A multi-criteria approach to robust outsourcing decision-making in stochastic manufacturing systems

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Abstract

Manufacturing outsourcing is a key industry trend towards greater operational efficiency and is related to the discussion of strategic core competencies. We study the issue of contract manufacturing at the strategic-tactical level and approach the topic from a multi-criteria decision-making perspective, since service, cost, quality, and more long-term value-related aspects are involved. To arrive at well-balanced and robust outsourcing decisions with respect to the aforementioned dimensions, we apply a scenario-based approach that is built within the concept of Data Envelopment Analysis (DEA). For this purpose, we use two types of Key Performance Indicators (KPIs): model-based KPIs, which are the result of a modeling approach, and non-model-based KPIs that are derived in an independent assessment from multiple stakeholders. The model-based KPIs are handled through an aggregate planning model which manages the trade-off of capacity vs. work-in-process costs and uses a queuing network-based approach to anticipate the stochastic and dynamic behavior of a manufacturing system. This allows us to balance customer service, derived from aggregate order lead times, and relevant costs of operations when determining volume/mix decisions for internal and external production. An industry-derived case example with distinct outsourcing options is used to highlight the benefits of the approach.

Keywords: Multi-criteria decision-making, stochastic models, outsourcing, manufacturing systems, aggregate planning

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1 Introduction

In the 1980s, a marked trend towards the reduction of internal added value was observable primarily in the automotive and service sector (Helper, 1991; Gottfredson, Puryear, and Phillips, 2005). Nowadays, in a more volatile world, corporate strategists talk about focusing on core competencies and see manufacturing outsourcing as a lever for increasing efficiency while managing operations risk. While in 1988 outsourcing in the pharmaceutical industry accounted for only around 20% of total production, in the 2000s about every 6 in 10 goods were supplied externally (van Arnum, 2000). Similarly, in 2000 outsourcing covered 10% of global electronics production (Plambeck and Taylor, 2005). Recent data reveal that the top 25 contractors earned 342 billion USD in global sales in 2013, corresponding to some 30% of the total electronics manufacturing market (Manufacturing Market Insider, 2014) which further confirms the relevance of manufacturing outsourcing.

Contract manufacturing (CM) agreements commission the contractor to provide on-demand manufacturing of variable production volumes. In this study, we focus on turnkey CM that covers the provision of finished goods in contrast to selective outsourcing at the component level (consignment CM) (Kim, 2003). The contractee transfers manufacturing obligations to the contractor, which increases its flexibility and can lead to cost efficiencies as well as service improvements. These effects are reinforced by the dynamics of stochastic manufacturing systems regarding workload-dependent lead times given volume/mix decisions in the master production schedule. Moreover, operations risk with respect to quality and compliance issues can be transferred to the contractor. Despite these benefits, some fundamental strategic concerns remain. The contractee might lose critical know-how regarding manufacturing procedures and might struggle to retain expertise in-house, while the contractor increases bargaining power and can even turn into a future competitor (Arruñada and Vázquez, 2006). Furthermore, outsourcing entails reputational or ethical risks such as poor working standards or the violation of worker participation rights.

The aforementioned setting implies a multi-criteria decision problem along four dimensions: service, costs, quality, and value. Service and costs reflect customer-perceived lead times and operations expenses that are considered from a tactical planning viewpoint. Quality relates to products as well as to production processes and thus requires appropriate approaches on a more strategic level. Likewise, value-related topics bear upon even more long-term aspects such as intellectual property concerns or reputational risks. To account for these multiple facets involving such decision-making, a decision support system needs to tackle the problem from a combined strategic-tactical perspective and must balance both qualitative and quantitative factors. While costs, lead times, and production volume/mix can be derived using quantitative models, qualitative factors such as value or risk must be assessed by subject matter experts or executives. Finally, a corresponding approach needs to provide robust decisions that lead to reasonable results irrespective of future developments, accommodating the strategic and partly irreversible character of outsourcing decisions.

The existing literature covers only selective aspects of the aforementioned problem, but mainly in isolation. For instance, Dotoli and Falagario (2012) apply Data Envelopment Analysis (DEA) for supplier selection, while Merzifonluoğlu, Geunes, and Romeijn (2007) consider subcontracting options in a tactical planning model and Asmundsson et al. (2009) study congestion phenomena in stochastic manufacturing systems. Moreover, robust decision-making has received increasing attention in the operations management context (see e.g., Hahn and Kuhn, 2012). With this paper, we close a current gap in the literature by integrating strategic outsourcing decision-making with tactical operations planning to consider the impact of sourcing decisions on operational performance in a stochastic manufacturing environment. Our contribution lies in the integration of these decisions and their respective methodologies. At each point, we use state-of-the-art methodology complemented with the necessary extensions for our decision problem.

In our approach, we also emphasize the issue of robust decision-making in this context. For this purpose, we use an Aggregate Production Planning (APP) model that coordinates volume/mix decisions between internal and external production and that integrates an aggregate stochastic queuing model to anticipate operational performance of the stochastic manufacturing system. To solve the multi-criteria decision problem and to ensure robust solutions, we build on DEA to evaluate and construct the ranking of several scenarios with respect to their DEA efficiency scores.

The remainder of the paper is structured as follows: we review the existing literature on multi-criteria decision-making in supplier selection and aggregate production planning of stochastic manufacturing systems in section 2. In section 3, we develop an approach for robust outsourcing decision-making in a stochastic manufacturing environment. An industry-based case example is presented in section 4 to illustrate the benefits of this approach and to investigate operational implications of CM on stochastic manufacturing systems. We end the paper with concluding remarks on our findings and suggest directions for future research in section 5.

2 Literature Review

The literature that is relevant for this research follows three streams: (i) aggregate production planning with subcontracting options, (ii) production planning with an emphasis on workload-dependent lead times as well as stochastic manufacturing systems, and (iii) multi-criteria decision-making in supplier selection.

As far as the first stream is concerned, an overview of deterministic and stochastic APP approaches can be found in Nam and Logendran (1992) and Mula et al. (2006). Building on this, Merzifonluoğlu, Geunes, and Romeijn (2007) integrate subcontracting options and introduce sales price decisions as well as economies of scale using concave revenue and cost functions. Similarly, Atamtürk and Hochbaum (2001) propose a model for balancing capacity expansion, subcontracting, internal manufacturing, and inventory holdings in a setting with non-stationary demand. The work of Carravilla and de Sousa (1995) features subcontracting embedded in a hierarchical framework that distinguishes aggregate planning, master production scheduling, and operational loading. Finally, Kim (2003) proposes an optimal control model to investigate outsourcing with two contractors that provide a range of price levels and improvement capabilities for future cost savings. While these approaches incorporate subcontracting, they omit the implications of variability and assume fixed lead times irrespective of the workload in the system. The latter will be explicitly taken into account in our approach using workload-based lead times.

The second stream of literature addresses the aforementioned deficits of conventional APP models. Armbruster and Uzsoy (2012) summarize corresponding approaches including clearing functions and discrete-event simulation (DES). An overview of clearing functions approaches that aim at capturing the non-linear relationship between work-in-process (WIP) and lead time can be found in Pahl, Voß, and Woodruff (2007) and Missbauer and Uzsoy (2011). Asmundsson et al. (2009) extend the basic clearing functions formulations of Graves (1986) and Karmarkar (1987) and develop a multi-stage multi-product planning approach. Similarly, Selçuk, Fransoo, and de Kok (2008) apply clearing functions in a hierarchical supply chain planning framework to predict lead times among other operational performance metrics. Missbauer (2011) considers transient behavior of manufacturing systems in order release planning using clearing functions. However, current clearing functions-based approaches fall short of capturing the impact of lot-sizing on the performance of stochastic manufacturing systems (Missbauer and Uzsoy, 2011).

DES represents an alternative approach to anticipate the performance of stochastic manufacturing systems in production planning which allows for a more detailed modeling of the shop floor level. Simulation-based approaches have received increasing attention since the early work of Hung and Leachman (1996), which is confirmed by a series of case studies from the semiconductor industry (see, e.g., Bang and Kim, 2010; Kacar, Irdem, and Uzsoy, 2012). Additionally, Almeder, Preusser, and Hartl (2009) outline a general framework for the iterative application of linear programming (LP) models and DES to obtain more accurate parameters. Gansterer, Almeder, and Hartl (2014) use simulation to improve values for lead times, safety stocks, and lot sizes in a hierarchical planning setting. However, a simulation-based optimization approach can result in prohibitive computing times (Armbruster and Uzsoy, 2012) and thus is not in focus of this work.

Multi-model approaches that combine classical APP models with more elaborate queuing models represent a compromise to resolve the aforementioned shortcomings of clearing functions-based approaches and simulation-based optimization. While Jansen, de Kok, and Fransoo (2013) use a local smoothing algorithm to determine aggregate order release targets and to anticipate lead times in mas-

ter planning, Hahn et al. (2012) apply an aggregate stochastic lot-sizing model to determine required capacity buffers and corresponding lead times. None of the approaches, however, takes external capacity options and their implications on operational performance into account. The approach presented in this paper addresses these issues.

For an overview of the third literature stream of multi-criteria decision-making in supplier/contractor selection, we refer the reader to the comprehensive reviews of de Boer, Labro, and Morlacchi (2001) and Ho, Xu, and Dey (2010). Dotoli and Falagario (2012) apply a hierarchical extension of DEA in a multi-sourcing context to assess the efficiency of potential sourcing strategies. Kuo and Lin (2012) combine DEA with the analytic hierarchy process and examine environmental protection issues. However, the aforementioned approaches omit the implications of sourcing decisions on the operational performance of stochastic manufacturing systems and do not explicitly consider the issue of decision robustness. We close this gap by developing a multi-criteria decision support system for robust outsourcing decision-making in stochastic manufacturing systems that combines DEA with aggregate production planning. Previous work entails a similar approach that has been developed in an R&D portfolio context by Vandaele and Decouttere (2013).

3 Decision Support System

3.1 Robust Multi-criteria Approach

Our approach builds on the DEA methodology (see Charnes, Cooper, and Rhodes, 1978) in order to solve the multi-criteria decision problem of selecting beneficial manufacturing outsourcing options while considering operational performance implications in stochastic manufacturing systems. DEA is a non-parametric approach to ranking entities with respect to their efficiency given multiple inputs and/or outputs that require a positive correlation but no formal relationship. Although inputs and outputs can have different units of measure or even represent ordinal scales, one obtains a unified comparative efficiency score. In this paper, we use an output-oriented and radial DEA model characterized by constant returns to scale as described in Charnes, Cooper, and Rhodes (1978). With this in mind, we focus on two important facets of the aforementioned decision problem: (i) balancing quantitative and qualitative factors that characterize available CM options, and (ii) obtaining robust decisions that are sufficiently independent of uncertain future developments.

First, we need to find input and output metrics that represent relevant quantitative and qualitative factors of the CM options that are to be ranked according to their efficiency. For this purpose, we use model-based KPIs such as costs, aggregate order lead times, and output quantities that originate from an aggregate planning model for the respective CM option. This planning approach is further detailed in the following subsection. Non-model-based KPIs capture qualitative factors such as outsourcing risk or management complexity and are assessed independently by subject matter experts and/or executives using ordinal scales.

Second, to ensure robustness, we create several parameter constellations to reflect uncertainty regarding to demand seasonality as well as demand and operations variability. Creating a full factorial design of CM options and parameter constellations, we arrive at a set of scenarios that serve as the instances in the DEA approach. Comparing the DEA efficiency scores allows us to find both robust sourcing decisions and optimal aggregate plans for the respective parameter constellations.

3.2 Aggregate Planning in Stochastic Systems

Modeling the stochastic and dynamic behavior of a manufacturing system for planning purposes would require a stochastic non-linear programming (SNLP) approach. Building on Hahn et al. (2012), we decompose the SNLP approach into a hierarchical framework according to Schneeweiss (2003) with a deterministic APP model as the top level and an Aggregate Stochastic Queuing (ASQ) model as the anticipated base level. The APP model balances capacity, WIP, and CM costs by coordinating external and internal production volume/mix decisions given dynamic demand. Complementing the APP model, the ASQ model covers the stochastic dimension of the problem and anticipates workload-dependent lead times as well as capacity buffers to compensate for non-productive setup times and

capacity losses due to machine failures.

The ASQ model corresponds to a stochastic lot-sizing approach that finds lead time-optimal batch sizes and is derived using queuing network approximations as presented in Lambrecht, Ivens, and Vandaele (1998). By keeping lead times under control, the ASQ model incorporates capacity slack to cope with stochasticity in the system parameters. Since we have dynamic demand, the ASQ model needs to be solved separately for each time bucket of the APP model due to its steady state assumption. Consequently, both levels of the hierarchical framework are solved iteratively with the APP model coordinating the results of the ASQ models. The algorithm terminates as soon as the objective value of the APP model cannot be further improved. Both the APP and ASQ models as well as their integration are described in subsequent paragraphs using the following notation:

Sets and indices

$p \in P$	set of products p
$r \in R^p$	set of operations r for product p ('product routing')
$s \in S$	set of external CM options s
t, z	offset and finishing time periods
$w \in W$	set of work centers w

Parameters

α_{wt}	capacity buffer (discount factor) for work center w in time period t [scale from 0 to 1]
γ_{wpzt}	binary lead time offset coefficient at work center w for product p in period t to be finished in period z
δ_{prw}	binary parameter indicating whether operation r of product p is performed at work center w
λ_p	arrival rate of orders for product p $(1/\overline{y_p})$
λ_{bp}	batch arrival rate of orders for product p
ρ'_w	adapted traffic intensity at work center w
μ_w	aggregate processing rate at work center w
Θ	weighted lead time
a_w	machine availability at work center w
$capX$	maximum amount of available working time [hours]
ca_w^2	SCV of the batch interarrival time at work center w
cs_w^2	SCV of the batch processing time at work center w
cm_{ps}	unit cost of CM for product p of contractor s
co	cost of overtime [monetary unit/hour]
cw_p	unit cost of holding WIP for product p
d_{pt}	demand for product p in period t
kx_{wp}	capacity requirement at work center w for product p [hours/unit]
l_w	aggregate arrival rate at work center w
l_{wp}	arrival rate of product p at work center w
lt_{pt}	lead time coefficient for product p in period t [periods]
M_{pt}^{max}	maximum allowable CM amount of product p in period t by contractor s
nm_w	number of parallel machines at work center w
O^{max}	maximum allowable overtime usage [hours]
$\overline{oq_p}$	average order size of product p
$\overline{pt_{pr}}$	average processing time of operation r of product p
$\overline{st_{pr}}$	average setup time of operation r of product p
$s^2_{\overline{pt_{pr}}}$	variance of the processing time of operation r of product p
$s^2_{\overline{st_{pr}}}$	variance of the setup time of operation r of product p
wq_w	average waiting time in queue in front of work center w
$\overline{y_p}$	average interarrival time for orders of product p

Decision variables

M_{pst}	external production quantity of product p in period t by contractor s
O_t	amount of overtime used in time period t
Q_p	batch size of product p

X_{pt} internal production quantity of product p in period t

Extending a conventional APP model (see Nam and Logendran, 1992) we incorporate a form of CM that can be used up to a certain allowable volume to serve customer demand at a fixed unit cost. The second group of enhancements centers around workload-dependent lead times and necessary capacity buffers that are derived from the ASQ models. Lead times are considered in the APP model in two ways: first, lead times are translated into average WIP costs which need to be balanced against capacity costs. Second, lead times are used to allocate capacity requirements to the respective lead time offset periods and work centers given the product routing and due date. The capacity buffer corresponds to a discount factor on gross capacity at the APP level to account for non-productive time due to setups or machine breakdowns.

The objective function in (1) minimizes total relevant costs consisting of the costs of overtime O_t, the costs of CM M_{pst} per product p and sourcing option s, and the holding costs of WIP inventory per product p until the planning horizon T. WIP costs per product p and period t are derived from the production lead time factor lt_{pt} and the production amount X_{pt} using average WIP cost cw_p per period. The lead time factor lt_{pt} is determined in the ASQ model and captures the average lead time expressed in time buckets of the APP model.

$$\min \quad \sum_{t=1}^{T}(co \cdot O_t) + \sum_{p \in P}\sum_{s \in S}\sum_{t=1}^{T}(cm_{ps} \cdot M_{pst}) + \sum_{p \in P}\sum_{t=1}^{T}(cw_p \cdot lt_{pt} \cdot X_{pt}) \tag{1}$$

The capacity restriction in (2) is modified in two ways: on the RHS, the capacity buffer α_{wt} represents a discount on the gross capacity given the number of parallel machines nm_w, the total available capacity $capX$, and the amount of overtime O_t in period t. On the LHS, the capacity load per product p is derived from the production amount X_{pz} and the capacity requirement kx_{wp} at work center w. The binary coefficient γ_{wpzt} determines whether a certain operation of product p at work center w is assigned to a particular lead time offset period t ($\gamma_{wpzt} = 1$) with the end item to be finished in period z. Both the capacity buffer α_{wt} and the lead time offset parameter γ_{wpzt} are workload-dependent and thus derived from the ASQ models.

$$\sum_{p \in P}\sum_{z=t}^{T}\gamma_{wpzt} \cdot kx_{wp} \cdot X_{pz} \leq (1 - \alpha_{wt}) \cdot nm_w \cdot (capX + O_t) \qquad \forall w \in W; t = 1...T \tag{2}$$

Equation (3) represents the mass balance constraint. Since we assume an MTO setting without finished goods inventories, demand d_{pt} for product p in period t must be satisfied with items either produced internally (X_{pt}) or sourced externally from a contractor (M_{pst}). Maximum overtime per period t is defined in (4). Equation (5) ensures that agreed-to CM volumes are not exceeded. Lastly, all decision variables need to be restricted to the non-negative domain in (6).

$$X_{pt} + M_{pst} = d_{pt} \qquad\qquad \forall p \in P; \forall s \in S; t = 1...T \tag{3}$$

$$O_t \leq O^{max} \qquad\qquad t = 1...T \tag{4}$$

$$M_{pst} \leq M_{pst}^{max} \qquad\qquad \forall p \in P; \forall s \in S; t = 1...T \tag{5}$$

$$M_{pst}, X_{pt}, O_t \geq 0 \qquad\qquad \forall p \in P; \forall s \in S; t = 1...T \tag{6}$$

Solving the APP model using a standard LP solver, one obtains optimal internal and external production quantities per product and period as well as the necessary overtime capacities as a first step. Planned internal production volumes and corresponding capacities including overtime provide the frame for the ASQ models and are handed over via average interarrival times per product and

time bucket according to (7). The ASQ model and additional required parameters are introduced in the following, building on the work of Lambrecht, Ivens, and Vandaele (1998).

$$\overline{y_{pt}} = \frac{capX + O_t}{X_{pt}} \qquad\qquad t = 1...T \quad (7)$$

The ASQ model considers a multi-product multi-machine job shop and determines lead time-optimal batch sizes Q_p for each product p assuming a strict FCFS discipline and no batch splitting. The expected weighted lead time $E(\Theta)$ that is minimized in (8) consists of three elements. The first term captures the waiting time to batch in front of the first work center for given product-specific average interarrival times $\overline{y_p}$ and average order sizes $\overline{oq_p}$. The weighting factor $\lambda_p \cdot \overline{oq_p}/\sum_{p \in P} \lambda_p \cdot \overline{oq_p}$ represents the relative importance of product p for the overall job shop according to the interarrival rate λ_p of product p compared with the sum of interarrival rates of all products.

$$\min_{Q_p} \quad E(\Theta) = \sum_{p \in P} \frac{\lambda_p \cdot \overline{oq_p}}{\sum_{p \in P} \lambda_p \cdot \overline{oq_p}} \cdot \frac{(Q_p \cdot \overline{oq_p} - 1) \cdot \overline{y_p}}{2 \cdot \overline{oq_p}} + \sum_{w \in W} E(wq_w)$$
$$+ \sum_{w \in W} \sum_{p \in P} \frac{\sum_{r \in R^p} \lambda_p \cdot \overline{oq_p} \cdot \delta_{prw}}{\sum_{p \in P} \sum_{r \in R^p} \lambda_p \cdot \overline{oq_p} \cdot \delta_{prw}} \cdot \left(\sum_{r \in R^p} \frac{\lambda_p \cdot \overline{oq_p} \cdot \delta_{prw}}{\sum_{r \in R^p} \lambda_p \cdot \overline{oq_p} \cdot \delta_{prw}} \cdot \left(\overline{st_{pr}} + Q_p \cdot \overline{oq_p} \cdot \overline{pt_{pr}} \right) \right)$$
$$(8)$$

$E(wq_w)$ denotes the expected waiting time in the queue at each work center w and is derived in (9) using a modified version of the well-known Kraemer and Langenbach-Belz approximation (see Kraemer and Langenbach-Belz, 1976). The mean and SCV of the batch interarrival times describe the aggregate arrival process at work center w. ρ'_w represents the adapted traffic intensity for work center w and is defined in (10). If competition for capacity at a work center intensifies, i.e., its utilization rises, waiting times get longer and the adapted traffic intensity increases. The batch arrival rate of product p is denoted by $\lambda_{bp} = \lambda_p/Q_p$ with a batch size of $Q_p \cdot \overline{oq_p}$ units.

$$E(wq_w) = \begin{cases} \frac{\rho'^2_w \cdot (ca^2_w + cs^2_w)}{2 \cdot l_w \cdot (1 - \rho'_w)} \cdot \exp\left\{ \frac{-2 \cdot (1 - \rho'_w) \cdot (1 - ca^2_w)^2}{3 \cdot \rho'_w \cdot (ca^2_w + cs^2_w)} \right\} & \text{if } ca^2_w \le 1 \\ \frac{\rho'^2_w \cdot (ca^2_w + cs^2_w)}{2 \cdot l_w \cdot (1 - \rho'_w)} & \text{if } ca^2_w > 1 \end{cases} \qquad (9)$$

$$\rho'_w = \sum_{p \in P} \sum_{r \in R^p} \lambda_{bp} \cdot \delta_{prw} \cdot \left(\overline{st_{pr}} + Q_p \cdot \overline{oq_p} \cdot \overline{pt_{pr}} \right) \qquad\qquad \forall w \in W \quad (10)$$

ca^2_w is the SCV of the batch interarrival time at work center w that can be computed using a set of system equations as described in Lambrecht, Ivens, and Vandaele (1998). The key idea is that for all operations the aggregate batch arrival rate equals the aggregate batch departure rate $\left(1 - \rho'^2_w \right) \cdot ca^2_w + \rho'^2_w \cdot cs^2_w$ of previous operations at work center w. This represents a convex combination of the interarrival time SCV and the service time SCV. If traffic intensity is low, the SCV of the aggregate batch departure time is close to the interarrival time SCV; otherwise, the SCV is approximately equal to the service time SCV under high capacity usage. The model has been adapted to integrate parallel servers and to account for the impact of machine breakdowns. The corresponding revisions are described in detail in Lieckens and Vandaele (2012).

$$cs^2_w = \left(\sum_{p \in P} \frac{l_{wp}}{l_w} \cdot \sum_{r \in R^p} \frac{\lambda_{bp} \cdot \delta_{prw}}{l_{wp}} \cdot \left(\overline{st_{pr}} + Q_p \cdot \overline{oq_p} \cdot \overline{pt_{pr}} \right)^2 \right) \cdot \mu^2_w - 1$$
$$+ \sum_{p \in P} \frac{l_{wp}}{l_w} \cdot \sum_{r \in R^p} \frac{\lambda_{bp} \cdot \delta_{prw}}{l_{wp}} \cdot \frac{s^2_{\overline{st_{pr}}} + Q_p \cdot \overline{oq_p} \cdot s^2_{\overline{pt_{pr}}}}{\left(\overline{st_{pr}} + Q_p \cdot \overline{oq_p} \cdot \overline{pt_{pr}} \right)^2} \qquad \forall w \in W \quad (11)$$

The SCV of the aggregate batch processing time (cs_w^2) is derived in (11). The term $l_{wp} = \sum_{r \in R^p} \lambda_{bp} \cdot \delta_{prw}$ denotes the aggregate batch arrival rate of product p at work center w, while $l_w = \sum_{w \in W} \sum_{r \in R^p} \lambda_{bp} \cdot \delta_{prw}$ is the aggregate arrival rate at work center w of all products combined. Consequently, l_{wp}/l_w measures the probability that a product in front of work center w is of type p. μ_w represents the aggregate processing rate at work center w and is derived in (12).

$$\frac{1}{\mu_w} = \left[\sum_{p \in P} \frac{l_{wp}}{l_w} \cdot \sum_{r \in R^p} \frac{\lambda_{bp} \cdot \delta_{prw}}{l_{wp}} \cdot \left(\overline{st_{pr}} + Q_p \cdot \overline{oq_p} \cdot \overline{pt_{pr}} \right) \right] \qquad \forall w \in W \quad (12)$$

The last term of the objective function in (8) calculates expected weighted setup and processing times. The binary parameter δ_{prw} indicates whether operation r of product p is performed on a specific work center w. We assume average setup times $\overline{st_{pr}}$ and processing times $\overline{pt_{pr}}$ for operation r of product p to be independent and identically distributed following a general distribution. Average setup and processing times as well as their corresponding standard deviations need to be divided by the availability a_w of work center w to obtain effective values (see Hopp and Spearman, 2008). It should be noted that this represents only a rough approximation which is found to be appropriate in this case (for further details see Vandaele, Van Nieuwenhuyse, and Cupers (2003)).

$$\alpha_{wt} = \sum_{p \in P} \sum_{r \in R^p} \frac{X_{pt}}{Q_p \cdot nm_w} \cdot \overline{st_{pr}} \cdot \delta_{prw} + (1 - a_w) \qquad \forall w \in W; t = 1...T \quad (13)$$

Having derived batch sizes using a dedicated optimization routine (see Lambrecht, Ivens, and Vandaele, 1998), we can determine the necessary capacity buffers α_{wt} per work center w and period t in (13) covering setup times and machine downtime due to failures. Note that the capacity buffer in terms of idle time (to cope with small variations in the system parameters) has been taken into account by solving equation (8). Machine availability is given as a fixed parameter a_w, while setup times need to be derived using batch sizes Q_p, the number of parallel machines per work center nm_w, and average setup time $\overline{st_{pr}}$ of operation r of product p.

Furthermore, actual lead times are derived from the ASQ model in two ways: first, by using a backwards scheduling approach starting from the due date period of the respective customer order, we determine binary lead time offset parameters γ_{wpzt} to allocate the capacity requirements to the respective time bucket and work center according to the production routing. Second, we determine aggregate lead times lt_{pt} in terms of APP time buckets which we can use to approximate WIP inventories. Lead time parameters and capacity buffers are derived from each ASQ model and handed over to the APP model to complete the current iteration of the approach.

4   Numerical Study

4.1   Problem Setting and Approach

For the numerical analysis we build on the case study of a medium-sized European automotive supplier which is described in Vandaele et al. (2000). The firm is affiliated with a large multi-national corporation and serves a range of customers in the B2B market. Our data set is based on a job shop environment with twelve products and ten machines. Manufacturing is performed during one shift of eight hours per day five days a week, yielding a total of 160 hours per month. This capacity can be extended to 280 hours using overtime for 500 EUR per hour. The WIP cost factor is set to 3 EUR per item and period. The planning horizon is divided into six periods with a length of two months each to span a full seasonal cycle.

The product portfolio consists of four product families: sleeves, gears, drums, and hubs. Their production processes can be summarized in four steps. After the raw steel is processed through rough machining operations in the cold steel shop, a heat-treatment hardens the parts. These hardened components are in turn treated by machining operations in the hard steel shop. In a last step, the rotating steel parts are installed into the housings and the products are finally assembled. Our

Figure 1 (machine data and routings):

Machine	Setup time (st) min/max [hours]	SCV st min/max [hours]	Processing time (pt) min/max [hours]	Machine units	Availability
Sawing	0.050/0.450	0.000/0.013	0.016/0.016	1	87%
Norm. Furnace	0.010/0.010	0.000/0.000	0.010/0.016	1	74%
Tumblast	0.010/0.010	0.000/0.000	0.001/0.008	1	86%
Lathe	1.196/3.931	0.143/1.545	0.037/0.111	5	96%
Press	0.725/0.879	0.052/0.077	0.011/0.012	1	84%
Gear Shaving	1.730/2.088	0.200/0.344	0.063/0.081	2	85%
Workbench	0.100/0.250	0.000/0.005	0.008/0.025	1	93%
Carb. Furnace	0.010/0.010	0.000/0.000	0.005/0.056	1	87%
Rotoblast	0.100/0.284	0.000/0.008	0.007/0.018	1	79%
Int. Grinding	0.901/1.476	0.081/0.218	0.051/0.051	2	84%

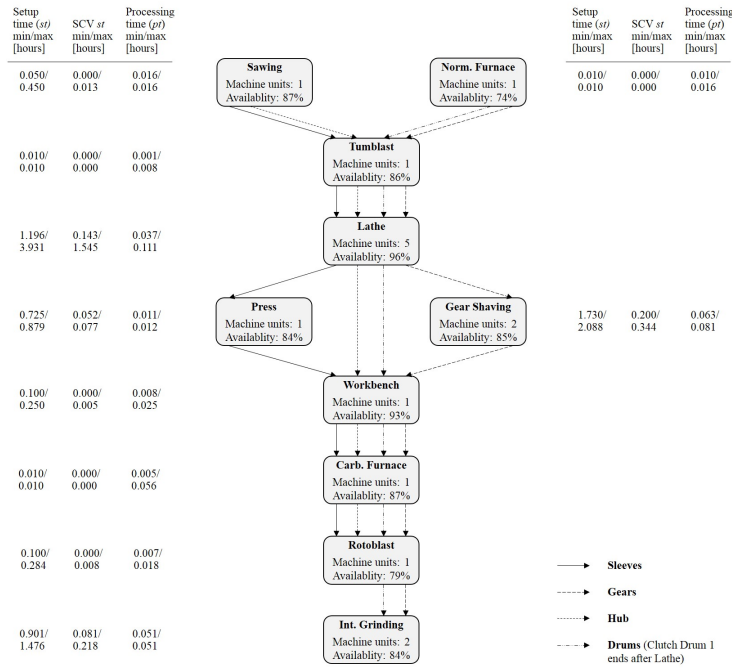Legend: Sleeves; Gears; Hub; Drums (Clutch Drum 1 ends after Lathe)

Figure 1: Product routings, machine data, and setup and processing times

case focuses on the first production phase which is the raw steel department. Figure 1 summarizes the master data pertaining to the machines and product routings as well as the ranges of setup and processing times. The processing times are deterministic while the setup times exhibit a certain degree of variability due to the complexity of the manual setup activities. The ranges of corresponding SCVs of the setup times are also given in Figure 1.

Demand follows a seasonal pattern with the base demand per product as shown in Table 1. Modeled as a harmonic oscillation, the demand peaks in the middle of the planning period and has a maximal amplitude according to a prespecified seasonality factor. Since the company in focus operates in an MTO setting, final goods inventories are non-existent. Every demand must be satisfied in the respective period and cannot be delayed beyond the due date. Besides the seasonal pattern, the arrivals of customer orders can exhibit variability which we investigate further below.

Following our approach described above, we generate several scenarios as a full factorial design of CM options and parameter constellations. The firm can source from two contractors that differ in terms of flexibility and price. Flexibility in this context relates to the range of products and the maximum volumes that can be commissioned to the contractor. Price levels are reflected in the unit cost of CM. We consider three CM options: single sourcing from an inflexible or flexible contractor

Product name	Base demand
Clutch Drum 1	95
Clutch Drum 2	594
Drum 1	1,320
Drum 2	679
Gear 54 Teeth	651
Gear 65 Teeth	849
Gear 69 Teeth	54
Hub	458
Sleeve 1	189
Sleeve 2	500
Sleeve 3	349
Sleeve 4	236

Table 1: Product master data

and a mixed setting with dual sourcing. The flexible contractor is capable of providing 35% of the base demand of every product for a given unit price between 3 and 15 EUR. The inflexible contractor is more limited and can only deliver 20% of the base demand of the drums and hubs, albeit at a price discount of 35% compared with the flexible contractor.

Parameter constellations		
Setup variability	low	*values given in the base case*
	moderate	constant term of 0.3 and scaling factor of 1.2
	high	constant term of 0.8 and scaling factor of 2.0
Demand variability	deterministic	*SCV of demand* = 0.0
	moderate	*SCV of demand* = 1.0
	high	*SCV of demand* = 2.5
Demand seasonality	flat	*seasonality factor* = 10%
	fluctuating	*seasonality factor* = 35%

Table 2: Parameter constellations for the scenario analysis

We consider three sources of uncertainty for the parameter constellations: setup time variability, demand variability, and demand seasonality. For the setup time variability, we distinguish three states (low, moderate, high) with respect to the product- and operation-specific SCVs. The case of low variability is characterized by the base data given in Figure 1. We apply a linear transformation to the values of the base case in order to consider moderate and high variability of setup times. Demand variability originates from volatile customer order behavior and is captured in product-specific SCVs for which we also investigate three distinct cases: deterministic demand as well as moderate and high demand variability. Distinct demand seasonality factors complete the parameter constellations in focus and cover flat versus fluctuating demand over the planning period. The parameter constellations are summarized in Table 2.

Creating a full factorial design of CM options and parameter constellations, we obtain 54 scenarios for which we need to conduct the aggregate planning approach and an independent assessment of the qualitative factors. Aggregate planning is performed using IBM ILOG OPL with CPLEX v12.6.0.0 for the APP model and a steepest descent algorithm implemented in C++ for the ASQ model. The iterative solution procedure was run on an Intel Core i5 machine with 1.8 GHz per core and 4 GB RAM, resulting in computation times of around four minutes per scenario. The algorithm terminates on average after three to four iterations. While the execution of the APP and ASQ models requires only a few seconds, the data consolidation and transformation between the calculation steps accounts for most of the computation time.

From the aggregate planning models we obtain CM volumes, aggregate order lead times, and total relevant costs. CM volumes represent the total number of production units that are sourced from a contractor over the course of the planning period. Aggregate order lead times are derived as weighted averages across planning periods and products according to the internal production volumes. Total relevant costs are calculated as the sum of overtime, CM, and WIP costs over the planning period and can be extracted from the objective function of the APP model.

In order to illustrate our approach, we apply a single metric to capture outsourcing risk as the major qualitative factor in our case with an ordinal scale from 1 (low risk) to 10 (high risk). In practice, these values are assessed through structured interviews and consensus group decision-making with relevant stakeholders. For the purpose of this paper and without loss of generality, we rely on the observation that a scenario with an inflexible contractor as well as high demand seasonality and high demand and/or setup variability exhibits the highest risk. In contrast, the lowest risk level is observed when a flexible contractor is opted for in a setting with low seasonality and low variability in demand and setup times. By applying a combinatorial scheme, we obtain risk assessments for each of the 54 scenarios.

Our DEA approach combines two inputs (risk, costs) and two outputs (external CM quantities, internal aggregate order lead times) which are all measured in categorically distinct units of measure:

number, monetary units, and time. For our calculations, the lead time metric is inverted to ensure a positive correlation between inputs and outputs, since a shorter lead time represents a higher output. The DEA efficiency scores are derived using SAS/OR 13.1 at negligible run times. The results of the aggregate planning models, the independent assessment of qualitative factors, and the DEA efficiency scores are summarized in Table 7 for the respective scenarios.

4.2   Discussion of the Results

In the following, we concentrate on interpreting the results pertaining to the selection of beneficial CM options and the implications of such a selection on operational performance. The overall results are summarized in Table 3 along the three sourcing options, showing minimum, average, and maximum efficiency scores across the parameter constellations. A single sourcing agreement with the inflexible contractor yields a mean value of only 76 while single sourcing with the flexible contractor and dual sourcing result in considerably higher mean efficiency values of 97 and 98, respectively. Comparing the efficiency values, we observe a wide range of outcomes between 52 and 98 for the inflexible contractor option in contrast to significantly narrower ranges for the flexible contractor option (92–100) and dual sourcing (95–100). We conclude that the flexible contractor option as well as dual sourcing largely outperform outsourcing to the inflexible contractor and lead to more robust results, since the efficiency scores are higher on average and exhibit less variability.

Sourcing Option	DEA Efficiency Scores		
	Minimum	Average	Maximum
flexible	92	97	100
mixed	95	98	100
inflexible	52	76	98

Table 3: Minimum, average, and maximum DEA scores

Continuing the investigation of the DEA results, we create partial views in terms of envelope curves along the input and output dimensions. This allows us to highlight additional characteristics of the solutions while keeping visualization complexity at a reasonable level. Since the partial views shown in Figures 2 and 3 cover only one output factor at a time, we need to consider the overall efficiency scores of the scenarios to interpret the results. To achieve this we highlight efficient scenarios from the overall DEA in black. Both partial views confirm that scenarios with the inflexible sourcing option are inferior to those involving the flexible contractor arrangement with the scenarios involving the mixed setting falling in between.

Analyzing the results for the output dimension CM volume, one can see on the vertical axis that higher risk penalizes the inflexible contractor option more than the mixed arrangement, which in turn is inferior to all scenarios involving the flexible contractor option. We conclude that the higher risk is not compensated for by higher CM volumes and corresponding contractor productivity. Reasoning horizontally, the ratio of CM volumes to costs clearly discriminates between the setting with an inflexible contractor and the other two sourcing options. However, the cost dimension does not discriminate between the flexible and the mixed sourcing setting. As there are some efficient scenarios below the efficient curve of this partial view, we conclude that lead time obviously has an additional efficiency impact on the scenario ranking.

Comparing scenario clusters in Figure 2, one can see the impact of demand fluctuation on the efficiency of distinct sourcing options. While we observe a clear separation for the inflexible contractor option (scenarios 1–9 vs. 10–18) and the mixed sourcing arrangement (scenarios 37–45 vs. 46–54), there is no analogous separation for the scenarios involving the flexible contractor option. This can be explained by the small product range and limited production volumes that can be commissioned to the inflexible contractor. As a consequence, the company cannot leverage the inflexible contractor to fully accommodate seasonal demand fluctuation, which results in lower contractor productivity and lower efficiency scores. Even in a mixed-source setting with additional benefits from lower CM costs, the negative impact of inflexibility on overall efficiency remains.
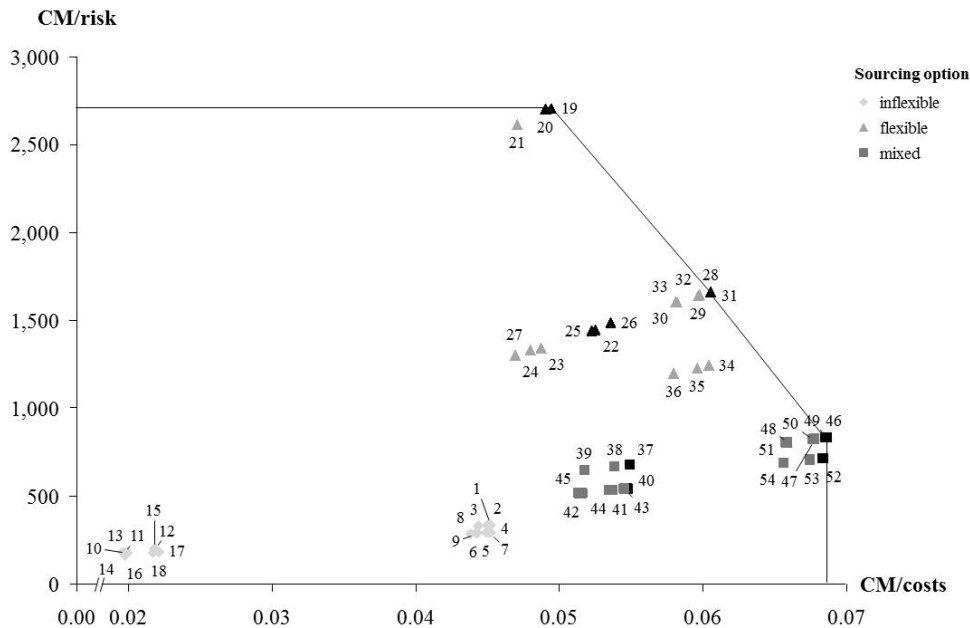
Figure 2: Envelope curve relating CM volumes to risk and costs

Examining the partial view of the lead time dimension (see Figure 3), we also observe the negative impact of demand fluctuation on the efficiency scores for the respective scenarios (scenarios 10–18, 28–36, and 46–54). While the flexible contractor can fully compensate for the negative impact via improved contractor productivity (see the black-colored items) at least for selective scenarios, all sourcing options exhibit comparably low efficiency scores for the lead time dimension in relation to both risk and costs. Comparing scenarios 1–9 vs. 37–45, one can see that, for flat demand patterns, both sourcing from the inflexible contractor and mixed sourcing result in comparably high efficiency values. Despite this, mixed sourcing exhibits a slightly lower risk exposure.

In the following, we examine the operational performance metrics of the stochastic manufacturing system in greater detail to investigate the impact of demand and setup variability as well as demand seasonality. Starting with demand seasonality, we compare average aggregate batch sizes and average aggregate lead times for flat and fluctuating demand. From Table 4 one can see opposing effects: while average aggregate batch sizes (+1.9%) and lead times (+3.1%) increase with outsourcing flexibility under flat demand, corresponding batch sizes (-5.8%) and lead times (-6.2%) decrease when demand fluctuates over time. This can be explained by the fact that outsourcing serves distinct purposes in the two cases. With flat demand, outsourcing is used to improve utilization by commissioning volumes of selective products to the contractor, which reduces non-productive setup times and allows for larger batch sizes. In contrast, when demand fluctuates, external production serves as a secondary capacity on a larger scale to smoothen operating levels with the respective effects on batch sizes and lead times.

Assuming moderate demand and setup variability, we further analyze the case of flat vs. fluctuating demand in Figure 4 using illustrative scenario results. In general, we observe significantly higher

	Flat demand		Fluctuating demand	
Sourcing Option	Averge aggregate batch size	Average aggregate lead time	Average aggregate batch size	Average aggregate lead time
flexible	110.1	43.9	102.1	44.4
mixed	109.5	43.9	103.3	45.2
inflexible	108.0	42.6	108.4	47.3

Table 4: Average aggregate batch sizes and lead times given flat vs. fluctuating demand
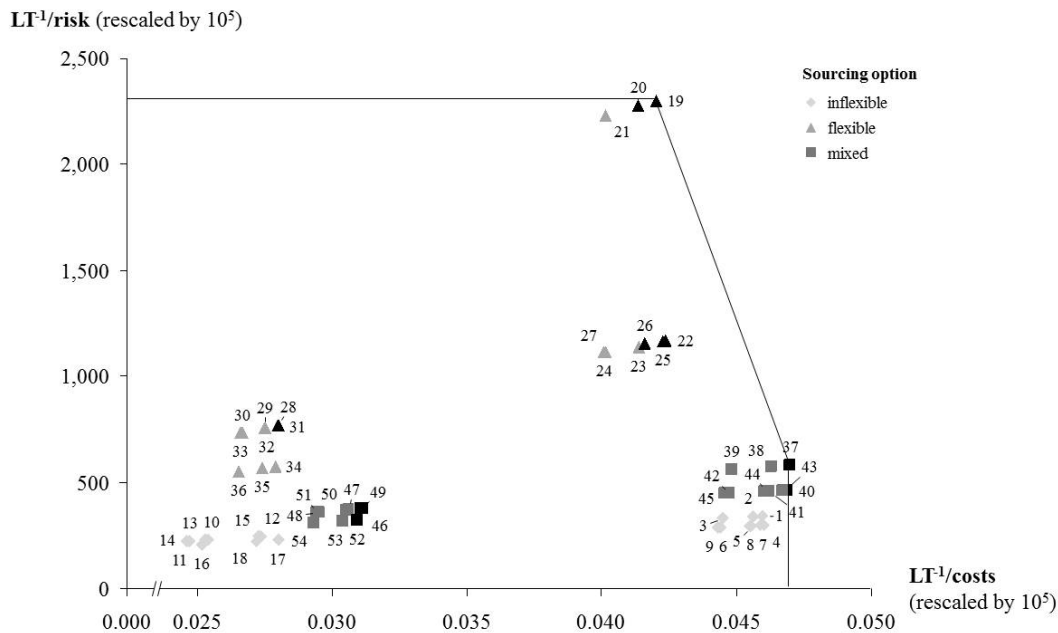
Figure 3: Envelope curve relating aggregate order lead times (LT) to risk and costs

relevant costs (+47–56%) associated with managing operations when demand fluctuates. The changes in average batch sizes support the abovementioned general findings. In both settings, overtime is used only with the inflexible contractor option. Higher flexibility of the contractor implies rising CM costs and a shift towards external production. Under a fully flexible outsourcing agreement and flat demand, 40% of the costs are allocated to CM. This figure rises as high as 60% if demand seasonality increases from flat to fluctuating. While the combination of an inflexible and a flexible contractor delivers mediocre results in terms of batch sizes and lead times, this setting yields the lowest-cost solution in both cases, with savings of about 10% compared with the results of a single sourcing agreement with the flexible contractor.

Sourcing	Demand variability			Setup variability		
Option	Low	Moderate	High	Low	Moderate	High
flexible	110.4	110.1	109.7	109.4	109.9	110.9
mixed	109.4	109.5	109.6	108.9	109.4	110.3
inflexible	107.8	107.9	108.2	107.4	108.0	108.6

Table 5: Average aggregate batch sizes for various demand and setup variability parameters given flat demand

Building on the previous results, we examine the impact of demand and setup variability separately for flat and fluctuating demand. From Table 5 one can see that the findings on outsourcing flexibility under flat demand still hold, i.e., average batch sizes increase with outsourcing flexibility, which is also confirmed by the respective external and internal production volumes. Comparing the results for differing levels of variability, we conclude that demand variability has virtually no impact on average aggregate batch sizes (±0.4%) while rising setup variability appears to increase average aggregate batch sizes (+1.1–1.3%), which is also true for the corresponding aggregate lead times. The effect of increasing batch sizes can be explained by the fact that the company offsets the negative impact of rising setup variability by building fewer but larger batches.

As can be seen from Table 6, the abovementioned findings on outsourcing flexibility for the case of fluctuating demand are reinforced for settings with the flexible contractor option or a mixed sourcing arrangement, i.e., average aggregate batch size decreases as outsourcing flexibility increases. Examining the impact of demand and setup variability, we observe similar results as for the case of flat
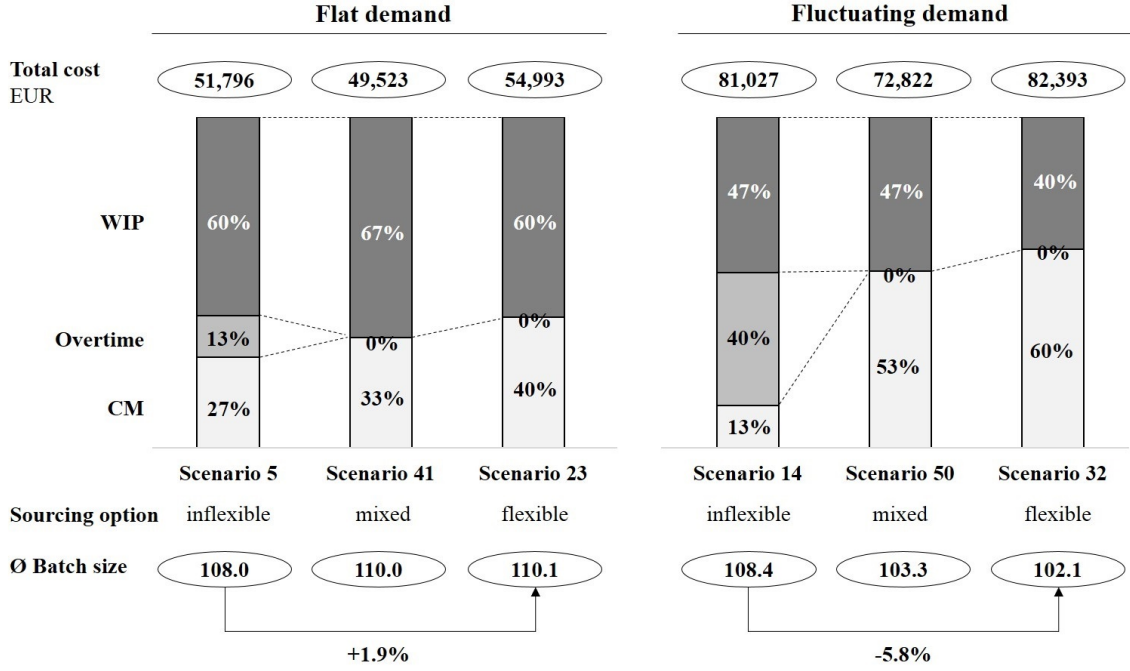
Figure 4: Cost breakdown for selected scenarios given flat vs. fluctuating demand

Sourcing	Demand variability			Setup variability		
Option	Low	Moderate	High	Low	Moderate	High
flexible	102.1	102.0	102.2	100.9	101.8	103.6
mixed	103.2	103.3	103.5	102.1	103.0	104.8
inflexible	109.7	109.9	105.5	112.7	110.1	102.3

Table 6: Average aggregate batch sizes for various demand and setup variability parameters given fluctuating demand

demand: virtually no changes in batch sizes for differing levels of demand variability ($\pm 0.2\%$) and increasing batch sizes for higher setup variability ($+2.7\%$), which are even amplified due to demand fluctuation. However, we obtain converse results for the case of single sourcing from the inflexible contractor: (i) considerably lower batch sizes when demand/setup variability is high and (ii) decreasing batch sizes when setup variability rises.

To further investigate the aforementioned matter, we conduct a breakdown for selected scenarios as shown in Figures 5 and 6, comparing inflexible and flexible sourcing options for various parameters of demand and setup variability. Analyzing the cost split as well as related internal and external production volumes, we conclude that in a setting with a flexible contractor additional variability can be passed on to the contractor with only marginal increases in total relevant costs. In contrast, with the inflexible sourcing option, the company needs to manage part of the variability on its own. Since both types of variability drive batch lead times and WIP, the company reduces average batch sizes to reduce WIP costs. However, this comes at the cost of additional CM volumes and overtime to compensate for the additional capacity loss due to setups.

5 Conclusion and Outlook

In this paper, we proposed a novel approach to address the strategic-tactical issue of outsourcing decision-making in a stochastic manufacturing environment. Our contribution is twofold: first, we presented a robust multi-criteria approach that considers multiple quantitative as well as qualitative factors and that accounts for parameter uncertainty. For this purpose, a DEA-based approach was
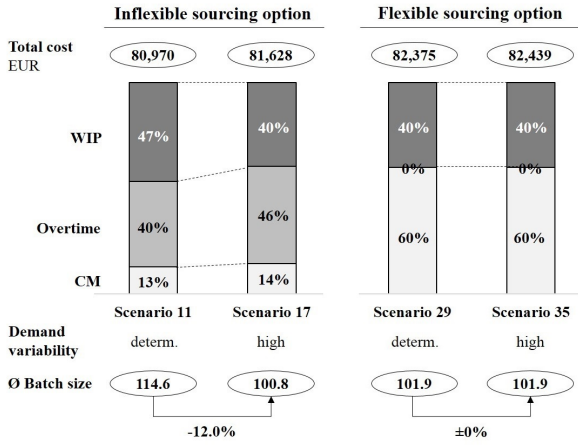
Figure 5 (left):

	Inflexible sourcing option		Flexible sourcing option	
Total cost EUR	80,970	81,628	82,375	82,439
WIP	47%	40%	40%	40%
			0%	0%
Overtime	40%	46%	60%	60%
CM	13%	14%		
	Scenario 11	Scenario 17	Scenario 29	Scenario 35
Demand variability	determ.	high	determ.	high
Ø Batch size	114.6	100.8	101.9	101.9
	-12.0%		±0%	

Figure 5: Cost breakdown for selected scenarios: focus demand variability

Figure 6 (right):

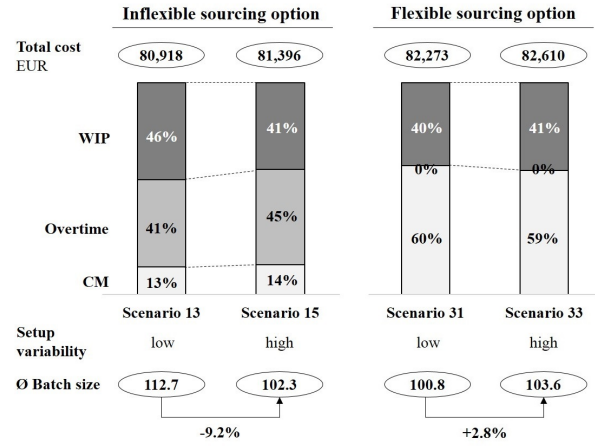|	Inflexible sourcing option		Flexible sourcing option	
Total cost EUR	80,918	81,396	82,273	82,610
WIP	46%	41%	40%	41%
			0%	0%
Overtime	41%	45%	60%	59%
CM	13%	14%		
	Scenario 13	Scenario 15	Scenario 31	Scenario 33
Setup variability	low	high	low	high
Ø Batch size	112.7	102.3	100.8	103.6
	-9.2%		+2.8%	

Figure 6: Cost breakdown for selected scenarios: focus setup variability

applied to rank several outsourcing options under various parameter constellations. Second, we introduced an APP approach for stochastic manufacturing environments with CM options to obtain operational performance metrics for the DEA. To this end, an aggregate stochastic queuing model was combined with a conventional APP model to capture workload-dependent lead times as well as capacity losses due to setup times and machine breakdowns.

A real-life case example was used to highlight our approach in which costs and risk exposure of the manufacturing system in focus were balanced against contractor productivity and customer service, which we represented by aggregate order lead times. For the analysis, we used a combination of overall efficiency scores and partial views of envelope curves to ease representation of the results given the multi-dimensional approach of DEA. These methods appeared to be very instructive and could support S&OP meetings with management professionals that have only limited knowledge of OR methods. Although we have only considered an illustrative example, the study revealed some general insights with respect to capacity management and outsourcing in stochastic manufacturing environments. Demand fluctuation appears to be the single most important factor that influences operational performance and determines the strategic role of outsourcing in this setting. Demand and operations variability have only minor effects on operational metrics given the fact that outsourcing options can compensate for them.

For future research, one can generalize the approach to include other types of decisions that are at stake in the S&OP context. This could include, for instance, aspects of new product introduction and profitable-to-promise planning. In this work, we integrated outsourcing risk as the single most relevant qualitative factor. However, there are many additional intangible criteria such as sustainability, strategic fit, or managerial complexity that could be considered to this end. Furthermore, this approach could be applied to a process industry context to elaborate on the impact of variable processing times and more complex changeover processes as well as product routings. Some additional work could be done from a methodological perspective by improving the aggregate stochastic queuing model with respect to batch splitting or the modeling of machine repair activities. Moreover, the robust DEA approach should be investigated further to examine novel methods for scenario analysis as well as for visualizing and interpreting the results.

Acknowledgment

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	Designs		Parameters		Model KPIs			Non-Model KPIs	DEA
#	Sourcing option	Demand seasonality	Demand variability	Setup variability	Cost [EUR]	CM [units]	LT [hours]	Risk [value]	Score
1	inflexible	flat	determ.	low	51,839	2,345	42	7	98
2	inflexible	flat	determ.	moderate	51,779	2,330	42	7	97
3	inflexible	flat	determ.	high	51,926	2,304	43	7	95
4	inflexible	flat	moderate	low	51,789	2,343	42	8	98
5	inflexible	flat	moderate	moderate	51,796	2,328	42	8	97
6	inflexible	flat	moderate	high	51,931	2,302	43	8	95
7	inflexible	flat	high	low	51,805	2,340	42	8	98
8	inflexible	flat	high	moderate	51,679	2,265	43	8	97
9	inflexible	flat	high	high	51,946	2,299	43	8	94
10	inflexible	fluctuating	determ.	low	80,879	1,611	49	9	54
11	inflexible	fluctuating	determ.	moderate	80,970	1,594	50	9	53
12	inflexible	fluctuating	determ.	high	81,397	1,777	45	9	58
13	inflexible	fluctuating	moderate	low	80,918	1,607	49	9	54
14	inflexible	fluctuating	moderate	moderate	81,027	1,589	50	9	52
15	inflexible	fluctuating	moderate	high	81,396	1,773	45	9	58
16	inflexible	fluctuating	high	low	80,982	1,599	49	10	54
17	inflexible	fluctuating	high	moderate	81,628	1,806	44	10	60
18	inflexible	fluctuating	high	high	81,413	1,768	45	10	58
19	flexible	flat	determ.	low	54,680	2,707	43	1	100
20	flexible	flat	determ.	moderate	55,050	2,702	44	1	100
21	flexible	flat	determ.	high	55,510	2,615	45	1	97
22	flexible	flat	moderate	low	55,053	2,892	43	2	100
23	flexible	flat	moderate	moderate	54,993	2,683	44	2	95
24	flexible	flat	moderate	high	55,538	2,607	45	2	92
25	flexible	flat	high	low	55,092	2,881	43	2	100
26	flexible	flat	high	moderate	55,531	2,976	43	2	100
27	flexible	flat	high	high	55,520	2,666	45	2	93
28	flexible	fluctuating	determ.	low	82,249	4,980	43	3	100
29	flexible	fluctuating	determ.	moderate	82,375	4,921	44	3	99
30	flexible	fluctuating	determ.	high	82,584	4,812	45	3	96
31	flexible	fluctuating	moderate	low	82,273	4,988	43	3	100
32	flexible	fluctuating	moderate	moderate	82,393	4,928	44	3	99
33	flexible	fluctuating	moderate	high	82,610	4,805	45	3	96
34	flexible	fluctuating	high	low	82,323	4,978	44	4	96
35	flexible	fluctuating	high	moderate	82,439	4,917	44	4	95
36	flexible	fluctuating	high	high	82,650	4,796	46	4	93
37	mixed	flat	determ.	low	49,276	2,710	43	4	100
38	mixed	flat	determ.	moderate	49,492	2,669	44	4	99
39	mixed	flat	determ.	high	50,017	2,591	45	4	96
40	mixed	flat	moderate	low	49,312	2,704	43	5	100
41	mixed	flat	moderate	moderate	49,523	2,662	44	5	98
42	mixed	flat	moderate	high	50,055	2,585	45	5	95
43	mixed	flat	high	low	49,357	2,694	43	5	99
44	mixed	flat	high	moderate	49,571	2,653	44	5	98
45	mixed	flat	high	high	50,101	2,576	45	5	95
46	mixed	fluctuating	determ.	low	72,643	4,993	44	6	100
47	mixed	fluctuating	determ.	moderate	72,789	4,937	45	6	99
48	mixed	fluctuating	determ.	high	73,110	4,824	46	6	96
49	mixed	fluctuating	moderate	low	72,679	4,987	44	6	100
50	mixed	fluctuating	moderate	moderate	72,822	4,932	45	6	99
51	mixed	fluctuating	moderate	high	73,145	4,819	46	6	96
52	mixed	fluctuating	high	low	72,724	4,976	44	7	100
53	mixed	fluctuating	high	moderate	72,870	4,922	45	7	98
54	mixed	fluctuating	high	high	73,192	4,810	47	7	96

Table 7: Results of the DEA for the 54 scenarios