A$ and $\beta^A$, specified in the parameter list (see section 5.1). Since $\sigma$ serves as a measure of risk, higher Sharpe ratios are better, meaning a greater differential return per unit of risk. So, the analyst will be guided towards the selection of less risky capacity allocations.

$$SR_p = \frac{(X^A_p - \bar{X}^A)}{\sigma}$$

5.3 Decision Support in Transaction Control

Within the scope of transaction control, the analyst has to decide about acceptance or denial of incoming requests, simultaneously the customers are informed about available manufacturing products and their prices (Martens 2009). As the current decision is subject to uncertainty about amount and worthiness of future requests (Talluri & van Ryzin 2004), the consequences of both alternate actions have to be balanced wisely against each other. So, the DSS should provide the analyst with information (retrieved from MC simulations) that is well prepared and can be used for transparent and justifiable decisions during bid-price comparison (solution and analysis stage; Shim et al. 2002).

The tolerance of a short-term loss in revenue today regarding a high-class customer who currently requests material goods early and therefore gets a discount, can turn out to be a long-term meaningful decision as this client will contribute predominantly high revenues (i.e. high $e_1$) with constant buying frequency in future booking periods. So, if the acceptance of a request may lead to an increase of customer’s loyalty (meaning higher repurchase probabilities), it even can be reasonable to accept reservations with a negative short-term contribution (Buhl et al. 2011). On the other hand, even a disestablishment of (long-term) unprofitable customers (by denying their requests) should be in the set of options (see Figure 1). By suitably adjusting the weights of $\alpha$ and $\beta$, bid-prices can serve as comparison values that explicitly account for long-term revenue components. These values can also be beneficial for determining a bottom price level (Rehkopf 2006; Becher 2008) in the process of iterative negotiations with clients. Whereas a client of lower-class segment can compensate lack of future potential by paying a higher surcharge for express delivery (case of skimming current willingness to pay), a high-class customer only interested in low-class product at present time may be reactivated by means of a higher discount (case of relationship investment). So, agents will be supported how the potential revenue scope during price negotiation can be best capitalized in terms of overall goal.

Until now, recommended actions and prices of (traditional) RM systems are reported to be occasionally overridden by analysts (Chandler et al. 2004; Becher 2008; Martens 2009). So, DSS should explicitly illustrate associated costs of recommendation’s deviation, i.e. (expected) loss in revenue compared to average opportunity costs, see equation (7), in order to enable a quantification and critical reflection of intended converse action. In particular, if the requesting client is an important reference customer in the B2B-market (given a certain level of service should be ensured; Sucky 2009), an override (e.g. in case of a small difference in both revenue situations only) seems reasonable.

In general, the acceptance of the request also depends on specific customer segment classification (given a weight for corresponding revenues). As customer value is a long-term measure that entails predictions of future transactions, thus causing some degree of subjective or statistically inferred uncertainty, the frontier between valuable and non-valuable customers does not possess sharp and clear boundaries (Sicilia & Garcia 2003). Moreover, due to insufficiently available indicators, the segment’s membership cannot be clearly determined (Martens 2009). This can result in a misclassifi-
cation, leading to a cannibalization of customer segments with revenue displacement. Mainly, a special and differential treatment for clients near the segment borders can become problematic (Sicilia & Garcia 2003). This may be the case if predominantly to be expected revenue \( e_k \) of requesting customer (classified to segment \( k \)) is close to the value continuum of an adjacent segment of different worthiness (Werro et al. 2006), or if a change in future buying behavior can be assumed, i.e. low current, but high potential future contributions (Martens & Hilbert 2011). In practice, such a situation can occur, if a request of low segment value is recommended to be denied, but given it was of medium worthiness, an acceptance would be suitable instead. Of course, this remains valid for contrary case (acceptance of high-class customer, but tendency of denial in case of attributed medium value only). Provided with the modified booking control decision in dependence of the segment classification, the analyst is sensitized to the critical cases (apart from clear and unambiguous situations) and may think about likelihood of divergent segment membership. Therefore, the DSS will alert the user if altered recommendations are to be expected as a result of request’s classification to possible other segments.

A specific intervention and alert of the DSS during opportunity costs comparison is provided if consequences of present product availability decision are of high significance due to past booking control actions. This may be if the request’s denial possibly leads to customer’s churn, as a result of several (consecutive) denials (Mohaupt & Hilbert 2012), see customer’s history in Buhl et al. (2011), leaving the provider with a huge loss in customer value. So, analysts can be notified that clients are classified as liable to churn due to their past behavior or have to be treated with priority next time (McGuire & Pinchuk 2009). This anticipation of avoidable costs for reactivation is explicitly modeled in the bid-price comparison (see formula 5) by means of an increased (individual) loss in customer value \( c^r_k \).

5.4 Decision Support in Analysis

One cannot overrate the importance of analysis as the final stage of the process in model-based decision support. This stage includes delivery of model solution in a usable form to enhance analyst’s ability to analyze and understand the problem and to gain further insight into the interdependence of different factors by studying the set of solutions (Shim et al. 2002). In a holistic approach for decision support, this also implies instruments for evaluation of capacity control (Martens 2009). In order to assess and control the implementation of RM in terms of formulated goals, a performance indicator system is necessary that appropriately operationalizes objectives and measures the degree to which performance targets are achieved (see section 3). That is why performance figures should relate realized success of capacity control to revenue potential or alternative booking controls (Martens 2009). In the B2B-context of manufacturing environment, both capacity and relationship-based indicators are of interest. Whereas former measures (such as load factor, revenue per available inventory unit) focus on performance of individual booking periods, the latter rests upon (long-term) estimates for a combination of such periods (Kimes 2005; Martens & Hilbert 2011). So, predominantly to be expected revenue of customer per booking, prospective buying frequency and duration of customer retention are focus of interest in the report generating functionality of the prototype (Venkatesan & Kumar 2004; Gupta et al. 2006; Martens 2009). Furthermore, the number of clients in the defined segments (both dimensions \( k \) and \( s \)) can be analyzed as well. In order to establish a long-term profitable customer base, a frequent monitoring of the overall worthiness of all customers and its past development (customer equity; Kumar & George 2007) is reasonable. By focusing on different levels of detail in analysis, the estimation of long-term measures such as \( c^{r_k} \) and \( c^c \) can be supported (see section 4). So in a retrospective view, the development of buying behavior as a result of varying booking control decisions can be analyzed at customer segment level or even for individual clients (Mohaupt & Hilbert 2012). Such uncovered relations can also be enriched with customer surveys on planned budget for manufacturing products (with share-of-wallet for provider) and potential reactions of clients in case of denial (Gupta et al. 2006; Wang & Bowie 2009). This information can then be used to draw conclusions of possible intervals for changes in customer values. So at highest level of detail, customers can be (re-)classified to segments suitably capturing their characteristics, be purposefully selected for marketing actions or be identified as preferential in booking control decisions (see section 5.3).
The formulated performance figures can also be used for both post solution and sensitivity analysis (Shim et al. 2002). In order to assess the effect of applied capacity control in isolation, value-related revenues earned should be measured in relation to ex-post optimal revenue, first-come-first-serve control or other booking control methods with specified values of $\alpha^c$ and $\beta^c$ (Martens & Hilbert 2011). So, by means of visualization and inspection of Sharpe-ratios (see section 5.2) for various streams of revenue (short vs. long-term), the analyst may switch to a capacity control with a slightly adjusted revenue weighting due to greater robustness in past periods. In addition, if the analyst wants to get a deeper insight for the effect of specific combinations of model parameters, analyzing the sensitivity of results is a means of first choice. Often neglected in favor of more attention paid to optimization itself instead of required inputs (Weatherford & Belobaba 2002), a systematic variation of a sole parameter can gain a better understanding of revenues’ overall stability. As a result, sensitivity analysis and “what-if” scenarios will lead to multiple solutions with revenue distributions (i.e. confidence intervals) the analyst can evaluate in detail. To support this type of analysis, the prototype is ready to execute simulation runs for evaluation purposes without influencing calculations in the present booking period.

6 DISCUSSION OF RESULTS AND FURTHER RESEARCH

With the literature review presented above, the paper contributes to theory through providing a more comprehensive view for a complex decision-making problem in manufacturing by integrating a range of research streams from different perspectives. It addresses the common frustration of managers and analysts in practice when dealing with conflicting ideas or theories generated by research community. The proposed framework that integrates RM and CRM with partly diametric goals is of high relevance to practice, especially when provided with an implemented (prototype) IT-system incorporating the developed optimization model and transaction control method and seeking for an improved analysts’ decision support. Of course, the emerging opportunity of huge revenue potential may be hampered by restrictions of legacy systems that decide about interfaces, availability and quality of data needed.

The paper forms the basis for further research on long-term oriented revenue maximization in manufacturing. The authors strive for further analysis and findings concerning more realism and robustness, by means of modeling demand with forecast errors during simulation. As revenue $\hat{\epsilon}_t$ to come varies in different customer lifetime phases, an incorporation of prospective customers with increasing demand for material goods and hence changing customer segment classification (albeit much more difficult to forecast) is worthy of further investigation. In case real-time decisions for incoming requests are desirable but hindered by computationally intensive tasks, e.g. need for sufficient number of simulation scenarios (Power et al. 2011), the prototype may be enhanced that all required comparison values for possible combinations of product request and customer segment are calculated and stored in advance. So after request’s occurrence, the corresponding values are retrieved and used as base for decision.

7 CONCLUSIONS

In practice, sales agents of the manufacturing company face a difficult task to master the complexity of the order acceptance decision problem. On the one hand, the efficient utilization of limited production capacity is a crucial success factor. But due to high degree of competition, strengthening of long-term customer relations is becoming increasingly important as well. However, desired incorporation of RM and CRM (with partly diametric goals) in the form of an implemented IT-system that provides the revenue analyst with greater insights in order to make transparent and comprehensible booking control decisions is still missing in the field of industry. So, the authors of this paper provide a software tool to aid such decisions, accounting for the strategic dimension of the problem. The DSS supplies the analyst with formatted and summarized data based on simulation results and integrated usage of provided information. We believe the integration of RM and CRM remains a highly promising research area with significant implications on improving competitiveness not only of manufacturers.
References


