Robust order promising

- Design and analysis of a capable-to-promise approach including order- and resource-related measures

Dissertation
zur Erlangung des akademischen Grades
Doctor rerum politicarum (Dr. rer. pol.)

an der Fakultät Wirtschaftswissenschaften
der Technischen Universität Dortmund

Sonja Kalkowski

Dortmund 2017

Table of contents

List of figures

List of tables

List of abbreviations

ad.	adaptation
AGFI	Adjusted-Goodness-of-Fit-Index
AP	acceptance probability
ATP	available-to-promise
B	batch
C	cost minimization
CCR	Charnes-Cooper-Rhodes
CMIN	minimum discrepancy
CN	capacity nesting
CS	customer satisfaction maximization
CTP	capable-to-promise
CTPM	capable-to-promise model
CV	coefficient of variation
D	demand
DEA	Data Envelopment Analysis
DF	degrees of freedom
DT	delivery time minimization
DP	detected parameter
E	increased order-related uncertainty
F	formula-conditioned relation
GFI	Goodness-of-Fit-Index
H	hypothetical relation
I	intermediate variable
L	adaptation of delivery dates
LP	linear programming
max.	maximization
MGA	multi-group analysis
min.	minimization
MIP	mixed-integer programming

MS	proposing modified order specifications
MTO	make-to-order
MTS	make-to-stock
N	no use of adaptation measures
ns	non-significant
OV	order volume maximization
P	profit maximization
PC	penalty costs
PD	partial deliveries
PP	production progressiveness maximization
QPD	demand quantity depending on price and delivery time
R	regular order-related uncertainty
RM	robustness maximization
RT	real-time
rel.	released
res.	restricted
RMSEA	Root Mean Square Error of Approximation
S	supply
SC	safety capacity
TW	time window
U	uncertainty
WL	workload maximization
WO	work overload minimization
Z	objective

List of symbols

Decision variables

B	inventory quantity
$\tilde{C}$	random variable of available capacity
D	delivery date
$\tilde{J}$	random variable of interarrival time
$\tilde{K}$	random variable of costs
M	quantity to be delivered
P	production quantity
$\tilde{P}$	random variable of price
Q	consumption quantity
$\tilde{Q}$	random variable of order quantity
u	auxiliary variable for linearization
V	deviation from requested delivery time interval/ contractually fixed delivery date
y	auxiliary variable for linearization
Z	acceptance decision
$\beta(\cdot)$	response function
δ	auxiliary variable for tardy/ premature delivery
Φ	discount

Parameters

a	replenishment quantity
b	production coefficient
e	efficiency value
$\hat{e}$	average efficiency value
C	deterministic production capacity
d	number of allowed partial deliveries
d^+	share of dominating solutions
F	probability distribution of available capacity
G	weighting factor delivery time deviation (premature delivery)
H	weighting factor discount (premature delivery)
k	cost ratio
M	weighting factor delivery time deviation (tardy delivery)
MS	shifting between order promising steps II and III
N	weighting factor discount (tardy delivery)
p	significance value
q	order quantity
QI	quality indicator
$\widehat{QI}$	average quality indicator
r_k	index value of first externally procured material
t_a	current planning period
z	number of relevant criteria
ZV	objective value
α	sufficiently large number
β	acceptance probability
βr	regression weight
γ	penalty costs
Δ	upper limit of step interval in the response function
ε	share of premium capacity
ζ	weighting function

ϑ	chance constraint probability value
η	time span for revision of production decisions
κ	capacity requirements per piece
μ	mean value
ρ	product price
σ	standard deviation
τ	length of batch interval
φ	robustness index
ψ	maximum discount
ω	lead time deferral

Indices and sets

Indices

c	product configuration
i	orders $(i = 1,...,I)$
l	steps of customers' response function $(l = 1,...,L)$
P	solution with detected parameters $(P \in [1,...,S])$
r	materials $(r = 1,...,R)$
s	included data sets $(s = 1,...,S)$
t	time periods $(t = 1,...,T)$

Sets

A	order inquiries that arrived in the batch interval
$\tilde{A}$	order inquiries with a profit chance / currently acceptable orders
$\hat{A}$	previously accepted, but not yet fulfilled orders
$\underline{A}$	rejected or completely fulfilled orders
$\underline{A}^{+}$	fulfilled orders
$\underline{A}^{-}$	finally rejected orders
$\bar{A}$	provisionally rejected orders / orders to be modified

Superscripts

c	contractually fixed
cap	capacity situation
CP	consecutive planning runs
des	desired delivery time interval
e	early
FP	finished product
l	late
L	inventory
M	manufacturing
max	maximum
min	minimum
P	premium capacity
PD	partial delivery
pr	planning run
prev	previous
R	material
real	realized compared to contractually fixed delivery date
S	standard capacity
Tr	transportation
UL	upper limit of desired delivery time interval

1 Motivation

1.1 Problem

In economic research, the decision regarding order acceptance or rejection has been discussed for a long time[1]. For make-to-order (MTO) production the order acceptance decision is an essential part of order promising which is characterized by interactive negotiations concerning order specifications with customers.[2] Nowadays, the ability to define economically advantageous order specifications represents a key success factor for companies and can induce long-term competitive advantages. Thereby customers' increasing request for shorter delivery times, more reliable completion dates as well as high levels of flexibility in changing order specifications, have to be considered.[3] MTO companies have a particularly high level of latitude for determining order specifications, since the majority of production decisions only have to be made after the receipt of an order inquiry[4]. Hence, the efficient design of order promising provides a high potential to fulfill growing customer requirements and to obtain a high degree of customer satisfaction in the long run.

In this context, it should be noted that the interests of the company and customers do not necessarily have to correspond; accordingly, requested order specifications may partially remain unsatisfied. Due to prevailing conflicts between the involved negotiating parties, the establishment of compromises and trade-offs are consequently in the focus of interest.[5] The company faces the challenge of balancing its own schedule with that of its customers. Furthermore, uncertainty concerning the future order and resource situation considerably complicates this problem[6]. Thereby, uncertainty

---

[1] Cf. e.g. Adam (1969); Friedman (1956); Goodman/Baurmeister (1976); Jacob (1971); Laux (1971); Schwendiger (1979); Stark/Mayer (1971); Wallace/Daugherty (1987).

[2] Cf. Mansouri et al. (2012), p. 25.

[3] Cf. Grillo et al. (2016), p. 239; Mansouri et al. (2012), p. 25.

[4] Cf. e.g. Seitz/Grunow (2016), p. 658.

[5] Cf. Mansouri et al. (2012), p. 25.

[6] For a distinction between order- and resource-related uncertainties see e.g. Choi et al. (2016), p. 382 and Vilko et al. (2014), p. 4.

is generally understood as the difference between information already available and information necessary to fulfill the task[1)].

To offer order specifications which are reliable and competitive from the customer's, as well as the company's, point of view and thus meet the needs of both parties, irrespective of existing uncertainty, this dissertation focuses on *robust order promising*. The term *robustness,* in general, describes the insensitivity of a system to random changes[2)]. The following two robustness dimensions are used to clarify this term[3)]: (1) planning robustness and (2) solution robustness.

The term *planning robustness* is applied in case of dynamic decision fields (e.g. rolling planning)[4)]. Receipts of customer inquiries, the non-availability of material, or internal factors like machine failures, cause revisions of production or delivery date decisions; which usually involve additional costs[5)]. In order promising, a high degree of planning robustness is present if plans are created in which the extent of plan revisions induced by order- and resource-related uncertainty is low[6)]. A high degree of robustness is therefore achieved, from the customer's point of view, if only a few adjustments of promised order specifications are necessary. On the other hand, a high level of *solution robustness* is present if changes in the planning data have an insignificant effect on the planning objective[7)]. In this case, uncertain planning data only causes small fluctuations in the company's achievement of objectives (e.g. profit maximization, cost minimization, etc.), so that the long-term continuance of the company can be ensured through a high degree of solution robustness.

---

1) Cf. Galbraith (1973), p. 5.
2) Cf. Scholl (2001), p. 93.
3) An overview of additional robustness criteria can be found in Roy (2010), pp. 629 ff.
4) Cf. Kimms (1998), p. 355; Scholl (2001), pp. 108 ff.
5) Cf. Pujawan/Smart (2012), p. 2253; Sridharan et al. (1988), pp. 148 ff.
6) Cf. Kimms (1998), pp. 355 ff.
7) Cf. Herroelen/Leus (2004), p. 1602; Mulvey et al. (1995), p. 265.

In the literature, *capable-to-promise (CTP) approaches* are in particular proposed to support order promising in MTO production environments[1]. These approaches are generally used to determine reliable responses to customer inquiries based on the available resources[2]. Thereby, order receipts trigger a detailed verification whether the start of production can ensure an on-time delivery with regard to material and capacity limitations. Thus, CTP approaches in general guarantee a high precision of order promises.[3] According to the response time[4] of the system, real-time and batch CTP approaches can be distinguished[5]:

- In real-time approaches, customers receive a response immediately after the arrival of their orders;
- whereas a main characteristic of batch approaches is the initial collection of customer inquiries during a predefined time interval (batch interval). Planning of order acceptance, quantities to be delivered and/or delivery dates is done simultaneously after the expiration of the time interval for all order inquiries which arrived during the past batch interval.[6]

The decision for/against one of the entitled modes needs to be made industry-specifically. In the present dissertation a batch approach, whose basic structure is visualized in figure 1.1.1, is chosen to support order promising. As visualized in the figure, in standard batch CTP approaches, decisions on the acceptance of orders arriving in the past batch interval, are made according to the principles of rolling planning[7] by taking into account available resources as well as orders accepted in a pre-

---

[1] Cf. Kilger/Meyr (2008), p. 187.

[2] Cf. Ball et al. (2004), p. 449.

[3] Cf. Fischer (2001), p. 33; Jung (2010), p. 369; Kilger/Meyr (2008), p. 187.

[4] Different classification approaches can for example be found in Ball et al. (2004), pp. 455 ff.; Framinan/Leisten (2010), pp. 3091 ff.; Jung (2010), pp. 369 ff.; Kilger/Meyr (2008), pp. 181 ff.; Pibernik (2002), pp. 349 ff. or Pibernik (2005), pp. 241 ff.

[5] Cf. e.g. Ball et al. (2004), p. 456; Chen et al. (2001), p. 478; Chen et al. (2002), p. 425; Framinan/Leisten (2010), pp. 3083 f.; Jung (2010), p. 370; Jung (2012), p. 1780; Pibernik (2002), p. 351; Pibernik (2005), p. 242; Robinson/Carlson (2007), p. 283.

[6] Cf. Ball et al. (2004), p. 456; Chen et al. (2001), p. 478; Chen et al. (2002), p. 425; Framinan/Leisten (2010), pp. 3083 f.; Pibernik (2002), p. 351; Pibernik (2005), p. 242.

[7] Cf. Scholl (2001), pp. 33 f.

vious planning run. Thus, those of the previously accepted orders, which have not been completely fulfilled yet, need to be considered and therefore still influence production. The delivery dates and quantities for all orders are determined, wherein the revision of already taken production decisions is permitted. Due to the fact that the next planning run is not carried-out until the expiration of another batch interval, the production plan is fixed for the periods of the next batch interval but is only of preliminary nature for the remaining periods of the planning horizon.

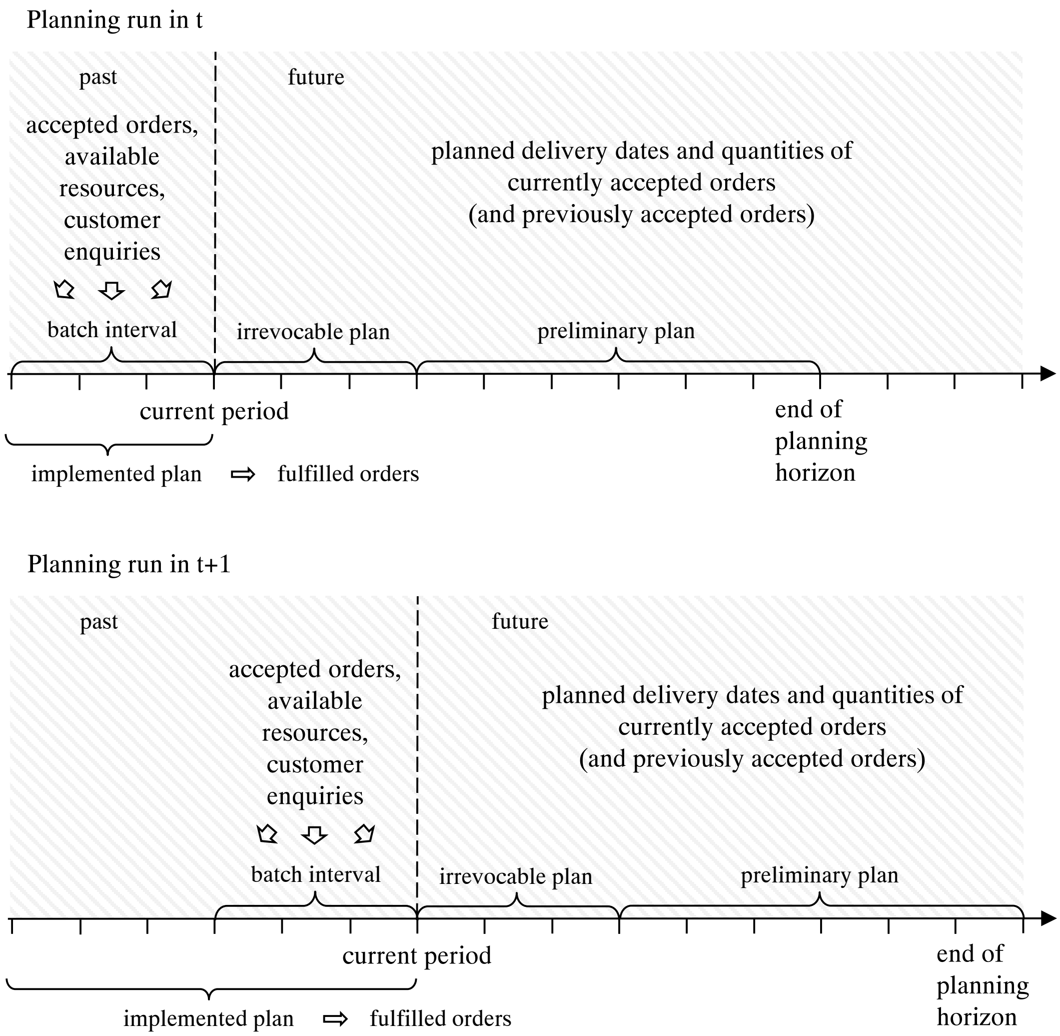

Figure 1.1.1: Basic structure of a batch CTP approach

Outlining the basic idea of CTP approaches illustrates the fundamental suitability of these planning approaches for supporting order promising under uncertainty. In particular, opportunities for revising taken decisions and consequently options, for adapting planning decisions to the change in uncertain environmental situations, are revealed. However, a largely unrestricted revision of decisions contradicts the intended robustness concept of order promising. Since basic options to implement an order promising, which is planning and solution robust at the same time, consist of integrating temporal and/or quantitative buffers or courses of action for possible events[1], the identification and integration of problem-related adaptation measures is recommendable. For this reason, the aim of the present dissertation is to extend a standard batch CTP approach to a robust planning model by integrating and coordinating order- and resource-related adaptation measures to handle uncertainty.

1.2 State of the art

1.2.1 Capable-to-promise approaches

Although the origin of CTP approaches is connected to statements made by Schwendinger in 1979[2], currently only a few quantitative CTP approaches exist[3]. A taxonomy of these approaches is presented in table 1.2.1. The applied criteria serve for revealing research focuses and deficits related to *general characteristics* of the approaches, the type of *considered uncertainty*, the consideration of *order- and resource-related measures* to cover uncertainty and the *interaction with customers*.

With respect to the *general characteristics*, the *type of CTP approach* can be considered for classifying the approaches. Thereby a distinction between batch (B) and real-time (RT) approaches is made. The selection of a specific mode depends on the objectives and characteristics of the company being considered.

---

1) Cf. Herroelen/Leus (2004), pp. 1602 ff.; Seitz/Grunow (2016), p. 657; Vorst/Beulens (2002), p. 412.

2) Cf. Fischer (2001), p. 11. See Schwendinger (1979) for a definition of the closely related concept *available-to-promise*.

3) Cf. Chen et al. (2001), p. 478; Chen et al. (2002), p. 426; Gao et al. (2012), p. 773; Halim/Muthusamy (2012), p. 4535; Jung (2010), p. 369; Pibernik (2002), p. 354, Pibernik (2005), p. 240; Zhao et al. (2005), p. 68.

	General characteristics			Considered uncertainty		Measures related to: orders			Measures related to: resources		
	Type of CTP approach	Objective	SC structure	Order-related	Resource-related	Order rejection	Deviating order specifications	Rescheduling	Resource nesting	Safety capacity	Interaction with customers
Aouam/Brahimi (2013)	B	C	-	x	x	x	-	-	x	x	-
Charnsirisakskul et al. (2004)	B	P	-	x	-	x	x	x	-	-	-
Charnsirisakskul et al. (2006)	B	P	-	x	-	x	x	x	-	-	-
Chen/Dong (2014)	B	P	x	x	-	x	x	x	-	x	-
Chen/Dong (2014)	RT	P	x	x	-	x	x	x	x	x	-
Chen et al. (2001)	B	P	x	x	-	x	x	x	x	-	-
Chen et al. (2002)	B	P	x	x	-	x	x	x	-	-	-
Chiang/Wu (2011)	RT	P	-	x	-	x	-	x	x	-	-
Gao et al. (2012)	B	P	-	x	-	x	-	x	x	-	-
Guillén et al. (2005)	B	P/CS	x	x	-	-	x	-	-	-	o
Halim/Muthusamy (2012)	B	C	x	x	x	x	x	x	-	x	-
Hempsch et al. (2013)	B	C/DT	x	x	-	o	x	x	-	-	o
Jeong et al. (2002)	RT	PP	x	x	-	x	x	x	-	-	-
Jung (2010)	B	C	x	x	-	o	x	x	-	-	-
Jung (2012)	B	C	x	x	x	o	x	x	-	x	-
Lečić-Cvetković et al. (2010)	RT	OV	-	x	-	x	x	x	x	-	-
Lim/Halim (2011)	B	RM	x	x	x	x	x	x	-	x	-
Lin et al. (2010)	B	P	x	x	-	x	x	x	-	-	-
Manavizadeh et al. (2013)	B	C/WO	x	x	-	x	x	x	x	-	o
Pan/Choi (2016)	B	C	-	x	x	o	x	x	x	-	o
Pibernik (2002, 2005)	RT	OV	-	x	-	x	x	-	-	-	-
Pibernik (2002, 2005)	B	P	-	x	-	x	x	-	-	-	-
Pibernik/Yadav (2008)	RT	OV	-	x	-	x	-	x	x	x	o
Renna/Argoneto (2010)	RT	P	x	x	-	-	x	x	x	-	o
Robinson/Carlson (2007)	RT	C	-	x	-	x	-	x	-	-	-
Seitz/Grunow (2016)	RT	P	-	x	x	x	x	x	-	-	-
Taylor/Plenert (1999)	B	OV	-	x	-	-	-	x	-	-	-
Wu/Liu (2008)	B	WL	-	x	-	x	-	x	-	-	-
Xiong et al. (2003)	RT	OV	x	x	-	-	-	x	-	-	-
Yang/Fung (2014)	B	P/OV	x	x	-	x	x	x	-	-	-
Zhao et al. (2005)	B	C	-	x	-	o	x	x	-	-	-

Table 1.2.1: Relevant modelling approaches (with x: considered, -: not considered, o: partially considered)

While response times to customer inquiries are shorter for real-time approaches, interactions between incoming orders can only be considered to a limited extent since order acceptance decisions are made separately. In case of periodic batch approaches, longer response times are tolerated in favor of capturing interdependencies between incoming orders.[1] The particular suitability of the mode needs to be verified with respect to the regarded industry sector. Although a batch CTP approach is developed in the course of the dissertation, it is recommendable to simultaneously include real-time approaches into the literature review. The justification for the latter is that independently of the chosen mode, all described CTP approaches intend an availability-oriented support of order promising and consider different measures to cover uncertainty.

Closely linked to the implemented mode are the *objectives* pursued in different papers whereby both monetary (maximization of profit (P); minimization of costs (C)) and non-monetary (maximization of order volume (OV), workload (WL), production progressiveness (PP), robustness (RM) or customer satisfaction (CS); minimization of delivery time (DT), work overload (WO)) objectives are focused. The overview table reveals that batch approaches primarily aim at monetary objectives in the form of a single- or multi-criteria objective optimization. Solely non-monetary objectives can be found in the approaches of Taylor and Plenert[2] as well as Wu and Liu[3]; whereby a maximization of the order volume and a high workload of the production system are intended. Furthermore, Lim and Halim are the only authors who explicitly pursue the non-monetary objective of robustness maximization by maximizing the certainty degree of the solution while ensuring a predefined aspiration level. However, economic implications of their procedure are not adequately taken into account.[4] The partly algorithmized real-time approaches pursue monetary and non-monetary

---

1) Cf. Jung (2012), p. 1780.
2) Cf. Taylor/Plenert (1999), pp. 50 ff.
3) Cf. Wu/Liu (2008), pp. 2258 ff.
4) Cf. Lim/Halim (2011), pp. 302 f.

objectives in a balanced manner. Of particular note is that especially younger publications aim at fulfilling monetary objectives[1].

Due to their cross-functional character, CTP approaches are suitable for capturing the multi-tiered nature of supply chains and allow for a better coordination between forecast-driven push-activities as well as order-driven pull-activities along the supply chain[2]. In the considered planning approaches, the specific *structure of the supply chain* is taken into account in different ways: According to Jung[3], Hempsch et al.[4] or Yang and Fung[5] one possibility is to model product- or order-related production and transport flows which take place across multiple locations and may take time due to limited capacity availability. In a similar way, Chen and Dong[6], Guillén et al.[7] as well as Jeong et al.[8] consider one sub-aspect of relations between goods in supply chains by examining product-related transports between multiple plants of a production company as well as various sales regions and distribution centers. Alternatively, multistage production processes are modeled by means of production coefficients in the approaches of Halim and Muthusamy[9] as well as Lim and Halim[10], whereby different suppliers provide the individual components. Renna and Argoneto[11] also incorporate various suppliers during a multi-agent-based negotiating process, but do not capture the product structure. In contrast, Chen et al.[12], Lin et al.[13] as well as

---

1) See e.g. Chen/Dong (2014), Chiang/Wu (2011), Renna/Argoneto (2010) or Seitz/Grunow (2016).

2) Cf. Chen et al. (2001), p. 478; Gao et al. (2012), p. 771; Zhao et al. (2005), p. 66.

3) Cf. Jung (2010), pp. 371 ff.; Jung (2012), pp. 1786 ff.

4) Cf. Hempsch et al. (2013), pp. 27 ff.

5) Cf. Yang/Fung (2014), pp. 4255 ff.

6) Cf. Chen/Dong (2014), pp. 6719 ff.

7) Cf. Guillén et al. (2005), pp. 7407 ff.

8) Cf. Jeong et al. (2002), pp. 193 ff.

9) Cf. Halim/Muthusamy (2012), pp. 4536 ff.

10) Cf. Lim/Halim (2011), pp. 300 ff.

11) Cf. Renna/Argoneto (2010), pp. 75 ff.

12) Cf. Chen et al. (2001), pp. 480 ff.; Chen et al. (2002), pp. 427 ff.

13) Cf. Lin et al. (2010), pp. 722 ff.

Manavizadeh et al.[1] take an individualized product structure for each order into account which is based on bills of material and specifies components as well as potential component suppliers or qualities. By additionally including lead times for each production stage, Xiong et al.[2] apply a dynamic bill of material in their planning approach and thereby allow for an easier estimation of the delivery date. However, this estimation ignores the influence of limited capacity on the lead-time and may therefore cause infeasible plans.

In addition to examining the general characteristics of relevant CTP approaches, the type of *considered uncertainty* is also investigated. Since, in the order-promising process, uncertainty is mainly caused by incoming orders and necessary production resources, the consideration of order- and resource-related uncertainty is focused. The analysis of relevant approaches reveals that almost all papers solely consider order-related uncertainty (e.g. in terms of uncertain order quantities, product configurations or delivery dates) and assume deterministic resource availability. In particular, the more realistic simultaneous consideration of order- and resource-related uncertainty is only done in the minority of approaches[3].

Due to the underlying robustness-oriented problem definition and the resulting need for taking into account the underlying uncertainty situation, the literature review consequently further focuses on *adaptation measures considered to cover uncertainty*. Thereby, emphasis is placed on the following order- and/or resource-related adaptation measures:

- *Order-related measures*:
    - Rejection of orders
    - Deviation from requested order specifications (e.g. temporal, quantitative or qualitative)

---

1) Cf. Manavizadeh et al. (2013), pp. 2535 ff.

2) Cf. Xiong et al. (2003), pp. 136 ff.

3) Cf. Auoam/Brahimi (2013), p. 508; Halim/Muthusamy (2012), p. 4538; Jung (2012), p. 1782; Lim/Halim (2011), p. 302; Pan/Choi (2016), pp. 546 f.; Seitz/Grunow (2016), pp. 660 ff.

- *Order- and resource-related measure*:
    - Revision of production and delivery date decisions
- *Resource-related measures*:
    - Resource nesting
    - Providing safety capacity

Order-related adaptation measures refer to the order-driven pull-activities along the supply chain. In this context the *rejection of orders* is discussed as a first measure. If the fulfillment of customer inquiries is economically disadvantageous under the chosen objective, e.g. due to scarce production capacities and/or insufficient material availability, order inquiries are rejected in the multitude of papers. The following planning approaches are exceptions:

- Analogously to Xiong et al.[1)], Taylor and Plenert[2)] include all incoming orders in the production plan. The afore-mentioned authors thereby consider the option to integrate alternative materials for order fulfillment by means of a bill-of-material explosion.

- Guillén et al.[3)] also do not implement the possibility of rejecting order inquiries but chose offers from the set of Pareto-optimal combinations of order specifications, which result from the considered divergent objective criteria named profit and customer satisfaction.

- Renna and Argoneto[4)], Hempsch et al.[5)] as well as Pan and Choi[6)] develop strategies for avoiding order rejections within the scope of multi-agent-systems. In the paper of Renna and Argoneto, a supplier agent places counteroffers in each negotiation round as long as customers' order specification requests cannot be fulfilled. In this process the decision about acceptance or rejection as well as the request of another counteroffer is up to the customer. Similarly, in the papers of Pan and Choi as well as of Hempsch et al. a negotiation agent places counteroffers which have to be evaluated in several negotiation rounds. Thereby, Pan and Choi reject

---

1) Cf. Xiong et al. (2003), pp. 138 ff.
2) Cf. Taylor/Plenert (1999), pp. 50 ff.
3) Cf. Guillén et al. (2005), pp. 7412 ff.
4) Cf. Renna/Argoneto (2010), pp. 75 ff.
5) Cf. Hempsch et al. (2013), pp. 33 ff.
6) Cf. Pan/Choi (2016), pp. 543 f.

customer inquiries after the expiration of a predefined negotiation period. In contrast, Hempsch et al. only involve those order inquiries for which an insufficient contribution to objective achievement was determined by a CTP model and order rejection was recommended as a consequence. The need for avoiding final order rejection is based on the argumentation that rejected customers might turn to competitors and a permanent impairment of customer relationship might result[1)].

- Furthermore, Jung[2)], as well as Zhao et al.[3)], intend to avoid order rejections by taking into account penalty costs for early or tardy (partial) delivery. Rejections only occur at the end of the planning horizon since options for further shifting orders no longer exist.

Moreover, additional strategies to prevent negative consequences of order rejections are pointed out in the presented CTP approaches. Even though Pibernik[4)] and Jeong et al.[5)] implement the measure of order rejection, they demand for an examination of several options for action so that order rejection has to be seen as a last option. An alternative approach is proposed by Lečić-Cvetković et al.[6)] whereby inadequately fulfilled orders are assigned higher priority values for the next planning iteration to increase the probability of order fulfillment.

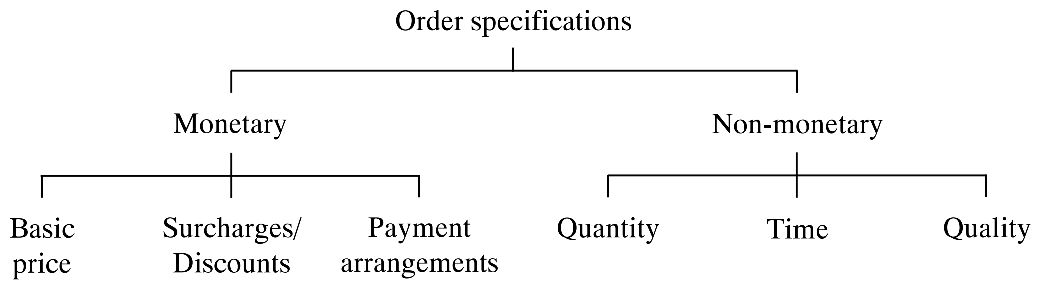

Figure 1.2.1: Classification of order specifications

1) Cf. Hempsch et al. (2013), p. 31.
2) Cf. Jung (2010), pp. 371 ff.; Jung (2012), p. 1788.
3) Cf. Zhao et al. (2005), pp. 70 ff.
4) Cf. Pibernik (2002), pp. 365 ff.; Pibernik (2005), pp. 246 ff.
5) Cf. Jeong et al. (2002), p. 201.
6) Cf. Lečić-Cvetković et al. (2010), pp. 789 f.

Another order-related adaptation measure consists in *deviating from requested order specifications*. Basic options for implementing this measure can be derived from the classification of order specifications shown in figure 1.2.1.

The *deviation from non-monetary order specifications* can thus occur with respect to quantity, time and quality. Investigating the considered quantitative CTP approaches reveals that in particular the options of quantitative and temporal deviation are widely used. In the event of *quantitative deviations,* the alternatives of a complete or partial deviation from the requested order quantity are implemented. While a lower quantity than requested is delivered in case of complete quantitative deviation[1)], multiple partial deliveries, for which a minimum quantity per delivery can be described[2)], take place in the event of partial deviations[3)]. To limit the occurrence of quantitative deviations, some approaches additionally consider penalty costs if requested order quantities are not met[4)]. Analog options of complete or partial deviations exist in the *temporal dimension*. In the first-mentioned case the (in)complete quantity is delivered at a deviating delivery date[5)], whereas a partial deviation from the requested delivery date is present in the second case since (un)punctual sub-quantities are delivered[6)]. Thereby, the alternatives of a quantitative/temporal deviation are considered

---

1) Cf. Charnsirisakskul et al. (2006), pp. 156 ff.; Chen et al. (2001), pp. 480 ff.; Chen et al. (2002), pp. 427 ff.; Halim/Muthusamy (2012), p. 4536; Lečić-Cvetković et al. (2010), pp. 786 ff.; Lim/Halim (2011), p. 301; Lin et al. (2010), pp. 724 ff.; Pibernik (2002), p. 365; Pibernik (2005), pp. 246 ff.; Renna/Argoneto (2010), pp. 76 ff.; Seitz/Grunow (2016), p. 663; Yang/Fung (2014), pp. 4255 ff.

2) Cf. Pibernik (2002), pp. 359 ff.; Pibernik (2005), pp. 244 ff.

3) Cf. Charnsirisakskul et al. (2004), pp. 699 ff.; Chen/Dong (2014), pp. 6722 ff.; Jung (2010), pp. 371 ff.; Jung (2012), pp. 1782 ff.; Zhao et al. (2005), pp. 69 ff.

4) See e.g. Charnsirisakskul et al. (2006), pp. 156 ff.; Chen/Dong (2014), pp. 6722 ff.; Halim/Muthusamy (2012), p. 4536 ; Lim/Halim (2011), p. 301.

5) Cf. Charnsirisakskul et al. (2006), pp. 156 ff.; Chen et al. (2001), pp. 480 ff.; Guillén et al. (2005), pp. 7412 ff.; Hempsch et al. (2013), pp. 35 ff.; Jeong et al. (2002), pp. 196 f.; Pan/Choi (2016), pp. 539 ff.; Renna/Argoneto (2010), pp. 77 f.; Seitz/Grunow (2016), p. 659; Yang/Fung (2014), pp. 4255 ff.

6) Cf. Charnsirisakskul et al. (2004), pp. 699 ff.; Chen/Dong (2014), pp. 6722 ff.; Jung (2010), pp. 371 ff.; Jung (2012), pp. 1782 ff.; Manavizadeh et al. (2013), pp. 2534 ff.; Pibernik (2002), pp. 359 ff.; Pibernik (2005), pp. 244 ff.; Zhao et al. (2005), pp. 69 ff.

with and without adherence to given intervals of accepted deviations from the requested date and/or quantity[1)].

In addition to the so far examined deviations from non-monetary order specifications, the option of *deviating from the requested product quality* further exists. Chen and Dong consider qualitative deviations by substituting specified products up to a maximum quantity defined by the customer and by taking into account penalty costs[2)]. Analogously, Pibernik permits access to substitute products provided that only insufficient quantities of requested products are available at the selected location[3)]. Deviations from the requested quality are alternatively modeled by involving substitute components. Thus, Chen et al. define a customer-specific set of suppliers from whom substitute components may be ordered if necessary[4)]. Accordingly, Lin et al. as well as Manavizadeh et al. model deviating product qualities by considering alternative bills of material[5)]. Besides the previously mentioned options, Hempsch et al. make offering value-added services a subject of discussion. Thereby, the authors emphasize that this qualitative adaptation measure provides the opportunity to compensate for a tardy delivery and/or reduced order quantity and thus can increase customer satisfaction[6)].

On the monetary level, the following order specifications can be distinguished: basic price, surcharges (e.g. obligatory fees, service charges) / discounts and payment arrangements (e.g. payment deadlines, means of payment, interest, debt retirement). However, additional fees or payment arrangements are primarily investigated in marketing (e.g. *drip pricing*, *partitioned pricing*) as well as financial literature and

---

1) Delivery time intervals are for example specified by the customers in Charnsirisakskul et al. (2004), pp. 699 ff.; Charnsirisakskul et al. (2006), pp. 156 ff.; Chen et al. (2001), pp. 480 ff.; Guillén et al. (2005), pp. 7412 ff.; Pibernik (2002), pp. 359 ff.; Pibernik (2005), pp. 244 ff. or Yang/Fung (2014), pp. 4255 ff.

2) Cf. Chen/Dong (2014), pp. 6722 f.

3) Cf. Pibernik (2002), pp. 365 ff.; Pibernik (2005), pp. 246 ff.

4) Cf. Chen et al. (2001), pp. 480 ff.

5) Cf. Lin et al. (2010), pp. 724 ff.; Manavizadeh et al. (2013), pp. 2533 ff.

6) Cf. Hempsch et al. (2013), p. 32.

are not in the focus of this dissertation.[1] Instead, basic price, potential surcharges/discounts or payment arrangements are considered to be aggregated in the product price. Sole exception from this aggregation is a deviation from the product price which compensates the customer's loss of utility induced by deviations from requested non-monetary order specifications. Consequently, the literature review of CTP approaches focuses on such *deviations from the product price*. So far, this adaptation measure has been increasingly used in negotiations with customers:

- Guillén et al. develop a negotiating process for determining delivery-date-price combinations, which represent compromises made from the customers' and company's point of view. For this purpose, both negotiating partners specify starting prices, which represent preferred sales or purchase prices and customarily define the upper/lower limit of the finally negotiated price.[2]

- Renna and Argoneto, Hempsch et al. as well as Pan and Choi negotiate product prices in multi-agent-systems. While the first-mentioned authors place counteroffers in terms of alternative delivery-date-quantity-price combinations[3], Hempsch et al. derive counteroffers e.g. utilizing reduced prices, offering value-added services or reducing delivery time[4]. In contrast, Pan and Choi model a two-stage negotiating process whereby the due date is negotiated at the first stage. Accrued intermediate losses of one negotiating partner are compensated at the second stage while determining the corresponding price.[5]

Furthermore, Charnsirisakskul et al. propose an approach which customizes product prices by allocating individual prices to customers according to the corresponding order quantity and delivery time. Thereby, the price accepted by the customer is modeled in accordance with the maximum willingness to pay.[6] Additionally, Manavizadeh et al. implement an option for deviating from requested monetary order speci-

---

1) Cf. e.g. Bertini/Wathieu (2008), pp. 237 ff.; Carlson/Weathers (2008), pp. 724 ff.; Greenleaf et al. (2016), pp. 106 ff.; Pesch (2010), pp. 217 ff.; Robbert/Roth (2014), pp. 413 ff.

2) Cf. Guillén et al. (2005), pp. 7412 f.

3) Cf. Renna/Argoneto (2010), pp. 75 ff.

4) Cf. Hempsch et al. (2013), pp. 34 ff.

5) Cf. Pan/Choi (2016), pp. 542 ff.

6) Cf. Charnsirisakskul et al. (2006), pp. 156 f.

fications by granting discounts depending on the order volume and the chosen product configuration.[1)]

In contrary to the exclusively order-related adaptation measures, the option of *revising production and delivery date decisions* simultaneously relates to orders and resources. This measure acknowledges the fact that it is not possible to completely cover the uncertainty emerging during the order promising and fulfillment process from an economic stand point. Rather, it must be assumed that in the course of order fulfillment, revisions of production and delivery date decisions are induced by order and/or resource-related uncertainty. The majority of current CTP approaches consider this aspect with respect to production decisions[2)]. The opportunity of revising previous contractually fixed-delivery-dates is only occasionally discussed; although this measure can be economically advantageous if currently present lucrative orders can thus be accepted[3)].

Resource-related adaptation measures refer to forecasting-driven push activities of a supply chain. In general, the option of *resource nesting* serves for allowing only lucrative orders to get access to a predefined share of resources. If such orders are not present in the current planning situation, the reserved resources can be used for fulfilling future, as yet unknown lucrative orders. For the adaptation measure, a differentiation needs to be made between limiting access to consumable (e.g. materials) as well as to non-consumable (e.g. capacity) resources. In CTP approaches, Chen et al. implement nesting of consumable resources by reserving a certain level of components necessary for producing future lucrative orders[4)]. Chen and Dong as well as Gao et al. simultaneously impede access to consumable and non-consumable resources. Taking into account penalty costs, Chen and Dong only allow highly priori-

---

1) Cf. Manavizadeh et al. (2013), pp. 2534 ff.

2) See e.g. Chiang/Wu (2011), pp. 764 ff.; Lin et al. (2010), p. 724; Pibernik/Yadav (2008), p. 602 or Zhao et al. (2005), p. 72.

3) See e.g. Seitz/Grunow (2016), p. 666.

4) Cf. Chen et al. (2001), p. 481.

tized orders to utilize reserved production capacity and needed components[1]. In contrast, Gao et al. consider pseudo orders for reserving resources for potential lucrative orders[2]. On the other hand, Aouam and Brahimi[3], Chiang and Wu[4], Lečić-Cvetković et al.[5], Manavizadeh et al.[6], Pan and Choi[7], Pibernik and Yadav[8] as well as Renna and Argoneto[9] implement strategies for nesting of non-consumable resources. For example, Chiang and Wu design a dynamic capacity-rationing strategy to protect capacity for high-prioritized orders. In contrast, Renna and Argoneto, Manavizadeh et al., as well as Pan and Choi, reserve resources by distinguishing between the capacity utilization costs in case of standard and over working time.

Besides resource nesting, *providing safety capacity* is also related to the resources of the production process. Due to a conservative capacity estimation, only as much capacity is involved in the planning process as necessary to fulfill capacity constraints according to a predefined probability level. In the context of present CTP approaches, Aouam and Brahimi, Lim and Halim, Halim and Muthusamy as well as Pibernik and Yadav, consider a corresponding idea by formulating service level constraints for meeting capacity restrictions[10]. Analogously, Jung models providing safety capacity by reducing the actual available capacity for planning purposes according to a predefined factor[11]. In contrast, Chen and Dong develop a separate pre-allocation model for determining the level of required safety capacity aiming at being able to

---

1) Cf. Chen/Dong (2014), pp. 6724 ff.

2) Cf. Gao et al. (2012), pp. 773 ff.

3 Cf. Aouam/Brahimi (2013), pp. 509 ff.

4) Cf. Chiang/Wu (2011), pp. 767 ff.

5) Cf. Lečić-Cvetković et al. (2010), pp. 786 ff.

6) Cf. Manavizadeh et al. (2013), pp. 2535 ff.

7) Cf. Pan/Choi (2016), pp. 537 ff.

8) Cf. Pibernik/Yadav (2008), pp. 594 ff.

9) Cf. Renna/Argoneto (2010), p. 79.

10) Cf. Aouam/Brahimi (2013), pp. 507 ff.; Halim/Muthusamy (2012), pp. 4538 f.; Lim/Halim (2011), pp. 302 f.; Pibernik/Yadav (2008), pp. 598 ff.

11) Cf. Jung (2012), pp. 1790 ff.

handle differences between the forecasted and actually incoming demand of the next period[1].

In addition to order- and/or resource-related adaptation measures, *the interaction with customers* is discussed in the following. The previous literature review has revealed that customer behavior and customers' responses to proposed order specifications influence the order promising process in a decisive manner. Nevertheless, basic concepts for considering the interaction with customers can so far only be detected in the following approaches:

- In the context of model tests Pibernik and Yadav consider an order placement probability which decreases with increasing deviation from the requested delivery date. The impacts of different courses of this function are analyzed during their model tests.[2]

- Manavizadeh et al. also assume that not all customer inquiries are produced with certainty. Due to this reason, they take into account the customer's acceptance probability, which is evaluated based on previous data and market studies, and solely capture the expected work load of an order. The specific resource allocation is only done after the proposed order specifications are accepted by the customer.[3]

- Renna and Argoneto model customer behavior in a multi-agent-based negotiating process by using an additive utility function which reflects the degree of customer satisfaction as percentage difference between requested and offered specifications. Counteroffers are accepted as long as they exceed a calculated utility threshold value. Thereby, counteroffers are determined based on decisions previously made about potential production alternatives.[4] In a comparable way, Hempsch et al. model potential customer responses by means of conditional utility functions. Based on the results of a CTP model, counteroffers are adjusted within each round of an isolated negotiating process.[5] Moreover, Pan and Choi implement an inter-

---

1) Cf. Chen/Dong (2014), pp. 6719 ff.
2) Cf. Pibernik/Yadav (2008), pp. 608 f.
3) Vgl. Manavizadeh et al. (2013), pp. 2537 ff.
4) Cf. Renna/Argoneto (2010), pp. 75 ff.
5) Cf. Hempsch et al. (2013), pp. 39 ff.

active negotiating process between a manufacturer agent and a supplier agent whose behavior is modeled by means of non-linear utility functions.[1)]

- Guillén et al. include interaction with customers by intending to find a trade-off between the objectives of maximizing profit and customer satisfaction. For estimating customers' responses, scoring functions are used which are approximated by means of linear functions to capture the deviation from the requested delivery date or product price. The resulting satisfaction values are assumed to be independent of each other and are thus aggregated to a total value using an additive function.[2)]

1.2.2 Identification of research gaps

In an entire view, the state of the art reveals that quantitative CTP approaches, suitable to support order promising in an uncertain environment, have already been proposed in the literature. Thus, the following tendencies concerning main research focuses can be derived:

- Approaches for less complex supply chain structures are predominantly formulated. Flows of goods and information between the stages of the supply chain are only captured occasionally and in aggregated form.
- Often a production-oriented perspective is chosen in the approaches. Customers' perspectives are neglected in most cases.
- Adaptation measures for handling upcoming uncertainty are integrated in the planning approaches. Most commonly adaptation measures are implemented which either focus order- or resource-related uncertainty.
    - Widely used order-related adaptation measures are the rejection of order inquiries, as well as temporal and/or quantitative deviations from requested order specifications. However, expected customer responses to these measures are ignored most of the time.
    - As a resource-oriented measure, resource nesting is increasingly addressed in the literature. In the CTP context providing safety capacity so far has only been investigated in a few approaches.

---

1) Cf. Pan/Choi (2016), pp. 542 ff.
2) Cf. Guillén et al. (2005), pp. 7412 ff.

-- Currently very few approaches take both sources of uncertainty into account. Detailed, situation-specific analyses of interactions between adaptation measures therefore hardly exist.

In summary, research is required with regard to the following thematic fields:

- interaction with customers during order promising;
- consideration of multiple adaptation measures to simultaneously cover order- and resource-related uncertainty;
- analysis of measure interactions, as well as
- coordination of parameter values of the measures.

To some extent, initial ideas for fulfilling required research are already available in the current literature. But although some papers exist, which include interactions with customers, central aspects remain yet to be considered:

- Pibernik and Yadav capture customer behavior solely in the course of model tests. Thereby, the authors neglect the opportunity to directly incorporate information about customer feedback in the planning approach.[1)]
- Manavizadeh et al. directly consider the customer's acceptance probability in the decision model. However, interactions between order specifications to be determined and the customer's acceptance probability are not explicitly captured.[2)]
- Analogously, Renna and Argoneto do not directly use customer feedback information when generating production alternatives. Instead, production is planned separately before counteroffers are derived based on these plans. However, authors do not explain to which extent empirical evidence is available for customer behavior modeled by means of utility functions in this process.[3)]
- In analogy to Renna and Argoneto, Hempsch et al. develop a multi-agent-based negotiating process using utility functions. Again this process is not directly considered in the CTP model, but counteroffers are rather adjusted in each round of the negotiating process. Since customer response is consequently not anticipated

---

1) Cf. Pibernik/Yadav (2008), pp. 608 f.
2) Cf. Manavizadeh et al. (2013), pp. 2533 ff.
3) Cf. Renna/Argoneto (2010), pp. 75 ff.

in the planning model itself, reorganizations of the entire supply chain follow successful negotiations.[1)]

- Pan and Choi capture interactions between a manufacturer and a supplier within the scope of a multi-agent-system. Thereby, order specifications required by the customer are considered in the manufacturer's negotiating model, but direct interaction with the customer does not occur.[2)]

- Guillén et al. directly incorporate customer behavior in their planning approach. Thereby, the authors assume an independency of satisfaction values which result from differences between requested and offered delivery dates or product prices.[3)] Opportunities to compensate for multiple deviations from desired specifications therefore remain unconsidered. Additionally, due to the chosen multi-objective optimization approach, immediate impacts of satisfaction values on the profit are not captured in the decision model.

It therefore appears that a stronger connection between production and customer perspective is to be pursued to meet the objectives and needs of both, company and customer. Customer's response to suggestions of order specifications needs to be directly anticipated during the order promising process in order to avoid subsequent revisions of production and order specification decisions.

Further research is also required regarding the analysis of measure interactions. Currently, the majority of approaches either take measures for covering order-, or resource-related uncertainty into account so that the effectivity of proposed measures is often only proved in isolated analyses. However, in general, it cannot be assumed that measure impacts, induced by multiple sources of uncertainty, unfold independently. Nevertheless, interactions between considered measures have been only occasionally investigated so far:

- Chen and Dong analyze their planning approach, with respect to a combined application of designed adaptation measures, based on different constellations of measure parameters. Key figures of the analysis are the overall profit, the order

[1)] Cf. Hempsch et al. (2013), pp. 39 ff.

[2)] Cf. Pan/Choi (2016), pp. 535 ff.

[3)] Cf. Guillén et al. (2005), pp. 7412 ff.

fulfillment rate as well as the profit contribution of each unit of production capacity/components.[1)]

- Chen et al. study the effects of varying batch interval lengths and of implementing their material reservation strategy, whereby the tangible (no record of penalty costs) profit, the overall profit as well as costs for order rejection, are chosen as key figures. Interactions are analyzed by generating scenarios with different batch interval lengths, in case of varying material scarcity as well as permitted ranges of the delivery date interval.[2)]

- Pibernik and Yadav deduce indications for an economically advantageous specification of measure parameters by extensively analyzing their planning approach. Thereby, they primarily concentrate on the key figures of the achieved service levels for high-prioritized orders, as well as fulfillment rates of required delivery dates for low/high prioritized orders and the whole system.[3)]

- Renna and Argoneto analyze the adaptation measures implemented in the multi-agent-system with respect to the average customer/supplier benefit as well as the unbalanced profit between the suppliers; which is defined as the difference between profits at most and at least achieved by suppliers. Purpose of the analysis is less an analysis of interactions between implemented measures, but rather the deduction of a performance estimation of an e-marketplace with different dynamic framework conditions.[4)]

Consequently, it has to be concluded that to some extent analyses of interactions between order- and resource-related adaptation measures have already been performed. But in an entire view, these analyses concentrate on a sub-quantity of identified adaptation measures and mainly focus on profit as well as cost effects. Impacts on the robustness of planning results are only occasionally addressed[5)].

As soon as multiple adaptation measures are applied in a combinative way and company-specific objectives are simultaneously pursued, apart from a pure analysis of

---

1) Cf. Chen/Dong (2014), pp. 6730 ff.

2) Cf. Chen et al. (2001), pp. 484 ff.

3) Cf. Pibernik/Yadav (2008), pp. 604 ff.

4) Cf. Renna/Argoneto (2010), pp. 81 ff.

5) See e.g. Aouam/Brahimi (2013), p. 509; Lim/Halim (2011), p. 303; Seitz/Grunow (2016), pp. 665 ff.

measure interactions, the deduction of findings concerning objective-oriented measure coordination becomes obligatory. Since analyses related to existing interactions have been only occasionally focused in the literature, there is a substantial need for further research regarding the downstream coordination of measures. In particular, there is a need for extending previous research results with respect to suggesting measure parameters; which may contribute to accomplish the robustness-oriented objective of a company in case of a combined measure application.

In an entire view, the following research-leading questions result from the identified research gaps:

- Which measures for handling order- and resource-related uncertainty are suitable for being integrated in a CTP model, if a high level of robustness and high profitability are strived for during order promising?

- How can customers' responses to order specifications suggested by the company be stronger focused at the same time?

- How do these measures need to be coordinated with respect to the objectives of robustness and profit, taking into account their interactions?

1.3 Objective and approach

The objective of this dissertation is to develop and analyze an extended batch CTP approach which helps to guarantee a high level of robustness of planning results from the customer's and company's point of view, as well as a high level of profitability.

<table>
<tr><td colspan="2">2) Tactical decision-making</td></tr>
<tr><td>Ex ante parameterization of order- and resource-related adaptation measures</td><td>1) Operative decision-making
Design of a decision model with order- and resource-related adaptation measures for supporting robust order promising</td></tr>
</table>

Figure 1.3.1: Basic structure of the dissertation

To achieve this overall aim, a *hierarchical procedure* has been chosen which can be divided into an operative and a tactical section according to the influence on decision making (cf. figure 1.3.1).

In accordance with the *operative character* of the order promising process as a first step, an existing standard batch CTP approach is extended by robustness generating adaptation measures which are suitable for handling order- and resource-related uncertainty. In addition to adaptation measures already established in literature, a new adaptation measure for directly considering customer interaction during planning is thereby focused. Since considered adaptation measures cannot be assumed to unfold their impacts independently, their coordination is required with respect to the objectives of profitability, as well as planning and solution robustness.

As a consequence, on the *tactical level of decision-making,* there is a need for ex ante coordinating order- and resource-related adaptation measures to balance the trade-off between the considered objectives. For this purpose, a detailed analysis of interactions between previously identified measures is substantial. Therefore, the aim of the tactical level is to recommend situation-specific combinations of measure parameters; which are judged to be economically advantageous with respect to balancing profitability as well as planning and solution robustness. Hence, it is not only intended to measure robustness of order promising but also to control robustness impacts.

This hierarchical procedure is successively developed within the following three papers of the cumulative dissertation. In the second chapter, the robustness-oriented CTP approach is designed in the course of the first two papers to support the *operative decision process*:

Section 2.1 provides the *first paper*, in which a basic CTP model is developed in conformity with assumptions common in CTP literature. To obtain first insights into the general behavior of the model, as well as into the impacts of different adaptation measures, only the presence of order-related uncertainty has been assumed. Analogously to the wide-spread argumentation of assuming certain resources due to the short-term character of operative planning[1)], resource availability is supposed to be deterministic. Given these central conditions, the advantageousness of the established measures of quantitative deviation from order specifications (partial deliveries), as well as capacity nesting, is herein investigated. Furthermore, customer responses to order specifications, which deviate from requested delivery dates (proposal of deviating delivery dates), are directly integrated into the planning approach. Following Pibernik and Yadav (2008), a discrete function is modeled capturing the fact that customer's acceptance probability decreases with an increasing deviation from the desired delivery date.

The first paper is therefore structured as follows: Subsequent to a short introduction to the problem (2.1.1), the basic model is developed based on the batch CTP approach of Chen et al. (2002). Thereby, the approach is successively extended by the adaptation measures of partial deliveries, capacity nesting as well as proposing deviating delivery dates (2.1.2). The impacts of these measures on solution times, profits, capacity utilization as well as planning robustness are subsequently analyzed during a numerical analysis (2.1.3). Planning robustness is quantified by means of a robustness measure developed according to Kimms (1998), which captures the extent of production plan adjustments made during planning. The main results, as well as further research needs, are finally summarized in a conclusion of the first paper (2.1.4).

The results of the first paper reveal the fundamental suitability of the planning approach for supporting the robustness-oriented objective. In particular the interaction with customers has always been advantageous from an economic stand point, whereas the advantageousness of the remaining measures strongly seemed to depend on the choice of measure parameters. However, as further research is required regarding the impact of different sources of uncertainty, results need to be verified for a simultaneous incorporation of uncertainty related to orders and resources. Due to previous framework conditions, delivery dates have always been met in the model experi-

---

[1)] See e.g. Ball et al. (2004), p. 449; Chen et al. (2001), p. 480.

ments of the first paper so that robustness was only considered with respect to production decisions but not to customer requirements. A more differentiated view of the robustness concept therefore needs to be established in further research work. Concerning the individual measure impacts on robustness, it became apparent that the option of partial deliveries can enhance planning robustness, whereas, under the given conditions, the remaining measures may have negative impacts on robustness. Nevertheless, further investigations indicated that proposing deviating delivery dates as well as capacity nesting are probably advantageousness in situations with uncertain production resources.

Based on the results obtained in the first paper, in section 2.2 an *extension of the basic CTP model* is made within the scope of the *second paper*. Thereby, the simultaneous occurrence of order- and resource-related uncertainty is assumed. To further increase the authenticity of the decision model and to allow for a more differentiated consideration of the robustness concept, revisions of previous contractually fixed-delivery-date decisions are permitted. Due to the changes in environmental conditions, the selection of adaptation measures, suitable for handling uncertainty, was critically scrutinized: To take account of resource-related uncertainty, following Pibernik and Yadav (2008) or Charnes and Cooper (1959), the adaptation measure of providing safety capacity is modeled besides capacity nesting. Furthermore, the identified high economical potential of customer interaction as well as assumed positive impacts on robustness unfolding in the event of resource-related uncertainty, substantiate the ongoing consideration of proposing deviating delivery dates. In contrast, the quantitative deviation from order specifications (partial delivery) is no longer studied, since the functionality of this measure is similar to that of proposing modified delivery dates. In case of partial deliveries, the delivery date is modified for part of the order. Thereby, it is assumed that customers certainly accept this modified delivery date, and the high potential of an explicit interaction with customers is not considered.

Since the effectiveness of proposing deviating delivery dates, capacity nesting and proving safety capacity so far has only been proven in isolated analysis, the aim of the second paper is to examine measure interactions with respect to the objectives of profitability as well as planning and solution robustness. For this purpose, the second paper is structured as follows: After a short introduction to the problem (2.2.1), a detailed explanation of the underlying planning situation is provided in the second section (2.2.2). Thereby, the considered planning object is discussed before the structure of the developed planning approach is further specified. Based on these insights, a decision model is developed in the course of the third section (2.2.3); which takes into account the robustness-generating measures capacity nesting, proposing deviating delivery dates as well as providing safety capacity. Another research focus of the paper is placed on the subsequent extensive numerical analysis (2.2.4). Following an initial clarification of the overall procedure, the underlying test data is revealed and scenarios to be analyzed are deduced. In total, there are 3,960 test constellations which have been studied with respect to generated profits as well as production and solution robustness. The mentioned robustness criteria are measured by means of the pursuing indicators: (1) In the form of penalty costs, weighted average deviations between contractually fixed and reached delivery dates serve for quantifying robustness from the customer's point of view (planning robustness)[1]. (2) In contrast, robustness from the company's point of view (solution robustness) is captured by comparing coefficients of variation of generated profits along with input data (order/capacity data). Subsequent to the presentation and interpretation of test results, the paper closes with a summarizing conclusion (2.2.5).

Analyzing the extended planning approach reveals that, as expected, order- and resource-related measures are not able to completely cover uncertainty from an economic stand point. However, an advantageous area is identifiable within which profitability, as well as planning and solution robustness, can be simultaneously increased by applying adaptation measures in a coordinated way. Since outside the advantageous area, there is a trade-off between the objectives of profitability and robustness, an essential need for research becomes apparent concerning the necessity of coordinating the measures. An isolated investigation of integrated measures fur-

---

[1] Cf. Sridharan et al. (1988), pp. 148 ff.

ther indicates that, in particular, the measure of proposing deviating delivery dates is suitable for increasing and stabilizing generated profits. These research results consequently motivate further investigations corresponding to the interaction between customer and company.

Taking into account the results of the second paper, the measure of proposing deviating delivery dates is at first generalized in the *third paper* to meet the identified high potential of this measure. While only customers' responses to deviating delivery dates were anticipated in the previous contributions, the current aim is to extend the measure by a dynamic time-related price differentiation[1]. Consequently, the measure of proposing deviating order-specifications relates to the dimensions delivery time and price. The remaining measures of capacity nesting and providing safety capacity are still taken into account without any changes. Apart from the outlined extension of the operative CTP model, the last paper additionally focuses the design of the superordinate *tactical level of decision-making*. Ex-ante parameter recommendations shall be derived for coordinating the measures with respect to the objectives of profitability as well as planning and solution robustness by means of a statistically substantiated procedure.

The following structure of the third paper has been chosen to achieve these aims: Subsequent to the explanation of the underlying problem (3.1.1), a literature review is given (3.1.2) before the research focus of the paper is summarized (3.1.3). Subsequently, the previous operative planning model is extended by the generalized measure of proposing deviating order specifications (3.2). Thereby, the underlying planning situation is described first (3.2.1), before assumptions made during modeling price- and delivery-date-dependent customer behavior are substantiated (3.2.2). The focus of the next section is on resulting implications for the planning model (3.2.3). The remainder of the paper addresses the tactical level of decision-making, whereby the aim of deriving situation-specific recommendations for choosing measure parameters is pursued. Due to previous results of model experiments, it cannot be assumed

[1] For dynamic time-related price differentiation see e.g. Talluri/Ryzin (2005).

that the complex causal relations between the measures can be completely identified by means of a deductive analytical procedure. Therefore, an inductive statistical procedure has instead been chosen. For this reason, a parameterization model is designed in the third section of the contribution (3.3) which applies the statistical method of structural equation modeling, or more precisely, of path analysis. In this context, first of all, a suitable multi-group path model as well as corresponding research hypotheses are derived (3.3.1). For the subsequent estimation of the developed path model (3.3.2), quantifying measure impacts with respect to the objectives is inevitable. One possibility for this quantification is to optimize the CTP model of the operative decision level in an extensive numerical study, whereby systematically-generated parameter combinations (24,000 constellations) are tested, and to record realized values of the objective values. Details of this procedure are presented while describing the resulting data basis of the multi-group path model (3.3.2.1). Based on the corresponding data basis, and the subsequent application of the multi-group path model, research hypotheses are verified (3.3.2.2). Obtained findings are afterwards used to deduce recommendations for a multi-criteria setting of measure parameters (3.4). For this purpose, a limited search for advantageous parameter combinations is proposed (3.4.1), before the quality of suggested parameter values is evaluated (3.4.2). Final conclusions summarize the main results of the paper (3.5).

After presenting the individual papers, the dissertation concludes with an overall summary in which given answers to initially formulated research questions are critically discussed and starting points for further research are pointed out. Thereby, the extent of how the identified adaptation measures can contribute to an enhancement of robustness from the customer's and company's point of view, is reviewed. In particular, the focus lies on the intended concentration on the customer's perspective by evaluating the potential of proposing modified order specifications while simultaneously anticipating customers' responses. Critically summarizing the analysis of measure interactions, the derived procedure for coordinating the adaptation measures is subsequently examined. Finally, the dissertation concludes with an illustration of options for further extending research directions.

2 Approaches

2.1 Basic approach with order-related uncertainty[1)]

Abstract: Increasing production requirements have strengthened the academic interest for planning approaches that generate reliable delivery promises. An extended batch capable-to-promise approach is presented in this paper which includes preventive and reactive measures to increase planning robustness. We extend existing approaches by considering both, proposals for delivery dates that deviate from the original order specifications and customers' reactions to these modifications, in the model. To verify the impacts of the extended planning approach it is numerically analyzed on the basis of real-world data of a manufacturer of customized leisure products.

2.1.1 Introduction

In the literature different capable-to-promise approaches are suggested to generate relevant information for reaching agreements on delivery dates with customers. Usually a production-oriented perspective is chosen, while customers' reactions on suggested delivery dates and their adherence are often ignored. Paying attention to these two aspects more reliable statements about feasible delivery dates already can be given in the contract award process. Furthermore, deviations from promised delivery dates can yet be minimized in the order fulfillment process. As a result a higher customer satisfaction and loyalty is attainable in the long run. Therefore, the aim of this paper is to extend an existing capable-to-promise approach (Chen et al. 2002) in such a way that it allows for meeting promised delivery dates and quantities to the greatest possible extent even though uncertain environmental situations (e.g. order situation) might occur.

---

1) Gössinger, R.; Kalkowski, S.: Order promising - A robust customer-oriented approach, in: Logistics Management. Products, Actors, Technology - Proceedings of the German Academic Association for Business Research, Bremen 2013, ed. by J. Dethloff et al., Cham et al. 2015, pp. 135-149. To ensure consistency, notations were adapted to dissertation style.

Capable-to-promise (CTP) approaches generalize available-to-promise (ATP) approaches that determine whether customer orders can be fulfilled, at which delivery date and in what quantity. In particular the generalization consists in the integration of additional information about capacities and intermediate product inventories in multi-stage production systems (Pibernik 2005). The existing CTP approaches can be classified according to the criteria and characteristic values represented in figure 2.1.1.

Criterion	Characteristic value				
Trigger of the planning process	incoming order (real-time)			defined time interval (batch)	
Objective	economic		technical		
	profit max.	cost min.	max. order acceptance	min. due date deviation	max. workload
Order rejection	not considered			considered	
Deviation from order conditions	not considered			considered	
Adaptation (ad.) measures	no ad.	time ad.	intensity ad.	quantity ad.	quality ad.
Capacity policy	global			nested	

Figure 2.1.1: CTP classification and profile of the proposed approach

The characteristic values of the approach to be discussed in this paper are marked in grey. Existing approaches with similar intentions can be characterized as shown in figure 2.1.2. The overview reveals that none of the existing approaches completely fits with the characteristics of the approach to be analyzed. Thus the considerations underlying the individual characteristics have to be explicated.

To model the two options of possible customer reactions on deviating delivery date proposals (placement or refusal of orders) Pibernik and Yadav (2008) integrate an order placement possibility that decreases with increasing deviation from the delivery date (reaction function) and analyze the impacts of different types of reaction functions. In the present paper their idea is adopted, but information about customers' reactions is integrated in the planning process itself.

Authors \ Criteria	Batch/ Real-time	Objective	Order rejection	Deviation/ adaptation	Nested capacity
Chen et al. (2002)	B	profit max.	x	-	x
Gao et al. (2012)	B	profit max.	x	-	x
Halim/Muthusamy (2012)	B	cost min.	x	x	-
Lim/Halim (2011)	B	cost min.	x	x	-
Jeong et al. (2002)	RT	cost min.	x	x	-
Jung (2012)	B	cost min.	-	x	-
Lečić-Cvetković et al. (2010)	RT	max. order acceptance	x	x	-
Pibernik (2005)	RT	max. order acceptance	x	x	-
	B	profit max.	x	-	-
Pibernik/Yadav (2008)	RT	max. order acceptance	x	-	x
Robinson/Carlson (2007)	RT	cost min.	x	-	-
Zhao et al. (2005)	B	cost min.	-	x	-

Figure 2.1.2: Relevant approaches

Additionally, different adaptation measures are analyzed with regard to their impacts on robustness. To extend the degrees of freedom in planning and to gain a lower sensitivity towards changes of the order situation the option of partial deliveries (Pibernik 2005), where delivery dates are met for sub-quantities, will be considered. The second measure integrated in the planning approach, is the idea of a nested policy of capacity utilization (Harris and Pinder 1995, Jacob 1971). Access to a certain amount of capacity or inventory is only given to exceptionally profitable orders. If such orders are not present in the relevant planning situation, this reservation can be used for yet unknown future profitable orders. In summary, planning robustness is to be achieved by the following features:

- Consideration of customers' reactions on delivery date proposals that deviate from delivery dates requested by the customers.

- Integration of measures to adapt to changing order situations.

For this purpose a two-stage CTP-approach is derived based on the capable-to-promise approach proposed by Chen et al. (2002) (section 2.1.2). At the first stage the decision about order acceptance or preliminary rejection of the orders is made. At the second stage alternative delivery date suggestions are generated for preliminarily rejected orders. Implications of this approach on the reliability of the delivery dates are analyzed numerically in chapter 2.1.3 by means of the AIMMS environment using real-world data of a manufacturer of customized products. Finally in chapter 2.1.4 we summarize the main results of the paper and give an outlook on our future research in this field.

2.1.2 Planning approach

2.1.2.1 Basic model

Starting point of our considerations are successively arriving orders with a specified desired delivery time interval $[t_i^e, t_i^l]$ and a quantity q_i of a product with a unit price ρ_i. The quantities $b_{i.r}$ of material r $(r = 1,...,R)$ required to produce one unit of order i, the associated material costs k_r^R and inventory holding costs $k_r^{L.R}$ and $k_i^{L.FP}$ for materials and finished products, given per quantity and time unit, are known. Additionally, information about the replenishment times and quantities of material stock $a_{r.t}^R$, the lead time deferrals ω_1 and ω_2 for products made in-house $(r = 1,...,r_{k-1})$ respectively externally $(r = r_k,...,R)$ procured materials $(\omega_2 < \omega_1)$ is available. Furthermore, the capacity requirements κ_i per unit of a finished product, the capacity C of the production system and the quantity and order independent transport costs k^{Tr} are known.

A rolling horizon with discrete time intervals and a length of T periods is the underlying planning procedure. At the beginning of the current planning period t_a orders are scheduled that arrived in between the periods $t_a - \tau$ and $t_a - 1$ (batch interval). The next planning run takes place at the beginning of planning period $t_a + \tau$ for orders that arrived in between the periods t_a and $t_a + \tau - 1$. Therewith in each planning run the planning horizon shifts by τ periods. Since the order fulfillment process covers multiple periods, the following order sets are to be distinguished at the beginning of the current planning period t_a:

- A: Set of orders that arrived in between the periods $t_a - \tau$ and $t_a - 1$.

- $\hat{A}$: Set of orders that were accepted before period t_a but are not completely fulfilled yet.

- $\underline{A}$: Set of orders that were rejected or completely fulfilled before period t_a.

In the basic model order- and resource-related *decisions* have to be made. With regard to orders it has to be determined whether to accept $(Z_i = 1)$ or to reject $(Z_i = 0)$ a present order that has not been considered up to period t_a. In case of order acceptance a delivery date $D_{i.t}$ is specified as well as the quantities $M_{i.t}$ to be delivered to the customer in period t. Decisions on *resources* are related to input quantities $Q^R_{i.r.t}$ of individual material types, production quantities $P_{i.t}$ of finished products and inventories $B^R_{r.t}$, $B^{FP}_{i.t}$ of materials and finished products. The *decision field* is restricted by the order specifications of the customers, the production conditions and logical requirements of the rolling horizon. *Customer-related* constraints are:

- The delivery quantity $M_{i.t}$ equals the ordered quantity q_i.

- The delivery date $D_{i.t}$ fits the desired delivery time interval $[t_i^e, t_i^l]$.

The following constraints are determined by the *production system*:

- The production capacity C cannot be exceeded by the capacity demand κ_i induced by the production of finished products $P_{i.t}$ required to fulfill the order.

- The quantities of the finished products $P_{i.t}$ to be produced determine the material consumption $Q^R_{i.r.t}$ in the preceeding periods according to the production coefficients $b_{i.r}$ and the lead time deferrals ω_1 and ω_2.

- The inventories $B^R_{r.t}$, $B^{FP}_{i.t}$ for material and finished products result from incoming quantities $a^R_{r.t}$ respectively $P_{i.t}$ and outgoing quantities $Q^R_{i.r.t}$ respectively $M_{i.t}$.

- In order to avoid a higher production quantity as needed for delivery, an empty stock of finished products at the end of the planning horizon is postulated.

Because of the rolling horizon, at the current planning period orders may exist that were accepted in previous planning periods but are not completed yet. Therefore inventories, production quantities, promised delivery dates and quantities from the previous planning run need to be considered as parameters of the current planning run.

In accordance with the operative character of the planning problem to decide about order acceptance and delivery dates, the usual objective of profit maximization is pursued. Thereby, the revenue is a positive component, while material, inventory holding and transportation costs are negative components. Several approaches suggested in literature (e.g. Chen et al. 2002, Halim and Muthusamy 2012, Lim and Halim 2011, Pibernik 2005, Robinson and Carlson 2007) take penalty costs for order rejection into account. These penalty costs are opportunity costs resulting from future lost sales due to former order rejections which were induced by decisions at the tactical level (capacity planning, customer acquisition). Due to this indirect relation penalty costs for order rejection are not considered in the proposed approach. On the other hand order rejection at the first stage of the planning approach is only of preliminary nature, since the attempt to accept these orders with deviating conditions is made at the second planning stage.

The resulting linear mixed-integer problem can be formulated as follows:

$$\text{(1)} \quad \max \sum_{t=t_a}^{T} \left(\sum_{i \in A \cup \hat{A}} \left(M_{i.t} \cdot \rho_i - k_i^{L.FP} \cdot B_{i.t}^{FP} - k^{Tr} \cdot D_{i.t} - \sum_{r=1}^{R} \left(k_r^R \cdot Q_{i.r.t}^R \right) \right) - \sum_{r=1}^{R} \left(k_r^{L.R} \cdot B_{r.t}^R \right) \right)$$

subject to

- Customer-related constraints

$$\text{(2)} \quad M_{i.t} = q_i \cdot D_{i.t} \qquad \forall t_a \le t \le T,\ i \in A$$

$$\text{(3)} \quad \sum_{t=t_i^e}^{t_i^l} M_{i.t} = q_i \cdot Z_i \qquad i \in A$$

$$\text{(4)} \quad \sum_{t=t_i^l}^{t_i^e} D_{i.t} = Z_i \qquad i \in A$$

$$\text{(5)} \quad \sum_{t=t_a}^{T} D_{i.t} = Z_i \qquad i \in A$$

- Production-related constraints

$$\text{(6)} \quad \sum_{i \in A \cup \hat{A}} P_{i.t} \cdot \kappa_i \le C \qquad \forall t_a \le t \le T$$

$$\text{(7)} \quad b_{i.r} \cdot P_{i.t+\omega_1} = Q_{i.r.t}^R \qquad \forall i \in A \cup \hat{A},\ r = 1,\dots,\mathrm{r}_k - 1,\ t_a \le t \le T$$

(8) $b_{i.r} \cdot P_{i.t+\omega_2} = Q^R_{i.r.t}$ $\forall i \in A \cup \hat{A}$, $r = r_k,\ldots,R$, $t_a \le t \le T$

(9) $B^R_{\mathrm{r.t}-1} + a^R_{r.t-1} - \sum_{i \in A \cup \hat{A}} Q^R_{i.r.t} = B^R_{r.t}$ $\forall r$, $t_a \le t \le T$

(10) $B^{FP}_{i.\mathrm{t}-1} + P_{i.t} - M_{i.t} = B^{FP}_{\mathrm{i}.t}$ $\forall i \in A \cup \hat{A}$, $t_a \le t \le T$

- Logical requirements

(11) $M_{i.t} = M^{prev}_{i.t}$ $\forall i \in \hat{A}$, $t_a \le t \le T$

(12) $D_{i.t} = D^{prev}_{i.t}$ $\forall i \in \hat{A}$, $t_a \le t \le T$

(13) $B^R_{r.t_a-1} = B^{R.prev}_{r.t_a-1}$ $\forall r$

(14) $B^{FP}_{\mathrm{i}.t_a-1} = B^{FP.prev}_{\mathrm{i}.t_a-1}$ $\forall i \in \hat{A}$

(15) $B^{FP}_{\mathrm{i}.t_a-1} = 0$ $\forall i \in A$

(16) $B^{FP}_{\mathrm{i}.T} = 0$ $\forall i \in A \cup \hat{A}$

(17) $P_{i.t} = 0$ $\forall i \in A$, $t_a \le t \le t_a + (\omega_1 - 1)$

(18) $P_{i.t} = P^{prev}_{i.t}$ $\forall i \in \hat{A}$, $t_a \le t \le t_a + (\omega_1 - 1)$

- Domain of decision variables

(19) $Z_i \in \{0,1\}$ $\forall i$

(20) $M_{i.t}, P_{i.t}, B^{FP}_{i.t} \ge 0$ $\forall i,t$

(21) $B^R_{r.t} \ge 0$ $\forall r,t$

(22) $D_{i.t} \in \{0,1\}$ $\forall i,t$

(23) $Q^R_{i.r.\mathrm{t}} \ge 0$ $\forall i,r,t$

2.1.2.2 Consideration of adjustment measures

One essential result revealed through the application of the basic model is the information about the orders to be accepted, their corresponding delivery dates as well as the orders to be preliminarily rejected. Reasons for order rejection can be order conditions that cannot be handled technically (e.g. desired delivery is before the earliest possible completion date) and/or that are economically not favourable (e.g. the order competes for scarce resources with more or less profitable orders that were already bindingly accepted). In the context of economically disadvantageous order conditions the producer can reduce the probability of occurrence (prevention) or adapt to these situations (reaction). Both opportunities aim at making robust delivery date decisions. The nested policy of capacity utilization and partial deliveries are considered as preventive measures that generalize the basic model. These measures enlarge the number of planning options in such a way that some of the otherwise appearing resource conflicts can be avoided. In contrast to these preventive measures the opportunity to adapt the desired delivery dates is considered as a reactive measure at the succeeding planning stage. At this second stage alternative delivery date proposals are generated for preliminarily rejected orders and customers decide on the acceptability of these suggestions.

Preventive measures: In the simplest form of a nested policy of capacity utilization the total capacity is splitted up into standard and premium capacity, and a cost premium for accessing premium capacity is introduced (Jacob 1971). As a result, premium capacity can only be used by more profitable orders. If these orders do not exist yet, it is reserved for profitable orders arriving in future. Implications for planning are on the one hand that the decision maker has ex ante to specify two additional parameters: the share of premium capacity ε and the costs k^P for utilizing premium capacity. On the other hand the basic model has to be extended by additional decisions, constraints and objective components. Additional decisions arise in the context of utilized units of standard $P^S_{i.t}$ and premium $P^P_{i.t}$ capacity. Therefore it is necessary to reformulate capacity constraint (6) for both capacity types (6a, 6b) and to ensure that the sum of capacity units used by an order equals its capacity requirements (6c). Finally the objective function (1) must be extended by the component of premium costs (1'). Formally these modifications can be formulated as follows:

$$\text{(1')} \quad \max \sum\nolimits_{t=t_a}^{T} \Big(\sum\nolimits_{i \in A \cup \hat{A}} \big(M_{i.t} \cdot \rho_i - k_i^{L.FP} \cdot B_{i.t}^{FP} - k^{Tr} \cdot D_{i.t} - \sum\nolimits_{r=1}^{R} \big(k_r^R \cdot Q_{i.r.t}^R \big) - k^P \cdot P_{i.t}^P \cdot \kappa_i \big) - \sum\nolimits_{r=1}^{R} \big(k_r^{L.R} \cdot B_{r.t}^R \big) \Big)$$

(6a) $\sum_{i \in A \cup \hat{A}} P_{i.t}^{P} \cdot \kappa_i \le \varepsilon \cdot C$ $\forall t_a \le t \le T$

(6b) $\sum_{i \in A \cup \hat{A}} P_{i.t}^{S} \cdot \kappa_i \le (1-\varepsilon) \cdot C$ $\forall t_a \le t \le T$

(6c) $P_{i.t}^{P} + P_{i.t}^{S} = P_{i.t}$ $\forall t_a \le t \le T,\ i \in A \cup \hat{A}$

Additional degrees of freedom result, if the desired order quantities are fulfilled by multiple deliveries. Pibernik's approach (Pibernik 2005) to allow two partial deliveries, is going to be extended to the allowance of d deliveries with a defined minimum quantity of q_i^{PD}. Partial deliveries are possible for a relation of $q_i^{PD} \le q_i / 2$ between order size q_i and minimum quantity q_i^{PD}, while the customer can avoid partial deliveries by specifications in the range of $q_i / 2 < q_i^{PD} \le q_i$. Although there is no need for extending the basic model with regard to decisions and constraints partial deliveries imply slight modifications of constraints:

- Individual partial deliveries contain at least the minimum quantity specified by the customer and
- delivery dates may not lie outside the desired time interval.

Formally the following changes are relevant:

(2a) $M_{i.t} \le q_i \cdot D_{i.t}$ $\forall t_a \le t \le T,\ i \in A$

(2b) $M_{i.t} \ge q_i^{PD} \cdot D_{i.t}$ $\forall t_a \le t \le T,\ i \in A$

(3a) $\sum_{t=t_i^e}^{t_i^l} M_{i.t} = q_i \cdot Z_i$ $\forall i \in A$

(3b) $\sum_{t=t_a}^{T} M_{i.t} = q_i \cdot Z_i$ $\forall i \in A$

(4a) $\sum_{t=t_i^e}^{t_i^l} D_{i.t} \ge Z_i$ $\forall i \in A$

(4b) $\sum_{t=t_i^e}^{t_i^l} D_{i.t} \le \left\lceil \frac{q_i}{q_i^{PD}} \right\rceil \cdot Z_i$ $\forall i \in A$

(5') $\sum_{t=t_a}^{T} D_{i.t} \le \left\lceil \frac{q_i}{q_i^{PD}} \right\rceil \cdot Z_i$ $\forall i \in A$

Adaptation of delivery dates as a reactive measure: For preliminarily rejected orders the second planning stage tries to find out which delivery dates outside the given delivery time interval can be met. The adjusted delivery dates are proposed to the customers and they decide themselves about whether to accept or reject the order. So the final order acceptance decisions are made by the customers. In this case a detailed distinction within order set $\underline{A}$ is necessary at the beginning of planning period t_a:

- $\underline{A}^+$: Set of orders that were completely fulfilled before period t_a.
- $\underline{A}^-$: Set of orders that were finally rejected before period t_a.
- $\overline{A}$: Set of orders that were preliminarily rejected before period t_a.

It is assumed that the producer has collected empirical data concerning customers' reactions on modified order conditions during past order negotiations. Furthermore, a function of acceptance probabilities depending on the extent of deviation from the given delivery time interval can be derived on the basis of this data by means of statistical tools. This reaction function $\beta(V_i^{UL})$ describes a non-increasing acceptance in case of increasing deviation (delay) V_i^{UL} of the delivery date from the upper limit t_i^l of the delivery time interval. It is modelled as a discrete distribution with L levels and maximum/minimum acceptance $\beta^{\max}$, $\beta^{\min}$ at the first/last level:

$$\beta(\mathrm{V}_i^{UL}) = \begin{cases} \beta^{\max} & : V_i^{UL} \le \Delta_1^{\max} \\ \beta_l & : \Delta_{l-1}^{\max} < V_i^{UL} \le \Delta_l^{\max}; l = 2,\dots,L-1 \\ \beta^{\min} & : \Delta_{L-1}^{\max} < V_i^{UL} \end{cases} \qquad \forall i \in \overline{A}$$

with $0 < \Delta_{l-1}^{\max} < \Delta_l^{\max}$, $0 < \beta_l \le \beta_{l+1} \le 1$ and $V_i^{UL} = \max\limits_{t \in [t_a;T]} \{D_{i.t} \cdot t\} - t_i^l$

Since the final decision of order acceptance under modified conditions is made by the customer *order-related decisions* in the basic model reduce to decisions concerning delivery dates and quantities of preliminarily rejected orders ($\overline{A}$). The *resource-related decisions* in the basic model (input quantities, production quantities, inventories) still have to be made for order sets $\hat{A}$ and $\overline{A}$. With regard to the decision field those *customer-related decisions* are omitted that were linked with the order acceptance decision and the adherence of the delivery time interval (3a, 4b). An additional easing of constraints arises because of the facts that

- the order acceptance by the producer is given ($Z_i = 1 \; \forall i \in A$, in constraints 3b and 5') and
- the delivery is permitted in the interval in between the earliest delivery date specified by the customer and the end of the planning horizon (4a').

Under the assumption of a robustness oriented planning behavior the impact of scheduling preliminarily rejected orders on capacity and material requirements are considered in such a way that all adjusted delivery dates can be met even though all corresponding customers agree with these dates (no overbooking). Therefore it is not necessary to modify the constraints of the production system and the rolling horizon approach.

Two implications for the *objective function* result from the new planning situation. On the one hand the omission of the order acceptance decision induces the irrelevance of success components that are solely affected by this decision. On the other hand customers' reactions to modified order conditions are uncertain. Thus, the objective function includes an additional uncertain component for orders with proposed deviating delivery dates $(\bar{A})$. This component captures delivery date dependent expected values of revenues as well as inventory holding, material requirements, transportation and premium costs. In case of already confirmed orders $\hat{A}$ delivery dates respective quantities and material requirements are specified. But the contingent scheduling of preliminarily rejected orders may reveal that modified dates or quantities of the finished products manufacturing, the storage of materials and finished products as well as a modified utilization of premium capacity induce lower costs. In comparison to the basic model a reduced deterministic (certain) component is therefore relevant in the objective function. The allocation of material inventory holding costs to both components cannot be made according to the principle of causation, since the material inventory is affected by the interaction of consumed materials of both order sets ($\bar{A}$ and $\hat{A}$). For estimating the expected inventory holding costs, the stock is hence considered in equivalence to the proportion of material requirements in both components. Formally these circumstances can be formulated as follows:

$$\text{(1'')}\quad \max \sum_{t=t_a}^{T} \Big(\sum_{i \in \hat{A}} \Big(-k_i^{L.FP} \cdot B_{i.t}^{FP} - k^P \cdot \mathrm{P}_{i.t}^{\mathrm{P}} \cdot \kappa_i - \sum_{r=1}^{R} k_r^{L.R} \cdot B_{i.r.t}^{R} \Big) + \sum_{i \in \bar{A}} \beta(\mathrm{V}_i^{UL}) \cdot \Big(M_{i.t} \cdot \rho_i - k_i^{L.FP} \cdot B_{i.t}^{FP} - k^{Tr} \cdot D_{i.t} - k^P \cdot P_{i.t}^{P} \cdot \kappa_i - \sum_{r=1}^{R} \big(k_r^R \cdot Q_{i.r.t}^R + k_r^{L.R} \cdot B_{i.r.t}^R \big) \Big) \Big)$$

with
$$B_{i.r.t}^{R} = \begin{cases} \dfrac{q_i \cdot b_{i.r}}{\sum_{i' \in \hat{A} \cup \bar{A}} q_{i'} \cdot b_{i'.r}} & : \sum_{i' \in \hat{A} \cup \bar{A}} q_{i'} \cdot b_{i'.r} > 0 \\ 0 & : \text{otherwise} \end{cases} \qquad \forall i \in \bar{A} \cup \hat{A},\ r,\ t$$

$$\text{(4a')}\quad \sum_{t=t_i^e}^{T} D_{i.t} \geq 1 \qquad \forall i \in \bar{A}$$

Because of the dependency of the acceptance probability and the delivery dates being planned as well as their multiplicative linkage in the objective function a nonlinear mixed-integer programming model results.

2.1.3 Numerical analysis

2.1.3.1 Test configuration

Within the numerical analysis the suitability of the proposed two-stage planning approach is analyzed based on real-world data of a manufacturer of customized leisure products. For this purpose plans with regard to order acceptance and termination of order quantities to be delivered are generated on the basis of order and resource data in a rolling horizon approach. The different model formulations are tested for varying simulated developments of reality in order to discuss the following questions:

- How do preventive and reactive measures affect the reliability of delivery dates?
- To which extent does the second planning stage influence the solution quality of the planning approach?

Starting point of the tests was a preliminary assessment of a planning horizon which is suitable according to the criteria solution time and profit. The planning horizons to be studied resulted from the latest delivery date accepted plus a share of the estimated maximum time necessary to complete all orders to be planned. For the present data constellation best results were obtained for a share of 10 percent.

In order to analyze impacts of preventive and reactive measures on planning robustness, the following parameter constellations are combined in the planning approach and tested for 5 order scenarios:

Partial deliveries (PD)		Capacity Nesting (CN)		Adaptation of delivery dates
Description	Value of q_i^{PD}	Description	Value of (ε, k^P)	
No PD (N)	q_i	No CN (N)	(0, 0)	No adaptation (N)
Average number of PD (PD1)	$\min\{q_i, 3\}$	Low level of CN (CN1)	(1/3, 2900)	Adaptation (L)
Maximum number of PD (PD2)	1	High level of CN (CN2)	(2/3, 3500)	

Figure 2.1.3: Tested parameter constellations

Real *order data* (scenario 1) from a period of three months was taken as the basis of the tests as well as realistically generated order data (scenario 2 to 5). The generated order data is a realization of random variables with regard to intermediate arrival times and order quantities that follow a normal distribution according to the parameters (expected value, standard deviation) revealed by the real data. A uniform two-week delivery time interval that starts with the period of the order receipt was assumed to be relevant for all orders. Furthermore, the reaction function has been empirical-qualitatively (expert survey) estimated:

$$\beta(\mathrm{V}_i^{UL}) = \begin{cases} 1.0 & : V_i^{UL} \leq 0 \\ 0.6 & : 0 < V_i^{UL} \leq 10 \\ 0.2 & : 10 < V_i^{UL} \leq 25 \\ 1 \cdot 10^{-10} & : V_i^{UL} > 25 \end{cases}$$

Within the planning process this function is applied and after a planning run the customer decision is simulated as a random variable with a probability value according to this function. Real data of the 7 best-selling product configurations was taken as a basis for *production-related data*:

Materials (A-parts)	Capacity	Prices/Costs (in €)
$R=56$, $r_k=45$	$C=3$	$k^{Tr}=59$, $\rho_i\in(2599, 5750)$, $k_r^R\in(6.71,125.21)$
$\omega_1=3$, $\omega_2=2$	$\kappa_i=1$	$k_i^{L.FP}$, $k_r^{L.R}$: 0.25% of invested capital per piece

Figure 2.1.4: Production-related data

Planning is done on a daily basis at the beginning of each week with a rolling horizon and an underlying batch interval of 5 days. The planning model was implemented in the AIMMS 3.13 environment. Plans at the first level (order acceptance, delivery dates and quantities for accepted orders) are exact solutions of the linear mixed-integer model determined by the solver CPLEX 12.5. In order to generate plans at the second level (delivery date and quantity suggestions for preliminarily rejected orders) locally optimal solutions are created with the "AIMMS Outer Approximation Algorithm", because of the nonlinearity of the mixed-integer model (Roelofs and Bisschop 2016). To avoid inacceptable computation times the maximum computation time permitted was set on 100 s per iteration and the amount of iterations was limited to 15.

Following Kimms (1998) a measure for planning robustness is considered to judge the reliability of delivery dates. In the discussed planning problem, robustness will be the higher the less production decisions $P_{i.t}$ have to be revised because of changing information between the planning runs. Then the robustness measure refers to

- those customer orders, that are planned to be processed in consecutive planning runs (set A^{CP}) and
- overlapping time periods (set T^{CP}) in consecutive planning runs $pr-1$ and pr:

$$T^{CP}=\left\{\min\left(t_a^{(pr-1)};t_a^{(pr)}\right),\ldots,\min\left(T^{(pr-1)};T^{(pr)}\right)\right\}$$

For a normalized robustness index the cumulative changes in production quantities in between planning run $pr-1$ and pr are set in relation to the cumulated production quantities in planning run $pr-1$. Additionally the weighting function ζ_t takes into account that - from an economic point of view - plan modifications in the distant future are less important than those that lie close to the current planning period. The lower the index $\varphi^{(pr)}$ is, the higher is the robustness between the planning runs $pr-1$ and pr. For the robustness of the whole planning the worst value indicated in all planning runs is considered:

$$\varphi = \max_{pr}\left(\varphi^{(pr)}\right)$$

with $$\varphi^{(pr)} = \frac{\sum_{i\in A^{CP}}\sum_{t\in T^{CP}}\zeta_t\cdot\left|P_{i.t}^{(pr)}-P_{i.t}^{(pr-1)}\right|}{\max\left\{\sum_{i\in A^{CP}}\sum_{t\in T^{CP}}\zeta_t\cdot P_{i.t}^{(pr-1)};1\right\}} \qquad \forall pr>1$$

and $$\zeta_t = \frac{1}{t-\min\left(t_a^{(pr-1)};t_a^{(pr)}\right)+1} \qquad \forall \min\left(t_a^{(pr-1)};t_a^{(pr)}\right)\le t\le \min\left(T^{(pr-1)};T^{(pr)}\right)$$

2.1.3.2 Test results

To point out the impacts of the second planning stage onto solution quality, the average values of computation times and profits achieved at the first and at both planning stages are compared. With regard to computation times it becomes obvious that although the nonlinear problem at the second stage (deviating delivery date suggestions) induces a higher computational effort (maximum time: 500 s) than the linear problem (order acceptance according to desired delivery dates) at the first stage (maximum time: 0.3 s), all computation times lie within an acceptable range. In order to ensure comparable profits, the generated profits (see figure 2.1.5) were adjusted by the access costs on premium capacity.

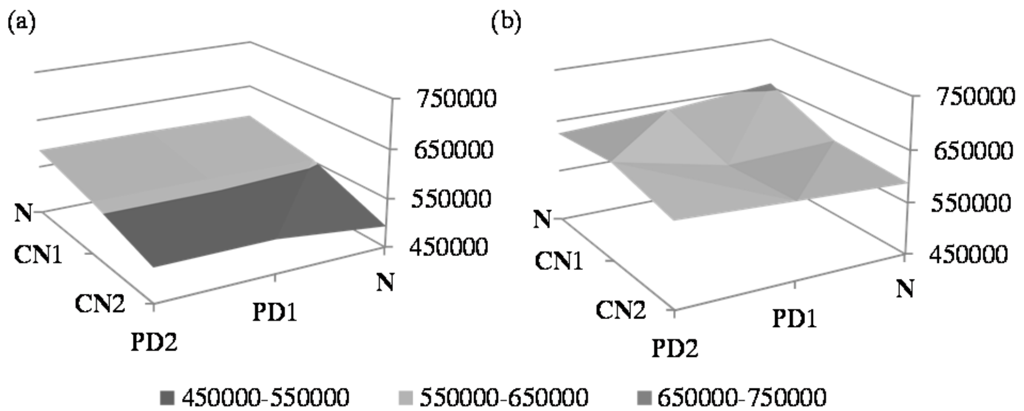

Figure 2.1.5: Generated profits ((a) one-stage and (b) two-stage planning approach)

The observation of these profits reveals that alternative delivery date suggestions considering customers' reactions are always economically advantageous. Regarding partial deliveries and nested policy of capacity utilization a heterogeneous picture emerges. In the majority of investigated parameter constellations profits can be increased by partial deliveries, whereas the nested policy mainly reduces profits. Therefore it can reasonably be assumed that the economic benefits of these measures are dependent on the fit between the chosen parameter values and the order situation.

Concerning the reliability of promised/suggested delivery dates it has to be pointed out that all planned delivery dates and quantities are met, because of the underlying certain resource and capacity availability. Although unexpected capacity or resource shortages were so far not directly taken into account, statements about the degree of reliability can be derived by consideration of the robustness measure and the average capacity utilization per period. As the one- and two-stage planning approaches achieve robustness values significantly below 0.5 (see figure 2.1.6), only few adaptions of production decisions caused by varying order situations are necessary. Production decisions are more robust, if only the first planning stage with partial deliveries is applied. The nested policy as well as the suggestion of modified delivery dates reduces planning robustness.

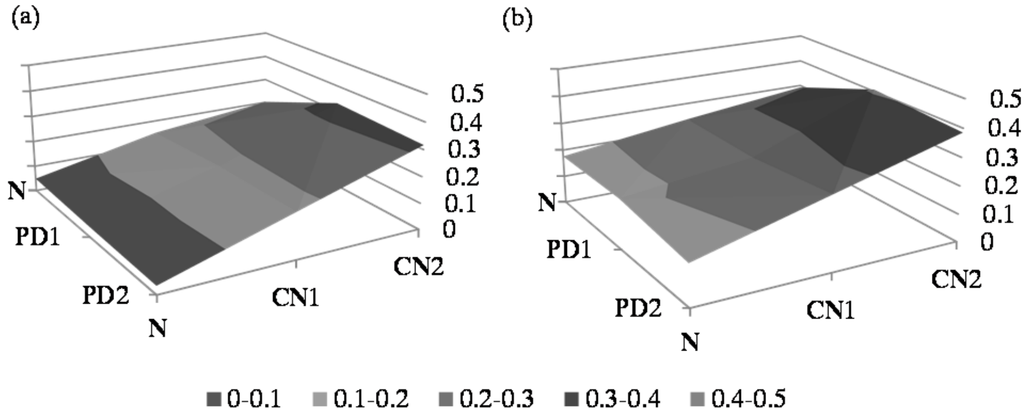

Figure 2.1.6: Robustness index ((a) one-stage and (b) two-stage planning approach)

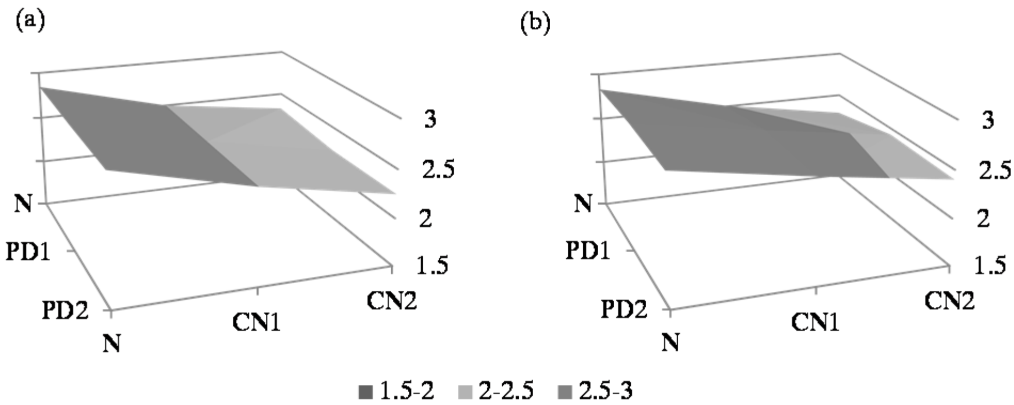

Figure 2.1.7: Capacity utilization ((a) one-stage and (b) two-stage planning approach)

On the other hand these measures provide flexibility to react to modified order situations by causing a low average level of capacity utilization (see figure 2.1.7). In the first case premium capacity leads to the opportunity to revise production decisions in favour of accepting additional orders. The consideration of orders with modified delivery dates in the latter case induces the uncertainty that customers do not accept deviating conditions and cancel the orders. With the released capacity it is possible to assign more advantageous production dates to accepted orders or to accept additional orders without endangering previously promised delivery dates.

2.1.4 Conclusions

In the present paper an extended capable-to-promise approach was developed and analyzed with the intention not only to generate high profits through order acceptance, but also to promise reliable delivery dates. The extensions refer to a nested policy of capacity utilization and partial deliveries as preventive measures and to the suggestion of modified delivery dates as a reactive measure. During the planning of modified delivery dates customers' reactions were considered with the help of an acceptance probability in dependency of the deviation from the originally desired delivery date. This approach can be seen as a significant extension of planning approaches proposed in the literature.

Using real-world data of a manufacturer of customized leisure products and several deduced test cases the solution quality and computational effort as well as impacts of the preventive and reactive measures on delivery reliability were numerically analyzed. It became apparent that

- all promised delivery dates could be met,
- suggesting modified delivery dates is economically advantageous and the benefit of the two other measures is dependent on the parameter choices,
- the computation time is acceptable and dependent on the application of the particular measures,
- partial deliveries directly increase planning robustness and
- the nested policy of capacity utilization and the suggestion of alternative delivery dates are additional options that can be used when deviating production situations occur.

Since material and capacity availabilities were assumed to be certain in the tests, the gained statements need to be verified in further analyses while considering stochastic influences. Furthermore, statements about optimal parameter choices for the different measures need to be generated in this context.

2.2 Extended approach with order- and resource-related uncertainty[1)]

Abstract: One important way to differentiate from competitors is to promise reliable delivery dates. Therefore, order promising not only aims at maximizing short-term profits, but also at achieving an acceptable degree of robustness. In capable-to-promise (CTP) approaches proposed for answering to customer order inquiries the order- and resource-related uncertainty is taken into account by several preventive measures. Up until now, the effectiveness of these measures has been proven in isolated analyses. Although they are directed to different uncertainty types it cannot be concluded that the observed impacts unfold independently. In this paper a CTP approach is presented and analyzed for the case of order- and resource-related uncertainty. Robustness is achieved by the preventive adaptation measures of capacity nesting, providing safety capacity and proposal of alternative delivery dates. Planning occurs at two stages: (1) order acceptance according to the order specifications requested by the customer or provisionally order rejection, and (2) proposal of alternative delivery dates for provisionally rejected orders. As a major extension to the current literature customers' response on alternative delivery dates is anticipated and considered at this stage. In contrast to currently existing approaches the suitability of this new approach, the impacts of preventive measures on profit and robustness and the interactions between the measures are systematically evaluated in a numerical analysis.

2.2.1 Introduction

Order promising comprises the decisions on order acceptance and order specification that are made during the contract awarding process interactively by customer and producer (Mansouri et al. 2012). The set of accepted orders in the company's point of view forms a master production schedule which has to maximize the expected profit with respect to order- and resource-related uncertainty as well as adaptation measures that are available to cope with uncertainty. Order acceptance decisions are studied as single-player auctions with a long tradition in economic research (cf. the reviews from Engelbrecht-Wiggans 1980, King and Mercer 1988 or the bibliography

---

1) Gössinger, R.; Kalkowski, S.: Robust order promising with anticipated customer feedback, in: International Journal of Production Economics, Vol. 170 (2015), pp. 529-542. To ensure consistency, notations were adapted to dissertation style.

provided by Stark and Rothkopf 1979). More recently the increasing importance of reliable order delivery dates led to a growing interest in developing planning instruments for enhancing on-time deliveries (e.g. Stevenson et al. 2005). In the context of make-to-order supply chains capable-to-promise (CTP) approaches are suggested to determine delivery dates and quantities based on the available resources (Pibernik 2005). Thereby normally a deterministic resource availability is assumed, substantiated by the short-term planning horizon of CTP approaches (Ball et al. 2004, Chen et al. 2001). But despite the operative focus of these approaches, in particular order- and resource-related uncertainty arises in practice (Pujawan and Smart 2012) and hampers the endeavors to achieve more reliable delivery dates.

The intention to propose *reliable delivery dates* can be operationalized with the aim to create plans that are characterized by robustness in two dimensions (cf. Roy 2010 for multiple robustness dimensions): (1) A risk-averse planning behavior prefers that changes in the planning data have a minimum impact on the value of the planning objective (*solution robustness*, Mulvey et al. 1995). (2) Plan revisions necessary to restore an optimal plan in case of updated planning data are accompanied by additional implementation costs (e.g. due to the nervousness of recently started distribution, production and procurement processes; Pujawan and Smart 2012, Sridharan et al. 1988). This motivates to generate plans in such a way that the extent of revisions is low (*planning robustness*, Kimms 1998). In order to achieve an order promising that is both, solution robust and planning robust, the general approaches for robustness generation, to provide temporal and quantitative buffers as well as to set up contingency plans that consider all possible courses of actions (Herroelen and Leus 2004), have to be put into problem-specific terms.

In the present paper a CTP approach is developed and analyzed that generates robustness by considering multiple adaptation measures during the order promising process. Different *adaptation measures* to cover uncertainty have been proposed in the CTP literature (see table 2.2.1). The overview reveals that the measures are mostly applied either to cover order- or resource-related uncertainty but the need for covering both uncertainty types is often neglected. Up to now the effectiveness of the adaptation measures is therefore solely proven in isolated analyses. But although the adaptation measures are related to different sources of uncertainty it cannot be assumed that their impacts unfold independently. Hence, one contribution of this paper is to give insight into the impacts of a joint measure application on profit, solution robustness and planning robustness.

		Type of CTP approach															
		Batch								Real-time							
		Chen/Dong (2014)	Chen et al. (2001)	Gao et al. (2012)	Guillén et al. (2005)	Halim/Muthusamy (2012)	Jung (2012)	Pibernik (2005)	Zhao et al. (2005)	Chen/Dong (2014)	Chiang/Wu (2011)	Christou/Ponis (2009)	Jeong et al. (2002)	Lečić-Cvetković et al. (2010)	Pibernik (2005)	Pibernik/Yadav (2008)	Renna/Argoneto (2010)
	Order-related uncertainty	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
	Resource-related uncertainty	X			X	X	X			X						X	
Adaptation measures	Nesting of non-consumable resources*	X		X						X	X	X		X		X	X
	Nesting of consumable resources	X	X	X						X							
	Safety capacity*															X	
	Proposal of deviating delivery quantities	X				X	X	X	X	X		X		X	X		X
	Proposal of deviating delivery dates*	X			X		X	X	X	X		X	X		X		X
	Considering customer response*				O											O	O

Table 2.2.1: Overview of relevant CTP approaches and applied preventive adaptation measures

Due to the results of previous studies in literature the adaptation measures highlighted by asterisks seem to be particularly suitable to unfold notable impacts on robustness and profit. In order to analyze the interaction of adaptation measures in the presence of resource- and order-related uncertainty the batch CTP approach proposed in this paper applies these asterisked measures. Therefore as a second contribution, in comparison to the existing literature a more comprehensive approach results. In the following review of current CTP approaches we concentrate on the preventive measures of capacity nesting (nesting of non-consumable resources), providing safety capacity and proposal of alternative delivery dates while considering customer response.

Capacity nesting (Harris and Pinder 1995, Jacob 1971) is applied in CTP approaches to cover order-related uncertainty (Chen and Dong 2014, Chiang and Wu 2011, Christou and Ponis 2009, Gao et al. 2012, Lečić-Cvetković et al. 2010, Pibernik and Yadav 2008). The underlying idea is to set protection levels by splitting up the total capacity in multiple segments (e.g. in standard and premium capacity) and defining segment-specific costs for utilizing capacity. Hence, the access to a share of capacity is made more expensive and thus this share can only be used by more profitable (lucrative) orders. That is, the discrimination between less profitable and more profitable orders is defined by the utilization cost difference. On this basis the risk of having to reject future lucrative orders can be covered. A greater share of premium capacity and higher utilization costs hinder the acceptance of low profitable orders and extend the chance for being able to accept lucrative orders in the future.

Safety capacity is provided to handle resource-related uncertainty. By a risk-averse estimation of availability only as much capacity is considered in the plan as it is necessary to meet capacity constraints with an economically acceptable probability (chance constraint, Charnes and Cooper 1959). In the CTP literature only Pibernik and Yadav (2008) consider this concept to cope with resource-related uncertainty.

As emphasized in literature the interaction with customers is of great significance in order promising. While in other research fields contributions concerning negotiations exist (see e.g. Renna and Argoneto 2010), there is a lack of CTP approaches taking into account customers' response in the order awarding process. Although the importance of methodologies directly incorporating customers is highlighted by decision makers with industrial experience, recently still a lack between the optimization techniques developed in literature and the decision support needed in practice can be observed (Mansouri et al. 2012). However, taking *customers' response* on suggested *deviating delivery dates* appropriately into account can enable the identification of more reliable delivery dates. In a long-term perspective this may lead to an increasing customer satisfaction and loyalty. Pibernik and Yadav (2008) consider a corresponding aspect in the tests of their CTP model by assuming an order acceptance probability that decreases with increasing delivery date deviation (response function). This response function is a specific case of probability distributions that have been proposed in the context of competitive bidding for orders with non-price features (Simmonds 1968) and have been made applicable for planning of make-to-order production by means of strike rate matrices (Kingsman et al. 1993, Kingsman and Mercer 1997). Recently, Thürer et al. (2014) have analyzed the implications of considering strike rates for workload control by means of simulations. Thereby strike rates are assumed to be independent from due dates and are used as a parameter which is systematically varied for different simulation runs. Renna and Argoneto (2010) consider the order promising situation my means of a Multi Agent System. Customer behavior is simulated with a customer negotiation agent that tries to maximize a utility function depending on proposed due date, order quantity and price. A utility threshold that varies with the number of negotiation rounds and the utility development implicitly models an acceptance probability. Since this behavior is not anticipated by the Supplier Negotiation Agent and the Supplier Production Agent the tested negotiations reveal similar results as the previously mentioned simulations/tests. In the stochastic model to support order promising before bargaining starts Guillén et al. (2005) consider customer behavior with an expected customer satisfaction. This construct is measured by means of a scoring system reflecting the distance between proposed order specification and values for delivery date and price preferred by the customer. Offers with a high customer satisfaction are expected to have a high acceptance probability in the subsequent bargaining process. However, the impact of this procedure to the profit generated with order promising is not analyzed. In contrast to this, in the approach developed in the present paper the response function builds a central element of the planning model in order to enhance the degrees of freedom and to increase the robustness of the plan. As a substantial extension to current approaches, the option of *proposing delivery dates that deviate* from those requested by the customers in the contract awarding process is considered. Thereby customers' response on proposed deviating delivery dates is anticipated in the planning process by means of a probability distribution.

One possibility to handle order-related and resource-related uncertainty in a reactive manner and to facilitate the application of preventive adaptation measures is to revise the delivery date and production decisions of past contract awarding processes by a *rescheduling* of orders under contract. The majority of papers consider this aspect with regard to production decisions (Chen et al. 2001, Halim and Muthusamy 2012, Jeong et al. 2002, Jung 2012, Lečić-Cvetković et al. 2010, Robinson and Carlson 2007, Zhao et al. 2005). Nevertheless it can also be advantageous to revise already contracted delivery dates and take upcoming penalty costs into account, in order to accept pending lucrative orders (Jung 2012, Pibernik 2005).

The remainder of this paper is organized as follows: The underlying planning situation is described in section 2.2.2. First the considered supply chain is characterized before the structure of the two-stage planning approach is explained. In section 2.2.3 the decision models are developed step-by-step, whereby the proceeding at the first stage is addressed first. Necessary modifications for the second planning stage follow. In a numerical analysis (section 2.2.4) the joint impacts of the considered adaptation measures on robustness and profit are analyzed for different order and capacity scenarios based on real data. Finally the main results and implications as well as directions of future research are summarized in section 2.2.5.

2.2.2 Planning situation

2.2.2.1 Planning object

The structure of the considered supply chain supplemented by corresponding symbols of decision variables and parameters is illustrated in figure 2.2.1. Planning is focused on the make-to-order part of a linear supply chain which comprises the processes of manufacturing, intermediate storing and delivering of customer-ordered final product quantities that fulfill demand (D). These processes are initiated by order requests submitted from individual customers (dotted line) and controlled by decisions on order acceptance, delivery dates as well as production quantities (preselection and order promising). The upstream make-to-stock part of the supply chain is considered insofar as required materials (produced in-house or externally procured) are taken out from stock with different lead times. The rest of the supply side (S) is taken into account by periodical material stock replenishments.

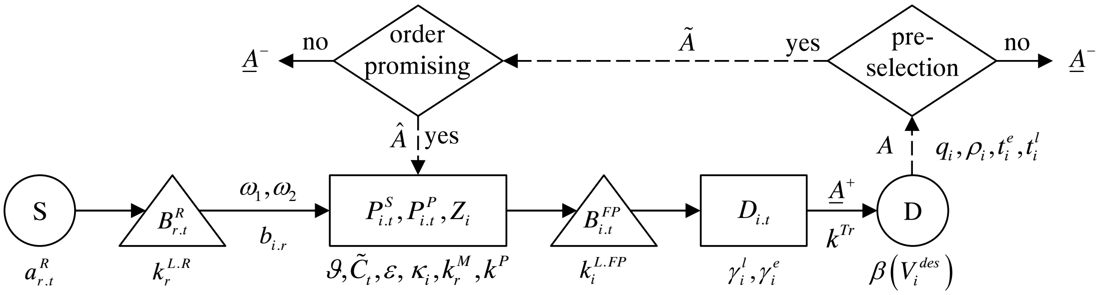

Figure 2.2.1: Structure of the supply chain

For reasons of planning five order sets have to be distinguished. Set A: order inquiries that arrived in the batch interval; set $\tilde{A}$: order inquiries with a profit chance; set $\hat{A}$: orders that have been accepted before the batch interval has started, but that are not yet fulfilled; set $\underline{A}^-$: rejected orders; set $\underline{A}^+$: fulfilled orders. All accepted orders have to be fulfilled.

With an order inquiry i $(i = 1,...,I)$ a customer specifies a product that needs to be delivered with quantity q_i during the time interval $[t_i^e, t_i^l]$ at a price ρ_i. Given the product specification the company is aware of the order specific production coefficients $b_{i.r}$ of materials r $(r = 1,...,R)$ as well as capacity requirements per piece κ_i. The lead time deferrals ω_1 for products made in-house and ω_2 for externally procured materials as well as exogenous given material replenishments $a_{r.t}^R$ are deterministic parameters. Cost rates relevant for decision making are transportation costs k^{Tr}, inventory holding costs for materials $k_r^{L.R}$ and finished products $k_i^{L.FP}$, costs for utilizing premium capacity k^P and manufacturing costs k_r^M (material and prime costs). For already accepted orders $(\hat{A})$ the delivery date $D_{i.t}^c$ and the penalty costs per planning period for premature γ_i^e or tardy γ_i^l delivery are contractually fixed.

Based on this deterministic data the producer decides on a *preselection* of orders $\tilde{A}$ with a situation-independent positive margin (price – manufacturing costs – transportation costs). The actual margin of these orders is dependent from the specific capacity supply and demand (order sets A and $\hat{A}$) situation in the planning horizon anticipated during order processing. Due to possibly induced costs of inventory holding and of deviating from contractually fixed delivery dates, it will not exceed the situation-independent margin. Hence, preselected orders have a profit chance. Since the residual requests $A \setminus \tilde{A}$ will never be profitable for the company they are finally rejected and not considered in the planning process.

According to the common practice of CTP approaches for *order promising* a rolling planning horizon of length T is applied. Each planning run is carried out after τ periods (batch interval) starting with the current planning period t_a. In addition uncertain information about the future is considered:

- Experiences with customer inquiries in the past allow for an estimation of customers' response to proposed deviations from the delivery time interval V_i^{des} in the form of a discrete probability function $\beta\left(V_i^{des}\right)$. On the basis of statistical data on past order inquiries the stream of inquiries expected for the future can be described by positive random variables of interarrival time $\tilde{J}$, order quantity $\tilde{Q}$, price $\tilde{P}$ and manufacturing costs $\tilde{K}^M$.
- The available capacity $\tilde{C}_t$ is uncertain and modelled as a F_t-distributed random variable. That is, the distribution can be put in a concrete time-dependent form in such a way that the standard deviation increases with increasing distance from t_a. The realization of this random variable is completely known for the current planning period t_a. Specific distributions F_t are taken as a basis for the remaining periods of the batch interval. These distributions are characterized by non-decreasing standard deviations as well as not necessarily identical expected values. For periods after the batch interval a probability distribution F_T with a constant expected value and standard deviation is assumed.

2.2.2.2 Structure of planning approach

In order to take the different adaptation measures into account a two-stage planning approach is proposed (see figure 2.2.2). At both planning stages the adaptation measures of capacity nesting and safety capacity are applied to cover order- and resource-related uncertainty.

At the *first planning stage* "order acceptance by the company" basically the common idea of batch CTP approaches is implemented: A set of customer requests is present and only those orders are accepted that can be fulfilled by means of the expected non-dedicated capacity within the specified delivery time interval in the most profitable way. For each accepted order delivery date, delivery quantity and penalty costs for premature/tardy delivery are contractually fixed and the order fulfillment process is started. In any case these orders utilize a share of standard capacity. In situations where the standard capacity is not sufficient and lucrative orders are present additionally a share of premium capacity is utilized. In contrast to conventional CTP approaches the other share of orders is not finally, but provisionally rejected.

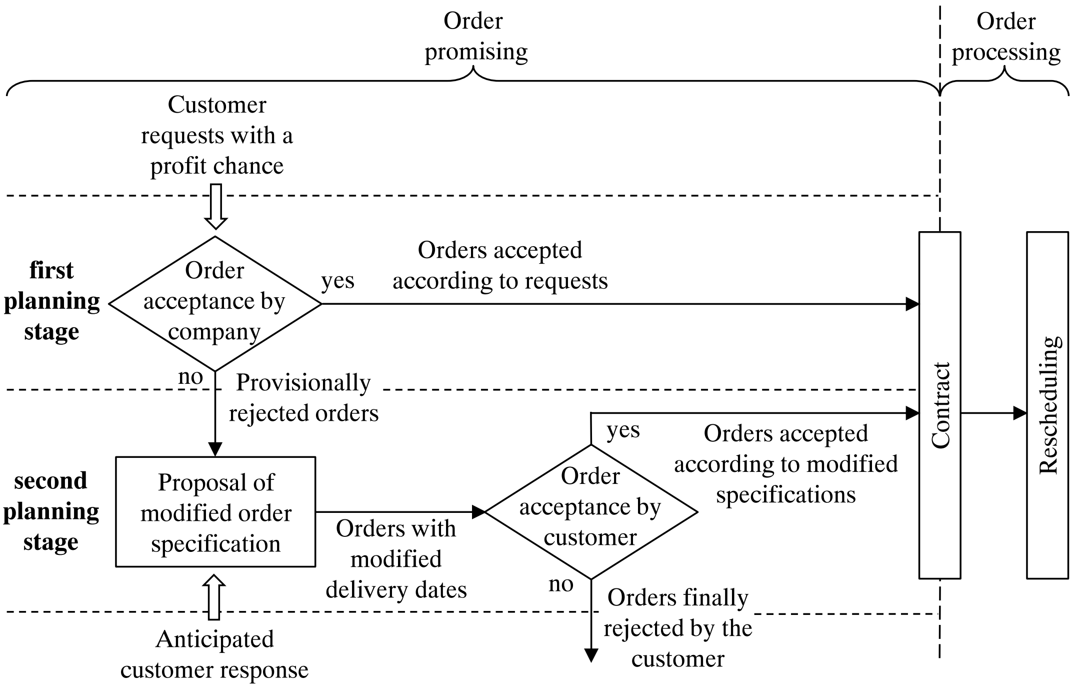

Figure 2.2.2: Structure of the planning approach

Provisionally rejected orders are included in the process at the *second planning stage* “proposal of modified order specification”. Although the set of these orders contains only orders with a profit chance, in the current situation and with respect to the desired delivery time interval they can be valued as to be in the range from not yet profitable via barely profitable up to lucrative. Since capacity supply and demand fluctuate randomly and the accuracy of information about the situation in a future period improves over time this valuation may be different when the delivery date proposed for such an order deviates from the desired interval. Therefore, the producer generates promises for provisionally rejected orders that do not take requested delivery time intervals and contractually fixed delivery dates as hard constraints into account. Instead of this on the one hand for provisionally rejected orders an anticipated customer response (acceptance probability) to delivery dates deviating from requests is considered. On the other hand for already accepted orders penalty costs for deviations from contractually fixed delivery dates are taken into account. Under these assumptions practicable delivery dates are determined that balance expected costs of displacing orders from their most beneficial processing period and expected costs of losing profit chances due to customers' rejections.

The two stage approach enables a simple interaction with clients whose order requests could be accepted with a deviating delivery date. The decision whether orders with a modified specification are accepted is no longer up to the company but to the individual customers. If one decides to reject this modification his order is finally rejected, otherwise the new order specifications are accepted. For orders accepted at the second stage the terms of contract (see first planning stage) are fixed. Just like at the first planning stage accepted orders in particular utilize a share of standard capacity and only if this is not sufficient for fulfilling lucrative orders additionally a share of premium capacity is dedicated to these orders.

In contrary to a comprehensive single-stage approach where decisions on acceptance and (modified) delivery dates of all orders are made simultaneously this two-stage structure enables a faster reaction to order inquiries which can exactly be met according to the customer specification, because customers' response is not necessary. On the other hand such a single-stage approach would allow for a higher expected value of profit. Since in this case acceptance and delivery dates of all orders cannot be confirmed until the customers' response to all deviating delivery dates is received completely the response time is indeterministic and longer by tendency. So, this procedure would only be preferable if the customers are willing to tolerate longer response times to their requests.

2.2.3 Planning models

2.2.3.1 First planning stage

On the basis of the order and resource situation at the time of planning and the orders' profitabilities, the company decides about the *acceptance or provisional rejection* $Z_i \in \{0,1\}$ of each newly arrived order request. In the first-mentioned case additionally the period $D_{i.t} \in \{0,1\}$ in which the order is to be delivered with quantity $q_i \geq 0$ as well as production quantities $P_{i.t}$ need to be determined. For already accepted, but not yet fulfilled orders these decisions have already been made in former planning runs, but can be revised, except the acceptance decision $(Z_i = 1)$.

The *decision field* is restricted by customer-, production- and measure-related constraints as well as logical requirements of the rolling horizon. *Customer-related constraints* for newly arrived order inquiries with a profit chance (2, 3) ensure the delivery of the whole requested quantity within the desired delivery time interval, if the order will be accepted (Chen et al. 2001). In the event of revising delivery dates of accepted, but not yet fulfilled orders, adjusted delivery dates can be set within the considered planning horizon (4). The agreed delivery time of an accepted order is a soft constraint. Violations are quantified (5) and penalized with contractually fixed costs in the objective function (1). Since there are different costs for delivery date deviations γ_i^e, γ_i^l a distinction between premature $(V_i^{real} < 0 \Rightarrow \delta_i = 0)$ and tardy $(V_i^{real} > 0 \Rightarrow \delta_i = 1)$ delivery is to be made (6, 7), where α is a sufficiently large number.

Constraints of the production system result from the available capacity $\tilde{C}_t$, the inventory of finished products $B_{i.t}^{FP}$ that is increased/decreased by production $P_{i.t}$ / delivery $q_i \cdot D_{i.t}$ (8) and the inventory of materials $B_{r.t}^{R}$ that is increased/decreased by exogenous given replenishments $a_{r.t}^{R}$ / material consumption by manufacturing processes $Q_{i.r.t}^{M}$ required to fulfill accepted orders (9). Materials produced in-house $(r = 1,...,r_k - 1)$ and materials procured from external sources $(r = r_k,...,R)$ are provided with different lead times ω_1 or ω_2 $(\omega_1 > \omega_2)$, respectively (10, 11).

Measure-related constraints (12-14) result from considering preventive adaptation measures. The available capacity is split up into standard $P_{i.t}^{S}$ and premium capacity $P_{i.t}^{P}$ according to share ε. With additional costs k^P for utilizing premium capacity the option of *capacity nesting* reserves capacity for highly profitable (lucrative) orders and thus handles order-related uncertainty. Both parameters have to be set in accordance to the uncertain order and resource situation. Due to multiple sources of uncertainty and interactions between the parameters it is unlikely that closed form analytical expressions do exist for an optimum parameter setting in the general case. Hence, one way of determining good parameter constellations is a grid search in which both parameters are varied systematically with respect to the evaluation of achieved planning results. Providing *safety capacity* serves as a measure to cope with uncertainty about the available capacity. On the basis of a risk-averse estimation of the capacity the capacity utilization is planned in such a way that capacity constraints are fulfilled with a given probability $\vartheta > 0.5$. In this case the factual available capacity exceeds estimated values most of the time. For the opposite situation it is assumed that the feasibility of the plan is reached by applying operative adjustment measures that are not explicitly modelled. The value of parameter ϑ has to be chosen in such a way that the trade-off between capacity idle time costs and costs of delayed order fulfillment due to scarce capacity is balanced. Since both cost components contain a share of opportunity costs they cannot always be measured with acceptable effort. In such cases a reasonable ϑ-value is predefined that covers the set of possible capacity situations with a high percentage.

The rolling horizon requires *logical consistency*. Data of already started order fulfillment processes need to be transferred from the last to the current planning run, whereby production decisions can be revised with respect to the lead time of required materials (15). That is, producing a higher quantity than originally planned is not permitted for those periods in which already started material supply processes are not yet finished. On the other hand, for order inquiries production quantities are zero in the first planning periods (16) and the finished product inventory is zero too (17). Additionally, the inventory data $B^{R}_{r.t_a-1}$ and $B^{FP}_{i.t_a-1}$ need to be transferred (18, 19). In order to avoid higher production quantities than necessary to fulfill the orders, the stock of finished products should be zero at the end of the planning horizon (20). Finally, domains of decision variables and auxiliary variables are specified (21-27). The decisions on acceptance (21) and delivery date (22) as well as the identification of the decisions' directions (23) are binary. Planned deviations are integer-valued (24). Decisions on manufacturing quantities (25), capacity utilization and inventory levels (26, 27) are non-negative real-valued.

The planning approach aims at maximizing the profit generated within the planning horizon. Due to the distinction of order sets, the objective function is split up into three deterministic components (1). For newly arrived order inquiries the revenue is diminished by holding costs of finished products $k_i^{L.FP}$, transportation costs k^{Tr}, costs for utilizing premium capacity k^P as well as manufacturing costs k_r^M. In case of already accepted orders only inventory holding costs of finished products and materials as well as costs for utilizing premium capacity are relevant. Additionally, the costs of the realized deviation V_i^{real} from the contractually agreed delivery date $D_{i.t}^c$ need to be considered. Although these penalty costs are included, considering the cost for inventory holding of finished products $k_i^{L.FP}$ is still necessary since producing the whole requested order quantity might not be possible in one planning period. The remaining success-related components are fixed, since the order acceptance decisions have already been made. As a third component inventory holding costs of materials $k_r^{L.R}$ are jointly taken into account for all present orders. The following mixed-integer, quadratic decision model results:

$$
\begin{aligned}
(1) \quad & \max \sum\nolimits_{t=t_a}^{T} \sum\nolimits_{i\in\hat{A}} \left(-k_i^{L.FP} \cdot B_{i.t}^{FP} - k^P \cdot P_{i.t}^P \cdot \kappa_i\right) \\
& - \sum\nolimits_{i\in\hat{A}} \left(V_i^{real} \cdot \gamma_i^e \cdot (\delta_i - 1) + V_i^{real} \cdot \gamma_i^l \cdot \delta_i\right) \\
& + \sum\nolimits_{t=t_a}^{T} \sum_{i\in\tilde{A}} \left(q_i \cdot \rho_i \cdot D_{i.t} - k_i^{L.FP} \cdot B_{i.t}^{FP} - k^{Tr} \cdot D_{i.t} - k^P \cdot P_{i.t}^P \cdot \kappa_i - \sum\nolimits_{r=1}^{R} k_r^M \cdot Q_{i.r.t}^M\right) \\
& - \sum\nolimits_{t=t_a}^{T} \sum\nolimits_{r=1}^{R} k_r^{L.R} \cdot B_{r.t}^R
\end{aligned}
$$

subject to:

- Customer-related constraints:
  - -- Newly arrived order inquiries with a profit chance:

$$(2) \qquad \sum\nolimits_{t=t_i^e}^{t_i^l} D_{i.t} = Z_i \qquad \forall i \in \tilde{A}$$

$$(3) \qquad \sum\nolimits_{t=t_a}^{T} D_{i.t} = Z_i \qquad \forall i \in \tilde{A}$$

  - -- Accepted, but not yet fulfilled orders:

$$(4) \qquad \sum\nolimits_{t=t_a}^{T} D_{i.t} = 1 \qquad \forall i \in \hat{A}$$

$$(5) \qquad V_i^{real} = \sum\nolimits_{t=1}^{T} \left(D_{i.t} - D_{i.t}^c\right) \cdot t \qquad \forall i \in \hat{A}$$

(6) $V_i^{real} \geq (\delta_i - 1) \cdot \alpha$ $\forall i \in \hat{A}$

(7) $V_i^{real} \leq \delta_i \cdot \alpha$ $\forall i \in \hat{A}$

- Production-related constraints:

(8) $B_{i.t-1}^{FP} + P_{i.t} - q_i \cdot D_{i.t} = B_{i.t}^{FP}$ $\forall i \in \tilde{A} \cup \hat{A}$, $t_a \leq t \leq T$

(9) $B_{r.t-1}^{R} + a_{r.t-1}^{R} - \sum_{i \in \tilde{A} \cup \hat{A}} Q_{i.r.t}^{M} = B_{r.t}^{R}$ $\forall t_a \leq t \leq T$, $r = 1, \ldots, R$

(10) $b_{i.r} \cdot P_{i.t+\omega_1} = Q_{i.r.t}^{M}$ $\forall i \in \tilde{A} \cup \hat{A}$, $t_a \leq t \leq T$, $r = 1, \ldots, r_k - 1$

(11) $b_{i.r} \cdot P_{i.t+\omega_2} = Q_{i.r.t}^{M}$ $\forall i \in \tilde{A} \cup \hat{A}$, $t_a \leq t \leq T$, $r = r_k, \ldots, R$

- Measure-related constraints:

(12) $\mathrm{Prob}(\sum_{i \in \tilde{A} \cup \hat{A}} P_{i.t}^{P} \cdot \kappa_i \leq \varepsilon \cdot \tilde{C}_t) \geq \vartheta$ $\forall t_a \leq t \leq T$

(13) $\mathrm{Prob}(\sum_{i \in \tilde{A} \cup \hat{A}} P_{i.t}^{S} \cdot \kappa_i \leq (1 - \varepsilon) \cdot \tilde{C}_t) \geq \vartheta$ $\forall t_a \leq t \leq T$

(14) $P_{i.t}^{S} + P_{i.t}^{P} = P_{i.t}$ $\forall i \in \tilde{A} \cup \hat{A}$, $t_a \leq t \leq T$

- Logical requirements of the rolling horizon:

(15) $\sum_{t=t_a}^{t_a+\eta} P_{i.t} \leq \sum_{t=t_a}^{t_a+\eta} P_{i.t}^{prev}$ $\forall i \in \hat{A}$, $\eta = 0, \ldots, (\omega_1 - 1)$

(16) $P_{i.t} = 0$ $\forall i \in \tilde{A}$, $t_a \leq t \leq t_a + (\omega_1 - 1)$

(17) $B_{i.t_a-1}^{FP} = 0$ $\forall i \in \tilde{A}$

(18) $B_{i.t_a-1}^{FP} = B_{i.t_a-1}^{FP.prev}$ $\forall i \in \hat{A}$

(19) $B_{r.t_a-1}^{R} = B_{r.t_a-1}^{R.prev}$ $\forall r = 1, \ldots, R$

(20) $B_{i.T}^{FP} = 0$ $\forall i \in \tilde{A} \cup \hat{A}$

- Domains of decision variables and auxiliary variables:

(21) $Z_i \in \{0,1\}$ $\forall i \in \tilde{A}$

(22) $D_{i.t} \in \{0,1\}$ $\forall i \in \tilde{A} \cup \hat{A}$, $t_a \leq t \leq T$

(23) $\delta_i \in \{0,1\}$ $\forall i \in \hat{A}$

(24) $V_i^{real} \in \mathbb{Z}$ $\forall i \in \hat{A}$

(25) $Q_{i.r.t}^{M} \geq 0$ $\forall i \in \tilde{A} \cup \hat{A}$, $t_a \leq t \leq T$, $r = 1,...,R$

(26) $P_{i.t}, P_{i.t}^{P}, P_{i.t}^{S}, B_{i.t}^{FP} \geq 0$ $\forall i \in \tilde{A} \cup \hat{A}$, $t_a \leq t \leq T$

(27) $B_{r.t}^{R} \geq 0$ $\forall t_a \leq t \leq T$, $r = 1,...,R$

2.2.3.2 Second planning stage

If the solution of the first planning stage leads to a non-empty set of provisionally rejected orders, the planning process is continued at the second planning stage. Now, *proposals for deviating delivery dates* are generated for provisionally rejected orders with respect to anticipated customers' response. Therefore as a subset of order set $\tilde{A}$ the set $\bar{A}$ has to be defined as the set of customer orders which were provisionally rejected at the beginning of planning period t_a. Thus, order sets $\hat{A}$ and $\bar{A}$ are relevant for planning at the second stage.

The decision about the acceptance of a suggested delivery date is no longer up to the company, but to the customer. In order to include customers' acceptance probability into the planning process, it is assumed that historical data about customers' response on deviating delivery date proposals is available. Furthermore, the decision maker is capable to derive a discrete response function $\beta\left(V_i^{des}\right)$ depending on the extent of the deviation V_i^{des} from the desired delivery time interval. Thereby a distinction between premature $(V_i^{des} < 0)$, punctual $(V_i^{des} = 0)$ and tardy $(V_i^{des} > 0)$ delivery is made (28-32):

(28) $V_i^{e} = \sum_{t=t_a}^{T} D_{i.t} \cdot t - t_i^{e}$ $\forall i \in \bar{A}$

(29) $V_i^{l} = \sum_{t=t_a}^{T} D_{i.t} \cdot t - t_i^{l}$ $\forall i \in \bar{A}$

(30) $V_i^{e'} = \min(V_i^{e}, 0)$ $\forall i \in \bar{A}$

(31) $V_i^{l'} = \max(V_i^{l}, 0)$ $\forall i \in \bar{A}$

$$\text{(32)} \qquad V_i^{des} = V_i^{l'} + V_i^{e'} \qquad \forall i \in \bar{A}$$

Customers' response is modeled as a discrete function with L steps, whereby the values $\beta_1,...,\beta_L$ represent the probability of accepting deviating delivery dates (33). Abstracting from further dimensions of order specification (e.g. price, partial deliveries) an acceptance probability of one can be assumed for punctual deliveries, whereas the remaining probability values for positive or negative deviations lie in the interval $(0,1]$:

$$\text{(33)} \qquad \beta\left(V_i^{des}\right) = \begin{cases} \beta_1 : \mathrm{V}_i^{des} \leq \Delta_1 \\ \beta_l : \Delta_{l-1} < \mathrm{V}_i^{des} \leq \Delta_l,\ l = 2,...,L-1 \\ \beta_L : \Delta_{L-1} < \mathrm{V}_i^{des} \end{cases} \qquad \forall i \in \bar{A}$$

with $\beta_1,...,\beta_L \in (0,1]\ \ \forall l$, and $\Delta_{l-1} < \Delta_l \ \ \forall l = 2,...,L-1$

Compared to strike rate matrices (Kingsman and Mercer 1997), where the lead time is modeled with equidistant intervals as index of one matrix dimension, this response function offers more flexibility in considering deviation intervals of different length.

Under these assumptions some *customer-related constraints* become irrelevant, since provisionally rejected orders only have to be delivered within the planning horizon and the decision about order acceptance is no longer up to the company $(Z_i = 1)$. Therefore constraints (2, 3) are omitted. Customer-related constraint (4) is still relevant for both order sets $(\hat{A} \cup \bar{A})$, whereas constraints (5-7) remain valid for accepted, but not yet fulfilled orders. Due to the intended robustness-oriented planning, the constraints of the production system remain the same (8-11), since all delivery dates and quantities are determined in such a way that they can be met even though all customers accept the suggested order conditions (no overbooking). Apart from an adaptation of the relevant order sets no modifications are necessary for *measure-related constraints* (12-14) and *logical requirements of the rolling horizon* (15-20).

The *objective function* has to be splitted up into a deterministic and a stochastic component (1'): Analogously to the first planning stage, costs induced by accepted orders $\hat{A}$ need to be considered in the deterministic component. Integrating the acceptance probability for order set $\bar{A}$ requires considering the expected values of the revenue, the transportation, inventory holding and material costs as well as costs for utilizing premium capacity. Since material requirements of both order sets interact, an allocation of material inventory holding costs cannot be made according to the principle of causation. Hence, the inventory is estimated according to the shares of materials consumed and considered with the decision variable $B^R_{i.r.t}$ (34). The following mixed-integer, nonlinear objective function results:

$$
\begin{aligned}
(1') \quad & \max \sum_{t=t_a}^{T} \sum_{i \in \hat{A}} \left(-k_i^{L.FP} \cdot B_{i.t}^{FP} - k^P \cdot P_{i.t}^P \cdot \kappa_i - \sum_{r=1}^{R} k_r^{L.R} \cdot B_{i.r.t}^R \right) \\
& - \sum_{i \in \hat{A}} \left(V_i^{real} \cdot \gamma_i^e \cdot (\delta_i - 1) + V_i^{real} \cdot \gamma_i^l \cdot \delta_i \right) \\
& + \sum_{t=t_a}^{T} \sum_{i \in \bar{A}} \beta\left(V_i^{des}\right) \cdot \left(q_i \cdot \rho_i \cdot D_{i.t} - k_i^{L.FP} \cdot B_{i.t}^{FP} - k^{Tr} \cdot D_{i.t} - k^P \cdot P_{i.t}^P \cdot \kappa_i \right. \\
& \left. - \sum_{r=1}^{R} \left(k_r^M \cdot Q_{i.r.t}^M + k_r^{L.R} \cdot B_{i.r.t}^R \right) \right)
\end{aligned}
$$

$$
\text{with (34)} \quad B_{i.r.t}^R = \begin{cases} \dfrac{q_i \cdot b_{i.r}}{\sum\limits_{i' \in \hat{A} \cup \bar{A}} q_{i'} \cdot b_{i'.r}} & : \sum\limits_{i' \in \hat{A} \cup \bar{A}} q_{i'} \cdot b_{i'.r} > 0 \\ 0 & : \text{otherwise} \end{cases}
$$

The operative character of the planning problem requires the avoidance of long solution times. One important driver of computational effort is the multiplication of the variables V_i^{real} and δ_i which leads to quadratic objective functions at both planning stages. Additional notable computational effort is induced by the L-step deviation-dependent acceptance probability function and its multiplication with the delivery date variable that determines the deviation. Whilst the first driver can be tackled by means of a standard linearization, this is not applicable for the second driver as long as the acceptance probability is a discrete function[1]. For that reason we linearized on the first-mentioned case (see appendix A). The formerly mixed-integer, quadratic decision model of the first planning stage is relaxed to a mixed-integer, linear model. In a similar way the model of the second planning stage has been freed from one non-linearity. But due to the existing dependencies between customers' acceptance prob-

---

[1] In cases with a richer information base it is possible to estimate a stepwise linear function and then to apply a standard linearization.

ability and the deviation from the desired delivery date interval this decision model remains nonlinear.

2.2.4 Numerical analysis

2.2.4.1 Procedure

The analysis aims at systematically investigating the suitability of the proposed CTP approach as well as the impacts of the adaptation measures “capacity nesting”, “safety capacity” and “proposing deviating delivery dates with respect to customer response” on robustness and solution quality. For reasons of applicability of our conclusions to real-world situations the planning approach is applied multiple times to (1) real data on orders and capacities from a manufacturer of customized leisure products, to (2) systematically generated data and to (3) combinations of both types of data. In order to identify interactions between the adaptation measures, the parameters of capacity nesting and safety capacity are varied systematically and the planning is carried out with/without consideration of proposing deviating delivery dates. In sum, 3,960 test constellations result (99.98% solved to optimality). According to the criteria “extent of capacity uncertainty”, “amount of safety capacity” and “customer response to proposed delivery dates” these constellations are grouped to 12 scenarios. The planning approach has been implemented by means of the modeling environment AIMMS 3.13 and optimized values of order acceptance and production decisions are determined for each test constellation with adequate solvers (Cplex 12.5, AIMMS Outer Approximation Algorithm).

During the tests the optimized plans are confronted with a simulated reality that is built by generating random numbers from realistic distributions of uncertain capacity and uncertain order specifications (product configuration, order quantity, interarrival time). Per individual test constellation 13 batch runs are performed to observe the generated profit and the occurred deviations from contractually fixed delivery dates. The analysis is based on descriptive statistics of these observed values for each scenario:

- The level of average profit in dependence of adaptation measures and uncertainty of capacity is used for evaluating the extent of monetary impact.

- The coefficients of variation of generated profits in comparison to the coefficients of variation of order and capacity data allows statements about the impact on solution robustness.

- The average weighted deviation between agreed and achieved delivery dates (penalty costs) sheds light on the impact on planning robustness (Sridharan et al. 1988).

2.2.4.2 Test data

Order-related uncertainty is present in the real order data on the seven best-selling product configurations with regard to order quantity and interarrival time.

Product configuration	c	1	2	3	4	5	6	7
Order quantity	μ_c^q	4.71	4.85	7.77	4.66	7.66	4.75	6.38
$\tilde{Q}_c \sim N_c(\mu_c^q, \sigma_c^q)$ *)	σ_c^q	3.25	2.54	3.90	3.51	0.58	3.30	2.56
Interarrival time	μ_c^j	13.00	11.38	9.10	22.75	30.33	22.75	11.38
$\tilde{J}_c \sim N_c(\mu_c^j, \sigma_c^j)$ *)	σ_c^j	5.94	12.66	4.89	16.76	22.50	31.50	7.42
Price per piece	ρ_c	5750	3999	3999	3299	2990	2699	2599
Manufacturing costs	k_c^M	570.93	384.93	416.5	281.19	289.65	251.72	462.44
*) truncated normal distributions that only permit positive values								

Table 2.2.2: Original order data

Original data from a period of three months forms the basis for order stream 1. The statistical characteristics of this data (summarized in table 2.2.2) are applied to generate further realistic order streams (2 to 5). For all orders a uniform delivery time interval of 10 periods starting with the period of order receipt is usual practice. Whereas positive deviations from contractually fixed delivery dates (delayed deliveries) are penalized with $\gamma^l = 3\%$ of order revenue, negative deviations (premature deliveries) are not penalized ($\gamma^e = 0$). Transportation costs per order are 59 and inventory holding costs are 0.25% per tied-up capital.

A fluctuating availability of capacity induces *resource-related uncertainty*. Due to missing statistical records we gathered subjective estimations of capacity levels from the production planners. Based on their experiences they were able to specify intervals of capacity situations with a low/high level of uncertainty (capacity situations III and IV). Assuming an increase of information accuracy over time the intervals were translated to parameters (mean, standard deviation) of symmetric triangular distributions. Whilst in each estimated capacity situation the mean μ^{cap} stays constant over time, the standard deviation σ^{cap} increases by tendency. Four streams of random variables are generated for each of these uncertain capacity situations. For further comparisons we defined two capacity situations (I and II) in which uncertainty is not present ($\sigma^{cap} = 0$) and the mean is identical with the means of uncertain capacity situations (see table 2.2.3).

Capacity situation		μ^{cap}	σ^{cap} in period					
			1	2	3	4	5	6 … T
defined	I	2.75	0	0	0	0	0	0
	II	2.50	0	0	0	0	0	0
estimated	III	2.75	0	0.0204	0.0408	0.0612	0.0816	0.1021
	IV	2.50	0	0.0408	0.0816	0.1225	0.1633	0.2041

Table 2.2.3: Defined and estimated capacity situations

In order to take the *response of the customer* in the contract awarding process into account based on the experience of sales managers a response function has been estimated empirically (Dumas et al. 2005). In this case proposed delivery dates that lie before and within the requested delivery time interval are usually accepted. Proposed delivery dates in periods after the requested delivery time interval are accepted with a probability that decreases with increasing deviation. The estimated discrete cumulative distribution of the deviation-dependent acceptance probability is:

$$(35) \qquad \beta\left(V_i^{des}\right) = \begin{cases} 1.0 & : V_i^{des} \leq 0 \\ 0.6 & : 0 < V_i^{des} \leq 10 \\ 0.2 & : 10 < V_i^{des} \leq 25 \\ 1 \cdot 10^{-10} & : 25 < V_i^{des} \end{cases} \qquad \forall i \in \overline{A}$$

The varied parameters of the adaptation measures *capacity nesting* and *providing safety capacity* are summarized in table 2.2.4:

Capacity nesting	k^P	500	1000	1500	2000	2500	3000	6000
	ε		1/3		1/2		2/3	
Safety capacity	ϑ		$0 \cdot \sigma^c$		$1 \cdot \sigma^c$		$2 \cdot \sigma^c$	

Table 2.2.4: Varied parameters of adaptation measures[1)]

In comparison to the situation-independent margins of orders the varied *costs* k^P *of utilizing premium capacity* are in the range from very low to very high. In the first case nearly all orders will have access to premium capacity. Hence, it is to expect that lucrative orders arriving in the future have to be rejected very often due to the lack of free capacity. The opposite is true for the latter situation, where hardly any order can utilize premium capacity because only a few of arriving orders is lucrative enough to cover the additional costs with the situation-independent margin. Therefore it is to expect that orders are rejected as soon as standard capacity is booked out. Both situations will lead to a reduced maximum profit. With the tests we try to identity an area of more advantageous values of k^P in dependence from the other varied parameters.

With regard to the *share* ε *of premium capacity* values from a moderate until a high share are tested. If the share is too low a greater number of future lucrative orders will be rejected and the number of accepted "normal" orders will increase. In contrast to this a too high share of premium capacity allows for accepting the most lucrative orders, whereas "normal" orders will be crowded out. Again at both extremes the supply chain cannot gain the highest profits. The test results will give indications to good values for ε in dependence from the other parameters.

---

1) The table does not appear in the published version of this paper due to publisher's mistake.

The amount of *safety capacity* ϑ is varied in the spectrum from no safety capacity to values in the manner common for this sector of industry. In situations with a misfit between safety capacity and capacity uncertainty the risk of deviations between accepted and realized delivery dates increases. Whereas realized capacity values above the expected capacity allow speeding up order fulfillment, values below the expectations induce delayed order fulfillment. The higher the safety capacity level is the more resource uncertainty is covered so that more timely deliveries can be guaranteed. On the other hand the inventory of finished orders increases and lesser orders can be accepted.

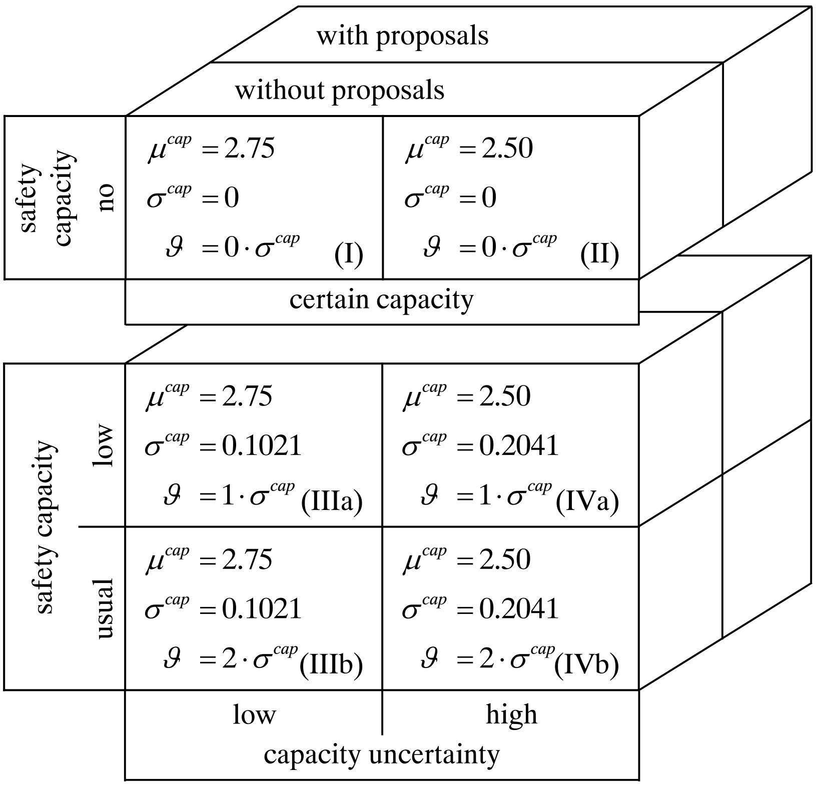

Figure 2.2.3: Scenarios to be analyzed

The fixed parameters of the 12 scenarios to be analyzed are shown in figure 2.2.3. While scenarios (I) and (II) serve as reference scenarios assuming certain capacity availability, scenarios (IIIa) to (IVb) take capacity uncertainty into account. The differentiation of scenarios represents a rough grid for identifying impacts of resource uncertainty, resource redundancies and proposal of deviating delivery dates onto the impacts of the other parameters. Furthermore, in each scenario a fine-grained analysis of the impacts of capacity nesting can be carried out to find out good parameter settings.

Planning is done on a daily basis at the beginning of a week with a batch interval of five periods. In preliminary tests based on the criteria solution time and generated profits a suitable planning horizon T has been identified which can be calculated as the sum of the latest delivery date and a share of 5% of the maximum time needed to fulfill all orders. To avoid inadequate solution times of the nonlinear model, the number of iterations has been set to 20 and the maximum solution time per iteration has been limited to 100 seconds.

2.2.4.3 Test results

To evaluate the monetary impacts of the adaptation measures and capacity uncertainty the *average profit* generated in scenarios (I) to (IVb) is analyzed for the cases without and with proposals to the customers. While figure 2.2.4 reveals the results for non-interactive order promising (without proposals), figure 2.2.5 represents the interactive case (with proposals). In both figures the observable matrix structure corresponds to the configuration of the scenarios as illustrated in figure 2.2.3. By depicting the profits in form of isoquants at different levels the results of a fine-grained analysis of capacity nesting are presented for each scenario. For reasons of comparability of the findings the profit is adjusted by the costs of utilizing premium capacity. Additionally, the case of not applying capacity nesting is used as a reference value to be able to evaluate the economic impact of this measure. Hence, those parameter constellations that lead to an increase of profits compared to zero premium capacity in the identical capacity situation are highlighted by dashed shadings.

Starting with an isolated analysis of the generated profits of non-interactive order promising figure 2.2.4 shows that the CTP approach generates positive average profits for each parameter setting. A detailed analysis discloses that capacity nesting only increases the profit in scenario (IIIb) for parameter constellation $(\varepsilon, k^P) = (1/3, 500)$. In the remaining parameter constellations capacity nesting leads to a reduction of profits compared to utilizing zero premium capacity. In particular, in every scenario the extent of profit reductions grows with an increasing share of premium capacity as well as increasing utilization costs, since the number of accepted orders decreases for the previously mentioned evolution of capacity nesting parameters. At maximum about 42% fewer orders are accepted compared to utilizing zero premium capacity for parameter constellation $(\varepsilon, k^P) = (2/3, 6000)$ which leads to a profit reduction of 63%. Apart from the profit reduction effect induced by capacity nesting, increasing safety capacity further decreases profits for low (IIIa, IIIb) and high (IVa, IVb) capacity uncertainty. This can be attributed to the increasing scarcity of capacity assessable for planning caused by a higher amount of safety capacity. Due to the risk averse estimation of capacity availability high capacity uncertainty additionally results in fewer capacity available for planning. Consequently comparing reference scenarios (I) and (II), as well as the uncertain scenarios (IIIa) and (IVa) respectively (IIIb) and (IVb) again a decrease of profits becomes obvious.

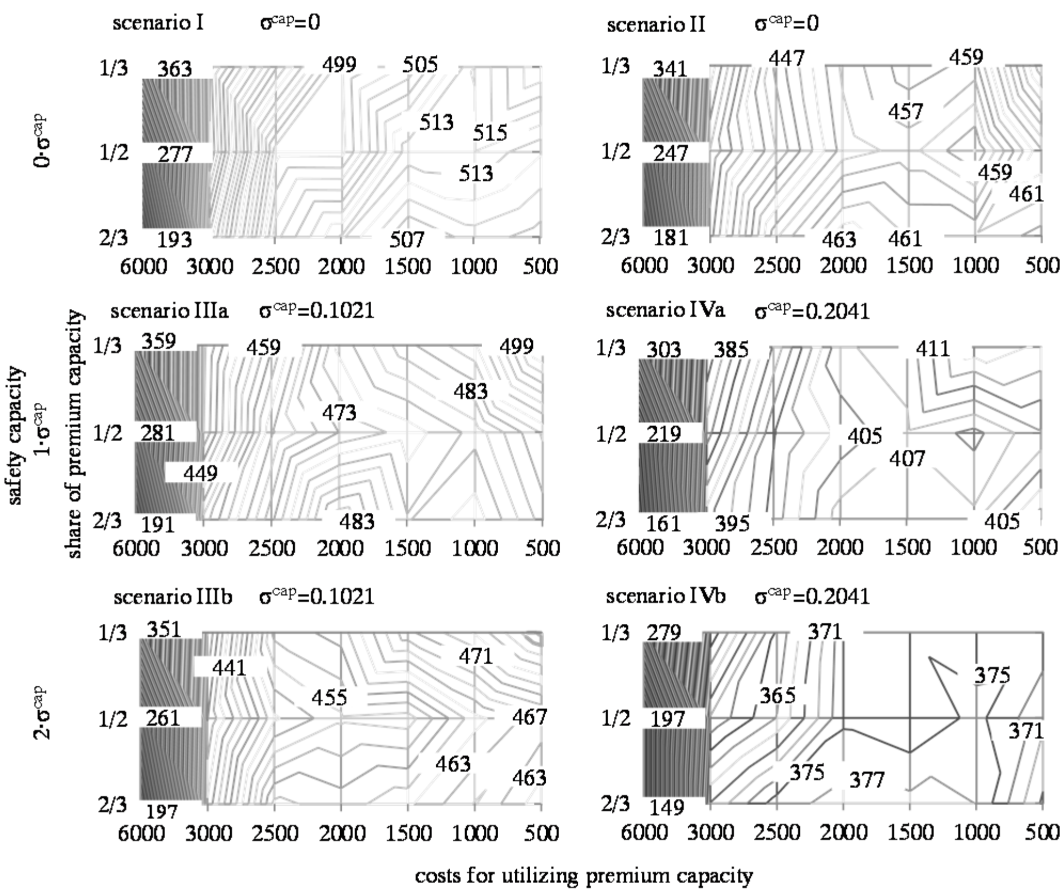

Figure 2.2.4: Generated profits of non-interactive order promising (in 100 thousand)

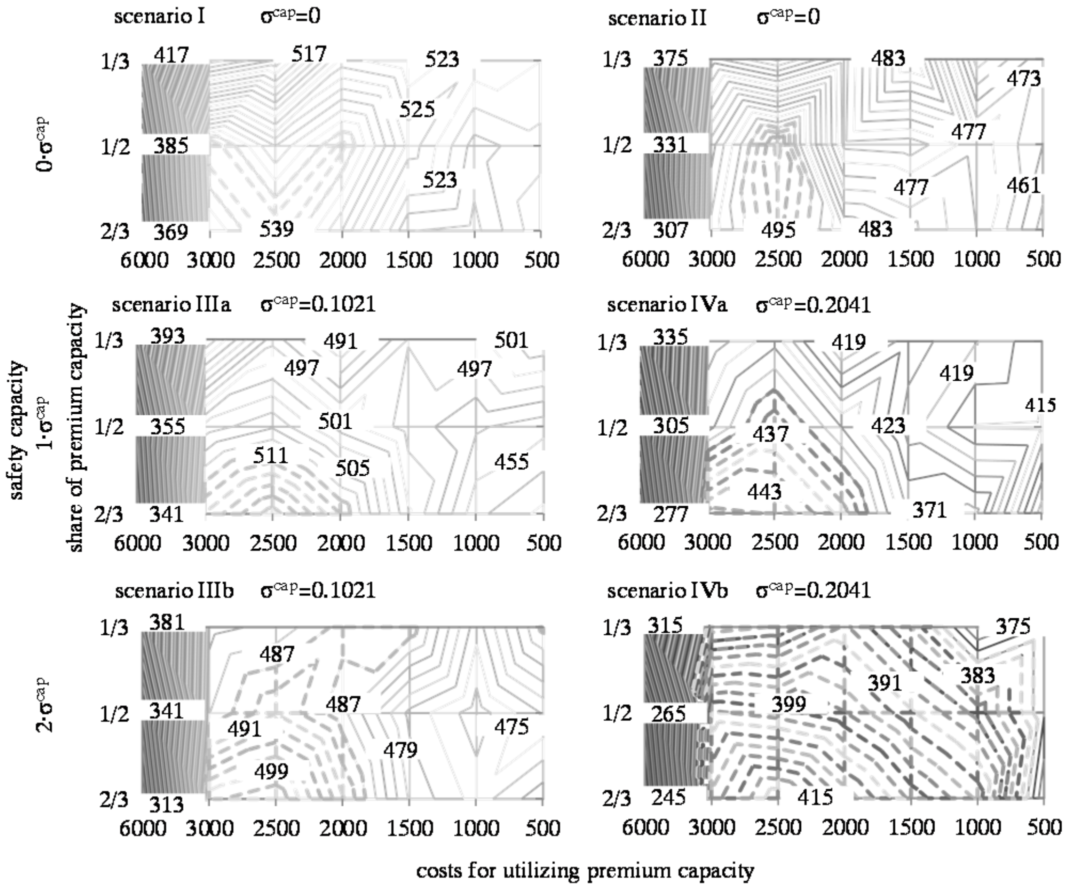

Figure 2.2.5: Generated profits of interactive order promising (in 100 thousand)

Since the structures of figure 2.2.4 and 2.2.5 are identical, the previous results can easily be verified for the case of interactive order promising. Again in each parameter setting only positive average profits are obtained by the CTP approach. Comparing the levels of profits for non-interactive and interactive order promising reveals that generated profits are higher in the majority of parameter constellations if customers' responses to proposed delivery dates are considered. Thereby, the differences between the generated profits strongly depend on the interactions between the remaining adaption measures so that detailed analysis is required. Taking a look at the advantageousness of capacity nesting shows that this measure is able to increase profits in every investigated scenario. In particular, the extent of the advantage area (dashed) grows with increasing capacity uncertainty as well as increasing safety capacity. This can be attributed to the increasing scarcity of capacity and to the increasing profits going along with the growing number of accepted orders induced by interactive order promising. On average 9% more orders than without interaction are accepted if costs for utilizing premium capacity are between 500 and 3000. This percentage is even higher for premium capacity costs of 6000 (15%) so that profits are increased by 5% resp. 40%. Despite the observed enhancement of profits initiated by considering customers' response outside the advantage areas again large profit reductions are induced by applying inadequate capacity nesting parameters since fewer orders are accepted. Considering the effects of safety capacity analogously to the results of non-interactive order promising less orders are accepted and lower profits are generated the greater the safety level and the capacity uncertainty are. Although costs of delayed order fulfillment are reduced the reduction is overcompensated by lost profits. Thus, orientating towards customary service level standards not necessarily enhances profits.

The impact of the adaptation measures on *solution robustness* can be measured by comparing the coefficients of variation (CV) of input data and generated profits. Therefore, an overview of the previously mentioned statistical values is given in table 2.2.5.

Planning data					Generated profits							
					$k^P \in \{500,...,3000\}$				$k^P = 6000$			
Order data (quantity, interarrival time)			Capacity data		Non-inter-active		Inter-active		Non-inter active		Inter-active	
1	2	3	I	II	I	II	I	II	I	II	I	II
(0.69,0.45)	(0.52,1.11)	(0.50,0.54)	0	0	0.06	0.08	0.06	0.07	0.13	0.12	0.16	0.11
4	5	6	III		IIIa	IIIb	IIIa	IIIb	IIIa	IIIb	IIIa	IIIb
(0.75,0.74)	(0.08,0.74)	(0.69,1.38)	0.04		0.07	0.08	0.06	0.07	0.12	0.13	0.10	0.15
7			IV		IVa	IVb	IVa	IVb	IVa	IVb	IVa	IVb
(0.40,0.65)			0.08		0.09	0.10	0.07	0.08	0.12	0.18	0.14	0.16

Table 2.2.5: Coefficients of variation of planning data and generated profits

Since all CV of generated profits are very low compared to those of order and capacity data the planning approach is able to cover uncertainty in a significant way and a high level of solution robustness is achieved. In particular, the CV of profits take exceptionally low values if costs for utilizing premium capacity are between 500 and 3,000. For those utilizations costs it can be observed that CV rise with increasing uncertainty as well as increasing safety capacity. In contrary, considering interactive order promising results in lower CV and therefore enhances solution robustness. Different indications are provided by the resulting CV for premium capacity costs of 6,000. In this case safety capacity partially compensates increasing uncertainty and the impact of interactive order promising must be described as non-monotonic.

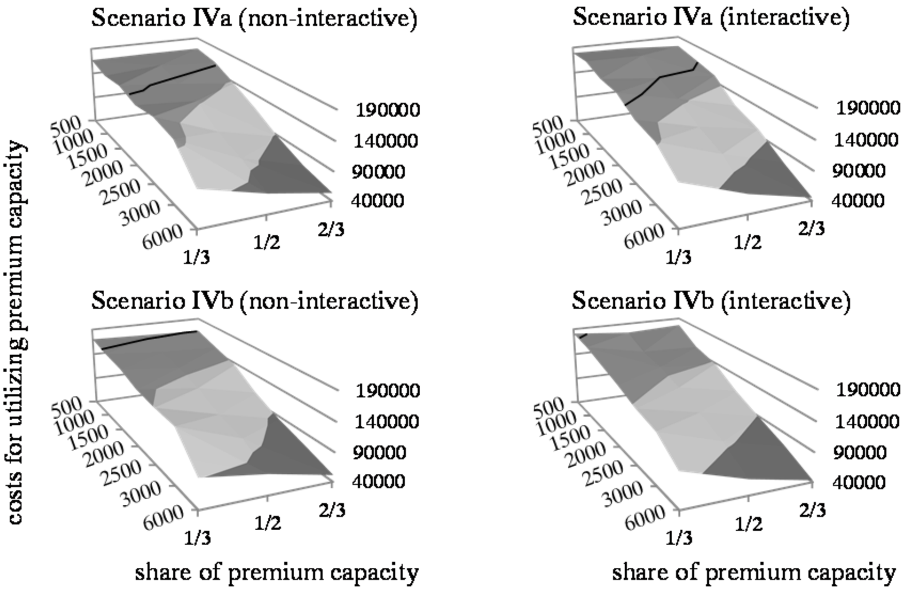

Figure 2.2.6: Penalty costs in representative capacity scenario IV

Although the adaptation measures are able to cover uncertainty in a significant way they are not able to completely cover uncertainty. Therefore an adjustment of planning might be necessary and contractually fixed delivery dates eventually cannot be met. The extent of plan revisions can be measured as the weighted average deviation between agreed and achieved delivery dates in form of penalty costs. Typical evolutions of these penalty costs are exemplary visualized in figure 2.2.6 for the representative scenario IV. Thereby the dark line represents the level of penalty costs in the case of zero premium capacity. The graphical representation reveals that capacity nesting has the strongest impact on penalty costs. But the influence direction strongly depends on the chosen parameter setting of capacity nesting as well as the remaining adaptation measures. Generally penalty costs decrease with an increasing share of premium capacity as well as increasing utilization costs. That is, planning robustness can be improved if the capacity nesting parameters are chosen high enough. Furthermore, safety capacity positively influences planning robustness since the advantage area of capacity nesting grows with increasing safety capacity. The evolution of penalty costs in dependence of capacity nesting as well as providing safety capacity is leveraged by interactive order promising. Due to the increasing number of orders accepted when considering customers' response moderate enhancements of penalty costs are observed in this case.

2.2.5 Conclusions

In the present paper a two-stage capable-to-promise approach is developed and analyzed that considerably extends current planning approaches by considering customers' response on delivery date proposals that deviate from order requests. Additionally the preventive measures capacity nesting and providing safety capacity are included to generate robust delivery dates even though the order and resource situation is uncertain. Complementary to the development of corresponding decision models, the impacts of those adaptation measures are not only analyzed in an isolated manner. Instead of this, interactions between the measures in case of a joint measure application are identified in the numerical analysis. By systematically varying the measure related parameters the following results are obtained:

- In case of simultaneously applying all application measures an advantage area exists within which profits and solution robustness can be increased if parameter settings are well coordinated. For the given data set a high share of premium capacity, medium utilization costs as well as considering the interaction with the customers turned out to be particularly beneficial. Compared to utilizing zero premium capacity planning robustness is as well enhanced in this area.

- Outside the advantage area different impacts on the assessment criteria are observed. Firstly there is a trade-off between planning robustness, solution robustness as well as generated profits before the joint measure application simultaneously reduces the values of these assessment criteria in extreme cases.

- Regarding the individual measures the impacts of interactive order promising have to be emphasized since profits were notably increased in almost every parameter constellation while additionally enhancing solution robustness. As expected, providing safety capacity according to an externally defined service level enhances planning robustness due to a higher amount of timely deliveries. But on the other hand the risk of an unbalance between costs of delayed order fulfillment and lost sales can be observed. Therefore, this trade-off needs to be taken into consideration when determining a suitable safety capacity level. Capacity nesting has the strongest reducing/increasing impact on solution and planning robustness. Since the strength of these effects strongly depends on the chosen capacity nesting parameters as well as the other adaptation measures applied the relation between the capacity nesting parameters and the impact of capacity nesting needs to be analytically substantiated.

So far, an advantage area whose surface depends on the application of the remaining adaptation measures has been identified for constant order-related uncertainty. Therefore, the presented CTP approach can be denoted as suitable and robustness enhancing for the underlying scenarios. Since the findings relate to the underlying data base, the results need to be verified for further data constellations in future research. In particular, the behavior at different levels of order-related uncertainty has to be subject of further studies.

In sum, the achieved results indicate that the developed planning approach is a suitable instrument to support make-to-order companies in the order awarding process. In contrast to previous studies insights are given into the impacts of a joint adaptation measure application on profit, planning robustness and solution robustness. Covering order- and resource-related uncertainty by these measures leads to a more comprehensive CTP approach which can help closing the gap between optimization techniques developed in literature and decision support needed in practice. In particular, the importance of methodologies directly incorporating customers' response to proposed order specifications is pointed out. The effectiveness of suggesting alternative delivery dates proven in this contribution therefore additionally strengthens the importance of producers' and customers' interaction during the contract awarding process and encourages future research in this field.

Appendix A

The multiplication of the variables V_i^{real} and δ_i is replaced by the additional variable y_i. The linearized objective function of the first planning stage is[1]:

$$
\text{(A1)} \qquad
\begin{aligned}
\max\ & \sum\nolimits_{t=t_a}^{T} \sum\nolimits_{i \in \hat{A}} \left(-k_i^{L.FP} \cdot B_{i.t}^{FP} - k^P \cdot P_{i.t}^P \cdot \kappa_i \right) \\
& - \sum\nolimits_{i \in \hat{A}} \left(\gamma_i^e \cdot \left(y_i - V_i^{real} \right) + \gamma_i^l \cdot y_i \right) \\
& + \sum\nolimits_{t=t_a}^{T} \sum\nolimits_{i \in \tilde{A}} \Big(q_i \cdot \rho_i \cdot D_{i.t} - k_i^{L.FP} \cdot B_{i.t}^{FP} - k^{Tr} \cdot D_{i.t} - k^P \cdot P_{i.t}^P \cdot \kappa_i \\
& \qquad - \sum\nolimits_{r=1}^{R} k_r^M \cdot Q_{i.r.t}^M \Big) - \sum\nolimits_{t=t_a}^{T} \sum\nolimits_{r=1}^{R} k_r^{L.R} \cdot B_{r.t}^R
\end{aligned}
$$

To ensure a behavior of decision variable y_i that is identical to the product of floating variable V_i^{real} and binary variable δ_i, the constraints (A2-A5) are introduced into the constraint set of the model:

(A2) $\quad y_i \geq V_i^{real} + \alpha \cdot (\delta_i - 1) \qquad \forall i \in \hat{A}$

(A3) $\quad y_i \leq V_i^{real} + \alpha \cdot (1 - \delta_i) \qquad \forall i \in \hat{A}$

(A4) $\quad y_i \leq \alpha \cdot \delta_i \qquad \forall i \in \hat{A}$

(A5) $\quad y_i \geq -\alpha \cdot \delta_i \qquad \forall i \in \hat{A}$

If $\delta_i = 1$, constraints (A2, A3) guarantee that the value V_i^{real} is assigned to y_i. In this case, constraints (A4, A5) do not limit variable y_i, as far as the value of α is sufficiently high. In the event of $\delta_i = 0$, constraints (A4, A5) ensure that $y_i = 0$. Analogously to the previous case constraints (A2, A3) do not influence y_i. Hence, the additional constraints force the decision variable y_i to behave analogously to the multiplicative linkage of V_i^{real} and δ_i.

---

[1] The considerations can be directly applied to the second planning stage.

3 Coordination of measures[1)]

Abstract: In order to support order promising, capable-to-promise (CTP) models are used to determine whether an order should be accepted, and if so, which order specifications are advantageous. Thereby, efforts are made to enhance reliability of promises by means of multiple robustness-generating measures. The analysis of relevant literature indicates two shortcomings of present CTP models: (1) Although order promising is a customer-interactive process, customer behavior is not explicitly taken into account. (2) A coordinated application of robustness-generating measures is not guaranteed as soon as interactions between measures exist. In order to cope with both issues, in the present paper, a combined deductive-inductive planning approach will be developed. The deductive part consists of a CTP model (MIP) which considers customer behavior and multiple robustness-generating measures. The coordination of multiple measures is addressed with the inductive part. Due to the complexity of interactions, the CTP model behavior is explored by an inferential statistical analysis (multi-group path analysis). A limited multi-criteria search for coordinated parameter values of robustness-generating measures is substantiated and tested on this basis. The test results reveal that a measure coordination is achieved that generates highly efficient solutions.

3.1 Introduction

3.1.1 Problem description

For make-to-order (MTO) production, order promising is a coordination task at the interface between the company and potential customers. In this process, decisions on the placement or acceptance of orders and their specifications are made interactively (Mansouri et al. 2012). The demand of individual customers and the company's capacity utilization are balanced according to product types and quantities, delivery/production times as well as prices/production costs. The decision of the customer/company to place/accept an order is consequently not only determined by the price, but also by non-monetary aspects which affect the decisions of both parties (Kingsman et al. 1993, Kingsman and Mercer 1997, Stevenson et al. 2005). Hence,

---

1) Gössinger, R.; Kalkowski, S.: Coordinating robustness-generating measures for a more reliable order promising in make-to-order systems; submitted for publication in the Journal of Production and Operations Management. To ensure consistency, notations were adapted to dissertation style.

the tendency for customers' increasing request for shorter delivery times, more reliable delivery dates as well as a high flexibility in changing order specifications, needs to be taken into account (Grillo et al. 2016, Mansouri et al. 2012). Against the background of order- and resource-related uncertainty inherent in MTO production (Choi et al. 2016, Pujawan and Smart 2012, Vilko et al. 2014), a high level of *delivery date reliability* is a central differentiation criterion in the competitive environment (Easton and Moodie 1999, Kaminsky and Kaya 2008, Seitz and Grunow 2016). The company's effort to achieve reliable delivery dates can be operationalized by aiming at generating robust plans. Different *robustness dimensions* may be relevant (Roy 2010) in the present context: (1) solution robustness, i.e. the impact of changes in the planning data on the objective value is minimal (Mulvey et al. 1995), (2) planning robustness, i.e. the extent of plan revisions, necessary to fulfill the planning objective in case of data changes, is minimal (Kimms 1998). In the case of order promising, solution robustness is higher the more uncertainty of planning data is absorbed by the plan, so that the expected objective value has a lower level of uncertainty. Planning robustness is higher the less plan revisions are needed to fulfill promised order specifications for given order- and resource-related uncertainty.

In order to obtain predefined results in an uncertain environment, in general one can generate and utilize scopes of action which become apparent in temporal, quantitative, product-, resource- and process-related degrees of freedom (Chaharsooghi et al. 2011, Charnsirisakskul et al. 2006, Framinan and Leisten 2010, Seitz and Grunow 2016). For order promising, capable-to-promise (CTP) approaches provide useful starting points in this regard, since customers' order inquiries are answered based on the available resources and expected incoming orders (Chen and Dong 2014, Chen et al. 2001, Seitz and Grunow 2016). In this paper we deal with *batch capable-to-promise* approaches: Customer inquiries are first collected during a predefined time interval in order to simultaneously decide on acceptance and specifications of potential orders, while considering the current and expected future order and resource situation (e.g. material and capacity availability).

Although the objective of promising reliable order specifications, is only partially formulated explicitly (Aouam and Brahimi 2013, Gössinger and Kalkowski 2015, Lim and Halim 2011, Seitz and Grunow 2016, Zhao et al. 2005), in the present CTP approaches *robustness-generating measures* are identified in advance (Zhang and Tseng 2009), which allow for the realization of a good match between promised and reachable/reached specifications in the order promising and fulfillment process. Supply-related measures already established in the literature include capacity nesting (CN; Harris and Pinder 1995, Jacob 1971) and providing safety capacity (SC; Charnes and Cooper 1959). Demand-related measures which are primarily applied during order promising are the rejection of orders and, due to the interaction with the customer, proposing modified order specifications (MS). In the latter case, specifications are proposed which differ from the order inquiry in terms of price, delivery date and quantity, product type etc. (Grillo et al. 2016). Consequently, the company is faced with the challenge of finding a delivery-date-price-combination which is acceptable for both, the customer and the company. In the present paper we will establish a new CTP approach that pursues monetary and robustness-oriented objectives by a coordinated application of these robustness-generating measures.

3.1.2 Literature review

Among the variety of batch CTP approaches proposed in the literature (Grillo et al. 2016), in particular those approaches which consider at least one additional robustness-generating measure besides rejecting orders are relevant for the analysis.

The overview in table 3.1.1 reveals that present batch CTP approaches

- predominantly pursue monetary objectives (profit maximization, cost minimization), whereas robustness objectives are usually implicitly expressed in form of robustness-generating measures. Only Lim and Halim (2011) formulate robustness in terms of “maximizing the certainty degree of the solution” as an explicit objective.

- in most cases do not simultaneously apply the “capacity nesting” and “safety capacity” measures. Exceptions are the models proposed by Aouam and Brahimi (2013) as well as Gössinger and Kalkowski (2015). However, measure parameters are not coordinated model-endogenously, but are exogenously given for these models.

	Objective	Considered uncertainty: Order-related	Considered uncertainty: Resource-related	Robustness-generating measures related to Demand: Rejection of orders	Robustness-generating measures related to Demand: Deviating specification	Robustness-generating measures related to Supply: Capacity nesting	Robustness-generating measures related to Supply: Safety capacity	Model of customer behavior
Aouam/Brahimi (2013)	C	x	x	x	–	x	x	PC
Charnsirisakskul et al. (2004)	P	x	–	x	x	–	–	PC, TW
Charnsirisakskul et al. (2006)	P	x	–	x	x	–	–	QPD, PC, TW
Chen/Dong (2014)	P	x	–	x	x	–	x	PC
Chen et al. (2001)	P	x	–	x	x	x	–	PC, TW*
Chen et al. (2002)	P	x	–	x	x	–	–	PC, TW*
Gao et al. (2012)	P	x	–	x	–	x	–	–
Gössinger/Kalkowski (2015)	P	x	x	x	x	x	x	AP, PC, TW
Halim/Mathusamy (2012)	C	x	x	x	x	–	x	PC
Jung (2010)	C	x	–	x	x	–	–	PC
Jung (2012)	C	x	x	x	x	–	x	PC
Lim/Halim (2011)	RM	x	x	x	x	–	x	PC
Lin et al. (2010)	P	x	–	x	x	–	–	PC
Manavizadeh et al. (2013)	C/WO	x	–	x	x	x	–	AP, PC
Pibernik (2002, 2005)	P	x	–	x	x	–	–	PC, TW
Yang/Fung (2014)	P/OV	x	–	x	x	–	–	PC, TW

Key: AP…acceptance probability, C…cost minimization, OV…order volume maximization, PC…penalty costs, QPD…demand quantity depending on price and delivery time, RM…robustness maximization, TW…time window, WO…work overload minimization, *…additional customers' flexibilities are considered

Table 3.1.1: Batch CTP approaches including robustness-generating measures

- primarily address order-related uncertainty and assume deterministic resource availability. More general analyses, which also take into account resource uncertainty, are given in the following papers:

  -- Aouam and Brahimi (2013) model workload-dependent lead times by means of piecewise linear clearing functions following queueing theory.

  -- Gössinger and Kalkowski (2015) capture the capacity available per period by means of stochastic variables whereby uncertainty (standard deviation) is higher, the further the realization period lies in the future.

  -- Halim and Muthusamy (2012) as well as Lim and Halim (2011) model the uncertainty of materials supply with fuzzy numbers.
  -- Jung (2012) models the uncertainty of production quantities and transport capacity with fuzzy numbers.

- in most cases can propose order specifications to customers, which deviate from their requested specifications. Thereby it is usually assumed that customers accept these deviations without any consequences. This assumption is repealed in the following papers:

  -- In their CTP model Charnsirisakskul et al. (2006) assume that customers choose their order quantity in dependence of the price offered by the contractor and accept a specific time window for delivery depending on the order quantity. The contractor plans customer inquiries in the desired specifications while considering ordering behavior. Building on that, order specific prices are proposed to the customers.
  -- Gössinger and Kalkowski (2015) model a stochastic objective function that captures a customer-independent order placement probability decreasing with increasing deviation between requested and offered delivery date.
  -- Manavizadeh et al. (2013) consider a customer-specific order placement probability when determining the workload and balancing it with production capacity.

Proposing beneficially modified order specifications (MS) presupposes that the extent of acceptable deviations in each dimension and acceptance-related interactions between dimensions can be estimated with sufficient accuracy (Zhang and Tseng 2009). Due to this reason, MS requires an explicit consideration of customer behavior in the planning approach. Following Zhang and Tseng (2009), relevant aspects of *customer behavior* can be captured by:

- the set of dimensions relevant to the customer,
- the ranges of values acceptable in the individual dimensions,
- the changes in customer behavior in case of value changes in
  -- one dimension,
  -- multiple dimensions (trade-offs).

In the present CTP approaches, the dimensions relevant to the customer (e.g. delivery date, price) and the ranges of acceptable values (e.g. time windows, willingness to pay) are predominantly explicitly captured. In contrast, changes in costumer behavior caused by value changes are predominantly implicitly considered with *penalty costs* depending on order delay. The spectrum of interpreting these costs, ranges from contractual penalties, granted discounts, additional costs for speeding up transports to opportunity costs due to pursuing cancelations and losses of goodwill for future incoming orders. If all these aspects are pooled in a general cost rate, the models can hardly support decision-making in an interactive order promising process.

In related problems, where order specifications are also relevant, customer response to value changes is explicitly modeled. In the context of *joint price, lead-time and capacity planning*, order specifications are simultaneously determined in the three dimensions while anticipating customer orders. The expected demand rate is thereby modeled as linear or log-linear price and delivery time dependent. Some authors suppose that both influencing factors are independent of each other (e.g. Boyaci and Ray 2003, Palaka et al. 1998, Webster 2002). To generalize, Ray and Jewkes (2004) as well as So and Song (1998) assume a substitutional impact of both factors on the demand rate. Similarly, *dynamic time-related price differentiation* (revenue management) is applied in case of customized industrial production. In order to adapt prices to changes in capacity utilization (Guhlich et al. 2015, Martínez and Arredondo 2010, Spengler et al. 2007, Volling et al. 2012), customer behavior is modeled by a heterogeneous time-dependent willingness to pay (Talluri and Ryzin 2005). Two ways of modeling are applied for *joint production scheduling and due date quotation*: Functions, which capture the demand quantity in dependence of price and delivery time (e.g. Chaharsooghi et al. 2011, Charnsirisakskul et al. 2006, Liu et al. 2007, Pekgün et al. 2008), are used to ex ante determine price and delivery time for *expected orders*. This can be beneficial if the capacity utilization of the production system only fluctuates to a low extent and/or customers behave quite homogenously with respect to price and delivery time. If this is not the case, a situation-dependent determination of price and delivery time for *contingent orders* seems to be appropriate. Since the placement of orders is uncertain, in this case, customer behavior is modeled by a delivery-date-dependent (Duenyas and Hopp 1995, Pibernik and Yadav 2008) or a price- and delivery-date-dependent acceptance probability (e.g. Akçay at al. 2010, Duenyas 1995, Easton and Moodie 1999, Watanapa and

Techanitisawad 2005). These considerations build on the theory of single-player auctions (competitive bidding) (e.g. Engelbrecht-Wiggans 1980, King and Mercer 1988, Stark and Rothkopf 1979) which analyzes how prices and non-monetary factors (Simmonds 1968) are to be determined by a profit-maximizing company. Thereby, expected customer's response to proposed order specifications is captured by a specification-dependent acceptance probability (distribution function) (Kingsman et al. 1993). In the context of *negotiations on order price and delivery date*, game theoretic analyses (e.g. Xiao et al. 2014, Zhao et al. 2012) or simulations motivated by game theory (z.B. Ata and Olsen 2009, Guillén et al. 2005, Hempsch et al. 2013, Moodie 1999, Moodie and Bobrowski 1999, Pan and Choi 2016) are performed. In these cases, utility functions of agents are modeled in dependence of price and delivery date as well as further order specifications.

Independent from the specific modeling (demand quantity or rate, time-dependent willingness to pay, acceptance probability or customer utility), the explicit consideration of customer behavior always assumes negative evaluations of increasing prices and/or longer delivery times/later delivery dates. Since joint production scheduling and due date quotation approaches have the closest content-related connection to the given order promising problem, customers' response to modified order specifications is modeled by means of an *acceptance probability* in the present paper. In contrast to due date quotation, this probability does not depend on absolute prices and delivery dates, but on deviations between preferred and offered price and delivery date.

Apart from inadequately capturing customer behavior, there is another shortcoming of CTP approaches in which multiple robustness-generating measures are applied simultaneously: It is assumed that the impacts of these measures on the fulfillment of order promising objectives unfold independently from each other. However, this is generally not the case. For instance, providing safety capacity simultaneously reduces utilizable capacity for capacity nesting. Furthermore, proposing modified order specifications affects order profitability with respect to mean value and variance. Consequently, the share of premium capacity and costs for utilizing premium capacity need to be adjusted to the changed data basis. Thus, there is a need for a *coordinated measure application*.

3.1.3 Research focus

The aim of the present paper is to reduce shortcomings of CTP approaches concerning the modeling of customer behavior and the coordination of robustness-generating measures. A combined deductive-inductive CTP approach, which considers multiple robustness-generating measures (CN, SC, MS) and coordinates their parameter values, is to be developed for this purpose. The *basic idea* is to hierarchically decompose the order promising problem into the superordinate problem of parameter value coordination and the subordinate problem of order acceptance and scheduling, while considering robustness-generating measures. At the *superordinate level*, coordination means to determine measure parameters in such a way that relevant objectives (e.g. maximization of profit, planning and solution robustness) are simultaneously achieved. This requires an anticipation of model behavior at the subordinate level (Schneeweiss 1998). The complexity of existing interactions between the measures implemented in the subordinate model (Gössinger and Kalkowski 2015), is to be handled by an inductive anticipation. That is, existing causal relations between parameter and objective values, are quantified by an inferential statistical analysis of the subordinate model behavior observed during numerical experiments. The resulting causal model of the subordinate level then forms the basis for a limited search for coordinated parameter values. Figure 3.1.1 summarizes these considerations.

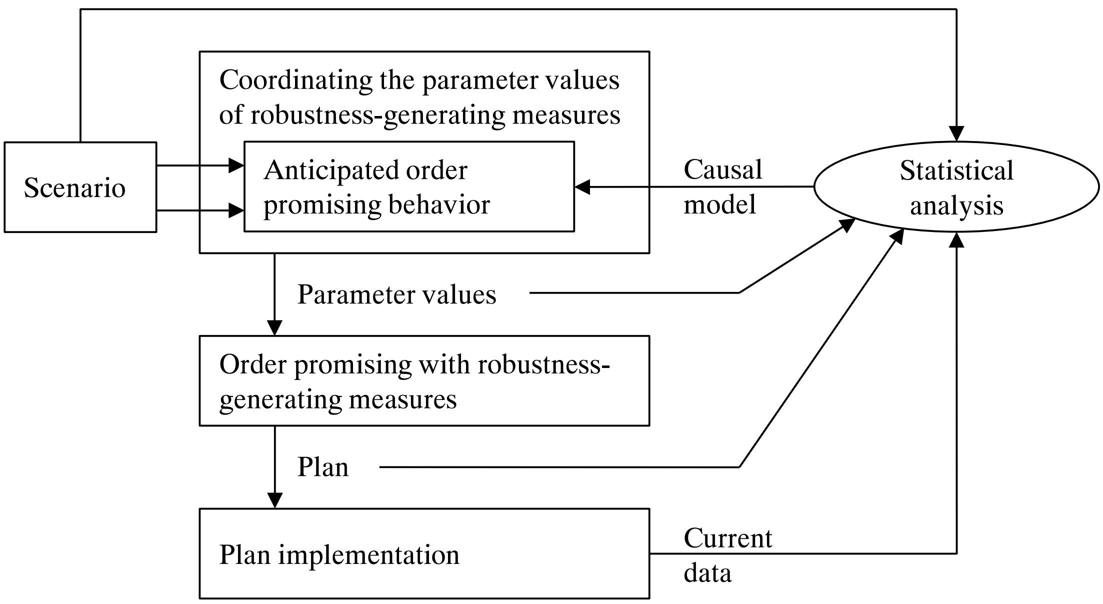

Figure 3.1.1: Combined deductive-inductive CTP approach

The *subordinate level* of the CTP approach includes a MIP-model that considers the measures CN, SC and MS. For MS, customer behavior is to be explicitly included by a two-dimensional response function. This function maps customers' acceptance probability with the deviation between requested and offered delivery dates and prices. Therefore, in this paper, the main characteristics of the two-dimensional response function are to be deduced, and the response function is to be modeled accordingly in order to extent an existing batch CTP model

The proposed approach contributes to scientific progress in three different ways: (1) A two-dimensional response function that explicitly captures customer behavior for order promising is developed and integrated into the batch CTP model. (2) In order to anticipate the behavior of this model, the causal relations of multiple robustness-generating measures are analyzed by means of inferential statistics. (3) The usual exclusively-deductive solution procedure for CTP models is supplemented by an inductive component.

The remainder of the paper is organized as follows: In section 3.2 a CTP model (CTPM) which considers the measures MS, CN and SC is substantiated. Thereby, MS relates to the order specifications delivery date and price and considers customer behavior by means of a two-dimensional response function. Section 3.3 contains the inferential statistical analysis of CTPM behavior. Starting with the derivation of the multi-group path model exogenous and endogenous variables as well as their formula-conditioned or hypothetical relations are presented in detail (3.3.1). Subsequently, the multi-group path model is estimated and evaluated for the generated model-data (3.3.2). The validity of hypothetical relations is verified based on the confirmed model and the impact of influencing factors is quantified with regard to multiple planning objectives. A procedure for determining coordinated measure parameter values with respect to multiple objectives is established in section 3.4. At first a statistically-controlled limited search for favorable parameter values is proposed (3.4.1). Subsequently, the operational capability of the search is evaluated (3.4.2). Finally, the essential contributions of the paper are summarized in section 3.5.

3.2 Planning at subordinate level

3.2.1 Planning situation

Planning relates to the order promising process of a supply chain in which production is performed at downstream/upstream stages in the MTO/MTS mode. The MTO section comprises the processes of production, intermediate storage and delivery of product quantities. These processes are initiated by customer orders and controlled by decisions on order acceptance, delivery dates, production quantities and delivery-date-dependent discounts. The upstream MTS section of the supply chain is taken into account in such a way that the required material can be taken out from stock with different lead times, according to the supply mode (in-house production, external procurement). The remaining supply is fulfilled by periodical stock replenishment.

With an order inquiry i $(i = 1,...,I)$, the customer specifies a product which shall be delivered with quantity q_i during the time interval $[t_i^e, t_i^l]$ at price ρ_i. Planning is done in a rolling horizon of T periods t $(t = 1,...,T)$ of equal length and t_a denotes the current planning period. In order to build on up to date order and resource information, planning runs are repeated after an interval of τ periods (batch interval). Results are decisions on

- the acceptance of newly arrived (set A) orders,
- processes for fulfillment of currently acceptable (set $\tilde{A}$) orders and orders (set $\hat{A}$) which were accepted in the past but are not completely fulfilled yet, as well as
- specifications of orders which may be accepted in a modified way (set $\overline{A}$).

A planning run consists of three steps: *I Preselection*: From newly arrived orders A, those orders $\tilde{A}$ are preselected which show a positive situation-independent profit margin $\rho_i - k_i^M - k_i^{Tr} > 0$. Orders $A \setminus \tilde{A}$ are finally rejected and passed on to set $\underline{A}^-$. *II Order acceptance by the company*: From the set of acceptable orders $\tilde{A}$, those orders are accepted which can be profitably fulfilled during the desired time interval, while considering current order and resource situation. Contracts on order fulfillment at the desired specifications (price ρ_i, delivery time $D_{i.t}^c$, delivery quantity q_i, penalty costs for premature γ_i^e and tardy γ_i^l order fulfillment) are concluded with corresponding customers. Therewith orders from set $\tilde{A}$ are passed on to set $\hat{A}$. *III Proposal of modified order specification*: For orders in set $\bar{A} = \tilde{A} \setminus \hat{A}$ suggestions on modified delivery dates and prices, which are profit-maximizing from the supply chain point of view, are proposed to customers while anticipating their response (acceptance probability). Decisions on order acceptance at modified specifications are thus up to the customers. If a customer rejects the new specifications, the corresponding order is finally rejected and passed on from set $\bar{A}$ to set $\underline{A}^-$. Otherwise the proposed specifications are considered to be accepted and a contract on order fulfillment with modified specifications (analogously to II) is concluded. Consequently, the order is passed from $\bar{A}$ to $\hat{A}$.

3.2.2 Price- and delivery-date-dependent customer behavior

If the customers' buying decisions are made during the order promising process, uncertainty about the order placement is present for the company. Since customers do not respond to (modified) order specifications in an identical manner, the expected customer behavior can be captured by a two-dimensional response function (Lu et al. 2013). This function maps the acceptance probability β with the deviation V_i^{des} from the desired delivery time interval and the discount Φ_i regarding offer i. This formulation takes into account general statements from literature concerning buying behavior (Gabor and Granger 1964, Kahneman et al. 1986, Rothkopf and Harstad 1994, Shen and Su 2007, Wangenheim and Bayón 2007, Wertenbroch and Skiera 2002): (1) Customers are usually well informed about customary delivery dates, prices and discounts. (2) Due to the high level of individualization present in MTO production, the individual combinations of order specifications occur infrequently. Thus, estimations of the willingness to pay are highly uncertain so that more aggregated demand models like the acceptance probability should be considered. (3) The acceptance probability becomes very low if the delivery-date-dependent price exceeds the customary price. (4) Specifying relative discounts is more transparent for the customer.

In order to derive a suitable response function, the determination of customer behavior proposed by Zhang and Tseng (2009) is taken into account with the following assumptions:

- *Set of dimensions relevant to the customer*: The deviations of the modified offer, with respect to delivery date and price, are relevant. The delivery date deviation V_i^{des} from an order inquiry i is measured in time units with positive/negative (premature/tardy) values. For measuring price deviations, the discount Φ_i is captured as relative reduction of the customary price of order inquiry i.

- *Ranges of values acceptable in the individual dimensions*: Delivery date deviations outside the interval $[V^{\min}, V^{\max}]$ are not accepted, i.e. $\beta(V_i^{des} < V^{\min}, \Phi_i) = 0$ and $\beta(V_i^{des} > V^{\max}, \Phi_i) = 0$ (Duenyas 1995, Watanapa and Techanitisawad 2005). Negative discounts are not accepted (Cheng and Cheng 2011), i.e. $\beta(V_i^{des}, \Phi_i < 0) = 0$. A positive discount may not exceed the relation ψ between manufacturing costs and customary price.

- *Changes in customer behavior in case of value changes*:

  -- *isolated consideration of individual dimensions*: With increasing delivery date deviation the acceptance probability does not increase (Duenyas and Hopp 1995), i.e. $\partial\beta(V_i^{des}, \Phi_i) / \partial V_i^{des} \le 0$ for $V_i^{des} > 0$ and $\partial\beta(V_i^{des}, \Phi_i) / \partial V_i^{des} \ge 0$ for $V_i^{des} < 0$. The acceptance probability is non-decreasing in Φ_i, i.e. $\partial\beta(V_i^{des}, \Phi_i) / \partial\Phi_i \ge 0$.

  -- *combined consideration of dimensions*: Interactions exist between the delivery date deviation and the discount (Duenyas 1995, Keskinocak et al. 2001, Ray and Jewkes 2004). If the delivery date is suggested as requested, the offer is certainly accepted as long as the discount is non-negative, i.e. $\beta(0, \Phi_i \ge 0) = 1$. The granted discount cannot decrease with an increasing delivery date deviation, since reductions of the acceptance probability need to be compensated (Duenyas 1995), i.e. $\partial^2\Phi_i / \partial V_i^{des\,2} \ge 0$.

An example for a corresponding two-dimensional response function is given by:

$$\beta(V_i^{des}, \Phi_i) = \begin{cases} e^{+G \cdot V_i^{des}} - e^{-H \cdot \Phi_i} + e^{+G \cdot V_i^{des} - H \cdot \Phi_i} & : V_i^{des} \in [V^{\min}, 0] \\ e^{-M \cdot V_i^{des}} - e^{-N \cdot \Phi_i} + e^{-M \cdot V_i^{des} - N \cdot \Phi_i} & : V_i^{des} \in [0, V^{\max}] \end{cases}$$

3.2.3 Extended planning model

As the basis for extending a CTP model with price- and delivery-date-dependent customer behavior, a model proposed for the second and third step of order promising (Gössinger and Kalkowski 2015) is chosen. The explanation of the extended model focuses on the new and modified elements; for additional details concerning the unmodified elements, the reader is referred to the original paper. For a compact model formulation the shift between order promising steps II and III is controlled by the parameter $MS \in \{0,1\}$ (model for step II: $MS := 0$, model for step III: $MS := 1$).

Decisions to be taken: In step II "order acceptance by the company", decisions are made on order acceptance $Z_i \;\; (i \in \tilde{A})$, delivery dates $D_{i.t} \;\; (i \in \tilde{A} \cup \hat{A},\; t \in [t_i^e, t_i^l])$, production quantities and inventory levels $P_{i.t}$, $B_{i.t}^{FP} \;\; (i \in \tilde{A} \cup \hat{A})$ and $B_{r.t}^{R}$, as well as on the allocation of production quantities to standard and premium capacity $P_{i.t}^{S}$, $P_{i.t}^{P}$ $(i \in \tilde{A} \cup \hat{A})$. In step III "proposal of modified order specification" the order acceptance decision ($Z_i = 1 \;\; \forall i \in \overline{A}$) is omitted since it is taken by the customer, whose behavior is anticipated with the response function (8, 9, 10, 11). Due to this function, the delivery date decision with enhanced temporal interval $D_{i.t} \;\; (i \in \overline{A},\; t \in [t_a, T])$ is linked to the decision on the discount $\Phi_i \;\; (i \in \overline{A})$.

The *decision field* is defined by customer-, production- and measure-related constraints, logical requirements of the rolling horizon and the necessity of an acceptable solution time.

Customer-related constraints: For non-rejected orders $(\tilde{A} \cup \hat{A} \cup \overline{A})$, a delivery date needs to be determined within the planning horizon $[t_a, T]$ (3, 4). In both order promising steps, the contractually fixed delivery date $D_{i.t}^{c}$ is a soft constraint for the accepted orders $(\hat{A})$, i.e. deviations (5) in terms of premature/tardy order fulfillment (6, 7) are accompanied by contractual penalties (1). The requested time window is a hard constraint (2) for acceptable orders $(i \in \tilde{A})$ in step II. In step III, it is a soft constraint for orders to be modified $(i \in \overline{A})$, i.e. deviations from the desired time window (8, 9) induce the risk of orders being rejected by the customer (10). According to the response function (10) this risk can be reduced with an economically acceptable discount (11).

Production-related constraints: Over time, inventories develop in line with supply and consumption decisions (12, 13). The consumption of material produced in-house (14) and of externally-procured material (15) is determined by dynamic bill of material explosion.

Measure-related constraints: The principles of CN and SC are taken into consideration by constraints (16, 17, 18). Due to CN, the available capacity is split into standard (share $1-\varepsilon$) and premium capacity (share ε). Both segments should preferably not be over-utilized by production quantities $P_{i.t}^{S}$, $P_{i.t}^{P}$ (16, 17). SC is applied in case of uncertain capacity availability. It ensures (16, 17) that the expected capacity can only be utilized to such an extent, that the probability of over-utilization does not exceed a value of $(1-\vartheta)$. Allocating the product quantity of an order to both segments is possible (18), but utilizing premium capacity induces additional costs (1).

Logical requirements of the rolling horizon: Planning data of order fulfillment processes that have already been started, needs to be transferred from the previous to the current planning run. Decisions on production quantities of accepted orders $(\hat{A})$ may be revised while considering processing times of the required material (19). For acceptable orders $(\tilde{A})$ or orders which need to be modified $(\bar{A})$, positive production quantities are possible as soon as the required material is available (20). There is no initial inventory of finished products (21). Inventories resulting from production and supply processes that have already been started are carried forward (22, 23). At the end of the planning horizon, the inventory of finished products is zero (24).

Necessity of an acceptable solution time: In order promising processes, customers expect relatively short response times to their order inquiries. Therefore, long solution times of the CTP model should be avoided. An objective function, in which

- the differentiation between premature and tardy order fulfillment and the extent of realized deviation (for $MS=0$ and $MS=1$),
- the delivery date and the delivery-date-dependent discount (only for $MS=1$), as well as
- the delivery-date- and discount-dependent acceptance probability and the delivery-date- and discount-dependent profit term (only for $MS=1$)

are multiplied, would be non-linear and, compared to linearity, would cause a considerably increased solution effort. In the first two cases, a binary and a continuous decision variable would be multiplied. To prevent this, a standard linearization can be used which includes additional decision variables and constraints in the model. Constraints 25 – 28 refer to the first-mentioned case and model the multiplication of δ_i and V_i^{real} by means of the variable y_i. Analogously, the multiplication of $D_{i.t}$

and Φ_i is captured by variable u_i. By means of constraints 29 – 32 it is guaranteed that u_i behaves like $\Phi_i \cdot D_{i.t}$. The last-mentioned non-linearity cannot be avoided since it results from the multiplication of a non-linear function and its variables.

The relevance of components in the objective function (1) is dependent from the order promising step. In the second step ($MS = 0$), profit margins resulting from accepted orders $\tilde{A}$ minus costs of orders $\hat{A}$ are maximized. Due to the proposal of modified order specifications in the third order promising step ($MS = 1$), the acceptance probability has to be taken into account. The expected profit margins of orders $\bar{A}$ minus the costs of orders $\hat{A}$ are to be maximized. Consequently, the objective function is linear in the second and non-linear in the third order promising step.

CTPM:

$$
\begin{aligned}
(1)\qquad & \max\ (1-MS)\cdot\sum_{t=t_a}^{T}\sum_{i\in\tilde{A}}\Big(q_i\cdot\rho_i\cdot D_{i.t}-k_i^{L.FP}\cdot B_{i.t}^{FP}-k^{Tr}\cdot D_{i.t} \\
& \qquad\qquad -k^{P}\cdot P_{i.t}^{P}\cdot\kappa_i-\sum_{r=1}^{R}k_r^{M}\cdot Q_{i.r.t}^{M}\Big) \\
& -\sum_{t=t_a}^{T}\sum_{i\in\hat{A}}\Big(k_i^{L.FP}\cdot B_{i.t}^{FP}+k^{P}\cdot P_{i.t}^{P}\cdot\kappa_i\Big)-\sum_{i\in\hat{A}}\Big(\gamma_i^{e}\cdot\big(y_i-V_i^{real}\big)+\gamma_i^{l}\cdot y_i\Big) \\
& +MS\cdot\sum_{t=t_a}^{T}\sum_{i\in\bar{A}}\beta\big(V_i^{des},\Phi_i\big)\cdot\Big(q_i\cdot\rho_i\cdot\big(D_{i.t}-u_i\big)-k_i^{L.FP}\cdot B_{i.t}^{FP}-k^{Tr}\cdot D_{i.t} \\
& \qquad\qquad -k^{P}\cdot P_{i.t}^{P}\cdot\kappa_i-\sum_{r=1}^{R}k_r^{M}\cdot Q_{i.r.t}^{M}\Big)
\end{aligned}
$$

subject to

(2) $\quad (MS=0)\Rightarrow \quad \sum_{t=t_i^e}^{t_i^l} D_{i.t} = Z_i \qquad \forall i\in\tilde{A}$

(3) $\quad (MS=0)\Rightarrow \quad \sum_{t=t_a}^{T} D_{i.t} = Z_i \qquad \forall i\in\tilde{A}$

(4) $\quad \sum_{t=t_a}^{T} D_{i.t} = 1 \qquad \forall i\in\bar{A}\cup\hat{A}$

(5) $\quad V_i^{real} = \sum_{t=1}^{T}\big(D_{i.t}-D_{i.t}^{c}\big)\cdot t \qquad \forall i\in\hat{A}$

(6) $\quad V_i^{real} \geq \big(\delta_i - 1\big)\cdot\alpha \qquad \forall i\in\hat{A}$

(7) $\quad V_i^{real} \leq \delta_i\cdot\alpha \qquad \forall i\in\hat{A}$

(8) $$(MS=1) \Rightarrow \quad V_i^{des} = \min\left(\sum_{t=t_a}^{T} D_{i.t} \cdot t - t_i^e, 0\right) + \max\left(\sum_{t=t_a}^{T} D_{i.t} \cdot t - t_i^l, 0\right) \qquad \forall i \in \bar{A}$$

(9) $$(MS=1) \Rightarrow \quad V^{\min} \le V_i^{des} \le V^{\max} \qquad \forall i \in \bar{A}$$

(10) $$(MS=1) \Rightarrow \quad \beta(V_i^{des}, \Phi_i) = \begin{cases} e^{+G\cdot V_i^{des}} - e^{-H\cdot\Phi_i} + e^{+G\cdot V_i^{des} - H\cdot\Phi_i} & : V_i^{des} \in [V^{\min}, 0] \\ e^{-M\cdot V_i^{des}} - e^{-N\cdot\Phi_i} + e^{-M\cdot V_i^{des} - N\cdot\Phi_i} & : V_i^{des} \in [0, V^{\max}] \end{cases} \qquad \forall i \in \bar{A}$$

(11) $$(MS=1) \Rightarrow \quad 0 \le \Phi_i \le \psi < 1 \qquad \forall i \in \bar{A}$$

(12) $$B_{i.t-1}^{FP} + P_{i.t} - q_i \cdot D_{i.t} = B_{i.t}^{FP} \qquad \forall t_a \le t \le T,\ i \in \tilde{A} \cup \bar{A} \cup \hat{A}$$

(13) $$B_{r.t-1}^{R} + a_{r.t-1}^{R} - \sum_{i \in \tilde{A} \cup \hat{A} \cup \bar{A}} Q_{i.r.t}^{M} = B_{r.t}^{R} \qquad \forall r,\ t_a \le t \le T$$

(14) $$b_{i.r} \cdot P_{i.t+\omega_1} = Q_{i.r.t}^{M} \qquad \forall t_a \le t \le T,\ r = 1,\dots,r_k - 1,\ i \in \tilde{A} \cup \bar{A} \cup \hat{A}$$

(15) $$b_{i.r} \cdot P_{i.t+\omega_2} = Q_{i.r.t}^{M} \qquad \forall t_a \le t \le T,\ r = r_k \dots, R,\ i \in \tilde{A} \cup \bar{A} \cup \hat{A}$$

(16) $$\text{Prob}\left(\sum_{i \in \tilde{A} \cup \hat{A} \cup \bar{A}} P_{i.t}^{P} \cdot \kappa_i \le \varepsilon \cdot \tilde{C}_t\right) \ge \vartheta \qquad \forall t_a \le t \le T$$

(17) $$\text{Prob}\left(\sum_{i \in \tilde{A} \cup \hat{A} \cup \bar{A}} P_{i.t}^{S} \cdot \kappa_i \le (1-\varepsilon) \cdot \tilde{C}_t\right) \ge \vartheta \qquad \forall t_a \le t \le T$$

(18) $$P_{i.t}^{S} + P_{i.t}^{P} = P_{i.t} \qquad \forall t_a \le t \le T,\ i \in \tilde{A} \cup \bar{A} \cup \hat{A}$$

(19) $$\sum_{t=t_a}^{t_a+\eta} P_{i.t} \le \sum_{t=t_a}^{t_a+\eta} P_{i.t}^{prev} \qquad \forall i \in \hat{A},\ \eta = 0,\dots,(\omega_1 - 1)$$

(20) $$P_{i.t} = 0 \qquad \forall t_a \le t \le t_a + (\omega_1 - 1),\ i \in \tilde{A} \cup \bar{A}$$

(21) $$B_{i.t_a-1}^{FP} = 0 \qquad \forall i \in \tilde{A} \cup \bar{A}$$

(22) $$B_{i.t_a-1}^{FP} = B_{i.t_a-1}^{FP.prev} \qquad \forall i \in \hat{A}$$

(23) $$B_{r.t_a-1}^{R} = B_{r.t_a-1}^{R.prev} \qquad \forall r = 1,\dots,R$$

(24) $$B_{i.T}^{FP} = 0 \qquad \forall i \in \tilde{A} \cup \bar{A} \cup \hat{A}$$

(25) $$y_i \ge V_i^{real} + \alpha \cdot (\delta_i - 1) \qquad \forall i \in \hat{A}$$

(26) $y_i \le V_i^{real} + \alpha \cdot (1 - \delta_i)$ $\forall i \in \hat{A}$

(27) $y_i \le \alpha \cdot \delta_i$ $\forall i \in \hat{A}$

(28) $y_i \ge -\alpha \cdot \delta_i$ $\forall i \in \hat{A}$

(29) $(MS = 1) \Rightarrow \quad u_i \le \psi \cdot D_{i.t}$ $\forall t_a \le t \le T,\ i \in \bar{A}$

(30) $(MS = 1) \Rightarrow \quad u_i \le \Phi_i$ $\forall i \in \bar{A}$

(31) $(MS = 1) \Rightarrow \quad u_i \ge \Phi_i - \psi \cdot (1 - D_{i.t})$ $\forall t_a \le t \le T,\ i \in \bar{A}$

(32) $(MS = 1) \Rightarrow \quad u_i \ge 0$ $\forall i \in \bar{A}$

The following domains are valid for decision variables and auxiliary variables:

(33) $(MS = 0) \Rightarrow \quad Z_i \in \{0,1\}$ $\forall i \in \tilde{A}$

(34) $D_{i.t} \in \{0,1\}$ $\forall i \in \tilde{A} \cup \bar{A} \cup \hat{A}$

(35) $\delta_i \in \{0,1\}$ $\forall i \in \hat{A}$

(36) $V_i^{real} \in \mathbb{Z}$ $\forall i \in \hat{A}$

(37) $(MS = 1) \Rightarrow \quad V_i^{des} \in \mathbb{Z}$ $\forall i \in \bar{A}$

(38) $(MS = 1) \Rightarrow \quad \Phi_i \ge 0$ $\forall i \in \bar{A}$

(39) $Q_{i.r.t}^{M} \ge 0$ $\forall i \in \tilde{A} \cup \bar{A} \cup \hat{A},\ r,\ t_a \le t \le T$

(40) $P_{i.t},\ P_{i.t}^{P},\ P_{i.t}^{S},\ B_{i.t}^{FP} \ge 0$ $\forall i \in \tilde{A} \cup \bar{A} \cup \hat{A},\ t_a \le t \le T$

(41) $B_{r.t}^{R} \ge 0$ $\forall r,\ t_a \le t \le T$

(42) $y_i \in \{0,1\}$ $\forall i \in \hat{A}$

(43) $(MS = 1) \Rightarrow \quad u_i \in \{0,1\}$ $\forall i \in \bar{A}$

3.3 Exploration of CTP model behavior

3.3.1 Developing the multi-group path model

To apply the measures CN, SC and MS in a coordinated manner for order promising, it is necessary to quantify their interactions with the relevant *objectives* and to deduce conclusions for an economically advantageous parameter setting. The following objectives are relevant in the present contribution: Profitability (Z_1), solution robustness (Z_2) and delivery date reliability (Z_3). Due to the variety of measure parameters and the interaction between robustness-generating measures, it is not expectable that the impacts of measure implementation can be analytically deduced (Chevalier et al. 2015, Martínez and Arredondo 2010). Based on test data systematically generated by model experiments, it is instead possible to explore the model behavior by verifying the validity of *hypothetical relations* (hypotheses) between measure application and impact. Since a share of the data is generated by solving the CTPM, *formula-conditioned relations* also exist between observed influencing factors and influenced factors. Their existence requires no further empirical verification, but the strength of their influence on other relations and the strength of influences from other relations need to be quantified.

It is assumed that the impact of measures does not solely directly unfold onto the outcome variables but also propagates on paths of intermediate variables. Therefore, the interaction of measures is empirically tested using *structural equation modeling*, in particular *path analysis* (cf. Bagozzi and Yi 2012, Wright 1921, Wright 1934). Thereby, measure application is modeled by *exogenous variables*, which represent measure parameters as well as prevailing conditions during measure application (cf. table 3.3.1).

Only a share of exogenous variables can be directly considered in the path analysis, due to their indicator scale and their hypothetical/formula-conditioned impacts. Assumed linear relations justify the direct consideration for CN_1, CN_2 and U_2. Resource-related uncertainty is reciprocally represented by U_2, since there is postulated a production system with constant maximum capacity. Thus, with a lower level of resource uncertainty a higher value of U_2 results.

		Parameter/Influencing factor	Modeling
Measure	CN	Share of premium capacity (CN_1)	Direct exogenous variable
		Costs for utilizing premium capacity (CN_2)	Direct exogenous variable
	SC	Safety factor (SC_1)	Moderating variable
	MS	Modification dimensions / Price elasticity (MS_0, MS_1, MS_2, MS_3)	Dummy variables resp. Reference category
Prevailing conditions		Order-related uncertainty (U_1)	Moderating variable
		Resource-related uncertainty (expected capacity U_2)	Direct exogenous variable

Table 3.3.1: Modeling the implementation of robustness-generating measures and prevailing conditions by exogenous variables

In contrast, order-related uncertainty U_1 is captured in the CTPM by stochastic quantities and interarrival times as well as fluctuating capacity requirements per piece. The safety factor SC_1 characterizes provided safety capacity as a multiple of the standard deviation of resource availability. Therefore, non-linear impacts on the strength of several relations have to be assumed for both, order-related uncertainty and the safety factor SC_1. For this reason, these variables are included as *moderating variables* within a *multi-group analysis* (MGA; Bagozzi and Yi 2012). Additionally, MS possesses nominally scaled values: no modification (MS_0), sole modification of delivery date (MS_1), modification of delivery date and price at low price elasticity (MS_2) resp. at high price elasticity (MS_3). Therefore, MS_1, MS_2 and MS_3 are modeled as *dummy variables* and MS_0 as the reference category.

Additionally, it is assumed that the *endogenous variables* “frequency of granted discounts” (I_1) and “frequency of revisions” (I_2) can provide additional explanatory contributions as links between measures and endogenous variables in terms of objectives (cf. table 3.3.2).

The formula-conditioned and hypothetical direct impacts between measure parameters, prevailing conditions, intermediate variables and objectives are visualized in table 3.3.3 in form of a matrix (instead of the usual path diagram). The filled-in matrix cells specify the index of the relation, the kind of justification of the relationship (F: formula-conditioned, H: hypothetical) and the direction of effects ($+$ resp. $-$) with the increasing value of the influencing factor. In addition to the direct effects, formula-conditioned and hypothetical indirect effects of the moderating variables SC_1 and U_1 are visualized. These indirect effects have to be verified using the multi-group analysis.

Endogenous variable	Definition
Profitability (Z_1)	Expected value of profits generated within the planning horizon
Solution robustness (Z_2)	Coefficient of variation (CV) of profits generated within the planning horizon; the higher the CV is, the lower the solution robustness
Delivery date reliability (Z_3)	Expected value of penalty costs for delivery date deviations within the planning horizon; the higher penalty costs are, the lower delivery date reliability
Frequency of granted discounts (I_1)	Number of orders accepted within the planning horizon, for which discounts are contracted
Frequency of revisions (I_2)	Number of internal delivery date modifications for already accepted orders within the planning horizon

Table 3.3.2: Modeling the impact of robustness-generating measures by endogenous variables

In the following paragraphs, first direct and subsequently indirect effects of measure parameters and prevailing conditions are substantiated: *MS* prevents an immediate rejection of customer orders which cannot be fulfilled as requested. In modified order specifications, which are tolerable for the customer, additional orders can be acquired and practicable delivery dates can be promised. To enable this, production plans for already accepted orders need to be revised. In addition to the formula-conditioned relations F.3.1 – F.3.3 (cf. (1), (8) in CTPM), the following hypotheses can be justified:

- *H.3.1*: In case of a higher price elasticity (MS_3 instead of MS_2) a higher I_1-value results since the loss of customer benefit, due to greater delivery date deviations, can be compensated with the same price discount.

- *H.3.2*: With an increasing number of modification dimensions (MS_0, MS_1, MS_2 resp. MS_3) I_2 is reduced since the modification of order specifications partially prevents (internal) delivery date revisions of already accepted orders.

- *H.3.3*: Z_3 is enhanced with an increasing number of modification dimensions (MS_0, MS_1, MS_2 resp. MS_3) since there is an increase of the range of action in handling customer requests, which cannot be economically fulfilled.

		Moderated effects			Influenced variables				
		MS	CN	U_2	I_1	I_2	Z_1	Z_2	Z_3
Influencing varibales	MS_1					3.2: F+ H−			3.3: F+ H+
	MS_2				3.1: F+ H+	F+ H−			F+ H+
	MS_3				F+ H+	F+ H−			F+ H+
	CN_1				4.1: H+	4.2: F−			4.5: F+
	CN_2				H+	F−	H.4.3 −	H.4.4 −	F+
	U_2				H.2.4 −	F.2.5 −	F.2.6 +	H.2.7 +	F.2.8 +
	I_1					H.5.1 +	F.5.2 −		
	I_2						H.6.1 +	H.6.2 +	H.6.3 −
	Z_2						F.7.1 +		
	Z_3						F.8.1 +		
Moderators	SC_1	H.1.1 −	H.1.2 +	H.1.3 +/−					
	U_1	H.2.1 +	H.2.2 +	F.2.3 −					

Table 3.3.3: Matrix of formula-conditioned and hypothetical relations

CN reserves capacity in order to accept future lucrative orders. Simultaneously, it reduces standard capacity. The impacts of this measure depend on the fit of CN_1 and CN_2 with order uncertainty: A CN_2-value which is too high, prevents access to premium capacity; a CN_2-value which is too low, causes premium capacity become ineffective. In addition to the formula-conditioned relations F.4.2 and F.4.5 (cf. (1), (8), (16), (17) in CTPM) the following relations can be hypothesized:

- *H.4.1*: I_1 increases with increasing CN_1 and increasing CN_2. The reduction of standard capacity leads to frequent attempts in shifting currently-requested non-lucrative, but profitable orders in subsequent periods of low capacity utilization and to compensate customer loss of benefit by discounts.

- *H.4.3*: The profitability Z_1 of orders accepted during the planning horizon decreases with an increasing value of CN_2. If costs for utilizing premium capacity rise, profitable orders will increasingly be rejected. Lost profit margins induced by order rejections are no longer compensated by the higher lucrativeness of accepted orders.

- *H.4.4*: Solution robustness Z_2 decreases with increasing CN_2-value. Due to higher costs for utilizing premium capacity, lucrative orders become rarer but their profitability improves so that profit margin fluctuations increase.

For parameter U_2 the impacts of *resource-related uncertainty* directly become apparent in the group-related path models. Besides the formula-conditioned relations

F.2.5, F.2.6 and F.2.8 (cf. (1), (8), (16), (17) in CTPM) the following hypotheses can be substantiated:

- *H.2.4*: With an increasing expected capacity U_2, it is to be expected that orders can be accepted according to customer requests more frequently and deviations from required conditions are less often necessary. Thus, the frequency of granted discounts I_1 decreases with an increasing U_2.

- *H.2.7*: If the U_2-value rises in case of given SC_1-values, Z_2 increases since decreasing uncertainty can be compensated to a greater extent by safety capacity.

The objectives of order promising also depend on *intermediate variables* (I_1, I_2), as well as on causal relations between *objectives* (Z_1, Z_2, Z_3) themselves. Supplementary to the formula-conditioned relations F.5.2, F.7.1 and F.8.1 (cf. (1) in CTPM), further relations can be hypothesized:

- *H.5.1*: Discounts are only granted for orders with a modified delivery date. Compared to pure delivery date modifications the compensation of customers' loss of benefit results in more opportunities to modify the internal schedule of already accepted orders. The amount of discount is calculated in such a way that costs of shifting already accepted orders are overcompensated by the expected profit margin of the additionally accepted order. The higher I_1 is the higher is I_2.

- *H.6.1*: It can be expected that the profitability Z_1 rises with increasing frequency of revisions I_2. Rescheduling only takes place if economic disadvantages of the previous plan, which would otherwise occur due to the changed situation, are avoided.

- *H.6.2*: Frequent rescheduling reduces the occurrence of negative monetary effects caused by uncertainty (such as penalty costs or lost sales) so that a more stable profitability is expected. Therefore solution robustness Z_2 rises with increasing I_2-value.

- *H.6.3*: With increasing frequency of revisions it is more unlikely that promised delivery dates are met. A higher I_2-value is accompanied by a lower Z_3-value.

By means of the MGA, the effect of *SC* can be identified by analyzing the moderating impact of SC_1. The expected capacity U_2, minus the amount of provided safety capacity determined by SC_1, is utilized for planning. Thus, capacity assessable for planning is lower the higher SC_1, and the lower U_2 are. Hence, the following hypotheses can be substantiated:

- *H.1.1*: The impacts of MS are weakened with increasing SC_1, since fewer orders can be accepted due to this reduction of utilizable capacity.

- *H.1.2*: The reduction of utilizable capacity induced by SC_1 is accompanied by a more restrictive order acceptance; i.e. in case of lowering capacity fewer and on average more profitable orders are accepted. CN_1 resp. CN_2 unfold stronger effects with increasing SC_1.

- *H.1.3*: The strength of impacts originating from U_2 is influenced by SC_1. In the event of a good fit between both values, stronger effects result than in the event of an inadequate fit.

The impact of *order-related uncertainty* U_1 becomes apparent by means of MGA. The following relations can be hypothesized in addition to the formula-conditioned relation F.2.3 (cf. (16), (17) in CTPM):

- *H.2.1*: If the level of order-related uncertainty U_1 rises, it is expected that stronger impacts originate from MS. This is due to the fact that more situations result in which MS can contribute to profitability. The more modification dimensions MS comprises, the stronger is the effect of U_1 because of the increase in degrees of freedom for adapting to changing demand.

- *H.2.2*: It is expected that with increasing U_1, by tendency stronger impacts on the endogenous variables originate from CN_1 and CN_2. With increasing fluctuation of capacity requirements of the orders, their profitability also varies strongly so that differences between lucrative and non-lucrative orders become more noticeable.

3.3.2 Estimating the multi-group path model

3.3.2.1 Data basis

The path model is estimated based on the data obtained by model experiments. To generate realistic and substantiated statistical statements, the CTPM has been solved for a variety of data constellations resulting from real order and capacity data from a manufacturer of customized leisure products, systematically generated data and combinations of both data types. Thereby, order- and resource-related uncertainty, as well as parameter values of the measures, are varied in a systematic way.

Order-related uncertainty persists according to the product type, the product quantity, the capacity requirement per piece, as well as interarrival times of orders (appendix A.1). Order streams 1 to 5 capture the situations of *regular order-related uncer-*

tainty, i.e. the capacity requirement per piece is non-varying. Order stream 1 includes real data of incoming orders related to the seven best-selling product configurations during a representative quarter. The data of order streams 2 to 5 has been randomly generated according to the statistical characteristics of order stream 1. *Increased order-related uncertainty* is represented by order streams 6 to 10. Those order streams differ from the previous mentioned ones by stochastically fluctuating capacity requirements per piece.

Resource-related uncertainty refers to the fluctuating capacity availability. By assuming that uncertainty does not decrease with increasing temporal distance of future events, the analysis is based on two situations (appendix A.2): In the case of *regular resource uncertainty*, the capacity data corresponds to the production planners' observations of real situations. Intervals of capacity availability have been specified due to their experiences and interpreted as symmetric triangular distributions. An *increased resource-related uncertainty* has been obtained by doubling the observed standard deviation and simultaneously reducing the expected value in such a way that the maximum availability value is identical. Four streams of random variables have been generated for both resource uncertainty situations.

The parameters of *capacity nesting* have been varied according to the values $\varepsilon = \mathrm{CN}_1 \in \{1/3, 1/2, 2/3\}$ and $k^P = \mathrm{CN}_2 \in \{500, 1000, 1500, 2000, 2500, 3000, 3500, 4000\}$. As a reference, the pair of values $(\varepsilon = 0,\ k^P = 0)$ has additionally been considered. The highest CN_2-value has been chosen in such a way that only orders for product configuration 1 can entirely utilize premium capacity. If the CN_2-value is equal to or lower than 2000, orders for all product configurations can entirely access premium capacity. *Safety capacity* ϑ has been varied as SC_1-fold of the standard deviation of capacity availability according to $\mathrm{SC}_1 \in \{0, 1, 2\}$. With respect to *proposing modified order specifications,* the cases of delivery date modification MS_1 "without discount", MS_2 "with discount and regular price elasticity" and MS_3 "with discount and increased price elasticity" (appendix A.3) have been compared to the case of unmodified delivery dates MS_0.

In total, the CTPM has been solved for 24,000 constellations resulting from the possible combinations of parameters and uncertainty situations. The solutions for these constellations (99.7% are solved to optimality), derived with Aimms 4.2, form the *data basis* of the following analysis. For deriving statements about the robustness of planning results, the 24,000 solutions have been aggregated to 4,800 data sets according to the associated five order scenarios. By randomly drawing data sets, two equally sized data bases with 2,400 solutions have been generated according to the relevant information (CN_1, CN_2, SC_1, MS_0, …, MS_3, U_1, U_2, I_1, I_2, Z_1, …, Z_3). The *test data* is applied to verify the hypotheses related to the multi-group path model and hence to derive recommendations for setting coordinated parameter values. The *verification data* is used to analyze the validity of gained recommendations. The behavior of the CTPM, which has been anticipated by means of causalities identified for the test data, is compared to the CTPM behavior captured by the verification data. If the application of parameter suggestions is systematically accompanied by values above average for the pursued objectives, then anticipated and real model behavior are essentially consistent.

3.3.2.2 Evaluation

After a positive verification (Kline 2005, West et al. 1995) of application preconditions (appendix D), two equally partially restricted multi-group path models have been estimated (AMOS) for the test data on the basis of the maximum likelihood discrepancy function (Bagozzi and Yi 2012, Baumgartner and Homburg 1996). In case of model R (E), test data for regular (increased) order-related uncertainty is applied.

Both path models (table 3.3.4 and 3.3.5) show a good model fit[1)] (R: CMIN/DF=0.9200, RMSEA=0.0000, GFI=0.9842, AGFI=0.9737; E: CMIN/DF= 0.8005, RMSEA= 0.0000, GFI=0.9858, AGFI=0.9764), indicate significant group differences (bold print) and contribute to the explanation of the variance of influenced variables in a mostly substantial (exception Z_2 weak/moderate) manner (Chin 1998). All in all, the preconditions for an informative detailed analysis are fulfilled.

---

1) The model fit is even better if deterministic resource availability is assumed. For detailed information cf. Gössinger/Kalkowski (2016), pp. 18 ff.

Influencing variables	Influenced variables: I_1	I_2	Z_1	Z_2	Z_3
MS_1	-	**0 : +0.80** *** 1 : +0.77 *** **2 : +0.74** ***	-	-	0 : +0.41 1 : +0.41 2 : +0.42 } ***
MS_2	0 : +0.53 1 : +0.53 2 : +0.53 } ***	0 : +0.38 *** 1 : +0.39 *** 2 : +0.34 ***	-	-	0 : +0.44 1 : +0.44 2 : +0.45 } ***
MS_3	0 : +0.90 1 : +0.90 2 : +0.90 } ***	~~0 : +0.17 **~~ ~~1 : +0.14 *~~ ~~2 : +0.15 *~~	-	-	0 : +0.47 1 : +0.47 2 : +0.48 } ***
CN_1	~~0 : −0.02~~ ~~1 : −0.02~~ ~~2 : −0.02~~ } ns	0 : −0.15 *** 1 : −0.17 *** **2 : −0.26** ***	-	-	~~0 : +0.18 ***~~ ~~1 : +0.15 ***~~ ~~2 : +0.15 ***~~
CN_2	~~0 : +0.08~~ ~~1 : +0.08~~ ~~2 : +0.08~~ } ***	~~0 : −0.13 ***~~ ~~1 : −0.15 ***~~ ~~**2 : −0.04 ns**~~	0 : −0.71 *** 1 : −0.62 *** 2 : −0.53 ***	0 : −0.46 *** 1 : −0.44 *** **2 : −0.28** ***	0 : +0.72 *** 1 : +0.71 *** 2 : +0.76 ***
U_2	~~0 : −0.09 ***~~ ~~1 : −0.06 *~~ ~~**2 : +0.01 ns**~~	~~0 : −0.08 **~~ ~~1 : −0.05 ns~~ ~~**2 : +0.04 ns**~~	**0 : +0.51** *** **1 : +0.64** *** **2 : +0.72** ***	~~0 : +0.18 ***~~ ~~1 : +0.20 ***~~ ~~**2 : +0.05 ns**~~	~~0 : +0.12~~ ~~1 : +0.12~~ ~~2 : +0.13~~ } ***
I_1	-	0 : +0.66 *** 1 : +0.66 *** 2 : +0.65 ***	~~0 : +0.01~~ ~~1 : +0.01~~ ~~2 : +0.01~~ } ns	-	-
I_2	-	-	0 : +0.56 *** 1 : +0.47 *** 2 : +0.36 ***	**0 : +0.30** *** 1 : +0.33 *** **2 : +0.43** ***	0 : −0.55 *** 1 : −0.56 *** 2 : −0.54 ***
Z_2	-	-	~~0 : +0.18 ***~~ ~~1 : +0.13 ***~~ ~~2 : +0.16 ***~~	-	-
Z_3	-	-	0 : +0.70 1 : +0.65 2 : +0.54 } ***	-	-
R^2	0 : 0.78 1 : 0.78 2 : 0.78	0 : 0.74 1 : 0.71 2 : 0.68	0 : 0.78 1 : 0.81 2 : 0.86	0 : 0.35 1 : 0.37 2 : 0.28	0 : 0.89 1 : 0.89 2 : 0.89

Table 3.3.4: Standardized direct causal effects in the partially restricted model R (bold-framed: unrestricted path coefficients, thin-framed: restricted path coefficients, not crossed out: essential explanatory contribution ($\beta r > 0.2$), *** : highly significant ($p < 0.001$), * * : very significant ($p < 0.01$), * : significant ($p < 0.05$), ns: not significant, bold print: significant differences to other groups)

	Influenced variables				
Influencing variables	I_1	I_2	Z_1	Z_2	Z_3
MS_1	-	0 : +0.79 *** 1 : +0.77 *** **2 : +0.74** ***	-	-	0 : +0.40 1 : +0.43 *** 2 : +0.42
MS_2	0 : +0.53 1 : +0.53 *** 2 : +0.53	0 : +0.46 *** 1 : +0.42 *** 2 : +0.39 ***	-	-	0 : +0.44 1 : +0.46 *** 2 : +0.46
MS_3	0 : +0.91 1 : +0.91 *** 2 : +0.91	0 : +0.22 *** 1 : +0.18 ** 2 : +0.19 **	-	-	0 : +0.46 1 : +0.49 *** 2 : +0.48
CN_1	0 : −0.02 1 : −0.02 ns 2 : −0.02	0 : −0.17 *** 1 : −0.24 *** 2 : −0.21 ***	-	-	**0 : +0.17** *** 1 : +0.14 *** **2 : +0.12** ***
CN_2	0 : +0.11 1 : +0.11 *** 2 : +0.11	0 : −0.13 *** 1 : −0.09 *** 2 : −0.09 **	0 : −0.76 *** 1 : −0.67 *** 2 : −0.61 ***	0 : −0.30 *** 1 : −0.38 *** 2 : −0.30 ***	**0 : +0.74** *** **1 : +0.73** *** 2 : +0.75 ***
U_2	0 : −0.03 ns 1 : −0.03 ns 2 : −0.02 ns	0 : −0.08 *** 1 : −0.04 ns **2 : +0.05 ns**	**0 : +0.48** *** **1 : +0.60** *** **2 : +0.67** ***	0 : +0.29 *** 1 : +0.19 *** 2 : +0.26 ***	0 : +0.14 1 : +0.15 *** 2 : +0.15
I_1	-	0 : +0.62 *** 1 : +0.63 *** 2 : +0.63 ***	0 : +0.01 1 : +0.01 ns 2 : +0.01	-	-
I_2	-	-	0 : +0.54 *** 1 : +0.50 *** 2 : +0.39 ***	0 : +0.32 *** 1 : +0.31 *** **2 : +0.41** ***	**0 : −0.53** *** 1 : −0.58 *** **2 : −0.58** ***
Z_2	-	-	0 : +0.18 *** 1 : +0.12 *** 2 : +0.12 ***	-	-
Z_3	-	-	0 : +0.73 1 : +0.63 *** 2 : +0.58	-	-
R^2	0 : 0.80 1 : 0.80 2 : 0.80	0 : 0.75 1 : 0.73 2 : 0.69	0 : 0.79 1 : 0.82 2 : 0.85	0 : 0.27 1 : 0.29 2 : 0.36	0 : 0.89 1 : 0.88 2 : 0.88

Table 3.3.5: Standardized direct causal effects in the partially restricted model E (bold-framed: unrestricted path coefficients, thin-framed: restricted path coefficients, not crossed out: essential explanatory contribution ($\beta r > 0.2$), *** : highly significant ($p < 0.001$), ** : very significant ($p < 0.01$), * : significant ($p < 0.05$), ns: not significant, bold print: significant differences to other groups)

The *standardized direct causal effects* provide information about the strength of relations between the variables. Analyzing the individual path coefficients reveals that the formula-conditioned relations are present with varying strength and that hypotheses are supported by the test data to a large extent. The validity of hypotheses concerning the influencing variables can be directly deduced from the standardized direct causal effects and the levels of significance (table 3.3.6).

Hypothesis		Result	Comment
MS	H.3.1	supported	substantial/moderate
	H.3.2	supported	substantial/moderate
	H.3.3	supported	in model R partially not significant
CN	H.4.1	partially disproved/ supported	the impacts of CN_1 are not significant and extremely weak negative; those of CN_2 are weak
	H.4.3	supported	substantial
	H.4.4	supported	moderate
U_2	H.2.4	not disproved	extremely weak, predominantly not significant, occasionally positive
	H.2.7	supported	moderate
I	H.5.1	supported	moderate
	H.6.1	supported	moderate
	H.6.2	supported	moderate
	H.6.3	supported	moderate

Table 3.3.6: Validity of hypotheses concerning the influencing variables

The validity of hypotheses concerning the moderators can be determined by comparing the direct causal effects which refer to the same relation. In case of SC_1, group values 0, 1 and 2 are compared, whereas comparisons of the values in the models R and E are made for U_1 (table 3.3.7).

The test results related to the moderating variables reveal that the moderators strengthen/weaken the impacts of influencing variables in a non-linear and heterogenous manner. The reason for a partial disproof/support of relevant hypotheses is often due to their simultaneous reference to multiple impacts of the particular influencing variables. Against the background of statistical results, only limited conclusions for determining SC_1 can thus be derived.

Altogether, the hypotheses underlying both path models have been predominantly confirmed and their predominantly substantial explanatory contribution has been proven. Thus, substantiated statements may be derived on the strength and direction of impacts, unfolded by the parameter values of robustness-generating measures on the objectives profitability Z_1, solution robustness Z_2 and delivery date reliability Z_3. For this purpose, the direct effects between the individual variables need to be aggregated to total effects between parameter values and objectives (table 3.3.8). Subsequently, an objective- and measure-related evaluation is required.

Hypothesis		Result	Comment
SC_1	H.1.1	partially disproved/ supported	MS-I_2 is moderated by SC_1; however, MS-I_1 and MS-Z_3 are not moderated.
	H.1.2	partially disproved/ supported	CN-I and CN-Z are moderated by SC_1; group differences hardly hint at consistent strengthening tendencies (R: CN_1-I_2), but rather at changing or consistent weakening tendencies; the moderated impact consequently depends on the fit between SC_1 and U_2.
	H.1.3	supported	Apart from the impact on Z_3, all impacts originating from U_2 are moderated by SC_1; cases in which a good fit between U_2 and SC_1 is present, depend on the considered relation.
U_1	H.2.1	partially disproved/ supported	MS-I and MS-Z are moderated by U_1, whereby mainly strengthening effects exist (exceptions concern group 0).
	H.2.2	partially disproved/ supported	CN-I and CN-Z are moderated by U_1, whereby the impacts of CN_1 are mainly weakened whereas those of CN_2 are mainly strengthened.

Table 3.3.7: Validity of hypotheses concerning the moderating variables

Objective-related evaluation: The aggregated impacts on Z_1 indicate that the analyzed robustness-generating measures predominantly lead to essential effects. Influences are observed to be moderate positive ($MS_1<MS_2<MS_3$) for MS and weak essential negative (CN_2) or inessential positive (CN_1) for CN. The distinct group differences for MS and CN, indicate a strong restraining influence of SC on the MS- and CN-impacts. The different values in the models R and E reveal that the essential impacts of MS and CN, are slightly strengthened by U_1, if SC is applied. For Z_2, the total effects indicate moderate positive effects for MS as well as moderate (CN_2) or weak inessential (CN_1) negative influences for CN. In contrary to MS destabilizing effects on profits originate from CN. The group differences tend to denote a strengthening impact of SC on MS and a heterogeneous impact on CN. The differences between the models R and E do not indicate a systematic moderation through U_1. Z_3 is essentially enhanced by CN; in fact, substantially by CN_2 and weakly by

CN_1. The influence of MS remains in a negligible range. Since group differences only exist to a very low extent, SC does not unfold essential moderating effects on the other measures. Minor differences also exist between the values of the models R and E so that U_1 barely moderates measure impacts.

	Model R			Model E		
	Z_1	Z_2	Z_3	Z_1	Z_2	Z_3
MS_1	0 : +0.47 1 : +0.39 2 : +0.33	0 : +0.24 1 : +0.26 2 : +0.32	~~0 : −0.03 1 : −0.02 2 : +0.03~~	0 : +0.46 1 : +0.40 2 : +0.33	0 : +0.25 1 : +0.24 2 : +0.30	~~0 : −0.02 1 : −0.02 2 : −0.01~~
MS_2	0 : +0.48 1 : +0.40 2 : +0.34	0 : +0.22 1 : +0.25 2 : +0.29	~~0 : +0.04 1 : +0.03 2 : +0.09~~	0 : +0.49 1 : +0.43 2 : +0.35	0 : +0.25 1 : +0.24 2 : +0.30	~~0 : +0.02 1 : +0.02 2 : +0.04~~
MS_3	0 : +0.51 1 : +0.42 2 : +0.37	0 : +0.23 1 : +0.24 2 : +0.32	~~0 : +0.06 1 : +0.06 2 : +0.09~~	0 : +0.51 1 : +0.44 2 : +0.37	0 : +0.25 1 : +0.24 2 : +0.31	~~0 : +0.04 1 : +0.05 2 : +0.05~~
CN_1	~~0 : +0.09 1 : +0.07 2 : +0.04~~	~~0 : −0.05 1 : −0.06 2 : −0.12~~	0 : +0.26 1 : +0.25 2 : +0.30	~~0 : +0.09 1 : +0.05 2 : +0.05~~	~~0 : −0.06 1 : −0.08 2 : −0.09~~	0 : +0.27 1 : +0.29 2 : +0.26
CN_2	0 : −0.30 1 : −0.23 2 : −0.16	0 : −0.48 1 : −0.47 2 : −0.27	0 : +0.76 1 : +0.77 2 : +0.75	0 : −0.29 1 : −0.26 2 : −0.21	0 : −0.32 1 : −0.39 2 : −0.31	0 : +0.77 1 : +0.74 2 : +0.76

Table 3.3.8: Standardized total causal effects in the partially restricted models R and E (not crossed out: essential explanatory contribution)

Measure-related evaluation: *MS* does not negatively influence any objective (Z_1, Z_2, Z_3). The impact is always positive as soon as price and delivery date are modified (MS_2 or MS_3). It is therefore advantageous from the perspective of all objectives, not only to modify the delivery date but also the price in all constellations. Compared to the other measures, MS has the strongest positive impact on Z_1 and Z_2. An ambivalent picture emerges for *CN*. Both parameters influence Z_3 in a positive way. Regarding Z_1 and Z_2, the weak positive or negative inessential impact of CN_1 and the weak to moderate negative essential effect of CN_2 cause a negative overall impact. When setting parameters, CN_2 therefore needs to be determined with greater care than CN_1. Compared to the other measures, CN has by far the strongest positive effect on Z_3 and the negative influence on Z_2 is slightly stronger than the positive impacts of MS resp. SC. The decision on the application of CN thus is to be made in dependency of the intended objectives: If only solution robustness is focused besides profitability, then applying CN is disadvantageous. In the event of simultaneously aiming at Z_1, Z_2 and Z_3, the reducing and destabilizing impacts on profit and the positive impacts on delivery date reliability need to be balanced. The impacts of *SC* depend on the fit between uncertainty situation (order- and resource-related uncertainty) and safety factor with regard to the objective. Tuning SC_1 with respect to uncertainty situations has different effects on the individual measures and objectives.

SC_1-Z_1: With increasing SC_1, the moderate positive impact of MS and the weak negative impact of CN are weakened in all uncertainty situations. In total, a negative effect results. SC_1-Z_2: For resource-related uncertainty and regular order-related uncertainty, the weak positive/moderate negative impacts of MS/CN are strengthened/weakened with increasing SC_1. On the contrary, these impacts are at first weakened/strengthened and then strengthened/weakened in case of increased order-related uncertainty. The overall impact is positive for regular order-related uncertainty. In case of increased order-related uncertainty, it is initially negative and then strongly positive. SC_1-Z_3: The impacts of MS are hardly influenced. Opposite effects emerge in CN_1 and CN_2. The positive weak/substantial effect of CN_1/CN_2 is firstly weakened/strengthened and then strengthened/weakened for regular order-related uncertainty. Overall, the impact is positive. In contrast to this, first a strengthening/weakening and subsequently a weakening/strengthening of the weak/substantial positive effects of CN_1/CN_2 can be observed for increased order-related uncertainty. All in all, it results in a weak heterogeneous overall effect. The decision regarding the application of SC could thus be made depending on the focused objectives (e.g. no implementation if only Z_1 is relevant). However, the hypotheses concerning SC_1 are only partially supported by the data so that the risk of a wrong decision is noticable. Table 3.3.9 summarizes the evaluation results.

		Impact on objective values	
		homogeneous	heterogeneous
Impact on other parameters	weak	MS $\begin{cases} Z_1\text{: positive} \\ Z_2\text{: positive} \\ Z_3\text{: positive} \end{cases}$	CN $\begin{cases} Z_1\text{: negative} \\ Z_2\text{: negative} \\ Z_3\text{: positive} \end{cases}$
	strong	-	SC $\begin{cases} Z_1\text{: negative} \\ Z_2\text{: positive} \\ Z_3\text{: positive/neutral} \end{cases}$

Table 3.3.9: Systematization of robustness-generating measures by means of their impacts

3.4 Coordination at superordinate level

3.4.1 Procedure of the limited search

One possibility to set parameter values of the individual robustness-generating measures with respect to the pursued objectives is to search the test data for parameter value combinations which result in a high degree of objective fulfillment. For the multi-criteria objectives (e.g. $Z_1 \wedge Z_3$ and $Z_1 \wedge Z_2 \wedge Z_3$) relevant in the present contribution, the search addresses combinations which are not dominated with respect to the relevant objective values. By means of *Data Envelopment Analysis* (DEA), the non-dominated parameter value combinations can be identified as those solutions that have a maximum relative efficiency (Cook et al. 2014). Since the objective values are cardinally scaled and the path model confirms that linear functions capture the relations with sufficient accuracy, the application of the *CCR-model* (Charnes et al. 1978) is considered to be appropriate. However, the effort of the DEA increases exponentially with the number s of included data sets and the number z of relevant criteria. The reason for this is that s LP-models with $s+z+1$ constraints in each model need to be solved. Thus, the computation time for a complete search would be unacceptably high for the present volume of the test data.

The statistical findings derived from the test data can be used to limit the search, while accepting the risk of achieving objective values that deviate from the optimum. Since the estimation error of the path models determines the risk level, a low risk is assumed due to the present good model fits. Therefore, constraining the search is based on the following considerations:

- Parameters with homogeneous impacts on the relevant objectives, as well as weak impacts on other parameters, can be determined in an isolated manner. In case of positive impacts, their parameter values need to be determined first; in case of negative impacts, the measure is not implemented.

- Parameters, which strongly influence the impacts of other parameters, need to be determined prior to those other parameters, namely in descending order of impact strength. This can be done by assuming average values in remaining parameters.

- Parameters, which have heterogeneous impacts on relevant objectives and are additionally influenced by other parameters, need to be determined in a final step. The specification is made in descending order of impact strength.

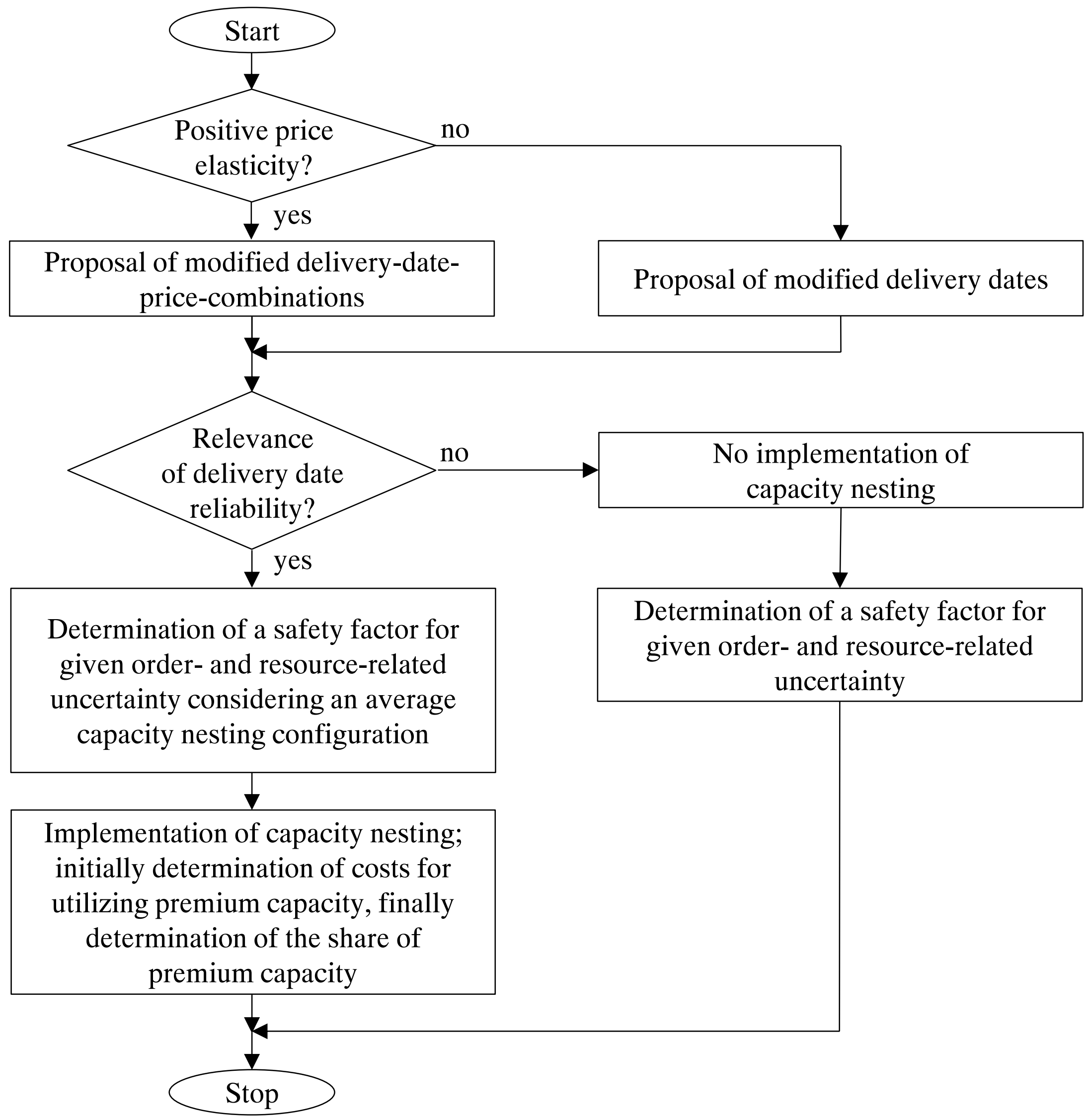

Figure 3.4.1: Flow-chart for measure parameterization

A specific procedure for searching good parameter values can be derived against this background by combining the results obtained for the analyzed data constellations. Due to non-negative impacts on all objectives, MS should always be implemented. If customers have positive price elasticities, MS_2 or MS_3 should be chosen. Since CN has ambivalent impacts on the objectives, a fundamental decision about the CN implementation needs to be made in accordance with the relevance of objectives. Only if Z_3 is relevant, the application of CN can be advantageous. Due to versatile effects, SC_1 is to be tuned with the present uncertainty situation, if required, considering an average CN-configuration. If CN is implemented, due to the higher impact strength, a CN_2-value needs to be initially determined considering already set parameters before a suitable CN_1-value is chosen. The resulting procedure (figure 3.4.1) limits the search to 6.5% of the sets in the test data.

If the uncertainty situations (regular/increased order-/resource-related uncertainty) are systematically combined and the test data is searched in regular/increased positive price elasticity (MS_2/MS_3), the results visualized in table 3.4.1, are obtained (for intermediate results cf. tables C.1, C.2 and C.3 in appendix C).

		Price elasticity							
		regular				increased			
		Resource-related uncertainty				Resource-related uncertainty			
		regular		increased		regular		increased	
Order-related uncertainty		Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3
regular	MS_0	0	0	0	0	0	0	0	0
	MS_1	0	0	0	0	0	0	0	0
	MS_2	1	1	1	1	0	0	0	0
	MS_3	0	0	0	0	1	1	1	1
	SC_1	1	0	2	2	2	2	1	1
	CN_1	2/3	2/3	2/3	2/3	2/3	2/3	2/3	2/3
	CN_2	4000	4000	4000	3500	4000	3500	4000	2500
		Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3
increased	MS_0	0	0	0	0	0	0	0	0
	MS_1	0	0	0	0	0	0	0	0
	MS_2	1	1	1	1	0	0	0	0
	MS_3	0	0	0	0	1	1	1	1
	SC_1	0	1	2	2	1	0	2	2
	CN_1	2/3	1/3	2/3	2/3	2/3	2/3	2/3	2/3
	CN_2	4000	500	4000	4000	4000	4000	4000	4000

Table 3.4.1: Determined parameter values for each constellation

3.4.2 Quality of the limited search

The quality of the limited search is evaluated based on the verification data, which includes two scenarios per constellation; each containing 144 solutions. Solutions, corresponding to the detected parameter values (DP-solutions), are in different ways compared with the remaining solutions of this data. On the one hand, the share of dominating solutions d^+ is determined. DP-solutions are better the lower/higher the share of dominating/dominated solutions is. On the other hand, the degree of achieving the objectives with the DP-solution is determined in an aggregated way as DEA efficiency (CCR-model). These values provide insight into the relative "average" fulfillment of all relevant objectives. Furthermore, degrees of achieving the individual objectives are calculated to gain detailed information. For the tri-criteria case these indicators are:

$$QI_{1P} = \frac{ZV_{1P} - \mu_1^+}{\overline{ZV}_1^+ - \mu_1^+} \quad \text{with} \quad \begin{aligned} \overline{ZV}_1^+ &= \max\left(ZV_{1s} \middle| ZV_{2s} \le ZV_{2P} \wedge ZV_{3s} \le ZV_{3P} \wedge s = 1,\ldots,S\right) \\ \mu_1^+ &= \mu\left(ZV_{1s} \middle| ZV_{1s} < \overline{ZV}_1^+ \wedge s = 1,\ldots,S\right) \end{aligned}$$

$$QI_{2P} = \frac{\mu_2^+ - ZV_{2P}}{\mu_2^+ - \underline{ZV}_2^+} \quad \text{with} \quad \begin{aligned} \underline{ZV}_2^+ &= \min\left(ZV_{2s} \middle| ZV_{1s} \ge ZV_{1P} \wedge ZV_{3s} \le ZV_{3P} \wedge s = 1,\ldots,S\right) \\ \mu_2^+ &= \mu\left(ZV_{2s} \middle| ZV_{2s} > \underline{ZV}_2^+ \wedge s = 1,\ldots,S\right) \end{aligned}$$

$$QI_{3P} = \frac{\mu_3^+ - ZV_{3P}}{\mu_3^+ - \underline{ZV}_3^+} \quad \text{with} \quad \begin{aligned} \underline{ZV}_3^+ &= \min\left(ZV_{3s} \middle| ZV_{1s} \ge ZV_{1P} \wedge ZV_{2s} \le ZV_{2P} \wedge s = 1,\ldots,S\right) \\ \mu_3^+ &= \mu\left(ZV_{3s} \middle| ZV_{3s} > \underline{ZV}_3^+ \wedge s = 1,\ldots,S\right) \end{aligned}$$

In the bi-criteria case QI_{2P} is not relevant, and QI_{1P} as well as QI_{3P} are calculated without ZV_2-conditions. The indicator calculation is designed in such a way that a dominated DP-solution can take values of $QI < 1$. With increasing difference between 1 and QI the objective fulfillment of the solution decreases. Positive/negative QI-values indicate an objective fulfilment above/below average. A non-dominated DP-solution is represented by $QI = 1$.

Average shares of dominating solutions, efficiency values and relative objective-achievement-degrees are summarized in table 3.4.2 (for individual values cf. tables D.1 and D.2 in appendix D). The analysis reveals that through the limited search by tendency

- solutions are found, which are partially dominated by a very small number of other solutions;
- high efficiency values of solutions are reached;
- the profitability objective is supported slightly below average/ moderately above average in the bi-criteria/ tri-criteria case;
- the objective of solution robustness is supported moderately above average; and
- the objective of delivery date reliability (planning robustness) is supported strongly above average.

Due to these reasons, the proposed limited search proves to be an efficient solution method (in terms of solution quality and time) for the problem of parameter value coordination.

	Bi-criteria case			Tri-criteria case			
	unfavorable*	favorable*	in total	unfavorable*	favorable*	in total	in total
$\hat{d}^+$	1.91%	0.51%	1.21%	2.77%	0.81%	1.79%	1.50%
$\hat{e}$	0.789	0.912	0.851	0.875	0.954	0.915	0.883
$\widehat{QI}_1$	-0.697	+0.318	-0.181	+0.285	+0.914	+0.599	+0.209
$\widehat{QI}_2$	--	--	--	+0.144	+0.925	+0.534	--
$\widehat{QI}_3$	+0.943	+0.976	+0.959	+0.773	+0.821	+0.797	+0.878
* 0.5 quantile of DP-solutions' efficiency values							

Table 3.4.2: Average shares of dominating solutions, efficiency values and relative objective-achievement-degrees

3.5 Conclusions

In the present paper, a combined deductive-inductive planning approach for robust order promising has been developed and tested. The intended robustness has been reached by considering multiple robustness-generating measures in a CTP model, and by coordinating measure parameters. Relevant robustness-generating measures were: Capacity nesting, providing safety capacity and proposing modified order specifications. While the first-mentioned measures have been established in earlier order acceptance models, recent literature increasingly refers to proposing modified order specifications. The analysis of existing modeling suggestions revealed that anticipating the customer behavior is not adequately taken into account. Furthermore, it became apparent that multiple, simultaneously applied robustness-generating measures are not coordinated by present CTP models. Thus, the contributions of the present paper are: (1) A proposal for an explicit consideration of customer behavior in CTP models, and (2) a proposal for coordinating multiple robustness-generating measures with respect to multiple objectives (profitability, solution robustness, delivery date reliability).

The central idea of the proposed CTP approach is the hierarchical decomposition of the order promising problem into a super- and a subordinate problem. While the superordinate problem consists of coordinating robustness-generating measures, the subordinate problem is deciding on order acceptance and scheduling while taking coordinated robustness-generating measures into account. Thereby, the parameter coordination is based on an inferential statistical anticipation of causal relations between parameter and objective values in the subordinate problem; and on a limited multi-criteria search for good parameter values which is directed by this anticipation. The problem of order acceptance and scheduling is captured by a CTP model, which considers the three robustness-generating measures. For proposing modified order specifications, customer behavior is explicitly included by a response function. This function models customer acceptance probability depending on the deviation between requested and offered delivery dates and prices.

Two data bases (test and verification data), having the same statistical characteristics, have been generated to evaluate the suitability of the proposed solution approach. The test data provided the basis for the parameter coordination. In contrast, the verification data was utilized for evaluating the solution quality obtained by recommended parameter values. Thereby, solutions corresponding to recommended parameter values were compared to solutions of systematically varied parameter values. The analysis demonstrated that the solution approach always leads to high efficiency values in the bi- and tri-criteria case. Thus, a suitable coordination of the three robustness-generating measures is achieved with respect to profitability, solution robustness and delivery date reliability.

Appendix A: Data basis for CTP model tests

Product configuration	c	1	2	3	4	5	6	7
Order quantity	μ_c^q	4.71	4.85	7.77	4.66	7.66	4.75	6.38
$\tilde{Q}_c \sim N_c(\mu_c^q, \sigma_c^q)$ *)	σ_c^q	3.25	2.54	3.90	3.51	0.58	3.30	2.56
Interarrival time	μ_c^j	13.00	11.38	9.10	22.75	30.33	22.75	11.38
$\tilde{J}_c \sim N_c(\mu_c^j, \sigma_c^j)$ *)	σ_c^j	5.94	12.66	4.89	16.76	22.50	31.50	7.42
Price per piece	ρ_c	5750	3999	3999	3299	2990	2699	2599
Manufacturing costs	k_c^M	570.93	384.93	416.5	281.19	289.65	251.72	462.44
Inventory holding costs	$k_c^{L.FP}$	14.375	9.9975	9.9975	8.2475	7.475	6.7475	6.4975
Penalty costs	γ_c^e	0	0	0	0	0	0	0
	γ_c^l	172.5	119.97	119.97	98.97	89.7	80.97	77.97
Transportation costs	k^{Tr}	59	59	59	59	59	59	59
Capacity requirement per piece: $\kappa_i = 1$ (regular) or $\kappa_i \sim U[0.9,1.1]$ (increased uncertainty)								
*) truncated normal distributions that only permit positive values								

Table A.1: Order data

Capacity situation	μ^{cap}	σ^{cap} in period					
		1	2	3	4	5	6 … T
Regular uncertainty	2.75	0	0.0204	0.0408	0.0612	0.0816	0.1021
Increased uncertainty	2.50	0	0.0408	0.0816	0.1225	0.1633	0.2041

Table A.2: Capacity data

	G	H	M	N	$V^{\min}$	$V^{\max}$	ψ
MS_1	0	-	0.02	-	-30	30	0
MS_2	0	0	0.02	10	-30	30	0.1
MS_3	0	0	0.02	20	-30	30	0.1

Table A.3: Parameters varied for MS

Further parameters, related to materials: lead times $\omega_1 = 3$, $\omega_2 = 2$; material types: $R = 56$, $r_k = 45$.

Appendix B: Verification of multi-group path models

The preconditions of applying the maximum likelihood discrepancy function (Bagozzi and Yi 2012, Baumgartner and Homburg 1996) are fulfilled for the models R and E:

- In both models, variables deviate from the univariate normal distribution in a tolerable extent (West et al. 1995), since the absolute values of skewness and kurtosis statistics do not exceed threshold values of 2 resp. 7 most of the time. Due to the largeness of the sample, as expected, critical ratios of named statistics and the Mardia coefficient (values differ between 12.43 and 18.17), do not indicate the existence of a *multivariate normal distribution*. However, these deviations from multi-normality often occur in case of large data sets. Thus, path analysis is still applied according to the suggestion of Kline (2005), as long as the univariate test statistics do not exceed thresholds of 3 (skewness) and 10 (kurtosis).

- The *unrestricted models* show a good *model fit* (R: CMIN/DF=0.9545, RMSEA=0.0000, GFI=0.9904, AGFI=0.9723; E: CMIN/DF=0.9492, RMSEA= 0.0000, GFI=0.9903, AGFI=0.9722). The group-specific analysis reveals limitations, whose influence on the model's plausibility needs to be evaluated (cf. table B.1): In some groups, deviations from the direction of specified causal relations are sporadically present. However, these deviations are not distinctive due to the very low regression weights. Furthermore, non-significant relations occur; but in relation to the number of analyzed relations, the share of non-significant cases (<13%) is low. Thus, the estimates of the unrestricted model can be classified as credible.

		Unrestricted model						Individually partially restricted model					
		Model R			Model E			Model R			Model E		
Group		0	1	2	0	1	2	0	1	2	0	1	2
Relation	U_2-I_1	✓ ***	✓ **	0.01 ns	✓ ns	✓ ns	✓ ns	✓ ***	✓ *	0.01 ns	✓ *	✓ *	✓ *
	U_2-I_2	✓ *	✓ ns	0.04 ns	✓ **	✓ ns	✓ ns	✓ **	✓ ns	0.04 ns	✓ ***	✓ ns	0.05 ns
	I_1-Z_1	0.01 ns	✓ ns	0.01 ns	✓ ns	0.03 ns	✓ ns	0.01 ns	0.01 ns	0.01 ns	0.01 ns	0.03 ns	✓ ns
	CN_1-I_1	-0.02 ns	-0.03 ns	✓ ns	-0.03 ns	-0.02 ns.	-0.02 ns.	-0.02 ns	-0.02 ns	-0.02 ns	-0.02 ns	-0.02 ns	-0.02 ns

Table B.1: Limitations in the unrestricted and partially restricted models ($***$: highly significant ($p < 0.001$), $**$: very significant ($p < 0.01$), $*$: significant ($p < 0.05$), ns: not significant)

- The *individually partially restricted models* (bold-framed path coefficients in tables B.2 and B.3 are unrestricted) show good model fits (R: CMIN/DF=0.8860, RMSEA=0.0000, GFI=0.9843, AGFI=0.9747; E: CMIN/DF=0.7508, RMSEA=0.0000, GFI=0.9861, AGFI=0.9777). Analogously to the unrestricted model, limitations are observable (cf. table B.1), which do not oppose the suitability of the formulated model for the MGA.

		Influenced variables				
		I_1	I_2	Z_1	Z_2	Z_3
Influencing variables	MS_1	-	**0 : +0.80** *** 1 : +0.77 *** **2 : +0.74** ***	-	-	0 : +0.41 1 : +0.40 } *** 2 : +0.43
	MS_2	0 : +0.53 1 : +0.53 } *** 2 : +0.53	0 : +0.37 *** 1 : +0.39 *** 2 : +0.34 ***	-	-	0 : +0.44 1 : +0.43 } *** 2 : +0.46
	MS_3	0 : +0.90 1 : +0.90 } *** 2 : +0.90	~~0 : +0.15~~ ~~1 : +0.15 } ***~~ ~~2 : +0.16~~	-	-	0 : +0.47 1 : +0.46 } *** 2 : +0.49
	CN_1	~~0 : –0.02~~ ~~1 : –0.02 } ns~~ ~~2 : –0.02~~	0 : –0.15 *** 1 : –0.17 *** **2 : –0.26** ***	-	-	~~0 : +0.16~~ ~~1 : +0.15 } ***~~ ~~2 : +0.16~~
	CN_2	~~0 : +0.08 ***~~ ~~1 : +0.05 *~~ ~~2 : +0.11 ***~~	~~0 : –0.13 ***~~ ~~1 : –0.15 ***~~ ~~**2 : –0.04 ns**~~	0 : –0.68 *** 1 : –0.65 *** 2 : –0.53 ***	0 : –0.46 *** 1 : –0.44 *** **2 : –0.28** ***	0 : +0.72 1 : +0.71 } *** 2 : +0.76
	U_2	~~0 : –0.09 ***~~ ~~1 : –0.06 *~~ ~~**2 : +0.01 ns**~~	~~0 : –0.08 **~~ ~~1 : –0.05 ns~~ ~~**2 : +0.04 ns**~~	**0 : +0.53** *** **1 : +0.62** *** **2 : +0.72** ***	~~0 : +0.18 ***~~ ~~1 : +0.20 ***~~ ~~**2 : +0.05 ns**~~	~~0 : +0.12~~ ~~1 : +0.12 } ***~~ ~~2 : +0.13~~
	I_1	-	**0 : +0.67** *** 1 : +0.65 *** **2 : +0.64** ***	~~0 : +0.01~~ ~~1 : +0.01 } ns~~ ~~2 : +0.01~~	-	-
	I_2	-	-	0 : +0.55 *** 1 : +0.48 *** 2 : +0.36 ***	**0 : +0.30** *** 1 : +0.33 *** **2 : +0.44** ***	0 : –0.56 1 : –0.54 } *** 2 : –0.54
	Z_2	-	-	~~0 : +0.18 ***~~ ~~1 : +0.13 ***~~ ~~2 : +0.16 ***~~	-	-
	Z_3	-	-	0 : +0.66 *** 1 : +0.70 *** 2 : +0.54 ***	-	-
	R^2	0 : 0.78 1 : 0.78 2 : 0.78	0 : 0.74 1 : 0.72 2 : 0.68	0 : 0.77 1 : 0.81 2 : 0.86	0 : 0.35 1 : 0.38 2 : 0.28	0 : 0.89 1 : 0.90 2 : 0.88

Table B.2: Standardized direct causal effects in the individually partially restricted model R (bold-framed: unrestricted path coefficients, thin-framed: restricted path coefficients, not crossed out: essential explanatory contribution ($\beta r > 0.2$), *** : highly significant ($p < 0.001$), ** : very significant ($p < 0.01$), * : significant ($p < 0.05$), ns: not significant, bold print: significant differences to other groups)

- Since MGA is performed independently for models R and E, *verifying the significance of group differences* between relations can only be done in an isolated manner for each model. The analysis reveals that SC_1 does not influence the causal relations with the same strength. In model R, significant differences (bold print in table B.2) exist for:

  (a) six group comparisons (U_2-Z_1);

(b) four group comparisons, whereby group 2 (CN_2-I_2, CN_2-Z_2, U_2-I_1, U_2-I_2, U_2-Z_2) stands out;

(c) two group comparisons, whereby group 1 (MS_1-I_2, CN_1-I_2, I_1-I_2, I_2-Z_2) does not stand out and

(d) no group comparison (MS_2-I_2, CN_2-I_1, CN_2-Z_1, I_2-Z_1, Z_2-Z_1, Z_3-Z_1).

Influencing variables	Influenced variables: I_1	I_2	Z_1	Z_2	Z_3
MS_1	-	0: +0.79 *** 1: +0.77 *** **2: +0.74** ***	-	-	0: +0.41 1: +0.43 2: +0.42 } ***
MS_2	0: +0.53 1: +0.53 2: +0.53 } ***	**0: +0.44** *** 1: +0.43 *** **2: +0.40** ***	-	-	0: +0.45 1: +0.47 2: +0.46 } ***
MS_3	0: +0.91 1: +0.91 2: +0.91 } ***	0: +0.19 1: +0.19 2: +0.21 } ***	-	-	0: +0.47 1: +0.49 2: +0.48 } ***
CN_1	0: −0.02 1: −0.02 2: −0.02 } ns	0: −0.18 *** 1: −0.24 *** 2: −0.21 ***	-	-	**0: +0.17** *** 1: +0.14 *** **2: +0.12** ***
CN_2	0: +0.11 1: +0.11 2: +0.11 } ***	0: −0.10 1: −0.10 2: −0.11 } ***	0: −0.76 *** 1: −0.69 *** 2: −0.60 ***	0: −0.30 *** 1: −0.38 *** 2: −0.30 ***	**0: +0.75** *** **1: +0.73** *** 2: +0.74 ***
U_2	0: −0.03 1: −0.03 2: −0.03 } *	0: −0.08 *** 1: −0.04 ns **2: +0.05 ns**	**0: +0.48** *** **1: +0.61** *** **2: +0.66** ***	0: +0.29 *** 1: +0.19 *** 2: +0.26 ***	0: +0.14 *** **1: +0.12** *** **2: +0.18** ***
I_1	-	**0: +0.64** *** 1: +0.62 *** **2: +0.61** ***	0: +0.01 ns 1: +0.03 ns 2: −0.01 ns	-	-
I_2	-	-	0: +0.55 1: +0.49 2: +0.40 } ***	0: +0.32 *** 1: +0.31 *** **2: +0.41** ***	**0: −0.54** *** 1: −0.59 *** **2: −0.57** ***
Z_2	-	-	0: +0.18 *** 1: +0.12 *** 2: +0.12 ***	-	-
Z_3	-	-	0: +0.72 1: +0.64 2: +0.58 } ***	-	-
R^2	0: 0.80 1: 0.80 2: 0.80	0: 0.75 1: 0.73 2: 0.69	0: 0.79 1: 0.82 2: 0.86	0: 0.27 1: 0.30 2: 0.36	0: 0.89 1: 0.88 2: 0.89

Table B.3: Standardized direct causal effects in the individually partially restricted model E (bold-framed: unrestricted path coefficients, thin-framed: restricted path coefficients, not crossed out: essential explanatory contribution ($\beta r > 0.2$), *** : highly significant ($p < 0.001$), ** : very significant ($p < 0.01$), * : significant ($p < 0.05$), ns: not significant, bold print: significant differences to other groups)

In contrast, significant differences (bold print in table B.3) exist for model E:

(a) six group comparisons (U_2-Z_1);

(b) four group comparisons, whereby group 2 (MS_1-I_2, U_2-I_2, I_2-Z_2) stands out;

(c) two group comparisons, whereby groups 0 (U_2-Z_3), 1 (MS_2-I_2, CN_1-Z_3, I_1-I_2, I_2-Z_3) or 2 (CN_2-Z_3) do not stand out and

(d) no group comparison (CN_1-I_2, CN_2-Z_1, CN_2-Z_2, U_2-Z_2, I_1-Z_1, Z_2-Z_1).

It should be noted that an increase of order-related uncertainty (model R to model E) influences the impact of SC: On the one hand, group differences become apparent for different causal relations. On the other hand, the significance of differences between the relations varies. In total, eleven relations are present (MS_1-I_2, MS_2-I_2, CN_1-I_2, CN_2-Z_1, CN_2-Z_2, U_2-I_2, U_2-Z_1, U_2-Z_2, I_1-I_2, I_2-Z_2, Z_2-Z_1), in which group differences, and thus the impact of SC, are confirmed independently from the level of order-related uncertainty.

- The variance explained by endogenous variables of the path model, indicates a substantial (cf. Chin 1998) explanatory contribution in most cases (cf. last row of tables B.2/B.3), which tends to intensify for I_1, I_2, Z_1 and Z_3 with increasing uncertainty. The only exception is the weak to moderate explaining variable Z_2 , whose explained variance decreases with increasing uncertainty.

To be able to derive statements about group differences due to order-related uncertainty, it is necessary to harmonize releases/restrictions in the models E and R. Thereby, it is expected that the fit of both models declines. For this reason, only modifications of relations, for which release differences between the models exist (CN_1-Z_3, CN_2-I_1, CN_2-I_2, CN_2-Z_3, U_2-I_1, U_2-Z_3, I_1-Z_1, I_2-Z_1, I_2-Z_3, Z_3-Z_1), are considered during harmonization. Additionally, a homogeneous releasing/restricting supports the evaluation of the impacts of MS. Therefore, relation MS_3-I_2 is released in both models, although a slight decline of model fit is induced (cf. table B.4).

Relation	Status in model R	Status in model E	Harmonized Status
MS_3-I_2	res.	res.	rel.
CN_1-Z_3	res.	rel.	rel.
CN_2-I_1	rel.	res.	res.
CN_2-I_2	rel.	res.	rel.
CN_2-Z_3	res.	rel.	rel.
U_2-I_1	rel.	res.	rel.
U_2-Z_3	res.	rel.	res.
I_1-Z_1	res.	rel.	res.
I_2-Z_1	rel.	res.	rel.
I_2-Z_3	res.	rel.	rel.
Z_3-Z_1	rel.	rel.	res.

Fit measure	Model fit in model R: value	model R: Δ	model E: value	model E: Δ
X^2	109.4844	0.5075	95.2536	2.9078
(p-value)	(0.7226)	0.0900	(0.9465)	0.0357
CMIN/DF	0.9200	0.0340	0.8005	0.0497
RMSEA	0.0000	0	0.0000	0
GFI	0.9842	0.0001	0.9858	0.0003
AGFI	0.9737	0.0010	0.9764	0.0013

Table B.4: Harmonization of releases and its impact on model fits (res.: restricted; rel.: released)

Appendix C: Intermediate results of limited search

In the following tables, $\hat{e}_2/\hat{e}_3$ represent the average efficiency values of bi-criteria $(Z_1 \wedge Z_3)$ / tri-criteria $(Z_1 \wedge Z_2 \wedge Z_3)$ objectives; determined for a parameter value combination considering different order- and resource-related streams of random numbers.

			Price elasticity							
			regular				increased			
			Resource-related uncertainty				Resource-related uncertainty			
			regular		increased		regular		increased	
Order-related uncertainty	regular	SC_1	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$
		0	0.905	0.948	0.883	0.902	0.900	0.900	0.734	0.784
		1	0.947	0.947	0.898	0.898	0.946	0.946	0.945	0.951
		2	0.892	0.892	0.930	1.000	0.947	0.947	0.878	0.922
	increased	SC_1	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$
		0	0.937	0.947	0.978	0.982	0.949	1.000	0.924	0.927
		1	0.930	0.9972	0.981	0.984	0.961	0.967	0.955	0.958
		2	0.903	0.9967	0.998	0.998	0.952	0.988	0.964	0.966

Table C.1: Average efficiency values for an average CN-configuration and varying safety factor

			Price elasticity							
			regular				increased			
			Resource-related uncertainty				Resource-related uncertainty			
			regular		increased		regular		increased	
		SC$_1$	1	0	2	2	2	2	1	1
Order-related uncertainty	regular	CN$_2$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$
		500	0.160	0.733	0.141	0.491	0.148	0.600	0.121	0.591
		1000	0.159	0.575	0.166	0.600	0.144	0.637	0.134	0.645
		1500	0.167	0.748	0.186	0.706	0.155	0.615	0.151	0.616
		2000	0.206	0.639	0.210	0.764	0.186	0.665	0.182	0.652
		2500	0.257	0.723	0.255	0.774	0.243	0.756	0.217	0.774
		3000	0.347	0.736	0.315	0.765	0.327	0.717	0.290	0.771
		3500	0.410	0.871	0.381	0.842	0.387	0.791	0.332	0.677
		4000	0.556	0.892	0.518	0.720	0.595	0.773	0.487	0.743
	increased	CN$_2$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$
		500	0.178	0.841	0.178	0.587	0.167	0.559	0.150	0.515
		1000	0.177	0.670	0.183	0.584	0.163	0.530	0.155	0.538
		1500	0.202	0.685	0.209	0.667	0.178	0.553	0.168	0.632
		2000	0.220	0.626	0.237	0.677	0.205	0.575	0.210	0.735
		2500	0.270	0.753	0.280	0.739	0.253	0.637	0.257	0.731
		3000	0.353	0.754	0.374	0.808	0.327	0.727	0.311	0.773
		3500	0.467	0.720	0.474	0.784	0.431	0.743	0.437	0.776
		4000	0.549	0.739	0.561	0.831	0.599	0.828	0.533	0.881
		SC$_1$	0	1	2	2	1	0	2	2

Table C.2: Average efficiency values for a predefined safety factor and varying costs for utilizing premium capacity

			Price elasticity							
			regular				increased			
			Resource-related uncertainty				Resource-related uncertainty			
			regular		increased		regular		increased	
		SC$_1$	1	0	2	2	2	2	1	1
		CN$_2$	4000	4000	4000	3500	4000	3500	4000	2500
Order-related uncertainty	regular	CN$_1$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$
		1/3	0.246	0.800	0.243	0.880	0.243	0.609	0.200	0.715
		1/2	0.448	0.889	0.415	0.661	0.560	0.851	0.387	0.617
		2/3	0.974	0.988	0.897	0.985	0.982	0.913	0.873	0.989
	increased	CN$_1$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_2$	$\hat{e}_3$
		1/3	0.264	0.941	0.274	0.716	0.299	0.859	0.241	0.829
		1/2	0.468	0.745	0.501	0.776	0.523	0.627	0.443	0.815
		2/3	0.914	0.836	0.908	1.000	0.975	1.000	0.916	1.000
		SC$_1$	0	1	2	2	1	0	2	2
		CN$_2$	4000	500	4000	4000	4000	4000	4000	4000

Table C.3: Average efficiency values for a predefined safety factor, predefined costs for utilizing premium capacity and varying shares of premium capacity

Appendix D: Detailed results of quality evaluation

			Price elasticity							
			regular				increased			
			Resource-related uncertainty				Resource-related uncertainty			
			regular		increased		regular		increased	
Order-related uncertainty	regular		Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3
		d^+	2.08%	2.08%	1.39%	0.69%	2.08%	0.00%	0.69%	0.00%
		e	0.755	0.717	0.695	0.948	0.829	1.000	0.945	1.000
		QI_1	-1.387	-0.600	-1.599	+0.357	-0.535	+1.000	+0.005	+1.000
		QI_2	--	-3.322	--	+0.936	--	+1.000	--	+1.000
		QI_3	+0.944	+0.912	+0.938	+0.898	+0.950	+1.000	+0.996	+1.000
	increased		Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3
		d^+	1.39%	17.36%	1.39%	0.00%	2.78%	0.00%	3.47%	2.08%
		e	0.701	0.602	0.767	1.000	0.898	1.000	0.718	0.735
		QI_1	+0.271	-0.137	-0.845	+1.000	+0.027	+1.000	-1.516	-1.338
		QI_2	--	+0.400	--	+1.000	--	+1.000	--	-0.861
		QI_3	+0.905	-0.526	+0.932	+1.000	+0.977	+1.000	+0.901	+0.901

Table D.1: Shares of dominating solutions, efficiency values and relative objective-achievement-degrees of DP-solutions (lower 0.5 quantile of DP-solutions' efficiency values)

			Price elasticity							
			regular				increased			
			Resource-related uncertainty				Resource-related uncertainty			
			regular		increased		regular		increased	
Order-related uncertainty	regular		Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3
		d^+	0.00%	0.00%	0.69%	0.00%	0.00%	0.00%	0.00%	0.00%
		e	1.000	1.000	0.755	1.000	1.000	1.000	1.000	1.000
		QI_1	+1.000	+1.000	+0.059	+1.000	+1.000	+1.000	+1.000	+1.000
		QI_2	--	+1.000	--	+1.000	--	+1.000	--	+1.000
		QI_3	+1.000	+1.000	+0.939	+1.000	+1.000	+1.000	+1.000	+1.000
	increased		Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3	Z_1,Z_3	Z_1,Z_2,Z_3
		d^+	2.08%	6.94%	0.69%	0.00%	0.69%	0.00%	0.00%	0.00%
		e	0.704	0.634	0.871	1.000	0.965	1.000	1.000	1.000
		QI_1	-0.104	+0.309	-1.791	+1.000	+0.376	+1.000	+1.000	+1.000
		QI_2	--	+0.399	--	+1.000	--	+1.000	--	+1.000
		QI_3	+0.886	-0.432	+0.985	+1.000	+0.995	+1.000	+1.000	+1.000

Table D.2: Shares of dominating solutions, efficiency values and relative objective-achievement-degrees of DP-solutions (upper 0.5 quantile of DP-solutions' efficiency values)

4 Conclusions

Having observed an existing and increasing need for efficient order promising processes in practice, formed the starting point of the dissertation. In MTO production, decisions on the placement or acceptance of orders and their specifications are made interactively by the customer and the company during order promising. These decisions are not only influenced by the price, but are also affected by non-monetary aspects[1]. Thereby, the aim is to balance growing customer requirements with the company's interests in such a way that the long-term customer satisfaction and the success of the company are ensured. Uncertainty, related to the current and future order and resource situation, complicates this challenge.

Due to this reason, the development of a planning approach for supporting robust order promising has been focused in the dissertation. Thereby, a high level of reliability from the customer's and the company's point of view (i.e. planning robustness and solution robustness) is to be achieved despite occurring uncertainty. In the literature, capable-to-promise (CTP) approaches have already been proposed in this context. These approaches serve for determining reliable answers to customer inquiries based on resource availability.[2] Since general possibilities for designing robust order promising consist of integrating quantitative and/or temporal buffers, or courses of action for possible events in the plan[3]; the existing CTP literature was analyzed with respect to considered problem-related, robustness-generating measures.

The literature review revealed that further research is required for the consideration of multiple measures: (1) A pure production-oriented perspective is predominantly chosen for measure selection. Thus, the potential of customer interaction is not adequately considered in current planning approaches. (2) Furthermore, considered

---

1) Cf. Kingsman et al. (1993), p. 60; Kingsman/Mercer (1997), pp. 251 f.; Stevenson et al. (2005), p. 873.

2) Cf. Ball et al. (2004), p. 449.

3) Cf. Herroelen/Leus (2004), pp. 1602 ff.; Seitz/Grunow (2016), p. 2; Vorst/Beulens (2002), p. 412.

measures handle either order- or resource-related uncertainty in most cases. Multiple adaptation measures to handle uncertainty, originating from both sources, are only occasionally taken into account. (3) In principle, interactions between the measures, as well as the resulting need for a coordinated measure application, remain unconsidered. For these reasons, the following research-leading questions resulted for the present dissertation:

- Which measures for handling order- and resource-related uncertainty are suitable for being integrated in a CTP model, if a high level of robustness and high profitability are strived for during order promising?
- How can customers' responses to order specifications suggested by the company be stronger focused at the same time?
- How do these measures need to be coordinated with respect to the objectives of robustness and profit, taking into account their interactions?

To answer these questions, a hierarchical procedure was successively developed in three papers. According to the influence on decision making, the procedure has been divided into an operative and a tactical level. In accordance with the *operative character* of order promising, a robust CTP model has been developed in the first two papers of the cumulative dissertation. For this purpose, a basic CTP model has been developed in the *first paper,* which is based on the ideas of Chen et al. (2002) and conforms to assumptions common in CTP literature. As common, exclusively order-related uncertainty was assumed, whereas resource availability was considered as deterministic. Under these prevailing conditions, the impact of the already established measures, capacity nesting and quantitative deviation from order specifications (partial deliveries), on profits and planning robustness was analyzed. In addition to these measures, customer interaction was directly modeled in the CTP model by anticipating customer responses to delivery dates which deviate from required specifications. Following Pibernik and Yadav (2008), a discrete acceptance probability was thus modeled, which does not increase with increasing deviation from the required delivery date interval.

The analysis of the developed basic model confirmed that the planning approach is suitable to generate a high level of robustness and a high profitability. In particular, the interaction with customers always proved to be economically advantageous, whereas the advantageousness of the remaining measures seemed to strongly depend on the choice of measure parameters. Moreover, it became apparent that all delivery dates were met due to prescribed general conditions. Thus, the analysis of robustness impacts could exclusively be performed with respect to production decisions, but not to customer requirements. A more differentiated view of the robustness concept was consequently formulated as an objective for further research. In the case of individual robustness impacts of analyzed measures, it appeared that the option of partial deliveries can enhance planning robustness. Negative impacts on planning robustness were detected for the remaining measures. However, further investigations encouraged the assumption that the advantageousness of capacity nesting and proposing modified delivery dates only unfolds in fluctuating resource availability.

Building on the results of the first paper, an extended CTP model for handling order- and resource-related uncertainty was developed in the *second paper*. Revisions of contractually fixed delivery date decisions have been correspondingly permitted to enhance the degree of model authenticity and allow a more differentiated view on the robustness concept. Due to changed environmental conditions, critical scrutinizing measure selection was recommendable: Providing safety capacity, which has often been neglected in CTP approaches, is considered in taking account the resource-related uncertainty along with the established resource-related measure capacity nesting. The high economical potential of customer interaction, identified in the basic model, as well as the supposed positive robustness impacts in case of uncertain resource availability, substantiated the ongoing consideration of proposing modified delivery dates. However, deviating from quantitative order specifications was no longer discussed since the functionality of this measure is similar to the previously mentioned one: In the case of partial deliveries, the delivery date is modified for part of the order.

The question of how far a combinative application of the considered measures proposing deviating delivery dates, capacity nesting and providing safety capacity, can contribute to an enhancement of profitability, as well as planning and solution robustness has been investigated in the numerical analysis of the extended CTP model.

As expected, the robustness-generating measures could not completely cover uncertainty in an economic manner. However, descriptive-statistically evaluating the results of an extensive numerical study revealed the existence of an advantage area. Within this area, the coordinated measure application led to an enhancement of planning and solution robustness, while simultaneously ensuring a high level of profitability. In particular, anticipating customer responses to modified delivery dates unfolded positive impacts on the objectives profitability and robustness. Moreover, the results of the numerical analysis confirmed the need for measure coordination, since the existence of a trade-off between robustness and profitability has been proven outside the identified advantage area.

Thus, a *new hierarchical CTP approach* has been developed in the *third paper*. To take account of the identified potential of proposing modified delivery dates, in an *extended operative CTP model,* the measure has been generalized to proposing modified order specifications pertaining to delivery dates and prices. For this purpose, the discrete one-dimensional response function is transferred to a continuous two-dimensional function. The transition from a discrete to a continuous acceptance probability function was carried out given that an increasing amount of considered dimensions induces a significantly higher solution effort for a discrete than for a continuous function.

On the *tactical level* of decision making, the aim of the hierarchical planning approach was to derive ex ante parameter suggestions for *coordinating measures* with respect to the objectives of profitability, as well as planning and solution robustness. Due to interactions between the measures (proposing modified delivery-date-price combinations, capacity nesting and providing safety capacity) observed in previous numerical analyses, it could not be assumed that coordinated parameter values could be deduced analytically. Therefore, attempts were made to utilize a statistically-founded procedure for the advantageous choice of measure parameters.

The recommendations for parameter choice are based on quantifying measure impacts by optimizing the extended CTP model in a profit-oriented manner. For this purpose, the objective values and robustness effects were recorded for a variety of parameter value combinations in different uncertainty situations. By randomly drawing solutions, the generated solutions were divided into two data bases of equal size (test and verification data). The test data was used to inferential-statistically analyze the results of the extended CTP model. Given the previous model experiments, it had to be assumed that measure impacts on objectives do not only unfold directly, but also indirectly propagate along intermediate variables. Consequently, the method of multi-group path analysis was chosen. It became apparent that hypothetical, as well as formula-conditioned relations between measure parameters, intermediate variables and objectives, have been broadly confirmed by path analysis.

Through acquired insights into CTP model behavior, indications for the choice of coordinated parameter values could be derived; which allow a statistics-oriented, multi-criteria limited search for good parameter values. The test data was thereby searched for parameter value combinations, which are accompanied by a high simultaneous fulfillment of intended objectives. In detail, solutions were sought which are non-dominated with respect to relevant objectives, i.e. have maximum relative efficiency. Since a complete search would involve considerable analysis effort, a procedure for limiting the search to a low proportion of solutions included in the test data is proposed based on the generated statistical results.

Subsequently, the quality of results deduced by the limited search has been evaluated with the verification data. Thereby, solutions corresponding to proposed parameter values were compared to the remaining solutions of the verification data. The shares of dominating solutions, the determined relative efficiencies, as well as relative objective-achievement-degrees were used as comparison criteria. Overall, evaluating the limited search confirmed that exceedingly well coordinated parameter values were found within a relative short time. Thus, the robustness-generating measures have been appropriately coordinated with respect to the objectives of profitability, as well as planning and solution robustness.

In the entire view, the planning approach developed in this dissertation is thus a suitable instrument to support profitable robust order promising.

Against the background of alternative possibilities for formulating the CTP model, the statistical investigation of model behavior and the design of the limited search, the planning approach can be considered as a basic concept which is extendable in multiple ways. Thus, there is a need for further research:

- In addition to the measures so far included, further adaptation measures to cover order- and resource-related uncertainty need to be analyzed with respect to their impacts on robustness and interactions to other measures.

- If further measures are integrated into the CTP model, the path model and the statistically-orientated limited search need to be extended. Thus, the efficiency of the proposed procedure needs to be reevaluated in the extended context.

- The consideration of customer interaction during order promising is to be extended in the planning approach due to the identified high potential of the related measure. Thus, apart from an extension of included modification dimensions, the extension from one to multiple interaction steps is recommendable, for example.

- Further methods of inferential-statistical analysis should be tested for their suitability to identify causal relations of the CTP model. Options for modeling non-linear relations are of particular interest.

References

To avoid redundancies, one bibliography is specified for the whole dissertation. However, to be able to reconstruct the bibliographies of each paper of the cumulative dissertation, literature is labeled as follows: [1)] citation in the first paper (chapter 2.1); [2)] citation in the second paper (chapter 2.2); [3)] citation in the third paper (chapter 3). In contrast, literature only cited in the motivation (chapter 1) or final conclusion (chapter 4) is not labeled for reasons of clarity.

Adam, D.: Produktionsplanung bei Sortenfertigung. Ein Beitrag zur Theorie der Mehrproduktunternehmung, Wiesbaden 1969

Akçay, Y.; Natarajan, H.P.; Xu, S.H.:[3)] Joint dynamic pricing of multiple perishable products under consumer choice, in: Management Science, Vol. 56 (2010), pp. 1345-1361

Aouam, T.; Brahimi, N.:[3)] Integrated production planning and order acceptance under uncertainty: A robust optimization approach, in: European Journal of Operational Research, Vol. 228 (2013), pp. 504-515

Ata, B.; Olsen, T.L.:[3)] Near-optimal dynamic lead-time quotation and scheduling under convex-concave customer delay costs, in: Operations Research, Vol. 57 (2009), pp. 753-768

Bagozzi, R.P.; Yi, Y.:[3)] Specification, evaluation, and interpretation of structural equation models, in: Journal of the Academy of Marketing Science, Vol. 40 (2012), pp. 8-34

Ball, M.O.; Chen, C.-Y.; Zhao, Z.-Y.:[2)] Available to promise, in: Handbook of Quantitative Supply Chain Analysis: Modeling in the E-Business Era, D. Simchi-Levi, ed. by S.D. Wu and Z.M. Shen, New York 2004, pp. 447-483

Baumgartner, H.; Homburg, C.:[3)] Applications of structural equation modeling in marketing and consumer research: A review, in: International Journal of Research in Marketing, Vol. 13 (1996), pp. 139-161

Bertini, M.; Wathieu, L.: Attention arousal through price partitioning, in: Marketing Science, Vol. 27 (2008), pp. 236-246

Boyaci, T.; Ray, S.:[3)] Product differentiation and capacity cost interaction in time and price sensitive markets, in: Manufacturing & Service Operations Management, Vol. 5 (2003), pp. 18-36

Carlson, J.P.; Weathers, D.: Examining differences in consumer reactions to partitioned prices with a variable number of price components, in: Journal of Business Research, Vol. 61 (2008), pp. 724-731

Chaharsooghi, S.K.; Honarvar, M.; Modarres, M.; Kamalabadi, I.N.:[3] Developing a two stage stochastic programming model of the price and lead-time decision problem in the multi-class make-to-order firm, in: Computers & Industrial Engineering, Vol. 61 (2011), pp. 1086-1097

Charnes, A.; Cooper, W.W.:[2), 3)] Chance-constrained programming, in: Management Science, Vol. 6 (1959), pp. 73-79

Charnes, A.; Cooper, W.W.; Rhodes, E.:[3] Measuring the efficiency of decision making units, in: European Journal of Operational Research, Vol. 2 (1978), pp. 429-444

Charnsirisakskul, K.; Griffin, P.M.; Keskinocak, P.:[3] Order selection and scheduling with leadtime flexibility, in: IIE Transactions, Vol. 36 (2004), pp. 697-707

Charnsirisakskul, K.; Griffin, P.M.; Keskinocak, P.:[3] Pricing and scheduling decisions with leadtime flexibility, in: European Journal of Operational Research, Vol. 171 (2006), pp. 153-169

Chen, J.; Dong, M.:[2), 3)] Available-to-promise-based flexible order allocation in ATO supply chains, in: International Journal of Production Research, Vol. 52 (2014), pp. 6717-6738

Chen, C.Y.; Zhao, Z.; Ball, M.O.:[2), 3)] Quantity and due date quoting available to promise, in: Information System Frontiers, Vol. 3 (2001), pp. 477-488

Chen, C.Y.; Zhao, Z.; Ball, M.O.:[1), 3)] A model for batch advanced available-to-promise, in: Production and Operations Management, Vol. 11 (2002), pp. 424-440

Cheng, C.-B.; Cheng, C.-J.:[3] Available-to-promise based bidding decision by fuzzy mathematical programming and genetic algorithm, in: Computers & Industrial Engineering , Vol. 61 (2011), pp. 993-1002

Chevalier, P.; Lamas, A.; Lu, L.; Mlinar, T.:[3] Revenue management for operations with urgent orders, in: European Journal of Operational Research, Vol. 240 (2015), pp. 476-487

Chiang, D.M.-H.; Wu, A.W.-D.:[2] Discrete-order admission ATP model with joint effect of margin and order size in a MTO environment, in: International Journal of Production Economics, Vol. 133 (2011), pp. 761-775

Chin, W.W.:[3)] The partial least squares approach to structural equation modeling, in: Modern methods for business research, ed. by G.A. Marcoulides, Erlbaum 1998, pp. 295-336

Choi, T.-M.; Wang, M.; Yue, X.:[3)] Emerging production optimization issues in supply chain systems, in: Annals of Operational Research, Vol. 240 (2016), pp. 381-393

Christou, I.T.; Ponis, S.:[2)] A hierarchical system for effective coordination of available-to-promise logic mechanisms, in: International Journal of Production Research, Vol. 47 (2009), pp. 3063-3078

Cook, W.D.; Ton, K.; Zhu, J.:[3)] Data envelopment analysis: Prior to choosing a model, in: Omega, Vol. 44 (2014), pp. 1-4

Duenyas, I.:[3)] Single facility due date setting with multiple customer classes, in: Management Science, Vol. 41 (1995), pp. 608-619

Duenyas, I.; Hopp, W.J.:[3)] Quoting customer lead times, in: Management Science, Vol. 41 (1995), pp. 43-57

Dumas, M.; Aldred, L.; Governatori, G.; Hofstede, A.H.M. ter:[2)] Probabilistic automated bidding in multiple auctions, in: Electronic Commerce Research, Vol. 5 (2005), pp. 25-49

Easton, F.F.; Moodie, D.R.:[3)] Pricing and lead time decisions for make-to-order firms with contingent orders, in: European Journal of Operational Research, Vol. 116 (1999), pp. 305-318

Engelbrecht-Wiggans, R.:[2), 3)] Auctions and bidding models: A survey, in: Management Science, Vol. 26 (1980), pp. 119-142

Fischer, M.E.: „Available-to-Promise": Aufgaben und Verfahren im Rahmen des Supply Chain Management, Regensburg 2001

Framinan, J.M.; Leisten, R.:[3)] Available-to-promise (ATP) systems: A classification and framework for analysis, in: International Journal of Production Research, Vol. 48 (2010), pp. 3079-3103

Friedman, L.: A competitive-bidding strategy, in: Operations Research, Vol. 4 (1956), pp. 104-112

Gabor, A.; Granger, C.W.J.:[3)] Price sensitivity of the consumer, in: Journal of Advertising Research, Vol. 4 (1964), pp. 40-44

Galbraith, J.: Designing complex organizations, Reading, Massachusetts et al. 1973

Gao, L.; Xu, S.H.; Ball, M.O.:[1), 2), 3)] Managing an available-to-promise assembly system with dynamic short-term pseudo-order forecast, in: Management Science, Vol. 58 (2012), pp. 770-790

Gössinger, R.; Kalkowski, S.: Order promising - A robust customer-oriented approach, in: Logistics Management. Products, Actors, Technology - Proceedings of the German Academic Association for Business Research, Bremen 2013, ed. by J. Dethloff et al., Cham et al. 2015, pp. 135-149

Gössinger, R.; Kalkowski, S.:[3)] Robust order promising with anticipated customer response, in: International Journal of Production Economics, Vol. 170 (2015), pp. 529-542

Gössinger, R.; Kalkowski, S.:[3)] Zuverlässige Auftragsvereinbarung - Entwurf eines statistisch fundierten Planungsansatzes, Nr. 11 der Diskussionsbeiträge zum Produktions- und Logistikmanagement, Dortmund 2016

Goodman, D.; Baurmeister, H.: A computational algorithm for multi-contract bidding under constraints, in: Management Science, Vol. 22 (1976), pp. 788-798

Greenleaf, E.A.; Johnson, E.J.; Morwitz, V.G.; Shalev, E.: The price does not include additional taxes, fees and surcharges: A review of research on partitioned pricing, in: Journal of Consumer Psychology, Vol. 26 (2016), pp. 105-124

Grillo, H.; Alemany, M.M.E.; Ortiz, A.:[3)] A review of mathematical models for supporting the order promising process under lack of homogeneity in product and other sources of uncertainty, in: Computers & Industrial Engineering, Vol. 91 (2016), pp. 239-261

Guhlich, H.; Fleischmann, M.; Stolletz, R.:[3)] Revenue management approach to due date quoting and scheduling in an assemble-to-order production system, in: OR Spectrum, Vol. 37 (2015), pp. 951-982

Guillén, G.; Pina, C.; Espuña, A.; Puigjaner, L.:[2), 3)] Optimal offer proposal policy in an integrated supply chain management environment, in: Industrial & Engineering Chemistry Research, Vol. 44 (2005), pp. 7405-7419

Halim, T.; Muthusamy, K.:[1), 2), 3)] Fuzzy available-to-promise system modelling under supplier uncertainty, in: Advanced Materials Research, Vols. 383-390 (2012), pp. 4535-4540

Harris, F.H. deB.; Pinder, J.P.:[1), 2), 3)] A revenue management approach to demand management and order booking in assemble-to-order manufacturing, in: Journal of Operations Management, Vol. 13 (1995), pp. 299-309

Hempsch, C.; Sebastian, H.-J.; Bui, T.:[3] Solving the order promising impasse using multi-criteria decision analysis and negotiation, in: Logistics Research, Vol. 6 (2013), pp. 25-41

Herroelen, W.; Leus, R.:[2] Robust and reactive project scheduling: A review and classification of procedures, in: International Journal of Production Research, Vol. 42 (2004), pp. 1599-1620

Jacob, H.:[1), 2), 3] Zur optimalen Planung des Produktionsprogramms bei Einzelfertigung, in: Zeitschrift für Betriebswirtschaft, Vol. 41 (1971), pp. 495-516

Jeong, B.; Sim, S.-B.; Jeong, H.-S.; Kim, S.-W.:[1), 2] An available-to-promise system for TFT LCD manufacturing in supply chain, in: Computers & Industrial Engineering, Vol. 43 (2002), pp. 191-212

Jung, H.:[3] An available-to-promise model considering customer priority and variance of penalty costs, in: International Journal of Advanced Manufacturing Technology, Vol. 49 (2010), pp. 369-377

Jung, H.:[1), 2), 3] An available-to-promise process considering production and transportation uncertainties and multiple performance measures, in: International Journal of Production Research, Vol. 50 (2012), pp. 1780-1798

Kahneman, D.; Knetsch, J.L.; Thaler, R.:[3] Fairness as a constraint on profit seeking: Entitlements in the market, in: The American Economic Review, Vol. 76 (1986), pp. 728-741

Kaminsky, P.; Kaya, O.:[3] Scheduling and due-date quotation in a make-to-order supply chain, in: Naval Research Logistics, Vol. 55 (2008), pp. 444-458

Keskinocak, P.; Ravi, R.; Tayur, S.:[3] Scheduling and reliable lead-time quotation for orders with availability intervals and lead-time sensitive revenues, in: Management Science, Vol. 47 (2001), pp. 264-279

Kilger, C.; Meyr, H.: Demand fulfilment and ATP, in: Supply Chain Management and Advanced Planning. Concepts, Models, Software, and Case Studies, ed. by H. Stadtler and C. Kilger, 4th edition, Berlin 2008

Kimms, A.:[1), 2), 3] Stability measures for rolling schedules with applications to capacity expansion planning, master production scheduling, and lot sizing, in: Omega, Vol. 26 (1998), pp. 355-366

King, M.; Mercer, A.:[2), 3] Recurrent competitive bidding, in: European Journal of Operational Research, Vol. 33 (1988), pp. 2-16

Kingsman, B.G.; Mercer, A.:[2), 3)] Strike rate matrices for integrating marketing and production during the tendering process in make-to-order subcontractors, in: International Transactions in Operational Research, Vol. 4 (1997), pp. 251-257

Kingsman, B.[G.]; Worden, L.; Hendry, L.; Mercer, A.; Wilson, E.:[2), 3)] Integrating marketing and production planning in make-to-order companies, in: International Journal of Production Economics, Vols. 30/31 (1993), pp. 53-66

Kline, R.B.:[3)] Principles and practice of structural equation modeling, New York 2005

Laux, H.: Auftragsselektion bei Unsicherheit, in: Zeitschrift für betriebswirtschaftliche Forschung, Vol. 23 (1971), pp. 164-180

Lečić-Cvetković, D.; Atanasov, N.; Babarogić, S.:[1), 2)] An algorithm for customer order fulfillment in a make-to-stock manufacturing system, in: International Journal of Computers, Communications & Control, Vol. 5 (2010), pp. 783-791

Lim, C.H.; Halim, T.:[1), 3)] Intelligent available-to-promise system under manufacturing uncertainty, in: Proceedings of the 2011 IEEE 5th International Conference on Cybernetics and Intelligent Systems (CIS 2011), Qingdao, 17th - 19th September 2011, ed. by Institute of Electrical and Electronics Engineers (IEEE), Piscataway 2011, pp. 300-305

Lin, J.T.; Hong, I.-H.; Wu, C.-H.; Wang, K.-S.:[3)] A model for batch available-to-promise in order fulfillment processes for TFT-LCD production chains, in: Computers & Industrial Engineering, Vol. 59 (2010), pp. 720-729

Liu, L.; Parlar, M.; Zhu, S.X.:[3)] Pricing and lead time decisions in decentralized supply chains, in: Management Science, Vol. 53 (2007), pp. 713-725

Lu, L.; Liu, Z.; Qi, X.:[3)] Coordinated price quotation and production scheduling for uncertain order inquiries, in: IIE Transactions, Vol. 45 (2013), pp. 1293-1308

Manavizadeh, N.; Goodarzi, A.H.; Rabbani, M.; Jolai, F.:[3)] Order acceptance/ rejection policies in determining the sequence in mixed model assembly lines, in: Applied Mathematical Modelling, Vol. 37 (2013), pp. 2531-2551

Mansouri, S.A.; Gallear, D.; Askariazad, M.H.:[2), 3)] Decision support for build-to-order supply chain management through multiobjective optimization, in: International Journal of Production Economics, Vol. 135 (2012), pp. 24-36

Martínez, E.; Arredondo, F:[3)] Order acceptance for revenue management and capacity allocation in make-to-order batch plants, in: Proceedings of the 20th Symposium on Computer Aided Process Engineering (ESCAPE-20), Ischia, 6th - 9th June 2010, ed. by S. Pierucci and G. Buzzi Ferraris, Amsterdam et al. 2010, pp. 1189-1194

Moodie, D.R.:[3)] Demand management: The evaluation of price and due date negotiation strategies using simulation, in: Production and Operations Management, Vol. 8 (1999), pp. 151-162

Moodie, D.R.; Bobrowski, P.M.:[3)] Due date demand management: Negotiating the trade-off between price and delivery, in: International Journal of Production Research, Vol. 37 (1999), pp. 997-1021

Mulvey, J.M.; Vanderbei, R.J.; Zenios, S.A.:[2), 3)] Robust optimization of large-scale systems, in: Operations Research, Vol. 43 (1995), pp. 264-281

Palaka, K.; Erlebacher, S.; Kropp, D.H.:[3)] Lead-time setting, capacity utilization, and pricing decisions under lead-time dependent demand, in: IIE Transactions, Vol. 30 (1998), pp. 151-163

Pan, A.; Choi, T.-M.:[3)] An agent-based negotiation model on price and delivery date in a fashion supply chain, in: Annals of Operations Research, Vol. 242 (2016), pp. 529-557

Pekgün, P.; Griffin, P.M.; Keskinocak, P.:[3)] Coordination of marketing and production for price and leadtime decisions, in: IIE Transactions, Vol. 40 (2008), pp. 12-30

Pesch, J.: Marketing, 2nd edition, Konstanz et. al 2010

Pibernik, R.:[3)] Ausgewählte Methoden und Verfahren zur Unterstützung des Advanced Available to Promise, in: Zeitschrift für Planung, Vol. 13 (2002), pp. 345-372

Pibernik, R.:[1), 2), 3)] Advanced available-to-promise: Classification, selected methods and requirements for operations and inventory management, in: International Journal of Production Economics, Vols. 93/94 (2005), pp. 239-252

Pibernik, R.; Yadav, P.:[1), 2), 3)] Dynamic capacity reservation and due date quoting in a make-to-order system, in: Naval Research Logistics, Vol. 55 (2008), pp. 593-611

Pujawan, I.N.; Smart, A.U.:[2), 3)] Factors affecting schedule instability in manufacturing companies, in: International Journal of Production Research, Vol. 50 (2012), pp. 2252-2266

Ray, S.; Jewkes, E.M.:[3)] Customer lead time management when both demand and price are lead time sensitive, in: European Journal of Operational Research, Vol. 153 (2004), pp. 769-781

Renna, P.; Argoneto, P.:[2)] Production planning and automated negotiation for SMEs: An agent based e-procurement application, in: International Journal of Production Economics, Vol. 127 (2010), pp. 73-84

Robbert, T.; Roth, S.: The flip side of drip pricing, in: Journal of Product & Brand Management, Vol. 23 (2014), pp. 413-419

Robinson, A.G.; Carlson, R.C.:[1), 2)] Dynamic order promising: Real-time ATP, in: International Journal of Integrated Supply Management, Vol. 3 (2007), pp. 283-301

Roelofs, M.; Bisschop, J.:[1)] AIMMS. The language reference, Aimms 4, 29th March 2016, Haarlem, available: http://download.aimms.com/aimms/download/manuals/AIMMS3_LR.pdf (access 7th April 2016)

Rothkopf, M.H.; Harstad, R.M.:[3)] Modeling competitive bidding: A critical essay, in: Management Science, Vol. 40 (1994), pp. 364-384

Roy, B.:[2), 3)] Robustness in operational research and decision aiding: A multi-faceted issue, in: European Journal of Operational Research, Vol. 200 (2010), pp. 629-638

Schneeweiss, C.:[3)] Hierarchical planning in organizations: Elements of a general theory, in: International Journal of Production Economics, Vols. 56/57 (1998), pp. 547-556

Scholl, A.: Robuste Planung und Optimierung. Grundlagen - Konzepte und Methoden - Experimentelle Untersuchungen, Heidelberg 2001

Schwendinger, J.: Master production scheduling's available to promise, in: Twenty First Annual Conference Proceedings, Hollywood, 24th - 27th October 1978, ed. by American Production and Inventory Control Society, Washington, D.C., 1979, pp. 316-330

Seitz, A.; Grunow, M.:[3)] Increasing accuracy and robustness of order promises, in: International Journal of Production Research, Vol. 55 (2017), pp. 656-670

Shen, Z.-J.M.; Su, X.:[3)] Customer behavior modeling in revenue management and auctions: A review and new research opportunities, in: Production and Operations Management, Vol. 16 (2007), pp. 713-728

Simmonds, K.:[2), 3)] Competitive Bidding: Deciding the best combination of non-price features, in: Operational Research Quarterly, Vol. 19 (1968), pp. 5-14

So, K.C.; Song, J.-S.:[3)] Price, delivery time guarantees and capacity selection, in: European Journal of Operational Research, Vol. 111 (1998), pp. 28-49

Spengler, T.; Rehkopf, S.; Volling, T.:[3)] Revenue management in make-to-order manufacturing - An application to the iron and steel industry, in: OR Spectrum, Vol. 29 (2007), pp. 157-171

Sridharan, S.V.; Berry, W.L.; Udayabhanu, V.:[2)] Measuring master production schedule stability under rolling planning horizons, in: Decision Sciences, Vol. 19 (1988), pp. 147-166

Stark, R.M.; Mayer, R.H.: Some multi-contract decision-theoretic competitive bidding models, in: Operations Research, Vol. 19 (1971), pp. 469-483

Stark, R.M.; Rothkopf, M.H.:[2), 3)] Competitive bidding: A comprehensive bibliography, in: Operations Research, Vol. 27 (1979), pp. 364-390

Stevenson, M.; Hendry, L.C.; Kingsman, B.G.:[2), 3)] A review of production planning and control: The applicability of key concepts to the make-to-order industry, in: International Journal of Production Research, Vol. 43 (2005), pp. 869-898

Talluri, K.T.; Ryzin, G.J. van:[3)] The theory and practice of revenue management, New York 2005

Taylor, S.G.; Plenert, G.J.: Finite capacity promising, in: Production and Inventory Management Journal: Journal of the American Production and Inventory Control Society, Vol. 40 (1999), pp. 50-56

Thürer, M.; Stevenson, M.; Silva, C.; Land, M.J.; Fredendall, L.D.; Melnyk, S.A.:[2)] Lean control for make-to-order companies: Integrating customer enquiry management and order release, in: Production and Operations Management, Vol. 23 (2014), pp. 463-476

Vilko, J.; Ritala, P.; Edelmann, J.:[3)] On uncertainty in supply chain risk management, in: International Journal of Logistics Management, Vol. 25 (2014), pp. 3-19

Volling, T.; Akyol, D.E.; Wittek, K.; Spengler, T.S.:[3)] A two-stage bid-price control for make-to-order revenue management, in: Computers & Operations Research, Vol. 39 (2012), pp. 1021-1032

Vorst, J.G.A.J. van der; Beulens, A.J.M.: Identifying sources of uncertainty to generate supply chain redesign strategies, in: International Journal of Physical Distribution & Logistics Management, Vol. 32 (2002), pp. 409-430

Wallace, T.F.; Dougherty, J.R.: APICS Dictionary, Falls Church 1987

Wangenheim, F. von; Bayón, T.:[3)] Behavioral consequences of overbooking service capacity, in: Journal of Marketing, Vol. 71 (2007), pp. 36-47

Watanapa, B.; Techanitisawad, A.:[3)] Simultaneous price and due date setting for multiple customer classes, in: European Journal of Operational Research, Vol. 166 (2005), pp. 351-368

Webster, S.:[3)] Dynamic pricing and lead-time policies for make-to-order systems, in: Decision Sciences, Vol. 33 (2002), pp. 579-599

Wertenbroch, K.; Skiera, B.:[3)] Measuring consumers' willingness to pay at the point of purchase, in: Journal of Marketing Research, Vol. 39 (2002), pp. 228-241

West, S.G.; Finch, J.F.; Curran, P.J.:[3] Structural equation models with nonnormal variables, in: Structural equation modeling. Concepts, issues and applications, ed. by R.H. Hoyle, Sage 1995, pp. 56-75

Wright, S.:[3] Correlation and causation, in: Journal of Agricultural Research, Vol. 20 (1921), pp. 557-585

Wright, S.:[3] The method of path coefficients, in: The Annals of Mathematical Statistics, Vol. 5 (1934), pp. 161-215

Wu, H.-H.; Liu, J.-Y.: A capacity available-to-promise model for drum-buffer-rope systems, in: International Journal of Production Research, Vol. 46 (2008), pp. 2255-2274

Xiao, T.; Shi, J.; Chen, G.:[3] Price and leadtime competition for make-to-order supply chains, in: Computers & Industrial Engineering, Vol. 68 (2014), pp. 23-34

Xiong, M.; Tor, S.B.; Khoo, L.P.; Chen, C.-H.: A web-enhanced dynamic BOM-based available-to-promise system, in: International Journal of Production Economics, Vol. 84 (2003), pp. 133-147

Yang, W.; Fung, R.Y.K.:[3] An available-to-promise decision support system for a multi-site make-to-order production system, in: International Journal of Production Research, Vol. 52 (2014), pp. 4253-4266

Zhang, Q.; Tseng, M.M.:[3] Modelling and integration of customer flexibility in the order commitment process for high mix low volume production, in: International Journal of Production Research, Vol. 47 (2009), pp. 6397-6416

Zhao, Z.; Ball, M.O.; Kotake, M.:[1, 2, 3] Optimization-based available-to-promise with multi-stage resource availability, in: Annals of Operations Research, Vol. 135 (2005), pp. 65-85

Zhao, X.; Stecke, K.E.; Prasad, A.:[3] Lead time and price quotation mode selection uniform or differentiated, in: Production and Operations Management, Vol. 21 (2012), pp. 177-193