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Telecommunications demand forecasting—a review

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Abstract

The last decade has seen rapid advances in telecommunications technology in an increasingly deregulated and competitive market place. Companies operating in these various markets have relied on demand forecasts to justify the considerable investment needed to ensure capacity availability at the right time. These new markets are typically composed of new consumers taking up a product or service for the first time, established users changing their usage patterns, users of competing services shifting to the alternative service and those exiting from this segment of the market altogether. This paper describes various models that have been used to understand market dynamics. Markets discussed include both established and new: mobile, the internet, and PSTN (public switched telephony network). Cross-sectional choice models of the mode of accessing the service are discussed along with models for usage in established markets. These models typically include price (and perceived price) differentials and use standard econometric methods, focusing on price elasticity estimation. Forecasting accuracy has been neglected. New product models may include additional 'drivers' such as aspects of service quality and the attributes of the products themselves. Both choice models of adoption of new products and Bass-type diffusion models have been used in forecasting. Because of the complexity of the 'drivers' of the adoption process, the successful modelling of these new markets has been limited, not least by inadequate data. Simulation models have been proposed to structure the problem more completely and overcome these inadequacies. Both these classes of model have not been effectively validated, researchers having been content just to propose a new approach without thoroughly testing it against alternatives. The only class of telecommunications forecasting problem that has been more thoroughly analysed are those needed to support operations such as call centres. This review paper describes the research that has been carried out on the three problem areas of established products, new products and operations, highlighting areas where further research is needed. The paper also serves as an introduction to the Special Issue on Telecoms Forecasting by describing how the papers contribute to the developing research agenda.

Keywords: Telecommunications; New products—evaluation; Call centre; Price elasticity estimation; Forecasting practice; Choice models—evaluation; Diffusion models; System dynamics; Internet; Simulation

1. Introduction

It is well over 10 years since the *International Journal of Forecasting* first called for papers on telecommunications forecasting. The papers were published over two issues (IJF, 1988, 4:2 and 4:4). Primarily these papers were concerned with established services where data spanning many years could be brought into play. Only Grandstaff, Ferris, and Chou (1988) examined the development of a competitive service. Other

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important early references are de Fontenay, Shugard, and Sibley (1990) and Taylor's substantially revised second edition of his book, *Telecommunications Demand in Theory and Practice* (1994). Both these books had a similar concentration on well-established markets with no competition. In this review we draw extensively on these works, only referencing the source material they discuss when it seems of particular relevance. The core concept at the heart of most models of telecommunications demand is simple—that expected usage determines access demand and these two in turn determine equipment requirements. But in the years since these contributions the market for telecommunications products and services, both as ends in themselves and also as a means to an end, for example interactive game play or video on demand, has changed beyond all recognition. Most recently, Loomis and Taylor (1999) (see the review in this issue; also Taylor, 2002) have produced an edited book which focuses more fully on forecasting with a greater emphasis on the changing shape of the telecommunications industry.

While the technology has developed rapidly to deliver a disparate range of services to the consumer and to organisations, an equally important change has been the privatisation and deregulation of the service providers. This has undermined the single industry data base that was used by most academic researchers and data provided by the regulators has only partially substituted. The combined effects of increased competition and new services with new uses has led to a proliferation of forecasting problems that operators and suppliers in the industry face. The failure of many companies to produce reasonably accurate forecasts on which to base their plans has recently produced dramatic and calamitous consequences, for example the oversupply of mobile phones and the corporate over-investment in WAP and consequent debt burden. The resulting growth in commercial suppliers of forecasts has not been matched by corresponding academic research. In part this dearth of academic research derives from the successful exploration of the theoretical notions of network externalities,[1] which often still apply in the new environment, e.g. interactive gaming and chat lines. A second related reason lies in the difficulties posed by modelling complex systems with little hard data where the theoretical foundations are already in place. Thus, the primary purpose of this review of the problems faced by telecommunications forecasters is to stimulate further methodological work by identifying the significant gaps that have opened up as the market has changed beyond the scope laid down a decade ago by the core references.

Different technologies support different final applications. At its simplest, POTS (plain-old-telephone-service) through the PSTN (public switched telephone network) can be seen as delivering a single homogeneous service through a single IXC (inter-exchange carrier) that in developed countries no longer competes with services that it once affected as a new product, most obviously post. Thus the models described by Taylor do not include competitive services. By 1997 however, alternative services such as the growth of business use of the internet (or even internet telephony, see for example, Raina, Fildes & Day, 1998) was transparently affecting POTS, at least in its long-distance (international) form. Information on the end uses of the expanding range of telecoms products is often extremely limited with low reliability (in part because they are so widespread), while the data on the adoption and use of the new services, when compared to the

[1] 'the idea underlying the network externality is . . . that a new subscriber joining the network will confer a benefit on existing subscribers because one more telephone can be reached' (Taylor, 1994, p. 212).

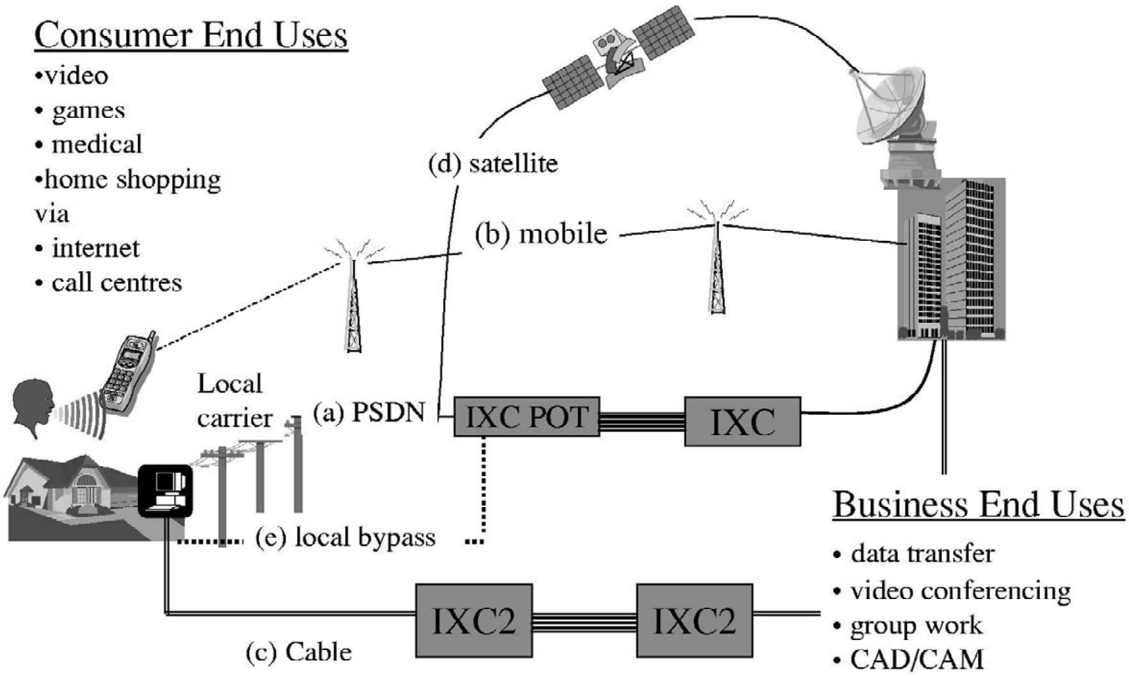

Fig. 1. A characterisation of telecommunications demand forecasting.

established PSTN usage, despite similar limitations, shows their increasing importance.

Fig. 1 is illustrative of the choices facing a consumer or business in meeting their end use requirements; for the consumer these include on-line gaming and gambling, internet access and home shopping etc., for a business, data transfer, video conferencing, group working such as CAD/CAM etc. An increasingly important development is the proliferation of broadband technologies that deliver this wide range of services. Fig. 1 includes a choice of technologies to supply the consumer and the business, including cable and mobile as well as PSTN. Different carriers may provide local and long distance services. Alternative inter-exchange carriers (IXCs) are available to the customer whatever the chosen technology in the home or office, and these may bypass the local carrier from the point-of-termination (labelled IXC POT in the diagram) of the IXC to the customer. In principle, the end-use requirements drive the access and usage decisions. Forecasters can then focus on, for example, the demand for video-on-demand, translating these requirements into the required bandwidth with the alternative technologies for servicing the end-use. Alternatively, the demand for the technology may be forecast directly.

The development of cable in the UK illustrates another element of complexity. Its initial position was as competition with other television channels, in particular satellite, but it failed, achieving penetration levels far lower than the US. However, a re-positioning and re-targetting of cable services focusing on telecoms has achieved greater success. Similarly, the terrorist attacks in 2001 led to videoconferencing making further inroads in the air travel market. In short, the key question in any forecasting problem, where to draw the system boundary, has become acute in telecoms demand forecasting, undermining established econometric approaches and highlighting the need for data bases.

In the next section we examine the variety of demand forecasting problems that those working in the industry face. Section 3 looks at models of established markets while Section 4 tackles the problem when the ‘product’ is new. Section 5 briefly examines operational forecasting issues. The final section summarises the key research issues, linked to the papers included in this Special Issue, and speculates on why so little academic research has been carried out recently in the area.

2. Telecommunications products and services

The first problem we face is the delineation of the telecoms sector itself. Since telecoms usage is primarily a derived demand, too narrow a definition is likely to undermine analysis, at least in the longer term. In addition to the established telecoms operators using fixed line, mobile operators and cable operators must also be included. More confusingly, the boundary between television and computer usage and telecoms is progressively being eroded through the growth of the internet and its service providers and the ability to use ‘smart boxes’ attached to the television to provide much of what the computer and fixed lines can offer. In principle therefore, we must consider innovations in use. As Antonelli (1993) points out, the introduction of new information technology significantly affects the demand for telecoms services. He uses as an example the effect of computer networking and its adoption, initially in banking, insurance and travel; the result was an increased need for data communications and call centres, thereby leading to demand for business-to-consumer broadband. (A further, not inconsequential addition, has been the restructuring of the three industries!)

From the perspective of the principal national carrier (pre deregulation) the growth in voice and data traffic is counterbalanced by direct competition from new entrants and substitution through alternative forms of access, e.g. email for telephone. Short term (18 months ahead) forecasting models of both these elements of the process are in principle straightforward enough (although few exist in the public literature but see Cracknell and Nott (1995) and Cracknell (1999)). A model based on call numbers using own and competitive price, ‘value for money’ and advertising would probably suffice. The reason is that adoption of a new use such as email substituting for PSTN is likely to be highly autoregressive, perhaps with a deterministic trend. In the US and UK competitive price elasticities can be estimated and these estimates can be used for other developed countries with newly liberalised telecoms systems. Volume (of message minutes) is more problematic and is also critical in short term revenue forecasts with a corresponding potential for affecting share price. The rapid adoption of mobile illustrates the problem where there has been two-way growth in fixed↔mobile calls as well as substitution from fixed to mobile. These changes demonstrate the need to monitor the market through careful data capture of volumes (competitor volumes and total market are not typically observed although the use of panel billing data would overcome this deficiency).

In the short-term there are a variety of operational telecoms forecasting problems faced by providers. They include the demand for operators (at call centres) by time-of-day, the churn experienced when customers shift between competitors (labour, revenue and cost consequences) and the point-to-point demand by time-of-day and its routing implications.

The longer term forecasting problems for the principal carriers mirror those of new entrants, the adoption and usage of the new services, substitution effects and equilibrium penetration levels. Many of the forecasting problems in the first instance fall into the category of ‘really new products’[2] where there are no data available on usage and the service has only a limited relationship with existing products or services, e.g. fax, teleconferencing. New and distinct end-uses, themselves perhaps ‘really new’, determine the demands on the network, e.g. the growth of call centres or developments in e-commerce.

Finally, equipment suppliers to the carriers face a yet more difficult problem in that while the demand for a particular product may be high, their potential customers are likely to be few. In the shorter term, for established products, the usual techniques of demand management apply and there is nothing unique to the telecoms market. Where ‘make-to-stock’ manufacture occurs, short term forecasting methods for volume products are appropriate. Where there are few customers, forecasts produced by the customers themselves can be used but may need de-biasing. In the longer term, with possible developments of new products and services by the carriers and new technology to service these, reliance on qualitative methods, ‘expert’ and customer opinion is typical and probably unavoidable (Lynn, Schnaars & Skov, 1999). The forecasts of carrier equipment requirements become part of the on-going networked negotiation between carriers and suppliers (Lane & Maxfield, 1996).

3. Models of established markets

In standard models of demand in the PSTN, modelling is through a two-stage procedure where usage (quantity in minutes demanded or number of calls) is modelled as a function of price, income and other relevant variables conditional on access while access is modelled through a model of the individual choices made between alternatives. Here the dependent variable is categorical and the logit framework, which we discuss later in this section, offers a suitable representation. The form of access chosen depends critically on how customers expect to use the service. Where the market can be considered established (e.g. fixed line) the expected benefits can be successfully modelled. The results, Taylor concludes, ‘establish a low price elasticity for the demand for residential access’. The choice depends on the consumer surplus, that is the benefits that accrue from calling minus the costs of those calls. This in turn depends on the demand function (dependent on the usage price and income as well as demographic variables) and the price of the corresponding calls including access. Extensions include the choice between different forms of access (flat rate vs. measured etc., Taylor, 1994), the choice of carrier and the likely take-up of by-pass services (where as Fig. 1 shows, the local exchange carrier can be bypassed and the calls routed directly to the long-distance carrier of choice).

3.1. Aggregate models of access and usage

The number and type of customers (or households) that choose to access a particular service may be modelled by aggregate models based on time series data, or cross-sectional data by region. More typically, consumer choice is modelled at a disaggregate level based on survey data and this is discussed in the next section. The key failure (for forecasting purposes) in this work is the unwillingness to recognize that the valuation of access changes over time, in part due to externalities, but more critically, due to the changing role of the telecommunications in society. While this has little effect in the short term, many of these

[2] There is no clear-cut definitive definition of a ‘really new product’. A requirement is that at least one key new product attribute is qualitatively distinct when compared with products servicing similar needs.

access studies are interpreted to apply over quite long horizons. For any cross-sectional study this is necessarily problematic. As an example of this, Taylor (1994, p. 259) notes that access price elasticities are declining. The underlying slowly-changing utilities (for access) also suggest that variable parameter or recursive estimation techniques would be useful as this type of model can capture the behavioural changes of customers in the market. More typically, access models are based on disaggregate cross-sectional data which we discuss in Section 3.2.

Models of the demand for services include similar 'drivers' to those of access, in particular price and income. Their development are fully discussed by Taylor (1994, Chap. 6) who comments in particular on their increasing econometric sophistication. Despite the stress on methodology, very few studies evaluate the out-of-sample performance of the proposed models and therefore their claims to be useful in forecasting must be questioned. Limited specification testing is carried out with little attention to diagnostics (but see Appendix 3, Taylor). Problems considered include point-to-point (toll) demand including international calls, and local demand (particularly relevant to the structure of the US market which in 1984 was split into LECS, the Baby Bells, and IXCs, in particular AT&T). Variables included are standard and include promotional effects (Cracknell & Nott, 1995) but also incorporate the concept of call-back in that an initial originating call stimulates a return call. With data on a number of origin–destination pairs, simultaneous models can be estimated (Larson, Lehman & Weisman, 1990). In their study, reverse traffic effects were strong. Taylor's conclusions as to the value of these 1980s studies are positive. They have 'sharpened previous estimates of the price elasticities for medium- to long-haul usage'. Price elasticity itself may be an increasing function of price. If correct, this implies an increased price sensitivity in long-distance calls (perhaps with larger duration effect as well, see Taylor, p. 314). In addition, Taylor (p. 260) argues there are independent 'distance' effects, perhaps deriving from the more discretional nature of long-distance calls. Tardiff (1999) examines this in the context of predicting the effects of a large price change. The study has both substantive and methodological implications. The estimated price elasticity is low at -0.20. The income elasticity is 0.75. Critically, the predictions of revenue loss depend on the functional form chosen. Income elasticities also affect the duration of the call more than the number of calls.

The structural changes in the market place, caused by technology and changed regulatory regimes, affect the demand for PSTN. The development of an econometric system for BT to support this type of analysis 'in order to retain the traditional strengths of whole market models' while acknowledging these changes is described by Cracknell and Mason (1999). Market demand can be segmented by customer, product and carrier to derive revenue forecasts. The advantages include the ability to 'flex the model-based forecasts to allow for a range of product and competitor scenarios', to ensure 'a quality controlled database of historical information' and, critically, to 'convert volume forecasts into revenues' taking into account the regulatory regime and the need for consistent pricing.

Estimated price elasticities are country-specific and are likely to be dependent on income, trade patterns and various cultural aspects of the country. Micro studies confirm this, when examining the calling behaviour of individuals, by exposing great disparities in behaviour. Das and Srinivasan (1999) examining local and long distance usage in India found higher price elasticities for long distance calls than those observed in developed countries. International calling habits provide rich empirical evidence for such differences. For example, Karikari and

Gyimah-Brempong (1999) analysed the demand for international telephone services between the US and Africa. They found the price to be elastic for calls originating in Africa whilst they are inelastic in the reverse direction. There is also complementarity between calls originating in Africa to calls from the US whilst there are substitution effects in the reverse direction. These analyses often pose methodological questions, in part because of the need to use the limited annual data. For example, the cross-sectional time series approach was used by Garín-Muñoz and Pérez-Amaral (1998) with 10 years of data for 27 countries (estimating a high own-price elasticity of -1.31, implausibly assumed fixed across countries). As Cracknell (1999) points out, along with a dramatic fall in real price, price elasticities have also fallen substantially. While 'call-back' is a strong feature of this market, distinct historical or trading affinities between particular origin–destination pairs suggest the need for individual market models. Examples include Layton, Defris, and Zehnwirth (1986) who achieved some limited success using economic indicators to examine the US links to Australian outgoing international traffic.

The specification of the demand function (in addition to the choice of variables to include) also remains a potentially important issue. For example, Hackl and Westlund (1995, 1996) argue that the evidence on international telecoms demand favours a time-varying parameter formulation, a highly plausible conclusion given the changing role of telecoms in society. It might be expected that the sensitivity to functional form Tardiff (1999) identified would carry over to longer term forecasting accuracy.

The 1980s also saw many studies on local call elasticities where in the US a variety of different pricing structures existed. They were able to establish 'greatly sharpened previous estimates of the price elasticities for short-haul toll'. Some recent studies have started to take into account the cross-price elasticities between various types of service, e.g. measured and flat-rate service, local service and toll. This has become an increasingly important issue as various new calling plans are rolled out in an attempt to attract and retain customers. The uptake of such plans needs to be forecast as well as the revenue consequences for both new and established services in order to make such schemes operational as this requires the development of an administrative and marketing function.

Despite the long history of PSTN, the last few years have seen major competitive developments. Various technologies now compete for parts of this market (see Fig. 1). These include mobile, cable, resellers and by-pass whereby the LEC (local exchange carrier, in the US, historically a 'baby-Bell', in Europe the national carrier) is by-passed through the use of a dedicated line to an alternative interexchange carrier. Different incentives exist for these services. Where a carrier offers essentially identical services such as AT&T and GTE, standard market share models might be thought to apply (Hanssens, Parsons & Schultz, 2001). Increasingly, different service providers offer bundled packages of services and customers' choice of package can be modelled through logit (modelling the service provider choice) and conditional logit approaches (modelling the package choice, conditional on a particular service provider having been selected), which when aggregated, provide market forecasts (Goungetas & Watters, 1997). In addition, churn, the movement between providers, itself is a variable of forecasting interest because of the operational and cost consequences (see Section 5). Williamson, Goungetas, and Watters (1997) in a study of duration of stay with a particular carrier show that as well as price, non-price elements are important such as quality. Different types of household group are more prone to move carrier, for example, higher spending groups are more prone to shift. Carrier loyalty, be it historical or based on loyalty schemes, proves important. Using cross-sectional survey data, Kridel, Rappoport, and Taylor (1997) have considered the choice of carrier and the usage demand as jointly determined (rather than sequential where usage depends on the chosen carrier). Usage for the alternative carrier is more price elastic than for the national carrier. Likewise, the number of calls and their duration are jointly determined (Heitfield & Levy, 2001).

Cross-sectional studies such as those just described do not help in forecasting the introduction of a competing service such as the UK reseller and call-back markets which are targeted primarily at international calling. There are barriers to adopting the new service despite any price advantage, including convenience and quality. These questions are covered in Section 4.

3.2. Micro-market analyses

Aggregate access studies and time series usage studies both have limitations from the point of view of a telecoms supplier wishing to understand the market and develop policies and forecasts. Within the relative stability of the established voice market, key marketing issues are affected by estimated elasticities (for calls and duration) for differing times of day, different call types and different customer segments, as Taylor (1994) discusses. For example, Atherton, Ben-Akiva, McFadden, and Train (1990) present a choice model that purports to explain how individual customers select between different service options and rate structures. A general model of individual choice is of the form:

$$\text{choice (or preference)} = f(\text{preferred uses, attributes of the service relative to alternatives, price, demographics}).$$

A standard model form is the multinomial logit (Ben-Akiva & Lerman, 1985) for $P_n(i)$, where the probability of the nth individual choosing alternative i, from choice set, C_n, is:

$$P_n(i) = \frac{e^{\beta' x_{in}}}{\sum_{j \in C_n} e^{\beta' x_{jn}}}$$

where x_{jnk} are the variables that explain the nth consumer's choice of alternative j, based on K personal and service characteristics, described by the vector $x_{jn} \equiv (x_{jn1},\ x_{jn2} \ldots x_{jnK})$. While individual choices and their determinants are of interest in their own right, the policy consequences can only be evaluated through aggregate forecasts, which can be calculated from the individual probabilities by either estimating the probabilities for each market segment or sampling from the population as a whole (see Ben-Akiva and Lerman (1985) for a fuller discussion).

The detailed cross-sectional data also permits a sharper focus on the determinants of price elasticities, for example a cross-sectional non-parametric approach is adopted by Levy (1999) who supports the view of a price-dependent elasticity. Since demand is segmented by household, with elasticities varying across the segments, the effects of a price cut depend on the behavioural differences between segments and how the cut is distributed. This analysis can be used as a basis for designing new product/price offerings.

In the public domain there have been relatively few micro-market analyses of such features as the geographical distribution and duration of calls (Taylor, 1994). However, 'bill harvesting' data has become more readily available for analysis. For example, Cassel (1999) has used information from a US survey of some 30,000 households while a more in-depth approach examining UK household behaviour over time is discussed by Anderson et al. (1999) and Lacohee and Anderson (2001).

Taylor's conclusions, now extended by further work bear repeating.

1. A non-normal distribution for call distance with a high degree of skewness.
2. A high degree of skewness in duration. Unpublished analysis for BT presented to OFTEL suggested a lognormal but noted that the tail frequencies required the adoption of a compound distribution. A Weibull was proposed by Heitfield and Levy (2001).
3. Significant day-to-day variation and within day variation (see also Cracknell, 1999).
4. Significant variation in call purposes (see also Anderson et al., 1999).
5. Significant variation depending on household demographics (see also Anderson et al., 1999).
6. Segmentation by calling behaviour, for example, in 1985 in the US two thirds of calls were by wives and teenage girls made the longest calls. UK calling habits are shorter (Cracknell & Nott, 1995), but again see also Anderson et al. (1999).
7. Differential price elasticities by income (Taylor, pp. 281–282).
8. The price elasticity for second lines is higher (estimated at -0.59 by Duffy-Deno, 2001) and is affected by internet use (Eisner & Waldon, 2001).

In essence, these studies help in targeting marketing activity. For example, Cassel (1999) looked at the propensity to purchase an additional line in terms of household characteristics, including both demographic descriptors (teenage children again!) and behaviour (i.e. internet usage). Their relevance to forecasting arises from changes in demography with a consequent change in aggregate projections. Equally important is the need to understand the implications when a particular market segment is affected by technological competition, e.g. the growth of business email affects both average duration and the distribution of call distance and therefore revenue projections.

3.3. Evaluation

The studies I have described suffer from a number of common flaws that arise from their genesis in the context of rate setting regulations. While superficially they can be regarded as price elasticity studies, Tardiff (1999) makes it clear that their focus usually includes *predicting* the effects of price change. In the developing markets of the last decade where substantial price changes are the norm, functional form and the specification of the price variable are both critical to predictive success. Current models in marketing (see for example, Mercer, 1996; Hanssens et al., 2001) demonstrate possible non-linear asymmetric effects. However, the models we have examined do not reflect the complexities of consumer response to price changes. With increased competition in these established markets, advertising variables (either directly or indirectly through a 'value for money' driver) are now likely to prove important drivers of market share but here again published work is limited.

Time series data is naturally more helpful in permitting the careful analysis of structural change. Despite the recognition that changes in the market place, particularly through competition, have undermined a constant elasticity assumption, this has not been incorporated into the modelling effort. In fact few of the published studies follow best econometric practice in thoroughly analysing the residuals for evidence of mis-specification, in particular structural instability and change though Madden, Savage and Coble-Neal (2002), examining international traffic, is an exception. It might reasonably be expected that time-varying parameter econometric models would outperform (and be more intuitively plausible than) fixed parameter models, a result that would fit with other studies of forecasting accuracy (Allen & Fildes, 2001). But forecasting tests and benchmark comparisons with simple models have not been carried out. In short there is considerable room for further research in modelling established telecoms markets and the increased use of 'best practice' econometric procedures.

The cross-sectional choice literature often seems to be confused as to its goals in that the policy context is inevitably over a forecast horizon, but this is not specified, nor have the implications of this been thought through. Kridel, Rappoport, and Taylor (2002, in this issue) explore the forecasting implications of a choice model approach more thoroughly in the context of short (IntraLATA) calls where the US market recently became more competitive.

4. New 'product' models

New products and services, applied to new uses, supported by new equipment, pose challenges to forecasters that most academic forecasters have eschewed although, in principle, new product and services forecasting in telecoms is no different from other areas (see for example, Wind, Mahajan & Cardozo, 1981). In fact Taylor in 1994 makes no mention of this problem area at all and only Rohlfs and Gilbert take up the specific issue of bypass in de Fontenay et al. (1990). But in the most recent books, Loomis and Taylor (1999, 2001) face the topic more directly. Fig. 2 attempts to capture a simple example of two technologies, competing over an expanding potential market, each of which has a unique customer segment as well as a segment potentially interested in both. In the early periods a number of adopters try the first generation technology. When the second generation technology comes on stream, it attracts both new users (from the potential market) and users already experienced with the first generation (switchers). Not all of the market po-

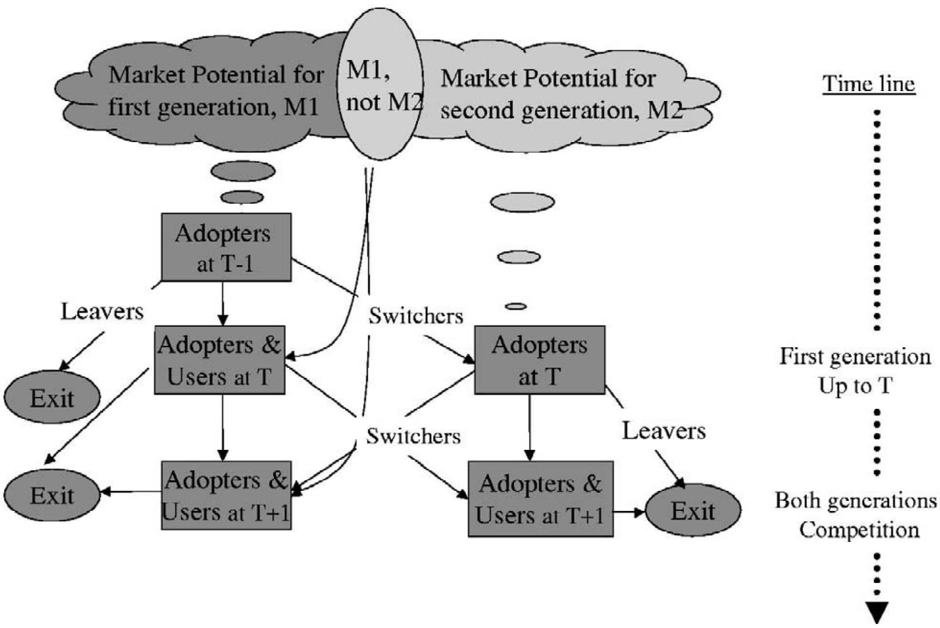

Fig. 2. Competition between generations of technologies.

tential for M1 are necessarily part of the market M2 (though that would be unusual in that M2 encompasses the attributes of M1). Users of both technologies may drop out over time, some may even shift back to M1 from M2. Although not part of the diagram, further generations may come on stream encouraging market expansion and permitting users to skip a generation.

A key element in modelling the new services market is the degree of interconnectedness of the potential market. Network externalities are important in that the number of users of the service affects the desirability of the service to customers. As Lyons, Lynch, and Skelton (1995) point out, 'The extent to which a customer using one service can communicate with customers in competing services will be a key choice factor'. Services may be: (i) wholly incompatible such as telex and fax, (ii) wholly compatible such as mobile and fixed PSTN, or (iii) partially compatible in that customers using one service can access all customers while customers with the second service can only access users of that service. Lyons et al. (1995) explore the implications of these different assumptions. Cases (ii) and (iii) above lead to equilibrium levels of adoption for both services depending on their relative desirability while case (i) leads to the preferred service taking over completely. A somewhat similar model was proposed by Loch and Huberman (1999) who show that where there is incremental improvement in performance and uncertainty in the appraisal of performance, a variety of equilibria are possible, whatever the relative attractiveness of the services.

The attractiveness of the competing telecoms products and services, as with established products, can be described by a set of attributes, for example a mobile phone service would include attributes such as reliability, range, voice-mail etc. In addition, there is an associated price and brand value. Potential customers value the service and accordingly are differentially likely to adopt the service compared to other alternatives depending on these perceived benefits (including the network externality) and the price asked. Effectively, the service is placed on a multidimensional product map and consumers, making the pending decision, trade off their valuation of individual attributes to reach an overall preference. Different groups of customers may fall into distinct benefit segments leading to targetted product strategies. As new products or services are envisioned they are placed within this attribute space, perhaps expanding its dimensionality. A key issue is the valuation of the attributes as this becomes the basis for estimating the relative benefit (and therefore demand) for the new product (a piece of equipment) or service (a new end-use such as videophone). Forecasting the demand for a new service could just be seen as calculating the desirability of its position compared to competitors by market segment. Conjoint analysis is the best established of the approaches within this framework and has been used, for example by Attenborough (1998) to determine pricing structures and their effect on demand. Wittink and Bergestuen (2001) examine its strengths in forecasting applications and offer principles that help enhance forecast accuracy.

The link between products or services (typically equipment or networks), their attributes, and end-uses has been explored by Weerandi, Hisinger, and Chien (1994). Let $\boldsymbol{x}$ represent the traffic volumes on various alternative services, then if n attributes characterise these services a matrix $\boldsymbol{A}$ can be constructed that describes which of the services possess which attributes, e.g. mobility, bandwidth etc. Let $\boldsymbol{b}$ represent the (latent) unobserved and often unmeasurable demand for the service attributes (an $n \times 1$ vector) then: $\boldsymbol{b} = \boldsymbol{A}\boldsymbol{x}$, i.e. demand for each attribute is the weighted sum of the traffic volumes, the weights being measures of how much each service possesses of each attribute.

This equation permits the tracking and forecasting over time of the demand for the service attributes. (For an established market the demand can be based on forecasts of $\boldsymbol{x}$, the traffic volumes, perhaps derived from an econometric model.)

An alternative equivalence is obtained by mapping end uses (applications traffic in Weerandi et al.'s terminology) into the service attributes. Let $\boldsymbol{y}$ be the vector of applications traffic volumes resulting from an application set of interest (e.g. email, video-on-demand, tele health care) and $\boldsymbol{V}$ a matrix of mappings of applications traffic into service attributes, then $\boldsymbol{b} = \boldsymbol{V}\boldsymbol{y}$, i.e. demand for each service attribute is the sum of the end use volumes weighted by the corresponding requirements for the attributes.

Based on an external forecast of the demand for new applications it is therefore possible to first estimate the latent demand for the various core attributes, $\boldsymbol{b}$. Now the aim from the point of view of the telecoms supplier is to predict, $\boldsymbol{x}$, the traffic volumes on the various services. Based on the notion that customers choose the services to minimise their cost, subject to meeting the service attribute constraints, $\boldsymbol{x}$ can now be estimated.

These ideas also form the core of an approach suggested by Taschner (1999) where the value of the attributes is estimated by industry experts.

For new products, both pre- and post-launch, two key forecasting problems must be faced, estimating the market potential of the various generations and, of equal importance, the diffusion path, that is to say the rate at which the new product is adopted, which in turn gives period-by-period sales. For many applications the usage rate of the new technology is also needed. Referring to Fig. 2, pre-launch the market potential and the entrants are the key factors that determine success but as time goes by, the 'churn', describing switching behaviour between technologies (and competitors), and the drop out rate and usage rates become more important.

4.1. Market potential

A key area of uncertainty in telecoms forecasting is the overall market potential of a new product or service. This may be an end use (video-on-demand) or a network service (ADSL) which itself serves many end-uses. The market potential for equipment suppliers is a derived demand from the network services themselves and is calculated from the principles described above that link equipment demand to attributes to end-uses.

For a new or developing end-use such as video-on-demand, choice experiments provide an appropriate framework of analysis. The data are collected either through survey methods or sometimes through experiments. Either a range of alternative services can be considered or the simple question asked as to whether the respondent intends to buy a particular service. Parker (1994) argues strongly for a model that includes dynamic market potential of the form $cM(t)$, where c measures the percentage of non-adopters in the potential market while $M(t)$ is based on the underlying social system and defines the number of units that could adopt (e.g. the number of households passed by cable, the number of people over the age of 6 for mobile). Examples include Islam and Meade (1996) who model market potential as a function of two indices representing IT intensive sub-sectors of GDP. Ahn and Lee (1999) used an international cross-section of countries to model access demand for mobile networks with various price measures and income as explanatory variables.

The choice framework described earlier can be used whether the focus is on choosing to access a particular service from within an established choice set, or on forecasting alternative new applications. In the latter case, time dependence may be explicitly included in the model. The choice framework effectively combines both terms in Parker's expression in that the model includes the demographic variables,

$M(t)$, that define the number of units that could adopt (over time).

There are usually a number of different network alternatives that will supply the preferred uses as discussed in the previous section. An optimising model could be developed to minimise consumer cost by selecting a range of network alternatives subject to meeting the end use requirements. The aim of such models is to find some measure of the 'distance' between the attributes required for the preferred uses and those deliverable through the alternative services. This issue is explored to a certain extent in Taschner (1999) although no clear methodological proposals are developed.

Madden and Simpson (1996,1997) adopt a simpler approach that only incorporates various end-uses (such as interest in entertainment services) as prompts in the interviews before focusing on the question of subscribing to household broadband services. They use logit and probit models based on demographic variables and price. Similarly, Kridel, Rappoport and Taylor (1999) examined the demand for access to the internet, comparing the results from the annual ReQuest consumer panel of 1996 and 1997. Income, age and education were the principal drivers of adoption while the price elasticity was low (at -0.27 and constant over the two surveys) as would be expected in the growth phase of the life cycle. Marketing and service variables were not included in either study. This type of analysis in itself, does not lead to convincing forecasts of market potential in that it fails to incorporate likely changes in end-uses. The growth of text messaging using mobile provides an example. The methodological challenge is to explore the compatibility of end use applications forecasts with the network and access choice forecasts.

Where there are a number of existing services with a new, competing service envisaged there are certain econometric problems that need to be faced. A key theoretical issue that arises is structuring the choice set. Standard methods depend on the relative choice probabilities between two alternatives, $P(i|Cn)/P(j|Cn)$ remaining unchanged if the choice set, Cn, is enlarged, i.e. it is independent of the existence and attributes of any other alternative, the independence of irrelevant alternatives (IIA) property. While plausible in some circumstances, in others it directly conflicts with an intuitive analysis of the problem, for example if a new product (delivering broadband say) is added to an existing range of products, the new product may enhance the overall attractiveness of broadband, or alternatively just add to the competition within that category. Fig. 3 illustrates these two distinct models of consumer choice; in the first case the three alternatives are considered simultaneously, while in the second

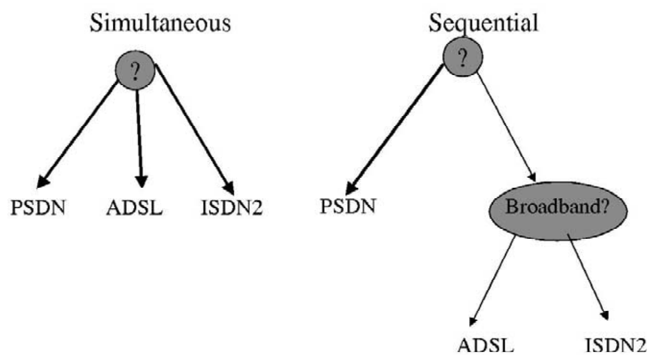

Fig. 3. Alternative models of choice—for households with internet access (see Rappaport et al., 2002).

case the first choice concerns whether or not to adopt broadband and conditional on this, a subsequent choice is the particular form within the broadband alternatives. Thus, the second set of choices (alternative modes of broadband delivery) is nested. The nested tree structure is estimated through a nested logit approach (Ben-Akiva & Lerman, 1985). However within the nest, the IIA property holds. Brownstone and Train (1999) make proposals that permit flexible substitution patterns. As an example, Rappoport, Kridel, Taylor, Alleman, and Duffy-Deno (2002) were forced to take these issues into account when examining demand for internet access because of the different access technologies available (cable, broadband, PSDN) to the household respondents.

Choice experiments, whether or not they are based on realised data or intentions data (such as Ahn (2001) applied to mobile subscription or Kridel (1988) applied to the adoption of flat rate tariff), suffer from a potentially serious defect. They model *current* attitudes. The researcher therefore must aim to fix the choice experiment in the mind of the respondent, embedding the alternatives in an envisaged future. A key issue is clarity as to the choices available and their respective benefits, so for example, a distinction should be made between usage benefits and the perceived benefits, ex ante, from having the option to use a service (Kridel, Lehman & Weisman, 1993) even though, ex post, this may not be exercised. Current intentions will be more or less accurate reflections of future choices in so far as the current environment faced is representative of the future in which the choices are to be realised, as with the Ahn and Kridel examples. Thus, experiments with consumers having experience of an established market are likely to provide accurate forecasts just because the setting is unlikely to alter. The forecasting principle here is 'place more reliance on predictions from intentions for behaviour in which respondents have previously participated' (Morwitz, 2001). Armstrong, Morwitz, and Kumar (2000) present an example of short term forecasting of mobiles which led to approximately a 33% improvement over a naïve forecast. But for many telecoms products/services it is their novelty (and the confusion surrounding their benefits) which presents the forecasting challenge. Urban, Hauser, and Roberts (1990) and Urban, Weinberg, and Hauser (1996) have attempted to design an experiment to elicit intentions both for established products (a new car) and for 'really-new' products (an electric car). This is done by combining what they call the 'information acceleration (IA) method' with established forecasting methods. Essentially potential customers are given information (through simulated advertising and word of mouth, etc.) and the effects of the information on the purchasing decision are then modelled using experimental intentions data. The aim is to simulate the environment in which the new product selection takes place as closely as possible in order to help in the design and launch decision for a new product development. This is probably more relevant to consumer products, for example various broadband alternatives, than industrial products or services.

Most telecommunications services have generic uses and a new generation of technology both substitutes for an existing service and expands the range of end uses, e.g. cable substituting for wire. Market potential can be estimated by decomposing the problem into the previous generation's market and that gained as a consequence of the expanded range of uses. The attractiveness of the new use can be modelled through a choice experiment. A potential problem arises in that certain new product attributes may be mis-valued as consumers cannot necessarily envisage how valuable various attributes of the new product may become. (The Urban IA approach is an attempt to overcome this problem but cannot include externalities.) However, in many forecasts of market potential, choice experiments have not been carried out. The standard alternative is a decomposition of the forecasting problem into a number of separate sub-problems, on each of which judgement is used. McGregor (2001) provides guidelines on how decomposition can best be used. Lyons, Jensen, and Hawker (1993) illustrate some of these principles carrying out the following steps in producing 'Traffic scenarios for the 21st century' with a 50-year horizon.

Step 1 Identify the most important services (in terms of load in bits per second on the network).
Step 2 Segment the population, e.g business and consumer, high and low intensity users.
Step 3 Using ideas of a time budget (the number of hours a day available for telecoms-related use) estimate the services each segment might use, by service, and the level of usage.
Step 4 Model the changes in the segments over time.
Step 5 Obtain total traffic by aggregating the individual forecasts of the usage profiles.

Wright (1998) also adopted a decomposition approach to the growth of broadband for business users. Although his decomposition was less complete, based on a static view of the economy, he included the novel idea of generating forecasts[3] from multiple perspectives and then combining the results.

4.2. The adoption and diffusion path of new technology

Various barriers to adoption will exist, for both consumers and organisations, before even an apparently highly desirable service is adopted. This leads to a typical S-shaped diffusion path (often observed only in idealised form, see the discussion in, for example, Parker, 1994). If we examine the organisational process of new product adoption, it starts with some perceived discrepancy between what is being achieved and the organisation's potential. This perception is affected by information, for example advertising and promotions, benchmarking studies, consultants etc. This in turn leads to the specification of a range of alternative technologies that could bridge the gap, the next step being the selection of a single solution. The implementation of the technology followed by its application complete the adoption process (Swan, Newell & Robertson, 1998). The choice of solution, including acceptance of the status quo, is seen by Rohlfs and Gilbert (1990) as based on: (i) the expected profits or benefits from the innovation, (ii) the riskiness of the alternatives, (iii) the ease of innovation, both in adoption and in continuing use, including its complexity and reliability, (iv) the capital stock including 'sunk' costs in the existing stock and its age, (v) the incremental nature of the adoption decision. The direct externalities also are likely to affect uptake in that for some services the expected number of adopters must be over some 'critical mass' in order for the service to be attractive (Mahler & Rogers, 1999). Since the adoption decision depends on the existence of suppliers, supply-side constraints are important (Baptista, 1999). These include the suppliers' reputation, industry concentration and ease of entry, and economies of scale (customer expectations of price affect uptake).

In addition to factors such as those listed, both inter and intra-organisational issues can affect the timing decision. The adoption of a new product or process in one part of an organisation does not immediately lead to its adoption in other organisational units. Thus the adoption activity can be better understood by decomposing it into the first decision to adopt and the rate and final level of its subsequent

[3]While claiming to use a Delphi, each perspective was in fact based on his own opinions, a potentially crippling weakness.

uptake. With such complexity it is perhaps unsurprising that few models of the process of organisational adoption exist and even fewer are oriented towards a quantitative forecast. Recent examples of the former include EDI into the pharmaceuticals and healthcare industries (Howells & Wood, 1995) and a model of adoption of video banking (Pennings & Harianto, 1992). Full reviews are given by Baptista (1999) and Geroski (2000). From a forecasting perspective the conclusions of these surveys are disappointing, 'technology diffuses faster in less concentrated markets . . . , large firms . . . adopt innovations earlier than small ones; information spreading is also important'. But 'diffusion will take place in very different ways for different technologies and industries' (Baptista, 1999). Where alternative technologies directly compete such as historically was the case with alternative video recording specifications and now broadband, the early adopters may be particularly influential as economic agent models show (Geroski, 2000).

For suppliers operating in organisational markets, these studies have marketing implications such as the need to disseminate information quickly through all available channels and to focus on the benefits of adoption. However, they do not lead directly to predictive models of the adoption path for a new product or process. Instead they are merely suggestive of categorisations useful in segmenting the potential market, leaving the adoption path and market potential still to be forecast.[4] As a consequence, aggregate models of the adoption path that eschew such complexity have gained extensive exposure in the marketing and forecasting literature.

Mahajan, Muller, and Bass (1990) give a full description of the genesis and extensions of 'new-product diffusion models' of which the best known is due to Bass (1969). A collection of research articles summarising developments in the field has been edited by Mahajan, Muller, and Wind (2000). Most generally, if m is the market potential and $N(t)$ the number of consumers (firms, families or individuals) who have adopted a new product, process or service by time t then Bass proposed that:

$$n(t) \equiv \frac{\mathrm{d}N(t)}{\mathrm{d}t} = g(t)(m - N(t)).$$

Different choices of $g(t)$ give different forms of the S-shaped curve that is assumed to characterise the typical adoption process of both individuals and organisations (see Mahajan, Muller and Bass, 1990, 1993). The original Bass model chose $g(t) \equiv p + qN(t)/m$, representing the probability at time t that a potential adopter (from those in the population who have not yet adopted, $m - N(t)$) adopts. The two terms are interpreted loosely as representing those in the market uninfluenced in the timing of their adoption by the number already using it, defined through the coefficient of innovation, p, and the latter term, the new adopters who are influenced by earlier buyers, the 'imitators' in the market (determined by q, the coefficient of imitation).

The solution to this differential equation is:

$$N(t) = m\left(\frac{1 - \exp(-(p+q)t)}{1 + \frac{q}{p}\exp(-(p+q)t)}\right).$$

This class of model has been widely applied, to new end uses (e.g. on-line shopping), to new organisational processes (e.g. EDI) and to adoption of new services (e.g. fax, mobile).

The basic model has many apparent limitations, the most important of which is the calibration of the parameters when limited data are available as is the case with new products. While the market potential can, in principle, be

[4] An organisation that has collected detailed survey data on organisational adoption and the perceived attributes of the product could utilise this in parameterising a choice model of adoption.

estimated from the data, many of the methods rely on estimates provided externally (as discussed in the previous section) so we focus here on the coefficients of imitation and innovation. Often, unfortunately, the parameters of a Bass diffusion model cannot be estimated, either because there are too few data points available or alternatively, unconstrained estimation leads to implausible results. As Meade and Islam (2001) point out, if statistical approaches are to be reliable then a data history that encompasses the point of inflection is needed. In this Special Issue, Venkatesan and Kumar (2002) have shown some success in overcoming this limitation by using genetic algorithms to estimate the diffusion parameters of mobile phone adoption more effectively with very limited data. As an alternative, different forms of meta analysis may be used to link the current product to earlier products (or product attributes) where p and q have been reliably estimated. Easingwood (1989) explored this issue, suggesting the use of such meta parameters, i.e. parameters estimated from earlier diffusions, either of other products or in other geographical regions (for a variant of this idea, see Kunisawa & Horibe, 1986) and these methods are described below. These prior estimates can then be updated as data become available (Sultan, Farley & Lehmann, 1990). Other approaches are discussed in Table 8.A1 (Mahajan et al., 1993).

There have been many extensions to the basic Bass model (surveyed in Mahajan et al., 1990; Parker, 1994; Meade & Islam, 1998) which have aimed at overcoming the limitations of its market assumptions. Table 1 summarises their applications to telecoms. Most have at least as strong a credibility as the basic Bass model. Bewley and Fiebig (1988), for example, argue for a more flexible form of the logistic that permits both the point of inflection and the degree of asymmetry to be data determined (which necessitates two additional parameters to Bass). They argue that both the adoption of direct-dial international calls and fax required the extra complexity, but did not compare forecasting performance. Forecasts from a priori equally plausible models may differ substantially, as Bewley and Fiebig illustrate. Where data are available for estimation, this raises the question of model choice. Meade and Islam (1995) using 25 telecoms series (e.g total number of lines) evaluated 17 different functional forms of growth curve. They concluded that the local logistic, a model that forces the solution to the Bass differential equation to pass through the current observation, thereby ensuring the forecasts are always above the latest observation, offered the best forecasting performance. The combination of forecasts from the different models has been shown by Meade and Islam (1998) to work better than any single method.

A natural extension of the basic Bass model is to incorporate marketing or economic variables. An extensive discussion has gone on as to whether they potentially affect the market potential or the diffusion parameters. A priori, for more expensive products one would expect both effects. An example of such a study incorporating the effects of advertising on telephone services is given by Simon and Sebastian (1987) who examine the adoption of PSTN in Germany and the effects of advertising on the various diffusion parameters. However, identification and estimation of the different functional forms has proved difficult and all but useless when analysing real data and subject to out-of-sample forecasting tests on limited data (Bottomley and Fildes (1998) in an analysis of various categories of consumer durables). An explanation lies in the declining real price of technological products, producing multicollinearity and an observationally equivalent Bass model (Bass, Krishnan & Jain, 1994; Sharp, 1984). One recent example of apparent success is Tishler, Ventura, and Watter's (2001) study of the mobile market in Israel where the logistic solution to Bass is used:

Table 1
Innovations in diffusion modelling applied to telecoms

Innovation context	Data	Result	Validation	Reference
Estimation	Limited, growth phase: mobile adoption in 7 countries	Advanced estimation techniques e.g. genetic algorithms beneficial		Venkatesan and Kumar (2002)
Model specification	Two international telecoms traffic series	More flexible forms of the diffusion model produce better forecasts	Compared to other models graphically	Bewley and Fiebig (1988)
	'Substantial', including inflection point for total telephone, main, residential and PABX	Use local logistic	17 models compared using MAPE and RMSE across lead times up to 11 years ahead	Meade and Islam (1995)
Including marketing drivers	German telephone connections	Several alternative ways of integrating advertising in Bass diffusion model and empirically tested	34 months ahead forecasts validated using RMSE, MAE, ME, and Theil-coefficient	Simon and Sebastian (1987)
Including economic drivers	UK business telephone connection	Multivariate growth models add insights to the adoption process. Market saturation made dynamic by relating it to economic environment	One to 11 steps ahead forecasts using RMSE	Islam and Meade (1996)
	Bell residential telephones	Flexible market saturation as function of economic and sociological variables found better than constant market saturation of logistic curve	Out of 26 years ahead forecasts, 4 years ahead forecasts validated with actual data and rest compared with another industry forecast	Chaddha and Chitgopekar (1971)
Incorporation of cross-sectional effects	Cross section of 11 countries, with 10 years of annual data on mobile adoption	Use of cross-sectional data leads to improved forecasting performance	Validation using two countries over 10+ years, using MAD and MSE compared with basic model	Ganesh, Kumar, and Subramaniam (1997)
	Cross section of 184 countries, with around 10 years of annual data on mobile adoption	Shows how various explanatory country characteristics affect diffusion patterns	None	Dekimpe, Parker, and Sarvary (1998)

Table 1. Continued

Innovation context	Data	Result	Validation	Reference
Incorporation of generation effects	Cross section of 11 countries, median 8 years of data on mobile	Incorporation of generation substitution effects improves forecasting	Validation using MAPE averaged over lead time (median 3 years)	Islam and Meade (1997)
Incorporation of generation effects and marketing effects	Two generations of mobile data for 'Nordic' telephone company including subscription and call prices Leapfrogging generations permitted (see Fig. 2). Subscriptions and sales included	Declining price elasticities between generations	Only fit used compared with simpler models	Danaher, Hardie, and Putsis (2001)
Incorporation of competitive effects	Mobile subscribers to competing networks for six markets, 14 years of quarterly data	Incorporation of switching effects from a new brand entrant	Validation using MAPE over six quarters	Krishnan, Bass, and Kumar (2000)
Incorporation of generation and competitive effects	Three generations of mobile for Korea	Incorporation of substitution and competitive effects improves forecasting	Limited validation using MAD and MAPE over 6 months	Jun, Kim, Park, Park, and Wilson (2002)
Supply restrictions	Telephone connections, Israel	Three-stage Bass diffusion curve to model supply restricted market	Two years ahead forecasts but not validated	Jain, Mahajan, and Muller (1991)
	Cross section of 46 countries, telephone connection data from supply restricted markets	Empirical analysis supports suitability of three-stage diffusion model proposed by Jain et al. (1991)	One to 5 years ahead forecasts validation using geometric means of the ratios of RMSE and MAPE	Islam and Fiebig (2001)
Disaggregate models	Business fax uptake by industry sector		Limited	Weerahandi and Dalal (1992)

$$\text{penetration} = \frac{1}{(\theta_1 + \theta_2 \exp(-\theta_3 z_t'))}$$

where z_t represents a vector of attributes including price and time. The model was linearised and estimated with 11 quarterly observations, price proving significant. Market potential (for large t) was estimated judgementally from which θ_1 was estimated.

A second example where price effects were successfully introduced was in a model of the effects of by-pass on the local exchange carrier. The incentive to by-pass the LEC is that the local connection has charges placed on it to subsidise access and there is therefore a price differential available for exploitation. Taylor (1994, pp. 144–146) described a model based on the comparative prices of the competing services. Since there are barriers to using the alternative service the adoption of the bypass can be modelled as a Bass-like diffusion model (see the next section) depending on current market share and the price differential (Weisman & Kridel, 1990). However since they were considering a new service with no data available, the parameters of the adoption model for the bypass were estimated from past data derived analogically from a different new service introduction, AT&T's loss of market share after other IXCs were permitted to compete.

In neither of these cases was any model validation attempted.

The price and other marketing instruments alone are theoretically insufficient to explain the adoption path and should be considered along with possible income effects. The business cycle may itself affect the diffusion path of various products identified. For example, Hopkins et al. (1995), when modelling broadband demand, used a logistic curve modified by a factor to represent GDP growth, $(G_t/G_0)^b$. An alternative (and plausible) approach to dealing with the effects of often unobserved marketing instruments is to assume the coefficients in the model are random and time-varying (see Putsis, 1998).

Much of the diffusion modelling has been conducted as if the product had been launched into a totally new market with no competition from existing products. Norton and Bass (1987) extended the basic Bass model to incorporate the idea of competing generations of technology (as illustrated in Fig. 2). Key simplifications include only permitting a shift from the first to the second generation and assuming the diffusion parameters are the same for each generation.

The model is:

$$N_1(t) = m_1 F_1(t)(1 - F_2(t - \tau))$$

$$N_2(t) = (m_2 + m_1 F_1(t))F_2(t - \tau)$$

were $N_i(t)$ represents the adoptions in the ith generation and τ the time of launch of the second generation. Norton and Bass applied it to two types of integrated circuit. Casado, Nunez Lopez, and Sanchez (1996) applied it to the substitution effects of mobile on PSTN in a model that included GDP growth. Islam and Meade (1997) extended the model by allowing the diffusion parameters to change between generations, with the expectation that the parameters would increase, leading to faster diffusion in the second and subsequent generations. They modelled the diffusion of cellular phones in 10 countries in Europe (as well as IBM mainframes) with, on average, improved forecasting accuracy and increased estimates of the first generation market potential and decreased estimates of the second. As expected, the experience garnered with the first generation led to faster diffusion in subsequent generations.

A second assumption made in this model (in contrast to Fig. 2) is that only the $M_1F_1(t)$ adopters by time t in the first generation will consider then adopting the second generation. In contrast the whole potential first generation market (whether they have adopted or not) are potential adopters in the second generation. They could skip the first generation. This idea was exploited by Mahajan and Muller (1996) analysing the IBM data. Danaher et al. (2001) have also included this aspect when modelling two generations of mobile, distinguishing between sales and new subscriptions. Pricing effects on the diffusion parameters were examined but alternative model forecasts were not considered and thus, the critique of Bottomley and Fildes (1998) was not effectively answered. Jun and Park (1999) have moved somewhat away from the diffusion framework of the earlier articles by incorporating the notion of consumer choice between generations (or substitute services) where the probability of choosing (or adopting) a product at t depends on the time it has been available and various marketing factors. A logit model is then used to model the probability. This model was subsequently applied to a new product, low earth mobile satellite service, using information from an intentions survey to estimate the choice parameters and elasticities (Jun et al., 2000). In this issue Jun et al. have taken this type of modelling further to incorporate both substitution and competition in the mobile market (Jun et al., 2002). Results from all these models suggest there are forecasting gains to be made in multi-generational competitive analysis.

Increasingly, as markets such as mobile get better established competition between companies becomes an increasingly important focus for modelling. Kumar, Nagpal, and Venkatesan (2002, this issue) present an eclectic modelling strategy that attempts to integrate a top-down diffusion model of category sales with current market share estimates based on a customer survey and intentions data to estimate future sales. The output is more accurate market share estimates than that from using any individual method.

Further extensions have included inter-category dynamics where complementarity and competition affect adoption. Kim, Chang, and Shocker (2000) applied this to pagers, cell phones (analog and digital) and CT2 (restricted cordless phone) in Hong Kong and also to pagers and mobile in Korea. In a limited forecasting test using four periods of quarterly data, overall improvements in forecasting accuracy were found. Krishnan, Bass, and Kumar (2000) have considered the case of competitive entry where a late entrant competitor may affect both the market potential and the speed of diffusion. A somewhat similar idea was proposed to incorporate the inter-regional diffusion of new products (Gatignon, Eliashberg & Robertson, 1989) where the history of a product or service released earlier in a geographically-related market is used in estimating the diffusion parameters in the market of interest (see Dekimpe, Parker & Sarvary, 2000 for a survey). These ideas have been applied to various telecoms markets with a focus on using the lead market to forecast slower developing, lagged markets. For the lag market the model proposed by Ganesh, Kumar, and Sabramaniam (1997) is:

$$\frac{\mathrm{d}F_2(y)}{\mathrm{d}t} = \left[p_2 + q_2F_2(t) + c\left(\frac{m_2}{m_1}\right)F_1(t) \right] *(1 - F_2(t))$$

where F_i is the cumulative penetration ratio in the ith country ($i = 1$ for the lead, 2, the lag), m_i the corresponding market potential and c, the learning coefficient for the lag country. The learning coefficient was then modelled over a cross section of countries as depending on geography, culture and the economy. It was applied to cellular phones and home computers in Ganesh et al. (1997) and Kumar, Ganesh, and Echambadi (1998) and evaluated for the forecasting improvement it offered, estimated as 60% as measured by the mean absolute error (MAE). Talukdat, Sudhir, and Ainslie (2002) modelling the same problem adopted a hierarchical Bayes procedure applied to fax machines and mobiles but unfortunately their assessment of improved accuracy was overly limited.

Dekimpe et al. (1998), developing Parker's (1994) argument, have also used this idea in an examination of global cellular adoption where the market potential was again decomposed into two factors, the social system size $M(t)$ independent of the innovation and c, the 'intrinsic utility ceiling'. They then estimated the diffusion parameters of their 184-country dataset using logistic models for the diffusion parameters, where they were modelled as functions of socio-economic and demographic exogenous variables. Gruber (2001) and Gruber and Verboven (2001) modelled the speed of diffusion of mobile telecommunications across the EU, using the lead–lag relationship and country-specific effects, including the competition and technology in the industry. Unfortunately none of the studies made the next step and evaluated the forecasting accuracy compared to a Bass-type benchmark and the Gruber studies generated very implausible estimates of market potential. In this Special Issue, Islam, Fiebig, and Meade (2002) have overcome this limitation and shown that the incorporation of cross-sectional country effects leads to improved forecasting performance, compared to single country analysis in an analysis of digital cellular diffusion, ISDN and fax.

As we pointed out earlier, the basis for aggregate diffusion models is ad hoc. In an attempt to make the assumptions more explicit Chatterjee and Eliashberg (1990) proposed a disaggregate micromodelling approach based on the individual consumer in a heterogeneous population who adopts according to the information received (a random variable). The various assumptions lead to a model of the individual probability of adoption. Depending on the assumptions made with regard to the flow of information and the market segments in the population, the disaggregate model leads to various standard aggregate diffusion models (including Bass). A more natural framework is based on models of the individual adoption decision where this depends on the demographics of the members of the population as well as such variables as price and, following Bass, the number in the population who have already adopted

$$\text{i.e. } \frac{\mathrm{d}P_i(t)}{\mathrm{d}t} = P(\text{demographic, product variables}) * (A(\text{advertising}) + B(N(t)).$$

Individual adoption decisions modelled over time combine elements of diffusion theory and choice modelling. Cox (2001) and Cox and Popken (2002, in this issue) use a short history of product/services adoptions and discards, segmented demographically to predict the purchase of a new product or service. The methodology essentially classes the sample into homogenous segments (using classification trees) who are more or less likely to adopt, depending on their past history. Aggregate forecasts can then be simulated.

Weerahandi and Dalal (1992) have applied this disaggregate formulation of individual adoption to the adoption of fax by industry sector (taken into account through dummy variables). Only four cohorts of data were used in estimation. Size and price proved important. To produce aggregate forecasts, forecasts of the size and number of firms in each industry were used. No comparisons with a benchmark model such as Bass was possible due to data limitations but a simulation study showed the potential benefits of a disaggregate model-based approach.

While the particular end-use of the components of the telecoms network (PSTN, broadband, mobile, etc.) is not specific to a particular customer, the adoption decisions of an individual are likely to differ from that of a small company which in turn differs from its larger cousin. Taylor (1994) suggested a geographical categorisation of organisations when attempting to predict demand (including access, usage and equipment). He does not offer any models, concluding 'that what is in short supply . . . is simply greater understanding of how a firm's telecommunications needs . . . evolve'. Cracknell, Majumdar, and Naik (2000) argue from empirical evidence that demand depends on industry and region. From the discussion earlier on the factors affecting diffusion, industry-specific drivers are likely to have a major influence, but from a new product forecasting perspective, the key variables characterising industry effects are likely to be unknown and unmeasurable. Because of these constraints Cracknell et al. (2000) adopted an indicator approach in their attempt to forecast BT business revenue. The indicators used include GDP output in IT and communications intensive sectors, economic and price factors and substitution (in particular the growth of mobile as an alternative). The models themselves are log-linear in form.

The alert reader will have noticed by now that there have been few comments on the forecasting performance of this class of diffusion models. Parker (1994) has evaluated the evidence up to that date and found it very limited, particularly as it applies to new products where there is little or no data. More recently, Meade and Islam (1995) carried out a large-scale study of forecasting performance of various growth curves applied to different telecoms series, arriving at firm conclusions on which model to use when substantial data are available. Islam and Meade (1996) have also provided evidence that a multivariate growth curve that incorporated economic indicators outperformed a linear model (which in turn was no better than a univariate growth curve when used ex ante with forecasts of the explanatory variables). Nevertheless, despite the limitations of the evidence, the models have both a firm theoretical foundation, some empirical support and, perhaps most important, have no readily available competitors.[5]

[5]In contrast to Islam and Meade (1996), Golder and Tellis (1998) propose a standard multiplicative econometric model, based on price, income, consumer sentiment and lagged sales. The results show better short-term forecasting performance compared to Bass, but its performance is heavily autoregressive and would probably not be helpful in long range forecasting with limited data.

The diffusion approach to modelling adoption, whether aggregate or disaggregate, suffers from the limited data on potentially important (and often unmeasured) variables that are thought to affect system behaviour in the longer term. The consistent failure to estimate marketing effects illustrates the problem as no economic model of adoption justifies their omission. Because many aspects of the adoption process are not explicitly modelled, or changes in a potentially relevant variable have yet to be observed, it may be impossible to examine the effects of a structural change in the system within a conventional econometric framework when the focus is on the examination of strategic options (Lyons, 1999). Simulation models decompose the system into potentially unobservable components, even to the level of the individual consumer and their interactions (Lyons, Adjali, Collings & Jensen, 2002). They may include decision variables and information flows and have therefore been suggested as an alternative to aggregate diffusion modelling, primarily as a tool for strategic analysis.

Perhaps the simplest and most established approaches in telecoms companies are spreadsheet style models in which the problem of the effects of competition is decomposed as follows.

1. Establish homogeneous market segments.
2. Estimate the market potential for the new product or service including new uses (through market research possibly adapted as discussed above)—this is likely to be time dependent.
3. Estimate and forecast the relative prices of the new product and its alternatives (perhaps using curve fitting, perhaps through judgemental estimation).
4. Estimate and forecast the switching probabilities as they depend on price (and other variables) as well as the growth from new uses.
5. Using diffusion style curves, (possibly esti-

mated or judgementally fitted to the past data) calculate the uptake of the new product and the steal from its alternatives.

The academic literature does not contain examples of the above approach but conference presentations, e.g. Hodges (1996), discuss this in more detail.

This approach has been formalised in the published literature, most often, using the modelling language of system dynamics which is based on a set of non-linear difference equations, easily programmed through various commercial languages such as 'IThink'. Fig. 4 represents the basic Bass model in system dynamics form based on equations (written in 'system dynamics form') of a level equation for the adopters and a flow equation for the adoption rate

Initial Conditions

Potential_Adopters = (*Market Potential* − *Adopters*)

Adopters = 0

Dynamic Equations

Potential_Adopters = −d*t* ∗ *adoption_rate*

Adopters = +d*t* ∗ *adoption rate*

Rate Equation: *adoption_rate* =

(*External_influence* +

Internal_Influence ∗ *Adopters*) ∗ *Potential_Adopters*

Constants:

Market potential, External influence, internal influence

This basic model has been extended to include both substitution and competition (Maier, 1997) with results that correspond to those obtained by using the aggregate Bass model and its extensions. Furthermore, Lyneis (2000) argues that this approach should (and does)

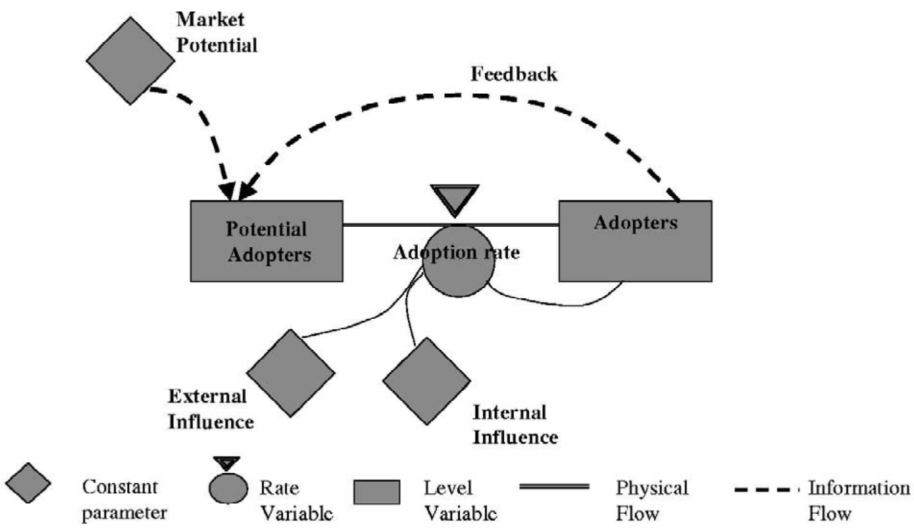

Fig. 4. The Bass diffusion-adoption process represented in system dynamics form.

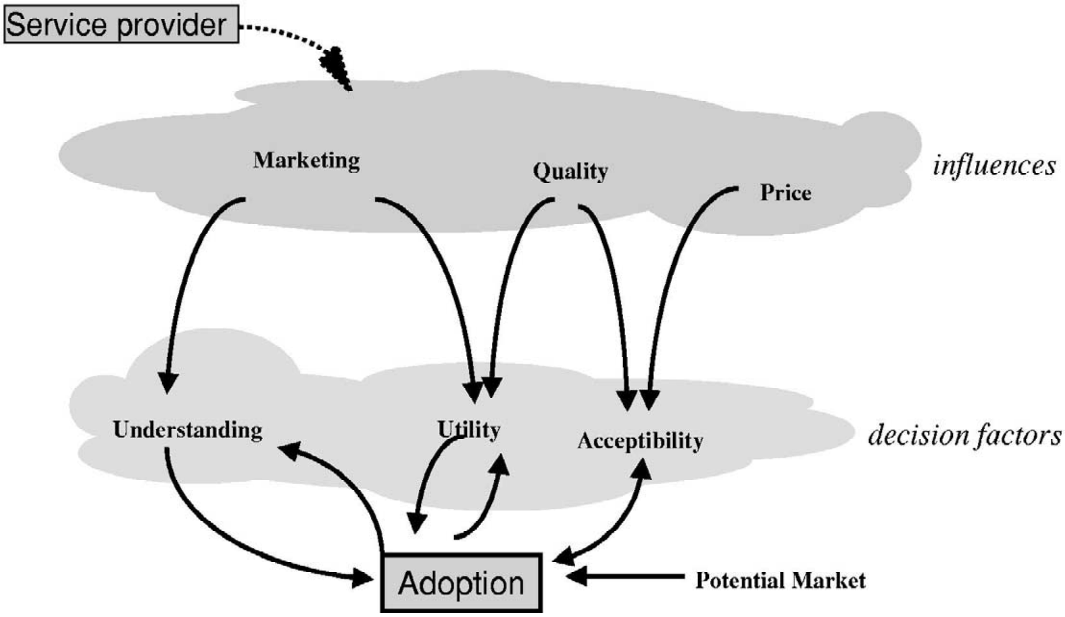

Fig. 5. A system dynamics representation of the adoption of new telecoms services.

produce improved short-term forecasting accuracy although the evidence he presents is very limited.

Fig. 5 extends this to represent a basic customer choice model and is used by Lyons, Burton, Egan, Lynch, and Skelto (1997) to examine competition between visual services such as cable, terrestrial TV, video-on-demand, video shop rental, satellite and, in a second example, the roll out of broadband. Three service characteristics (marketing, quality, price) influence the consumer's valuation of the service and these in turn lead to adoption. Despite the focus of these models on policy, they may also be used in forecasting, in part because of the transparent inadequacies of statistical methods as we have described them above. Thus, to model and forecast the demand for videophones (Hopkins et al., 1995), awareness ('understanding' in the Fig. 5) is seen as a pre-cursor to possible adoption, but no measurements were available on this variable and its growth was seen as affected by both marketing plans and culture-specific preferences (c.f. mobile phones). The compound diffusion path resulting from a developing awareness and subsequent adoption is then simulated based on guess-estimated parameters. A key output of this model was a set of forecasts.

4.3. Evaluation

The models of market potential and the diffusion-adoption path have become increasingly ingenious. Few of them have been seriously evaluated with regard to their forecasting effectiveness, at least in so far as they apply to telecoms. Models of market potential cannot be evaluated directly (since market potential is unobservable). However, repeated surveys, designated here by I_t (defined to capture the survey history to the end of period t) offer the prospect of examining the plausibility and the stability of the estimates, $M_{t+T}|I_{t+k}$ for $k=0$, 1, etc., and when combined retrospectively with observed and estimated diffusion paths provide a variety of measures of convergence on the 'true' market. Where evaluations of Bass-type diffusion paths have been carried out the results have not been reassuring, not least because of the paucity of studies (Parker, 1994). Papers in this Special Issue have added to the evidence and those innovations in model building that have been shown to be effective in telecoms are summarised in Table 1. But there remains considerable scope for further research including extending the database of telecoms series with which to evaluate the various models including brand-based data. In addition, conditional forecasts (based on an ex post estimates of market potential) could be used to evaluate where the strengths and weaknesses lie in the alternative diffusion specifications.

The simulation models (of which the system dynamics variant is one example) have not been validated at all in a forecasting context despite their implicit forecasting application. The system dynamics literature has always been clear that the aim of their models is 'understanding' rather than forecasting, particularly of policy questions. Probably Lane (1995) offers the fullest discussion of validation of this type of modelling but, even so, his discussion of predictive accuracy is cursory. Lyons et al. (1997) recognise the problem when they say 'it is essential to constrain the [system dynamics] model by the real data available . . . [for they] are used where little hard information exists'. The use of these models in policy analysis such as determining the balance between spend on marketing compared to investment in infrastructure depends critically on issues such as timing and the relative peaks and turning points of the model outputs, e.g. rate of return. Thus, the neglect of predictive validation is disingenuous, as the time scale associated with a response (such as diffusion) is critical to understanding and decision making. There is no reason in principle why predictive validation, rather than historical validation based on 'fit', could not be used as one aspect of model validation to complement other dimensions including structural validation as well as aspects of user-acceptability (Lane, 1995). Interestingly, Lyneis (2000) makes the claim of improved forecasting, despite its rejection by most of the system dynamics community. We are, however, left then with an approach to forecasting new product competitive diffusion that has a high face validity but an untested record of success.

While new product forecasts are bound to have a higher level of error than those in established markets, what the forecaster requires from the research literature is a recommendation as to which of the alternative approaches is the most reliable. As Mahajan and Wind (1988) pointed out, there has been too little research done that compares and contrasts different approaches that would provide benchmarks to help practitioners. In telecoms such rough measures would be extremely helpful but remain beyond current research ambitions.

5. Forecasting for operations

Operational forecasting issues have not been much studied despite their ubiquity. Problems include estimating point-to-point traffic at wire centre level (see the Bell System Technical Journal, 61:1, 1982) where standard time series methods are used. At an even more detailed level still, fault forecasting can be used to ensure the accurate determination of billing systems (Tzvieli, 1996). Telecoms problems have led to innovative time series methods. For example, Grambsch and Stahel (1990) examined point-to-point forecasts of special services and showed that by exploratory analysis of the cross-sectional data characteristics, an extrapolative forecasting method, designated 'robust trend', could be designed with excellent comparative forecasting attributes (Fildes, Hibon, Makridakis & Meade, 1998). Its advantage over conventional methods was that it overcame the problem of outliers in the trend. The link with network design and investment has not been examined. It might be expected that forecast uncertainty would influence network developments.

For any geographical set of point-to-point routes the activity level, connections and disconnects determines manpower requirements. The 'churn' therefore must be forecast. Greis and Gilstein (1991) examine how this can be done, using Stein-type cross-sectional information from the whole set to estimate key parameters in an extrapolative model.

Call centres have been a major telecoms growth area during the 1990s. Forecasting requirements include most of those associated with any new service, in particular the effects of marketing on the adoption of the service, its impact on established services and the associated levels of usage. Without data on the promotional activities proposed, the flows of traffic will remain highly unpredictable. These problems are compounded by the importance of 'churn', e.g. the switchers category in Fig. 2. Forecasts are needed at a highly disaggregate level, by type of call and by daily or even hourly intervals in order to schedule call centre staff (usually planned using a simulation model). Commercial consulting companies sell such systems. Recent examples include Andrews and Cunningham (1995) who describe an ARIMA-based transfer function approach to forecasting daily incoming calls (split by type) applied to a primarily mail order sportswear retailer, following a catalogue mailing. Antipov and Meade (2002) have also examined daily telephone applications for loans (to a financial services company) which are mainly driven by advertising. Their model includes harmonic seasonal factors, dummy variables for bank holidays as well as daily dummies, supplemented by the advertising effects of the different media. Their basic model (omitting advertising) outperforms a standard ARIMA approach while adding in advertising improves forecasting accuracy by around 40% across lead times up to a month. At a more detailed level, Tych, Pedregal, Young, and Davies (2002, in this issue) describe a state space model and associated forecasting system for incorporating the complex seasonality that is observed in hourly data.

A quite different operational problem is to forecast the demand for customer calling features such as call waiting, call forwarding, call back etc. where there is historical demand patterns available on the feature. Here standard econometric or time series methods will suffice with advertising a potentially important driver. Alternatively it may be a new set of features or a new bundle (by which a number of the features are bundled together) for which forecasts are needed. This is a potentially complicated problem where choice models or conjoint methods can be considered. Kridel and Taylor (1993) recognised the dependence between the features. Ben-Akiva and Gershenfeld (1998) develop a choice modelling approach with experimental data that overcomes the problem of the multitude of choices that exist when even a small number (e.g. seven) customer-calling features must be examined. Commentators on their article agreed that the approach offers a greater richness in the choices that can be considered compared with conjoint analysis.

6. Conclusions

This paper summarises recent work on forecasting telecommunications demand in markets that have changed dramatically due to the demise of the monopolistic national suppliers on the one hand and rapid developments of competitive new technologies on the other. This leads to an increased emphasis on techniques suitable for forecasting the demand for new products and services. Unfortunately, while the literature contains suggestions on how these problems can be structured, examples of successful applications are few. In particular there has been limited discussion comparing the usefulness (and accuracy) of alternative approaches when applied to the same problem.

What are the factors that influence forecasting accuracy in firms in the telecoms industry? They include environmental factors, aspects of the product or service, competitive market factors as well as how forecasting is managed within the firm. Organisations that give little weight to the forecasting function with poorly motivated and trained staff (in the forecasting function) employing limited resources are unlikely to produce effective forecasts. While there is no direct evidence on this issue from within the telecoms sector, Gartner and Thomas (1993) examined new product forecasting accuracy in software companies. The size of the marketing research budget, the use of interviews with potential customers and the number of forecasting methods used were all predictors of improved accuracy. Some markets also proved more easy to forecast: those where individual buyers were not important and those where the government was influential.

Industrial market surveys with similarities to telecoms have provided limited evidence on forecasting approaches adopted. The results suggest a heavy reliance on qualitative methods (Lynn, Schnaars & Skov, 1999). In their survey of high tech companies (not solely telecoms), expert judgement, customer interviews and interviews with salespeople were the preferred methods. Low tech companies used more methods than those in high tech sectors. But as Lynn et al. (1999) warn, these conventional market research methods have limited applicability to new product forecasting. In a small survey of forecasters working in telecoms I found a similar result although there was some weak evidence of the use of quantitative methods including diffusion models and econometrics. There is considerable commercial interest in demand forecasting in telecoms, probably reflecting the deregulated and highly competitive industry environment. A measure of this interest is provided by IIR and IQPC, organisers of professional seminars, who have attracted many thousands of attendees in the past 7+ years.[6] Thus, some of the conditions are in place for the increased use of more sophisticated approaches such as those described here. Certainly some of the consultancies (who present at such seminars) develop and sell models that incorporate these advanced methods.

While forecasting models for established services are well developed (but could learn something from the forecasting/econometric literature on demand and market share model specification), within the new product/service areas, opportunities for research are considerable although the commercial sensitivity of the work may be limiting in practice. Models of market potential using choice modelling based on intentions data offer potential when combined with the ideas in Urban et al. (1996). Diffusion modelling remains in its infancy as far as evaluation is concerned across the wide range of telecoms applications, not least because standard models, if they are to be useful, require data sets longer than are available. Parker's suggestions, therefore, of identifying the determinants of the diffusion parameters, partially implemented in Dekimpe et al. (1998), could overcome the problem and forecasters would not need to rely on judgemental estimates.

[6] A more reflective and demanding forum, the International Telecommunications Forecasting Conference, has seen a fall in attendance since the days when it was organised within the Bell System.

Comparison with multivariate approaches such as that carried out by Islam and Meade (1996) is also required.

The potential for serious examination of simulation models (perhaps adopting a system dynamics philosophy) is if anything larger. Almost no evaluative research has been carried out; neither those who are attracted to the intellectual framework espoused nor those who reject it have any basis in forecasting effectiveness for their choice. In short, the approaches to telecoms forecasting described in this review, designed to operate in an environment of fast changing technology and intense competition, offer concepts, structure and models but little reassurance to the practising forecaster that the final result will be any more accurate than the industry expert's best guess. Research in other areas of forecasting lead to a positive conclusion as to the potential for improvement – model based techniques incorporating expert judgement in a structured process will almost inevitably lead to improved accuracy (Armstrong, 2001). However, it would reassure those working in the industry to see more comparative evaluation of alternative methods and rough bounds to the resulting errors. Such an objective poses an exciting intellectual challenge to future telecoms researchers.

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In preparing this paper I should like to acknowledge the debt I owe to Dave Cracknell of BT who stimulated my interest in the area and whose untimely death in 2000 has exacerbated the gap between practice and academia. I hope this paper and the Special Issue will go some way towards bridging the two. Thanks are also due to the reviewers of this article, in particular V. Kumar, Nigel Meade and Gary Madden.

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