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Impact of the shape of demand distribution in decision models for operations management

Anssi Käki [a,*], Ahti Salo [a,1], Srinivas Talluri [b,2]

[a] Department of Mathematics and Systems Analysis, School of Science, Aalto University, P.O. Box 11100, 00076, Finland

[b] Department of Supply Chain Management, Eli Broad College of Business, Michigan State University, N370 Business Complex, East Lansing, MI 48824, USA

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ABSTRACT

Decision support tools are increasingly used in operations where key decision inputs such as demand, quality, or costs are uncertain. Often such uncertainties are modeled with probability distributions, but very little attention is given to the shape of the distributions. For example, state-of-the-art planning systems have weak, if any, capabilities to account for the distribution shape. We consider demand uncertainties of different shapes and show that the shape can considerably change the optimal decision recommendations of decision models. Inspired by discussions with a leading consumer electronics manufacturer, we analyze how four plausible demand distributions affect three representative decision models that can be employed in support of inventory management, supply contract selection and capacity planning decisions. It is found, for example, that in supply contracts flexibility is much more appreciated if demand is negatively skewed, i.e., has downside potential, compared to positively skewed demand. We then analyze the value of distributional information in the light of these models to find out how the scope of improvement actions that aim to decrease demand uncertainty vary depending on the decision to be made. Based on the results, we present guidelines for effective utilization of probability distributions in decision models for operations management.

1. Introduction

Organizations use mathematical models to support decision making in uncertain environments. Such models often account for many uncertain variables: in manufacturing, product demand varies from period to another; cost parameters change over time due to fluctuating raw-material prices or rising wages; and suppliers may not supply as promised due to constrained capacity or quality problems. Uncertain demand, in particular, is a key variable for operations management and supply chain planning: for example, push type supply chains are typically coordinated using a forecast of demand for a given planning period. This demand forecast is built on expert knowledge and/or mathematical forecast and serves as a basis for other supply chain planning activities from operational to strategic level decisions [41]. In principle, accurate forecasts would allow cost-efficient coordination, but forecasting is difficult in turbulent environments. As a result, increasing attention has been paid to the question of how demand and supply uncertainties should be accounted for in supply chain modeling [10]. These uncertainties impact all levels of operations management: strategic (e.g., [14,26]), tactical (e.g., [18]) and operational (e.g., [36]).

Considerable efforts have been made to develop both stochastic (distribution based) and robust (distribution free) models to support decision making under uncertainty. Such models can be used to derive insights under very general assumptions; for example, they can be used to study how a given supply contract shares demand risk in a supply chain, or how lead time variability reduction can systematically lower inventory levels while keeping the shortage risk constant. But at a more concrete level (such as when implementing decision support systems) detailed assumptions about the uncertainties are required for setting numerical contract parameters or calculating target inventory levels, for example. Thus, the estimation of uncertainties is critical for model implementation.

In this paper, we study how the shape of demand distribution can impact the results of decision making models in operations management, and discuss the value of distributional knowledge in these models. In particular, we focus on demand uncertainty and show how seemingly similar but qualitatively different uncertainties impact three widely employed models. We use different

* Corresponding author. Tel.: +358 9 470 25885; fax: +358 9 470 23096.
E-mail addresses: anssi.kaki@aalto.fi (A. Käki), ahti.salo@aalto.fi (A. Salo), talluri@bus.msu.edu (S. Talluri).
1 Tel.: +358 9 470 25885; fax: +358 9 470 23096.
2 Tel.: +1 517 432 6430; fax: +1 517 432 1112.

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demand distributions, which exhibit at least one of the following statistical properties: (i) symmetry, (ii) positive skewness, (iii) negative skewness, and (iv) bimodality. Arguably, these properties can be used to describe the qualitative attributes of a large share of realistic demand types. We assume demands which have identical expected value and variance, but which differ in shape with respect to (i)–(iv). By drawing upon these examples, we also analyze how much value the knowledge about a distribution can offer, compared to a case where the distribution is not known. Similar analysis has been done before for individual decision models, but not extensively for multiple models as we do here. Based on the resulting insights we provide high-level guidelines for managers who seek to address uncertainties in all levels of decision making in operations.

Our study is motivated by a large consumer electronics company which is in the process of designing a new sourcing strategy. The company sought better understanding on how demand uncertainty can be managed when there are different types of demand, depending on the product category and market segment. Such challenges are not unique: because common planning systems make only use of point demand forecast, and deviation at best, the impact of the shape of demand distribution is largely neglected. According to Van Nieuwenhuyse et al. [32], companies lack capability to analyze demand uncertainty and use the results as decision support. For example, they note that SAP's Advanced Planning and Optimization module "disregards uncertainty". However, the same authors have developed an advanced software module that accounts for stochastic demand and they report promising results from two cases in different manufacturing industries.

Other promising applications have been reported in this area: Talluri et al. [42] present a simple enhancement for lead time demand estimation that could lead to large saving in inventory costs at a pharmaceutical company. Nagali et al. [31] describe the Procurement Risk Management approach at Hewlett-Packard, where instead of a point forecast, a scenario-based approach to demand forecasting has been applied successfully with improved component availability and significant cost savings. Sodhi [40] presents exploratory work on managing Sales and Operations Planning process (S&OP) at a consumer electronics manufacturer. He demonstrates how the value of flexibility and risk of shortages or excess inventories can be analyzed with a stochastic demand model. Finally, according to survey of 180 executives by Jain et al. [20], "Non-normal demand distributions that make traditional forecast modeling difficult" was pointed out as one of the biggest challenges of demand management across companies. Jain et al. concluded that companies with best-in-class demand management capabilities reap multiple benefits in form of, e.g., improved invetory turns and higher order fulfillment rates.

The rest of the paper is structured as follows: Section 2 relates our work to earlier approaches in uncertainty modeling and operations management. Section 3 covers the example demand distributions and Section 4 describes the models and corresponding numerical results. Subsequently, Section 5 elaborates the value of distributional information in these models. Finally, Section 6 discusses the implications for managers and Section 7 presents conclusions.

2. Approaches to uncertainty modeling in operations management

Extensive reviews of quantitative research in operations management include Kouvelis et al. [22], Tang [43] and Peidro et al. [34], who also refer to many applications that consider uncertainties. We discuss mostly optimization based approaches in connection with uncertainty modeling. In this respect, two complementary approaches can be identified: *stochastic optimization* and *robust optimization*. Gupta and Maranas [18] further divide stochastic optimization to *scenario approach* where uncertainties are presented by a set of discrete scenarios, and *distribution approach* where probability distributions are used; this latter approach is the focus in this paper, but our aim is to study the sensitivity of models with respect to demand distribution. Robust optimization, on the other hand, has recently received attention as a distribution-free optimization approach (e.g., [16,4]). There are also studies that fall into both categories: e.g., Andersson et al. [1] select a distribution based on entropy maximization principle, which makes the approach both distribution based and robust at the same time.

We use safety stock calculation for inventory management as an example of an operational model. Various studies have discussed the impact of demand distribution in this context: Naddor [30] compares inventory costs under Poisson, beta, negative binomial, uniform, and 2-point (extreme) distributions. He finds that false assumptions about a distribution can become costly in extreme cases, but with realistic distributions, inventory management is insensitive to distribution choice and only first two moments of the distribution are essential. Fortuin [15] studies a similar inventory policy with Gaussian, logistic, gamma, log-normal, and Weibull distributions. He finds that these yield similar policies and thus recommends using logistic distribution, because it results in simple ordering formula. Lau and Zaki [25] note that mean and variance are not sufficient for safety stock calculation, but also skewness and kurtosis should be accounted for. Eppen and Martin [12] study safety stock calculation when demand distribution is estimated from data; they also present a bimodal demand distribution in their motivational example, which is one of the rare cases that bimodality is explicitly considered at least in some level. In robust approaches, in his seminal paper Scarf [37] considers ordering when only the minimum and maximum demands are known and develops a (conservative) ordering policy which is currently known as the *Scarf's rule*. More recently, Gallego and Moon [16], Yue et al. [44], Perakis and Roels [35] and Andersson et al. [1] have extended the literature of robust inventory management; the latter found that maximum entropy approach works well under both risk-neutral and risk-averse objective in a newsvendor setting. We note that all aforementioned references treat the specific topic of inventory management in more detail than we do. In this respect, our contribution relates to ability to compare insights from this case with two other models' outcomes, which yields a more complete picture over all planning horizons of a company.

Our second model is for tactical level sourcing with capacity reservation options, introduced by Cachon and Lariviere [5]. They characterize demand with the scaled distribution family, and note that most their results hold for arbitrary distributions. Pasternack [33] also studies sourcing in a two stage setting; he focuses on buyback contracts and gives both generic results and examples based on normal distribution. Barnes-Schuster et al. [2] study various supply contracts and find that their relative value grows along with demand variation, when demand follows normal distribution. Lariviere and Porteus [24] study the impact of demand distribution in a procurement setting, where manufacturer sets the wholesale price of a product. They conclude that pricing is critically dependent of the coefficient of variation of demand. The results hold for a large family of distributions, but this family contains only unimodal distributions. Ben-Tal et al. [3] compare a robust approach with perfect hindsight (deterministic demand) in a simulation study for dynamic inventory management with flexible supply contracts. They find that the mean difference in costs grows from 8% to 38% (the robust setting being more costly) when demand fluctuation changes from 10% to 70%