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Forecasting for inventory planning: a 50-year review

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Abstract

Forecasting and planning for inventory management has received considerable attention from the OR community over the last 50 years because of its implications for decision making, both at the strategic level of an organization and at the operational level. Many influential contributions have been made in this area, reflecting different perspectives that have evolved in divergent strands of the literature, namely: system dynamics (SD), control theory and forecasting theory (both statistical and judgemental). Although this pluralism is healthy in terms of knowledge advancement, it also signifies the fragmentation of the OR discipline and the lack of cross-fertilization of ideas to develop more comprehensive approaches towards the resolution of the same issues. In this paper, the relevant literature is reviewed and synthesized to promote some convergence between these different approaches to inventory forecasting and planning. The review concludes with an inter-disciplinary agenda for further research.

Keywords: Forecasting; Inventory Management; System Dynamics; Control Theory

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Introduction

From its foundation, Operational Research (OR) has made many substantial contributions to inventory forecasting and planning. These contributions have influenced supply chain practices in public and private organizations across the world over the last 50 years.

In this paper, we focus on inventory forecasting and planning from the perspective taken by divergent strands of the literature, namely: system dynamics (SD), control theory and forecasting theory (both statistical and judgemental)[1]. Although this plethora of different perspectives to the same problem may be perceived as a healthy development in terms of knowledge advancement, it also signifies the fragmentation of the Operational Research discipline into sub-disciplines that are not adequately cross-informing theory and practice. These sub-disciplines have grown into disciplines in their own right, prohibiting a constructive exchange of ideas for the benefit of solving problems of common interest. This fragmentation is exemplified by the different conferences (and corresponding audiences) organized by different societies (eg, SD, Forecasting, Inventories Research) that in turn produce different journals with, in our opinion, inadequate cross-referencing. There is great scope for their cross-utilization (Akkermans and Dellaert, 2005) to develop more comprehensive approaches to inventory forecasting and planning. This review intends to promote convergence between these different approaches to addressing forecasting

[1] Control theory is the inter-disciplinary branch of mathematics and engineering that deals with the behaviour of dynamical systems. Its applications overlap with many of the interests of the OR community, such as production and inventory problems, machine maintenance and replacement and marketing. The interface between Control Theory and OR is discussed in Sethi and Thompson (2000).

and planning for inventory management. We do not attempt to review all the interactions between forecasting and OR, as this has already been done recently (Fildes *et al*, 2008a).

The remainder of our paper is organized as follows: in the following section we examine strategic planning, followed, in section 3, by the control theoretic approach to supply chain inventory planning. In section 4, we review the contributions made in the last 50 years to forecasting for the replenishment of fast moving items. This is followed, in section 5, by the developments over the same time period, for the control of slow and intermittent demands. In section 6, we discuss the issue of human judgement in forecasting. Finally, our conclusions are discussed in section 7, where we also present an agenda for inter-disciplinary future work. We offer an integrative framework linking four OR approaches, namely Statistical Forecasting, Judgemental Forecasting, Control Theory and System Dynamics.

Strategic planning and System Dynamics

Early work on forecasting and inventory management focussed on operational improvements. Brown (1951:21) remarked: "*The quantitative study of the operation is made by statistical analysis of operational data to predict the outcome of similar conditions.*" Although this statement referred to OR in general, it also encapsulates the OR approach to inventory management at the time. For example, detailed operational models, based on statistical analysis, were developed by the Field Investigation Group at the National Coal Board (eg, Lawrence *et al,* 1961; Mitchell, 1962; Boothroyd and Tomlinson, 1963).

Comprehensive operational computerised forecasting and stock-control systems became more prevalent in the 1960s and 1970s, stimulated by the pioneering work of Brown (1959, 1963, 1967). These computer systems became ever more complex, but tended to lack strategic capabilities. An important paper by Johnston (1980) described the design and implementation of a forecasting and stock control system that enabled the quantification of strategic decisions, such as the consequences of changing the total investment in stock, or the overall service level. His system enabled managers to appreciate, for each stock grouping, how various control settings would affect stock values, out of stock percentages, excess stocks and working stocks. Cooper (1984) adopted a similar approach at Rolls-Royce (Aero). The stock-control programs in use at the time had not been designed or implemented as aggregate level control systems. The Rolls-Royce OR Group at Derby responded by introducing a 'development testbed' approach to mimic some of the features of a testbed for aero-engines. One of the operating modes of the new software was called 'strategic'. It enabled managers at Rolls-Royce to evaluate the consequences of alternative market trend assumptions, terms of business and control policies.

Starr and Miller (1962) advocated the use of an 'optimal policy curve', derived using Lagrange multipliers, showing the trade-off between inventory investment and workload (annual orders). This approach was extended by Gardner and Dannenbring (1979), who proposed the determination of an 'optimal policy surface' based on inventory investment, workload (annual orders) and percentage of requisitions short. This enables managers to explore the policy surface and to determine the best policy mix, in the light of organizational priorities. Johnston *et al* (1988) developed more ambitious 'response curves', showing the effect on 'stock cover' (ratio of the average total stock to the average monthly demand) of average lead times, reorder intervals and service level percentages (using the fill-rate or P_2 measure). Gardner (1990) used a simpler approach to construct 'trade-off curves' between inventory investment and average delay in filling back orders. His analysis took a step forward by examining separate trade-off curves for each forecasting method, allowing the 'best' method to be identified. The 'best' method is simply the one whose trade-off curve dominates all others, if such a curve exists. More recently, Catt (2007) has advocated a formula-driven approach to the calculation of the Cost of Forecast Error, based on analysis of individual products, using the cycle service level or P_1 measure. Boylan (2007) recommended that, before employing such an approach, the following factors should be considered: i) ensuring that an appropriate service measure is employed, ii) using the most appropriate level of aggregation, iii) applying sensitivity analysis to the cost estimates, since they are approximate, and iv) using different carrying charges for different groups of products, according to the risk of obsolescence.

A number of algebraic formulae have been proposed to estimate the relative costs of holding stock centrally or at a range of decentralised locations. Maister (1976:124) postulated the following 'square root law': "*The total inventory in a system is proportional to the square root of the number of locations at which a product is stocked*". This law applies to both safety stocks and cycle stocks. For safety stocks, the law holds when the demands at each decentralised location are uncorrelated and have equal variances, and the safety stocks are controlled by setting them at a constant multiple of the standard deviation of demand, assuming a P_1 service measure. For cycle stocks, the law holds if the mean demands at each decentralised locations are equal and the cycle stocks are controlled by an Economic Order Quantity approach.

Zinn *et al* (1989) provided a more general formula for safety stocks for a two-depot problem, which takes into account the ratio of the standard deviations of demand at the two depots and the correlation of demand between them. This safety stock formula was generalized to any number of depots by Mahmoud (1992), who also discussed rules for deciding between sub-consolidations (of a subset of depots) and a super-consolidation (of all depots). Further extensions were analyzed by Das and Tyagi (1997), taking into account inventory and transportation costs. A broader management perspective is offered by Wanke and Zinn (2004) who consider make to order / make to stock and push / pull deployment, in addition to inventory centralization decisions.

Whilst inventory centralization models may have quite a simple structure, interactions between echelons of a supply chain call for a more sophisticated approach. The first major contribution to this field was by Forrester (1958). In his ground-breaking article on 'industrial dynamics' (which later became known as system dynamics), he illustrated his new approach using the Production and Distribution functions of an organization. This showed how relatively small variations in demand can be amplified through the supply chain, a phenomenon later known as the 'bullwhip effect'. Case study evidence for this phenomenon was provided by Forrester (1961). Forrester's group at MIT introduced the *Beer Game*, involving independent inventory decision making by players. Sterman (1989) discusses the bullwhip effect in this game and how the irrational behaviour exhibited by the players contributes to this effect.

System dynamics focuses on stocks and flows, allowing the effect of feedback loops to be analysed. It is therefore a natural modelling tool for inventory planning. For example, Akkermans and Vos (2003, 2004) analysed demand variance and workload amplification effects in service supply chains. System Dynamics can be used in a qualitative mode, concentrating purely on system structure, or in a quantitative mode, predicting the effect of policy changes. It can also be used as a foundation for other modelling methods, such as the control theory models (to be reviewed in the next section of the paper). Wolstenholme (1982) argued that system dynamics is often misunderstood by soft systems methodologists as a hard systems modelling technique. Although quantitative SD is 'hard', he argued that Qualitative System Dynamics (QSD) should be seen as a 'soft' method. QSD was supported by software developments in packages such as *Powersim*^{TM} and *Vensim*^{TM} allowing icon-based models to be drawn on screen very simply (Moorcroft and Sterman, 1992).

The qualitative approach to SD has been somewhat neglected in inventory management. Akkermans and van Helden (2002) used a QSD approach to understand the interrelationships between critical success factors in the implementation of an Enterprise Resource Planning system, but such examples are not plentiful. Similarly, soft systems methodology (SSM) has not been employed extensively in problems related to forecasting and planning. Boylan and Williams (2001) reported a case-study of the application of SSM that enabled managers to reconceptualise the role of forecasting from an adjunct activity to an integral part of their planning. This was achieved through a vigorous debate on the purposes of the planning systems. The Conceptual Models were high-level and were not greatly significant in helping managers gain a greater understanding of planning systems. Recently, Paucar-Pecares and Rodriguez-Ulloa (2007) have shown how system dynamics models can be embedded within SSM, taking over the role of Conceptual Models.

The application of cognitive mapping to identify 'cognitive feedback loops' was advocated by Eden *et al* (1983), who commented on their similarity with influence diagrams used in system dynamics, while noting that cognitive maps were subjective (or inter-subjective) and no claims were made for their objectivity. Ackermann *et al* (1997) showed how cognitive maps can be used as a basis for system dynamics models. This seems a promising approach to modelling logistical problems, as structural feedback loops can be embedded within a broader model that encompasses behavioural factors (Boylan *et al*, 2008). The potential for QSD as an integrated modelling tool will be explored in the final section of this paper.

Control theory

Control theory is a well-developed inter-disciplinary approach for studying dynamic systems. The first application of control theory to supply chains was by Simon (1952) who investigated a production and inventory control problem. He used the Laplace transform to study a stylised inventory replenishment rule in continuous time. The continuous time representation was used by Forrester in his famous industrial dynamics work discussed in the previous section.

This continuous time approach was quickly extended into discrete time by Vassian (1955) with the newly discovered z-transform. Vassian (1955) showed that if Work-In-Progress (WIP) information were to be incorporated into a discrete version of Simon's inventory replenishment policy, then this would minimize the inventory costs for any forecasting method. Early text books documenting the z-transform approach include Magee (1958), in a production and inventory management context, and Brown (1963), in a forecasting context. The approach became more popular in the 1960s (see, for example, Adelson, 1966; Deziel and Eilon, 1967; Bessler and Zehna, 1968). Major contributions on the use of the classical z-transform approach were made by Jury (1964, 1976) and Tsypkin (1964). The field of control theory has developed over time, with a move away from transfer functions to state space representations.

The seminal contribution to state space theory was made by Kalman (1960) with the introduction of the Kalman Filter. This is the basis of the Bayesian updating of prior distributions (possibly based on human judgment) proposed by Harrison and Stevens (1971, 1976). The Kalman Filter is also used to compute estimators for the state-space models developed by Harvey (1989). The state space representation led to what is now known as 'modern control theory' and it became popular in the 1970s and 1980s. Notable supply chain contributions came from Gaalman (1978), Schneeweiβ (1975) and Bertrand (1986) who used the state space approach to identify optimal policies for certain cost functions. This research approach remains productive and new single-echelon (Gaalman and Disney, 2008) and multi-echelon (Gaalman and Disney, 2006) supply chain strategies are still being discovered.

Towill (1982) developed the IOBPCS classification system for replenishment policies. IOBPCS stands for 'Inventory and Order Based Production Control System', and has been extended to cover many different inventory replenishment systems. A recent overview of the classification system in given in Lalwani *et al* (2006). Towill's original 1982 paper was concerned with exploiting hardware control engineering knowledge in production and inventory control via a device called the 'co-efficient plane'. Recent research that is inspired by hardware engineering includes the 'ideal filter' (Towill *et al*, 2003) and 'h-inifinity' approaches (Ouyang and Daganzo, 2006).

Popplewell and Bonney (1987) and Grubbström (1996) exploited control theory to study Materials Requirements Planning (MRP) systems. It is possible to use matrices to capture the structure of products via the Bill of Materials and transforms to capture the time dependencies. Much work has been done to develop this field by Robert Grubbström, although the impact of forecasting here is often not explicitly considered.

The ground-breaking work of Lee *et al* (1997a, b), although not in the control theory tradition, led to a resurgence of academic interest in the bullwhip effect, yielding new insights into the influence of forecasts on production rates and inventory levels in multi-echelon supply chains. Chen *et al* (2000) studied the impact of moving average and exponential smoothing forecasting methods on the bullwhip effect on a supply chain with AR(1) consumer demand. Lee *et al* (2000) analyzed minimum mean squared error (MMSE) forecasts for the same demand process. They identified potential reductions in total inventory costs resulting from demand information sharing between downstream and upstream members.

In single and multi echelon supply chains, the focus may be on minimizing inventory costs and production (capacity) costs. We may assume linear inventory holding and backlog costs, as is common in the OR literature. In this case, the target safety stock is set to satisfy the critical fractile of demand via the newsboy approach. When this is done, the inventory costs are a linear function of the standard deviations of inventory levels over time (Disney *et al*, 2006).

In order to minimize inventory costs in a single level of a supply chain, it has long been recognized that accurate forecasts of the demand over the lead time and review period are required. This is because the variance of the forecast error of the demand over the lead time and review period is equal to the inventory variance, for certain inventory control policies. Thus, in a single echelon of a supply chain, optimal forecasts that minimize the mean squared error over the lead time and review period are required. However, if our objective is to minimize inventory costs in a multi-echelon supply chain, then the situation is much more complex, as non-optimal forecasts at the first echelon of the supply chain can have a smoothing effect on the demand placed on the supplier. This smoothing effect may mean that it is easier for the supplier to predict his future demand and may even be able to reduce his inventory costs more than the corresponding increase at the first echelon. Thus, the interaction between forecasting and inventory is complex in multi-echelon supply chains. There are many issues that need to be taken into account, including altruistic behaviour, trust and game-playing (eg, Hosoda and Disney, 2006a, b).

In a like manner, we may also assume linear over-capacity costs and under/lost-capacity costs and set the capacity level via the newsboy principle. In this case, the capacity costs are a linear function of the standard deviation of the order rates over time. This also results in a very complex relationship between forecasting methods and total (inventory plus capacity) costs, even in a single echelon of a supply chain, (Disney and Hosoda (2008).

Multi-echelon supply chains raise a number of issues related to information sharing. We could, for example, transmit consumer demand up the supply chain to other members. Thus, a supplier could base his forecasts on the end consumer demand rather than the orders received. If a non-optimal forecasting method is used (for example using exponential smoothing to predict an AR(1) process), then the theory shows that there is a benefit to information sharing (Dejonckheere *et al*, 2004). However, if we use optimal forecasts (for example using conditional expectation to forecast an AR(1) process), then there is no benefit to information sharing (Raghunathan, 2001; Hosoda and Disney, 2006a), assuming that the demand process and demand parameters at the first echelon are known throughout the chain. In theory, this allows us to derive the end consumer demand information, rendering information sharing redundant. Hosoda *et al* (2007) attempt to link the theory to real-life and conclude that, with real data, there is a benefit of sharing end consumer demand.

Statistical forecasting (fast-moving items)

Exponential smoothing was originated by RG Brown in his work as an OR analyst for the US Navy. His work on single exponential smoothing (SES) was first presented in a conference of the American Operations Research Society in 1956. That presentation formed the basis of his first book, published in 1959, followed in 1963 by a more general exponential smoothing methodology, where he also established a formula for the variance of smoothed data. This work was driven by the practical requirements of designing and implementing inventory systems.

The simple smoothing procedure discussed above is based on a model without a trend and therefore is inappropriate when the underlying demand pattern involves such a change over time. Holt (1957) suggested a procedure that is a natural extension of single exponential smoothing with two smoothing constants. A reprinted version of his 1957 report to the Office of Naval Research (ONR 52) appeared in the International Journal of Forecasting in 2004 (Holt, 2004a) to provide greater accessibility, followed by a brief commentary (retrospective) by Holt (2004b) himself. Harrison (1967) showed, amongst others, that the Holt procedure minimizes the expected one-period-ahead mean square forecast error for a state space model that incorporates trend. However, a single parameter updating procedure suggested by Brown (1963), has also received considerable attention and recommended for application in contexts where no seasonality is present (Silver *et al*, 1998). Besides involving only a single smoothing parameter, Brown's procedure has the intuitively appealing property of being derived from minimising the sum of geometrically weighted forecast errors for a constant trend model. Chatfield *et al* (2001) noted that this type of 'discounting' is theoretically dubious. If the trend were constant, then ordinary least squares should be used. The empirical performance of Brown's method was evaluated in the forecast accuracy competition undertaken by Makridakis *et al* (M1 competition, 1982) and it is worth contrasting the negative conclusions of the authors regarding the accuracy of this estimator with the actual reported empirical results. The method was not included in the M3-competition (Makridakis and Hibon, 2000).

Sometimes, data is so noisy, or the trend is so erratic, that a linear trend is not accurate (Roberts, 1982), especially when forecasting several periods ahead. Gardner and McKenzie (1985) introduced a damped trend procedure that works particularly well in these situations. The method follows closely Holt's procedure and is quite easy to use in practical applications. It incorporates a dampening parameter ϕ (with $\phi = 1$ indicating a linear trend). Exponential smoothing methods have also been extended to incorporate seasonality. Winters (1960) developed a form of smoothing, later known as the Holt-Winters method that smooths level, trend and seasonality. The method is intuitively appealing and is a natural extension of the Holt procedure for trended demand.

For fast-moving SKUs with short demand histories, the estimation of seasonal components can be challenging. Miller and Williams (2003) proposed a 'shrinkage' method that dampens seasonal estimates towards unity. Dekker *et al* (2004) suggested a variation of the Holt-Winters method, where the level and trend components are estimated at the individual item level, but with seasonality at the group level. Rules for basing seasonality on groups, for non-trended series, have been derived and empirically tested by Chen and Boylan (2007, 2008).

An important consideration in dealing with exponential smoothing methods having separate trend and seasonal aspects is whether or not the model should be additive or multiplicative. Pegels (1969) provided a simple but very useful classification framework that included consideration of additive and multiplicative models. This framework was extended by Taylor (2003), who included damped additive and multiplicative trend methods to the classification.

In the early 1960's some influential work was performed with respect to signalling a bias in the forecasting procedure, indicating that either the parameters of the underlying demand model have been incorrectly specified or that the model itself is incorrect. Harrison and Davies (1964) suggested the use of the cumulative sum techniques to monitor the bias in a forecasting procedure. Trigg (1964) suggested the use of a tracking signal based on the ratio of the smoothed (signed) error to the smoothed (absolute) error. The general idea of adaptive smoothing is that the smoothing constants are increased (smoothing becomes faster) when the tracking signal gets too far away from zero. Various adaptive smoothing procedures have been proposed in the literature, the one developed by Trigg and Leach (1967) having perhaps attracted most attention. Although these procedures have intuitive appeal, substantial research findings suggest that adaptive methods are less accurate than regular, non-adaptive smoothing (see, for example, Chatfield, 1978 and Ekern, 1981).

Autoregressive Integrated Moving Average (ARIMA) models have been studied extensively. Their theoretical underpinnings were described by Box and Jenkins (1970) and later by Box *et al* (1994). Although ARIMA models are currently included in some generic forecasting software packages (eg, Forecast Pro) they never gained popularity in stock-management software solutions and, more generally, within inventory forecasting and planning.

Most linear exponential smoothing models have equivalent ARIMA models, the only notable exception being the multiplicative form of Holt-Winters. However, a state-space model underpinning multiplicative Holt-Winters, characterized by a single source of randomness, was identified by Ord *et al* (1997). The researchers built on the work of Snyder (1985) to develop a general class of state-space models with a single source of error (SSOE). State space models for exponential smoothing may also be formulated based on multiple sources of error (MSOE). For example, SES is optimal for a model with two sources of error (Muth, 1960).

In practice, smoothing methods continue to dominate supply chain forecasting applications. They are embedded in the great majority of, if not all, relevant inventory control software packages. Gardner (2006) summarized all studies published after 1985 that present empirical results for exponential smoothing. Out of the 65 studies considered, there were only 7 that did not report reasonable forecast accuracy with exponential smoothing, and those unfavorable outcomes may be explained, according to Gardner, in terms of the underlying demand characteristics or experimental structure related details.

Statistical forecasting (slow and intermittent items)

Intermittent demand is characterized by occasional demand arrivals interspersed by time intervals during which no demand occurs. As such, demand may be built, for modelling purposes, from constituent elements (demand arrivals and demand sizes) rendering the management of the relevant SKUs a very challenging exercise. Classical and widely used estimators discussed in the previous section, such as Single Exponential Smoothing (SES), have long been shown to over-estimate the mean level of intermittent demand, if applied immediately after a demand occurrence. Most work on intermittent demand forecasting is based on Croston's (1972) influential article which, although neglected for many years, has seen 40 citations in the last four years.

Croston (1972) proposed a method that captures the compound nature of the underlying demand structure (i.e., demand arrivals and demand sizes, when demand occurs). In particular, he suggested using SES for separately forecasting the interval between demand incidences and the demand sizes. The ratio of the latter to the former may then be used to estimate the mean demand per time period. The method was claimed to be unbiased but, despite its theoretical superiority, modest benefits were recorded in the literature when it was compared with simpler forecasting techniques (Willemain *et al*, 1994). Some empirical evidence even suggested losses in performance (Sani and Kingsman, 1997). Syntetos and Boylan (2001) showed Croston's method to be biased. More recently, Syntetos and Boylan (2005, 2006) proposed a correction factor that accounts for the bias in Croston's method and presented an approximately unbiased estimator, the Syntetos-Boylan Approximation (SBA). SBA deflates Croston's method by a factor of $1-\alpha/2$, where α is the smoothing constant used to update the SES estimates of the mean inter-arrival time for demands. The empirical validity and utility of this estimator have been independently established in work conducted by Eaves and Kingsman (2004) and Gutierrez *et al* (2007). Correction factors to overcome the bias associated with Croston's approach have also been discussed by Boylan and Syntetos (2003) and Shale *et al* (2006). Finally, Teunter and Sani (2008) discuss an almost unbiased estimator that suffers from a somewhat increased variance of the estimates, as compared to the SBA.

The application of all the above estimators in an inventory management context necessitates a hypothesized demand distribution, the Poisson being a natural candidate for representing very low demands. The Normal distribution is typically inappropriate, although some empirical evidence suggests that for long lead times (that permit Central Limit Theorem effects) the Normality assumption may be more reasonable (Syntetos and Boylan, 2008). The Negative Binomial Distribution (NBD) has attracted attention for representing intermittent demand patterns. The NBD is a compound distribution (Poisson arrivals and Logarithmic sizes being one of its possible compound representations) and in that respect its choice may be justified theoretically. In addition, empirical evidence exists in its support (Kwan, 1991; Eaves, 2002).

An assumption about the underlying demand distribution is essential unless a non-parametric procedure is utilized to reconstruct the empirical distribution of demand. In terms of non-parametric forecasting, the bootstrapping approach has received considerable attention (and criticism) in the academic literature. Classical bootstrapping (Efron, 1979) involves consecutive sampling, with replacement, from an available data set, to construct an empirical distribution of the data under concern. A large number of replications (say 10,000) is typically used, and, although this procedure is computationally demanding, bootstrapping is nowadays fairly easy to apply given recent advances in computing. An important underlying assumption in such applications is that the past behaviour of data pertains also to the future. The two main drawbacks of classical bootstrapping can be summarized as follows: i) any potential autocorrelation of the data is not taken into account; ii) values generated in the reconstructed empirical distribution may not differ from the observations in the original sample.

Porras and Dekker (2008) proposed a bootstrapping approach that samples consecutive demand observations from the available data set. The number of consecutive observations, sampled in each replication, is equal to the length of the lead time. Such an approach addresses the issue of autocorrelation directly. Willemain *et al* (2004) proposed a patented non-parametric forecasting method specifically developed for intermittent demand data. Their method is essentially a heuristic that combines bootstrapping, a Markov process and 'jittering' to simulate an entire distribution for lead time demand. Estimation of transition probabilities between the two states of occurrence and non-occurrence of demand is achieved by the application of Markov process modeling. This addresses autocorrelation of demand occurrence. Jittering is an ad-hoc procedure designed to allow simulated values to differ from those already observed. The researchers claimed significant improvements in forecasting accuracy achieved by using their approach over SES and Croston's method. Gardner and Koehler (2005) criticized this study in terms of its methodological arrangements and experimental structure, pointing out that: i) the authors did not consider published modifications to Croston's method, such as the SBA, and ii) Willemain *et al* did not use the correct lead time demand distribution for either SES or Croston's method. This second criticism consisted of arguments against the use of the classical lead time demand variance estimation procedure and the use of the normal distribution for representing demands.

Further empirical evidence is required in order to develop our understanding of the benefits offered by such a non-parametric approach. In particular, a comparison between the recently developed adaptations of Croston's method (in conjunction with an appropriate distribution) with the bootstrapping approach should prove to be beneficial from both theoretical and practitioner perspectives.

Judgemental forecasting

Notwithstanding the advances made over recent decades in statistical forecasting, empirical research suggests that practitioners rely heavily on judgemental methods such as the direct use of managers' opinions (eg, Klassen and Flores, 2001; McCarthy *et al*, 2006). Further, when quantitative forecasting methods are used, they are very frequently judgementally adjusted. According to Sanders and Manrodt's (1994) survey of forecasters at 96 US corporations, about 45% of the respondents claimed that they always made judgemental adjustments to statistical forecasts, while only 9% said that they never did. Goodwin (2002) discusses a number of reasons for the prevalence of judgemental adjustment, including a desire to reflect the effects of special events on the forecast and a need for a sense of ownership of the forecasts. Sanders and Manrodt (1994: 100) noted that "*….the majority of practitioners judgementally adjust quantitative methods. This suggests that an important area of forecasting research should be developing guidelines for how best to combine the judgement of practitioners with quantitative methods*". Moreover, Armstrong and Collopy (1998: 289) suggested that "*given the importance to decision makers of incorporating judgement into their forecasts, and the importance to business and society of unbiased and accurate forecasts, this seems to be a most promising area for further research*". However, despite this appeal for further work, only a few studies have been conducted to advance knowledge in this area. Subsequently, the relevant literature is reviewed, followed by a discussion of a number of issues that still need to be addressed by the academic community.

There is substantial evidence from the economic forecasting literature that statistical forecasts can be made more accurate when experts judgmentally adjust them to take into account the effects of special events and changes that were not incorporated into the statistical model (eg, Turner, 1990). However, few studies have investigated judgmental adjustment in the context of company forecasts of the demand for SKUs. This limited literature is divided into laboratory-based research (eg, Lim and O'Connor, 1995; Goodwin and Fildes, 1999) and empirical studies (eg, Mathews and Diamantopoulos, 1990, 1992). In the former case, given a controlled environment, subjects (typically students) are provided with data and contextual information and they are asked to adjust forecasts. The benefit of such an approach is the control that may be imposed on the environment, enabling extensive experimentation with many hypothetical scenarios. Nevertheless, adjustments are generally recommended when forecasters have good domain knowledge based on industrial experience; the experience of the students is highly questionable.

Regarding the empirical studies, the strongest evidence that judgemental interventions can be effective when applied to SKU data come from four studies, all based on the same company, from Matthews and Diamantopoulos (1986, 1989, 1990, 1992). They showed that judgemental 'revision' improves accuracy, albeit sometimes only marginally. The first study (1986) examined the improvement of judgemental interventions over only one period (quarter) and the outcome was that the revised forecasts were at least of lower variance. The longitudinal extension of this work came in the next study (1989) where data and forecasts over six consecutive quarters were examined. Stronger evidence was found regarding the improvement in the forecasting accuracy as a result of the judgemental interventions. The third study

(1990) showed the effectiveness of forecast selection; the final study (1992), an examination of the relative performance of judgementally revised versus non-revised forecasts, indicated that there were significant differences in favour of the former approach.

In general, judgemental adjustments of statistical forecasts appear to be most effective when the adjustments are made on the basis of important information that is not available to the statistical method (Sanders and Ritzman, 2001). Adjustments made in the absence of this information may result from the forecaster reading false patterns in the noise associated with the time series and these adjustments are likely to damage accuracy (O'Connor *et al*, 1993). One approach to the improvement of managerial adjustments would be to require a justification linked to key pieces of information. For example, Goodwin (2000) found that the frequency of unnecessary and damaging adjustments was reduced when forecasters were required to indicate a reason for making the adjustment.

More recently, Fildes *et al* (2008b) empirically examined issues such as the direction of the adjustments and the importance of the magnitude of the adjustments for fast-moving SKUs coming from four companies. Their main findings are summarised as follows: (a) managerial adjustments do improve accuracy; (b) small adjustments, less than 10%, are not worth making and should be discouraged; (c) negative adjustments are more effective than positive ones.

Syntetos *et al* (2008) examined the monthly intermittent demand forecasts for the UK branch of a major international pharmaceutical company that was also included in the study conducted by Fildes *et al* (2008b). The study provided evidence that judgemental adjustments can be effective when they are applied to forecasts of products with intermittent/slow demand. However, the effectiveness was found to be conditional on the nature of the adjustments and the characteristics of the demand time series and the results were consistent with those discussed above for products that are not subject to intermittent demand.

Additional conclusions from Syntetos *et al* (2008) relate to: i) the lack of learning effect, ie, the adjustments do not tend to improve over time, and ii) the improved forecast accuracy achieved by judgementally adjusting forecasts is also reflected in the stock control performance of the estimates under concern. The linkage between judgemental adjustments and inventory management constitutes a promising avenue for further research. Some managers adjust the replenishment orders suggested by a software package rather than the forecasts that inform stock control decisions (Kolassa *et al*, 2008). The relative merits of judgemental adjustments of forecasts and orders have yet to be researched. Regarding the performance of adjustments over time, ie, the question of whether there is any learning effect, Kolassa *et al* (op. cit.) discussed the gradual learning of trusting the quantitative model in use, as opposed to improving the quality of adjustments, offering a different perspective on ‘learning’.

Conclusions and framework for further research

The area of inventory planning and forecasting has experienced tremendous advances over the last 50 years. There have been significant methodological developments, such as the emergence of system dynamics, control theory and statistical forecasting methods. These developments have been mirrored by new software applications, reflecting their importance in practical situations.

High-level strategic modelling has been facilitated by the introduction of system dynamics models showing the interaction between stocks and flows of materials and information. This generic approach has direct application to studying supply chains from both qualitative and quantitative perspectives. In addition to this simulation-based approach, trade-off analyses and algebraic models have been developed to inform strategic target setting, choice of forecasting method and policies on inventory centralization.

The modelling of multi-echelon supply chains has been facilitated by advances in control theory. For example, z-transform techniques have offered the opportunity to model the evolution of supply chains through discrete time. Analytical and control theory models of the bullwhip effect have been developed in parallel, leading to similar conclusions with regards to inventory systems. However, control theory has provided greater insights into more complex systems incorporating production (eg, the Inventory and Order-Based Production Control System (IOBPCS) model). It has also furthered our understanding of the potential benefits of sharing downstream demand information with upstream partners, although this issue is yet to be completely resolved.

Statistical forecasting for inventories has advanced significantly over the past 50 years. Effective forecasting for the replenishment of fast-moving items has been facilitated by the developments associated with exponential smoothing methods and the establishment of their theoretical properties. ARIMA models have proven to be useful for strategic modelling purposes and for developing insights into the bullwhip effect. However, they have not been used extensively at an operational level mainly due to their complexity and similar performance to simpler smoothing methods, as demonstrated by the M-competitions.

The statistical forecasting of slow/intermittent demand items was advanced considerably through the identification of the limitations associated with the use of exponential smoothing and the development of Croston’s (1972) method. Further advancements include: i) the critique of Croston’s method and the development of bias-reduction adaptations; ii) the development of non-parametric (bootstrapping) approaches for forecasting intermittent demand requirements.

Survey evidence of the prevalence of judgemental forecasting in practical situations has motivated a considerable amount of research on the factors driving judgemental adjustments and their implications for decision making. Empirical studies have explored the benefits arising from judgementally forecasting demand (or judgementally adjusting statistical forecasts). They have demonstrated improved accuracy when the adjustments are made on the basis of important information that is not available to the statistical method. Research into the linkages to the learning effect and stock control implications of such forecasts is expected to further advance knowledge in this area.

Although there have been substantial advances in SD, control theory and forecasting (statistical and judgemental), there has been comparatively little research on the interaction between these areas. In Figure 1 we identify existing linkages between areas and highlight promising opportunities for further consideration. We discuss these linkages in more detail, followed by an inter-disciplinary agenda for further research.

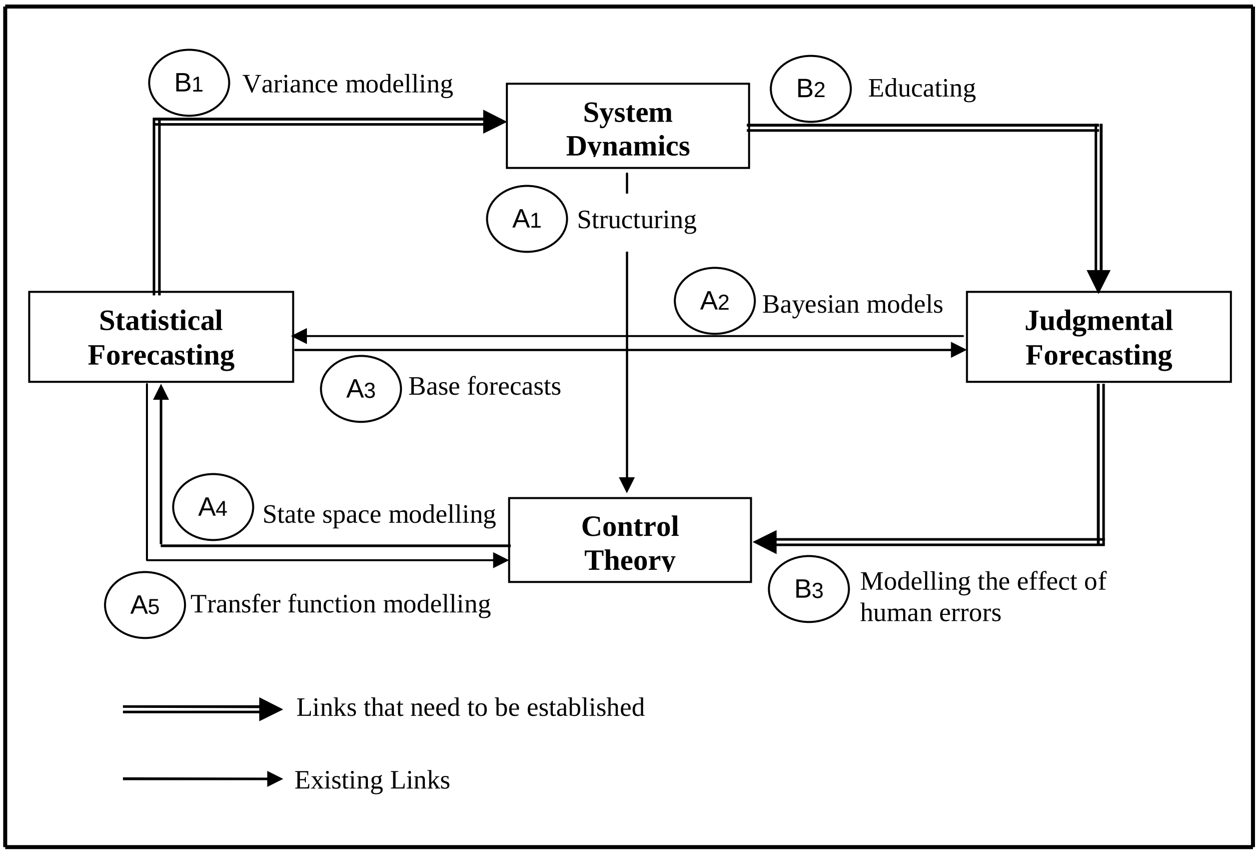

Figure 1. Interactions between areas and opportunities for further developments

The current linkages between the areas discussed in this paper can be summarized as follows: A1) The influence diagrams of Qualitative System Dynamics (QSD) may be used as a precursor of more formal stock and flow diagrams in SD (Wolstenholme, 1982). Such causal loop diagrams can also be used as a structuring device to aid the development of control theory block diagrams, as shown by Dejonckheere *et al*

(2003). A2) Judgmental estimates can be used to specify prior distributions in a Bayesian forecasting approach. Similarly, subjective prior distributions can be incorporated into regression models (Zellner, 1971). A detailed discussion on encoding subjective beliefs on the estimation of parameters of statistical models is provided by Bunn and Wright (1991). A3) Baseline predictions, generated using statistical forecasting methods, are often subsequently adjusted using judgmental approaches (see previous discussion in this paper). A4) The Kalman Filtering approach has been exploited by Harrison and Stevens in Bayesian forecasting and by Harvey (1989) in his Basic Structural Model, based on state-space modelling. A5) Conversely, some recent research has incorporated ARMA models in control theory models (for example, Hosoda and Disney, 2006a).

The above discussion indicates the considerable synergy that currently exists between System Dynamics (SD), control theory and forecasting and the scope for inter-disciplinary approaches to problem solving. In addition to further informing and developing these existing links, we believe that the following should also attract some attention from the academic community: B1) Variance modelling, showing the effect of differing forecasting methods with differing variances of forecast error, on the performance of an inventory system, using system dynamics. Achievement of service targets or physical inventory volumes relate directly to the statistical bias associated with an estimator and the variance of the related forecast errors. However, the incorporation of the latter variable in SD (stocks and flows) models has not attracted sufficient attention from the academic community. B2) There has been considerable interest in the educative benefits of the principles of system dynamics. Sterman (1989) describes how the Beer Game can be used to convey the counter-intuitive effects of misaligned inventory policies. However, there has been little work done on the potential of SD to inform judgemental forecasting by means of demonstrating its implications upstream in supply chains. This should be of significant practical importance given: i) the frequency with which decision makers exercise judgement; ii) the lack of formal models that incorporate judgement. B3) The effect of biases and reduced/increased variance of judgemental forecast errors has not been assessed using system dynamics modelling. Such an exercise necessitates further research into the reasons and rationale driving judgemental estimates and further empirical insights into this area that will allow effective modelling of human judgement to take place.

In conclusion, the last 50 years has seen great advances in inventory forecasting and planning. Major contributions have been made in this area reflecting differing discipline-based perspectives on the resolution of the same issues. However, inter-disciplinary opportunities have not been adequately addressed. The next half-century should be exciting, as there are so many opportunities for further research and for a healthy cross-utilization of ideas.

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