國立交通大學

管理科學系

博 士 論 文

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中 華 民 國 九 十 八 年 六 月

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國 立 交 通 大 學

管理科學系

博 士 論 文

A Dissertation

Submitted to Department of Management Science

College of Management

National Chiao Tung University

in Partial Fulfillment of the Requirements

for the Degree of

Doctor of Philosophy

in

Management

June 2009

Hsin-Chu, Taiwan, Republic of China

中華民國九十八年六月

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中文摘要

成長曲線模型常常被使用來預測科技產品之走向與趨勢，本研究利用 22 組科技產品資料來比較 The simple logistic model, the Gompertz model, and the time-varying extended logistic model，此三種科技預測模型之預測準確度，再歸納出此三種模型之優缺點及建議使用時機。結果發現，The time-varying extended logistic model 對在 70%的科技產品上，都有比 Simple logistic model 與 Gompertz model 兩個模型較好的預測準確度；但由於 The time-varying extended logistic model 在模型設定時需要有較多的參數來估計成長上限，在資料點太少的情況下，有約 20%的機率無法得到收斂的結果，因此本研究建議若欲使用 Extended logistic model，最好有 15 點以上之連續資料，且產品成長曲線有 S 曲線的軌跡，將會有較準確的預測結果。本研究亦提出一個選擇預測模型的決策流程，建議若在 Extended logistic model 無法收斂的情況下，但該產品成長曲線之反曲點已出現，則 Simple logistic model 與 Gompertz model 可被使用來預測產品未來的發展空間。本研究亦利用大陸 RFID 專利申請案數量為一應用該決策流程之個案，並進一步預測未來 RFID 產業的發展趨勢。最後，本研究也提出對產品生命週期各階段之策略建議。

關鍵詞：科技預測、簡單羅吉斯模式、甘伯茲模式、廣泛羅吉斯模式、產品生命週期、無線射頻識別、專利分析

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ABSTRACT

Many successful technology forecasting models have been developed but few researchers have explored a model that can best predict short product lifecycles. This research studies the forecast accuracy of long and short product lifecycle datasets using simple logistic, Gompertz, and the extended logistic models. Time series datasets for 22 electronic products were used to evaluate and compare the performance of the three models. The findings show that the time-varying extended logistic model fits short product lifecycle datasets 70% better than the simple logistic and the Gompertz models. A decision diagram is proposed to select a suitable forecasting model among the three models. The results suggest that there should be at less fifteen data points for the extended logistic model to reach better predictions. However, if the extended logistic model cannot be applied and the inflection point of the growth curve is revealed, the simple logistic and the Gompertz models can be the alternatives for forecasting the future trend of the product. A case study of China RFID patent forecast is also presented to demonstrate the selection procedure proposed in this research. Finally, the suggestions for product lifecycle management strategies in different lifecycle stages are also discussed.

Keywords: Extended logistic model; Technology forecasting; Simple logistic model; Gompertz model; Short product lifecycle; Radio Frequency Identification; Patent Analysis

致謝辭

在交大這四年來，受到許多的照顧及幫助，最感謝的當然是指導教授 Dr. Charles Trappey，張力元教授，雖然老師對學術上的嚴謹，讓學生吃了不少苦頭，但也因此培養出對研究的謹慎態度及邏輯推理上的能力；而老師為了培養學生成為優秀的研究者，不僅鼓勵我參加各種國際研討會，增加與國外學者交流的機會，更積極推薦我申請國科會千里馬計畫，前往美國普渡大學與 Prof. Feinberg 進行合作研究，深入瞭解外國的學術環境，也發展出不同的研究方向。而老師也常以幽默風趣的方式向我說明一些做人處事的道理，讓我學習到如何在工作與生活上取得平衡點。另外一位我要特別感謝的是清大工工系教授，現任國立台北科技大學管理學院院長的張瑞芬教授，在學生研究及生活上給予諸多的協助與提點，在與張教授合作研究的期間，學生也學習到縝密的思維方法與效率的工作習慣。而在本論文初審及口試階段，也要感謝國立中山大學企管系趙平宜教授、國立交通大學管科系黃仁宏教授、王耀德教授給予學生寶貴的意見與指導，讓學生受益匪淺，亦使本論文能更臻完美，在此一併致上最大感謝。

感謝交大的師長，教導我各方面的知識；感謝交大學長姐 CoCo、二姐、登泰、佳誼、千芬在學業、研究及生活上的經驗分享，讓我的博士生生涯走來不致惶恐；感謝同窗裕真、順鵬、旭鋒、琬真、易淳，我不會忘記大夥一起上課、一起準備資格考的一切，謝謝你們無私的分享，讓我可以順利的完成學位；特別感謝愛華同學，一直給予我精神上的鼓勵，與我一同克服許多生活上及研究上的困難。感謝系助理葉姐、林姐、淑燕、王姐、玉娟，在庶務上的幫助及對我生活上的關心。也要謝謝清大工工的維承學長、梓安學長、學弟盈碩、助理淑慧的協助，讓我可以順利的完成研究工作。還有許多一路上所有幫助我、鼓勵我的朋友，雖然我沒辦法一一列出大家的名字，但是我要謝謝你們的支持，請與我一起分享這份喜悅。

在此，我要將此論文獻給我親愛的家人。爸、媽，感謝你們縱容任性的女兒，總是無條件支持我，給予我強大的後援，成全我無數無理的要求，讓我一路走自己想走的路，我要你們知道，你們是我最大的支柱，我愛你們；柏廷，謝謝你總是包容迷糊的姊姊；我的公婆，謝謝你們體諒我跟豐騰在外地求學，無法時常陪伴你們兩位；最後，我要跟我一生的摯愛，我的先生，豐騰，一起分享取得博士學位的喜悅，謝謝你一直的陪伴與鼓勵，支持我度過每個低潮與不安，我們終於都拿到博士了，我們做到了！

吳欣穎

謹誌於　新竹交通大學

中華民國九十八年六月

Table of Contents

List of Figures

List of Tables

1. Introduction

This chapter presents the research background of forecasting lifecycle products and the importance of selecting the suitable forecasting models. The motivation, purpose and process of this research are also discussed in this chapter.

1.1 Motivation

With the rapid introduction of new technologies and fast design to satisfy consumer demand, electronic products and services are often replaced within a few years. The product life cycle for electronic goods, which used to be about ten years in the 1960's, fell to about 5 years in the 1980's and is now less than two years for consumer electronic products such as cell phones and computers. As product life cycles become shorter, less data are available for market analysis and technology forecasting. Given the current market situation, smaller datasets must be used to forecast future trends of new electronic products and services. Hasted and Ehlers (1989) define a small dataset as the dataset which covers only short time intervals with fewer than 30 data points.

A product life cycle is typically divided into four stages that include introduction, growth, maturity and decline (Kotler, 2003). The product lifecycle is often modeled using growth curves or sigmoid curves which have an inflection point and approaches a fixed limit (Bass, 1969; Mahaian, Muller, & Bass, 1990; Morrison, 1995; Morrison, 1996; Kurawarwala & Matsuo, 1996; Kurawarwala & Matsuo, 1998; Bengisu & Nekhili, 2006). Growth curves are widely used in technology forecasting (Frank, 2004; Levary & Han, 1995; Meade & Islem, 1995; Meade & Islem, 1998; Meyer & Ausubel, 1999; Meyer, Yung, & Ausubel, 1999; Rai & Kumar, 2003) since technology product growth is often very slow during the introduction stage (e.g., a new product replacing a mature product) which is then followed by rapid exponential growth when barriers to product adoption fall. The growth then approaches a market share limit. The limit reflects the saturation of the marketplace with the product or the replacement of the product with another. The curve also models an inflection or break point where growth ends and decline begins.

Many growth curve models have been developed to forecast the penetration rate of technology based products with the simple logistic curve and the Gompertz curve the most frequently referenced (Morrison, 1995; Morrison, 1996; Bengisu & Nekhili, 2006; Meade & Islem, 1995). However, when using these two models to forecast market share, care must be taken to set the upper limit of the curve correctly or the prediction will become inaccurate (Bengisu & Nekhili, 2006). The upper limit is the maximum possible value and represents the maximum penetration rate or sales volume. Setting the upper limit to growth can be difficult and ambiguous. If the product will likely be popular and used for decades, then the upper limit is set to 100% of the penetration rate. This means that the product will be completely replaced only after everyone in the market has purchased the product. However, when marketers consider new technology products such as computer games or new model cell phones, the value for the upper limit to market share growth can be difficult to estimate. That is, a computer game can be quickly replaced by another game after only reaching 10% market share.

In order to avoid the problem of estimating the market share capacity for the simple logistic and the Gompertz models, Meyer and Ausubel (1999) proposed the extended logistic model. Under this model, the capacity (or upper limit) of the curve is not constant but is dynamic over time. Meyer and Ausubel (1999) also proposed that technology innovations do not occur evenly through time but instead appear in clusters or "innovation waves." Thus, they formulated an extended logistics model which is a simple logistics model with a carrying capacity $k(t)$ that is itself a logistics function of time. Therefore, the researchers extend the constant capacity (k) of the simple logistic model by embedding the carrying capacity in the constant. Chen (2005) applies the embedded carrying capacity concept to develop a time-varying extended logistic model and the study uses the durable electronics products to confirm the model has better performance than the Fisher-Pry model and the Gompertz model. However, it will need more data to verify whether the time-varying extended logistic model can also better forecast the short lifecycle technology products.

1.2 Research Purpose

The emergence of short product lifecycles has been addressed in the supply chain and inventory management literature (Kurawarwala & Matsuo, 1996; Kurawarwala & Matsuo, 1998; Zhu & Thonemann, 2004) and there is general agreement that improved prediction of these lifecycles will benefit the management of supply chains, inventories, and product design. However, these new technology lifecycles are a modern phenomenon and the data sets (which characteristically have fewer data points and shorter time periods) challenge the assumptions and applications of traditional forecasting methods.

Traditional forecasting models, like the simple logistic and Gompertz models, require that the upper limit of the curve be estimated prior to the forecast. Since it is difficult to estimate the demand of a new product or the arrival of a substitute product with limited data, traditional approaches are considered unreliable and inaccurate. Therefore, a time-varying extended logistic model with flexible capacity is proposed where the capacity (or upper limit) of the curve is not constant but is dynamic over time.

The purpose of this research is to evaluate the performance of the time-varying extended logistic model, the simple logistic model and the Gompertz models when forecasting both long and short technology product lifecycles. Six time-series datasets describing market penetration rates and sixteen datasets describing cumulative sales volumes were used to evaluate model performance. The electronic consumer goods datasets consist of six sets representing long product lifecycles and 16 sets representing short product lifecycles. Not only to compare the fitting and forecasting performances, and the pros and cons of the three models, but a decision diagram of selecting a suitable forecasting model is also proposed, and the China RFID patent applications is used as a case study to demonstrate the model selection process. The case is also an example to present how to apply the technology forecasting model to realize the current and future development of an industry.

1.3 Research Process

Chapter 1 of this paper provides an introduction and Chapter 2 discusses literatures about technology forecasting methods, the challenges of forecasting short product lifecycles and traditional and newly developed technology forecasting models including the simple logistic model, the Gompertz model, and the time-varying extended logistic model. Chapter 3 presents the methodology and the analytical process of this study. Chapter 4 describes comparison results of the models' prediction performances and provides the suggestions for using the models. Chapter 5 provides an empirical case of China RFID patent analysis. The last chapter provides a summary and conclusion as well as the limitations of the study. Figure 1 presents the research framework and process of this dissertation.

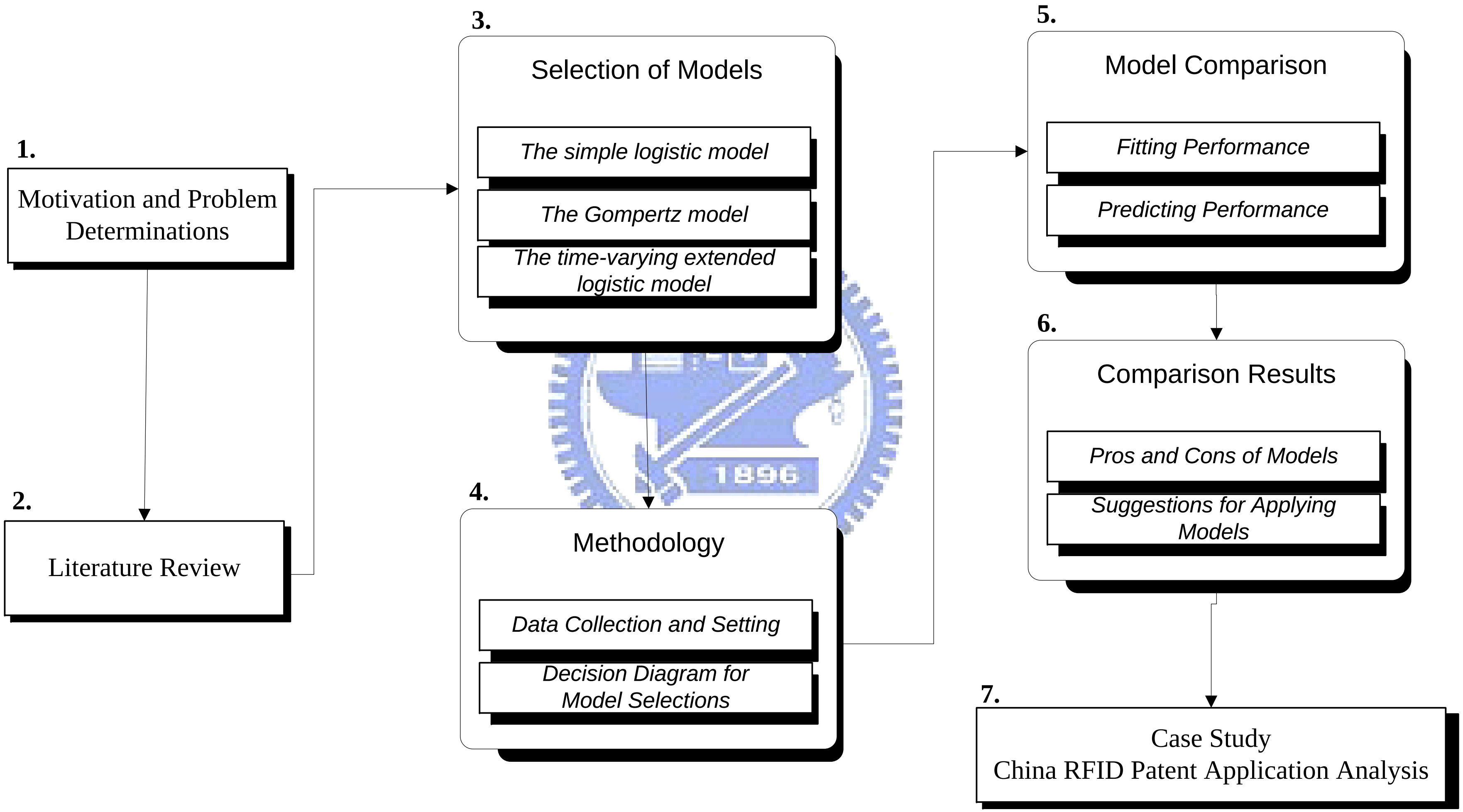


Figure 1　Research framework and process

2. Literature Review

The lifecycle concepts have been used in different field. Nieto, Lopez, and Cruz, (1998) proposed that the lifecycles of technologies, industries and products follow similar S-shape curve which is the pattern of biological growth of living beings. Therefore, the authors relate the growth curve models to lifecycle management. However, the product lifecycle analysis focuses on the evolution of sales of products to provide marketing and management strategies for firm and business unit; while technology lifecycle analysis concentrates on the effects of evolution of given technology to generate strategies for production and technology management. This research applied the concepts that the product lifecycle and technology lifecycle can both be forecasted using growth curve models, a kind of technology forecasting methods.

Furthermore, this research studies the lifecycle of technology products, which are different with durable or service products. The lifecycle of technology products become shorter and shorter as technology improves, since the new technology products are easily to be developed and to replace the old ones. The present situation makes the management of short lifecycle products become more important than before. Thus, forecasting technology product lifecycles can be viewed as forecasting short product lifecycles. Kurawarwala & Matsuo (1996) state that the duration of short product lifecycle usually is one to two years. Hasted and Ehlers (1989) define a small dataset as the dataset which covers only short time intervals with fewer than 30 data points. Therefore, I follow these definitions and define the product lifecycle of one or two years with less than thirty data points as short product lifecycle. This chapter begins with the discussion of technology forecasting models, and then the literatures of forecasting short lifecycle products are reviewed. Finally, the three growth curve models used in this research are presented.

2.1 Technology Forecasting Methods

In general, technology forecasting methods can be classified into quantitative and qualitative methods. Martino (1993) outlines ten forecasting methods, including Delphi, analogy, growth curves, trend extrapolation, correlation methods, causal models, probabilities methods, environmental monitoring, combining forecasts, and normative methods. The following section will separates these methods into quantitative and qualitative categories and discuss their contents and applications. Furthermore, the criteria of selecting forecasting models are also presented.

2.1.1 Qualitative forecasting methods

Qualitative forecasting methods are those forecasting methods do not use mathematical or statistical technologies, therefore, based on this definition, Delphi, analogy, environmental monitoring, and normative methods.

1. Delphi

Delphi is a kind of expert opinion methods and a series of questionnaire are used to collect the panelists' opinion. Panelists are the experts familiar with the specific industries or problems that the research focuses on. Delphi is usually applied in the three conditions. The first condition is there is no historical data can be used; the second condition is when important external factors happen and the previous data can not be applied, and the third condition is when ethical or moral considerations dominate the development of technology (Martino, 1993). Delphi can gain the extensive opinions and panelists do not need to interact with each other, so they won't be influenced by others and shift their opinions. Levary & Han (1995) suggest that all participants should be experts about the given technology.

2. Analogy

The assumption of analogy is if the background or characteristics of two technologies are similar, they may have the same similar development trends; therefore, the forecast can be based on historical analogy. There are nine dimensions need to be taken into consideration when applying analogy, and they are technological dimension, economic dimension, managerial dimension, political dimension, social dimension, cultural dimension, intellectual dimension, religious-ethical dimension, and ecological dimension.

3. Environmental monitoring

A breakthrough of a technology is the end result of a chain and is not easy to predict. Environmental monitoring method then can be applied to detect the breakthrough and is a systematic forecast method that involves evaluating kinds of environmental sectors, including the technological sector, the economic sector, the managerial sector, the political sector, the social sector, the cultural sector, the intellectual sector, the religious-ethical sector, and the ecological sector (Martino, 1993).

4. Normative methods

Normative methods are the goal oriented forecast methods and are different from the exploration forecasts which are used to predict future development using the previous or present data. Setting a goal is the first task of applying the methods, and therefore, when, who, what, why, and the know-how of a technology should be clearly set. The representative models of normative methods are relevance trees, morphological models, and mission flow diagrams.

2.1.2 Quantitative forecasting methods

When a forecasting method uses mathematical or statistical data to forecast, the method is a kind of quantitative forecasting methods, such as growth curve, trend extrapolation, correlation method, causal models, probabilities methods, and combining forecasts. Valid time series datasets are the key to forecasting accuracy of quantitative methods and forecasters believe that the historical data present a logical trend for future and can be used to project the prospect development (Martino, 2003).

1. Growth curve model

Growth curve model, also names as S-curve model, is often applied to forecast the technology or product lifecycles since the growth of technology/product lifecycle is usually follows an S-shape curve. Growth curve model uses the historical date to forecast the future performance of the technology or product. Three assumptions need to be fulfilled before applying the traditional growth curve models. The first assumption is the upper limit to the growth curve is known; the second assumption is the chosen growth curve to be fitted to the historical data is the correct one, and the third assumption is the historical data gives the coefficients of the chosen growth curve formula correctly (Martino, 1993). Since the growth curve model is the main method of this study, the detailed discussion will be presented in the next section.

2. Trend extrapolation

Every technology will reach its maximum performance level, i.e. the upper limit, and new technology will appear to replace the old one. Trend extrapolation is used to forecast the progress beyond the upper limit of the existing technology. Even we do not know what and when the breakthrough technology will be, the previous technology development and historical data can be used to forecast the future technology. However, if a technology is known that it will not have further development, the trend extrapolation is not suitable to be used. Levary & Han (1995) suggest every trend extrapolation model need to have assumptions and satisfying these assumptions is the determinate of forecast accuracy.

3. Correlation method

Correlation method is similar to analogy method. The predicted technology should have the similar characteristics to the previous technology. However, correlation method uses the quantitative historical data of the similar technology to forecast and analogy method uses qualitative dimension to project the similar technology development. Martino (1993) introduces several correlation methods for forecasting a technology, including a technological precursor, cumulative production, total capacity, and economic factors.

4. Causal models

Causal models are used to realize the reasons that induced the development of the technology. Once the reasons are defined, the future development can be forecasted. Martino (1993) introduces three types of causal models. The first type is technology-only models, such as the growth of scientific knowledge and a universal growth curve, and these models assume that the technological changes can be explained by internal factors of the system of technology. The second type is techno-economic models and the assumption of these models is that the technological development is caused by economic factors. The third type of causal models is economic and social models which assume economic and social factors are the reasons that induce the technological development, and KSIM and differential equations models are the major representative models.

5. Probabilities methods

Probabilistic methods are used to predict the range that a technology can develop and reach to and the probability distribution over the range. Martino (1993) outlines two types of the probabilistic forecasts. The first type of methods relates a range of possible future values and the probability distribution over the range and the second type of probabilistic method is based on a probability distribution of the factors that produce technological changes. Probabilistic forecasts can be operated using simulation techniques.

6. Combining forecasts

Every forecast method has its advantages and disadvantages, and therefore, different methods can be combined to improve the accuracy of prediction. Combining forecasts then are popular in predictors to avoid problems of selecting only one forecast method. Researchers should study the strengths and weakness of individual forecast methods to know how to combine different forecasts to reach better predictions. Usually combining forecasts can be quantitative and/or qualitative methods. Trend and growth curves combination, trend and analogy, components and aggregates, cross-impact models, and scenario analysis are most used combining methods. Levary & Han (1995) suggest the cross-impact analysis should be applied when the factors that affect the future technology are known, and the scenario developers should expert all aspect of the technology.

2.1.3 The selection of technological forecasting models

Levary and Han (1995) outline six factors that influence the selection of forecasting methods. First, money available for development, the more money invest in the given technology, the more opportunity the technology can be realized and the shorter the development time. Second, data availability, what data researchers can retrieve affect the methods selection. Third, data validity also affects the choice. Fourth, uncertainty surrounding the success of technological development, some technology forecasting methods are suitable to high uncertainty situation while other are not. Fifth, if similarity of proposed and existing technologies is high, analogy or correlation methods can be applied. Finally, number of variables affecting the development of technology, the more influence factors, the more complex models should be applied, and therefore, combining forecast methods may be needed.

Young (1993) applies nine growth models to determine the procedure of selecting an appropriate growth models. The author concludes that the most important procedure is to identify the characteristics of datasets before fitting the data into the growth curve models. Predictors intend to apply growth curve model need to know the knowledge of upper limit, to observe whether the fifty percent takeover point has been achieved in the dataset, and to study the length of datasets.

2.2 Forecasting Short Product Lifecycles

Short product lifecycles of one or two years have become more common in high technology and fashion-based industries which need to continuously introduce new consumer products to remain competitive (Kurawarwala & Matsuo, 1996; Zhu & Thonemann, 2004). New electronic products with more functions, faster speed, and finer quality are continuously being introduced and quickly replace models which may only be one year old. Quell, Olshavsky, and Michaels (1981) analyzed 37 types of home appliance from 1922 to 1979 and demonstrated that the shortening of product life cycles is an important issue for product designers and planners. Given the reality of this market condition, the development of new forecasting techniques will improve the competitive response and manufacturing strategy of companies.

In 1969, Bass (1969) proposed a diffusion model to forecast the sales volume of new products that used the adoption rates of innovators and imitators. Innovators are buyers that are not influenced by the previous buyers when making purchase decisions while imitators are those who are influenced by earlier buyers. The Bass model has been widely applied by practitioners and modified by researchers to forecast short product lifecycles. Kurawarwala and Matsuo (1996) proposed a growth model that forecasts the seasonal sales volume demand of short product lifecycles based on the Bass diffusion model. Thirty-eight monthly data points for five different personal computer products were used to estimate seasonal demand and to compare the fit and forecast performance for three models. The measures used for model comparison were the sum of squared error (SSE), the root mean squared error (RMSE), and the mean absolute deviation (MAD). Zhu and Thonemann (2004) used the discrete version of the Bass diffusion model and improved on Kurawarwala and Matsuo (1998) model to develop an adaptive forecasting algorithm. The demand data for a PC manufacturer was used to test the forecasting performance of the algorithm. Chen (2005) proposed an extended logistic model, which is called the time-varying extended logistic model. The researcher use seven durable home appliance datasets to compare the fit and prediction accuracy of the Fisher-Pry model, the Gompertz model, and the time-varying extended logistic model. Chen concluded that the proposed extended logistic model had better fit and forecast performances while the Fisher-Pry can have fine fit performance when the product has reached 100% penetration rate. Chen also suggested that the Gompertz model should be used only when the right capacity can be correctly set. This research uses the model from Chen's study to demonstrate that the extended logistic model improved the forecast of both long and short lifecycle datasets.

Lackman (1993) reported that the simple logistic and the Gompertz models are suitable for forecasting high technology products. Morrison (1996) also showed that the simple logistic and the Gompertz models can be used to forecast the growth of new products. However, when the author applied the models, the upper limit was set subjectively. Bengisu and Nekhili (2006) used the simple logistic and the Gompertz models to predict emerging technologies using publications and patents from science and technology databases and Boretos (2007) used the simple logistic model to show that the diffusion of mobile phone technology follows an S-curve.

Meade and Islam (1995) compared seventeen growth models based on 25 time series datasets describing the telecommunications market. Their literature review shows that the simple logistic model is the most widely used. The authors conclude that basic forecasting models using two or three parameters, such as the simple logistic and Gompertz model, offer the best forecasting performance. Their research used datasets for traditional land-line telephones to compare forecasting models. However, the classic telephone introduced in the 1960s and which remained in use through the 1980s has a long product lifecycle that lasted over 30 years. When there are sufficient data points, the trajectory of the product growth curve is clear and the point of inflection can be calculated. If the point of inflection can be estimated, then the upper limit of the simple logistic and the Gompertz models can also be estimated. The simple logistic model is symmetric about the point of inflection. So if the inflection point is defined, the upper limit is twice the market share that occurs at the inflection point. For the Gompertz model, the point of inflection occurs at 37.79% of the upper limit and the upper limit can also be calculated when the inflection point is found. Bengisu and Nekhili (2006) showed that the simple logistic and the Gompertz models are quite valid if the upper limit is correctly identified. However, the data points may not be sufficient (too few) to see the point of inflection and to set the correct upper limit when forecasting short lifecycle products. Therefore, a model with more parameters, for example, the time-varying extended logistic model, is needed to project the trajectory of the growth curve. The time-varying extended logistic model uses a dynamic upper limit that can be estimated from the data.

2.3 Growth Curve Models

Most biological growth follows an S-shape curve or logistic curve which best models growth and decline over time (Meyer & Ausubel, 1999). Since the lifecycle of technology and technology based products is similar to biological growth, the growth curve models are used to capture the future development of the technology or products. There are many growth curve models, and Meade & Islam (1998) classify twenty-nine growth curve models into four categories: trend curve models, linearised trend models, nonlinear auto-regressive models, and hybrid models. However, the simple logistic and the Gompertz models are the two most applied models when forecasting the lifecycle of technology products. Nevertheless, the limitation of setting the correct upper limit for these two traditional models increases the difficulties of applying the models. Therefore, the extended logistic model with dynamic upper limit is introduced to see if this model can reach better performances in forecasting short lifecycle products than the two traditional models.

2.3.1 Simple logistic curve model

The simple logistic model is widely used for technology forecasting. Many new forecasting models were proposed based on the simple logistic model and include innovations such as the Bass diffusion model and extended logistic model (Meade & Islam, 1995). The most important characteristic of simple logistic model is that it is symmetric about the point of inflection. This feature indicates that the process which will happen after the point of inflection is the mirror image of the process that happened before the point.

The model for the simple logistic curve is controlled by three coefficients, a, b, and L is expressed as:

$$y_t = \frac{L}{1 + ae^{-bt}} \tag{1}$$

where y_t is the value of interest, L is the maximum value of y_t, a describes the location of the curve, and b controls the shape of the curve. To estimate the parameters for a and b, the equation of the simple logistic model is transformed into a linear function using natural logarithms. The linear model is expressed as:

$$Y_t = \ln(y_t / L - y_t) = -\ln(a) + bt \tag{2}$$

where the parameter a and b are then estimated using a simple linear regression. The simple logistic model (equation 1) and the linear model (equation 2) are quoted from Martino's book (Martino, 1993) and the derivations are shown in Appendix 1.

2.3.2 Gompertz model

The Gompertz model was first used to calculate mortality rates in 1825 and has been widely applied to technology forecasting (Martino, 1993). Although the Gompertz curve is similar to the simple logistic curve, it is not symmetric about the inflection point which occurs at $t = (\ln(b)/k)$. The Gompertz model reaches the point of inflection early in the growth trend and is expressed as:

$$y_t = Le^{-ae^{-bt}} \tag{3}$$

where L is the upper bound which should be set before estimating the parameters a and

b. Similar to the methodology of estimating the parameters of the simple logistic model, natural logarithms are used to transform the original Gompertz model to linear equation:

$$Y_t = \ln(\ln(L/y_t)) = \ln(a) - bt \tag{4}$$

and then the parameters are estimated (Martino, 1993). Equation (3) and equation (4) quoted from Martino's book and the derivations are shown in Appendix 2.

Although the predictive performance of the simple logistic model and the Gompertz model has been validated by many researchers (Meade & Islam, 1998), the models have definite limitations when used to forecast short product lifecycles. The reason is that it is almost impossible to estimate the correct upper limit for a new product when it is first introduced to market place.

Figure 2 depicts the importance of setting the correct upper limit in the simple logistic and the Gompertz models. As can been seen in Figure 2, curves A and B start at the same point but have different upper limits, L1 and L2. Since the upper limits are set at different level, the two curves are different, and the prediction results will also be different.

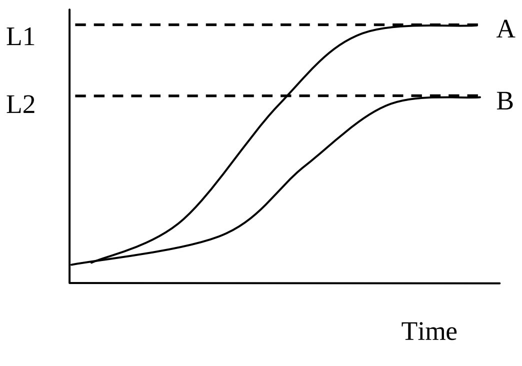


Figure 2 Curves with different upper limits

2.3.3 Time-varying extended logistic model

The simple logistic model and the Gompertz model assume that the capacity of technology adoption is fixed and there is an upper bound to growth for these models. However, the adoption of new technology is seldom constant and changes over time. Therefore, researchers have proposed a dynamic carrying capacity and the carrying capacity can be any function (Meyer & Ausubel, 1999; Cohen, 1995). As shown by Meyer & Ausubel (1999), the original form of simple logistic model is written as:

$$\frac{dy_t}{dt} = b \times L \times y_t \left(1 - {}^{y_t}\!/_{L}\right) \tag{5}$$

Let $\alpha = b \times L$ and replace the constant L in equation (5) with a function $k(t)$, and then the equation (5) is extended to:

$$\frac{dy_t}{dt} = \alpha \times y_t \left(1 - {}^{y_t}\!/_{k(t)}\right) \tag{6}$$

where L is the upper limit of the logistic curve and $k(t)$ is the time-varying capacity function similar to the logistic curve.

In Meyer and Ausubel's study, a special $k(t)$ was set to represent a technology which has a bio-logistic growth rate. Chen (2005) follows the concept of Meyer and Ausubel and proposes a time-varying extended logistic model with dynamic capacity $k(t)$. This thesis applies Chen's setting of $k(t)$ and uses the extended logistic model to forecast the future trend of technology product. The setting of $k(t)$ in Chen's is expressed as

$$k(t) = 1 - d \times e^{-ct} \tag{7}$$

and c and d are parameters that are estimated. Chen defines the value of d can be any number and the value of c is larger than zero. The research also assumes that the penetration rate capacity will fluctuate with time and may reach 100% but may also be as low as 30% or 50%. The reason for this assumption is that some new products may be introduced to the market and substitute older products. Thus, a product may not always achieve 100% market penetration and may be replaced earlier than expected.

Finally, the time-varying extended logistic model is expressed as:

$$y_t = \frac{k(t)}{1 + a \times e^{-bt}} = \frac{1 - d \times e^{-ct}}{1 + a \times e^{-bt}} \tag{8}$$

where $k(t)$ is the capacity that fluctuates with time, and a, b, c, and d are the parameters computed using a nonlinear least squared estimation method provided by a statistic software package like SYSTAT. When this model is tested using sales volume data, the equation is changed to:

$$N_t = m * y_t = m * \frac{1 - d \times e^{-ct}}{1 + a \times e^{-bt}} \tag{9}$$

where Nt is cumulative volume by time t, and the coefficient m represents the total market sales which is estimated using nonlinear least squares method.

The time-varying extended logistic model is similar to the Bass diffusion model which can be viewed as a special case of this model. The Bass model was developed for predicting sales volume, whereas the time-varying extended logistic model can be modified to predict sales volume as well as other proxies including market penetration rates. Therefore, the time-varying extended logistic model was selected for evaluation over the Bass model.

There is little published research which compares the performance of forecasting models used on both long and short product lifecycle datasets. Thus, to see if the time-varying extended logistic model with dynamic upper limit has better fit and prediction results over the simple logistic and the Gompertz models, this study applies

Chen's time-varying extended logistic model and compares the performance of the three models. Moreover, based on the comparison results, this research outlines the pros and cons of the three models and proposed a models selection chart to provide a suggestion of applying the three forecasting models.

3. Methodology

This chapter presents the methodology used in this study, including the data collection and setting, the analytical process for comparing the fitting and predicting performances of forecasting models, and the proposed model selection procedure.

3.1 Data Collection

Twenty-two time-series datasets describing Taiwan penetration rate and cumulative sales volume of electronic products were collected to test the forecast accuracy of the simple logistic model, the Gompertz model and the time-varying extended logistic model. In order to see what kinds of products can be fitted and forecasted by the three models, the datasets are not pre-selected. The datasets for market penetration rates were providing by the Directorate General of Telecommunications and Chunghwa Telecom Co. (2007) and the Directorate General of Budget (2007). The market penetration rate datasets cover six products including color TVs, telephones, washing machines, Asymmetric Digital Subscriber Lines (ADSL), mobile Internet subscribers, and broadband networks. The cumulative sales volume datasets were provided by the Taiwan Market Intelligence Center (2007). These datasets cover sixteen products including LCD-TV, 19 inch LCD monitors, digital cameras with Charge Coupled Device image sensors (CCD DC), digital cameras with more than 5 million pixels (DC >5m), 802.11g wireless local area networks devices (WLAN 802.11g), cable modems, combo optical disk drives (combo ODD), Barebone computers (Barebone), China personal wireless access systems (China PAS), LCD panels for TV, LCD panels for notebooks, color mobile phones with 65K pixels (color-65k mobile phone), servers, over 30 inch wide LCD-TVs (LCD-TV >30”), Voice over Internet Protocol Integrated Access Devices (VoIP IAD), and Voice over Internet protocol (VoIP) routers.

3.2 Data Settings

As shown in Table 1, the estimated sample period, predicted sample period, and sample sizes are presented. The data for color TVs, telephones and washing machines are yearly data points. Since the sample period for these data is greater than 30 years, these products depict a complete product life cycle (Figure 3). This research classifies the data for color TVs, telephones and washing machines as long product lifecycles with large datasets for forecasting. The other datasets (ADSL, mobile Internet subscribers, etc.) represent products rapidly brought to market and are categorized as short lifecycle products with limited or small (less than 30 data points) datasets for forecasting. Table 2 lists the detail data of cumulative sales volume dataset.

Figure 3 shows the penetration rate for the six products and Figure 4 shows the cumulative sales volume for the sixteen short lifecycle products. Figure 3 shows that color TVs, telephones, and washing machines have entered the mature stage of the product life cycle. Therefore, a clear upper limit for these products can be set. On the other hand, the curves for ADSL, mobile Internet subscribers, and other short lifecycle products are still evolving, making it difficult to define the stage of product life cycle or to predict when these products will stop growing.

For the long product lifecycle datasets, the upper limit is set at 100%. For the short product lifecycle datasets, different upper limits are set to achieve the best estimates. The possible upper limit for the short lifecycle is set at 3 different levels to include optimistic, a conservative, and a pessimistic settings. An optimistic upper limit means that the product is new to the market and has potential to grow. A pessimistic setting means that the product almost reached the upper limit to market growth. Between the optimistic and pessimistic limits is the conservative setting. The conservative setting models a product that has been in the market for a while and has reached about one-third or one-half of the upper limits to growth.

Table 1 Estimated and predicted sample period and sample size

Proxy	Product	Estimated sample period		Predicted sample period		Sample size
		From	To	From	To	
Penetration rate	Color TV	1974	1999	2000	2004	31
	Telephone	1970	1999	2000	2004	35
	Washing Machine	1974	1999	2000	2004	31
	ADSL	2000Q2	2005Q2	2005Q3	2006Q3	26
	Mobile Internet	2001Q4	2005Q2	2005Q3	2006Q3	20
	Broadband networl	2000Q2	2005Q2	2005Q3	2006Q3	26
Cumulative sales volume	LCD-TV	2003Q1	2006Q1	2006Q2	2007Q2	18
	19”LCD monitor	2003Q1	2006Q1	2006Q2	2007Q2	18
	CCD DC	2003Q1	2006Q1	2006Q2	2007Q2	18
	DC >5m	2003Q1	2006Q1	2006Q2	2007Q2	18
	WLAN (802.11g)	2003Q1	2006Q1	2006Q2	2007Q2	18
	Cable Modem	2003Q1	2006Q1	2006Q2	2007Q2	18
	Combo ODD	2003Q1	2006Q1	2006Q2	2007Q2	18
	Barebones	2003Q1	2006Q1	2006Q2	2007Q2	18
	China PAS	2003Q1	2006Q1	2006Q2	2007Q2	18
	LCD panel for TV	2003Q1	2006Q1	2006Q2	2007Q2	18
	LCD panel for notebook	2003Q1	2006Q1	2006Q2	2007Q2	18
	Color-65k mobile phone	2003Q1	2006Q1	2006Q2	2007Q2	18
	Server	2003Q1	2006Q1	2006Q2	2007Q2	18
	LCD-TV >30”	2004Q1	2006Q2	2006Q3	2007Q2	14
	VoIP IAD	2004Q1	2006Q2	2006Q3	2007Q2	14
	VoIP router	2004Q1	2006Q2	2006Q3	2007Q2	14

Source: Directorate General of Budget, Directorate General of Telecommunications and Chunghwa Telecom Co. (2007), and Market Intelligence Center Taiwan (2007).

Table 2 Cumulative sales volume dataset

Sample period	Products: LCD-TV	19”LCD monitor	CCD DC	DC >5m	WLAN (802.11g)	Cable Modem	Combo ODD	Barebone	China PAS	LCD panel for TV	LCD panel for notebook	Mobile color-65k	Server	LCD-TV >30”	VoIP IAD	VoIP Router
2003Q1	26.900	49.921	1540.638	33.759	56.588	1752.000	2946.440	2300.000	3815.000	25.340	2559.158	390.000	410.000			
2003Q2	63.100	389.660	3706.334	132.559	215.973	3614.000	5230.362	4720.000	9096.000	97.940	4956.234	490.000	850.000			
2003Q3	164.100	763.660	6537.814	302.049	500.027	5379.000	8882.726	7229.000	14799.000	359.369	8059.782	2893.000	1295.000			
2003Q4	407.500	1245.868	9196.234	602.352	958.930	7552.000	12461.777	10677.000	21275.000	795.749	11955.402	7557.000	1792.000			
2004Q1	787.500	2173.868	12021.892	1159.524	1572.550	9832.000	16351.273	14115.000	30759.000	1307.749	15826.702	11353.000	2295.000	84.000	425.000	30.800
2004Q2	1194.500	3273.868	15788.372	1905.414	2244.595	12385.000	20438.203	17378.000	39869.000	2280.749	19619.702	14937.000	2809.000	146.000	1055.200	68.800
2004Q3	1603.900	4025.868	20911.238	3480.309	3154.315	15865.000	26021.378	21389.000	48429.000	3207.749	23735.702	19398.000	3334.000	225.000	1869.500	267.600
2004Q4	2178.600	5417.368	25733.319	5189.401	4499.246	19520.000	32006.914	25943.000	55984.000	4821.049	28662.202	24106.000	3900.000	338.000	2739.500	769.300
2005Q1	2993.600	7735.268	30158.223	7221.865	5928.487	22604.000	36858.493	31263.000	62744.000	6606.549	33278.502	28003.000	4487.300	509.000	3698.500	1309.300
2005Q2	4059.600	10957.768	36820.687	10907.315	7716.311	26086.000	41830.072	36523.000	69737.900	9046.649	38795.202	32758.000	5083.605	781.000	4773.500	1923.300
2005Q3	5432.200	15307.768	45611.350	15795.081	9722.111	31326.000	47856.446	42451.000	76124.574	12112.899	44874.202	37099.000	5699.927	1219.000	6337.500	2345.300
2005Q4	7101.652	20404.988	55382.907	22373.650	12482.311	35912.000	53790.890	49106.000	81922.139	17078.509	52274.002	54268.000	6353.141	1712.000	8489.500	2661.300
2006Q1	8883.652	26032.988	63007.848	28958.121	14918.811	40315.000	58765.654	55533.000	85990.326	21967.809	59708.202	69451.000	7014.901	2403.000	11166.500	2967.300
2006Q2	10896.652	32548.245	71902.554	37172.826	17202.311	45434.900	64048.872	61134.000	89875.326	26745.219	67162.002	84473.000	7681.721	3284.000	13853.950	3471.300
2006Q3	13379.652	41731.245	83420.201	48149.297	19519.511	51546.900	68619.391	67911.000	93475.326	33127.219	74899.002	101103.000	8369.621	4330.000	16776.350	3880.300
2006Q4	16097.652	52201.245	94502.554	59281.062	21876.301	56997.900	73063.269	74853.000	96525.326	40059.219	83663.352	117994.000	9076.997	5505.000	19727.650	4178.300
2007Q1	18563.652	61755.245	102643.731	67488.821	24246.615	63382.900	76889.575	81808.000	99545.326	46143.219	92258.352	132689.000	9789.320	6699.000	22328.650	4575.300
2007Q2	21794.652	71821.525	114524.165	79399.864	26800.515	70106.900	81083.108	86487.000	102795.326	54545.239	102214.352	146140.000	10506.950	8355.000	25181.450	4836.300

Unit: thousand; Source: Market Intelligence Center Taiwan (2007)

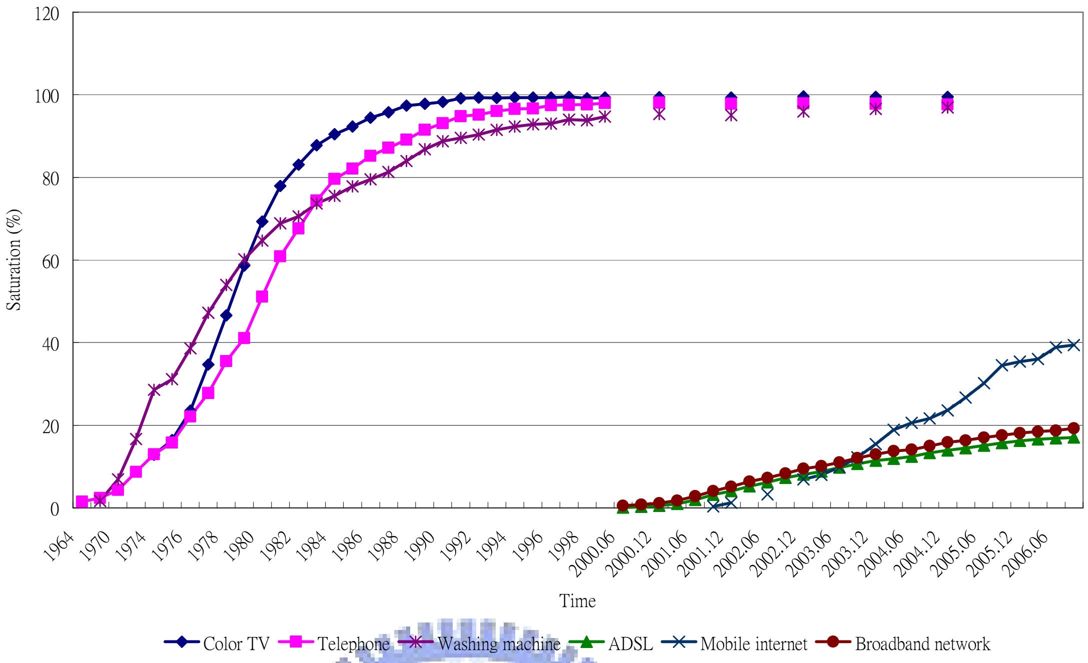


Figure 3 Market growth for saturation datasets

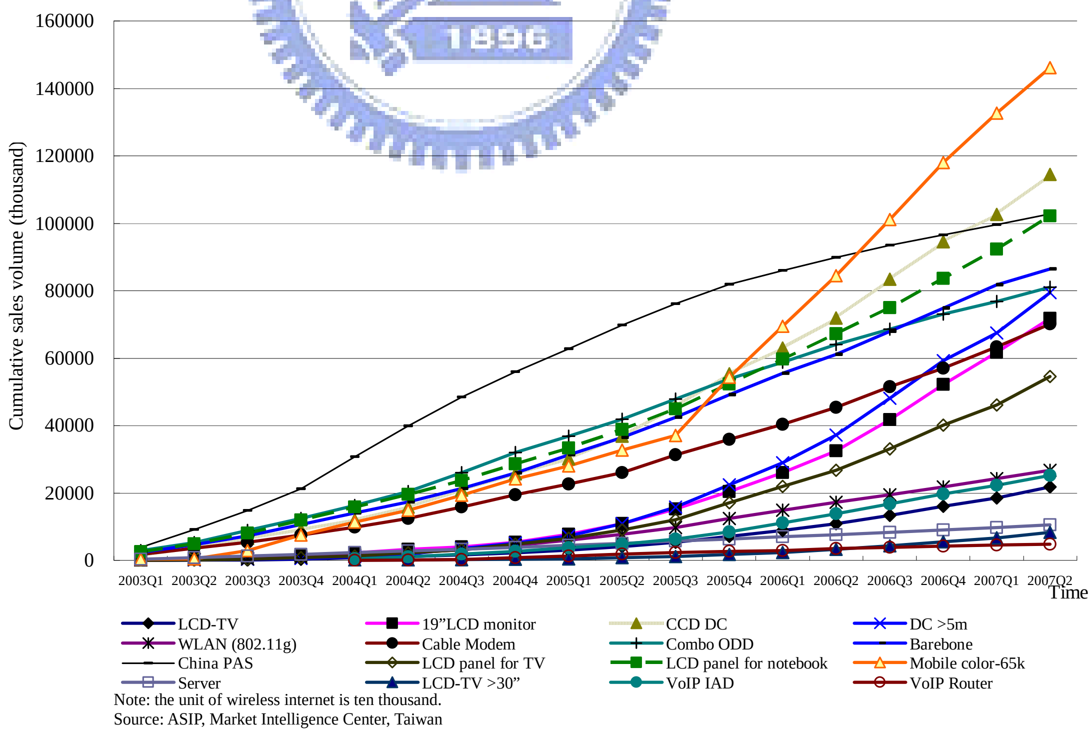


Figure 4 Market growth for cumulative datasets

The penetration rate datasets use upper limits of 100%, 50%, and 30%. However, since the current penetration rate of the mobile Internet is 40%, the pessimistic setting is change to 50% and conservative upper limit is changed to 60%. For the cumulative sales volume datasets, the upper limit is set based on the multiple of the most recent observation as recommended by Meade and Islam (1998). The optimistic, conservative, and pessimistic upper limits are 5 times, 3 times, and 1.5 times the most recent observation which is based on the cumulative sales volume of the second quarter in 2007. In fact, 5 times the most recent observation means that the proportion of the current cumulative sales volume to maximum sales volume (upper limit) is 20%. Thus, the current cumulative sales volume only reaches 20% of the upper limit and there is still 80% of the maximum sales volume remaining to sell. So the setting of 5 times the most recent observation is an optimistic setting. A pessimistic setting of the cumulative sales volume dataset is set at 1.5 times the most recent observation. Using the cable modem dataset as an example, the most recent cumulative sales volume is 70,106,900 units and the pessimistic upper limit is 105,160,350 units. This means that the current cumulative sales volume has already reached two-third of the upper limit and has entered the mature stage of the product lifecycle.

3.3 Model Comparison Analytical Process

In order to test the forecast accuracy of the simple logistic, Gompertz, and the time-varying extended logistic models, the analytical process is divided into two steps.

Step 1: Model estimation

The first step is used to estimate the models. After reserving the last five data points to test forecast accuracy of the simple logistic, Gompertz, and the time-varying extended logistic models, the remaining data points were used to fit the three models. For the simple logistic and the Gompertz model, equation (2) and (4) are used to estimate coefficients using a simple linear regression. For the time-varying extended logistic model, the coefficients of the models are estimated using nonlinear least squares with SYSTAT statistical software (Chen, 2003). After the coefficients were computed and the models fitted, the estimated values were calculated.

Step 2: Fit and forecast performance

After the models are constructed, the fit and forecast performance between the three models is conducted. The test consists of checking residuals between actual values and estimated values to measure model performance (Kurawarwala & Matsuo, 1996; Meyer & Ausubel, 1998). Two measurements, mean absolute deviation (MAD) and root mean square error (RMSE) are used to calculate residuals.

For the simple logistic and the Gompertz models, the upper limit must be set to obtain accurate results. Setting different upper limit levels of these two models will achieve different prediction results and the fit and predict performance will also be influenced. Thus, several upper limits of the simple and the Gompertz models were set to determine which upper limit would yield the best fit performance.

For forecast performance, the derived models are used to forecast the last five data points of the datasets. In this study, the Mean Absolute Deviation (MAD) and Root Mean Square Error (RMSE) are used to measure performance as recommended in the literature (Kurawarwala & Matsuo, 1996; Meyer & Ausubel, 1998; Islam & Meade, 1996). The mathematical representations are shown below:

$$MAD = \frac{\sum_{t=1}^{T} |y_t - \hat{y}_t|}{n} \tag{10}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T} (y_t - \hat{y}_t)^2}{n}} \tag{11}$$

where y_t is the actual value at time t, $\hat{y}_t$ is the estimate at time t, and n is the number of observations. These measurements are based on the residuals, which represent the distance between real data and predictive data. Consequently, if the values of these measures are small, then the fit and prediction performance is acceptable.

3.4 The Proposed Model Selection Procedure

According to previous literatures, this research proposed a decision chart for how to select a forecasting model among the simple logistic model, the Gompertz model and the time-varying extended logistic model. Figure 5 presents the decision flow for selecting the forecasting models. This study assume that the time-varying extended logistic model will have the best forecasting result, so it is firstly recommended for predicting the technology product life cycle. Extended logistic model can be used to forecast the future trend at the early lifecycle stage even when the point of inflection of the growth curve has not occurred. Young (1993) suggests that the predictors need to study the characteristics of datasets. Therefore, in Figure 5, the first step is to see if the cumulative quantity of the technology product can be drawn as an S-shape curve. If an

S curve is identified, then the time-varying extended logistic model can be applied, and if a convergent result can be reached with the extended logistic model, then the prediction process ends. However, since there are more parameters needed to be estimated in the time-varying extended logistic model, it may sometimes produce a non-convergent result. Thus, due to the characteristics and limitations of the extended logistic model, the data which can be plotted as an S-curve with more than fifteen data points is strongly recommended when using the extended logistic model. Besides, because the time-varying extended logistic model is developed based on S-curve, flat curves or curves with obvious jump are not suitable to be forecasted using extended logistic model.

Under the non-convergent condition, predictors can check whether the point of inflection of the S-curve has occurred or not. If an inflection point occurred, the capacity of the simple logistic and Gompertz models can be estimated, and then these two models can be applied. Therefore, researchers can select the simple logistic or the Gompertz models based on their understandings of the product and the market. My suggestion is that if the researchers think the market has more potential to develop in the future, then the Gompertz model is more suitable for that kind of products than the simple logistic model since the inflection point of the Gompertz model occurs at 37.79% of the upper limit, and there will be another 62.21% to grow. For the simple logistic model, it is a symmetric model and its point of inflection happens at the half of the curve, there will be only 50% potential to grow after the inflection point. Besides, when the analytical data is patent document data, the simple logistic model is suggested to use since it is the most applied model in the previous patent analysis literatures. However, if an inflection point has not occurred, the growth curve methods are not suitable for technology forecasting, and other technology forecasting methods, such as

Delphi, analogy forecast, trend extrapolation, correlation method, or scenario can be tried to use (Martino, 1993). This decision process will be demonstrated with a RFID case study presented in next chapter and the forecasting results will be verified with industrial experts to see if the proposed procedure has the validity.

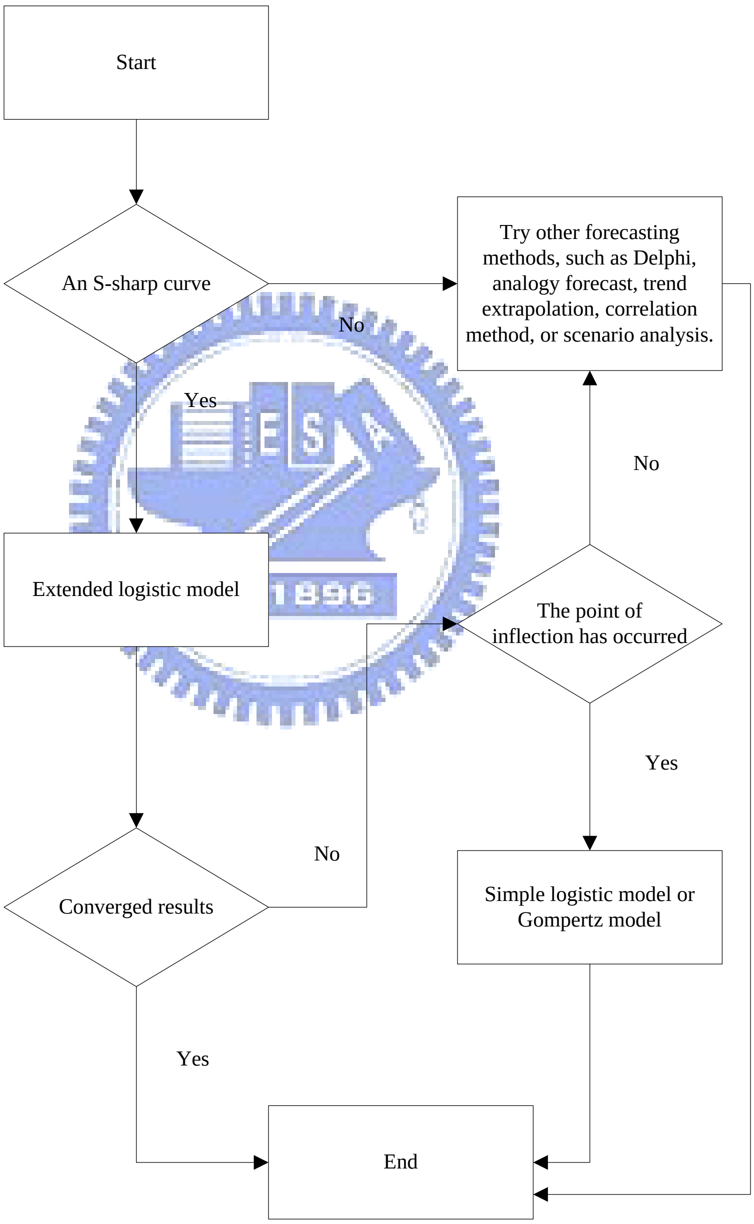


Figure 5 Decision chart for applying forecasting models

4. Comparison Results

This chapter discusses the comparison results for evaluating the simple logistic, the Gompertz, and the time-varying extended logistic models. The fit and forecast performances are evaluated by using Mean Absolute Deviation (MAD) and Root Mean Square Error (RMSE). A sign test is also performed to show that there are statistically significant differences for the comparison results to reach more precise conclusions. Finally, suggestions for applying the three models and a decision diagram for model selection are presented for future researchers.

4.1 Comparison of Performances

Table 3 and Table 4 provide the fit and forecast performance for the penetration data set. The evaluation rule is that the smaller the value for MAD and RMSE, the better the fit and prediction performance. As shown in the Table 3 and Table 4, the time-varying extended logistic model has the best fit and prediction for both long and short lifecycle products. Table 5 and Table 6 provide the fit and forecast performance for the cumulative sales volume data set. Table 5 shows that time-varying extended logistic model has the best fit performance for all products. Table 6 shows that the time-varying extended logistic model has the best forecast performance for the majority of the products.

Table 7 summarizes the comparative results of the time-varying extended logistic model, the simple logistic and the Gompertz models. The fit and forecast performance are compared and ranked using the root mean square error (RMSE) which is widely used for measuring the performance (Kurawarwala & Matsuo, 1996; Meyer & Ausubel, 1998; Cohen, 1995). As can be seen in Table 7 the time-varying extended logistic model has the best predictive performance for 13 products among the 18 products for which the model converged. The model has the second best predictive performance for 4 products, and the worst predictive performance for LCD-TV >30” data. The Gompertz model predicts best for 4 product datasets and has the second best forecast performance for three models. The simple logistic model only predicts well for the LCD-TV >30” data. In summary, the time-varying extended logistic model is 70% better in prediction than the other models.

Table 3 Fitting performance measures for the time-varying extended logistic, Gompertz, and the simple logistic models: penetration rate datasets

Model	Index	Color TV	Phone	Washing Machine	ADSL L=100%	ADSL L=50%	ADSL L=30%	Mobile Internet L=100%	Mobile Internet L=60%	Mobile Internet L=50% *	Broadband network L=100%	Broadband network L=50%	Broadband network L=30%
Extended logistic	MAD	**0.0053**	**0.0063**	**0.0098**		**0.0036**			**0.0057**			**0.0027**	
	RMSE	**0.0071**	**0.0083**	**0.0118**		**0.0043**			**0.0073**			**0.0032**	
Gompertz	MAD	0.0297	0.0290	0.0192	0.0154	0.0140	0.0102	0.0134	0.0077	0.0059	0.0146	0.0114	0.0075
	RMSE	0.0502	0.0440	0.0290	0.0228	0.0170	0.0119	0.0156	0.0094	0.0076	0.0176	0.0132	0.0084
Simple logistic	MAD	0.0361	0.0323	0.0276	0.0329	0.0274	0.0212	0.0337	0.0256	0.0217	0.0243	0.0075	0.0153
	RMSE	0.0551	0.0453	0.0384	0.0483	0.0372	0.0264	0.0439	0.0304	0.0248	0.0328	0.0084	0.0180

Note: L: upper limit

*The current saturation rate of mobile Internet is over 30%

Boldface number means the best performance among three models.

Table 4 Forecasting performance measures for the time-varying extended logistic, Gompertz, and the simple logistic models: penetration rate datasets

Models	Index	Color TV	Phone	Washing Machine	ADSL L=100%	ADSL L=50%	ADSL L=30%	Mobile Internet L=100%	Mobile Internet L=60%	Mobile Internet L=50% *	Broadband network L=100%	Broadband network L=50%	Broadband network L=30%
Extended Logistic	MAD	**0.0025**	**0.0049**	**0.0021**		**0.0140**			**0.0117**			**0.0036**	
	RMSE	**0.0026**	**0.0057**	**0.0034**		**0.0147**			**0.0152**			**0.0041**	
Gompertz model	MAD	0.0042	0.0125	0.0095	0.1037	0.0671	0.0345	0.0627	0.0132	0.0146	0.0842	0.0531	0.0237
	RMSE	0.0043	0.0130	0.0100	0.1060	0.0688	0.0352	0.0699	0.0154	0.0166	0.0867	0.0545	0.0243
Simple Logistic model	MAD	0.0045	0.0171	0.0140	0.2846	0.1688	0.0833	0.2397	0.0991	0.0503	0.1895	0.1185	0.0556
	RMSE	0.0046	0.0174	0.0143	0.2933	0.1716	0.0839	0.2503	0.1021	0.0518	0.1958	0.1210	0.0562

Note: L: upper limit

*The current saturation rate of mobile Internet is over 30%

Boldface number means the best performance among three models.

Table 5 Fitting performance measures for the time-varying extended logistic, Gompertz, and the simple logistic models: cumulative shipment volume data

Model	Saturation specification	Index	LCD-TV	19”LCD monitor	CCD DC	DC >5m	WLAN 802.11g	Cable Modem	Combo ODD	Barebones	China PAS	Panel for TV	LCD-TV >30”	VoIP IAD
Extended logistic		MAD	***51***	***167***	***451***	***161***	***586***	***207***	***435***	***165***	***398***	***147***	***11***	***82***
		RMSE	***58***	***212***	***593***	***188***	***772***	***282***	***538***	***184***	***483***	***182***	***15***	***100***
Gompertz	5*2007Q2 volume	MAD	192	364	1314	205	3219	1022	2204	1412	12717	430	54	199
		RMSE	268	434	1542	274	4634	1293	2802	1740	14616	579	82	222
	3*2007Q2 volume	MAD	141	412	998	297	2026	770	1696	1036	12298	305	70	198
		RMSE	174	495	1120	440	2637	927	2095	1208	14041	412	104	224
	1.5*2007Q2 volume	MAD	134	13488	989	582	2026	354	678	553	2762	401	99	314
		RMSE	172	15179	1226	954	2510	443	740	655	3357	575	143	386
Simple logistic	5*2007Q2 volume	MAD	900	1958	3853	2461	14679	2484	4570	3543	14105	2445	65	660
		RMSE	1767	3925	5931	5439	27124	3656	6438	5080	16670	4943	119	1021
	3*2007Q2 volume	MAD	823	1803	3487	2238	13007	2259	4076	3170	9084	2231	54	588
		RMSE	1569	3521	5160	4842	23147	3213	5542	4390	11961	4371	98	875
	1.5*2007Q2 volume	MAD	656	1456	2615	1744	9414	1705	2820	2270	6280	1773	29	423
		RMSE	1148	2635	3440	3562	14974	2187	3478	2817	7605	3182	49	551

Note: Boldface number means the best performance among three models.

Table 6 Forecasting performance measures for the time-varying extended logistic, Gompertz, and the simple logistic models: cumulative shipment volume data

Model	Saturation specification	Index	LCD-TV	19”LCD monitor	CCD DC	DC >5m	WLAN 802.11g	Cable Modem	Combo ODD	Barebones	China PAS	Panel for TV	LCD-TV >30”	VoIP IAD
Extended logistic		MAD	***265***	6072	***923***	10068	12030	***2253***	***1878***	***2040***	***3115***	5217	497	1342
		RMSE	***301***	7758	***1157***	12434	***12505***	***2911***	***2029***	***2153***	***3305***	5846	734	1740
Gompertz	5*2007Q2 volume	MAD	1820	***2372***	11176	***1813***	63530	7910	23077	14504	16194	5076	583	1548
		RMSE	1913	***2706***	12062	***2303***	69259	8238	24689	15519	20024	5433	697	2034
	3*2007Q2 volume	MAD	280	6805	3223	5194	32902	3396	15549	7971	11017	***604***	887	***302***
		RMSE	360	7814	3452	5582	35553	3419	16541	8421	13492	***703***	1077	***403***
	1.5*2007Q2 volume	MAD	2707	13488	9608	14066	***11484***	4205	2651	3031	14329	6885	1364	2069
		RMSE	3116	15179	10662	15342	12692	5052	2764	3530	14703	7865	1668	2426
Simple logistic	5*2007Q2 volume	MAD	26450	64846	70320	104201	365213	36609	61892	53560	43670	78644	2433	11727
		RMSE	29106	72596	76969	116523	396302	39564	66579	58014	51122	86272	3142	14568
	3*2007Q2 volume	MAD	17740	44268	50134	68273	241342	26680	44945	38728	78007	51581	1643	8250
		RMSE	18836	47682	53567	73370	254235	28212	47516	41109	81173	54536	2060	10020
	1.5*2007Q2 volume	MAD	6734	16090	16953	25192	86925	9222	16668	13437	29775	19611	***295***	2516
		RMSE	6786	16182	17113	25473	87717	9271	17002	13582	30183	19761	***356***	2881

Note: Boldface number means the best performance among three models.

Table 7 Fitting and forecasting performance ranks of the extended logistic, Gompertz, and the simple logistic models

Product	Fitting			Forecasting		
	Extended logistic	Gompertz	Simple logistic	Extended logistic	Gompertz	Simple logistic
Color TV	1	2	3	1	2	3
Phone	1	2	3	1	2	3
Washing Machine	1	2	3	1	2	3
ADSL	1	2	3	1	2	3
Mobile Internet	1	2	3	1	2	3
Broadband network	1	3	2	1	2	3
LCD-TV	1	2	3	1	2	3
19”LCD monitor	1	2	3	2	1	3
CCD DC	1	2	3	1	2	3
DC >5m	1	2	3	2	1	3
WLAN (802.11g)	1	2	3	1	2	3
Cable Modem	1	2	3	1	2	3
Combo ODD	1	2	3	1	2	3
Barebones	1	2	3	1	2	3
China PAS	1	2	3	1	2	3
LCD panel for TV	1	2	3	2	1	3
LCD-TV >30”	1	3	2	3	2	1
VoIP IAD	1	2	3	2	1	3

Note: 1 means the model with the lowest RMSE and best performance

For the Gompertz and the simple logistic models, the capacity with the lowest RMSE is compared.

4.2 Test of the Comparison Results

In order to test whether the root mean square error of the time-varying extended logistic (RMSEei) is smaller than error of the simple logistic (RMSEsi) and Gompertz (RMSEgi) models, we first calculate the statistics RMSEei-RMSEsi and RMSEei-RMSEgi. Then these statistics are used to test the null hypotheses that RMSEei=RMSEsi (H0a) and RMSEei=RMSEgi (H0b) using one-tail sign test. The reason why the one-tail sign test is chosen is because the distribution of RMSE is unknown and the sample size is small, so a nonparametric test is used. A sign test only needs a count of the number of sample value exceeding a defined constant which is equal to zero in this case (Sprent & Smeeton, 2007).

Table 8 presents the P-values for the fit and forecast performance between the time-varying extended logistic model, the simple logistic model and the Gompertz model. As shown in Table 8, all P-values of sign test are smaller than 0.05, which means there are statistically significant differences among the three models at the 95% level. Further, the time-varying extended logistic model outperforms than the simple logistic and Gompertz models in both fit and forecast performance.

Table 8 The P-value of sign test

	Fitting performance	Forecasting performance
$H0_a$: $RMSE_{ei}=RMSE_{si}$ $H1_a$: $RMSE_{ei}<RMSE_{si}$	0.0000***	0.0001***
$H0_b$: $RMSE_{ei}=RMSE_{gi}$ $H1_b$: $RMSE_{ei}<RMSE_{gi}$	0.0000***	0.0482***

Note: The equation for P-value of one-tail sign test can be expressed as:

P-value of sign test= $\sum_{k=0}^{s^+}\binom{n'}{k}(0.5)^{n'}$

Where

S^+= the number of $RMSE_{ei}$> $RMSE_{si}$ (or $RMSE_{gi}$)

n'= the number of ($n-S^0$)

n= sample size

S^0= the number of $RMSE_{ei}$= $RMSE_{si}$ (or $RMSE_{gi}$)

$RMSE_{ei}$= the RMSE value of time- varying extended logistic model

$RMSE_{si}$: the RMSE value of the simple logistic model

$RMSE_{gi}$: the RMSE value of the Gompertz model

***: 95% significant level

4.3 Suggestions for Applying Forecasting Models

Based on the comparison and sign test results, the time-varying extended logistic model statistically significant outperforms than the simple logistic and Gompertz models. Since the time-varying extended logistic model uses more parameters to capture the trend of products, the fit and forecast performance are improved. This research used 22 product datasets to test the performance of the simple logistic, the Gompertz and the time-varying extended logistic model. However, the datasets for LCD panel for notebooks, color-65k mobile phones, servers, and VoIP routers, would not converge when using the time-varying extended logistic model to estimate the coefficients. A similar situation was reported by Meade and Islam (1998). Their research used 25 telecommunications market datasets to compare the performance of seventeen growth curve models. For their study, half of the datasets would not converge when estimating the coefficients of models. Our study showed four products would not converge among 22 products yielding a proportion less than 20%. Therefore, our convergence results are consistent with earlier research.

The four products with data that would not converge provide some insight. These datasets are linear and the curve for the color-65k mobile phone has an obvious jump (Figure 4). Meade and Islam's (1995) research used telephone data from Sweden to compare the simple logistic, extended logistic, and the local logistic models. They concluded that the extended logistic model had the worst performance. Although the setting of the extended logistic model is different with this research, Meade & Islam's study serves as a useful example. The growth curve of the Swedish telephone data set is linear. Therefore, the time-varying extended logistic model should not have been used. If forecasters wish to apply the time-varying extended logistic model, then they should confirm that the data has an S-shape prior to the forecast.

When using the simple logistic and Gompertz models, the upper limit (L) must be set and then a linear transformation method is applied to calculate parameters using equation (2) and (4). Since only two parameters are estimated, it is easy for the models to converge. However, since the upper limit of the time-varying extended logistic model is dynamic with time, more parameters are needed to capture the trace. Therefore, the linear transformation method used in the simple logistic and Gompertz models cannot be used to estimate the parameters and a nonlinear estimation method must be used. For the cumulative sales volume dataset, five parameters are estimated using nine to thirteen data points which causes an increase in non-convergence for the extended logistics model. Therefore, this research suggests there should be at least fifteen data points in a database to apply the time-varying extended logistic model to reduce the probability of non-convergence.

The problem of the simple logistic and the Gompertz models is because they are limited by the characteristic and the shape of the growth curve. For example, the simple logistic curve is symmetric about the point of inflection, so if the current data points have not reach the point of inflection of the growth curve, then the upper limit can not be estimated and the simple logistic does not predict well. The Gompertz curve is an asymmetric S-curve and the Gompertz model reaches the inflection point before the market penetration has reached half the upper limit (Meade &Islam, 1998). Thus, the Gompertz model may be more suitable for certain types of short lifecycle products than the simple logistic model. As shown in Table 4 and Table 6, the different capacity setting will lead to different forecasting results, and the wrong capacity will lead to an error in prediction. If industrial policy or enterprise decisions are made based on a model using the wrong upper limit, a serious forecast error can be made. However, if the point of inflection of the growth curve has occurred, the maximum value can be estimated based on the characteristics of the simple logistic and the Gompertz models and then these two models can also be good forecasting models. Based on the discussions, a comparison for the pros and cons of the three models applied in this research is presented in Table 9. Table 9 also outlines the model setting, characteristics, and the timing for applying the three models.

Table 9 The comparison of the time-varying extended logistic, Gompertz, and the simple logistic models

	Extended logistic model	Simple logistic model	Gompertz model
Model setting	$y_t = \frac{k(t)}{1+a\times e^{-bt}} = \frac{1-d\times e^{-ct}}{1+a\times e^{-bt}}$	$y_T = \frac{L}{1+ae^{-bt}}$	$y_t = Le^{-ae^{-bt}}$
Characteristics	• The upper limit is dynamic with time	• Symmetric about the point of inflection • The point of inflection occurs at half of the upper limit	• Asymmetric about the point of inflection • The point of inflection occurs at 37.79% of the upper limit
Pros	• A time-varying upper limit • Suitable for predicting both long and short lifecycle products at early stage	• Only two parameters to estimate, so it is easy to apply • Suitable for long historical data	• Only two parameters to estimate, so it is easy to apply • Suitable for long historical data
Cons	• Can be used to the data with an S-shape curve • More parameters needed	• Need a clear upper limit setting before forecasting	• Need a clear upper limit setting before forecasting
When to apply	• The point of inflection has not occurred and the dataset has more than fifteen data points • An S-shape curve (no obvious jumps or a flat curve)	• The extended logistic model cannot reach convergent results • The point of inflection occurred	• The extended logistic model cannot reach convergent results • The point of inflection occurred
Note	• Can shorten the time interval of data to create more data points		

5. Case Study of China Radio Frequency Identification Patent Analysis

After evaluating the predicting performances of the time-varying extended logistic, the simple logistic and Gompertz models, a decision diagram for selecting the forecasting models has been validated. Although the decision diagram is tested with product lifecycle, the growth curve models can be applied to forecast both product lifecycle and technology lifecycle according to Nieto, Lopez, and Cruz (1998). Moreover, patent can serve as important indictors for technology development and can be used to explore the technology lifecycle (Ernest, 1997). Therefore, this chapter takes China patent applications for Radio Frequency Identification (RFID) as a case study to demonstrate how to apply this decision diagram to choosing a suitable model. Besides, this case will also explain how to apply a forecasting model to map the future trend of the technology. Section 5.1 introduces the background of RFID industry first and section 5.2 describes patent technology forecasting and the model selection procedure. Section 5.3 presents the results of China RFID patent analysis and section 5.4 provides the future development of China RFID industry.

5.1 RFID Industry Introduction

Radio Frequency Identification (RFID) tags are small silicon microchips (often less than one centimeter) designed as wireless identification systems to store and broadcast information while tracking things or people. RFID tags equipped with an antenna send information to readers which can be placed hundreds of meters away. RFID technology has a wide range of applications including retail inventory management, drug security, customer service, national defense, and health care (Want, 2006). RFID greatly reduces management and labor cost and enhances the efficiency and security of business processes by adding a "voice" to the objects it is attached to. The barcode is being replaced by RFID technology and this substitution has increased the demand for related market applications, products, and services.

Since RFID automatically broadcasts signals, it facilitates a myriad of processes such as inventory control, delivery, pricing, product recall, and real time accounting (Taghaboni-Dutta, & Velthouse, 2005). Thus, the retail and logistics industries have accepted RFID technology as an important means to monitor, manage, and control business processes (Walton, 2005). For example, BEA Systems (2006) predicted that Wal-mart would save up to US$8.35 billion per year after building RFID capabilities into their supply chain. IDTeckEx reported that the global market scale for RFID products and systems was US $4.93 billion in 2007 and US $5.29 billion in 2008. The products and systems include tags, readers, software and services for RFID cards, labels, and chips. ABI Research (2008) estimates that global RFID expenditures will exceed US $8.49 billion in 2012 with the Asia-Pacific region to become the largest user of RFID tags. Clampitt (2005) also claims that China will be the largest potential RFID market of the world. Figure 6 shows the RFID global market distribution in 2008 with China and the US leading the other countries in this technology.

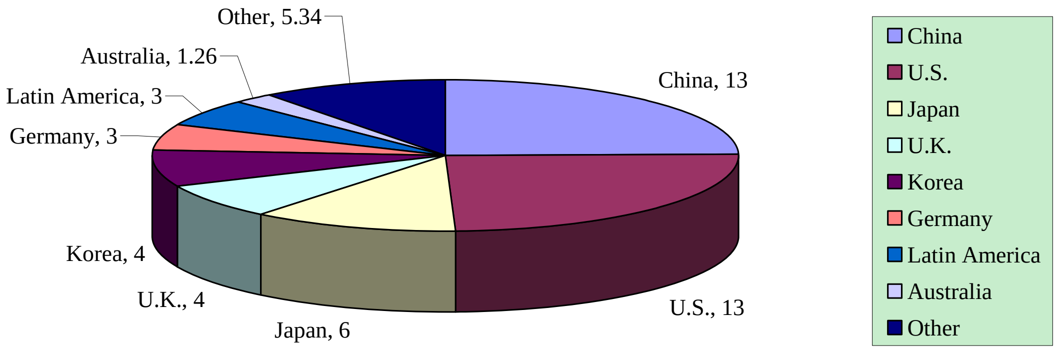
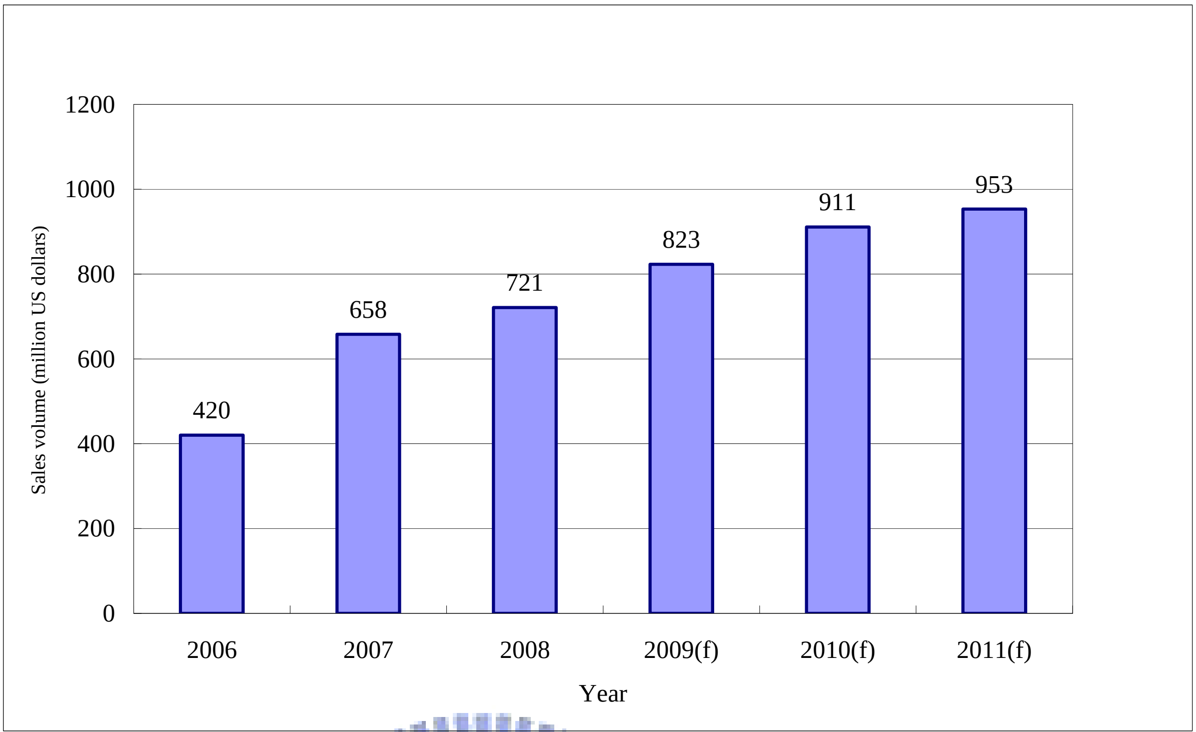


Figure 6 RFID global market distribution in 2008
(by country, billion U.S. dollars)

In 2008, China's Gross Domestic Product experienced a growth of 9% (Ma, 2009) and was the global leader in receiving foreign direct investment (Hussain & Fernandez, 2005). China is widely recognized as an important player in this high-tech industry (Radjou, 2005), requiring the investors to better understand the marketplace and players before committing investments. China RFID technology was first deployed in the transportation industry and included rail car and freight container identification systems, entrance guard systems, parking lot control systems, and highway toll systems. Research by Wu et al. (2007) showed that the efficiency of global supply chain and the domestic logistics infrastructure and manufacturing operations would increase if China's manufacturers placed more RFID tags on pallets and cases. Figure 7 illustrates the scale of China's RFID market for the years 2006 to 2008 and forecasts the sales volume for the years 2009 to 2011.

In this case study, patent content analysis is applied to the patent data from the State Intellectual Property Office of the People's Republic of China (SIPO) to better understand China's RFID industry development and trends.



Data Source: ICT Country Report, MIC, July 2008.

Figure 7 2006-2011 RFID market scale of China

5.2 Patent Technology Forecasting

Patents contain detailed specifications used to define and protect the legal use boundaries of an invention. Through patent analysis, companies can monitor the development of a technology and evaluate the position of potential competitors in the market. Since patents provide exclusive rights and legal protection for inventors, patents play an important role in the development and fair diffusion of technology. This case study uses patent content analysis to map the current RFID technology development trends in China. The methodology first clusters patent documents into homogenous groups and then applies a technology forecasting model to evaluate possible market opportunities for new patent research and development.

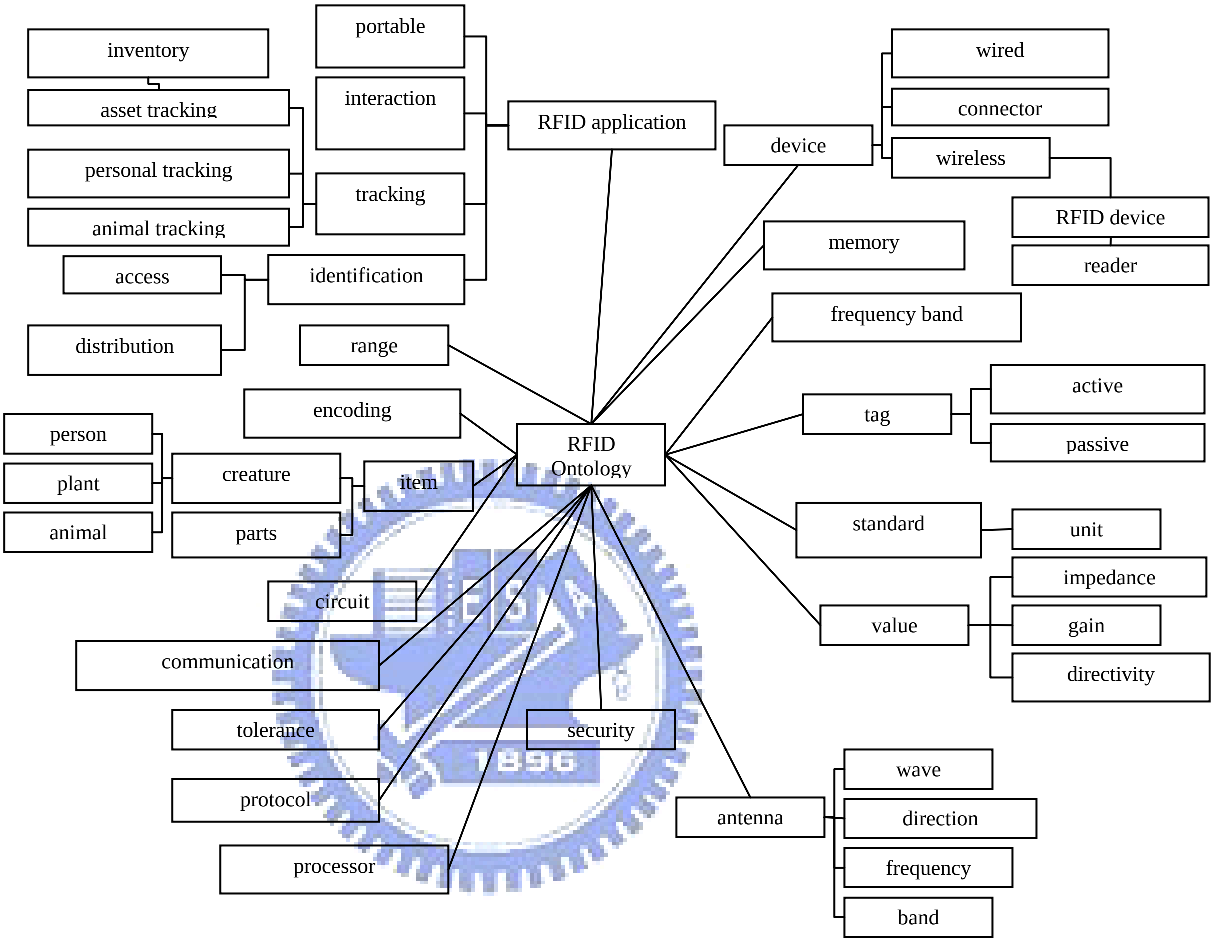
5.2.1 Technology and patent document clustering

Clustering is widely used for text mining, pattern recognition, webpage analysis, and marketing analysis (Berkhin, 2002; Chen et al., 2005). Clustering is used to separate a heterogeneous population into a number of homogeneous subgroups without predefined classes (Berry & Linoff, 1997). The purpose of clustering is to select elements that are as similar as possible within groups but as different as possible between groups. Groups are clustered based on entities' similarity according to specified variables and the meanings of clusters depend on the context of the analysis. In this research, the clustering technique proposed by Hsu (2006) has been used to extract clusters from China RFID patent documents. The process includes data preprocessing and key phrase extraction, key phrase correlation measure, patent technology clustering and patent document clustering. Since Hsu used English patent documents, some of the processes are modified to accommodate Chinese language patent analysis.

Step 1: Data preprocessing and key phrase extraction

Patent document key phrase extraction requires preprocessing the patent documents into a standard format. The standard format is created by removing the spaces between words and phrases. Then, word processing software is used to count the frequencies of words and phrases. Ontology serves as the specification of related concepts used to extract meaningful words and phrases from the patent document. Since the ontology is domain specific, experts must define the key words and phrases related to the patent concepts. Then, the concept related key words and phrases of the patent document are extracted for analysis. The frequency of these key words and phrases are used as input for patent technology clustering.

The RFID ontology tree for this research is a modification of the tree originally defined by Pitzek (2005). Since the RFID patent documents downloaded from SIPO use simplified Chinese characters, the 46 English phrases of the original ontology were translated into Chinese. Figure 8 shows the ontology, and the simplified and traditional Chinese character translations for the Chinese language RFID ontology tree are presented in Appendix 3.



Source: modification from Pitzek (2005)

Figure 8 RFID technology ontology tree

Step 2: Key phrase correlation measures

The key phrase extraction generates a list of important phrases from each patent document which is then used to form logical link between ideas and methodologies. Hsu (2006) and Hsu et al.'s (2006) algorithm uses four stages for key phrases analysis. First, the patent document is transformed into a key phrases vector by analyzing the frequency of the key words and phrases. Second, by eliminating redundant phrases, the key phrase frequency vector is derived. Third, the correlation values between key phrases are computed as shown in Formula (12). Finally, the number of different key phrases occurring in the document is used to derive the correlation coefficients as shown in Table 10.

$$R_{ij} = \frac{\sum_{l=1}^{N_D} X_{i,l} X_{j,l} - N_D \overline{X}_i \overline{X}_j}{\sqrt{\left(\sum_{l=1}^{N_D} X_{i,l}{}^2 - N_D \overline{X}_i{}^2\right)\left(\sum_{l=1}^{N_D} X_{j,l}{}^2 - N_D \overline{X}_j{}^2\right)}}, \tag{12}$$

where N_D is the total number of documents and $X_{i,l}$ is the number of key phrase I occurring in document D_l

Table 10 Key phrases correlation matrix

	KP_1	KP_2	KP_3	…	KP_n
KP_1	$R_{1,1}$	$R_{1,2}$	$R_{1,3}$	..	…
KP_2	$R_{2,1}$	$R_{2,2}$	…	…	…
KP_3	$R_{3,1}$	…	…	…	…
…	…	…	…	…	…
…	…	…	…	…	…
KP_n	…	…	…	…	…

Step 3: Patent technology clustering

Once the key phrase correlation matrix is derived, it is used for patent technology clustering. The key phrase correlation matrix is the input for the clustering algorithm and represents the technology contained in the patent documents. By applying the key phrases correlation matrix as input, the K-means algorithm generates patent technology clusters. Patent technology clusters provide insight into the relationships between patents.

Step 4: Patent document clustering

Patent document clustering, unlike technology clustering which clusters technology represented by key phrases, splits many documents into groups according to the similarity between documents. Using the K-means algorithm, the technology clusters which are generated from the correlation matrices are then used as the key variables to cluster patent documents. As shown in Table 11, the matrix is constructed as an input for patent document clustering. Patent document clustering derives the internal relationship based on the key aspects of the technologies and groups patents that are within the same technology field. In addition to generating the characteristic of each patent document cluster, the frequency of each key phrase (KP) appearing in each patent cluster is calculated as shown in Table 12. The KP_n is the representative phrase of the patent cluster TC_M if F_{nM} is the largest frequency in TC_M. For example, if F_{12} is the largest frequency among TC_1 to TC_M, then KP_1 is the representative phrase of TC_2.

Table 11 The matrix of patent documents with M patent clusters

	Patent $_1$	Patent $_2$	Patent $_3$	…	Patent $_N$
TC_1	N_{11}	N_{12}	N_{13}	…	N_{1N}
TC_2	N_{21}	N_{22}	N_{23}	…	N_{2N}
TC_3	N_{31}	N_{32}	N_{33}	…	N_{3N}
.	.	.	.	…	.
.	.	.	.	…	.
TC_M	N_{M1}	N_{M2}	N_{M3}	…	N_{MN}

Notation: $N_{ij} = \sum_{m=1}^{N(KP_i)} KPF_m$, where $N(KP_i)$ is the number of key phrases (belonging to technology cluster i) that are included in patent j and KPF_m is the frequency of the key phrase m (belonging to technology cluster i) of the document j. TC_M: Total Patent cluster $_M$.

Table 12 The frequency of key phrase in M patent clusters

	TC_1	TC_2	TC_3	…	TC_M
KP_1	F_{11}	F_{12}	F_{13}	…	F_{1M}
KP_2	F_{21}	F_{22}	F_{23}	…	F_{2M}
KP_3	F_{31}	F_{32}	F_{33}	…	F_{3M}
.	.	.	.	…	.
.	.	.	.	…	.
KP_n	F_{n1}	F_{n2}	F_{n3}	…	F_{nM}

5.2.2 Patent technology forecasting

Patents are important indicators that can be used to explore technological trends and development (Campell, 1983; Ernst, 1997; Anderson, 1999). Ernest (1997) states that patent applications are easily retrieved and can measure the impact of R&D activities. Anderson (1999) suggests that the accumulations of patents are useful for measuring technology trends and reflect the diffusion of the technology. Therefore, in this case study, cumulative patent applications are used for forecasting future RFID technology development trends. Patent application volume reveals the maturity of a new technology and can be viewed as shared knowledge. If the volume of patent applications is growing, then there are many resources creating the technology and the innovation. In such cases the technology may soon reach its peak. On the other hand, if the volume of applications is declining, then the technology may be is in the processes of being substituted by a new technology and thus entering the decline stage of the technology life cycle. Using forecasting models, one can forecast how many patent applications will be submitted in the future.

The most common technology forecasting model is the S-curve which is used to model product life cycles (Levary & Han, 1995; Meade & Islem, 1995; Meade & Islem, 1998; Meyer & Ausubel, 1999). In this thesis, a decision diagram of selecting predicting model among the time-varying extended logistic, the simple logistic and Gompertz models is presented. Based on the decision diagram proposed in Figure 5, the step one is to check if the cumulative volume of patent application can be plotted as an S-curve. If so, the time-varying extended logistic model will be firstly applied to forecast the future trend of China RFID patent applications. If the data points are enough to produce a convergent result with the time-varying extended logistic model, the procedure is end. However, if a convergence results could not be reached, then we have to check whether the point of inflection has occurred or not. If the inflection point appears, then the simple logistic or the Gompertz models can be selected based on the researchers' understands about the market. In this case study, cumulative patent application volume is modeled as an S-curve with a point of inflection. Therefore, all the three forecasting models can be applied in this case study. For the simple logistic and Gompertz models, once the possible ceiling value of cumulative applications (L) is determined, the stage of the technology life cycle is estimated and time when the saturation of the technology will occur is computed.

5.2.3 Technology life cycle analysis

Patent activities can be used to interpret the technological stage of an industry. Ernst (1997) suggests that the cumulative patent applications for a particular technology over time can be plotted as S-shape curve to represent its technology life cycle. The technology life cycle has four stages including introduction, growth, maturity and saturation (Ernst, 1997). During the introduction stage, there is little growth in the number of patent applications. The growth stage, on the other hand, is characterized by exponential growth. As the patent application rate declines, the mature stage is entered. The saturation stage indicates limited growth with few patent applications. Anderson

(1999) used simple logistic models to plot the technology lifecycle and uses different cyclical points to calculate the duration of the four stages of the life cycle. After the upper limit L is estimated using the forecasting model, and then the technology's life cycle stage is determined. For the simple logistic model, Meyer, Yung and Ausubel (1999) propose that the range from 10% to 90% of the limit L represents the growth stage. Additionally, Ernest (1997) defines the maturity stage beginning from the inflection point, or 50% of the upper limit, for a simple logistic curve.

In this case study, the 10%, 50%, and 90% of the limit L are used to define the three cyclical points for classifying the four stages of the technology life cycle. Thus, if $y(T)$ represents the cumulative patent applications at time T, L is the maximum value of $y(T)$. Then, $y(T)/L<10\%$, $10\%\leqq y(T)/L<50\%$, $50\%\leqq y(T)/L<90\%$, and $90\%\leqq y(T)/L$, mark the range for technology in introduction, growth, maturity, and saturation stages respectively.

5.3 China RFID Patent Analysis

In order to understand the development of RFID technology in China, the patent database maintained by the State Intellectual Property Office of the People's Republic of China (SIPO) was used. The SIPO database covers all patent information filed in China since September, 1985. The SIPO database does not provide a function to search for key phrases among full text patent documents. Patents can only be searched using attributes set by the SIPO database. The search attributes are limited to the patent title, abstract, the application number, the application date, publication number, publication date, international classification, name of the applicant(s), inventor's name, priority, patent cooperation treaty (PCT), grant publication date, attorney and agent, and the address of the applicant. Since the database does not allow a key phrase search among the full text of the Chinese document, the search and analysis is limited to the electronic text contained in the abstract. Thus, the patents abstracts from 1995 to 2008 with either the key phrases of "RFID" or "Radio Frequency Identification" were downloaded and archived for analysis.

Figure 9 shows the patent counts and cumulative number of RFID patent applications generated from the SIPO patent database from the earliest filings until the year 2008.

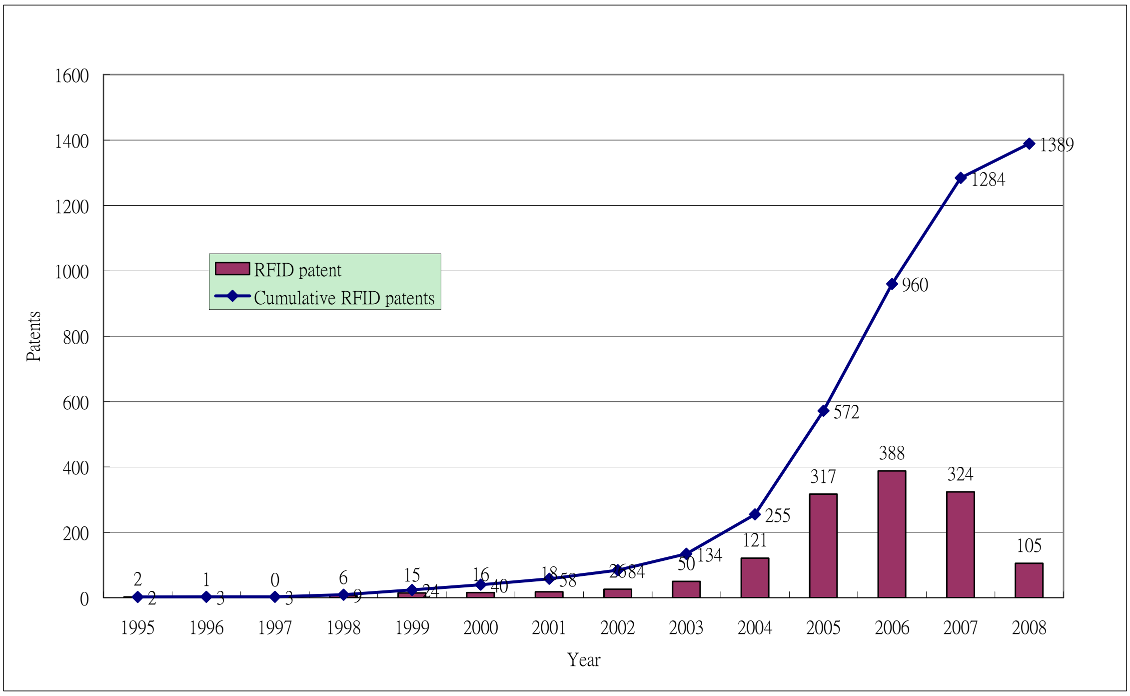


Figure 9　Number of RFID patent applications per year in SIPO database

The patent abstracts are written in simplified Chinese so a modified ontology tree with 46 translated key phrases was used to extract key words and phrases. Since the Chinese translation of five key phrases; wired device (无线装置), passive tag (被动式标签), directivity (方向系数), personal tracking(个人跟踪), and animal tracking (动物追踪) do not appear in any patent abstracts, only 41 key phrases are used for our analysis. After key phrases extraction, the correlation matrix was derived as shown in Table 13.

The key phrase correlation matrix is used for patent technology clustering. In this step, patent technology clusters are computed using the K-means clustering method. The 41 key phrases are clustered into six technology clusters. Figure 10 presents the six clusters and the key phrases of each cluster.

Table 13 Key phrase correlation matrix (partial)

	device	connector	wireless	reader	memory	tag	active	standard
device	1.0000	-0.0125	0.0175	-0.0172	0.0284	-0.0465	-0.0161	-0.0104
connector	-0.0125	1.0000	-0.0093	0.0202	-0.0053	0.0136	-0.0021	-0.0083
wireless	0.0175	-0.0093	1.0000	0.0036	-0.0080	-0.0058	0.0049	0.0037
reader	-0.0172	0.0202	0.0036	1.0000	-0.0237	0.1384	0.0066	0.0141
memory	0.0284	-0.0053	-0.0080	-0.0237	1.0000	0.0273	-0.0033	0.0074
tag	-0.0465	0.0136	-0.0058	0.1384	0.0273	1.0000	0.0764	-0.0255
active	-0.0161	-0.0021	0.0049	0.0066	-0.0033	0.0764	1.0000	-0.0053
standard	-0.0104	-0.0083	0.0037	0.0141	0.0074	-0.0255	-0.0053	1.0000

Patent document clustering is a method that classifies patents based on the similarity of the technologies. Patents with similar technologies fall into the same clusters which enables researchers to readily analyze the characteristics or features of the patent documents within the cluster. By comparing the frequency of each key phrase appearing in the patent document cluster, the representative phrases of each document clusters can be generated. As shown in Table 14, six clusters are classified from the patent documents and the representative phrases of each cluster are shown in Table 14.

The clustering results are then used to forecast the future trends of the clusters. According to decision diagram as Figure 5, the time-varying extended logistic model was first applied to forecast the future trend of China RFID patent applications, however, a convergence results could not be researched. Besides, although there are only fourteen data points for China RFID patent dataset, the point of inflection of the growth curve is revealed. Therefore, based on the model usage criteria concluded in Figure 5 and suggestions by literature, this study applies the simple logistic model to predict the development of China RFID patent applications. The simple logistic model is a widely used S-curve forecasting model (Boretos, 2007; Bengisu & Nekhili, 2006; Lackman, 1993; Morrison, 1996). The most important characteristic of the simple logistic model is its symmetry about the point of inflection. Therefore, if the point of inflection of an S-curve has occurred, then it is easy to forecast the remaining trend.

The growth curves of the six clusters are depicted in Figure 11. Using the simple logistic model, the trajectory of the Chinese RFID patents and the maximum cumulative RFID patent applications (upper limit) are estimated. The data are then used to determine the stage of cluster's technology life cycle as shown in Table 15.

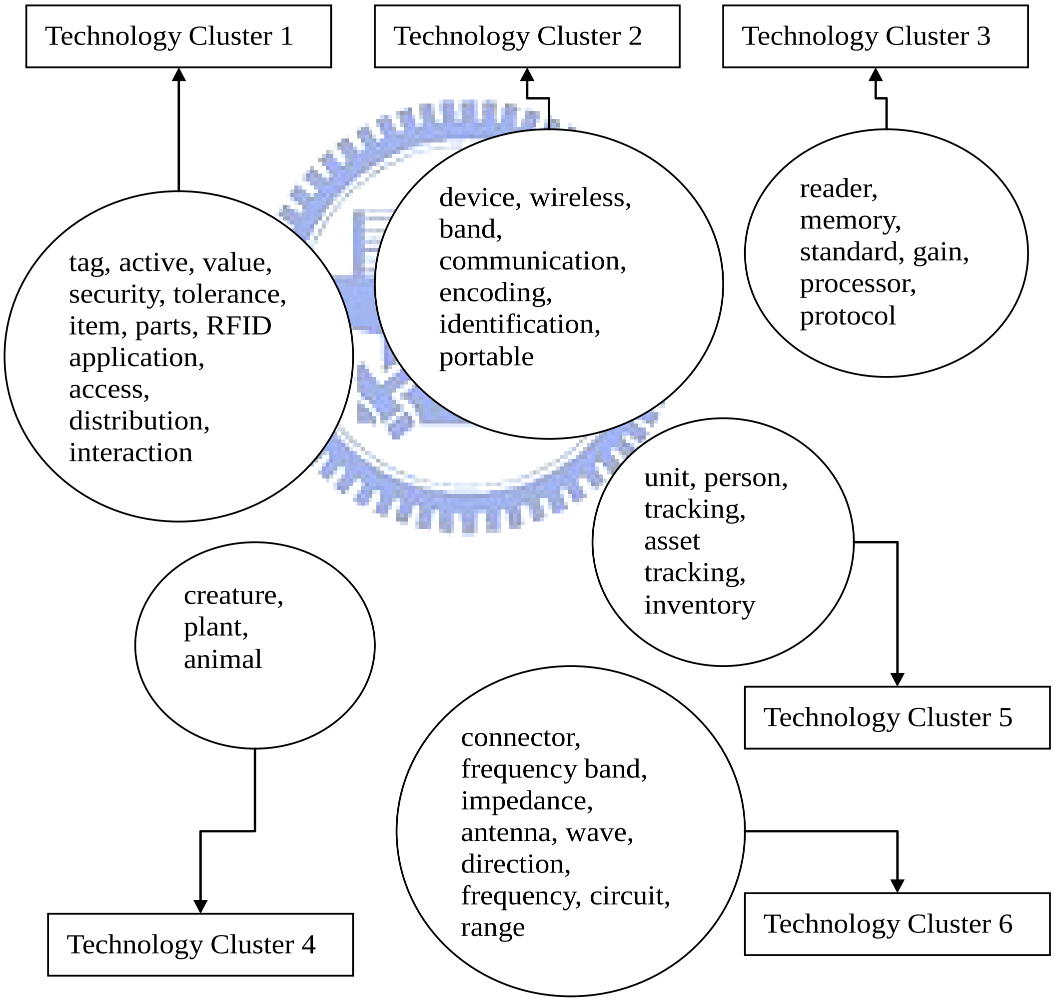


Figure 10　Technology clusters for RFID

Table 14 The patent document clustering result

Clusters Number	Cluster Features	Representative Phrases	The number of Patent in the cluster
1	RFID concepts and application	tag, security, interaction, item, distribution, active, value, access, tolerance	217
2	Wireless communication device	device, wireless, communication, identification, portable, band, parts	134
3	RFID architecture	reader, protocol, processor, standard	73
4	Frequency band and wave	frequency band, wave	54
5	RFID tracking implementation	RFID application, tracking, asset tracking, inventory, creature, person, animal, memory, unit, gain, encoding, plant	686
6	RFID transmission apparatus	antenna, circuit, connector, direction, frequency, impedance, range	225

Table 15 The forecasting results

	Patent Applications (1995-2007)*	Estimated Maximum Patent Applications	Year of upper limit	Share of upper limit	Stage of technology life cycle
Cluster 1	201	279	2018	72.04%	Mature
Cluster 2	128	142	2013	90.14%	Saturated
Cluster 3	70	90	2016	77.78%	Mature
Cluster 4	48	73	2018	65.75%	Early Maturity
Cluster 5	644	927	2021	69.47%	Mature
Cluster 6	193	240	2018	80.42%	Mature
Total	1284	1734	2020	74.05%	Mature

*: Since SIPO only published the patent applications applied before August, 31, 2008 when retrieving; only applications from 1995 to 2007 are used for forecasting.

5.4 The Development of China's RFID Industry

To interpret the current and future trends of RFID development in China, the data was further analyzed. The first cluster, RFID concepts and applications, contains the fundamental RFID technologies, including the concepts of developing a tag and the interaction system. Some basic functions of RFID, such as security and distribution are also included in this cluster. The patents in this cluster provide innovations for providing improvements such as the modification to RFID tags and security system to increase the safety in using RFID tags. One purpose of this case study is to determine if there are RFID technology gaps that can be exploited for further R&D. From the technology life cycle analysis (Table 15), the first cluster appears to be in the maturity stage and the number of patent applications is forecasted to reach its upper limit (279) in 2018.

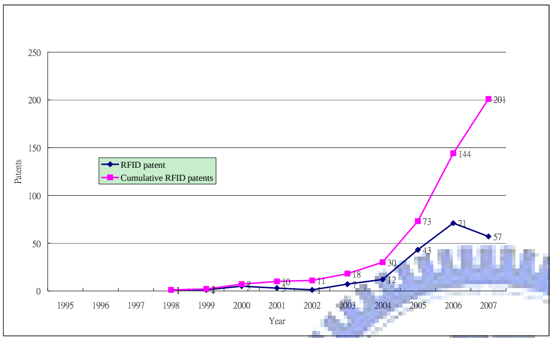
The second cluster, wireless communication devices, introduces techniques for tag identification and includes RFID wireless transmission technologies. Communication devices are the main focus of this cluster and many patents describe the wireless signal transmission technologies, and the communication of different kinds of messages. For example, there is a patent in this cluster which utilizes an RFID tag in an IC card to automatically send messages to other electronic devices. The life cycle analysis shows the second cluster to be in the saturation stage with a predicted 90% share of upper limit to be reached in the year 2013. This cluster is the only cluster in the saturation stage.

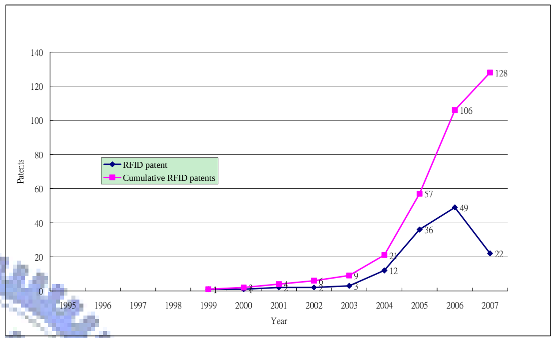
Cluster number 3, RFID architecture, contains key phrases like "reader," "protocol," "processor" and "standard" and these terms describe the essential architecture of RFID. The patents in this cluster focus on how to improve the functions of RFID readers or protocols and increase the efficiency of RFID operations. For example, a patent in this cluster describes a method and protocol to communicate between different RFID readers and simultaneously transmit data. The ability to strengthen the processors for RFID readers is also mentioned in this cluster. As shown in Table 15, the current share of RFID patent applications is at 78%, which means this cluster has entered the mature stage and will reach an upper limit (90 applications) in 2016.

The fourth cluster contains patents relating to frequency bands and waves. Frequency bands and waves are the means by which RFID systems transmit data. Different waveforms use different transmission methods and carry different amounts of data with different efficiencies. Therefore, methods to improve wave patterns are a crucial R&D direction. Noting that this cluster has the fewest patent applications and a continuing growth rate shown in Figure 11, there is good potential for the development of related technology. As shown in Table 15, this cluster has only reached 66% of its upper limit and the life cycle is in the early part of the mature stage. Therefore, inventors and investors should analyze potential opportunities in this cluster.

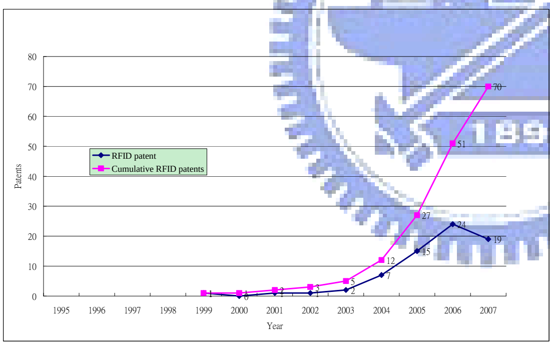
The fifth cluster represents the implementation and applications of RFID related technologies used for tracking. There are more patents in this cluster (686) than any other cluster. The technologies developed within this cluster contain technologies needed in monitoring and tracking of inventories, people and animal. The patented technologies in this cluster define how RFID technology can be implemented in the public transportation system, mobile phones, community security systems and animal tracking systems. This cluster includes patents from the earliest application period (i.e. 1995), is in the mature stage, and is forecasted to reach its upper limit in 2021 (Table 15).

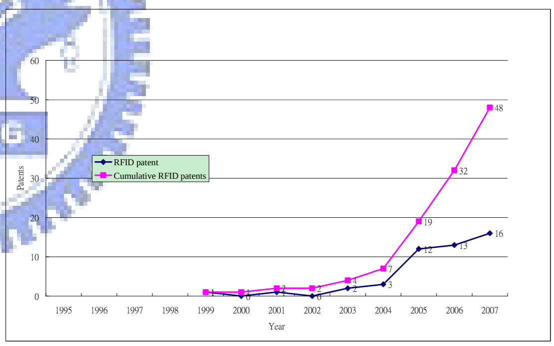
Finally, cluster number 6, RFID transmission apparatus, defines the framework and architecture for RFID transmission apparatus and systems. Most patents in this cluster are related to the antenna, circuits and connectors which improve the functions of RFID. Some device innovations for data transmission and the activation range are introduced in this cluster. As shown in Table 15, the sixth cluster has entered the mature stage of the technology life cycle with 80% share of its upper limit. This cluster is predicted to reach saturation in the year 2018.



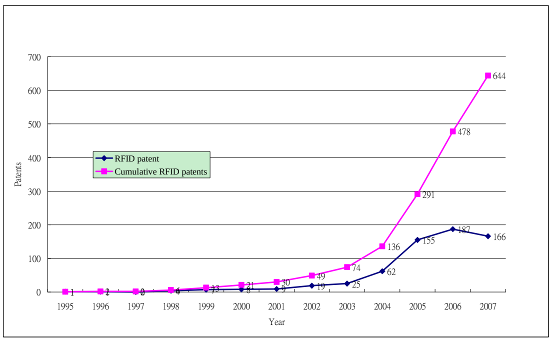


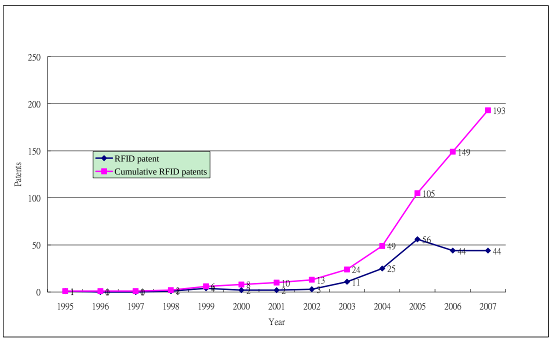
Cluster 1　RFID Concepts and Application　　Cluster 2　Wireless Communication Device





Cluster 3　RFID Architecture　　Cluster 4　Frequency and Wave





Cluster 5　RFID Tracking Implementation　　Cluster 6　RFID Transmission Apparatus

Figure 11　China RFID patents application and cumulative patent number

In summary, the results show that RFID wireless communication devices have entered the saturation stage and the technology in this cluster is mature with little room for development. Four clusters: RFID concepts and applications, RFID architecture, RFID tracking implementation, and RFID transmission apparatus, have also entered the maturity stage. One clusters, RFID frequency and waves is still in the early growth stage with the most potential for further development. The RFID operating frequencies are generally organized into four main frequency bands including low frequency (LF), high frequency (HF), ultra high frequency (UHF) and microwave (Ward & Kranenburg, 2006). Higher frequencies cover longer ranges and have higher data transfer rates and offer better security. RFID can be further applied in tracking and managing living things (e.g., medical care) and there is a growing need for RFID systems that can better utilize high frequency bands for communication.

Patent management strategy should be planned according to the technology life cycle (Liu, 2000). Therefore, for those RFID manufacturers in RFID frequency and waves area, modifying the core technology and searching for more applications is a critical objective for them. For those in RFID wireless communication devices subarea, they should not to invest in this area and start to create a new technology to replace the old technology, and the old technology patents can be resold or licensed as needed. As for the RFID manufacturers in other four subareas, since they are in the maturity stage, patent applicants should avoid invading other's patent intellectual property and innovators should seek the cooperation of the other applicants (i.e. formation of alliances).

Based on the forecasting model used in this case study and given the rate of applications filed in China, it appears that the China RFID patent applications will reach an upper limit of 1734 in the year 2020. Although there will likely be another ten years of growth and innovation, each subarea does not have the same potential for development. Using the patent clustering and forecasting methods, the most promising niche to invest in appears to be the improvement of the RFID frequencies and waves, a technology development area that will yield more reliable RFID systems and applications.

6. Conclusion and Discussion

6.1 Conclusion

This study compares the fit and prediction performance of the simple logistic, Gompertz, and the time-varying extended logistic models for 22 electronic products, proposes a decision process for selecting forecasting models, and demonstrates a case study to predict the future trajectory of RFID industry using the proposed procedure. Since the simple logistic and Gompertz curves require the correct upper limit settings for accurate market growth rate predictions, these two models may not be suitable for short product lifecycles with limited data. Therefore, to solve this problem, the time-varying extended logistic model was tested. Since the time-varying extended logistic model estimates the time-varying capacity from the data, it tends to perform better for both long and short lifecycle products if the data are not linear. The results show that the time-varying extended logistic model statistically significant outperforms the simple logistic and the Gompertz models in most of product datasets where the data has the beginnings of an S-shape.

A decision diagram is proposed after comparing the three models to help select a suitable forecasting model among the three models. Although the time-varying extended logistic model has better prediction performance, its advantage of having more parameters is also a limitation for it. Since the time-varying extended logistic model have more parameters to capture the dynamic upper limit, it sometimes will produce non-convergence results. For avoiding this problem, this research recommends that there should be at least fifteen data points in the database for applying the time-varying extended logistic model. However, if a non-convergence result happened using the time-varying extended logistic model but the point of inflection of the curve has occurred, then the simple logistic or Gompertz models can be alternative forecasting models. The simple logistic model is a symmetric model about its point of inflection and this means the upper limit will be twice the volume occurring at the inflection point. For the Gompertz model, although it is an asymmetric model, the point of inflection occurs at 37.79% of the upper limit and the upper limit can then be calculated when the inflection point is found. Therefore, if the inflection point has occurred, then the simple logistic model and the Gompertz model can be used to forecast. Moreover, if a forecaster perceives there will be a larger market potential, the Gompertz model may be a suitable alternative forecasting model. Thus, a forecaster needs to master the market situation to select a suitable prediction tool. This research also presents a case study of China RFID patent analysis to demonstrate the process of applying forecasting models. The forecasting results show that the China RFID patent applications will reach an upper limit of 1734 in the year 2020. A subarea, RFID frequency and waves, has the most potential for future development rather than other subareas and the results has been confirmed with industrial experts. Therefore, the forecasting process proposed by this research has the validity.

In product lifecycle management, different strategies need to be deployed to adapt different lifecycle stages. This research recommends several strategies which can be applied in PLC management based on the works of Chen, Liu, and Tzeng (2000) and Kotler, Keller, Ang, Leong, and Tan (2006). Table 16 generated and tablets the marketing, R&D, innovation, and patent strategies of different product lifecycle stages.

Take the RFID case study as an example. From the previous forecasts results, the whole China RFID industry is current in the mature lifecycle stage. However, the RFID industry can be classified into six subareas and different subareas have different development trajectories. Most subareas are in mature stage while wireless communication device (cluster 2) is in saturation stage. Therefore, the strategies for mature and saturation stages should be different. In mature stage, the basic characteristic is a peak growth. Sixty eight percent of the customers, called majority, adopt the product or technology in this stage. The competition is fiercer and the development of the product or technologies is mature, therefore, the marketing objective in maturity stage is to maximize profit while defending market share. Thus, to provide distinguished product form other competitors, RFID manufacturers need to diversify their products which can satisfy different potential customers' demand, stress brand difference and benefits, set the price to match or beat competitors', and build more intensive distribution. Moreover, a customer-orientated R&D strategy is needed to improve or design a RFID product or technology which can attract more customers. Therefore, marketers and researchers can apply quality function deployment (QFD) method, a customer-centric market research method, to investigate the product features that the potential customers like. Besides, since customers will put more emphasis on the quality, RFID manufacturers should stable and standardize their products by improving their production process and robust design. In maturity stage, the existing manufacturers have developed and owned many patents related to the products, so if new functions or designs will be added on the product or technology, patent search is strongly recommended before production. Patent licensing then may be needed when offending other inventor's intelligence property.

As for saturation stage, its characteristic is that the growth begins to slow down and decline. Laggards which count for 16% of the customers are used to describe the adopters in this stage for their late to adopt the product or technology. The market is stable and strong brands appear, so there are no fierce competitions in this stage. Some new products or technologies will replace the existing ones, so the marketing objective for those companies in the subarea of wireless communication device is to reduce marketing expenditure and milk the brand. Therefore, weak items and models must be phased out, the promotions have to be reduced to the level needed to loyal customers, cut the retail price, and eliminate the unprofitable distribution points to lower the operation cost. In addition, a price-orientated R&D strategy is appropriate. Since there will be new substitutions for this product or technology, the leading manufacturers need to sell their stock items with lower price. For those producers with no strong brand, they can only provide additional functions with much lower price to survive in the market. Thus, the function combinations or alternative materials or technologies are useful innovations strategy in maturity stage. Patent strategy is focus on the development of new designs or accessories.

6.2 Implication and Limitation

Forecasting models are useful for product lifecycle management (PLC), if the lifecycle stage of the product or technology can be defined, a development project can be planed in time. By using the decision diagram proposed in this research, researchers can select a proper forecasting model based on the pattern of the database to predict the lifecycle stages of a product and technology. Then the strategies of different stages can be designed in advance to face the challenge and minimize the failure of the products. Therefore, the PLC concept is not only a forecasting tool; it can also be used for planning and controlling (Kotler, 2003).

When forecasting the future growth and market for products, forecasters need to study the shape and the characteristics of the growth curve before selecting a suitable model. Although the time-varying extended logistic model has better performance for forecasting short lifecycle products, care must be taken when using this model. Since the extended logistic model is developed under the assumption of S-curve model, the extended logistic model may only be suitable for data that grows as an S-curve and may not be suitable for linear data or for curves with many anomalous data points.

One contribution of this study is to verify that the time-varying extended logistic model can better predict the technology product lifecycle than the simple logistic model and the Gompertz model. Therefore, the problem of setting the correct upper limit for the two traditional growth curve models can be avoided by using the extended logistic model. Another contribution is to propose a decision procedure to help predictors select suitable model among the three models. So when the time-varying extended logistic model cannot produce the convergent results and the inflection point of the growth curve has occurred, predictors can utilize the characteristics of the simple logistic and the Gompertz models to set the upper limit and to forecast.

The assumption of growth curve models may be the limitation for this study. This research evaluates the forecasting performance of the three growth curve models. When using the growth curve models, predictors assume the historical data will contain all information that will influence the future development of the given technology or products. However, future is very uncertain and may not be predicted solely with historical data. Therefore, in addition to the growth curve models, some qualitative forecasting methods which do not use historical data, such as Delphi, scenario, or environmental monitoring can also be applied at the same time to gain more accurate prediction results.

The result of this study can be applied to forecast the technology product lifecycles and to define what the lifecycle stage the product is current in to help managers plan strategies in advance. However, the lifecycle of technology products becomes shorter and shorter, when the existing product will be substituted be new products is a challenging issue. There are some forecasting models to discuss and forecast the substitution process. Therefore, the future research can focus on comparing these substitution models to see which one is more suitable for technology products, especially for short PLC technology products.

Table 16 Strategies for different product life cycle stages

	Introduction	Growth	Maturity	Saturation
Characteristics	• Low growth	• Rapidly rising growth	• Peak growth	• Declining growth
Adopters	• Innovators (2.5%)	• Early adopters (13.5%)	• Majority (68%)	• Laggards (16%)
Marketing objectives	• Create product awareness and trail	• Maximize market share	• Maximize profit while defending market share	• Reduce expenditure and milk the brand
Product strategy	• Offer a basic product	• Offer products extensions, service, and warranty	• Diversify products	• Phase out weak items and models
Promotion strategy	• Build product awareness among early adopters and dealers	• Build awareness and interest in the mass market	• Stress brand differences and benefits	• Reduce to level needed to loyals
Price strategy	• Charge cost-plus	• Price to penetrate market	• Price to match or beat competitors'	• Cut price
Place strategy	• Build selective distribution	• Build intensive distribution	• Build more intensive distribution	• Go selective: phase out unprofitable outlets
R&D strategy	• Innovation orientation	• Function orientation	• Customer orientation	• Price orientation
Innovation strategy	• Personal inspiration • Brainstorming • Combination with current product concepts	• Former R&D experiences • Imitation	• Quality function deployment (QFD) • Manufacturing process improvement • Robust design	• Functions combinations • Alternative materials or technologies
Patent strategy	• Intensive patent applications	• Patent allocation	• Patent license	• Design patent • Patent development on accessories

Sources: Adapted from Chen, Liu, & Tzeng (2000) and Kotler, Keller, Ang, Leong, and Tan (2006).

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Appendix 1　Simple logistic model derivations

$$y_t = \frac{L}{1 + ae^{-bt}} \tag{1}$$

where L is the upper limit to the growth of the interest variable y_t, e is the base of the natural logarithms, t is time, a and b are the coefficients obtained by fitting the curve.

After multiple by $(1 + ae^{-bt})$, we can get

$$y_t + y_t ae^{-bt} = L$$

then both sides of equation subtract by yt and divide by yt, and the equation becomes

$$ae^{-bt} = \frac{L - y_t}{y_t}$$

take inverse and then take natural logarithm. The equation is now expressed as

$$\ln\left(\frac{1}{a}e^{bt}\right) = \ln\left(\frac{y_t}{L - y_t}\right)$$

$$-\ln a + bt = \ln\left(\frac{y_t}{L - y_t}\right)_t \tag{2}$$

let the transformed variable be Y_t. Y_t is performed by taking the natural logarithm of data value Y_t, divided by the difference between the data value y_t and the upper limit L. Y_t is then a linear function of time t, where the constant term is –lna and the slope is b.

$$\therefore Y_t = \ln\left(y_t / L - y_t\right) = -\ln a + bt$$

Appendix 2　Gomperz model derivations

$$y_t = Le^{-ae^{-bt}} \tag{3}$$

where L is the upper limit; e is the base of natural logarithm; a and b are coefficients to be obtained from fitting the curve.

After Equation (3) is divided by L, the equation becomes

$$\frac{y_t}{L} = e^{-ae^{-bt}}$$

by taking natural logarithm, we get

$$\ln\left(\frac{y_t}{L}\right) = -ae^{-bt}$$

then multiple by -1, the equation is

$$\ln\frac{L}{y_t} = ae^{-bt}$$

take natural logarithm again.

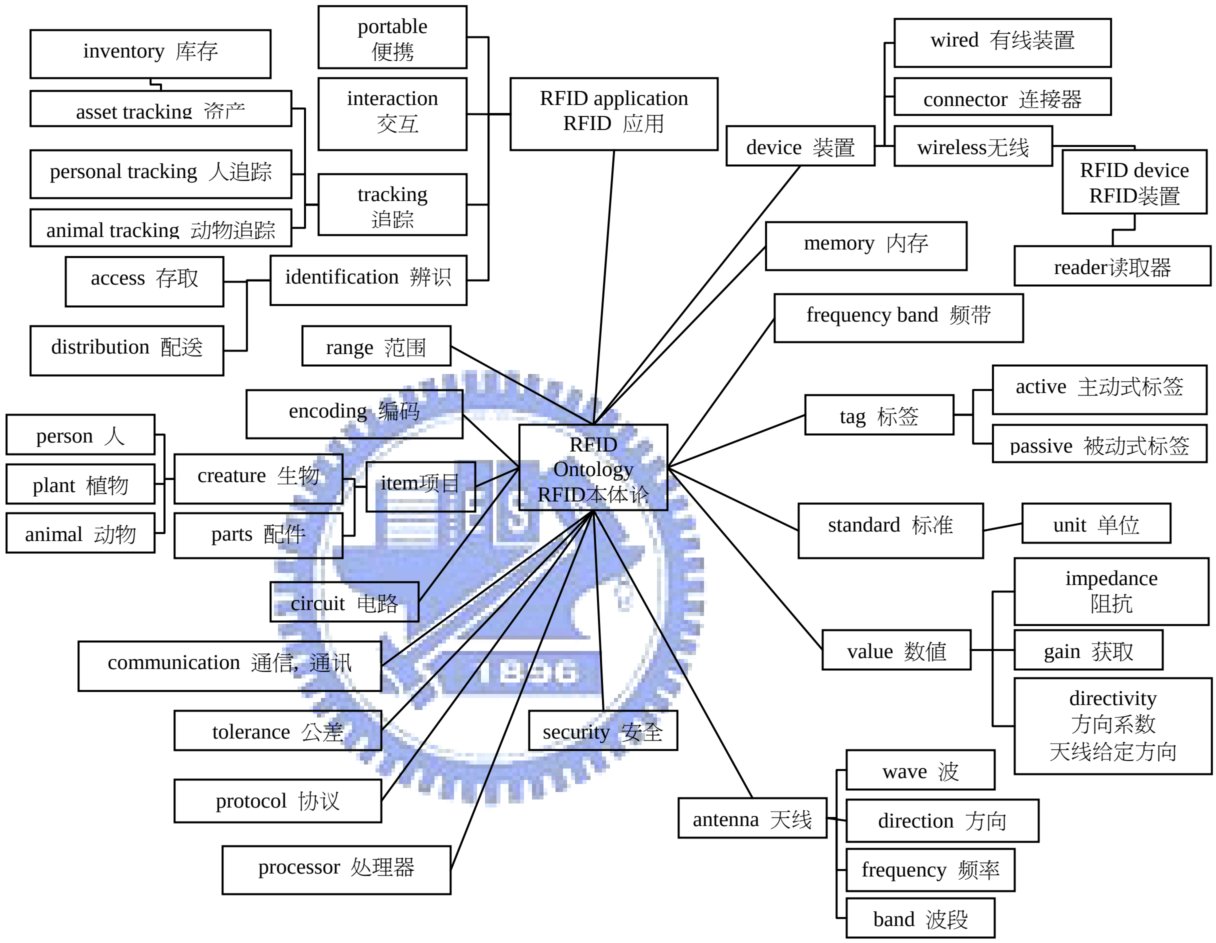
$$\ln\left(\ln\frac{L}{y_t}\right) = \ln\left(ae^{-bt}\right)$$

Let Yt be the transformed variable, so

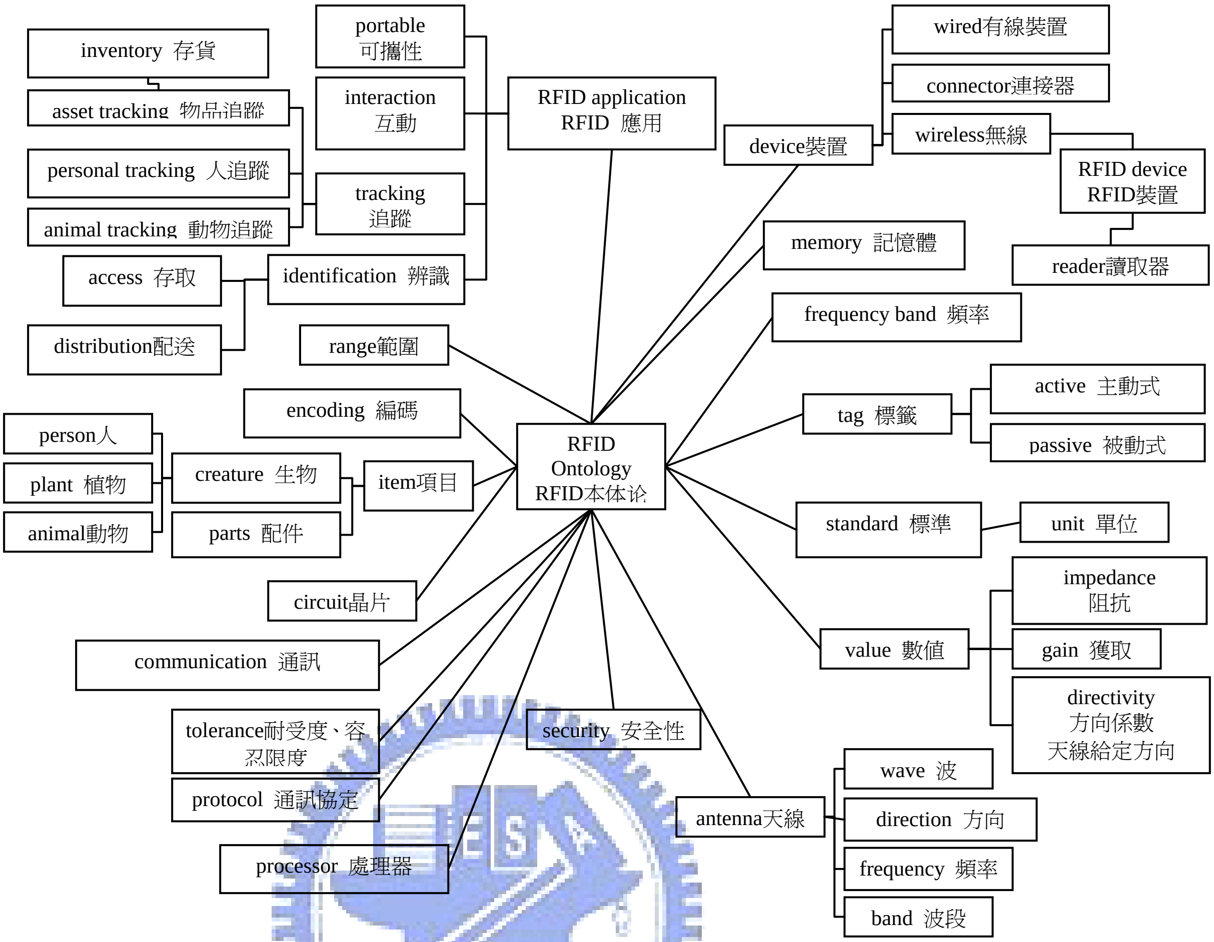
$$\therefore Y_t = \ln(\ln(L/y_t))\ln a - bt \tag{4}$$

where Yt is regressed on t, the constant term is lna, and the slope is –b.

Appendix 3 RFID technology ontology tree with simplified and traditional Chinese characters



RFID technology ontology tree with simplified Chinese characters



RFID technology ontology tree with traditional Chinese characters

Autobiography

Hsin-Ying Wu (Cindy Wu, 吳欣穎)

Education

2000	Exchange student, Ohio State University, USA
2001	BS, Agricultural Marketing, National Chung Hsing University, Taiwan
2003	MS, Marketing, National Chung Hsing University, Taiwan
2009	PhD candidate, Management Science, National Chiao Tung University, Taiwan.

Professional Experience

2005 – Present	Research Assistant and PhD student. Department of Management Science, National Chiao Tung University, Hsinchu, Taiwan
2008	Visiting scholar, Purdue University, Indiana, USA
2007	Teaching Assistant. Marketing Management and International Marketing, IMBA program, National Chiao Tung University, Hsinchu, Taiwan.
2007	Certificate, New Century WTO Law Training Program, Taiwan New Century Foundation, Taiwan
2004 – 2005	Product Manager. Consumer Appliance & Service Sector, TECO Group, Taipei, Taiwan
2002 – 2004	Research Assistant. Department of Marketing, National Chung Hsing University, Taichung, Taiwan
2003	Teaching Assistant. Statistical Analysis Training Program, Taichung subsidiary, Taiwan Tobacco & Liquor Corporation, Taichung, Taiwan.
2003	Teaching Assistant. Consumer Behavior, EMBA program, National Chung Hsing University, Taichung, Taiwan.
2001	Certificate, The 3rd China Synergy Programme for Outstanding Youth, The Hong Kong Jockey Club Charities Trust, Hong Kong

Awards

2008 Feb. – Sep.	Taiwan's National Science Council prestigious Graduate Students Study Abroad Program scholarship
2007 July	Best paper of the session, CE2007, São José dos Campos, SP, Brazil
2006 – 2008	Scholarship, Kaohsiung Computer Association, Taiwan
2006 – 2008	Scholarship, Department of Management Science, National Chiao Tung University, Hsinchu, Taiwan
2006 – 2008	Scholarship, Kaohsiung Wu Clan Association, Taiwan
2002	Scholarship, Kaohsiung Computer Association, Taiwan
2000	Exchange scholarship, National Chung Hsing University, Taichung, Taiwan
1999	Excellent student, Department of Marketing, National Chung Hsing University, Taichung, Taiwan

Journal Publications

1. Trappey, C.V. and Wu, Hsin-Ying, 2008, "An Evaluation of the Time-Varying Extended Logistic, Simple Logistic, and Gompertz Models for Forecasting Short Lifecycle Products and Services," *Advanced Engineering Informatics*, Vol. 22, pp. 421-430. (SCI, Impact factor: 1.172).

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2. Feinberg, R., Wu, H.-Y., and Trappey, C.V., 2009, "The diffusion of innovation and perceived risk for the adoption of alternative energy vehicles," Technology Innovation and Industrial Management 2009, June 18-20, Bangkok, Thailand.

3. Feinberg, R., Wu, H.-Y., Trappey, C.V., 2009, "If you build it will they come? Consumer use of biofuels as a diffusion of innovation problem," the Second Generation Biofuels Symposium 2009, May 18-19, West Lafayette, USA.

4. Trappey, C.V. and Wu, Hsin-Ying, 2007, "An Evaluation of the Extended Logistic, Simple Logistic, and Gompertz Models for Forecasting Short Lifecycle Products and Services," *Proceedings of the 14th ISPE International Conference on Concurrent Engineering*, CE2007, July 16-20, São José dos Campos, SP, Brazil. (Best paper of the session)

5. Trappey, A.J.C., Chiang, Tzu-An, Wu, Hsin-Ying, and Hou, J.-R., 2007, "A DEA Benchmarking Methodology for Strategic Management of New Product Development Based on Decentralized Profit-Center Business Model," *Proceedings of the 11th World Multi-Conference on Systemics, Cybernetics and Informatics*, WMSCI 2007, July 8-11, Orlando, Florida, USA.

6. Lee, Hwang-Jaw, Wu, Hsin-Ying, 2002, "The Impact of Women's Time Allocation on Expenditures for Food Away from Home and Home Service," *Proceedings of the 1st Conference on Applied Economics*, October 25, Taichung, Taiwan.

Thesis

1. Wu, Hsin-Ying, 2009, *An Evaluation of Models for Forecasting Technology Product Lifecycles*, Doctoral dissertation, National Chiao Tung University, Hsinchu, Taiwan.

2. Wu, Hsin-Ying, 2003, *Cultural Value, Consumption Value and Consumer Behavior - An Empirical Study on College Students' Mobile Phone Purchasing Decisions in Taiwan and Mainland China*, Master thesis, National Chung Hsing University, Taichung, Taiwan.

Taiwan Government or University Reports

1. Trappey, C.V., Wu, Hsin-Ying, and Tzang, Ai-Hua, 2007, "Technology Forecasting Model Development, Comparison and Case Research in the Electronics Industry: First Year Report," NSC 95-2416-H-009-014-MY2, Taiwan National Science Council.
2. Trappey, C.V., and Wu, Hsin-Ying, 2009, "Integrated Patent Analysis Methodologies for RFID Technology Forecasting and Management: Final Report," NSC 97-2410-H-009 -008 -MY3, Taiwan National Science Council.

Research Projects

Position	Title	Year	Subsidy Institution	Project Code
Research Assistant	Integrated Patent Analysis Methodologies for RFID Technology Forecasting and Management	2008.8.1~ 2009.7.31	National Science Council	NSC 97-2410-H-009 -008 -MY3
Research Assistant	Technology Forecasting Model Development, Comparison and Case Research in the Electronics Industry	2006.8.1~ 2008.7.31	National Science Council	NSC 95-2416-H-009 -014 -MY2
Research Assistant	A study of Marketing Strategy for Taiwan's Flower Exports to Japan	2002.1.1~ 2002.12.31	Taiwan Council of Agriculture, Executive Yuan	91AS-1.5.4-ID-I1
Research Assistant	A Study on the Quarantine of Taiwan's Export Flowers	2002.9.1~ 2002.12.31	Bureau of Animal and Plant Health Inspection and Quarantine Council	91AS-7.1.3-BQ-B2

Research Area

Technology Management, Industry Analysis, Knowledge Management, Technology Forecasting, Patent Analysis, International Marketing, Consumer Behavior