On the Efficiency of Grey Modeling in Early-Stage Technological Diffusion Forecasting

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ABSTRACT

The issue of how to obtain an accurate short-term forecast in the beginning stage of the technological diffusion is of great importance for policy makers, researchers and managers. Time-series forecasting has been noticeably neglected in the specific research area due to the prerequisite of having enough data in order to create a time-series. In this paper, Grey modeling is examined as an alternative tool for technology diffusion forecasting in the early diffusion process, where the commonly used aggregate diffusion models usually fail to deliver accurate forecasts. Grey modeling is a unique time-series methodology that requires only a few data points in order to make a forecast. The GM(1,1) model is tested against a classic aggregate diffusion model, the Gompertz model, using only the first four data of mobile broadband diffusion to make an one-step-ahead prediction. The results in the EU15 countries reveal that the Grey model outperforms the Gompertz model in every case, thus stimulating new research guidelines in terms of combinations of the two approaches and further investigation of the value of Grey modeling in the specific area.

Keywords: Gompertz Model, Grey Modeling, Technological Diffusion, Technology Diffusion Forecasting, Time Series Forecasting

INTRODUCTION

One of the key objectives of technology management is accurate diffusion forecasting, even at the beginning of the diffusion process, where the available data are not sufficient for application of well-known models. As the rapid pace of technological innovation allows heterogeneous technologies to coexist and converge, emerging innovations have been introduced to overcome the limitations of existing ones and to meet consumers' requirements. Accurate early forecasting allows policy makers, researchers and managers to control the changeable market and enhance competition. This research topic is always up-to-date, and recent research papers in the area stimulate the scientific interest (Goodwin et al, 2014, Nguimkeu, 2014, Shi et

al, 2014, Lin 2013). It is obvious that an accurate and easily applicable method for forecasting the diffusion of innovations would be an extremely beneficial tool for companies, especially when they need to estimate the diffusion of new-to-the-market products. It is crucial for a company seeking sustainable competitive advantage to anticipate future developments on its markets. The usual techniques used for this purpose are divided into two categories: Qualitative and Quantitative techniques (Fildes & Kumar, 2002, Gruber and Verboven, 2001). In the world of research, there are two general approaches to gathering and reporting information: qualitative and quantitative approaches. The qualitative approach to research is focused on understanding a phenomenon from a closer perspective. The quantitative approach tends to approximate phenomena from a larger number of individuals using survey methods.

Qualitative techniques in the specific research area include:

- Delphi method converges answers from a panel of experts
- Scenario planning envisions multiple possible futures and their implications
- Qualitative diffusion models describe a bell curve of innovators, early adopters, early majority, late majority, and laggards and the process of how innovations diffuse from one group to the next.

Quantitative techniques in the specific research area include:

- "S-curves," such as the Bass model which provides a mathematical model based on a population of innovators and imitators, the Logistic model and the Gompertz model, based on biological population dynamics.
- Causal techniques use regression testing to identify key variables that determine a specific technology's penetration.

When studying the relevant bibliography on the issue of very early technological diffusion forecasting, one can easily discover that it is monopolised by applications of the well-known aggregate diffusion models, which cannot guaranty accurate forecasts due to the limited amount of available data. These models are based on the anticipation that the new technology will have a sigmoid diffusion pattern based on the experience gained from similar cases (Fourt and Woodlock (1960), Mansfield (1961), Floyd (1962), Rogers (1962), Chow (1967) and Bass (1969)). In other cases, the forecasting is realised using the other qualitative and quantitative methods that were mentioned earlier in the text. One can easily identify the lack of time-series forecasting methods in the specific area. Even though some studies have been realized in later stages of the diffusion process investigating the use of such methods opposite the commonly used aggregate diffusion models (Gottarsky and Skarso 1994, Christodoulos et al 2010, Christodoulos et al 2011), the early-stage predictions do not involve the use of time-series models, as the available data is not enough for such applications. The recent research papers of Christodoulos et al. (2010, 2011) investigate the use of time series modelling in the mid-term and the long-term evolution of the diffusion process, after having enough data to use an appropriate time-series model. If the obstacle of the prerequisite for a great number of data was surpassed, time-series forecasting could also be examined in the beginning area. Towards this direction and following the recent research on the topic for mid-term and long- term horizon, a unique time-series method is investigated in this paper, the grey model, which only requires four available data in order to produce one-step-ahead prediction (Lin and Yang, 2003, Hsu, 2003). With such a small dataset, even the aggregate diffusion models fail to produce an accurate prediction for the next period, information which could be extremely valuable to everyone in the technology business. The assessment of the grey modelling predictions has been conducted in parallel with one of the most commonly used aggregate diffusion models, the Gompertz model (Gompertz 1825), which has an inflection point of 37/%,

meaning that it reaches relatively quickly the peak of the constantly growing phase of the diffusion process.

The fast diffusion of mobile communications has been the subject of many empirical studies about the diffusion of innovation. For instance, Gruber and Verboven (2001) adopted the Logistic model to study mobile diffusion in 15 EU countries. Over the past decade, the Internet market and mobile telephone services have both grown explosively and have recently converged in terms of mobile broadband services. The two methods are tested in recent mobile broadband diffusion data obtained from the international Telecommunications Union (ITU) (http://www.itu.int/ITU-D/ict/statistics). The EU15 countries were chosen for the application in order to ensure the generalization of the results and the investigation of the methods in well-developed countries with more-or-less steady economies and experience in smooth adoption of new technologies.

The rest of the paper is organized as follows. The next section provides an overview of the grey methodology, followed by a section giving information on the diffusion models and on the Gompertz model in particular, which is used for the evaluation. Section 4 presents the results, after the application in the mobile broadband data. Finally, Section 5 concludes.

GREY MODELS: GM(1,1) FOR TIME-SERIES FORECASTING

Grey system theory is an interdisciplinary scientific area that was first introduced in the early eighties by Professor Deng (1982). Since then, the theory has become quite popular with its ability to deal with the systems that have partially unknown parameters. As superiority to conventional statistical models, grey models require only a limited amount of data to estimate the behaviour of unknown systems (Deng 1989). The main task of grey system theory is to extract realistic governing laws of the system using available data. This process is known as the generation of the grey sequence (Liu & Lin,

1998). It is argued that even though the available data of the system, which are generally white numbers, is too complex or chaotic, they always contain some governing laws. If the randomness of the data obtained from a grey system is somehow smoothed, it is easier to derive any special characteristics of that system.

During the last two decades, the grey system theory has been developed rapidly and has caught the attention of many researchers. It has been widely and successfully applied to various systems such as social, economic, financial, scientific and technological, agricultural, industrial, transportation, mechanical, meteorological, ecological, hydrological, geological, medical, military, etc., systems.

Grey theory, originally developed by Deng, focuses on model uncertainty and information insufficiency in analyzing and understanding systems via research on conditional analysis, prediction and decision-making. In the field of information research, deep or light colours represent information that is clear or ambiguous, respectively. The Grey method has numerous applications. Similar to fuzzy set theory, grey theory is a feasible mathematical means to deal with systems analysis characterized by poor information is lacking. Research and its application covered by grey theory include systems analysis, data processing, modelling, prediction, as well as decision-making and control. The grey system puts each stochastic variable as a grey quantity that changes within a given range. It does differ from statistical analysis method to deal with the grey quantity. It deals directly with the original data and searches the intrinsic regularity of the data. The grey system theory include the following fields: (a) grey generating, (b) grey relational analysis, (c) grey forecasting, (d) grey decision making, and (e) grey control.

Grey forecasting differs from other statistical regression models. With a basis in probability theory, conventional regression requires amount of data for establishing forecast model. Grey forecasting is based on the grey generating function, GM(1,1) model, which uses the variation within the system to find the relations between sequential data and establish then the

prediction model (Hsu, 2003). This approach only requires short-term, current and limited data. We examined the forecasting performance of the models just after the release of the item when the small number of model calibration data is available.

The grey model GM(1,1) is a time series forecasting model. Grey models predict the future values of a time series based only on a set of the most recent data depending on the window size of the predictor. It is assumed that all data values to be used in grey models are positive, and the sampling frequency of the time series is fixed. It has three basic operations: (1) accumulated generation, (2) inverse accumulated generation, and (3) grey modelling. The grey forecasting model uses the operations of accumulated to construct differential equations. Intrinsically speaking, it has the characteristics of requiring less data.

The grey model GM (1,1), i.e., a single variable first-order grey model, is summarized as follows:

Step 1. For an initial time sequence

$$X(0) = \{x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\} \quad (1)$$

here $x^{(0)}(i)$ the time series data at time i, n must be equal to 4.

Step 2. On the basis of the initial sequence $X^{(0)}$, a new sequence $X^{(1)}$ is set up through the accumulated generating operation in order to provide the middle message of building a model and to weaken the variation tendency, i.e.

$$X^{(1)} = \{x^{(1)}(1), x^{(2)}(2), ..., x^{(1)}(n)\} \quad (2)$$

where

$$x^{(1)}(k) = \sum_{i-1}^{k} x^{(0)}(i) \ k = 1, 2, ..., n \quad (3)$$

Step 3. The first-order differential equation of grey model GM(1,1) is then the following

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \quad (4)$$

and its difference equation is

$$X^{(0)}(k) + aZ^{(1)}(k) = b \ k = 2, 3, ..., n \quad (5)$$

and from Equation 5, it is easy to get

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ . \\ . \\ . \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -Z^{(1)}(2) \ 1 \\ -Z^{(1)}(3) \ 1 \\ . \quad . \\ . \quad . \\ . \quad . \\ -Z^{(1)}(n) \ 1 \end{bmatrix} \times \begin{bmatrix} a \\ b \end{bmatrix} \quad (6)$$

where a and b are the coefficients to be identified. Let

$$Y_n = [x^{(0)}(2), x^{(0)}(3), ..., x^{(0)}(n)]^T \quad (7)$$

$$B = \begin{bmatrix} -Z^{(1)}(2) \ 1 \\ -Z^{(1)}(3) \ 1 \\ \vdots \quad \vdots \\ -Z^{(1)}(n) \ 1 \end{bmatrix} \quad (10)$$

Also take

$$Z^{(1)}(k+1) = 1/2(x^{(1)}(k) + x^{(1)}(1)(k+1)) \quad (9)$$

$$k = 1, 2, ..., (n-1)$$

And

$$A = [a, b]^T \qquad (10)$$

where Y_n and B are the constant vector and the accumulated matrix respectively. $Z^{(1)}(k+1)$ is the $(k+1)^{\text{th}}$ background value.

Applying ordinary least-square method to Equation 6 on the basis of Eqs. 7, 8, 9 and 10, coefficient A becomes

$$A = (B^T B)^{-1} B^T Y_n \qquad (11)$$

Step 4. Substituting A in Equation 5 with Equation 11, the approximate equation becomes the following

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - b/a) \times e^{-ak} + b/a \qquad (12)$$

where $x^{(1)}(k+1)$ is the predicted value of $x^{(1)}$ $(k+1)$ at time $(k+1)$. After the completion of an inverse-accumulated generating operation on Equation 12, $x^{(0)}(k+1)$, the predicted value of $x^{(0)}(k+1)$ at time $(k+1)$ becomes available and therefore,

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \qquad (13)$$

where $k=0,1,2,3, \dots$

The GM (1, 1) model can only be used in positive data sequences. In this paper, since all the primitive data points are positive, the grey model can be used to forecast the future values of the primitive data points.

DIFFUSION MODELS: THE GOMPERTZ MODEL

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:

$$\frac{dN(t)}{dt} = \delta \times f(N(t)) \times [K - N(t)] \qquad (14)$$

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. Diffusion models are hard to calibrate prior to launch and the models tend to be unstable until the point of inflection occurs. 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.

As far as the Gompertz models are concerned, two variations have been introduced in the literature (labeled as Gompertz I and Gompertz II models, respectively). The Gompertz I model is described by:

$$Y(t) = Se^{-e^{-a-b \times t}} \qquad (15)$$

where $b>0$ is a scaling factor, S represents the saturation level and a is the parameter that is related to the point of inflection. $Y(t)$ is the estimated diffusion level at time t. The parameters that have to be estimated are S, a and b. The exponential part of Equation can be rewritten as by substituting $e^{-\alpha}$ with a constant parameter, A. In this way, the alternative formulation of the Gompertz model is

$$Y(t) = Se^{-Ae^{-b \times t}} \qquad (16)$$

The second formulation of the Gompertz model is similar to the first and its parameters are defined similarly. In both formulations, the parameters α and A are related to the time that diffusion reaches 37% of its upper level ($S\,e^{-1}$), and parameter b is a measure of the diffusion speed, or how rapidly the adoption progresses.

Chow (1967) first adopted the Gompertz model to the Information and Communication Technology (ICT) field. The Gompertz model is commonly applied in diffusion studies of the Internet. For instance, Kiiski and Pohjola (2002) referred to Chow (1967) in selecting a diffusion model for analyzing Internet diffusion. Chow (1967) also indirectly influenced some empirical studies on mobile communications based on the Gompertz model (Rouvinen, 2006).

APPLICATION AND RESULTS

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 latter stage, they were applied in business economics. On the other hand, grey modelling derives from mathematics and statistics tradition and is met in several different forecasting applications, usually after the gathering of a significant number of recorded data points.

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 (Christodoulos et al. 2010).

A good recent example of newly introduced high-technology service in which one could apply the two methods is mobile broadband. It has been introduced in the international market only a few years ago and it is ideal for investigating early diffusion forecasting with the availability of only a few data. As demand for mobile broadband services increases, being able to accurately forecast subscriber take-up becomes a critical skill required to build a business case for infrastructure investment. Furthermore, using these forecasts to accurately predict required backhaul bandwidth will enable mobile operators to meet customers' performance expectations without costly overbuilds. With huge investments required to launch, market and grow mobile broadband services, being able to accurately forecast subscriber take-up and revenues is key. An accurate forecast of backhaul bandwidth requirements and costs is also critical to building an effective business case, to profitably pricing the services, and to dimensioning the backhaul network.

In Figure 1, the diffusion of mobile broadband technology for a four-year period in the EU15 countries is depicted. Analytically, the countries are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. All countries have a relatively smooth adoption of the new technology with the exception of Finland, where mobile broadband diffusion has made an enormous increase between the third and fourth period. Historically, the Nordic area has been a 'hot bed' for mobile telephony, achieving very high mobile phone penetration well before the larger Western European countries and the USA. When it comes to 4G mobile broadband services, the Nordic countries and operators look set to maintain their status as 'mobile leaders'.

No universally preferred measure of accuracy estimation and forecasting exists, therefore experts often disagree as to which measure should be used. Mean Absolute Percentage Error (MAPE) was selected to be the measure of the present evaluation, as it is widely used
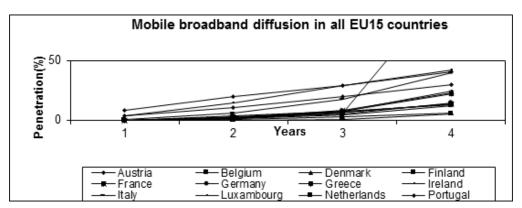
Figure 1. Mobile broadband diffusion in the EU15 countries

in cases of combining and selecting forecasts (see for example Makridakis and Hibon, 1979 and Makridakis et al., 1984). It is calculated by the following equation:

$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \left| \frac{(Pt - Zt)}{Zt} \right| \qquad (17)$$

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 following table (Table 1) illustrates the results after the application of the two approaches for one-step-ahead forecasting. It is obvious that the GM(1,1) model surpasses the Gompertz model in every country under investigation in terms of forecasting accuracy. The most significant improvement of the forecast in terms of accuracy is observed in the case of Ireland and the worst in the case of Finland (0,217 and 0,0025 respectively). For validation purposes, another common measure of accuracy, the Mean Square Error (MSE) was used. The results where similar for every case, just like MAPE (Table 2). Its expression is depicted below:

$$MSE = \sum_{t=1}^{T} \frac{(Pt - Zt)^2}{T} \qquad (18)$$

Therefore, these results raise the question of how the grey methodology could be used in more detail and to further extend alone or in combination with the traditional forecasting methods of the area.

CONCLUSION

This paper presented the application of grey theory to the production of short-term forecasts of the new high technology's diffusion at the early stages of the procedure. Experiments were conducted using real diffusion and country data to evaluate the performance. After obtaining the minimum data points for the application of the grey theory (4 points), a diffusion model and the GM(1,1) model are applied over the sample.

Application of the methodology in the case of EU15 broadband penetration verified its accuracy and illustrated its performance capabilities. It is generally known that forecasting is demanding, but the existence of a turbulent and dynamic environment like telecommunications makes the forecasting even more challenging. 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 a classic aggregate diffusion model used for early diffusion forecasts, the Gompertz model.

The one-period-ahead forecasts of each approach were compared based on a widely

Table 1. MAPE comparison after the use of each method for all EU15 countries

	MAPE (Gompertz)	MAPE(GM(1,1))
Austria	0,06090	0,03802
Belgium	3,28720	3,22427
Denmark	0,13867	0,01792
Finland	0,41316	0,41068
France	0,08795	0,08508
Germany	0,23738	0,08727
Greece	0,50666	0,42580
Ireland	0,50035	0,28314
Italy	0,48678	0,46285
Luxembourg	0,18401	0,09265
Netherlands	0,38391	0,34099
Portugal	0,06936	0,00107
Spain	0,15281	0,13535
Sweden	0,40395	0,39385
UK	0,09389	0,00667

Table 2. MSE comparison after the use of each method for all EU15 countries

	MSE (Gompertz)	MSE(GM(1,1))
Austria	13,5357	5,27582
Belgium	1053,28	1013,34
Denmark	5,77436	0,09651
Finland	5660,31	5592,53
France	8,60056	8,04803
Germany	53,3592	7,21185
Greece	339,766	239,967
Ireland	526,259	168,519
Italy	811,985	734,135
Luxembourg	462,133	117,155
Netherlands	67,3471	53,1291
Portugal	30,0596	0,00718
Spain	70,7497	55,5037
Sweden	3981,70	3785,05
UK	7,44483	0,03761

used measure of accuracy, the Mean Absolute Percentage Error (MAPE), as noted in other similar studies of forecast combinations. 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 superiority of the grey methodology seems limited, it should be taken into consideration that the forecasting improvement is for one-period horizon. This single period'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. The application of Grey modelling for the forecasting of a technology's diffusion is a simple procedure, suitable for cases of raw forecasting with limited data points, that is why it is tested opposite a well-known, but also simple forecasting procedure, as the aggregate diffusion modelling approach. Thus, comparison with other high-end techniques is avoided in this research paper, but it is definitely a research topic that can be examined as a following step of research.

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 apply the GM(1,1) model 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 period ahead. Future research in this topic includes the application of the Grey theory 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. Future work includes development of suitable framework of corresponding methodologies, based on the other approaches as well, in order to comprehensively study the different aspects of the telecommunication market. Future tests should test the predictive validity of the proposed framework by splitting the existing diffusion data into separate modelling and validation periods. Moreover, the presented methodology can be extended to separately consider each market competitor in order to describe in a more detailed level the structure of the market and the degree of competition. Finally, the combination with other forecasting models should also be thoroughly examined.

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