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Comparison of Diffusion Models for Forecasting the Growth of Broadband Markets in Thailand

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Abstract

The aim of this paper is to investigate the most accurate S-curve model, the Logistic, Gompertz, and Bass models, in forecasting the diffusion of telecommunication markets Thailand. The analyses apply the data of mobile telecommunication market and fixed-broadband market separately without the interaction between both services. The originality of this study is at the diffusion path segmentation intervened by technological change that accelerates or decelerates each market. Parameters of each model are estimated by nonlinear model estimation methodology. By applying those parameters, the accuracy of each model can be identified compared to the actual data. Following the evaluation of the goodness-of-fit and forecasting ability, the Gompertz model shows the best performance in forecasting the diffusion of mobile telecommunication and fixed broadband markets. With the more suitable forecasting model to the markets, the ultimate total number of users in the future period could be more accurately predicted.

Keywords: Broadband diffusion; Empirical comparison; Logistic model; Gompertz model; Bass model

1. Introduction

The forecasting of broadband diffusion is crucial for policy makers and service providers to adjust policy and strategy to match consumer's demand which has been changing extremely fast and sometimes faster than expectation. The directly or indirectly change of diffusion speed or total level of an innovation by any intervention is defined as induced diffusion (Diaz-Rainey, 2009). Pieces of literature on induced diffusion has mostly been focused on how regulatory or policy intervention accelerate the adoption process and the long-term penetration rate of an innovation (Diaz-Rainey, 2009; Mahajan, Muller, & Srivastava, 1990; Rixen & Weigand, 2014). However, in reality, there are many external interventions from complementary services or new technology that come to accelerate or decelerate the diffusion of the markets. Major presence of technological intervention, for instance, the coming of many applications, generate network traffic dramatically and consequently increase broadband users (Gupta, Jha, Koc, & Vannithamby, 2013; Islam, Islam, & Mazumder, 2010). The accurate model for the prediction, therefore, is necessary for forecasting the possible number of maximum broadband users and the speed of the market to reach that limit.

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This study challenges to search for the best predictive function for the diffusion of telecommunication markets with intervention from new ICT technologies and applications. It attempts to evaluate the goodness-of-fit and forecast ability of predictive models. The analysis includes three types of commonly used diffusion models; symmetric model - simple Logistics, asymmetric model - Gompertz, and flexible model - Bass (Meade & Islam, 1995). It applies each model to time series data from two markets including mobile telecommunications and fixed broadband in Thailand as cases of the study. The country has a strong ambition, in many telecommunications policies and frameworks initiated by the Thai government, to develop broadband markets in order to meet social need for increasing bandwidth. This study analyzes each market separately without the interaction between both services.

The originality of this study is at the diffusion path segmentation intervened by technological change that accelerates or decelerates each market. The analysis divides the diffusion path of each market into different stages by the major presence of technological intervention, for instance, the coming of smartphone and LINE into the mobile market that accelerates the adoption, and the rise of YouTube that boosts fixed broadband market. This segmentation will capture major changes both in the speed and altitude of the diffusion curves.

Parameters of each model are estimated by nonlinear model estimation methodology. By applying those parameters, the accuracy of each model can be identified compared to the actual data. In order to capture the model's accuracy, the goodness-of-fit of the models based on the obtained parameters in each market are compared by the Root Mean Square Error (RMSE). The accuracy of forecasting is evaluated by Forecast Error and Mean absolute percentage error (MAPE).

The rest of this paper is organized as follows. The following section discusses relevant empirical studies. Section 3 describes the three commonly used predictive diffusion models and performance evaluation parameters. Section 4 provides an overview of and major interventions in telecommunication market in Thailand. Section 5 explains the methodology. Main results and interpretations are presented in Section 6. Finally, Section 7 concludes the study and its contribution.

2. Literature review

Numbers of previous studies indicate Logistic model as the most appropriate function in explaining telecommunications market. Lee & Cho (2007) show the result comparing with time series autoregressive moving average (ARMA) model in explaining the diffusion of mobile telecommunications services in Korea. Similarly, Gamboa & Otero (2009) show the better performance of the Logistic model comparing with Gompertz in the case of mobile phone market in Colombia. Chu, Wu, Kao, & Yen (2009) prove among four predictive functions including Logistics, Gompertz, Bass, and Bass discrete. The analysis evaluates both fitness of the cumulative subscription and the annual adoption (increase number of new adopters) of mobile telephony market in Taiwan. Those works treat the aggregate data as a single set of diffusion path. Additionally, Kanjanatarakul & Suriya (2012) show that the Logistic model tops Bass model in sale forecasting with limited information. Moreover, Kanjanatarakul, Suriya, Hsiao, & Gourieroux

(2014) upgrade the Logistics model to increase the accuracy of sales forecasting using the technique of rolling windows which clearly outperforms the cumulative observations technique.

Other popular models that show high performance in the study of diffusion process are the Gompertz and Bass model. Cik, Zagar, & Kordic (2016) compare forecasting ability of four S-curve analytical models of fixed broadband service in the Republic of Croatia (RoC). The analysis divides the diffusion path by the product life-cycle: introduction phase, growth phase, maturity phase, and decline phase. They find that the Gompertz and Bass models have better forecast abilities than Logistic and Richards models. The Gompertz model gives the most accurate forecast abilities in introduction and growth phase while Bass model shows the best performance in maturity phase. For Taiwan's mobile telephony market, in contrast, Wu & Chu (2010) finds that the Gompertz model beats the other models for the period before take-off stage, while the Logistic model outperforms after the inflection. The work develops the diffusion-path segmentation by dividing the take-off and compares the performances of the Gompertz, Logistic, Bass, and ARMA models.

It seems like the concerns of modelling is on the segmentation of the diffusion path. However, Wu & Chu (2010) mention that there is no effective model in predicting the take-off trend. In reality, moreover, it is hard to identify clear life-cycle phases of a market knowing just information at the current stage of the diffusion. Thus, the focus of the present paper is on interventions that come to accelerate the diffusion path.

3. Predictive diffusion models and evaluation parameters

3.1 Predictive diffusion models

Refer to a S-curve models reviewed by Meade & Islam (1995), the analysis of this study includes three types of commonly used diffusion models; symmetric model - simple Logistics, asymmetric model - Gompertz, and flexible model - Bass.

1) Logistics model

The simple Logistic model is defined by

$$Y(t; M, a, b) = \frac{M}{1 + e^{-a(1-b)}}$$

where Y represents the number of adopters over period t , M reflects the ultimate number of adopters or long-term level of diffusion, a reflects the speed of the adoption, and b denotes the point of inflection (Cik et al., 2016; Michalakelis, Varoutas, & Sphicopoulos, 2008).

2) Gompertz model

Gompertz model is defined by $Y(t; M, a, b) = M \cdot e^{-e^{-a(t-b)}}$ where parameters are the same as for the Logistic model. The Gompertz and Logistic models are very similar but the inflection point for the Logistic model is at the 50% of the curve, as a symmetric model, while the point for the Gompertz model is at the 37% of the long-term saturation levels, an asymmetric model (Cik et al., 2016; Meade & Islam, 1995; Michalakelis et al., 2008).

3) Bass model

The Bass model is one of the commonly used models for prediction of innovation diffusion. The model accounts for the interaction between two groups of potential adopters (M) which affect their decision to adopt a new service. One is “Innovators”; the consumers with a permanent tendency for buying. The other group is “Imitators” who are influenced their purchase by the quantity of previous purchases (Bass, 1969; Chu et al., 2009; Cik et al., 2016; Wu & Chu, 2010).

The model is defined by

$$Y(t; M, p, q) = M \cdot \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} \cdot e^{-(p+q)t}}$$

where parameter p represents the coefficient of innovation, q represents the coefficient of imitation. Bass (1969) noted that the “Bass Curve” focuses on the current purchase at time t rather than the cumulative purchase.

3.2 Evaluation parameters

The accuracy of the goodness of fit of estimation model can be evaluated by Root Mean Square Error (RMSE). The values that are closer to zero show smaller random errors of the model (Cik et al., 2016; Trappey & Wu, 2008).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (e_i)^2}{n}}$$

where $e_i = Y_t - \hat{Y}_t$ is the estimation error at period t , Y_t is the actual value at training period t , and \hat{Y}_t is the estimated value for period t , and n is the number of value which are used for estimation.

The accuracy of forecasting can be evaluated by the aggregate error - Mean absolute percentage error (MAPE). The smaller value of the MAPE denotes the better prediction performance model (Lin, 2013; Michalakelis et al., 2008).

$$\text{MAPE} = \frac{\sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100}{n}$$

where y_t is the actual value at period t , and \hat{y}_t is the forecast value for period t , and n is the number of predictions which are used for the error calculation.

4. Changes in telecommunication market in Thailand

The huge amount of applications and services on the Internet shows significant changes today in shifting consumer behaviors towards their easy-to-use and well-respond to consumers' needs years (Ericsson, 2015a, 2015b). These shifts motivate the development of cross-platform access and stimulate consumer's demand for higher bandwidth.

In 2011, there was a significant change in Thailand in higher Internet consumption of individual consumers after the launch of many devices e.g. smartphone, iPad, and Tablet. The more daily-life activities such as e-book and songs download through applications, and the use of social media has been enabled. In addition, the business sector has been using YouTube and Social network such as Facebook, MySpace, and Twitter as a marketing tool to influence consumers' response, access to consumers and attract them to purchase such as sports marketing, digital branding, and brand engagement.

Since 2013, LINE service showing its impact to mobile telecommunications market indicated by the decline in voice service revenue of Internet service providers. The service gained more and more popularity among Thai people in using as a channel for communication among friends as well as information consumption and online financial activities (MGR online, 2016).

Since 2014, the number of broadband user has been increasing significantly (SME Thailand Club, 2017). At the same time, there were a significant growth of YouTube service. The rise of YouTube partners and creators resulting in the higher number of channel which further resulting in 110% growth from the past year in number of hour for content watched of the Thai people. Half of Thai people access YouTube through mobile and another half through fixed-line. Analysts in Thailand see that the rapid growth of the two services strongly influence each other (POSITIONING, 2015).

In 2015, the competition among fixed-broadband ISP became very concentrate after "3BB", one of the fixed-broadband incumbents, upgraded its network technology from ADSL to VDSL and offered higher capacity and speed to the customers. Other ISP had to develop and invest in their network in order to meet consumers' demand for more bandwidth and protect their market share (MATICHON ONLINE, 2016). 53% of Thai people who are in the Internet available area access to the Internet every day. Moreover, 51% of users who surf the Internet more than 4 hours per day, spend most of the time on YouTube (Biz Pop Team, 2016).

5. Methodology

The process of understanding and forecasting the diffusion path of telecommunications market is very important for both government and business planning for infrastructure investment in order to meet consumer's demand. The diffusion can be described by the S-curve models representing the aggregate adoption (Meade & Islam, 1995).

This paper focuses on the assessment of goodness-of-fit and forecasting ability of the Logistic, Gompertz, and Bass models for the case study data. Based on the available data from the National Broadcasting and Telecommunications Commission, it applies time series data from two telecommunication markets in Thailand including mobile telecommunications and fixed broadband. For mobile telecommunications, the data presents for the period from 2002 to 2014. Fixed-broadband subscription data presents for the period from 2008 to 2016. This study analyzes each market separately without the interaction between both services. Each sample dataset was divided into training and testing data subsets by the major technological change that accelerates or decelerates the market. The training data set is used for estimating model parameters and testing the goodness-of-fit. The testing data set is used for determining the model's accuracy of forecasting values.

The diffusion path segmentation of this study based on market information in Section 4. Therefore, the scenarios were conducted concerning with:

- 1) The year 2011 which is the 1 year after the gaining attention in the use of YouTube, Social network such as Facebook, MySpace, and Twitter that change consumer behavior in the demand for Internet and bandwidth.
- 2) The year 2013 which is the year of realizing the impact of LINE service on mobile telecommunications market.
- 3) The year 2014 which is the 1 year after the booming of YouTube consumption through both mobile and fixed telecommunication services.
- 4) The year 2015 which is the year of significant development in telecommunication infrastructure and services, and the continuous growth of YouTube users.

5.1 Diffusion path segmentations

Mobile telecommunications market

- 1) Training data: 2002-2009 (t=1 to t=32)
- 2) Training data: 2002-2011 (t=1 to t=38)
Testing data: 2012-2013 (t=39 to t=52)
- 3) Training data: 2002-2013 (t=1 to t=48)
Testing data: 2014 (t=49 to t=52)
- 4) Training data: 2002-2014 (all data)

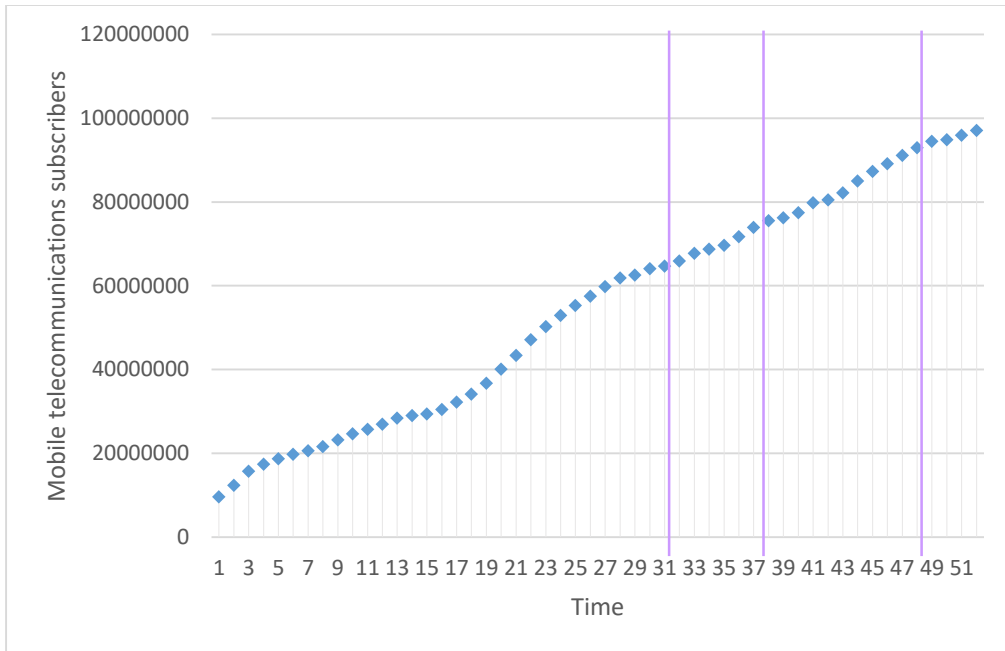


Figure 1: Diffusion path segmentation of mobile telecommunications market

Fixed-broadband market

- 1) Training data: 2008-2011 (t=1 to t=16)
- 2) Training data: 2008-2014 (t=1 to t=28)
Test data: 2015-2016 (t=29 to t=35)
- 3) Training data: 2008-2015 (t=1 to t=32)
Testing data: 2016 (t=33 to t=35)
- 4) Training data: 2008-2016 (all data)

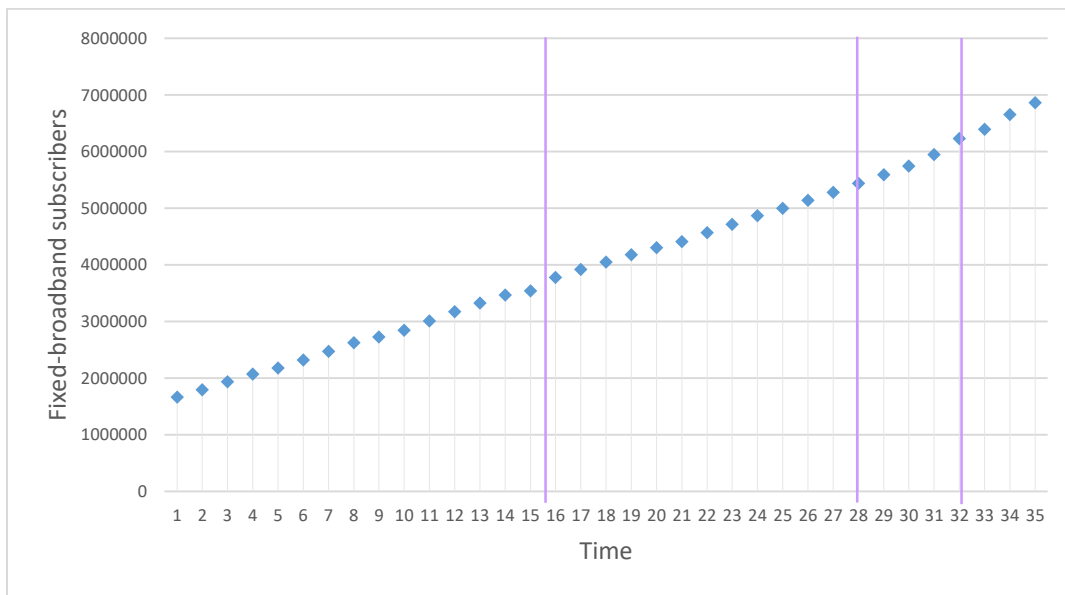


Figure 2: Diffusion path segmentation of fixed-broadband market

5.2 Method

The procedure of numerical methods suggested by Jaun (n.d.) and Wang (2012) is, first, conducted to estimate the best describe parameters of each model in each market by using the training data sets. The adjustments of best-fit parameters are done by using the Matlab. In order to capture the model's accuracy, the goodness-of-fit of the models based on the obtained parameters in each market are compared by the Root Mean Square Error (RMSE). The future adoption path can be seen by using the estimated parameters and evaluate the forecasting ability by comparing with the actual adoption in testing data sets. The accuracy of forecasting will be evaluated by Forecast Error and Mean absolute percentage error (MAPE).

6. Results and interpretations

The estimated model's parameters and the model's accuracy between the predicted and the actual values are listed in Tables 1 and Table 2.

6.1 Mobile telecommunication market

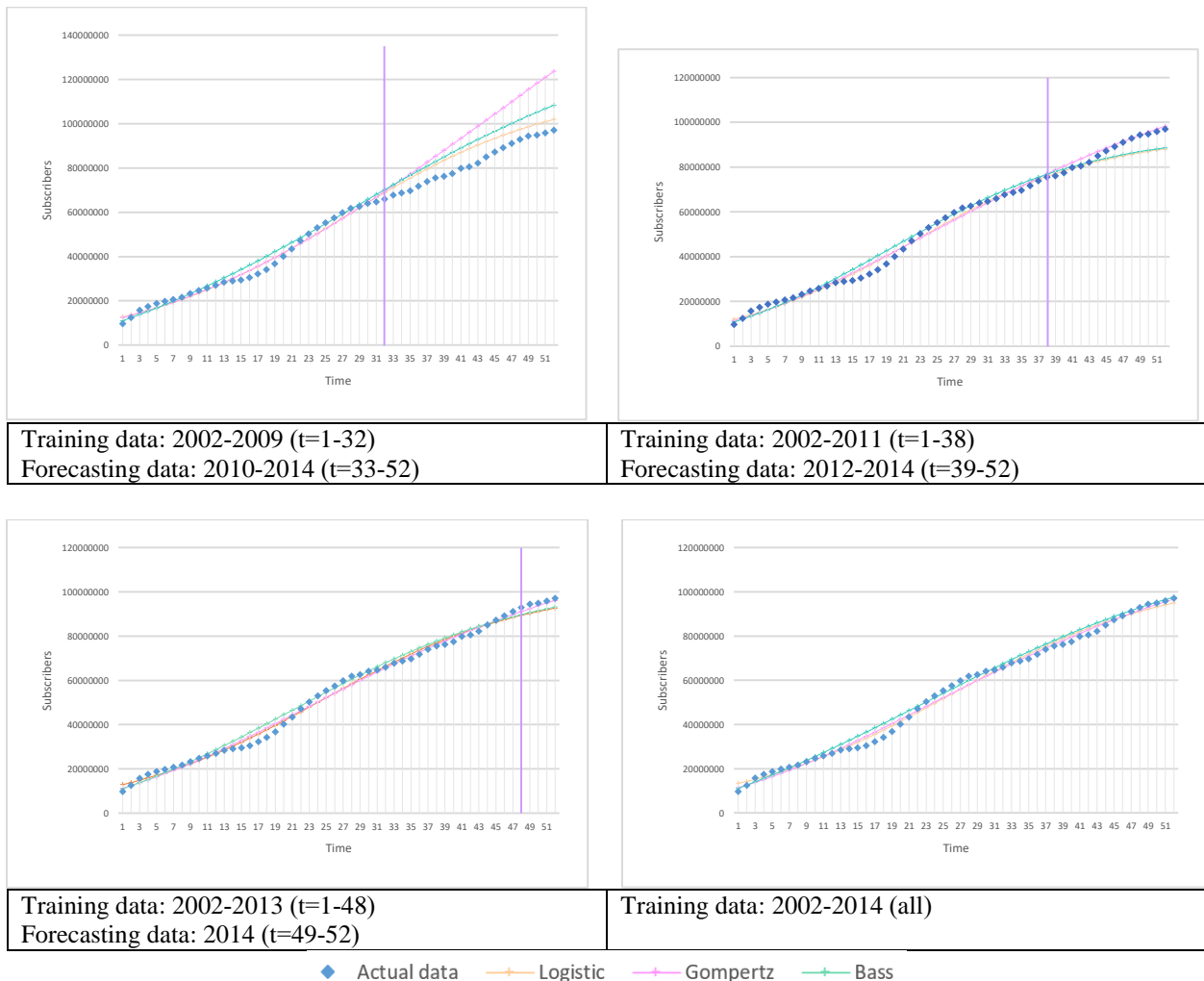


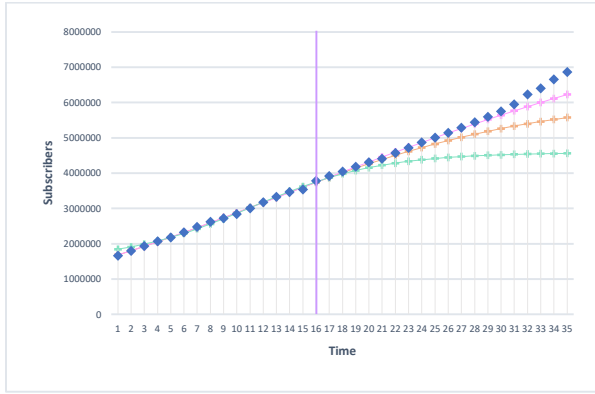
Table 1: Results of statistical analyses of mobile telecommunications market

Mobile market	Model	Logistic model		Gompertz model		Bass model	
Training: 2002-2009 Forecasting: 2010-2014	Estimated parameters	a	0.07986	a	0.02517	p	0.00960
		b	27.23345	b	46.94362	q	0.04328
		M	116019857.79	M	298,291,836.84	M	145495651.68
	RMSE	1	1966622.51305	2	2061962.50943	3	2424172.41009
	MAPE	1	7.21008	3	17.62053	2	9.57180
Training: 2002-2011 Forecasting: 2012-2014	Estimated parameters	a	0.09001	a	0.03971	p	0.01354
		b	22.29613	b	23.95880	q	0.06914
		M	94241397.86	M	136510999.70	M	95294491.09
	RMSE	1	1994318.57053	2	2255626.87190	3	2304719.05561
	MAPE	2	4.65805	1	1.88629	3	5.69977
Training: 2002-2013 Forecasting: 2013-2014	Estimated parameters	a	0.082413653	a	0.041138209	p	0.013193224
		b	24.54458441	b	22.71275579	q	0.05570922
		M	102318777.51	M	129757499.64	M	105674531.29
	RMSE	1	2085673.27896	2	2132456.68299	3	2310089.11134
	MAPE	2	4.24756	1	1.31657	3	5.18128
Training: 2002-2014	Estimated parameters	a	0.07815	a	0.04012	p	0.01229
		b	25.98843	b	23.38020	q	0.04092
		M	107452848.38	M	132996038.46	M	123247456.68
	RMSE	2	2152423.29669	1	2067581.91138	3	2203094.62051
	MAPE		n/a		n/a		n/a

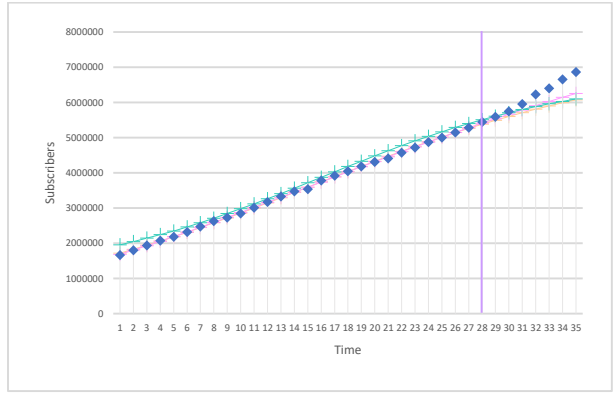
In accordance with the studies of Lee & Cho (2007), Gamboa & Otero (2009) and Chu et al. (2009), the Logistic model shows the best performance of data fitting in mobile telecommunication market. However, our results indicate that the forecasting ability of the model follows the Gompertz model which support the findings from Cik et al. (2016). With a lower MAPE value, the Gompertz performs the best in forecasting the diffusion of mobile market especially with the impact of LINE service on the market from 2013. Although the forecasting ability of the Gompertz model with the impact of the use of YouTube and social network in 2011 is slightly higher than that from 2013, this can be explained by the effect of the length of training data pointed out by Michalakelis et al. (2008) and Christodoulos, Michalakelis, & Varoutas (2010) on the different predictive performances.

It is clear that the Bass model lacks both goodness-of-fit and forecasting performance comparing to the two models with its high RMSE and MAPE. This result is in accordance with the analysis of Michalakelis et al. (2008).

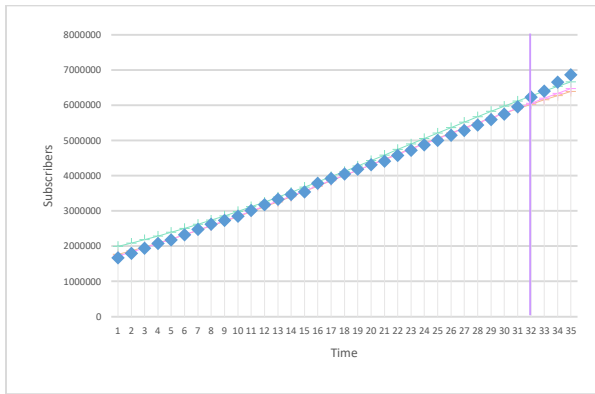
6.2 Fixed broadband market



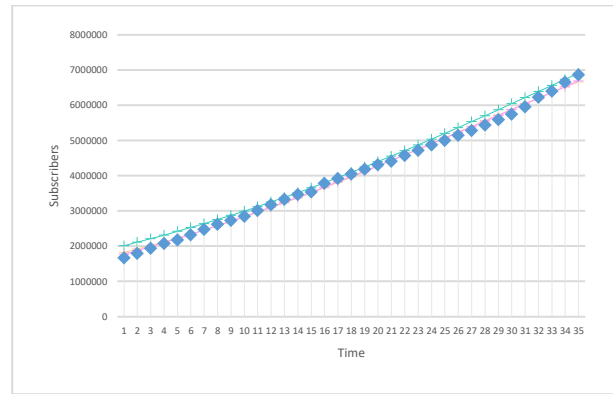
Training data: 2008-2011 (t=1-16)
Forecasting data: 2012-2016 (t=17-35)



Training data: 2008-2014 (t=1-28)
Forecasting data: 2014-2016 (t=29-35)



Training data: 2008-2015 (t=1-32)
Forecasting data: 2015-2016 (t=32-35)



Training data: 2008-2016 (t=1-35)

◆ Actual data — Logistic — Gompertz — Bass

Table 2: Results of statistical analyses of fixed-broadband market

FBB market	Model	Logistic model		Gompertz model		Bass model	
Training: 2008-2011 Forecasting: 2012-2016	Estimated parameters	a	0.09345	a	0.04119	p	0.01055
		b	11.51261	b	14.42736	q	0.19579
		M	6195781.48	M	9556508.08	M	4581792.51
	RMSE	2	24703.93776	1	23369.17589	3	136972.9188
	MAPE	2	6.31357	1	2.11005	3	23.30170
Training: 2008-2014 Forecasting: 2015-2016	Estimated parameters	a	0.08187	a	0.04025	p	0.01260
		b	15.35492	b	15.03474	q	0.02298
		M	7289953.33	M	9786191.80	M	12028774.90
	RMSE	2	30906.04586	1	23069.13023	3	56854.52168
	MAPE	2	6.37284	1	4.72018	3	9.90101
Training: 2008-2015 Forecasting: 2016	Estimated parameters	a	0.07192	a	0.03354	p	0.00985
		b	19.59267	b	20.85761	q	0.06089
		M	8499128.70	M	12054534.22	M	9285729.41
	RMSE	2	58311.40151	1	45425.40067	3	77032.2676
	MAPE	3	5.48873	2	4.56893	1	4.34805
Training:		a	0.06226	a	0.02595	p	0.00692

FBB market	Model	Logistic model		Gompertz model		Bass model	
2008-2016	Estimated parameters	b	25.97566	b	32.52614	q	0.04356
		M	10465060.38	M	17079774.16	M	13488616.37
	RMSE	2	79363.4807	1	64071.56608	3	85945.21556
	MAPE		n/a		n/a		n/a

The results from fixed-broadband data clearly show the high performance of both goodness-of-fit and forecasting ability of the Gompertz model. Although the results from the third analysis (Training data: 2008-2015 and Forecasting data: 2016) indicate that the Bass model has the lowest MAPE at 4.34805, the Gompertz model has a very close MAPE at 4.56893.

In summary, the Gompertz shows the best performance in forecasting the diffusion telecommunications market in Thailand after the shift of the curve due to external interventions. The finding is in line with the results from Chu et al. (2009) that the Gompertz model shows the greater difference than the Logistic and Bass models between before and after diffusion take-off. The result implies that the Gompertz model is very sensitive to the change of the market. The forecasts of the model are very similar to those of the Logistic model. However, the Logistic model has a limitation in forecasting the upper bound or the market potential (M). The model gives the lowest forecast values of M comparing to those of the Gompertz and Bass models. This adds to Cik et al. (2016) who points out the effect of different positions of the curves inflection points on the difference of forecasting accuracy between the Logistic and Gompertz models.

7. Implications and conclusion

The continued growth in consumption of applications and services according to their new values created to societies. Major presence of technological intervention, for instance, the coming of many applications, has been resulting in the dramatic increase of the Internet use. The forecasting of broadband diffusion is crucial for policy makers and service providers to adjust policy and strategy to match consumer's demand which has been changing extremely fast and sometimes faster than expectation.

This paper aims at finding the best model of explaining and forecasting the diffusion of telecommunication markets in Thailand. The analysis includes three types of commonly used diffusion models; symmetric model - simple Logistics, asymmetric model - Gompertz, and flexible model - Bass. It concerns the major technology and service such as the coming of smartphone and LINE into mobile market that accelerate the adoption, and the rise of YouTube that boosts fixed broadband market as interventions of telecommunication market. The diffusion path of each market is divided into different stages by the presence of those interventions. Each analysis composed of two parts of data set, the training and the testing data sets. The estimation methodology for nonlinear models using Matlab was conducted to estimate models' parameters. We, then, evaluate the goodness-of-fit by using RMSE and forecast ability by MAPE of each predictive model.

The results show that the Gompertz model has the most accurate in forecasting the diffusion of telecommunication markets with responding to external interventions that drive service adoption. For the explaining ability, the Logistic shows the lowest RMSE in explaining mobile telecommunications market while the Gompertz model shows as the best forecasting ability in both markets. In the more dynamic market like mobile telecommunications, the Gompertz model seems to response to the impact of external intervention more than the Logistic model. Most of the cases, the Logistic model underestimates the market potential comparing to Gompertz and Bass models. In practice, we may use the prediction from the Gompertz model as the main target of market potential while prediction value from the Logistic model as a minimum level.

Based on historical data, the diffusion of mobile telecommunications is more fluctuated than the diffusion of fixed- broadband market. The results of the model with the best goodness-of-fit between both markets were not totally congruence. This leaves a room for further study with some alternative frameworks in examining the difference of predictive models' performances between fluctuated versus non-fluctuated markets.

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