Technological Forecasting & Social Change 77 (2010) 558–565

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

Forecasting with limited data: Combining ARIMA and diffusion models

Charisios Christodoulos *, Christos Michalakelis, Dimitris Varoutas

Department of Informatics and Telecommunications, University of Athens, Athens, Greece
National and Kapodistrian University of Athens, Panepistimioupolis, 15784, Ilissia, Greece

ARTICLE INFO

Article history:
Received 29 March 2009
Received in revised form 11 January 2010
Accepted 23 January 2010

Keywords:
Technology diffusion
Time-series forecasting
Linear Logistic model
ARIMA models
Mobile and broadband penetration

ABSTRACT

Forecasting diffusion of new technologies is usually performed by the means of aggregate diffusion models, which tend to monopolize this area of research and practice, making the alternative approaches, like the Box-Jenkins, less favourable choices due to their lack of providing accurate long-term predictions. This paper presents a new methodology focusing on the improvement of the short-term prediction that combines the advantages of both approaches and that can be applied in the early stages of a diffusion process. An application of the methodology is also illustrated, providing short-term forecasts for the world broadband and mobile telecommunications' penetration. The results reveal that the methodology is capable of producing improved one-year-ahead predictions, after a certain level of penetration, as compared to the results of both methods individually. This methodology can find applications to all cases of the high-technology market, where a diffusion model is usually used for obtaining future forecasts. The paper concludes with the limitations of the methodology, the discussion on the application's results and the proposals for further research.

1. Introduction

There are a large number of studies focusing on modelling the diffusion of innovations, aiming to provide accurate estimates and forecasts. The increasing academic interest in this area began in the 1960s, when a significant number of related papers came to light. Fourt and Woodlock [1], Mansfield [2], Floyd [3], Rogers [4], Chow [5] and Bass [6] were the first to consider the modelling of a technology's diffusion. Their work has encouraged many modifications often adopted and studied, even in recent research efforts.

Time series were mainly studied under a deterministic prism, until Yule [7] introduced the notion of stochasticity in 1927. According to him, every time-series approach can be regarded as the realization of a stochastic process. This simple idea launched a number of time-series methods, varying in parameter estimation, identification, model checking and forecasting.

Nevertheless, it was the work of Box and Jenkins in their publication *Time Series Analysis: Forecasting and Control* [8] that integrated the existing knowledge and made a breakthrough in the area. The Box-Jenkins approach is a coherent, versatile, three-stage iterative cycle for time series identification, estimation and diagnostic checking. The evolution of computers made the use of autoregressive integrated moving average (ARIMA) models popular and applicable in many scientific fields.

The gap in research concerning the comparative performance of sales forecasting models in a given situation was underlined by Armstrong, Brodie and McIntyre [9]. Furthermore, the use of ARIMA models has not been widely investigated in the case of forecasting the diffusion of innovations. In addition, Meade [10] stated in 1984 that the popular diffusion models are among the heavily used forecasting techniques in a corporate environment.

The forecasting accuracy of ARIMA models has been compared with a selection of diffusion models, among which the models of Floyd, Bass and Gompertz [11,12], by Gottardy and Scarso [13]. Their findings revealed that the non-symmetric variation of the

* Corresponding author. Tel.: +30 210 7275318; fax: +30 210 7275214.
E-mail addresses: christod@di.uoa.gr (C. Christodoulos), michalak@di.uoa.gr (C. Michalakelis), arkas@di.uoa.gr (D. Varoutas).

0040-1625/$ – see front matter © 2010 Elsevier Inc. All rights reserved.
doi:10.1016/j.techfore.2010.01.009

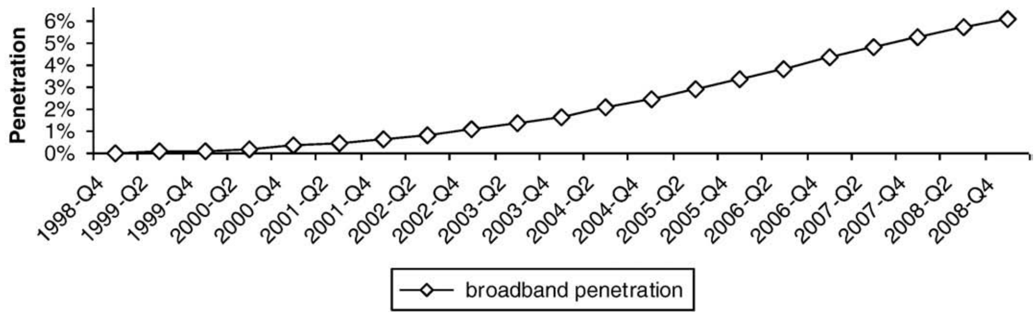

Fig. 1. World broadband penetration from 1998 to 2008.

logistic model of Easingwood [14] provided the lowest mean absolute percentage error (MAPE) and, thus, was the most accurate in the cases tested by them. However, Meade and Islam [15] in their recent review on the modelling and forecasting of the innovation's diffusion, criticized the value of their findings on the ground that many of the data sets used were inappropriate, as they described consumption or production, rather than diffusion.

This paper focuses on forecasting a diffusion process when limited data are available, by introducing a new methodology for short-term predictions, especially in the case of the high technology market, which is characterized by short life cycles due to the rapid technological substitution. The methodology can be applied by the time the take off of the diffusion process has been initiated. The premature use of the widely used diffusion models often delivers diverged prediction of the process's future values. According to Modis and Debecker [16], the further the fit is made in the growth process, the more significantly the expected error of the logistic curve parameters decreases. On the other hand, the ARIMA models are capable of providing acceptable short-term predictions at this stage of the diffusion, given that the data points are enough. ARIMA models are unemployable, for theoretical reasons, in "short" series [13] and can provide acceptable results when at least 16–20 data points are available (see for example Lusk and Neves [17]).

In the context of this work both of the above modelling approaches are combined into a single framework, aiming to provide more accurate short-term forecasts. To the best of the authors' knowledge, this is the first paper presenting such a combination of two completely different approaches (ARIMA and Linear Logistic models) for technology diffusion predictions. A similar approach that combines seasonal ARIMA models with a different forecasting method (neural networks) was presented by Tseng, Yu and Tzeng in 2002 [18]. The authors proposed the use of a hybrid model (SARIMABP) that combines the time series SARIMA model and the neural network model to predict seasonal time series data. Nevertheless, their approach has a different orientation as the two forecasting methods can be combined for a different purpose and in a different manner. In this work, the basic concept is the use of the most appropriate ARIMA model when at least 16 semi-annual data points (eight years of the technology's penetration) have been recorded along with the use of the following year's predictions of the data set in order to remake a forecast for this year using a diffusion model.

The penetration of two different technologies, the world broadband and the mobile telecommunications' penetration, is forecasted in this paper, illustrating the predictive ability of the proposed methodology in two separate cases that are investigated in a global basis, independently of country-related characteristics. The data used in this work are published in the official site of the International Telecommunication Union (ITU) (http://www.itu.int/ITU-D/icteye/Indicators/Indicators.aspx). The recorded world penetration begins in 1998 and reaches up to 2008 (21 semi-annual data points) (Figs. 1 and 2). The methodology is applied from the 16th observation and forth, with a two-step ahead forecast (1 year), for four times in every dataset.

The rest of the paper is organized as follows. The next section provides an overview of the diffusion models and the Box-Jenkins approach. Section 3 describes and justifies the methodology as well as presents the results, after its application in the world broadband and mobile penetration. Finally, Section 4 concludes.

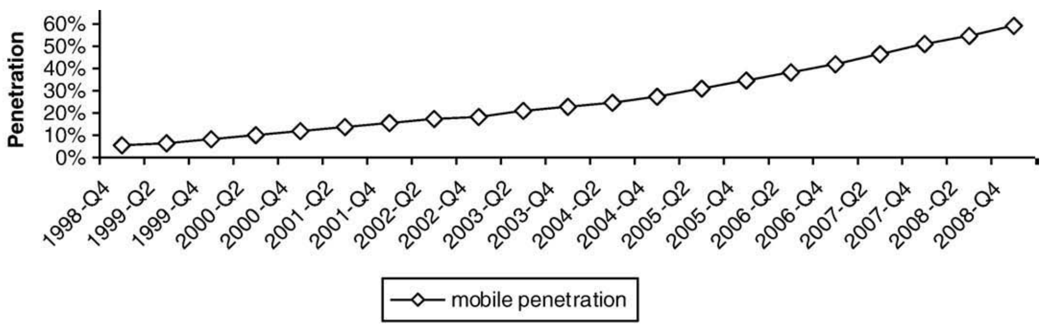

Fig. 2. World mobile penetration from 1998 to 2008.

2. Diffusion models and the Box-Jenkins approach

2.1. Diffusion models

Diffusion models are mathematical functions, mainly of time, used for estimating the adoption of technological innovations or other products or services. The cumulative diffusion shapes of innovations are often described by sigmoid growth patterns. The aggregated S-shaped diffusion models can be derived from a differential equation such as

$$\frac{dN(t)}{dt} = \delta \times f(N(t)) \times [K - N(t)] \tag{1}$$

where $N(t)$ represents the total penetration at time t, K the saturation level of the specific technology and δ is a so-called coefficient of diffusion, which describes the diffusion speed and correlates the diffusion rate with the actual and maximum penetration. Each aggregate diffusion model has an appropriate form of the $f(N(t))$ function, which describes the diffusion process of the innovation. For example, this function in the Linear Logistic model is simply $N(t)$, whereas in the Gompertz model it is represented by $\ln(N(t)/K)$.

The most commonly used diffusion models are the Bass, the Gompertz and the logistic family models.

The Bass model was developed for sales forecasting. It rearranges the five categories of adopters developed by Rogers [19]. The general form of the Bass model is described by the following equation:

$$A(t) = \frac{(m \times (p+q)^2)}{p} \times \frac{e^{-(p+q)t}}{[(q/p)e^{-(p+q)t} + 1]^2} \tag{2}$$

where m is the market potential (maximum possible adoptions envisaged) over the total period of reference. It corresponds to the peak value of instantaneous adoption. Parameter p is the coefficient of innovation and corresponds to the probability of an initial purchase at the beginning of the product's life cycle. Parameter q is the coefficient of imitation and represents the imitative behavior of future adopters. $A(t)$ represents the adoption during time period t.

The Gompertz model is described as:

$$Y(t) = Se^{-e^{-a-bxt}} \tag{3}$$

where S represents the saturation level and $Y(t)$ is the estimated diffusion level at time t. Parameter a is related to the time that diffusion reaches 37% of its upper level and parameter b measures the speed of the adoption process. The model was employed in early technological studies and was named after the English actuary who originally proposed it as a law governing mortality rates.

Finally, the Linear Logistic model, also known as Fisher-Pry model [20], is described by the following formulation:

$$Y(t) = \frac{S}{(1 + e^{(-a-bxt)})}. \tag{4}$$

S represents the saturation level and a, b are parameters to be estimated, describing the speed of diffusion. The Linear Logistic model is based upon the concept that the level of the technological capability can be specified as the function of time, t, and the inherent upper limit, S, to that capability. It is graphically depicted by a symmetric S-curve and has an inflection point that occurs when $Y(t) = S/2$, meaning that the maximum growth rate is met when Y reaches half of its saturation level.

Each model has the same chances of being more suitable to describe a specific growth pattern as each has unique characteristics. For instance, Griliches [21] found that the Logistic model explained successfully the adoption of hybrid corn in the United States. Chow [5] dealt with the diffusion of computers in the United States and resulted to the Gompertz model as the best fitting model, opposite to the Logistic model. Bass [6] used his novel model in 1968 in order to predict the peak of colour TV sales. There is no established rule concerning the superiority of an aggregate diffusion model opposite to the others. In addition, many important factors, such as the type of innovation, the initial "critical mass" of adopters, the introductory price and the communication channels, influence the diffusion rate and establish different growth patterns. Nevertheless, the major differences in the future values that are predicted by each model appear in the case of long-term forecasting. The evaluation of the proposed methodology in this work was based on the Linear Logistic model, which is a widely used diffusion model in the relative bibliography.

2.2. The Box-Jenkins approach

Time-series methods have been available to explain and forecast the behaviour of longitudinal variables for several decades. The Box-Jenkins approach is one of the most powerful forecasting techniques available and it can be used to analyse almost any set of data. It is expressed through the development of an ARIMA model, which is a generalisation of an ARMA model [22]. These models are fitted to time-series data in order to predict future points in the series. The model is generally referred to as an ARIMA (p,d,q) model where p, d and q are integers, greater than or equal to zero and refer to the order of the autoregressive, integrated

Table 1
Best ARIMA model for each set of data points and its MAPE (broadband).

Data points	ARIMA model	MAPE
16	(1,2,0)	5.744
17	(1,2,0)	5.303
18	(0,2,0)	5.944
19	(0,2,0)	5.503

Table 2
Comparison of MAPE for each approach — one year forecast (broadband).

Data points	ARIMA model MAPE	Linear Logistic MAPE	New methodology MAPE
16	0.0097	0.0549	0.0055
17	0.0162	0.0524	0.0054
18	0.0184	0.0417	0.0072
19	0.0329	0.0265	0.0169

Table 3
Best ARIMA model for each set of data points and its MAPE (mobile).

Data points	ARIMA model	MAPE
16	(0,2,0)	1.657
17	(0,2,0)	1.547
18	(0,2,0)	1.45
19	(0,2,0)	1.364

and moving average parts of the model, respectively. Given a time-series of data X_t where t is an integer index and X_t are real numbers, corresponding to values at time t, then an ARIMA (p,d,q) model is described by

$$(1-B)^d(1-\sum_{i=1}^{p}\varphi_\iota B^\iota)X_t = (1+\sum_{i=1}^{p}\theta_\iota B^\iota)\varepsilon_t \tag{5}$$

or:

$$(1-B)^d\phi(B)X_t = \theta(B)Z_t \tag{6}$$

where B is the backward shift operator, expressing the length of previous data the model uses to provide forecasts, φ_i are the parameters of the autoregressive part of the model, the θ_ι are the parameters of the moving average part and Z_t are error terms. The error terms Z_t are generally assumed to be independently, identically distributed variables (iid) sampled from a normal distribution with zero mean. The d integer is positive and controls the level of differencing. If $d=0$, then the ARIMA is equivalent to an ARMA model. In simple words, AR stands for "autoregressive" and describes a stochastic process that can be described by a weighted sum of its previous values and a white noise error, while MA stands for "moving average" and describes a stochastic process that can be described by a weighted sum of a white noise error and the white noise error from previous periods.

Following the model formulation, the participating parameters are required to be estimated with the aid of gradient-based method, seeking to zero gradient of mean squared sum of fitting errors over the historical data. The parameter estimation basically aims to the minimization of the forecasting error. The next step is the validation of the model's adequacy and as a final stage the forecasted values are provided.

Summarizing, the ARIMA time-series analysis uses lags and shifts in the historical data to uncover patterns (e.g. moving averages, seasonality) and predict the future.

3. Methodology description, justification and evaluation

The methodology presented in this paper combines the forecasting advantages of the diffusion models and the ARIMA models, in order provide better short-term predictions than when both approaches were individually applied. The target is to make a short-term forecast of the new high technology's diffusion that has not been yet widely spread over a market.

The two approaches have been developed within different research perspectives and referring to different kinds of phenomena. Diffusion models originated from the biology (population theory, mortality rates) and the industrial economics. On a later stage, they were applied in business economics. On the other hand, ARIMA models derive from mathematics and statistics tradition and are met in several different forecasting applications, usually after the gathering of a significant number of recorded data points. The use of time-series forecasting after a few years of diffusion is in line with the technology life cycle in general, since innovations and products particularly in the area of high technology usually enjoy short life cycles mainly because of the rapid and frequent substitution of a product's generation by its descendant ones. Furthermore, the application of the approach at the specific stage of the diffusion process with a relatively limited data set is also supported by the fact that the growth is anticipated to continue.

Even though the two approaches can give adequate successful forecasts separately, they cannot be exactly accurate in their predictions. The application of a diffusion model at this stage, for making a short-term forecast, would result to predictions of medium success, as compared to the later recorded actual data. Furthermore, an unrealistic saturation point is expected to be estimated and the corresponding diffusion would probably appear as a very slow process over the following years. Based on observations of similar cases, it is fair to say that the diffusion of a new technology is usually more rapid than the diffusion of other products. Therefore, the predictions will not be of great value. On the other hand, an application of the ARIMA model would result to predicted values that are higher than the actual data. This is explained by the fact that the ARIMA modelling and forecasting is mainly based on the more recent historical data. Once the rapid increase of the diffusion process begins, it is only logical that the predicted values each time will depend on the recent, fast changing past data and will be interpreted as an orientation for even greater values. The increase is constrained by the gradual approximation from a point and forth to the upcoming saturation point.

The combination of forecasts is a widely investigated issue in the statistical field. Many researchers have recognized the value of combining forecasts produced by various techniques as a means of reducing forecast error (see for example [23]). Armstrong's meta-analysis [24] revealed that combining is more useful for short range forecasting, like in the present work, where random errors are more significant. Because these errors are off-setting, a combined prediction should reduce them. Many techniques for combining forecasts have been introduced over the past years, varying in level of complexity and success. Timmermann [25] argues that simple combinations, which ignore correlations between forecast errors, often dominate more refined combination schemes aimed at estimating the theoretically optimal combination weights. The use of a simple average has proven to do as well as more sophisticated approaches. Nevertheless, there are situations where one method is more accurate than another. If such cases can be identified in advance, simple averages would be inefficient [24].

Therefore, this paper introduces a methodology for combining the two methods in this special case of forecasting, taking into account the above mentioned facts. The methodology relies on the use of the first two predictions of the most suitable ARIMA model measured by the Mean Absolute Percentage Error (MAPE) (Tables 1 and 3), incorporated into the diffusion model as actual data in order to construct a new diffusion model. The hypothesis is that the short-term forecast of one year produced by the ARIMA model is better than the one produced by the Linear Logistic model at this stage of the diffusion process, which is validated in the present work. As this forecast is anticipated to be over-optimistic, the predicted values are taken into consideration in order to construct a new diffusion model, which will be more effective than the first one. After the calculation of the new model's parameters, the first two values are recalculated. These forecasts incorporate the effects of the ARIMA and the Linear Logistic models and are anticipated to be more precise than each approach separately. This procedure avoids the simple averages approach, which would not be sufficient in this case as the ARIMA models produce noticeable improved short-term predictions compared to the diffusion models. The use of weights as a method of combination is also avoided, as it involves personal judgement regarding their value or evaluation of correlations between forecast errors that are likely to change from period to period.

If the same innovation is introduced in different geographical areas, it is quite possible that one model will not be able to describe corresponding diffusion processes, and that a different model may be more appropriate to describe diffusion in each case. In order to avoid special cases of countries and large geographical areas with different characteristics (factors such as the Gross Domestic Product and the population density affect the growth curve of an innovation), the global diffusion process of two cases is examined in this work. Two popular telecommunications' innovations were chosen for the application of the methodology (broadband and mobile telecommunications), so as to demonstrate its effectiveness in different applications of high technology.

There is no universally preferred measure of accuracy estimation and forecasting, therefore experts often disagree as to which measure should be used. Three of the most common measures of accuracy are the Mean Square Error (MSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). Their expressions are depicted below:

$$\mathrm{MSE} = \sum_{t=1}^{T} \frac{(Pt-Zt)^2}{T} \tag{7}$$

$$\mathrm{MAE} = \sum_{t=1}^{T} \frac{|Pt-Zt|}{T} \tag{8}$$

$$\mathrm{MAPE} = \frac{1}{T}\sum_{t=1}^{T} \frac{|Pt-Zt|}{Zt} \tag{9}$$

Table 4
Comparison of MAPE for each approach — one year forecast (mobile).

Data points	ARIMA model MAPE	Linear Logistic MAPE	New methodology MAPE
16	0.0017	0.0433	0.0011
17	0.0025	0.0173	0.0006
18	0.0015	0.0086	0.0014
19	0.0019	0.0081	0.0014

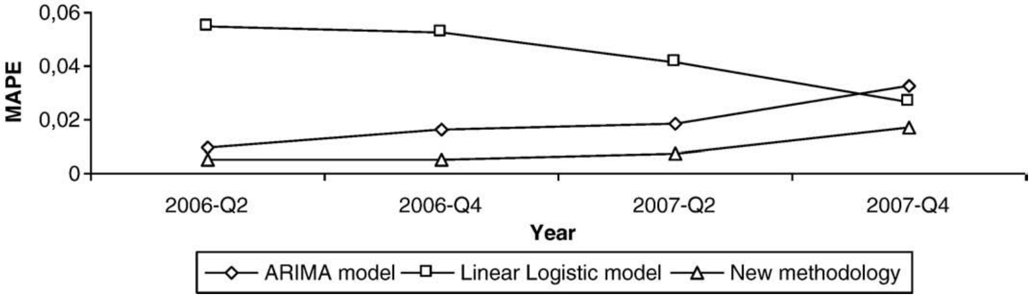

Fig. 3. MAPE for each approach — World broadband penetration.

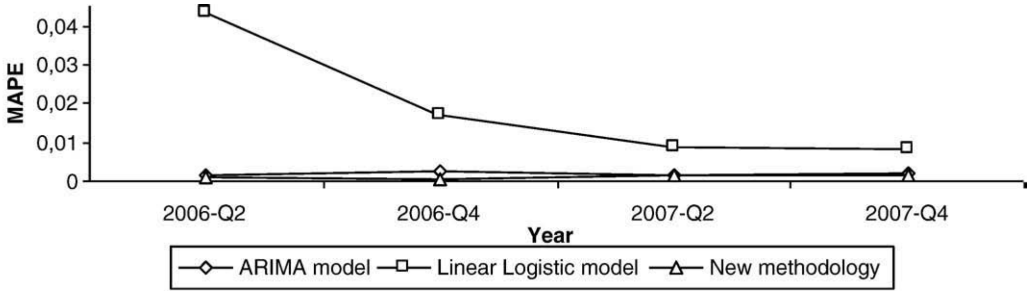

Fig. 4. MAPE for each approach — World mobile penetration.

where *Pt* is the predicted value at time *t*, *Zt* is the actual value at time *t* and *T* is the number of predictions. The MAPE was selected to be the main measure of the present evaluation, as it is widely used in cases of combining and selecting forecasts (see for example [26,27]). ARIMA models' evaluation was performed by the SPSS software, while parameter estimation and calculation of statistical measures of accuracy were performed with the aid of the DATAFIT software.

The data were derived from the International Telecommunication Union (ITU) official site for the decade 1998–2008 [28]. The annual time series data were converted to semi-annual by interpolation, which is an appropriate disaggregation method for the specific sample size and for relatively stable data evolution, as underlined in [29].

The global diffusion of both technologies' penetration is shown in separate figures, each followed by two tables: the one illustrates the selection of the best ARIMA model best on its MAPE. The other presents the recorded MAPE for each approach separately, for one-year-ahead forecasts (Tables 2 and 4). The new approach has better MAPE in all cases. The forecasts were made for the periods 2006Q2–2007Q2, 2006Q4–2007Q4, 2007Q2–2008Q2 and 2007Q4–2008Q4. These four periods of testing were determined by the available amount of information. In 2006Q2, the number of recorded data points is large enough to properly run the ARIMA model and the sigmoid diffusion is already at the rapid growth stage. The last recorded data point by the ITU is in 2008Q4, which allows four sets of one-year-ahead predictions.

The application in both technologies resulted in some interesting observations regarding the efficiency of the two established approaches. The earlier the ARIMA model is applied in the *S*-curve, the better the MAPE for this approach and the worst for the diffusion model. On the contrary, the Linear Logistic model improves its prediction from step to step, as the sigmoid curve approaches

Table 5
Comparison table of all error metrics for each approach (mobile).

Data points	Error metric	ARIMA model	Linear Logistic	New methodology
16	MAPE	0.001667656	0.0432847	0.001106
	MSE	4.12525E−07	0.000176	2.28E−07
	MAE	0.0003775	0.0091591	0.000252
17	MAPE	0.002503895	0.0173093	0.000619
	MSE	8.67925E−07	3.542E−05	4.41E−08
	MAE	0.0006125	0.0041146	0.000147
18	MAPE	0.00150515	0.0086301	0.001412
	MSE	3.65E−07	1.002E−05	2.89E−07
	MAE	0.0004	0.0022377	0.000372
19	MAPE	0.001924763	0.008078	0.001385
	MSE	7.085E−07	1.032E−05	6.12E−07
	MAE	0.000555	0.0022614	0.000408

Table 6
Comparison table of all error metrics for each approach (broadband).

Data points	Error metric	ARIMA model	Linear Logistic	New methodology
16	MAPE	0.009677	0.054869	0.005495
	MSE	1.48E−07	3.19E−06	3.86E−08
	MAE	0.00023	0.001195	0.000127
17	MAPE	0.016174	0.052447	0.005422
	MSE	4.2E−07	3.56E−06	6.72E−08
	MAE	0.000423	0.001267	0.000131
18	MAPE	0.018353	0.041689	0.007184
	MSE	8.66E−07	2.49E−06	8.84E−08
	MAE	0.00053	0.0011	0.0002
19	MAPE	0.032876	0.026481	0.016888
	MSE	2.34E−06	1.26E−06	5.07E−07
	MAE	0.001013	0.000762	0.000504

the forecasted saturation point, while the ARIMA model's accuracy gradually diminishes. These facts are better recorded for the case of the broadband technology, where the diffusion follows a clearer *S*-shape. As illustrated in Figs. 3 and 4.

The accuracy of each approach's forecast is measured in terms of MAPE in the above applications, as noted earlier in this manuscript. Nevertheless, the three approaches have also been compared based on the other two measures of accuracy, the Mean Square Error (MSE) and the Mean Absolute Error (MAE) in order to confirm the superiority of the new approach opposite the ARIMA and the Linear Logistic models. The observation of the other two measures resulted in the same conclusions as well. For demonstration purposes, Tables 5 and 6 illustrate the three error metrics for all modelling approaches and for each technology separately.

4. Conclusion

This paper presented a new methodology that delivers short-term forecasts of the new high technology's diffusion at the early stages of the procedure. After obtaining enough actual data to construct a time-series, a diffusion model and an ARIMA model are applied over the sample and the first forecasts of the ARIMA model are used to perform an improved short-term prediction using a conventional aggregate diffusion model. Since the two categories of modelling are of completely different concepts and implementations, the choice of combining their forecasts in the most suitable manner has been made. Given the superiority of one approach towards the other in the specific area of study, other complicated or simple methods of combination, such as the use of weights and the simple averages approach, are avoided.

Application of the methodology in the case of world broadband and mobile phones penetration verified its accuracy and illustrated its performance capabilities. When penetration is at its initial stage of rapid increase and given the availability of adequate number of data points, the proposed approach provides improved forecasts, as compared to these of the other two models.

The one-year-ahead forecasts of each approach were compared based on three widely used measures of accuracy: the Mean Square Error (MSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE), with the MAPE being the main measure, as noted in other similar studies of forecast combinations. Even though the new methodology provided better predictions than each model separately in both technologies and for every application, all three approaches provide more-or-less reliable predictions for the period considered. Another important observation is that the forecasting accuracy of the ARIMA model diminishes gradually at this stage of the growth process, from period to period, whereas the corresponding predictions of the Linear Logistic model improve. The differences in numbers may not seem of great importance. Nevertheless, these small differences represent, in reality, some thousands of new subscribers. Even though the forecasting power of the methodology seems limited, it should be taken into consideration that the forecasting improvement is for one-year horizon. This single year's improved forecast could make the difference in the sense of corporate competition, as this knowledge is a useful guideline for the upcoming year's strategy programming.

This methodology can be probably applied over all cases of the high-technology market, where a diffusion model is usually used for obtaining future forecasts. Its main limitations consist of the prerequisite for having enough historical data points in order to create a time-series and that the diffusion process should be at the time point when the take off stage of the diffusion process is initiated. The study was limited to a forecasting horizon of one year ahead. Future research in this topic includes the application of the methodology in other cases of high technology innovations diffusion, as well as the further investigation of its use in other stages of the diffusion process and for other forecast horizons. Finally, the combination with other forecasting models should also be thoroughly examined.

References

[1] L.A. Fourt, J.W.G. Woodlock, Early prediction of early success of new grocery products, J. Mark. 25 (1960) 31–38.
[2] E. Mansfield, Technical change and the rate of imitation, Econometrica 29 (1961) 741–766.

[3] A. Floyd, Trend forecasting: a methodology for figure of merit, in: J. Bright (Ed.), Technological Forecasting for industry and government, 1962, pp. 95–105.
[4] E.M. Rogers, Diffusion of innovations4rth ed., The Free Press, New York, 1962.
[5] G.C. Chow, Technological change and demand for consumers, Am. Econ. Rev. 57 (1967) 1117–1130.
[6] F.M. Bass, A new product growth model for consumer durables, Manag. Sci. 15 (1969) 215–227.
[7] G.U. Yule, On the method of investigating periodicities in disturbed series, with special reference to Wolfer's sunspot numbers, Philos. Trans. Roy. Soc. London Ser. A 226 (1927) 267–298.
[8] G.E.P. Box, G.M. Jenkins, Time series analysis: Forecasting and control, Holden Day, San Francisco, 1970.
[9] G.S. Armstrong, R.J. Brodie, S.H. Mclntyre, Forecasting methods for marketing — review of empirical research, Int. J. Forecast. 3 (1987) 355–376.
[10] N. Meade, The use of growth curves in forecasting market development — a review and appraisal, J. Forecast. 3 (1984) 429–451.
[11] B. Gompertz, On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contigencies, Phil. Trans. Roy. Soc. London 115 (1825) 513–585.
[12] L.P. Rai, Appropriate models for technology substitution, J. Sci. Ind. Res. 58 (1) (1999) 14–18.
[13] G. Gottardi, E. Scarso, Diffusion models in forecasting: a comparison with the Box-Jenkins approach, Eur. J. Oper. Res. 75 (1994) 600–616.
[14] C. Easingwood, V. Mahajan, E. Muller, A non-symmetric responding logistic model for forecasting technological substitution, Technol. Forecast. Soc. Change 20 (1981) 199–213.
[15] N. Meade, T. Islam, Modelling and forecasting the diffusion of innovation — a 25-year review, Int. J. Forecast. 22 (2006) 519–545.
[16] T. Modis, A. Debecker, Chaoslike states can be expected before and after logistic growth, Technol. Forecast. Soc. Change 41 (1992) 111–120.
[17] E.J. Lusk, J.S. Neves, A comparative ARIMA analysis of the 111 series of the Makridakis competition, J. Forecast. 3 (1984) 329–332.
[18] F.-M. Tseng, H.-C. Yu, G.-H. Tzeng, Combining neural network model with seasonal time series ARIMA model, Technol. Forecast. Soc. Change 69 (2002) 71–87.
[19] E.M. Rogers, Diffusion of innovations, The free press, New York, 1962 (Chapter 6).
[20] J.C. Fisher, R.H. Pry, A simple substitution model of technological change, Technol. Forecast. Soc. Change 3 (1) (1971) 75–88.
[21] Z. Griliches, Hybrid corn: an exploration in the economics of technological change, Econometrica 25 (4) (1957) 501–522.
[22] P. Newbold, ARIMA model building and the time-series analysis approach to forecasting, J. Forecast. 2 (1983) 23–35.
[23] D.W. Bunn, Combining forecasts, Eur. J. Oper. Res. 33 (1988) 223–229.
[24] J.S. Armstrong, Combining forecasts: the end of the beginning or the beginning of the end? Int. J. Forecast. 5 (1989) 585–588.
[25] A. Timmermann, Chapter 4: forecast combinations, Handb. Econ. Forecast. 1 (2006) 135–196.
[26] S. Makridakis, M. Hibon, Accuracy of forecasting: an emprirical investigation, J. Roy. Stat. Soc. 142 (1979) 97–125.
[27] S. Makridakis, A. Anderson, R. Carbone, R. Fildes, M. Hibon, R. Lewandowske, J. Newton, E. Parzen, The accuracy of major forecasting procedure, John Wiley, New York, 1984.
[28] http://www.itu.int/ITU-D/icteye/Indicators/Indicators.aspx.
[29] W.S. Chan, Disaggregation of annual time-series data to quarterly figures: a comparative study, J. Forecast. 12 (1993) 677–688.

Charisios Christodoulos holds a diploma in Electrical and Computer Engineering (major in Telecommunications and Information Technology) from the University of Patra (Engineering school) and an M.Sc. degree in Business Mathematics (joint course of the Athens University of Economics and Business and the University of Athens). He is a PhD candidate in the area of telecommunications and technoeconomics in the Department of Informatics and Telecommunications at the University of Athens. He has been involved in the implementation of several telecommunicational projects and he now participates in technoeconomic activities for telecommunications, networks and services with the University of Athens. His research interests include the economics of telecommunications, the study of the market's structure, performance and forecasting, mergers and acquisitions, industry life cycle, and adoption theory. He is a member of the Technical Chamber of Greece (TEE).

Christos Michalakelis holds a Mathematics degree (University of Athens, Department of Mathematics), a M.Sc. degree in Software Engineering (The University of Liverpool, UK) and an M.Sc. degree in "Administration and Economics of Telecommunication Networks" from the National and Kapodistrian University of Athens (Department of Informatics and Telecommunications, Interfaculty course of the Departments of Informatics and Telecommunications and Economic Sciences). He is a high school teacher of Informatics and Computer Science and he recently completed his PhD in the area of technoeconomics and especially in demand estimation and forecasting of high technology products. He has been working for 7 years with the Greek Ministry of Education, as an IT supervisor. Mr. Michalakelis has participated in a number of projects concerning the design and implementation of database systems and he now participates in several technoeconomic activities for telecommunications, networks and services such the CELTIC/ECOSYS project pricing and regulation. He has also developed or had a major contribution in the development of a number of information systems and applications. His research interests include the study of diffusion models over the technology products and services, the application of economic theories over the telecommunication and wider informatics area, price modelling and indexing. He authored a number of papers published into scientific journals and conferences. He has also contributed as a co-author in two book chapters.

Dimitris Varoutas holds a Physics degree and M.Sc. and PhD diplomas in communications and technoeconomics from the University of Athens. Since 2005, he is a lecturer on telecommunications technoeconomics in the Department of Informatics and Telecommunications in the same university. He has been participating in European R&D projects since early '90s in the areas of telecommunications and technoeconomics. He also participates in or manages related national and European activities for technoeconomic evaluation of broadband strategies, telecommunications demand forecasting, price modelling etc. His research interests include telecommunications and technoeconomic evaluation of network architectures and services. He has published more than 40 publications in refereed journals and conferences, including leading IEEE publications. He is an IEEE member and serves as a reviewer in several, including IEEE, publications and conferences.