

Forecasting accuracy of the Generalized Bass Model versus the most widespread diffusion models in wind power system

Alessandra Dalla Valle and Claudia Furlan

Abstract The Kyoto Protocol of 1997 planned for all the subscribing countries a reduction of greenhouse gases by 5.2% with respect to the values of 1990. The production of electric energy through renewable energy systems is one of the ways to respect Kyoto limits. For this reasons, the countries that signed the protocol started to promote incentive policies for the adoption of these new technologies. The US, although not subscribers of the protocol, is also committed in some way to create renewable electric energy and, with respect to wind energy systems, is classified as one of the leading countries. Since when analyzing the capacity of installed wind turbines, it is important to compare similar geographic areas, we compare the US with Europe. Some leading European countries are also included in the analysis. Generalized Bass models are performed, detecting the effects of local incentive policies. In this work, we show how this class of models came first in the ranking of forecasting accuracy performance over a set of accuracy measures and forecasting horizons, when compared with the Standard Bass, Logistic, and Gompertz models.

Key words: Comparative studies, Diffusion models, Intervention analysis, Technology forecasting, Time series analysis

1 Introduction

An enhanced sensibility with respect to environmental problems, such as alarming global warming and air pollution, and to energy problems, such as oil depletion, is spreading all over the world. Moreover, air pollution, greenhouse gases, and envi-

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ronmental damage caused by the use of fossil fuels for the production of energy and for other targets (for instance, the production of plastic matter) are becoming a serious threat to our health and environment. Energy production, by means of fossil fuels, induces negative externalities because it imposes social costs in increased health expenses, in reduced agricultural productivity, and in the worldwide global warming when carbon dioxide or other air pollutants are produced by burning.

In this scenario, new sources of energy that are both clean and cost-effective have to be promoted to maintain the same standard of living and to preserve the environment. Wind energy, in particular, is a kind of clean, inexhaustible, readily available energy with the advantage that this type of energy aids in the reduction of greenhouse gas emissions because wind energy does not produce any type of air pollution. Moreover, wind power has negligible fuel costs and low maintenance costs, which are low marginal cost and a high proportion of capital cost.

Despite growing public interest in environmental protection, very little research has been done on clean technology, as a subcategory of technology, and only slight attention has been given to quantitative analyses and forecasts. With their review, Kemp and Volpi hope to stimulate, in general, wider research in the area of clean technologies [9]. Until now, to the best of our knowledge, Diaz-Rainey has performed the only analysis on the process of adopting wind power, in which the diffusion pattern was based on logistic and log-logistic models [5].

In technological diffusion, it is well known that the timing of adoption is affected not only by endogenous mechanisms but also by exogenous dynamics. However, until now, only a few efforts have been made to unify endogenous and exogenous mechanisms, especially for clean technology Montalvo and Kemp for which the main factor that exogenously affects the rate of adoption is represented by incentive schemes [13]. The Generalized Bass Model (GBM) seems to be particularly suited for evaluating both endogenous and exogenous mechanisms, as it allows for the inclusion of the innovative and imitative behavior of the adopters of a particular technology and the assessment of the strength of incentive policies passed by the local governments of a given country.

In this work, the proposed GBMs are compared with the common models used in diffusion studies (Bass, Logistic, and Gompertz) in terms of forecasting accuracy (1 and 3-year-ahead) using a set of accuracy measures.

2 The Model

In the field of innovation studies technological diffusion has a long scholarship starting in the 1960s with the works of Fourt [6] and Rogers [14]. In their review [12], Meade and Islam highlight the wealth of research on modelling and forecasting the diffusion of innovations and propose several alternative models, including the Bass Model (BM), which was first presented by Bass [2]. The BM (and its generalization) is the only model among the *S*-shaped curves (e.g., Logistic and Gompertz models) that includes the innovative and imitative behaviour of adopters intro-

duced by Rogers [14]. Typically, the diffusion of a technology is initially very slow since adopting it means taking a risk in a situation of uncertainty. Only a few brave adopters are disposed to take these risks, while “*the great majority adopts a wait-and-see approach*” [9]. Here, wind power satisfies the assumptions required by the BM to be applied. In particular, the members of the social system adopting this innovation are the individuals who decide to support the companies involved in wind projects, or to install small wind turbines for self-consumption of electricity (single home, farm, ranch, or business). The external communications channels that rule the innovative behavior, are represented by mass-media, newspaper ads, and specialized information meetings, while word of mouth among neighbours/acquaintances represents the interpersonal communication channels. Finally, market saturation is achieved when spatial or environmental constraints do not allow for new installations, and when a new form of innovative technology is introduced to replace the preexisting one.

The GBM representation is:

$$z(t) = m \frac{1 - e^{-(p+q) \int_0^t x(\tau) d\tau}}{1 + \frac{q}{p} e^{-(p+q) \int_0^t x(\tau) d\tau}} \quad 0 \leq t < +\infty, \quad (1)$$

where m is the potential market (the maximum number of adoptions achievable during the life-cycle), p and q are the parameters referred to as the quota of innovators and imitators, respectively, and $x(t)$ is an integrable function that oscillates around 1 [3]. Through $x(t)$, interventions of a political and economic nature are included in the GBM as exogenous variables. Note that Equation (1) includes the BM for $x(t) = 1$. For $x(t)$ greater than 1, the adoption process is accelerated over time, and for $x(t)$ smaller than 1, the adoption process is delayed.

Following the work of Guseo and Dalla Valle [7], the representation for $x(t)$ of an exponential $S_{exp}(t)$ and a rectangular shock $S_{rect}(t)$ is the following:

$$x(t) = 1 + S_{exp}(t) + S_{rect}(t) = 1 + c_1 e^{b_1(t-a_1)} I_{[t \geq a_1]} + c_2 I_{[a_2 \leq t \leq b_2]}. \quad (2)$$

An exponential shock $c_1 e^{b_1(t-a_1)} I_{[t \geq a_1]}$ identifies a locally intense impulse that progressively loses its effect. In detail, a_1 coincides with the beginning of the shock, b_1 expresses how rapidly the shock decays toward 0 and is usually negative, and c_1 indicates the intensity of the beginning of the shock. A *rectangular* shock $c_2 I_{[a_2 \leq t \leq b_2]}$ is another kind of impulse for intervention function $x(t)$ that identifies a perturbation whose effect stays unchanged over a bounded time interval. This impulse begins at time a_1 and ends at time b_1 , keeping a given intensity c_2 over the interval (a_1, b_1) . Note that setting $S_{rect}(t) = 0$ in Equation (2) allows the mathematical form of $x(t)$ to be obtained with only one exponential shock.

Data consist of yearly cumulative installed wind turbine capacity, in megawatts (MW), until 2008 (Figure 1) for Europe, the US, and for the leading countries in Europe: Germany, Spain, Denmark, and Italy. For all countries, GBMs are performed with Equation (2) for $x(t)$: note that, for Europe, Germany, Spain, and Italy, only one exponential shock is included, setting $S_{rect}(t) = 0$ in Equation (2).

Figures (1) and (2) show the estimated models and life-cycles (with short-term forecasts) for all the analyzed countries. Results and discussions are presented by the authors in [8]. In brief, the US still has great potential in the field of electrical energy production from wind power, when compared to Europe. The large gap depends on the minor and less certain incentive schemes. Regarding the analyzed European countries, we can say that, while the life-cycle of the wind adoption process in Germany is approaching the final stage, the process in Spain is still in its middle stage. In Denmark, the change of the incentive scheme from the feed-in-law to the Green Certificate system in 2003 abruptly stopped the adoption process, leading the life-cycle of wind power technology to the very final stage. In Italy, the life-cycle is still at an early stage.

3 Model validation

In this section, we assess the forecasting accuracy of the GBMs proposed in Section 2. GBMs are compared in terms of performances with the most widespread diffusion models: the BM model (Equation (1) with $x(t) = 1$), the Logistic model $z(t) = m/(1 + c \exp(-qt))$, and the Gompertz model $z(t) = m \exp(-c \exp(-qt))$, where $z(t)$ is the cumulative number of adoptions at time t , m the potential market, and c and q are parameters. In particular, we check the forecasting performances of each model taken into account through a set of out-of-sample tests that can furnish a rating about selected models. The out-of-sample approach consists of splitting data into two parts: models are implemented in the fit period and are checked in the test period. For each step ahead, the forecast errors are defined as the absolute value

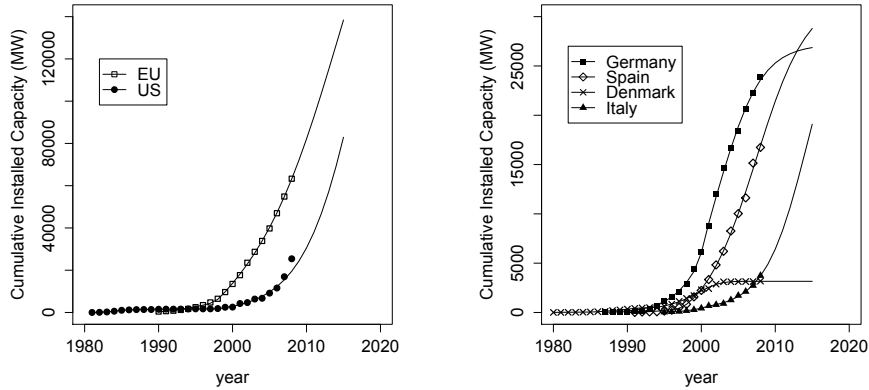


Fig. 1 Short-term forecasts (lines), up to 2015, for Europe and the US (left panel), and for the leading European countries (right panel). Points correspond to observations.

difference between the model forecasts and the observations (not used in the estimation step). In a rolling-origin evaluation, we fixed the origin t of the forecasting period in 2003 and made forecasts for the next five years until 2008. By rolling t one year ahead, 2004 is included in the fit period, and we forecast four years ahead again until 2008. This procedure is iterated until $t = 2007$, where the last forecast for 2008 is produced [15]. The choice of $t = 2003$ is principally due to the need for at least three forecasts for every step-ahead: in this case, we have five forecasts for 1-year-ahead, four for 2-year-ahead and three for 3-year-ahead.

Forecast accuracy is assessed with multiple measures (see [1] and [10]) for two single forecasting horizons: 1-year and 3-year-ahead. We used the square root of the Mean Square Error (RMSE) and the Absolute Percentage Error (APE), where the latter was summarized for each forecasting horizon by the mean (MAPE) and the median operator (MdAPE). We also used an adjustment of the Relative Absolute Error (RAE), proposed by Armstrong and Collopy [1], for cumulative functions: the random walk is intended as a constant linear growth over years. Armstrong and Collopy defined the RAE as follows:

$$RAE_{m,t+h} = \frac{|F_{m,t+h} - O_{t+h}|}{|F_{rw,t+h} - O_{t+h}|}, \quad (3)$$

where m represents the model, t the rolling-origin, h the forecasting horizon, O_{t+h} the observed values at time $t+h$, $F_{m,t+h}$ the predicted values for the forecasting horizon h for model m , and $F_{rw,t+h}$ the correspondent predicted values for the random walk [1]. The idea of a random walk intended as a constant function that assumes over years the value observed at origin t is translated here in a linear function, which grows every year of the increased value observed in t :

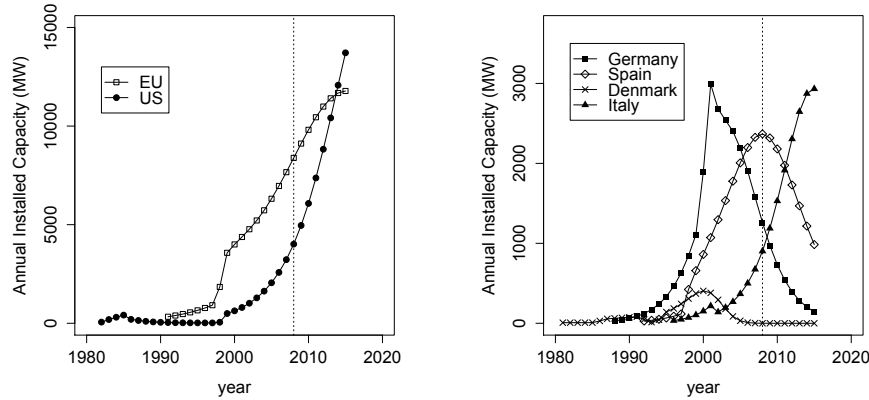


Fig. 2 Predicted life-cycle (points and lines), up to 2015, for Europe and the US (left panel), and for the leading European countries (right panel). Vertical bar corresponds to 2008.

$$F_{rw,t+h} = O_t + h(O_t - O_{t-1}). \quad (4)$$

The proposed RAE was summarized for each forecasting horizon by the mean (MRAE) and the median operator (MdRAE). Moreover, instead of comparing methods for single forecasting horizons, we also summarized the RAE across different forecasting horizons, by a cumulative sum, giving rise to the CumRAE. Finally, we average all the measures across the six series.

Table 1 1 and 3-year-ahead forecasting accuracy for the GBM, BM, Logistic, and Gompertz models across countries.

	MAPE				MdAPE				MdRAE			
<i>1-ahead</i>	GBM	BM	Log	Gomp	GBM	BM	Log	Gomp	GBM	BM	Log	Gomp
EU	2.8	4.6	7.0	6.4	3.0	5.7	5.9	3.2	1.73	5.01	4.16	3.76
US	13.4	33.5	19.7	16.9	14.4	34.8	21.0	18.6	1.28	2.02	1.40	1.28
Germany	4.0	4.3	4.3	5.9	3.3	3.5	3.5	3.0	2.12	2.12	2.08	3.89
Spain	7.5	5.3	5.8	5.0	6.0	1.7	2.2	3.5	1.18	0.57	0.74	0.81
Denmark	2.2	10.4	10.5	15.3	1.0	10.3	10.6	15.3	3.23	53.60	55.31	89.90
Italy	9.6	9.7	14.4	11.3	5.1	7.7	14.3	10.0	1.14	1.07	1.32	1.33
mean	6.6	11.3	10.3	10.1	5.5	10.6	9.6	8.9	1.78	10.73	10.83	16.83
<i>3-ahead</i>	GBM	BM	Log	Gomp	GBM	BM	Log	Gomp	GBM	BM	Log	Gomp
EU	10.6	11.8	12.1	8.7	14.6	14.6	11.1	11.0	1.44	1.44	1.10	1.10
US	21.7	56.3	41.8	39.5	22.0	57.1	43.7	42.2	0.82	1.67	1.35	1.30
Germany	8.4	8.4	8.2	21.8	10.0	10.0	9.9	19.1	1.56	1.56	1.57	9.61
Spain	10.9	19.1	20.0	1.1	8.0	18.4	19.5	1.4	0.94	2.16	2.26	0.13
Denmark	5.4	24.5	24.5	38.1	2.6	23.3	23.6	41.9	0.66	24.41	25.16	49.71
Italy	26.5	29.0	41.3	29.0	15.9	32.5	40.4	29.5	1.16	1.23	1.85	1.57
mean	13.9	24.8	24.6	23.1	12.2	26.0	24.7	24.2	1.10	5.41	5.55	10.57

It is understood that, a priori, no accuracy measure can be considered better with respect to another for ranking the proposed models [1]. Among the accuracy measures introduced above, we decided to present, in Table 1, only those indicators that altogether are unit-free, reliable when few sets of series are available and offer protection against outliers: MAPE, MdAPE, and MdRAE (for each country, model, and forecasting horizon). However, all accuracy measures used in the work and not reported here lead to the same conclusions. The average measures across the countries in Table 1 show that GBMs have the lowest forecasting error over accuracy measures, models, and forecasting horizons, and the differences in numeric terms are sizable, especially for MdRAE with 1-year-ahead forecasting horizon. Among the remaining models, the Gompertz model is the most accurate forecasting model, in terms of both MAPE and MdAPE, followed by the Logistic model and BM; however, in terms of MdRAE, the ranking is diametrically opposite. This ranking is not always kept if the analysis moves to the accuracy measure of single countries. For example, for Spain, the Gompertz model is the most accurate for 3-year-ahead forecasts and the differences with respect to the other models are significant; on the

other hand, Germany does not have a benchmark model over measures or forecasting horizons.

Makridakis and Hibon highlight that sophisticated or complex models do not necessarily perform better than simpler ones and that the ranking of models in terms of forecast accuracy depends on the accuracy measures [11]. However, Table 1 gives enough evidence that GBM, on average, and also in the majority of the country time series, outperforms the remaining simpler models. The reason probably lies in the fact that the S-shape of the wind power diffusion process is strongly affected by incentive policies, and consequently, the GBMs are hardly outperformed by simpler models that do not allow for local stationarities or sudden changes in growth, and the issue of adapting speed to changes in data is one of the main topics in model comparison [4]. In this sense, the strength of the GBM is due to the speed with which it adapts to exogenous shocks as incentive laws, that are periodically released.

Are the GBM forecasts optimistic because of the effect of the current economic crisis? The crisis is global, but it affects some areas more than others. In general, it is not easy to assess the effects of financial crises still in progress, especially on forecasts made with earlier data. This is particularly true in renewable energies, which are a particular subcategory of technology strongly linked to incentives periodically released by the governments. In the time-frame of the collected data, in lieu of a significant evidence of a fall of adoptions of wind power in correspondence of strong crises, as the one in 1991-93, a firm connection has been found between its diffusion pattern and incentive policies (which may be linked to government choices in critical periods). With respect to the current global crisis, it would be natural to expect a fall also in the sector of renewable energies; however, according to the first estimates of cumulative installed capacity in 2009 in Europe, our forecasts for 2009 were not optimistic but absolutely coherent with the actually realized investments. On the contrary, for the US the installed capacity was underestimated (approximately 25000 MW forecasted vs 35000 MW observed), probably due to the election of Obama, who is a strong promoter of green energies, and also for the quicker capacity of the US of reacting to crises. Therefore, the evidence is that wind power still represents a sector that allows to make profit during the financial crisis through long-term investments. The incentive schemes are crucial to encourage the wind industry, but they are scheduled to decrease in the future as the technology becomes economically competitive. Policy makers should evaluate carefully the evolution of the incentive schemes in the future, in order not to stop the adoption process at least until the wind sector is thriving and socially accepted.

4 Conclusions

In the analysis of forecasting accuracy, the GBMs were compared with the Bass, Logistic, and Gompertz models in the frame of out-of-sample tests with a rolling origin. This method allowed several accuracy measures to be evaluated, among which MAPE, MdAPE, and a revised version of MdRAE, for short-term forecasting hori-

zons (1 and 3 years ahead). The analysis gives enough evidence that the GBM class outperforms the remaining models, and it is first in the ranking of performance for all the accuracy measures and forecasting horizons. Anyway, forecasting comparisons are sample-specific and the superiority of the GBMs is to be intended for wind power systems or for other diffusion data with similar characteristics, with stationarities or sudden changes in growth related to exogenous interventions as incentive schemes.

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