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Value-based performance and risk management in supply chains: A robust optimization approach

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A B S T R A C T

Integrated performance and risk management is the key lever to increase shareholder value holistically. In this paper, we develop a corresponding framework for value-based performance and risk optimization in supply chains. Economic Value Added (EVA) as a prevalent metric of value-based performance is applied to mid-term sales and operations planning (S&OP). Robust optimization methods are utilized to deal with operational risks in physical and financial supply chain management due to the uncertainty of future events. Multiple aspects of robustness and general implications of the framework are highlighted using a case-oriented numerical analysis.

1. Introduction

Creating shareholder value is commonly considered the paramount business goal (Young and O'Byrne, 2001) and requires an integrated approach to performance and risk management (cf. Ritchie and Brindley, 2007; Oehmen et al., 2009). Value-based management (VBM) provides a corresponding framework utilizing value driver trees and risk-adjusted performance metrics as major concepts for performance and risk management (Kaplan and Atkinson, 1998). Value driver trees drill down a top-level performance metric into operational levers for performance management (Rappaport, 1998). Risk implications are considered within the performance metrics via risk-adjusted cost of capital (Young and O'Byrne, 2001). From an operations research perspective, there are two major drawbacks of this common VBM approach. First, value driver trees are only explanatory frameworks and do not provide decision support. Second, risk implications are only covered indirectly omitting scenario-based information to derive robust plans.

Conceptual frameworks for value-based performance (cf. Walters, 1999; Lambert and Pohlen, 2001) and risk management (cf. Cavinato, 2004; Oehmen et al., 2009) are widely discussed in the supply chain context. Lainez et al. (2009) and Hahn and Kuhn (2011) provide decision models for value-based performance optimization at the long-term and mid-term level of supply chain management. However, the authors cover risk implications only indirectly via risk-adjusted cost of capital and the management of supplier–customer relationships. Therefore, the aim of this paper is to develop a framework for integrated value-based performance and risk optimization with a primary focus on the mid-term level. Robust optimization methods are applied to account for the risk-averse attitude of corporate decision-makers and to immunize financial performance against the impact of imperfect information (cf. Mulvey et al., 1995; Bai et al., 1997).

The remainder of this paper is structured as follows: Section 2 provides a literature review on decision-oriented approaches to financial performance and risk management in supply chains as well as robust optimization methods. The conceptual framework for value-based performance and risk optimization is derived in Section 3. In Section 4, a corresponding decision model for the supply chain context is presented. Multiple aspects of robustness and general implications of the framework are highlighted in Section 5 using a case-oriented example. Section 6 concludes the paper with a summary of the findings and an outlook for further research.

2. Literature review

Recent papers show increasing interest in decision-oriented approaches to financial performance and risk management. Guillen et al. (2007) optimize change in equity as a financial performance metric in their approach for integrated supply chain planning and scheduling in the chemical industry. Comelli et al. (2008) combine supply chain master planning with activity-based costing for aggregated supply chain processes. Bertel et al. (2008) maximize average cash position in their decision model for operational supply chain planning based on a flow shop scheduling

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formulation. Hahn and Kuhn (2011) develop a deterministic decision framework to optimize Economic Value Added (EVA) as a value-based performance metric at the mid-term level of sales and operations planning (S&OP). As opposed to the three aforementioned papers, the authors consider risk implications at least indirectly via risk-adjusted cost of capital in the calculation of EVA.

OR-based approaches to risk management mainly focus on the physical domain of supply chain management and omit financial implications (cf. Tang, 2006). Pongsakdi et al. (2006) and You et al. (2009) provide two-stage stochastic programming approaches to risk management in chemical supply chains. Pongsakdi et al. (2006) investigate a case study in refinery operations planning and utilize risk curves as well as the sample average approximation method to reduce risk impact. You et al. (2009) evaluate different risk metrics and their implications for global supply chain planning. Multi-stage frameworks for risk management are provided in Goh et al. (2007) and Sodhi and Tang (2009). However, only Sodhi and Tang (2009) consider material and financial flows simultaneously in their approach to supply chain risk management motivated by asset–liability management.

Mulvey et al. (1995) introduce robust optimization as a generalization of stochastic programming focusing on optimality and feasibility of the solution. An alternative approach to robust optimization is provided in Kouvelis et al. (1992) mainly focusing on the worst-case scenario. As a consequence, their approach omits scenario probabilities and does not utilize scenario-specific control variables in the decision model (Scholl, 2001). Properties of risk-averse utility functions in robust optimization are examined in Bai et al. (1997). Scholl (2001) develops a generalized framework for robust planning and optimization. Bayraksan and Morton (2006), Kaut and Wallace (2007), and Zenios (2007) investigate the impact of scenario generation methods on the robustness of results. Whilst Zenios (2007) focuses on statistical quality criteria to evaluate the generated scenario set, Bayraksan and Morton (2006) and Kaut and Wallace (2007) consider decision quality to decide whether the approach leads to superior decisions or not.

A large body of literature deals with stochastic production and supply chain planning to cover different sources of risk (cf. Wang and Liang, 2005; Mula et al., 2006). Robust optimization methods according to the aforementioned concepts are applied to problems in supply chain master planning at the mid-term level in Yu and Li (2000) and Leung et al. (2007). Eppen et al. (1989), Bok et al. (1998), and Aghezzaf (2005) investigate robust approaches to capacity expansion and facility location planning at the long-term level.

In summary, stochastic programming and robust optimization methods are prevalent in physical supply chain planning as well as financial performance and risk management. However, current decision frameworks only consider selected aspects and do not provide a comprehensive robust approach to value-based performance and risk optimization. Therefore, we extend the value-based optimization approach of Hahn and Kuhn (2011) towards a robust framework for integrated performance and risk management. Implications for scenario generation are considered to account for robustness from both the data and the decision model perspective.

3. Conceptual approach

3.1. Value-based performance and risk management

Business creates shareholder value if earnings exceed total costs of invested capital (Rappaport, 1998). We utilize the EVA concept as a prevalent metric of value-based performance at the mid-term level (cf. Young and O'Byrne, 2001). In (1), *EVA* in period t is calculated from net operating profit after tax *NOPAT* in period t minus total costs of invested capital in net operating assets *NOA* at the end of the previous period $t-1$ considering weighted average cost of capital i^{wacc} (Kaplan and Atkinson, 1998).

$$EVA_t = NOPAT_t - NOA_{t-1} \cdot i^{wacc} \tag{1}$$

Since shareholder value creation is a composite function of multiple interdependent factors, value driver trees are common frameworks to illustrate causal relationships between operational levers and a value-based performance indicator such as EVA (Rappaport, 1998). Walters (1999) identifies three relevant operational value drivers from a mid-term planning perspective. Customer retention and sales growth as well as synergies from the integration with supply chain partners increase *operating profit margin*. Improved capacity management drives cost efficiency in operations and enhances *asset utilization*. Working capital management shortens the cash conversion cycle and increases *operational cash flow*.

Although an integrated approach to performance and risk management is required to increase financial performance holistically (cf. Stulz, 1996), the aforementioned frameworks for value-based performance management consider risk impact indirectly via risk-adjusted cost of capital. However, a direct approach to risk management is recommended to consider comprehensive scenario-based information instead of the expected value of the distribution.

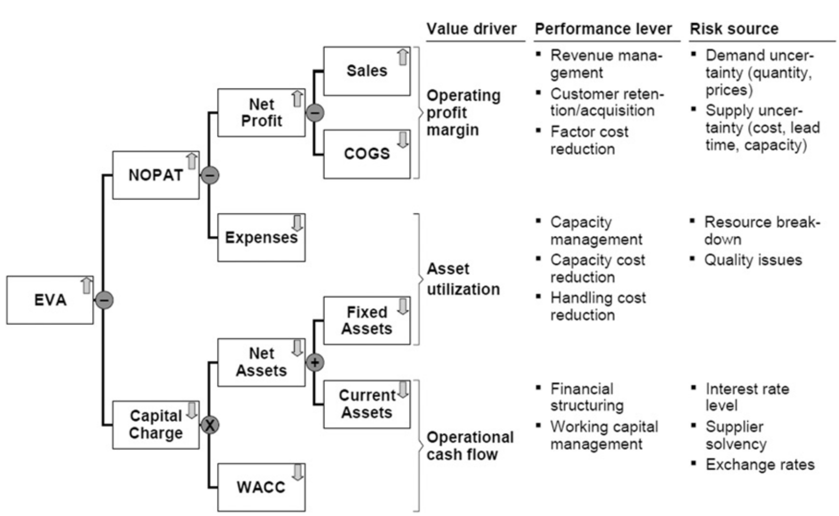

Fig. 1. Value-based performance and risk drivers.

To avoid misinterpretations regarding risk considerations in the cost of capital (cf. Young and O'Byrne, 2001), we assume an externally predefined hurdle rate in the following.

There are various approaches to describe and classify risks in supply chain management (cf. Waters, 2007). However, two general types of risk can be distinguished according to Tang (2006): *disruption* risks cover natural and man-made disasters such as floods or major economic crises; *operational* risks relate to the uncertainty of future events in the ordinary course of business. Due to the focus of this paper on mid-term S&OP, we cover operational risks and integrate corresponding sources of risk into the EVA-based framework for value-based planning and management as described in Fig. 1.

Risk management approaches can be classified into four categories (Mullai, 2008): risk *avoidance* aims at eliminating the source of risk. Risk *mitigation* reduces the probability and/or the business impact of potential risks (Oehmen et al., 2009). Cooperation contracts and insurances can be used for risk *sharing* with business partners or other parties (Ritchie and Brindley, 2007). Risk *adoption* is a passive approach and does not pursue any action (Waters, 2007). OR-based approaches to risk management such as stochastic programming and robust optimization anticipate risks and develop contingency plans to mitigate risk impact (Scholl, 2001).

3.2. Integrated performance and risk optimization

Decision theory commonly resorts to variance-based ('symmetric') measures to quantify the variability of possible outcomes in both an upward and downward directions (March and Shapira, 1987). In contrast, corporate risk management takes a more managerial perspective to assess risk focusing on 'asymmetric' downside risk (March and Shapira, 1987; Stulz, 1996). A generalized definition of downside risk is given in Fishburn (1977) with the concept of lower partial moments (LPM):

$$LPM(\Omega,q) = \sum_{s \in S} pr_s \cdot \max\{0; \Omega - Z_s\}^q \tag{2}$$

S is the set of discrete scenarios s with the probabilities pr. Ω denotes the aspiration level for the value of the objective function Z in scenario s. q covers the level of risk aversion deriving expected downside risk for $q=1$. Higher levels of risk aversion can be implemented with $q>1$. For $q=0$, the LPM results in the probabilistic definition of risk (Barbaro and Bagajewicz, 2004) and represents a risk-seeking decision-maker (Nawrocki, 1999).

Since the EVA concept contains an internal benchmark of 0, i.e., that total costs of capital are covered, a decision-maker balances the upside potential of creating economic value ($EVA>0$) and the downside risk of destroying economic value ($EVA<0$). We define downside risk (DR) as the first-order lower partial moment $LPM(0,1)$ with the aspiration level 0; upside potential (UP) is derived as the complementary upper partial moment. Utilizing the risk preference parameter $\delta \in (0;1]$, the objective function in (3) covers the full range the risk preferences from risk-averse ($\delta \to 0$) to risk-seeking ($\delta = 1$).

$$\Phi(\delta) = \delta \cdot UP - (1-\delta) \cdot DR \tag{3}$$

For $\delta = 0.5$, the objective function equates to the risk-neutral expected value criterion since upside potential and downside risk complement one another to the expected value of the entire distribution.

Robust optimization assumes a risk-averse decision-maker (Scholl, 2001) and thus an objective function only covering the spectrum of risk-averse preferences is sufficient. Applying the concepts of upside potential and downside risk, the resulting objective function is

$$\begin{aligned} \Phi'(\gamma) &= \gamma \cdot UP - DR = \gamma \cdot (UP - DR) - (1-\gamma) \cdot DR \\ &= \gamma \cdot EV - (1-\gamma) \cdot DR \end{aligned} \tag{4}$$

with $\gamma \in (0;1]$. UP becomes obsolete since upside potential and downside risk complement one another to the expected value (EV). $\gamma = 1$ results in the risk-neutral expected value criterion and $\gamma \to 0$ represents a highly risk-averse preference. In contrast to the objective function in (3), (4) can be implemented without binary auxiliary variables (cf. Section 4.1).

3.3. Robust optimization methods

Robust optimization represents a generalization of stochastic programming explicitly considering the risk-averse preference of the decision-maker and thus aims at deriving plans that are sufficiently insensitive to the influence of imperfect information (Scholl, 2001). In our approach, we build on the fundamental robustness concepts developed in Mulvey et al. (1995) and apply two-stage stochastic programming as described in Birge and Louveaux (1997). Thus, we utilize scenario-independent structural variables ('here-and-now' decisions) and scenario-specific control variables ('wait-and-see' decisions) in the optimization model (Birge and Louveaux, 1997).

Approaches to robust optimization distinguish two conflicting criteria of robustness (cf. Mulvey et al., 1995): solutions are considered *model robust* if they are 'almost' feasible for each scenario and *solution robust* if they are 'close' to optimal for each scenario. Furthermore, we focus on objective robustness to ensure a certain aspiration level is attained in 'almost' every scenario (Scholl, 2001). Probabilistic constraints and control variables are methods to quantify and manage model robustness but could lead to partially infeasible solutions for individual scenarios (Birge and Louveaux, 1997). Therefore, we apply a completely model robust 'fat solution' design to obtain decisive and feasible solutions for each scenario although this implies a high level of risk aversion (Kall and Wallace, 1994).

The decision-maker balances solution and objective robustness depending on the risk preference parameter in the objective function. Utilizing the objective function in (4), we obtain relative solution robustness for a risk-neutral decision-maker with $\gamma = 1$ (Scholl, 2001) corresponding to the mean-value approach typically applied in stochastic programming (cf. Birge and Louveaux, 1997). For $\gamma \to 0$, a highly risk-averse decision-maker mainly focuses on objective robustness with respect to the aspiration level implemented in the downside risk measure. Furthermore, we calculate the expected value of perfect information (EVPI) to quantify the impact of uncertainty. The EVPI equals the maximum amount a decision-maker is willing to pay for perfect information and is derived as the difference between the objective value of the here-and-now and the wait-and-see approach (Birge and Louveaux, 1997).

Finally, we consider information robustness and require results to be sufficiently independent of the level of information applied in the decision model (Scholl, 2001). The level of information is mainly affected by the scenario generation method determining the size of the discrete scenario set (Birge and Louveaux, 1997; Di Domenica et al., 2007). Since we aim at limiting the number of contingency plans to a manageable size, we determine a relatively information robust size for the scenario set. According to Bayraksan and Morton (2006) and Kaut and Wallace (2007), we evaluate information robustness with respect to resulting decision quality utilizing the other robustness criteria. Thus, we examine the ex ante influence of uncertainty and the ex post performance impact in the event of deviating realized scenarios.

4. Decision model

In the following, we derive a decision model for value-based performance and risk optimization. A make-to-stock supply chain in the consumer goods industry with single-stage production and constrained capacities is considered. Material and financial flows of mid-term S&OP are optimized simultaneously for value-based performance in terms of EVA. Robust optimization methods are applied to manage risk impact due to demand uncertainty. Demand information is provided as a discrete scenario set with respective probabilities.

With respect to the physical domain, the model calculates sales quantities and the amount of marketing activities. Procurement, production, and transportation as well as storage quantities are also derived considering production and storage capacity. Production capacity can be extended using overtime provided by subcontractors. Sales prices, cost prices, and cost unit rates are fixed due to long-term contracts. Regarding the financial domain, short-term financial investments and short-term borrowing are covered with a one-period horizon considering interest rates and a given bank line of credit. Open items from accounts receivable and accounts payable have a payment term of one period but factoring and early payment deducting a cash discount can be used to manage liquidity.

Inventory levels and the amount of overtime are modeled as first-stage variables since mid-term capacity decisions have to be determined before the actual scenario is realized due to the time delay ('here-and-now' decisions). All other physical decisions and the financial decisions can be postponed and thus are modeled as scenario-specific 'wait-and-see' variables of the second stage. In a hierarchical planning framework detailed decisions on procurement, distribution, and sales quantities as well as financial positions are determined within short-term planning below the level of S&OP (Fleischmann et al., 2008). The following notation is used:

Sets and indices

$p \in F,R,P$	final products, raw materials, all products and materials
$l \in L^E,L^{Op},L^A$	procurement locations, operations locations, sales locations
$(p,l) \in PL^E,PL^{Op},PL^A$	valid product–location combinations for procurement, operations, sales
$(l,j) \in TC$	transportation connections between locations
$(p,(l,j)) \in PC$	valid product–transportation connection combinations
$(p,r) \in BOM$	output–input combinations in the bill of materials
t	periods
$s \in S$	scenarios

Decision variables

I_{plt}	inventory of product p at operations location l at the end of period t
X_{plst}	production quantity of product p at operations location l for scenario s in period t
Y_{pljst}	transportation quantity of product p from location l to location j for scenario s in period t
O_{lt}	overtime at operations location l in period t
M_{plst}	amount of marketing activities for product p at sales location l for scenario s in period t
$FI_{st},AR_{st},C_{st},DS_{st},AP_{st}$	position in financial investments, accounts receivable, cash, short-term debts, accounts payable for scenario s at the end of period t
AR^-_{st}	amount of accounts receivable for factoring for scenario s in period t
AP^-_{st}	amount of accounts payable for early payment for scenario s in period t

Auxiliary variables

EVA_s	economic value added for scenario s
U_s	positive fraction of EVA for scenario s
D_s	negative fraction of EVA for scenario s
λ_s	binary auxiliary variable for scenario s
$TCM_{st},NS_{st},VCO_{st}$	total contribution margin, net sales, variable costs of operations for scenario s in period t
CA_{st}	net operating current assets for scenario s at the end of period t
IC_t	change in inventory in period t
OCF_{st},OM_{st},FM_{st}	cash flow from operations, open items management, financial investment management for scenario s in period t

Parameters

δ, γ	risk preference parameters
pr_s	probability of scenario s
T	planning horizon
z	tax rate
i^{hr}	hurdle rate
fa	average balance of net operating fixed assets
fc	fixed costs per period
fd,cd	factoring discount rate, cash discount rate
v_p,e_p	sales price, cost price of product p
cx_l,ci_l,co_l	unit cost of production, storage, overtime at operations location l
cy_{lj}	unit cost of transportation from location l to j
cm_p	unit cost of marketing for product p
kx_p,ki_p,ky_p	production, storage, transportation capacity need per unit of product p
α_{pr}	direct demand coefficient of raw material r for final product p
h^E,h^{Op}	lead time coefficient for procurement, production
$capX_l,capI_l$	production, storage capacity at operations location l
$O^{\max}$	maximum overtime expressed as a fraction of standard capacity
d_{plst}	demand for product p at location l for scenario s in period t
n	coefficient of marketing effectiveness
$M^{\max}$	maximum demand extension expressed as a fraction of normal demand
$DS^{\max}$	bank line of credit
ec_t	exogenous cash flow in period t
i^{FI}_t,i^{DS}_t	interest rate for financial investments, short-term debts in period t
FI^0,AR^0,C^0,DS^0,AP^0	initial position in financial investments, accounts receivable, cash, short-term debts, accounts payable
$bigM$	big number

The supply chain consists of external suppliers (L^E), internal operations locations for production and storage (L^{Op}), and sales markets (L^A). Raw materials R are turned into final products F. PL^E, PL^{Op}, and PL^A contain all valid product–location combinations for procurement, operations, and sales. PC denotes the set of all valid product–transportation connection combinations within the supply chain. The set of valid output–input combinations is captured in the bill of materials BOM. S denotes the set of scenarios s. t captures all time periods in the scope of the current planning run within a rolling horizons approach.

4.1. Objective function

In the following, we implement the two alternative robust objective functions developed in Section 3.2. The first concept in (3) results in

$$\max \quad \delta \cdot \underbrace{\sum_{s \in S} pr_s \cdot U_s}_{\text{upside potential}} - (1-\delta) \cdot \underbrace{\sum_{s \in S} pr_s \cdot D_s}_{\text{downside risk}} \tag{5}$$

with U and D covering the positive and the negative fractions of EVA for scenario s to calculate upside potential and downside risk. pr denotes the probability of scenario s within the discrete set of scenarios S.

$$EVA_s - U_s + D_s = 0 \quad \forall s \in S \tag{6}$$

$$U_s - bigM \cdot \lambda_s \le 0 \quad \forall s \in S \tag{7}$$

$$D_s - bigM \cdot (1-\lambda_s) \le 0 \quad \forall s \in S \tag{8}$$

$$U_s, D_s \ge 0; \quad \lambda_s \in \{0;1\} \;\; \forall s \in S \tag{9}$$

Eqs. (6) to (8) are required to calculate the positive and the negative fractions of EVA. The binary variable λ for scenario s ensures that either U or D takes a positive value for scenario s as defined in (9). $bigM$ is an auxiliary parameter and denotes a big number. Besides (6)–(9), no further constraints are required to implement the robust optimization approach in this alternative.

Alternatively, the second concept introduced in (4) with the restriction on risk-averse preferences can be implemented as

$$\max \quad \gamma \cdot \sum_{s \in S} pr_s \cdot EVA_s - (1-\gamma) \cdot \sum_{s \in S} pr_s \cdot D_s \tag{10}$$

$$EVA_s + D_s \ge 0 \quad \forall s \in S \tag{11}$$

$$D_s \ge 0 \quad \forall s \in S \tag{12}$$

with D as the negative fraction of EVA for scenario s. D is determined in (11) and restricted to the non-negative domain in (12). Besides (11)–(12), no further constraints are required for the robust approach in this alternative.

EVA for scenario s is calculated as net operating profit after tax (NOPAT) minus the capital charge for the planning period in (13). NOPAT is derived from total contribution margin TCM for scenario s in period t and fixed costs fc considering tax rate z. The capital charge results from the invested capital in net operating assets and the hurdle rate i^{hr}. Invested capital corresponds to net operating assets consisting of fixed assets fa and current net assets CA for scenario s at the end of the previous period $t-1$. Fixed costs fc and fixed assets fa cannot be influenced at the mid-term level and thus are parameters of the decision model.

$$EVA_s - \left(\sum_{t=1}^{T} (TCM_{st} - fc) \cdot (1-z) - \sum_{t=1}^{T} (fa + CA_{st-1}) \cdot i^{hr} \right) = 0 \quad \forall s \in S \tag{13}$$

Total contribution margin TCM for scenario s in period t is derived in (14) from net sales NS and variable costs of operations VCO considering change in inventory IC in period t. In (15), net operating current assets CA for scenario s at the end of period t cover inventory I of product p at operations location l evaluated with the cost price e of product p, accounts receivable AR, and cash position C. Accounts payable AP are deducted since they are non-interest-bearing debt capital (Kaplan and Atkinson, 1998).

$$TCM_{st} - (NS_{st} - VCO_{st} + IC_t) = 0 \quad \forall s \in S; \;\; t = 1 \ldots T \tag{14}$$

$$CA_{st} - \left(\sum_{(p,l) \in PL^{Op}} I_{plt} \cdot e_p + AR_{st} + C_{st} - AP_{st} \right) = 0 \quad \forall s \in S; \;\; t = 0 \ldots T \tag{15}$$

Net sales NS for scenario s in period t are covered in (16) as the difference between sales revenues and the costs for marketing activities. Sales revenues result from transportation quantities Y of product p delivered to sales location l for scenario s in period t and sales price v of product p. M depicts the amount of marketing activities for product p at sales location l for scenario s in period t; cm captures unit cost of marketing for product p. Eq. (17) derives the change in inventory IC in period t from inventory I of product p at operations location l at the end of period t and $t-1$ evaluated with the cost price e of product p.

$$NS_{st} - \left(\sum_{(p,(j,l)) \in PC: l \in L^A} Y_{pjlst} \cdot v_p - \sum_{(p,l) \in PL^A} M_{plst} \cdot cm_p \right) = 0 \quad \forall s \in S; \;\; t = 1 \ldots T \tag{16}$$

$$IC_t - \sum_{(p,l) \in PL^{Op}} (I_{plt} - I_{plt-1}) \cdot e_p = 0 \quad t = 1 \ldots T \tag{17}$$

Variable costs of operations VCO for scenario s in period t are considered in (18) covering procurement, production, overtime, storage, and transportation costs as well as factoring losses. The costs of procurement are derived from transportation quantities Y of raw materials p delivered from procurement location l at the cost price e of product p. Gains from cash discounts are deducted according to the amount of accounts payable for early payment AP^- and the discount rate cd.

The costs for production, storage, and transportation are derived using respective quantities X, I, Y as well as capacity factors kx, ki, ky and cost rates cx, ci, cy. O captures the overtime required at operations location l in period t at the cost rate co. Factoring losses result from the amount of sold accounts receivable AR^- and the discount rate fd.

$$\begin{aligned} VCO_{st} - \Bigg(& \sum_{(p,(l,j)) \in PC: l \in L^E} Y_{pljst} \cdot e_p - AP^-_{st} \cdot cd + \sum_{(p,l) \in PL^{Op}: p \in F} X_{plst} \cdot kx_p \cdot cx_l \\ & + \sum_{(p,l) \in PL^{Op}} I_{plt} \cdot ki_p \cdot ci_l + \sum_{(p,(l,j)) \in PC} Y_{pljst} \cdot ky_p \cdot cy_{lj} \\ & + \sum_{l \in L^{Op}} O_{lt} \cdot co_l + AR^-_{st} \cdot fd \Bigg) = 0 \quad \forall s \in S; \;\; t = 1 \ldots T \end{aligned} \tag{18}$$

4.2. Constraints for the physical domain

Eqs. (19) and (20) ensure mass balance of inventory I of final product p and raw material r at operations location l at the end of period t. Transportation quantities Y capture inflows and outflows at operations location l for scenario s in period t. X denotes the production quantity of final product p at location l for scenario s in period t with α containing the direct demand coefficient of raw material r for final product p. Initial inventory and target inventories are considered in (21) to account for seasonal stocks in a rolling horizons approach.

$$I_{plt-1}+\sum_{(p,(j,l))\in PC} Y_{pjlst}+X_{plst}-\sum_{(p,(l,j))\in PC} Y_{pljst}-I_{plt}=0$$
$$\forall (p,l)\in PL^{Op}: p\in F \quad \forall s\in S;\ \ t=1\ldots T \tag{19}$$

$$I_{rlt-1}+\sum_{(r,(j,l))\in PC} Y_{rjlst}-\sum_{(p,r)\in BOM:(p,l)\in PL^{Op}} \alpha_{pr}\cdot X_{plst}-I_{rlt}=0$$
$$\forall (r,l)\in PL^{Op}: r\in R;\ \ \forall s\in S;\ \ t=1\ldots T \tag{20}$$

$$I_{pl0}=I^0_{pl};\quad I_{plT}=I^T_{pl}\ \ \forall (p,l)\in PL^{Op} \tag{21}$$

Eq. (22) determines a fraction h^E of raw material r required for production at operations location l in period $t+1$ to be already in stock at the end of period t to consider procurement lead times. Production lead times are implemented accordingly in (23) requiring a fraction h^{Op} of transportation quantity Y of final product p from operations location l to sales locations j in period $t+1$ to be available in stock at the end of period t.

$$h^E\cdot \sum_{(p,r)\in BOM:(p,l)\in PL^{Op}} \alpha_{pr}\cdot X_{plst+1}-I_{rlt}\le 0$$
$$\forall (r,l)\in PL^{Op}: r\in R;\ \ \forall s\in S;\ \ t=1\ldots T-1 \tag{22}$$

$$h^{Op}\cdot \sum_{(p,(l,j))\in PC:j\in L^A} Y_{pljst+1}-I_{plt}\le 0$$
$$\forall (p,l)\in PL^{Op}: p\in F;\ \ \forall s\in S;\ \ t=1\ldots T-1 \tag{23}$$

Since supply chains in the consumer goods industry have a deliver-to-order decoupling point, safety stocks are introduced at different distribution stages to prevent stockouts (Fleischmann et al., 2008). We assume accurate demand data and exclude safety stocks in the following. However, they could easily be introduced to the model. Limited production capacity $capX$ and storage capacity $capI$ at each operations location l is considered in (24) and (25).

$$\sum_{(p,l)\in PL^{Op}:p\in F} kx_p\cdot X_{plst}-O_{lt}\le capX_l\quad \forall l\in L^{Op};\ \ \forall s\in S;\ \ t=1\ldots T \tag{24}$$

$$\sum_{(p,l)\in PL^{Op}} ki_p\cdot I_{plt}\le capI_l\quad \forall l\in L^{Op};\ \ t=1\ldots T \tag{25}$$

Production capacity already reflects average capacity loss due to setup times (Fleischmann et al., 2008). kx and ki denote the capacity need of product p per unit of production and storage. Production capacity at operations location l in period t can be extended in (26) using overtime O capped at a maximum level depicted as fraction $O^{\max}$ of standard capacity.

$$O_{lt}\le capX_l\cdot O^{\max}\quad \forall l\in L^{Op};\ \ t=1\ldots T \tag{26}$$

In (27), transportation quantities Y of product p delivered to sales location l are restricted to customer demand but can be extended using marketing activities. The amount of marketing activities for product p at sales location l for scenario s in period t is captured in M. n contains the coefficient of marketing effectiveness converting the amount of marketing activities into additional customer demand. Eq. (28) caps M at a maximum level depicted as fraction $M^{\max}$ of normal customer demand. Physical decision variables are restricted to the non-negative domain in (29).

$$\sum_{(p,(j,l))\in PC} Y_{pjlst}-n\cdot M_{plst}\le d_{plst}\quad \forall (p,l)\in PL^A;\ \ \forall s\in S;\ \ t=1\ldots T \tag{27}$$

$$n\cdot M_{plst}\le d_{plst}\cdot M^{\max}\quad \forall (p,l)\in PL^A;\ \ \forall s\in S;\ \ t=1\ldots T \tag{28}$$

$$O_{lt},I_{plt},M_{plst},Y_{pljst},X_{plst}\ge 0 \tag{29}$$

4.3. Constraints for the financial domain

Eqs. (30) and (31) determine the amount of accounts receivable for factoring AR^- and the amount of accounts payable for early payment AP^- for scenario s in period t according to sales revenues and purchases of raw materials. AR and AP capture the balance of remaining accounts receivable and payable in scenario s at the end of period t.

$$\sum_{(p,(j,l))\in PC:l\in L^A} Y_{pjlst}\cdot v_p-AR^-_{st}-AR_{st}=0\quad \forall s\in S;\ \ t=1\ldots T \tag{30}$$

$$\sum_{(p,(l,j))\in PC:l\in L^E} Y_{pljst}\cdot e_p-AP^-_{st}-AP_{st}=0\quad \forall s\in S;\ \ t=1\ldots T \tag{31}$$

Cash position in scenario s at the end of period t is determined by (32)–(35). Eq. (32) calculates cash C considering cash flow from operations OCF, open items management OM, financial management FM, and exogenous cash flow ec. Exogenous cash flow ec covers cash-relevant fixed costs, interest on long-term debts, taxes, and dividend payout in period t.

$$C_{st-1}-OCF_{st}+OM_{st}+FM_{st}-C_{st}=ec_t\quad \forall s\in S;\ \ t=1\ldots T \tag{32}$$

In (33), cash flow from operations OCF for scenario s in period t considers payments for marketing, production, overtime, transportation, and storage due in the same period. Payments for marketing activities are calculated from the amount of marketing activities M for product p at sales location l for scenario s in period t at the cost rate cm for product p. Payments for production quantities X as well as storage quantities I are derived using respective capacity factors kx and ki as well as cost rates cx and ci. O captures the amount of overtime used at location l in period t and co depicts the corresponding unit cost of overtime. Payments for transportation quantities Y are derived using capacity factor ky for product p and cost rate cy for the transportation connection from location l to j.

$$OCF_{st}-\left(\sum_{(p,l)\in PL^A} M_{plst}\cdot cm_p+\sum_{(p,l)\in PL^{Op}:p\in F} X_{plst}\cdot kx_p\cdot cx_l\right.$$
$$+\sum_{l\in L^{Op}} O_{lt}\cdot co_l+\sum_{(p,(l,j))\in PC} Y_{pljst}\cdot ky_p\cdot cy_{lj}$$
$$\left.+\sum_{(p,l)\in PL^{Op}} I_{plt}\cdot ki_p\cdot ci_l\right)=0\quad \forall s\in S;\ \ t=1\ldots T \tag{33}$$

Open items for scenario s incurred in period t are due in the following period. Accounts receivable can be sold to a factor at a discount rate fd and suppliers offer a cash discount rate cd for early payment in the same period. Eq. (34) considers cash flows from open items carried forward from the previous period and cash flows from the current period due to factoring and early payment. Financial management in (35) covers the positions in short-term investments FI and short-term borrowing DS for scenario s at the end of period t considering interest rates i^{FI} and i^{DS} in period $t-1$.

$$OM_{st}-(AR_{st-1}+AR^-_{st}\cdot(1-fd)-AP_{st-1}-AP^-_{st}\cdot(1-cd))=0$$
$$\forall s\in S;\ \ t=1\ldots T \tag{34}$$

$$FM_{st}-(FI_{st-1}\cdot(1+i^{FI}_{t-1})-FI_{st}-DS_{st-1}\cdot(1+i^{DS}_{t-1})+DS_{st})=0$$
$$\forall s\in S;\ \ t=1\ldots T \tag{35}$$

A minimum cash position $C^{\min}$ to serve short-term financial obligations is required by the bank and implemented in (36). In (37), short-term borrowing DS is restricted to the bank line of credit $DS^{\max}$. Balances of financial positions are initialized in (38) and (39) restricts financial decision variables to the non-negative domain.

$$C_{st} \geq C^{\min} \quad \forall s \in S; \; t = 1 \dots T \tag{36}$$

$$DS_{st} \leq DS^{\max} \quad \forall s \in S; \; t = 1 \dots T \tag{37}$$

$$FI_{s0} = FI^0; \quad AR_{s0} = AR^0; \quad C_{s0} = C^0; \quad DS_{s0} = DS^0; \quad AP_{s0} = AP^0 \;\; \forall s \in S \tag{38}$$

$$FI_{st}, DS_{st}, AR_{st}, AP_{st}, C_{st}, AR^-_{st}, AP^-_{st} \geq 0 \tag{39}$$

5. A case-oriented example

A case-oriented example is utilized to highlight the flexibility of the robust framework for value-based performance and risk optimization developed in this paper. The case description and the approach for scenario generation are provided in Section 5.1. We analyze the base case and conduct a sensitivity analysis for major parameters from the physical and financial domain in Section 5.2. In Section 5.3, we illustrate the trade-off between solution and objective robustness depending on the risk preference parameter and evaluate the impact on upside potential as well as downside risk in terms of EVA. To determine a robust level of information for data gathering and scenario generation, we examine on information robustness ex ante and ex post in Section 5.4.

5.1. Case description and scenario generation

The example covers a planning period of 13 periods (each equal to four weeks) and thus comprises one seasonal cycle and one financial year. The company manufactures three products (P1–P3) in two plants (F1 and F2). Two suppliers (S1 and S2) provide the required raw materials (R1–R3). Final products are stored in two warehouses (W1 and W2) before being delivered to five sales markets (M1–M5). Supply chain layout, transportation unit cost, and product allocation to locations is presented in Fig. 2.

Both plants F1 and F2 provide a production capacity of 600,000 capacity units (cu) and storage capacity for raw materials of 500,000 cu. The unit cost of production is 2 monetary units (mu) per cu and the unit cost of storage is 0.1 mu per cu. Production capacity can be extended up to 40% using overtime at a cost of 0.5 mu per cu. Both warehouses W1 and W2 provide a storage capacity of 1 million cu at a unit cost of 0.1 mu per cu. Lead time for procurement and production is 0.25 (equal to one week) respectively.

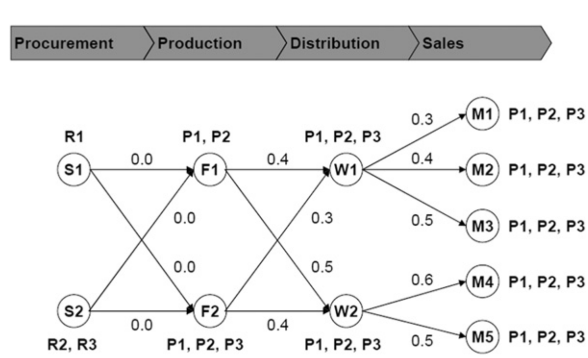

Fig. 2. Supply chain layout, transportation unit cost [mu/cu], and product allocation.

Products P1 and P2 are made of 1 unit of raw material R1 as well as R2 and consume 2 cu of production capacity. Product P3 consists of 1 unit of raw material R1 and R3; manufacturing requires 2 cu of production capacity. Storage and transportation requires 1 cu for each product. In Table 1, sales prices, cost prices, and cost for marketing activities are provided. Initial and target inventory levels for all materials and products can be found in Table 2.

Different seasonal demand scenarios are derived from a base level of customer demand (cf. Table 3) using probabilistic scenario factors as well as a harmonic oscillation with an amplitude $amp = 35\%$. The distribution of the scenario factors can be pragmatically derived based on expert estimates. The underlying stochastic process determining the scenario factors is assumed to be specified correctly by a triangular distribution with minimum $a = 0.7$, mode $c = 0.9$, and maximum $b = 1.2$. Demand d for product p at sales location l for scenario s in period t is calculated as

$$d_{plst} = sf_s \cdot d^b_{pl} \cdot \left(1 + amp \cdot \cos\left(\frac{2 \cdot \pi}{T} \cdot \left(t + \frac{T-1}{2}\right)\right)\right) \tag{40}$$

with the scenario factor sf for scenario s, d^b as the base level of customer demand for product p at sales location l and T as the length of the seasonal cycle. The seasonal peak is reached in the mid of the seasonal cycle. Customer demand can be increased up to 10% using marketing activities with a factor of marketing effectiveness equal to 1.

Initial balances are 0 mu in short-term financial investments, 11 million mu in accounts receivable, and 2 million mu in cash as

Table 1
Product master data.

Products	Sales price (mu)	Cost price (mu)	Marketing cost (mu)
P1	12.0	11.0	3.0
P2	16.0	14.5	4.0
P3	19.0	17.0	5.0
R1	–	1.0	–
R2	–	2.0	–
R3	–	5.0	–

Table 2
Initial and target inventory levels (units).

Products	Operations locations			
	F1	**F2**	**W1**	**W2**
P1	0	0	10,000	15,000
P2	0	0	30,000	30,000
P3	0	0	40,000	30,000
R1	80,000	80,000	0	0
R2	50,000	30,000	0	0
R3	0	80,000	0	0

Table 3
Base level of customer demand (units).

Products	Sales locations				
	M1	**M2**	**M3**	**M4**	**M5**
P1	32,000	27,000	30,000	32,000	34,000
P2	48,000	49,000	52,000	52,000	55,000
P3	60,000	65,000	57,000	60,000	64,000

well as 9 million mu in short-term debts and 4 million mu in accounts payable. The average balance of fixed assets amounts to 50 million mu. Interest rates over the planning period are 0.2% for short-term investments and 0.7% for short-term borrowing (before tax) as well as 0.6% for the hurdle rate (after tax). The bank line of credit is restricted to 11 million mu and minimum cash must exceed 2 million mu. Discount rates are 4% for factoring and 2% for early payment. Monthly exogenous cash flow is 4.2 million mu. Fixed costs per period add up to 4.1 million mu including depreciation.

5.2. Base case and sensitivity analysis

For the base case, we assume a relatively risk-averse decision-maker with a risk preference parameter $\gamma = 0.3$ and consider a scenario set of size 5 derived from the demand distribution as specified above. The optimization model is implemented in ILOG OPL v6.3 according to Eqs. (10)–(39) and consists of 4945 continuous variables and 5179 constraints. Optimal solutions can be found using CPLEX v12.1 on a computer with a 2.13 GHz processor and 3 GB RAM at a computing time below 1 s. We obtain an expected EVA of 1.28 million mu covering an upside potential of 2.34 million mu and a downside risk of 1.06 million mu. The corresponding scenario-specific probabilities and results are listed in Table 4.

In the following, we conduct a sensitivity analysis on four parameters of the decision model: maximum overtime (O^{max}), the bank line of credit (DS^{max}), the amplitude of demand seasonality (amp), and the hurdle rate (i^{hr}). To obtain sensitivities, we vary the parameters in the ranges of $\pm 5\%$ and $\pm 15\%$. The results are summarized in Fig. 3.

As can be seen in the figure, the hurdle rate i^{hr} is negatively correlated with expected EVA and shows significant impact since a variation of $\pm 5\%$ and $\pm 15\%$ results in a change in expected EVA of between 20% and 60%. Increasing the hurdle rate induces higher costs of capital and thus directly reduces EVA. For demand seasonality, variation of the seasonal amplitude amp leads to changes in the EVA expected within a range of -25% to 18%. A more volatile demand seasonality requires additional overtime and inventories to manage capacity during the seasonal cycle. Therefore, operating profits decrease while working capital rises and ultimately EVA deteriorates.

In contrast, maximum overtime O^{max} and the bank line of credit DS^{max} are positively correlated with the expected EVA. Since they represent restrictions of the decision model, a relaxation increases EVA. The results of the sensitivity analysis vary within a range of -21% to 14% (maximum overtime) and -207% to 12% (bank line of credit). The sharp decline in the expected EVA when reducing the bank line of credit by 15% originates from the fundamentally poor financial situation of the company in focus.

5.3. Solution and objective robustness

In this section, we illustrate the trade-off between solution and objective robustness depending on the risk preference of the decision-maker. The expected value of perfect information (EVPI) is utilized to quantify the impact of uncertainty. We examine the base case with the corresponding decision model for the 'here-and-now' (HN) approach as described above and vary the risk preference parameter $\gamma \in (0; 1]$. The results for the 'wait-and-see' (WS) approach are derived solving the deterministic equivalent of the decision model for each scenario.

Upside potential (UP) and downside risk (DR) are calculated for the HN and WS approach according to the risk preference parameter (cf. Fig. 4). The values of the WS approach are upper and lower bounds for UP and DR in the HN approach with 2.83 million and 0.90 million mu respectively. The gap between the HN and WS approach equals the EVPI for a specific risk preference and covers the manageable risk in a planning-based risk management approach. Given the upper and lower bounds, the decision-maker balances solution and objective robustness as well as UP and DR to select the appropriate plan according to the individual risk preference.

For $\gamma < 0.2$, a highly risk-averse decision-maker is willing to further reduce downside risk at the cost of a significant loss in upside potential. Consequently, objective robustness increases due to reduced downside risk but at the same time leads to less solution robustness since the EVPI increases. A relatively solution robust plan can be found for less risk-averse preferences of $\gamma > 0.2$ and decreasing objective robustness. Investigating the first-stage variables for overtime and seasonal inventories in the risk-neutral and the extremely risk-averse case, we obtain the results in Fig. 5. As can be seen from the figure, a risk-averse decision-maker manages asset utilization more restrictively and determines lower levels of inventories and overtime.

Table 4
Scenario-specific results of the base case.

	Scenario				
	S1	**S2**	**S3**	**S4**	**S5**
Probabilities	0.035	0.208	0.398	0.307	0.052
EVA (million mu)	−9.94	−3.44	1.48	4.70	5.97

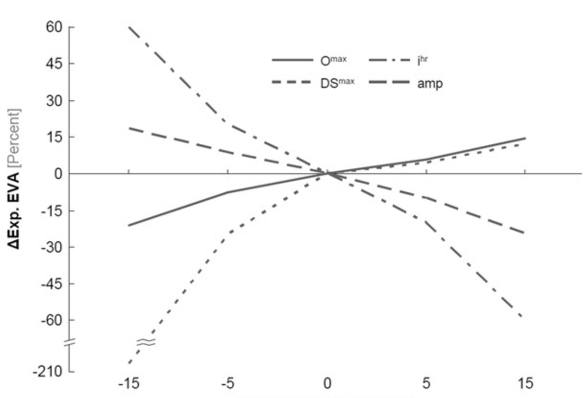

Fig. 3. Results of the sensitivity analysis.

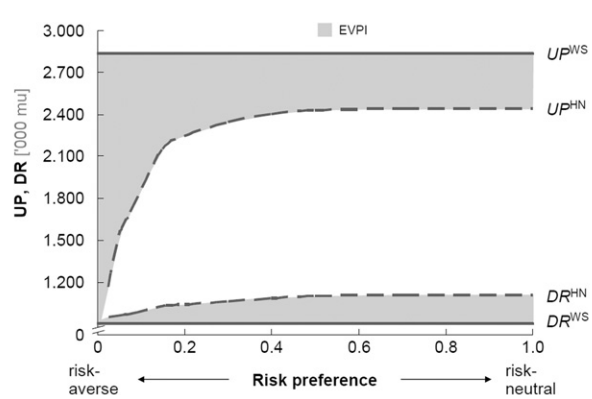

Fig. 4. Trade-off between solution and objective robustness.

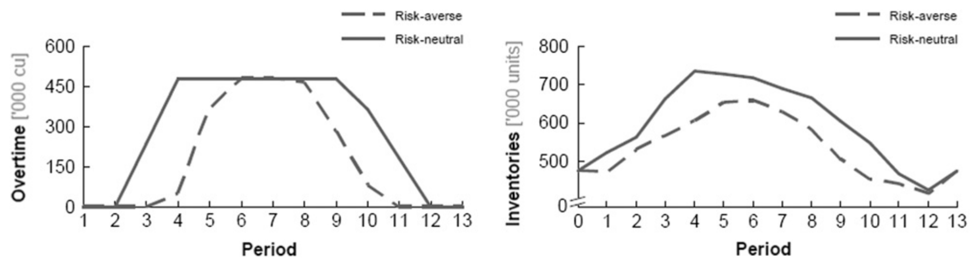

Fig. 5. Inventories and overtime for different risk preference parameters.

5.4. Information robustness

In the following, we examine ex ante and ex post information robustness with respect to the size of the scenario set. The continuous distribution of the scenario factors is discretized in scenario sets of uneven size $|S|=3,\ldots,15$ in such a way that the first-order moments match the continuous probability distribution. This approach is sufficient according to Høyland and Wallace (2001) since we solely use measures based on first-order moments in the optimization model. The discretization method described in Klugman et al. (2004) is applied deriving probabilities as

$$pr_s[x] = \begin{cases} \dfrac{E[\min(X,a)]-E[\min(X,a+h)]}{h}+1-cdf(a), & x=a \\ \dfrac{2\cdot E[\min(X,x)]-E[\min(X,x+h)]-E[\min(X,x-h)]}{h}, & a<x<b \\ \dfrac{E[\min(X,b)]-E[\min(X,b-h)]}{h}-1+cdf(b), & x=b \end{cases} \tag{41}$$

whereas $x=a,a+h,\ldots,b-h,b$ denotes the $|S|$ equidistant knots with the distance $h=(b-a)/(|S|-1)$ and the lower and upper bound a and b. pdf and cdf cover the probability density function and the cumulative distribution function of the continuous distribution. $\min(X,u)$ denotes the limited expected value of u defined as

$$\int_{-\infty}^{u} x\cdot pdf(x)+u\cdot(1-cdf(u)) \tag{42}$$

Ex ante information robustness considers the influence of uncertainty on the solution and can be measured using the EVPI. We apply an 'in-sample' approach according to Kaut and Wallace (2007) and sample 30 independent replications of the discretized distribution for each size of the scenario set based on $|S|\cdot 50$ random numbers per replication. The resulting instances are solved for the HN and the WS approach with the risk preference parameters $\gamma=0.3$ and 0.7 using CPLEX v12.1. The corresponding optimization models are implemented as described above and optimal solutions can be found on a computer with a 2.13 GHz processor and 3 GB RAM at computing times below 1 s per instance. The results are provided in Table 5.

The impact of deviating realized scenarios on EVA is utilized to evaluate ex post information robustness. We apply an 'out-of-sample' approach according to Kaut and Wallace (2007) and sample 30 independent replications for a scenario set of size 15. The resulting instances are solved with the HN approach for $\gamma=0.3$ and 0.7 using CPLEX v12.1 but first-stage variables are fixed according to the ex ante decisions above. The results are summarized in Table 6.

Expected value (*EV*), coefficient of variation (*CV*), and two-sided confidence intervals (*CI*) at 95% are calculated. With an increasing number of scenarios the expected value of the EVPI and thus the impact of uncertainty decreases within a range of 206,000 to 224,000 mu. The coefficient of variation and the confidence interval also diminish by 0.04 to 0.05 as well as $\pm$14,000 to $\pm$16,000 mu and lead to more robust results ex ante.

Table 5
Analysis of ex ante information robustness.

EVPI ['000 mu]	**Size of scenario set** $\lvert S\rvert$						
	3	5	7	9	11	13	15
$\gamma=0.3$							
EV	793	651	622	614	612	588	587
CV	0.07	0.05	0.03	0.04	0.03	0.03	0.02
$CI_{95\%}$	$\pm$20	$\pm$12	$\pm$8	$\pm$9	$\pm$8	$\pm$7	$\pm$4
$\gamma=0.7$							
EV	768	598	559	557	544	542	544
CV	0.06	0.04	0.04	0.03	0.03	0.03	0.02
$CI_{95\%}$	$\pm$18	$\pm$9	$\pm$7	$\pm$7	$\pm$6	$\pm$6	$\pm$4

Table 6
Analysis of ex post information robustness.

EVA ['000 mu]	**Size of scenario set** $\lvert S\rvert$						
	3	5	7	9	11	13	15
$\gamma=0.3$							
EV	1252	1329	1333	1347	1339	1365	1374
CV	0.10	0.09	0.09	0.09	0.09	0.08	0.09
$CI_{95\%}$	$\pm$46	$\pm$43	$\pm$43	$\pm$44	$\pm$43	$\pm$43	$\pm$46
$\gamma=0.7$							
EV	1271	1382	1400	1409	1408	1410	1417
CV	0.09	0.09	0.09	0.08	0.08	0.08	0.09
$CI_{95\%}$	$\pm$44	$\pm$45	$\pm$45	$\pm$45	$\pm$44	$\pm$45	$\pm$45

For the ex post perspective, we also calculate expected value, coefficient of variation, and two-sided confidence intervals. Average EVA increases between 122,000 and 146,000 mu at constantly low and robust levels for the coefficient of variation (approx. 0.09) and the confidence interval (approx. $\pm$44,000 mu). In summary, we already obtain relatively information robust results for scenario sets of size 5 to 7. Consequently, data gathering and scenario generation can be focused on the most relevant aspects and the decision-maker can limit the number of contingency plans to a manageable size to ensure practicability without compromising on robustness.

6. Conclusion and outlook

In this paper, we present a holistic framework for value-based performance and risk management in supply chains. Value drivers of mid-term supply chain management are highlighted and performance levers as well as sources of operational risk are examined from a decision-oriented perspective. The concept of Economic Value Added (EVA) as a prevalent performance indicator is applied to manage upside potential and downside risk in terms of value creation. Different criteria of robustness are integrated into a comprehensive approach for robust optimization.

The optimization-based framework presented in this paper provides real decision support for value-based management as opposed to common explanatory approaches. A direct approach to risk management is pursued utilizing scenario-based information instead of expected values and risk-adjusted cost of capital. Different implications of a robust optimization approach are derived using a case-oriented example. Solution and objective robustness are conflicting criteria and depend on the risk preference of the decision-maker. However, the risk preference should be calculated in retrospect by balancing upside potential against downside risk for different values of the risk preference parameter. Information robust results can be derived even for comparably small scenario sets which allows the decision-maker to focus on the most relevant scenarios for data gathering and scenario generation.

Regarding further research, there are multiple opportunities to extend the presented framework. Integrated pricing could be covered to improve operating profit margin as one major value driver. The influence of an 'incorrect' forecasting model for scenario data could be analyzed to derive implications for data preparation and model selection. Moreover, the decision model could be extended towards a hierarchical planning framework by introducing a short-term planning level below mid-term S&OP. This would allow investigation into the effects of detailed lot-sizing and scheduling as well as short-term financial planning in the supply chain.

Mid-term investment and financial planning covering purchase and sale of technical equipment as well as further means of funding could be considered to enhance asset utilization as a key value driver. (Dis-)Investment and capacity adjustment planning promise to be interesting aspects since they enable performance gains due to business growth but at the same time imply significant risk due to limited reversibility.

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