Technological Forecasting & Social Change 78 (2011) 163–170

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

On the combination of exponential smoothing and diffusion forecasts: An application to broadband diffusion in the OECD area

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ARTICLE INFO

Article history:
Received 3 February 2010
Received in revised form 13 August 2010
Accepted 17 August 2010

Keywords:
Combining forecasts
Holt's damped trend method
Gompertz model
Linear logistic model
Long-term forecasting

ABSTRACT

The innovation diffusion literature has established that the spread of a successful innovation over time typically follows a sigmoid curve. Therefore, the forecasting in this area has been monopolized by the use of well known aggregate diffusion models. Time series forecasting has been surprisingly neglected, as it provides mainly accurate short term forecasts. In this work, a method of exponential smoothing, the Holt's damped trend with a modification, is applied in recent broadband diffusion data of two large regions after the reach of the inflection point. As validated with holdback sample data ranging from 6 up to 30 months, the key for successful forecasting is the use of the estimated saturation level calculated from a diffusion model, in order to specify the appropriate trend. The results indicate improved predictions compared to two popular diffusion models, the Gompertz and the Linear Logistic model. The paper concludes with the application of the proposed method in a 48-month forecasting horizon, as well as the suggestions for further research.
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1. Introduction

DIFFUSION forecasting of innovations over a long future time horizon in the most accurate manner is an important prerequisite for efficient production planning. It is also vital for proper policy decisions taken from regulators, governments and companies. The range of research in modelling the diffusion of innovations is impressive and confirms its continuing importance as a scientific topic. Various diffusion models have been used since the 1960s in order to capture this diffusion trend in the form of mathematical equations (e. g. Bass [1], Chow [2] and Rogers [3]. There are some extensive literature reviews on the subject [4–8]. In such reviews the advancement and improvements of the models are covered. Nevertheless, the initial models are still in use by academics and practitioners of the area, and are often compared to the various modifications that have come up over the years.

In their review regarding the modelling and forecasting of the diffusion of innovation, Meade and Islam [4] state that one would expect a diffusion model to be more accurate than a time series model such as the Holt–Winters' model with a linear trend [9,10]. Exponential smoothing methods have been around since the 1950s, and are still among the most popular forecasting methods used in business and industry. Nevertheless, exponential smoothing can be used with any discrete set of repeated measurements. The major advantage of these models in providing mainly accurate short term forecasting has surprisingly led to lack of research regarding their application in long-term diffusion forecasting.

Gardner and McKenzie made a breakthrough in the research area of exponential smoothing with a series of papers ([11–13]) by developing new versions of the Holt–Winters methods that damp the trend as the forecast horizon increases. Their work has stimulated the interest in this area, resulting to the inclusion of the damped trend exponential smoothing methods in the successfully applied approaches in empirical studies, as discussed by Gardner [14]. In addition, the damped trend is recommended

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doi:10.1016/j.techfore.2010.08.007

by Armstrong [15] as a well established forecasting method that should improve accuracy in practical applications. The area of exponential smoothing has undergone a substantial revolution in the recently past years.

The aim of this paper is the modified use of the Holt's damped trend method, by taking into account the forecasted saturation point of the diffusion model. The novelty of the approach relies on the use of the saturation point as the asymptotic horizontal straight line to which the time series dampens, thus specifying the appropriate damping parameter in the model. Without this orientation towards the proper direction, the accuracy of the Holt's damped trend method is constrained to short term forecasting horizons. With the proposed approach, the predictive power of the method extends to longer predictions. This modification combines the advantages of both approaches, as the diffusion models are influenced by the anticipated sigmoid shape of the process, while the exponential smoothing methods are mainly affected by the recently recorded historical data. To the best of the authors' knowledge, this is the first paper presenting such a combination. A similar approach, with the difference that the damped trend approximated the historical average trend, has been used for the Holt–Winters seasonal forecasting in the case of long lead-time forecasting of United Kingdom's air passengers by Grubb and Mason [16].

The proposed method is tested in recent broadband diffusion data obtained from an internationally accredited and reliable source, the Organization for the Economic Co-operation and Development (OECD, http://www.oecd.org/sti/ict/broadband). Although various minimum bandwidths have been used in definitions of broadband, ranging up from 64 kbit/s up to 2.0 Mbit/s, OECD defines broadband as having download data transfer rates to or faster than 256 kbit/s. The choice of the application in the broadband technology has been made on the ground that it is the most recent technology (and thus the most representative for future high technologies), for which one can find enough historical data to properly apply the methodology. In addition, its rapid development has already proven to be normal, in accordance with classic modelling approaches, and rarely involves sudden major changes. Two large population groups, the total sum of the OECD countries and the United States of America were chosen for the application in order to ensure the generalization of the method. This choice covers big areas of population, including a large number of countries or states, in the case of the American continent. Finally, the availability of the data from 1997 for these two large groups of subscribers ensures the adequate number of time points in order to properly run the exponential smoothing method.

The rest of the paper is organized as follows. The next section provides an overview of the diffusion models and Holt's additive and damped trend methods. Section 3 describes the methodology. Section 4 presents the results, after its application in the broadband data. Finally, Section 5 concludes.

2. Diffusion models — Holt's additive trend and damped trend methods

2.1. (a) Diffusion models

Diffusion is the process by which a new product or service is accepted by the market. Diffusion models are mathematical growth functions that provide an S-shaped time pattern. The emphasis is on predicting the ultimate level of penetration (saturation) and the rate of approach to saturation. There are strong parallels with epidemiology, the study of how a contagious disease spreads. The general differential equation of the aggregated S-shaped diffusion models has the following form:

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

where $N(t)$ represents the total penetration at time t , K is 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. Diffusion models are hard to calibrate prior to launch and the models tend to be unstable until the point of inflection occurs.

Next, two popular diffusion models, the Gompertz and the Linear Logistic models, are described in more detail, as they are used for the application of the proposed method later on in this paper.

The Gompertz model was employed in early technological studies and was named after the English actuary who originally proposed it as a law governing mortality rates [17]. It is described as:

$$Y(t) = Se^{-e^{-a-b\times t}} \tag{2}$$

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 Linear Logistic model, also known as Fisher–Pry model [18], 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. It is described by the following formulation:

$$Y(t) = \frac{S}{\left(1 + e^{(-a-b\times t)}\right)}. \tag{3}$$

S represents the saturation level and a, b are parameters that describe the speed of diffusion.

2.2. (b) Holt's additive trend and damped trend methods

Exponential smoothing is a technique that can be applied to time series data to make forecasts. Whereas in moving averages the past observations are weighted equally, exponential smoothing assigns exponentially decreasing weights as the observation gets older. In other words, recent observations are given relatively more weight in forecasting than the older observations. The robustness and accuracy of exponential smoothing forecasting have led to its widespread use in applications where a large number of series necessitates an automated procedure. Although the Holt's method has tended to be the most popular approach for trending series, its linear forecast function has been criticized for tending to overshoot the data beyond the short term. Gardner and McKenzie [11] address this problem by including an extra parameter in the Holt's method to dampen the projected trend. Empirical studies show that the damped method tends to offer improvements in accuracy (e.g. Makridakis et al. [19], Makridakis & Hibon [20]).

The standard Holt's additive trend method estimates the local growth, T_t, by smoothing successive differences, $S_t - S_{t-1}$, of the local level, S_t. The forecast function is the sum of level and projected growth:

$$S_t = aX_t + (1-a)(S_{t-1} + T_{t-1}) \tag{4}$$

$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1} \tag{5}$$

$$\hat{X}_t(m) = S_t + mT_t \tag{6}$$

where X_t s the actual observation, $\hat{X}_t(m)$ is the m-step-ahead forecast, and a and γ are smoothing parameters.

Gardner and McKenzie [11] describe how a dampening parameter,φ, can be used within the Holt's method to give more control over trend extrapolation. The damped Holt method is presented in the following equations:

$$S_t = aX_t + (1-a)(S_{t-1} + \varphi T_{t-1}) \tag{7}$$

$$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)\varphi T_{t-1} \tag{8}$$

$$\hat{X}_t(m) = S_t + \sum_{i=1}^{m} \varphi^i T_t \tag{9}$$

They explain that if $0<\varphi<1$, the trend is damped and the forecasts approach an asymptote given by the horizontal straight line $S_t + T_t\varphi/(1-\varphi)$. If $\varphi=1$, the method is identical to the standard Holt method. If $\varphi=0$, the method is identical to standard simple exponential smoothing. If $\varphi>1$, the forecast function has an exponential trend.

3. The methodology

The forecast profile of the Holt's damped trend method is similar to the sigmoid curve, from the inflection point and forth. After this threshold, the diffusion process is anticipated to approximate gradually the saturation point. The problem is the identification of the right value of the parameter φ, which will determine the appropriate evolution of the predictions. By taking into account the forecasted saturation point of the diffusion model, each forecast using the Holt's damped trend method will have a specific orientation (final point). Decreasing the value of φ increases the degree of dampening but the forecast profile remains concave in shape. The difference between a linear and a damped trend can be substantial at long horizons, even with a relatively large φ of say 0.9 or 0.95 [11].

As mentioned in the previous section, if $0<\varphi<1$, the trend is damped and the forecasts approach an asymptote given by the horizontal straight line $S_t + T_t\varphi/(1-\varphi)$. In every forecast, this horizontal line is set equal to the forecasted saturation point using the diffusion model. The next step is the calculation of the value of φ that produces a forecast that results to this final horizontal line. The predictions of the future values towards this final point will be different than the ones produced by the diffusion model, as they will be determined by the level and growth of the time series. In other words, the method combines the advantages of both disciplines, the historical evolution of the data expressed through the exponential smoothing model, and the anticipated S-shaped curve that is expressed through the diffusion model. The combination of different methods for forecasting is stressed out as a very promising area by various researchers (see for example [21]).

The parameters a and γ depend on the type of the time series. Makridakis et al. [19] and Chatfield [22] found that the most accurate parameters were frequently in the range between 0.3 and 1. For the case of diffusion time series, the values of the smoothing parameters were chosen to be 0.7 in all cases, as a range of values (between 0.5 and 0.95) produced more-or-less the same long-term predictions. When this modification is included, the values of the smoothing parameters α and γ are less important in the long-term forecasts. Calculations with all reasonable values result in little change in the predictions, since the damped trend, oriented by the forecasted saturation point of the diffusion model, has the most important impact and stabilises the predictions. Grubb and Mason [16], in their work regarding the forecasting of long lead-time forecasting of United Kingdom's air passengers using the historical average trend, validate that the trend is the most important component to forecast for long-term predictions.

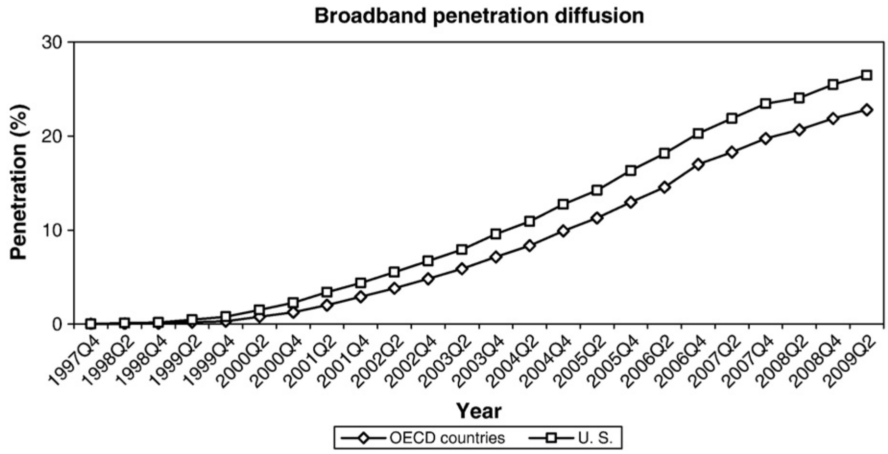

Fig. 1. Broadband penetration diffusion development in the total sum of OECD countries and in the U.S.

All the popular mathematical growth functions are equal candidates for successfully predicting a diffusion process and no established rule exists concerning the superiority of one opposite to the others. For example, Chow [2] comments that the Gompertz model fits best the diffusion of computers in the United States than the Logistic model. Each model has the same chances of being more suitable to describe a specific growth pattern as each has unique characteristics. The growth process can be influenced by many important factors, such as the type of innovation, the initial “critical mass” of adopters, the introductory price and the communication channels. In the present work, the new method is tested with the estimated saturation points from the Gompertz and the Linear Logistic models, as they are two of the most commonly used models for innovations' diffusion modelling and forecasting.

The Mean Absolute Percentage Error (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 Makridakis and Hibon, [23] and Makridakis et al. [24]). It is calculated by the following equation:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{(Pt-Zt)}{Zt}\right|. \tag{10}$$

Pt is the predicted value at time *t*, *Zt* is the actual value at time *t* and *T* is the number of predictions. The difference between *Zt* and *Pt* is divided by the actual value *Zt* again. The absolute value of this calculation is summed for every fitted or forecast point in time and divided again by the number of fitted points. Nevertheless, two other popular error measures are calculated as well, the Mean Square Error (MSE) and the Mean Absolute Error (MAE), in order to ensure the accuracy of the results. Their equations are depicted below:

$$MSE = \sum_{t=1}^{T}\frac{(Pt-Zt)^2}{T} \tag{11}$$

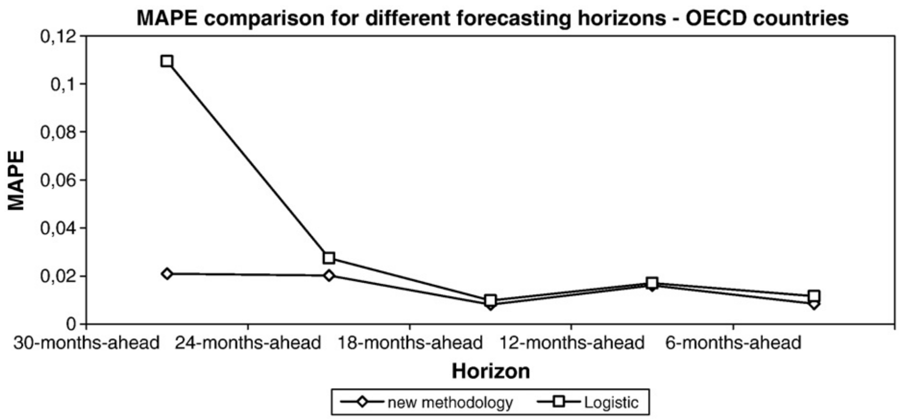

Fig. 2. MAPE comparison between the Linear Logistic model and the new method for different forecasting horizons — OECD countries.

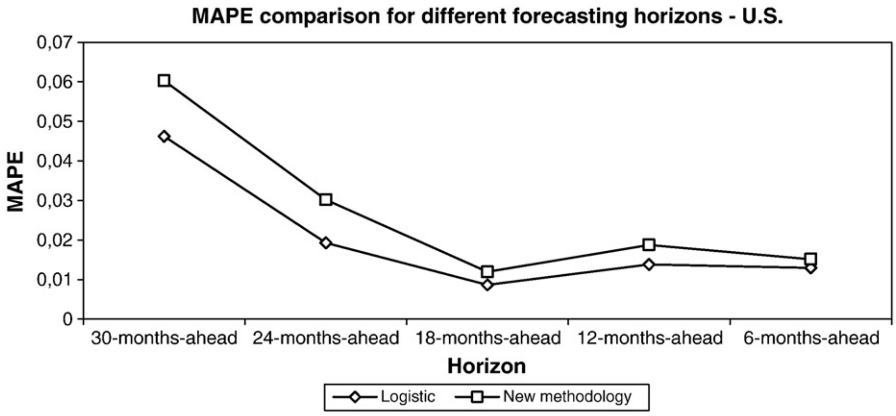

Fig. 3. MAPE comparison between the Linear Logistic model and the new method for different forecasting horizons — United States.

$$MAE = \sum_{t=1}^{T} \frac{|Pt - Zt|}{T} \tag{12}$$

4. Application and results

The semi-annual broadband diffusion data were obtained from the Organization for the Economic Co-operation and Development (OECD) official site for the period 1997–2009. The annual time series data for the period 1997–2009 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 by Chan [25]. The historical development of the broadband penetration diffusion is illustrated in Fig. 1.

In the figures, according to the definition given to the broadband diffusion data, the percentage represents the part of the population that has or will adopt the specific technology. The application of the methods for each dataset begins after obtaining enough data points in order to properly run the models. For the specific case, 19 data points (10 years of broadband penetration) are adequate for the running of the exponential smoothing model. As being a method of time series forecasting, the Holt's damped trend method cannot deliver reliable results with fewer data points in the case of broadband diffusion. In addition, the sigmoid curve, in both cases, has begun to approximate the forecasted saturation point by the diffusion models. At this point, the predicted saturation levels are realistic. So the form of the curve at the 19th observation and the concept of the proposed model have led to the initiation of the application from this point forth. Nevertheless, the proper choice of the time point to start the method's application depends on the type of innovation and the frequency of data points (monthly, quarterly, annually, etc.) and should be carefully selected. Since the available data reach up to June of 2009, the next five recorded data points are used for the holdback sample procedure in order to test the method's accuracy.

As stressed out by Gardner [11], even a relatively large φ of 0.9 or 0.95, which almost approximates but does not reach 1, can make the difference in long horizons and produce substantially more accurate forecasts than the classic Holt's linear trend method. For instance, the damping parameter varied between 0.928 and 0.942 when using the Gompertz model. In this case, the saturation is predicted to occur later on and with a greater penetration value than the one predicted by the Linear Logistic model. Even this relatively large value of φ delivers noticeable differences compared to the results obtained with the use of the classic Holt's linear trend method. On the other hand, the use of the Linear Logistic model resulted to a range of between 0.777 and 0.812. So, these values are interpreted by the fact that the Gompertz model delivered more optimistic predictions than the Linear Logistic model in both cases and for all the forecasting horizons (Figs. 2 and 3).

Table 1
MAPE for every method for different forecasting horizons — OECD countries.

MAPE (OECD)	Combined Gompertz	Gompertz	Combined Logistic	Logistic
30-months-ahead	0.051	0.052	0.02	0.109
24-months-ahead	0.047	0.072	0.02	0.027
18-months-ahead	0.034	0.054	0.008	0.0097
12-months-ahead	0.022	0.037	0.016	0.017
6-months-ahead	0.002	0.03	0.008	0.011

Table 2
MAPE for every method for different forecasting horizons — United States.

MAPE (U.S.)	Combined Gompertz	Gompertz	Combined Logistic	Logistic
30-months-ahead	0.032	0.034	0.046	0.06
24-months-ahead	0.037	0.043	0.019	0.03
18-months-ahead	0.04	0.054	0.008	0.012
12-months-ahead	0.019	0.03	0.013	0.019
6-months-ahead	0.001	0.025	0.013	0.015

Table 3
MSE for every method for different forecasting horizons — OECD countries.

MSE (OECD)	Combined Gompertz	Gompertz	Combined Logistic	Logistic
30-months-ahead	0.410	0.444	0.067	1.302
24-months-ahead	0.433	1.011	0.091	0.133
18-months-ahead	0.301	0.794	0.019	0.037
12-months-ahead	0.497	0.75	0.14	0.15
6-months-ahead	0.002	0.479	0.037	0.069

The following tables demonstrate the Mean Absolute Percentage Error in each case for different forecasting horizons ranging from 6 months up to 30 months forth (Tables 1 and 2).

In all cases, the proposed method performs better than the diffusion model, the forecasted saturation point of which it has used. The degradation of the MAPE level as the prediction period becomes shorter is better illustrated using the Linear Logistic model. Throughout the forecasting horizon, the predictive performance of the proposed method is significantly better than the one that the Linear Logistic model delivers. This fact is presented for each case separately in the following two figures.

For demonstration purposes, the following tables depict the results of the other two measures of accuracy, that were used as well, the Mean Square Error (MSE) and the Mean Absolute Error (MAE). They are in accordance with the results of the Mean Absolute Percentage Error in all cases (Tables 3–6).

Table 4
MSE for every method for different forecasting horizons — United States.

MSE (U.S.)	Combined Gompertz	Gompertz	Combined Logistic	Logistic
30-months-ahead	0.255	0.304	0.405	0.612
24-months-ahead	0.377	0.548	0.121	0.223
18-months-ahead	0.532	1.013	0.037	0.054
12-months-ahead	0.433	0.655	0.133	0.251
6-months-ahead	0.001	0.445	0.117	0.16

Table 5
MAE for every method for different forecasting horizons — OECD countries.

MAE (OECD)	Combined Gompertz	Gompertz	Combined Logistic	Logistic
30-months-ahead	0.277	0.282	0.112	0.551
24-months-ahead	0.343	0.528	0.147	0.197
18-months-ahead	0.377	0.6	0.089	0.109
12-months-ahead	0.518	0.839	0.36	0.37
6-months-ahead	0.0517	0.692	0.192	0.263

Table 6
MAE for every method for different forecasting horizons — United States.

MAE (U.S.)	Combined Gompertz	Gompertz	Combined Logistic	Logistic
30-months-ahead	0.206	0.215	0.287	0.371
24-months-ahead	0.313	0.368	0.164	0.253
18-months-ahead	0.51	0.695	0.107	0.153
12-months-ahead	0.523	0.787	0.357	0.489
6-months-ahead	0.044	0.667	0.342	0.4

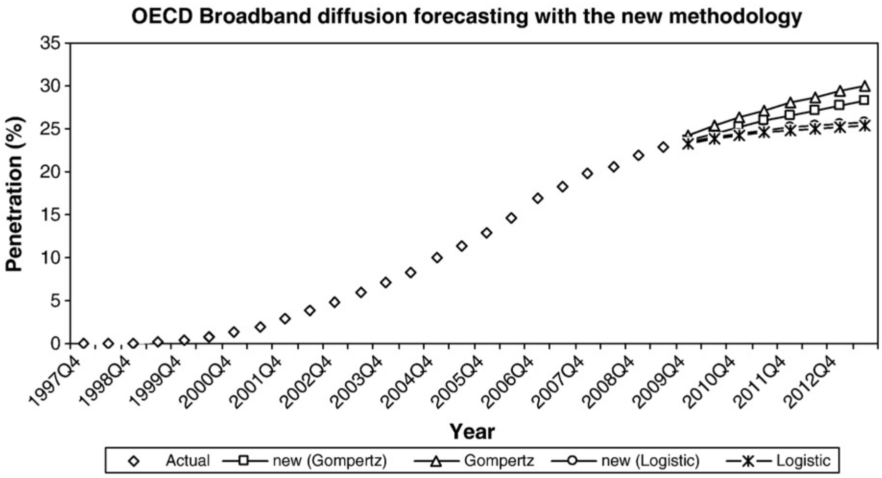

Fig. 4. Long-term broadband diffusion forecasting with the new method in OECD countries.

After validating the superiority of the method in the case of broadband penetration diffusion, an attempt to make a longer forecast, using the whole range of actual data, was realized. The prediction was made for 48 months ahead. The next figures present the forecasted broadband diffusion development in both cases until June of 2013, using the two diffusion models (Figs. 4 and 5).

As illustrated in the above figures, the broadband diffusion has evolved significantly by mid 2009. As a result, both the Gompertz and the Linear Logistic models make narrower predictions regarding the saturation point, and their differences are not as great as it was in previous data points. The approximation of the forecasts and, therefore, the Holt's damped trend method that is oriented by the close forecasted saturation points, delivers results that do not have enormous differences, as they might have had before. In the following table, the last predicted penetration levels in June of 2013 are depicted (Table 7).

The choice of a 4 year ahead forecast has been taken on the ground that the diffusion was already high in both cases. As the forecasting horizon increases, the predictive superiority of the method diminishes. For extreme long-term forecasts, the method delivers more-or-less the same results as the diffusion model. This characteristic has been anticipated, because the closer the diffusion process comes to saturation, the more the diffusion model becomes the absolute determinant of the forecast and the influence by the exponential smoothing procedure becomes weaker.

5. Conclusion

This paper presented a new method that delivers improved long-term forecasts of the innovations' diffusion compared to two conventional aggregate diffusion models, the Gompertz and the Linear Logistic models. After obtaining enough actual data to run exponential smoothing and after reaching the inflection point of the sigmoid curve, the Holt's damped trend method was applied oriented by the predicted saturation point of a diffusion model. Application of the method in the case of broadband penetration in the total sum of the OECD countries and the United States from 1997 until 2009, for different forecasting horizons ranging from

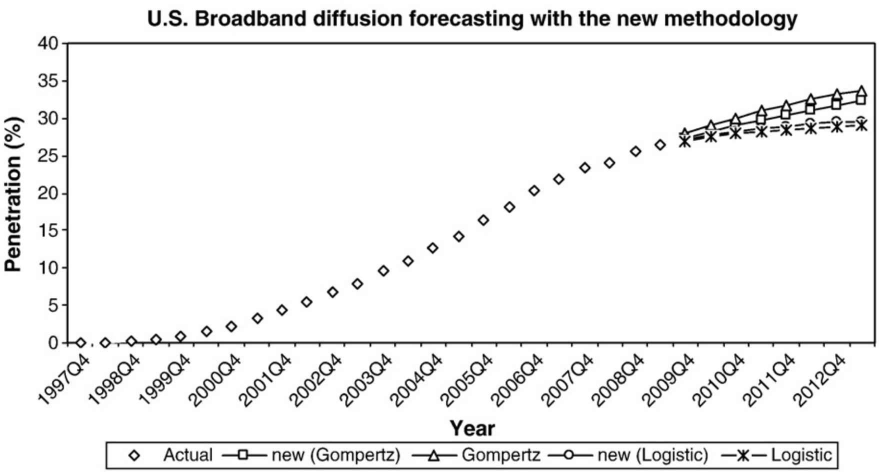

Fig. 5. Long-term broadband diffusion forecasting with the new method in the U.S.

Table 7
Forecasts for the broadband diffusion penetration in the end of 2011 — OECD countries and United States.

Broadband penetration in mid 2013	Gompertz	Combined Gompertz	Logistic	Combined Logistic
OECD	29.98%	28.26%	25.32%	25.72 %
U. S.	33.75%	32.27%	28.98 %	29.56 %

6 months up to 30 months forth, verified its accuracy and illustrated its performance capabilities. The forecasts of each approach were compared based on the three widely used measures of accuracy estimation, comparison and forecasting. After its validation with the hold back sample, the proposed method was applied for a 48-month forecasting horizon, until mid 2013.

The method's 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 a time point after the inflection point, approximating the forecasted saturation.

This paper concludes with the suggestions for future research. The achieved forecasting results are quite satisfactory and promising. The study was limited to a forecasting horizon of four years ahead. The application of the method in other cases of high technology innovations diffusion, as well as the further investigation of its efficiency for greater forecast horizons is strongly recommended. The proposed method was tested with two of the most commonly used diffusion models. The testing with other popular models is anticipated to validate its broader suitability and accuracy. As mentioned before, the closer the diffusion process comes to saturation, the more the diffusion model becomes the absolute determinant of the forecast and the influence by the exponential smoothing procedure becomes weaker. The limits of the proposed method's efficiency should be investigated in more detail.

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