FORECASTING TOURIST DEMAND TO SINGAPORE: A MODERN TIME-SERIES APPROACH

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ABSTRACT

This dissertation examines the application of modern time series forecasting methods in the forecasting of inbound tourists from the six major tourist generating markets to Singapore, namely the USA, Australia, Japan, UK, India and China. The purpose of the study is to assess the capacity of modern time-series models with regard to their relative forecasting accuracy.

The modern time-series forecasting models applied are Neural Networks and the Basic Structural Model. The time period for the analysis is from 1985 Quarter 1 to 2001 Quarter 4. The time series are disaggregated into Holiday, Business, and Total tourist arrivals into Singapore. Multi-step, one one-step and 4-step ahead forecasts are made. The forecasting performance comparison between the modern time-series models are compared using the mean absolute percentage error (MAPE), against the Winters model and the naïve process.

The empirical results show that Neural Networks outperform the BSM and Winters for the Holiday, Business and Total flows with the Direct multistep forecast. The BSM outperforms the Neural Network model and Winters model for one-step-ahead and four-step-ahead forecasts.

The findings indicate that the Neural Network model is an excellent and practical time-series model for forecasting disaggregated tourist flows.

Overall, the study vigorously tested the Neural Networks and BSM modern time series models, and demonstrates their superiority for tourism demand forecasting over simpler time-series methods, and highlights to the business practitioner the importance of these models for short-term tourism demand forecasting.

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DECLARATION

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university or other institution, and to the best of my knowledge, contains no material previously published or written by another person, except where due reference is made in the text of this thesis.

Signed: [redacted]

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CHAPTER 1 INTRODUCTION

Introduction

The rapid growth of international tourism arrivals worldwide has been impressive since the end of the Second World War. According to the World Tourism Organisation (WTO), international tourist arrivals grew by 7.4% in 2000, and world inbound tourism receipts for 2000 totalled US$455.4 billion. Factors that contributed to worldwide tourism growth are: (a) on the supply side – lower transportation costs, government reforms, deregulation and opening of tourist and related sectors; (b) on the demand side – changing demography with ageing and retirement, global business travel, rising affluence, new forms of tourism such as eco-tourism, arts tourism, religious and adventure tourism.

For the Asia Pacific region, the Annual Average Growth Rate (AAGR) grew by almost twice the world average from 1999 to 2000 and exhibited the highest regional growth rate (Turner and Witt 2001), as shown in Table 1.1.

Table 1.1

International Tourist arrivals by Region (mil)

Destination region	Tourist arrivals 2000 (million)	AAGR 1999-2000 (%)
Africa	27.6	7.4
Americas	129.0	5.6
Asia Pacific	118.3	14.4
Europe	403.3	6.1
Middle East	20.6	13.2
WORLD	**698.8**	7.4

Factors that contributed to this growth of tourism in the Asia Pacific region include rapid economic growth, continued improvement of communications and transportation modes, higher per capita personal disposable incomes and more short-haul intra-regional travel. These factors have resulted in tourism becoming a major component of economic development and an important source of foreign exchange for many of the countries in the region. This has raised the intensity of competition in the tourism industry in the Asia Pacific region as countries become more aggressive in their tourism marketing and promotion campaigns. At the same time, visitors will be looking for new, exciting and different holiday experiences while choosing from a wider selection of tourist destinations. This increased growth and competition for international tourism (Wahab and Cooper 2001) in the Asia Pacific region, and the importance and contribution of tourism to Singapore's economic performance that is discussed later highlight the need for accurate tourism demand forecasts for Singapore.

The importance of tourism demand forecasting is emphasised by Frechtling (1996) with the following reasons: (a) The perishable nature of the tourism 'product' (Archer 1987), (b) People are inseparable from the production-consumption process, (c) Customer satisfaction depends on complementary services, (d) Leisure tourism demand is extremely sensitive to natural and manmade disasters, and (e) Tourism supply requires large, long lead-time investments in plant, equipment and infrastructure. At present, the residual effects of terrorism fears, conflicts and economic uncertainty in the US, Europe and Middle East is seen to have an affect on the tourism industry in 2002.

Witt et al. (1991) states: 'Reliable forecasts of tourism demand are essential for efficient planning by airlines, shipping companies, railways, coach operators, hoteliers, tour operators, food and catering establishments, providers of entertainment facilities, manufacturers producing goods primarily for sale to tourists, and other industries connected with the tourism market.' Tourism demand forecasting models have been reviewed by Crouch (1994) who found that nearly two-thirds of them define demand in terms of arrivals or departures; and about one-half of them measured demand in terms of tourism expenditures and receipts. Frechtling (1996) states that visitor arrivals in a country or local area constitute tourism demand since visitors avail themselves of the services of a destination in arriving there. In essence, the availability of accurate tourist arrivals forecasts can assist governments in tourism planning and development for the tourism industry.

This study is a significant contribution to the current literature by examining and testing modern time-series forecasting models for generating accurate disaggregated tourist arrival forecasts, in the short-term.

1.1 Objective of the Research

Questions relating to the best methodology to use in forecasting tourism arrivals have been discussed extensively in the literature (Martin and Witt 1989; Crouch and Shaw 1990; Witt and Witt, 1992; Witt et al. 1994). There are basically two kinds of methods: time-series and causal methods. Each method has different strengths and weaknesses. The causal models require the need to identify and forecast independent variables in the defined model in order to use the model. This represents a significant challenge as the incorrect prediction of these independent variables will result in an incorrect forecast from the causal model. Moreover, the causal based methodologies have become very complex in recent years with the use of cointegration modelling and hence very expensive for use by business. Time-series methods do not have the above causal requirements and can be more practical for business use, primarily because they cost less to execute within a business workplace. Furthermore, purely from the point of view of accuracy, time-series models can be at least as accurate as causal models in the short term. So in cases where practical forecasting of arrivals numbers is the primary aim (as opposed to determining cause) time-series models are very useful for industry application.

From the perspective of practical forecasting in industry the greatest need is for short-term tourist arrival forecasts (Turner and Witt 2001). Industry needs in the hospitality, transport and accommodation sectors have become more short-term focused, and designed to change rapidly with changing market demand. Partly in consequence of this, the longer term econometric modeling (as opposed to short-term processes) have become less relevant to industry. However, the best short-term modeling processes are not well understood, especially given the development of new methods such as Neural Network forecasting and structural modeling.

Furthermore, tourist visits can occur for a variety of reasons, such as holidays, business trips, visits to friends and relatives, business and pleasure, and other reasons such as education or accompanying someone else. However, most of the empirical studies of tourism demand functions have examined either (annually or quarterly) total tourist visits or holiday visits; with only a few studies concerned with business tourism flows. The reason is that most tourist flows have been for holiday and pleasure purposes, and therefore the determinants of demand for holiday trips are assumed to be the same for total tourist flows. This may not always be the case. As such, modelling business and holiday arrivals is important. Also, Witt et al. (1991) state that 'tourist spending on a business trip is likely to be much higher than on a holiday, so the contribution of business tourism to the total will be higher in value.' Davidson (1994) also highlighted that Business travel is the fastest growing and most profitable segment of tourism. In addition, business travel tends to exhibit less seasonality compared to holiday travel thereby allowing better planning and utilisation of tourism infrastructure. Some recent business travel tourism demand analyses have been conducted by Morley and Sutikno (1991), Witt et al. (1995), Turner et al. (1998), Turner and Witt (2001).

The purpose of this study is to:

(1) Identify the most accurate modern time-series models for short-term forecasting of the main disaggregated (Holiday, Business, Total) tourists flows into Singapore.
(2) Identify the best structure for Neural Network methods when applied to forecasting tourism data.
(3) Analyse the relative forecasting performance of the latest time-series forecasting models, these are defined as the structural model and Neural Network model.

Given the different character of business flows it is necessary to test modern time series methods to include business travel separately. In many cases Visiting Friends and Relatives (VFR) flow should also be included separately. However, for Singapore such flows are relatively small and less important relative to holiday and business travel, and are therefore not included in this study.

Forecasts generated from the structural and Neural Networks are compared with those generated from the Holt-Winters model and the naïve model, as these two methods are widely used in business applications, and can serve as benchmarks for comparison of forecast accuracy. In this way, the practical application of modern time-series methods for industry can be assessed.

1.2 Outline of the Thesis

This thesis contains five chapters starting with the introduction, which presents the research background, research objectives, and a discussion of Singapore tourism forecasting.

Chapter 2 reviews the relevant literature on the application of qualitative and quantitative forecasting models that include causal models, time-series models, moving average, exponential smoothing, decomposition method, Basic Structural Time Models and Neural Networks in tourism demand forecasting.

Chapter 3 describes the selection of forecasting models for this study, the data used to test these models, and the methodology adopted to empirically test the modern time-series forecasting models of Neural Networks, BSM and Winters.

Chapter 4 discusses forecasting performance evaluation and presents the results of the forecasting performance comparison. The most accurate modern time-series forecasting model is identified for each of the disaggregated tourist flows. It also highlights the key findings gathered from the empirical results.

Chapter 5 provides the conclusions from this practical research. Finally, recommendations for future study are offered.

1.3 Tourism Overview

Tourism relates to leisure and business travel activities that centre on visitors to a particular destination. The abstract nature of tourism has resulted in many different interpretations, definitions and concepts being discussed by Leiper (1979), Mattieson and Wall (1982), Burkart and Medlik (1989), and Morley (1990), Hunt and Layne (1991). Definitions of tourism include:

"The temporary movement to destinations outside the normal home and workplace, the activities undertaken during the stay and the facilities created to cater for the needs of tourists" (Mathieson and Wall, 1982, p.1).

Tourism also denotes "the temporary, short-term movement of people to destinations outside the places where they normally live and work and their activities during their stay at these destinations" (Burkart and Medlik, 1981, p. v).

The World Tourism Organisation (WTO, 1993) defines three forms of tourism as: (1) domestic tourism – comprised of residents visiting their own country; (2) inbound tourism – comprised of non-residents travelling into a given country; and (3) outbound tourism – comprised of residents travelling to another country. The WTO also highlighted that 'travellers' refer to all individuals making a trip between two or more geographical locations, either in their country of residence (domestic travellers) or between countries (international travellers). All travellers who engage in the activity of tourism are considered to be 'visitors'. A secondary division of the term visitors is divided into two categories: (1) 'Tourists' (overnight visitors), and (b) 'Same-day visitors' also called 'excursionists' (Vellas and Becherel 1995).

1.3.1 The Tourism Product

The tourism 'product' is a combination of components including accommodation, food, transportation, entertainment, and tourist sites and attractions. The characteristics of the tourist product include: (a) it is intangible, that is it cannot be inspected by prospective buyers before they buy, (b) it cannot be stockpiled, and (c) it is not homogenous, that is it tends to vary in standard and quality over time. Burkart and Medlik (1981) differentiate between (a) resource-based products which tend to be unique attractions created by nature or past human activity (such as mountains), and (b) user-oriented products which are those created specifically for tourist use (such as a sports stadium or convention centre). Smith (1994) presented a useful model that describes the tourism product as consisting of five elements: the physical plant, service, hospitality, freedom of choice, and involvement. The characteristics of tourism products may be positive or negative. In recent years, the negative characteristics of tourism products such as the incidence of terrorism, political instability and reliability of essential services such as an airline's safety record have affected tourism travel.

1.3.2 The Tourism Industry

The tourism industry is regarded as a service industry and has been defined as: "... the aggregate of all businesses that directly provide goods and services to facilitate business, pleasure and leisure activities away from the home environment" (Smith 1988). The Australian Government Committee of Inquiry into Tourism (1987) has described the tourism industry as "not one discrete entity but a collection of inter-industry goods and services which constitute the travel experience".

Because of the complex range of businesses within the tourism industry, tourism has been categorised (Holloway 1990; Middleton 1988) into the following sectors: (a) carriers and transportation companies, (b) accommodation providers such as hotels, (c) attractions both 'permanent' and 'temporary' such as events and festivals, (d) private sector support services, (e) public sector support services, and (f) 'middlemen' such as tour wholesalers and travel agents. Travel agents buy travel services at the request of their customers while tour wholesales or operators buy a range of tourist products in bulk, such as airline seats and hotel rooms, and package these as a holiday package at an all-inclusive price for subsequent sale to travel agents or directly to customers.

Past research on the tourism industry has been classified by Sinclair and Stabler (1991) into three main categories: (a) descriptions of the industry and its operation, management and marketing (Burkart and Medlik 1989; Cleverdon and Edwards 1982; Hodgson 1987; Holloway 1990; Lundberg 1989; McIntosh and Goeldner 1990); (b) the spatial development and interactions which characterise the industry on a local, national and international scale (Mill and Morrison 1985; Pearce 1987, 1989; Robinson 1976), and (c) the effects which result from the development of the industry, including economic, social, cultural, political and environmental repercussions (Mathieson and Walls 1982; OECD 1981; World Tourism Organisation 1980, 1988a).

1.3.3 Tourism Models

Various models and systems of tourism have been developed over the years in attempting to incorporate the various elements of the tourism product and industry (Culpan 1987; Morley 1990). Leiper (1979) identified three geographic elements of a tourism system: (a) the Tourist Generating Region, (b) the Transit Region, and (c) the Destination Region. The tourist generating region is the region or market from which a destination draws its visitors or clientele. The transit region is the region where visitors stop when travelling between the tourist generating and destination region and the tourist destination region is the place or location that is chosen by, or sold to, the visitors from the generating region. Mill and Morrison (1985) state that the tourism system has four components: Market, Travel, Destination and Marketing. The Market refers to the individual tourist demand. The Travel component is concerned with travel flows and transportation. The Destination refers to the destination relevant policy, regulatory framework and development plans. The Marketing component refers to how the destination reaches out to potential tourists. Poon (1993) states that the four components of the tourism system are: producers; distributors; facilitators; and consumers. Cooper et al. (1993) also describe tourism as having four elements: demand; the destinations, industry and government organisations; and marketing.

Other types of system models introduced in tourism research are: (a) a model which emphasises the supply and demand dimensions of tourism and focuses on the importance of the tourist experience (Murphy 1983, 1985), and (b) a tourism market system model which integrates the behavioural and socio-cultural context of tourism with the demand and supply of the tourism experience (Hall 1995).

Morley (1990) concluded that models of tourism are usually limited in their scope by the concerns of their framers and proposed a dynamic and encompassing model based on two dimensions of tourism: the Tourist-Tour-Others dimension and the Demand-Supply-Impacts dimension.

1.3.4 Tourism Marketing

The task of tourism marketing requires understanding tourist behaviour (Witt and Moutinho 1989; Pearce and Stringer 1991; Dann and Cohen 1991; Mansfeld 1992, Swarbrooke and Horner 1999) and performing segmentation based on tourist types.

Krippendorf (1986, 1989) stated that people 'need to escape the burdens of their normal life' and highlighted the role of travel in physical recuperation. The motivating factors that serve to push and pull people to travel have drawn the interest of various researchers (Lundberg 1989; Mercer 1970; McIntosh and Goeldner 1990). 'Push' factors which encourage the tourist to leave home include the desire to escape the crowding, noise and traffic of cities while 'pull' factors include the attractions of the destination that are away from familiar home surroundings. Major motivational categories (Hall 1995) include: (a) physical motivations which relate to health, pleasure and the physical refreshment of body and mind, (b) cultural motivations which serve to satisfy the curiosity about foreign places, people and culture, (c) social motivations which include the desire to visit friends and relatives, and prestige and status motivations, (d) spiritual motivations which include visiting places for religious reasons, and (e) fantasy motivations (Dann 1977) to enhance one's ego and to experience the excitement of travel. These motivations have contributed partly to seasonality in tourism (Bar On 1975; Baum 1999). Moore (1989) has defined seasonality as movements in a time series during a particular time of year that recur similarly each year. Butler (1994) highlighted the two basic origins of seasonality: 'natural' and 'institutional'. Natural seasonality is the result of regular variations in climatic conditions such as temperature, snowfall and rainfall. Institutional seasonality is the outcome of a combination of religious worship, holidays, cultural, ethnic and social factors. Frechtling (1996) classifies the causes of seasonality as climate, social customs, business customs, calendar effects and supply constraints.

As tourist consumers are not homogeneous (Crompton 1979; Pearce 1982), the tourism market can be segmented allowing marketers (a) to perform differentiated marketing, and (b) to examine varying economic constraints and contributions, and formulate policy based on behavioural or psychological economics (Katona 1975).

Mattieson and Wall (1982) describe four different types of tourist for tourist segmentation. These are:

(1) The organised mass tourist – This role is typified by the package tour in which itineraries are fixed, stops are planned and guided, and all major decisions are left to the organiser. Familiarity is at a maximum and novelty at a minimum.

(2) The individual mass tourist – In this role, the tour is not entirely planned by others, and the tourist has some control over his itinerary and time allocations. However, all of the major arrangements are made through a travel intermediary. Familiarity is still dominant.

(3) The explorer – Explorers usually plan their own trips and try to avoid developed tourist attractions as much as possible. Novelty dominates and the tourist does not become fully integrated with the host society.

(4) The drifter – Drifters plan their trips alone, avoid tourist attractions and live with members of the host society. They are almost entirely immersed in

the host culture, sharing its shelter, food and habits. Novelty is dominant and familiarity disappears.

Bull (1995) highlighted three methods of tourist segmentation:

(1) segmentation by purpose of travel - where the various types of tourists are classified into (a) Leisure, (b) Business, (c) Business and Leisure, (d) Visit Friends and Relatives (VFR), (e) Convention/exhibition delegates, and (f) Others.

(2) psychographic segmentation - where tourists are categorised by a consideration of lifestyles (sometimes called activities, interests and opinions or AIO), motives and personality traits which are important for both marketing and economic analysis. Traits identified to be especially important (Schewe and Calantone 1978) in tourists are: (a) Venturesome - the degree of 'risk' tourists want, (b) Hedonism - the degree of comfort required on a trip, (c) Changeability - the extent to which tourists are impulsive or seeking something new, (d) Dogmatism - the extent to which a tourist cannot be persuaded to change ideas, and (e) Intellectualism - the degree of 'culture' tourists want. These traits are seen to influence the tourist activity or the purchasing characteristics of tourists, which thereby enables tourist market segmentation.

(3) interactional segmentation - where the tourists are classified by the effect on the tourism destination, into (a) Explorer, (b) Elite, (c) Hosted or 'second homers', (d) Individual or incipient mass, and (e) Mass or charter.

Plog (1974) developed a cognitive-normative model that can be used to segment tourism markets based on their degree of 'venturesomeness'. This model identified tourists as being on a continuum from 'allocentric' (high venturesome) through to mid-centric (liking to explore, but with home comforts), to 'psychocentric' (disliking the unfamiliar or risky). Understandably, the mid-centric category represents the mass of the tourism market. This static model was criticised for not accommodating change in market taste, and a new model that incorporates a dynamic element, whereby allocentrics can pick up new products and pass them through each of the groups, was proposed.

Regardless of the approaches to defining, understanding, and marketing tourism as discussed above, the power that drives the engine of tourism development is the market dynamics that result from supply and demand factors (Burns and Holden 1995). Supply-side issues are concerned with the provision of communication, services, transport, accommodation and attraction. One unique characteristic of tourism supply has been its static nature. For example, the number of rooms cannot be easily increased to meet short-term changes in demand thereby introducing the problem of seasonality.

1.3.5 Tourism Demand

Song and Witt (2000) defined 'tourism demand' for a particular destination as the quantity of the tourism product (a combination of tourism goods and services) that consumers are willing to purchase during a specified period under a given set of conditions. The three groups of variables likely to influence and constrain tourism demand are classified in Table 1.2 based on Leiper's (1979) system model. Link variables are those between one generating region and one destination; that is they will act only on demand for that destination from the one generating region. The next step is to examine the forms of effect that these variables are likely to have on overall demand (Bull 1995).

Table 1.2

Variables influencing tourism demand

Tourist Generating Region variables	Tourist Destination Region variables	Link variables
Personal disposable income levels	General price level	Comparative prices between generator and destination
Distribution of incomes	Degree of supply competition	Promotional effort by destination in generating regions
Holiday entitlements	Quality of tourism products i.e. attractions, amenities, etc.	Exchange rates
Value of currency	General economic and political condition	Time to travel
Tax policy and controls on tourist spending	Physical and geographical factors	Cost of travel

Cooper et al. (1993) highlighted demand for tourism as affected by overall concomitant economic and psychological factors resulting in the following types of tourism demands:

(1) Actual demand: the number of people who actually purchase travel and tourism;

(2) Potential demand: those people who will travel when their circumstances allow it; and

(3) Deferred demand: where supply elements such as transport or accommodation availability, and actual or psychological climate, have temporarily been affected in some way, causing travel to be delayed.

In addition, the tourist experience and how the 'hosts' and 'tourists' interact (Doxey 1975; Ryan 1991) in the host country will affect the tourist decision whether to return to that destination again.

More importantly, tourism demand analysis can be used to not only ascertain the contribution of the tourism industry to the country's economy; it can also assist in tourism strategic planning.

1.4 Economic Impacts of Tourism

The economic benefits and costs of tourism have been extensively documented in Bryden (1973), Archer (1977), Archer and Fletcher (1990), Eadington and Redman (1991), Bull (1991), Gray (1992), Burns and Holden (1995) and Lundberg et al. (1995).

The benefits or positive impacts of tourism include that it is an important source of foreign exchange earnings which can be used, amongst other earnings, to finance developments, and offset balance of payments problems. O'Clery (1990) highlighted the potential of tourism to reduce levels of overseas debt. Tourism can also create employment opportunities that can be both directly and indirectly related to tourism. Direct employment opportunities in the tourism industry are, for example, tour wholesalers, tour operators, tour agencies, airlines, hotels, and restaurants. Indirect employment opportunities are created in the construction, agriculture and manufacturing industries. The economic significance of tourism (Mathieson and Wall 1982; Bull 1991) can be determined by its contribution to a country's Gross Domestic Product (GDP), balance of payments (that is, the measure of a nation's total receipts from and total payments to the rest of the world (Salvatore 1990)), income levels, employment opportunities, government revenue creation, economic diversification and regional stimulation.

Mathematically, in an open economy, GDP is expressed as:

GDP = Consumption (C) + Investment (I) + Exports (X) - Imports (M).

In tourism, expenditure by tourists can be regarded as (a) consumption spending, C, (b) expenditure by business on buildings, plant, equipment which is part of investment, I, to provide tourism services, and (c) 'importing' services which occurs when money is spent by that country's nationals in a foreign country when travelling as tourists. This expenditure is a leakage from the national economy. Finally, 'exporting' is the situation when a country is able to sell its transportation or tourism services to international tourists. In many countries, tourism can play a significant part in contributing to GDP as it has a demonstrated ability to grow faster than other economic sectors even under generally slow conditions.

The economic impact of tourism also includes the negative consequences of tourism, or its costs, to residents. Thus while tourism contributes to a country's' GDP and its economic growth, it also imposes social, cultural, moral and environmental changes upon the host country. Social impacts (Dann and Cohen 1991; Dogan 1989; Pearce 1989) refer to the effects tourism has on collective and individual value systems, behaviour patterns, community structures, lifestyle and quality of life. The relationship of tourism to the environment was examined by Budowski (1976), who suggested that three basic relationships can occur: (a) conflict, (b) coexistence, and (c) symbiosis where tourism and environmental conservation are mutually supportive resulting in economic advantages and a better quality of life in host communities. In recent years, the emphasis for sustainable tourism development (Romeril 1989; Taylor and Stanley 1992; Hall and Page 1999) is growing and this reflects the concern for the environment. Two major negative effects that may arise from inbound tourism are: (a) Demonstration effects (Bryden 1973) where the emulation by residents of inbound tourists could result in changes in consumption patterns leading to a higher propensity to consume imported goods which tourists are seen to have, and (b) Tourism-imported inflation as highlighted by Bull (1991) where the extra demand from the tourists can lead to price pressures and eventually a higher price for local consumers. Other negative effects include the 'cannibalisation' of other industry sectors and a potential for overdependence on the tourism industry. In essence, external effects (Pigou 1950; Boadway and Wildasin 1984; Stiglitz 1988) or externalities of tourism can have positive or negative effects on third parties (i.e., outside the specific tourism activity) through economic, social, cultural and environmental impacts.

Once the economic benefits and economic costs of tourism are obtained, the net economic benefits of tourism can be calculated. As travel and tourism services consumed are not easily identifiable, the measurement of a country's tourism contribution to GDP is a major problem. Frechtling (1987) highlighted that methods of estimating economic impact are numerous and vary widely in their approaches and output. He suggested a set of criteria for judging economic impact methods including: (a) relevance, (b) coverage, (c) efficiency, and (d) accuracy, and (e) applicability.

The economic impact of tourism in relation to a country's economy may be analysed using input-output analysis and tourism multipliers (Archer 1991; Fletcher 1989; Frechtling 1987; Briassoulis 1991; Johnson and Moore 1993). The total impact of tourism consists of primary and secondary effects. Primary or direct impacts are economic impacts that are a direct result of tourist spending. Secondary impacts are either indirect or induced impacts. Indirect impacts are the result of the re-spending of money in the form of local business transactions, while induced impacts are the additional income generated by further consumer spending. The tourist multiplier is a measure of the total impacts (primary plus secondary) that result from additional tourist expenditure. Pearce (1989) describes the tourism multiplier effect as: 'the way, in which expenditure on tourism filters throughout the economy, stimulating other sectors as it does so'. The six tourism multipliers identified by Fletcher and Snee (1989) are: (a) output multiplier, (b) sales or transactions multiplier, (c) income multiplier, (d) employment multiplier, (e) government revenue multiplier, and (f) import multiplier. The value of a multiplier depends on the nature of the economy concerned and on the degree to which the sectors which supply tourists trades with other sectors in the economy (Archer 1991). However, the value of the multiplier effect is diminished by leakage, and by the costs incurred in attracting and securing the infrastructural needs of the tourism industry. Studies on tourism in Singapore using Input-Output techniques include those of Diamond (1979), Seow (1981), and Toh and Low (1990).

1.4.1 Tourism Planning and Development

The desirability for tourism planning (Gunn 1994; Athiyaman 1995; Inskeep 1997; Hall 2000) is a response to the potential negative economic, social and environmental impacts of unplanned tourism development. Tourism planning, according to Gertz (1987), is 'a process, based on research and evaluation, which seeks to optimise the potential contribution of tourism to human welfare and environmental quality.' Gunn

(1994) highlighted that tourism planning can avert negative impacts of tourism development and it must be strategic and integrative involving social, economic, and physical dimensions. The four broad approaches of tourism planning identified by Gertz (1987) are:

(a) Boosterism - where little consideration to any potential negative impacts of tourism is made and tourism development is regarded inherently as good and beneficial to the country,
(b) Economic, industry-oriented approach - where a government utilises tourism to achieve economic growth and goals,
(c) physical/spatial approach - where tourism development is based upon spatial patterns that would minimise the negative impacts of tourism on the physical environment, and,
(d) A community-oriented approach - where the community and residents, and not the tourists, are regarded as the focal point in tourism planning. Kaufman and Jacobs (1987) refer to this as strategic planning at a community level.

Gunn (1994) highlighted the need to consider three levels for overall tourism planning: (a) continuous tourism planning which focuses collaboration between players in the public and private sectors; (b) regional strategic planning which provides guidelines and concepts in both physical and programme development; and (c) local tourism planning which avoids sporadic development that is not able to integrate with broader objectives and planning.

Overall, a government's tourism development policy (Hartley and Hooper 1990) is likely to reflect a range of objectives such as: (a) economic (b) environmental (c) social (d) educational (e) political (Hall 1994) and others (Ferguson 1988) geared towards correcting market failures, and optimising the total economic and noneconomic value that tourism can bring to a country. Tourism development policies vary between governments (Richter and Richter 1985) with controversy on whether tourism contributes to development or hinders development. Williams and Shaw (1988) show that development issues are not confined to poor countries.

This important task of tourism planning and development is carried out by the National Tourism Organisation (NTO) in most countries. Soteriou and Roberts (1998) proposed a model for the strategic planning process for NTOs and highlighted that the comprehensiveness of the strategic planning process is determined by an internal capability for strategic planning, and dimensions of the external environment that reinforce or undermine the employment of this process. Key activities of the strategic planning process (Chon and Olsen 1990; Camillus and Datta 1991; Choy 1993) include: (a) defining vision and mission, (b) defining goals and objectives, (c) environmental scanning, (d) internal analysis, (e) developing and evaluating alternatives, (f) strategy selection, (g) developing and executing operational plans, and (h) strategic control.

In addition, the need for some form of crisis management (PATA 1991; Pottorff and Neal 1994) seems critical for a national tourist organisation (Henderson 1999) given the nature of travel and tourism. Henderson (2002) concluded that conventional crisis management theories and models required modification to take into account the magnitude of the crises the NTO may face; and many of these crises arising in external environments where they have no authority and over which they can exercise little control. Planning for disasters and preparing responses was also emphasised with Barton (1994) claiming that "tourism related organisations that ignore the need for a crisis plan do so at their own peril."

1.5 Tourism in Singapore

1.5.1 Singapore History and Economic Development

Singapore's strategic location within the Asia Pacific region has enabled it to become a gateway into the region in terms of trade and capital flows. Singapore has a tropical climate that is warm and humid throughout the year, moderated by cool sea breezes. The temperature ranges from about 24 degrees Celsius to 32 degrees Celsius with most of the rainfall occurring during the months of November to January. Singapore consists of a main island and about 50 smaller islands at the southern tip of the Malaysian Peninsular. Singapore's main island is about 42 kilometres long and 23 kilometres wide with an area of 574 square kilometres. The total land area is about 639 square kilometres. The country is linked to the Malaysian peninsular by a 1.2 kilometre causeway that carries a road, rail and water pipeline link across the Straits of Johor. The terrain is generally flat and low lying, with the highest point, the Bukit Timah Hill at 163 meters above sea level. The main urban area and the financial centre are located on the southern part of the island.

Singapore was founded by Sir Stamford Raffles in 1819 as a trading post for the British East India Company. In 1826 Singapore was grouped with Malacca and Penang to form the Straits Settlements that became British colonies in 1867. During World War II, Singapore was occupied by the Japanese from 1942. After the war in 1946, Singapore was made a separate crown colony of the United Kingdom. In 1959, the British granted partial independence. In 1963 Singapore joined Malaya as one of the constituent states of the new Federation of Malaysia. However, Singapore was separated from Malaysia and became a republic on August 9, 1965 with full independence from Britain. Since gaining independence the country has been ruled by the People's Action Party (PAP) and for over thirty years Mr. Lee Kuan Yew was Prime Minister. As a whole, since independence, the country has remained politically stable.

The population of Singapore is approximately 4 million in 1999 with a multi-racial society comprising 78% Chinese, 14% Malay, 7% Indian and 1% other races. Population density is about 4,000 people per square kilometre making Singapore one of the most densely populated countries in the world. There are four official languages: English, Mandarin, Malay and Tamil with English being the language of commerce and administration. The country enjoys religious freedom, with the main religions being Buddhism, Christianity, Islam and Hinduism.

Singapore is one of East Asia's New Industrialising Countries (NICs) often referred to as the 'Four Tigers' together with South Korea, Taiwan, and Hong Kong. This classification is based on their rapid economic growth (World Bank 1991) and performance since the 1960s. In 1979, the Organisation for Economic Co-operation and Development (OECD) defined NICs as countries with per capita incomes between US$1100 and US$3500 in 1978, and with manufacturing sectors which accounted for at least 20% of GDP. The NICs economic success has been attributed to the transition and adoption of export-oriented industrialisation (EOI) strategies from import substitution industrialisation (ISI) strategies. Advantages of the EOI strategy include: more efficient allocation of resources and pressure for domestic firms to be more efficient and active in world trade. Further, EOI has generated employment by fulfilling demand in international markets through the supply of labour-intensive manufactured goods. Finally, EOI has increased the earnings of foreign exchange in activities where there is no dependence on imported inputs or foreign capital. The disadvantages of the EOI strategy include the increased vulnerability of Singapore to: (a) economic shocks, (b) technological changes that could reduce the country's comparative advantage, (c) sudden changes in consumer demand in world markets, (d) intense competition, and (e) increasing tariff and non-tariff barriers from target markets. Furthermore, with the EOI strategy the increase in educational attainments of women in employment and incomes has been accompanied by declining fertility rates and an upward pressure on wage rates as the labour market tightens. However, empirically it can be shown that the EOI strategy is more conducive to rapid, efficient and sustainable economic development than the ISI strategy.

The change by Singapore, following a short exposure to an import substitution strategy in the early 1960s, to an EOI growth strategy was due to its very small domestic market, the tariff and quota restrictions on imports from Malaysia after separation, and the intention of the British government to withdraw all its military forces (which was an important source of employment) within four years after Singapore's independence. Economic initiatives in support of the EOI strategy include the formation of the Economic Development Board (EDB) whose aim is to administer and coordinate relations between government and capital on proposed investments; the Jurong Town Corporation (JTC) which is charged with the responsibility for the development of industrial estates; the International Trading Company (INTRACO) which provides assistance in developing overseas markets for Singapore-made products and also helps to find cheaper sources of raw materials for local industries through bulk-buying; the Development Bank of Singapore which provides finance for industry at below market rates, and stimulates investments through equity participation; the Central Provident Fund (CPF); and the Post Office Savings Bank (POSB) through which Singapore captures the major share of its domestic savings. In 1979 the intention to move Singapore up in the hierarchy of the new international division of labour (NIDL), and to take it out of direct competition with the lower-wage countries, caused the government to promote a shift from labour-intensive production to higher value-added production. This shift consisted of four main actions: (a) 'corrective' wage policy where substantial wage cost increases were introduced between 1979 to 1981, (b) expansion and improvement of social and physical infrastructure supporting preferred higher value-added industries, (c) introduction of various selective fiscal and tax concessions and incentives that encourage the investment of higher-value added products and processes by firms, and (d) maximising its institutional control of organised labour through its direct representation in and control over the National Trade Union Council (NTUC).

With the EOI growth strategy, Singapore is today a leading competitive player in the petrochemicals, oil-refining, consumer electronics, financial services, and tourism industries. Currently, more than 5,000 multinational companies are represented on the island.

1.5.2 Economic Importance of Tourism in Singapore

Tourism has emerged as an important industry for Singapore since the late 1970s. The Singapore tourism receipts are shown in Table 1.3 (Turner and Witt 2001).

Table 1.3
Singapore Tourism Receipts (1990 to 2000)

Year	Tourism Receipts (US$ mil)
1990	4,751
1991	4,498
1992	6,141
1993	6,970
1994	7,466
1995	8,347
1996	7,955
1997	6,864
1998	5,637
1999	5,939
2000	6,560

Tourism receipts for Singapore increased by 11.2% in 1999 to US 5.94 billion. This constituted 24.3% of Singapore's services exports and 4.1% of total export of goods and services (STB, 2000). Tourism receipts reached a post-crisis high of US 6.56 million in 2000, a 10.5 per cent increase over 1999.

1.5.3 Tourism Growth

Tourism in the Asia-Pacific region has grown twice as fast as the global average of 3% per annum. This rapid advance of tourism in the region has been much discussed with almost universally shared optimism for continued growth (Hall and Page 1996; Go and Jenkins 1997). Asia-Pacific absorbed 14% of global tourism and it is forecast arrivals will reach 190 million and account for 20% of global tourism by 2010 (STPB 1996). The annual number of visitor arrivals to Singapore is shown in Table 1.4.

Table 1.4

Visitor Arrivals to Singapore (1978 to 2000)

Year	Annual Visitor Arrivals	AAGR % (Comments)
1978	2,019,831	-
1979	2,247,091	11.3%
1980	2,562,085	14.0%
1981	2,822,282	10.2%
1982	2,956,690	***4.8% (worldwide recession)***
1983	2,853,577	***-3.5%***
1984	2,991,430	4.8%
1985	**3,030,970**	1.3%
1986	3,191,058	5.3%
1987	3,678,809	15.3%
1988	4,186,091	13.8%
1989	4,829,950	15.4%
1990	5,322,854	10.2%
1991	5,414,651	***1.72% (Gulf war)***
1992	5,989,940	10.6%
1993	6,425,778	7.2%
1994	6,898,951	7.3%
1995	7,137,255	3.4%
1996	7,292,521	2.1%
1997	7,197,963	***-1.30% (The haze)***
1998	6,242,153	***-13.2% (Asian financial crisis)***
1999	6,958,205	11.5%
2000	7,685,638	10.5%
2001	7,522,155	***-2.2% (September 11)***

Source: Pacific Asia Travel Association, Bangkok Head Office.

1970s –1980s

During the late 1970s, Singapore experienced a period of rapid growth in tourist arrivals, sparking optimism about future growth rates and leading to overexpansion of hotel space. By 1982, visitor arrivals into the country were approaching 3 million. However, the drop in tourism growth rates since 1982 due to world economic downturn, the appreciation of the Singapore dollar, and loss of tourist attractions due to rapid industrialisation, presented Singapore with a challenge to further promote and develop itself as an attractive tourist destination (Cheong and Khem 1988). In particular, 1983 tourist arrivals fell by 3.5%. Singapore suffered a recession in 1985, and in 1986 together with hotel overbuilding, occupancy rates were as low as 25% in some major properties, resulting in serious financial losses.

The Singapore government's recognition that the poor performances of 1982 and 1983 were not due just to cyclical effects led to the development of the Tourism Development Plan (1986-1990). The emphasis of the plan was to 'create a unique destination combining elements of modernity with oriental mystique and cultural heritage' (Millar 1989; Henderson 1997; Chang et al. 1996; Teo and Huang 1995; Teo and Yeoh 1997) which resulted in a five-year restoration effort costing S$1 billion. The success of the Tourism Development Plan has resulted in an increase in visitor arrivals into Singapore; and in 1985 tourist arrivals passed the 3 million mark.

Arrivals in 1987 totalled 3.69 million, up 15.3% over 1986. In 1988, arrivals of foreign visitors reached a total of 4.19 million up 13.8% over 1987. By 1989, inbound tourists increased by 15.4% to a total of 4.83 million, with hotel occupancy levels ranging from the high 80s to mid-90s.

1990s – 2000

In 1990, with an increase of 10.2% over the number of arrivals in 1989, Singapore has a total of 5.32 million visitor arrivals. In 1991, tourism world-wide was hit by the effects of the Persian Gulf war and Singapore's tourism industry registered only a 1.7% increase in tourist arrivals. Nevertheless, in 1992 the total number of visitor arrivals into Singapore was on the increase again and reached 5.99 million, which represents an increase of 10.6% over 1991. In 1994, total visitor arrivals into Singapore reached 6.9 million up 7.3% from 1993. In 1995, the total number of tourist arrivals exceeded 7 million.

The Southeast Asian region faced many challenges in 1997. In 1997, Singapore annual tourist arrivals were 7.2 million, a 1.3% decline over 1996, due to the Asian financial crisis and the environmental pollution caused by forest clearance through burning on the two largest islands of Indonesia (Henderson 1999). When the haze cleared in November 1997, STB launched a worldwide marketing programme, Invitation to Blue Skies, to get both media and tour operators to come over and see that clear skies had returned to Singapore. The financial crisis in late 1997 continued through 1998, and Singapore like the rest of the countries in Southeast Asia was hit badly resulting in a negative double-digit growth of 13.2%.

In 1999, most Asian economies began to recover from the crisis that plagued the region the year before. At the same time, Singapore implemented a 15-month events-packed campaign that ran from June 1999 to September 2000 called Millenia Mania and this bold initiative resulted in visitor arrivals returning to double-digit growth rates of 11.5% in 1999 and 10.5% in 2000. In 1999, total visitor arrivals into Singapore were 6.95 million. For 2000, total arrivals reached 7.69 million, the highest number of visitors ever reached.

Singapore welcomed 7.52 million visitor arrivals in 2001; it's second highest in the history of tourism, inspite of the aftermath of September 11 and the global economic slowdown. The 7.52 million arrivals represented a drop of 2.2% over year 2000's record 7.69 million.

1.5.4 Inbound Tourism Market Characteristics

The inbound tourism market characteristics are reviewed using tourism statistics from the STB Annual Report on Tourism Statistics 2000 (STB 2001). The percentage distribution for each region by residence from 1990 to 2000 is shown in Table 1.5.

Table 1.5

Percentage Distribution of Regions by Visitor Arrivals by Residence (1990 to 2000)

Region	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Americas	6.33	6.04	6.13	6.06	6.2	5.97	6.3	6.4	6.82	6.38	6.28
Asia	64.39	68.02	68.91	69.57	71.3	73.3	72.94	72.26	67.67	68.95	69.18
Europe	17.73	16.58	15.99	15.86	14.74	13.53	13.75	13.72	15.74	15.09	14.66
Oceania	10.35	8.31	7.8	6.97	6.29	5.98	5.91	6.43	8.33	8.11	8.02
Africa	1.06	1.03	1.16	1.52	1.46	1.22	1.09	0.98	1.27	1.3	1.29
Not Stated	0.15	0.02	0.01	0.01	0.01	0	0	0.21	0.18	0.17	0.57

The selected countries Australia, Japan, UK, and USA for this study are chosen because they are the largest markets in each of their respective regions. China and India are included in this study because they are the largest potential tourism growth markets in Asia. The percentage distribution of visitor arrivals from each of these countries from 1990 to 2000 is shown in Table 1.6.

Table 1.6

Percentage Distribution of USA, Japan, China, India, UK and Australia By Visitor Arrivals by Residence (1990 to 2000)

Region	Country	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Americas	USA	4.91	4.69	4.8	4.78	4.98	4.84	5.13	5.23	5.49	5.05	5.01
Asia	**Japan**	18.25	16.09	16.71	15.58	16.08	16.52	16.07	15.2	13.52	12.37	12.09
	China	0.53	0.78	1.55	3.51	2.39	2.83	3.11	3.27	4.7	5.36	5.65
	India	4.07	3.87	3.26	2.8	2.52	2.64	2.8	3.15	3.9	4.14	4.50
Europe	**UK**	5.57	5.07	5.06	4.84	4.38	4.04	4.29	4.63	5.73	5.77	5.79
Oceania	**Australia**	8.58	6.8	6.43	5.68	5.04	4.86	4.82	5.3	6.84	6.7	6.64

Japan accounts for about a million arrivals each year out of the seven million visitors Singapore received from around the world. This makes them the number one source of Singapore's visitor arrivals. In the year 2000, the number of visitor arrivals from Japan was 929,895.

Australia has been a growth market for Singapore even during the difficult tourism times stemming from the Asian economic crisis in 1988. The Singapore Tourism Board opened a Marketing Representative Office in Melbourne, Australia in November 1998. Within Australia, the STB has identified the state of Victoria as having excellent potential for further tourism growth. Victoria overtook Western Australia in 1992 as the second largest source of visitors to Singapore from within Australia while New South Wales remained the largest source of visitors to Singapore. Singapore's tourism presence in Australia is represented in the three biggest visitor-generating cities and states - Sydney (NSW), Melbourne (Victoria) and Perth (Western Australia). In the year 2000, the number of visitor arrivals from Australia was 510,347.

The United States has been consistently one of the top visitor-generating markets with a buoyant growth rate of 9.7% in 2000 resulting in 385,585 American arrivals.

The UK is the largest market from Europe contributing 444,976 arrivals in the year 2000. European markets are significant tourism growth areas as they collectively accounted for more than 14 per cent of visitor arrivals. For 2000, Europe as a region demonstrated a healthy growth of 7.4%.

China has been one of the star performers for Singapore in terms of tourist arrivals. In 1999, China overtook the United States as the sixth top visitor-generating market for Singapore with 372,881 tourist arrivals. In 2000, the arrivals totalled 434,335. Singapore's tourist growth in the future will increasingly depend on attracting visitors from the new tourist generating markets of China and India.

India ranks 8th among Singapore's top visitor-generating markets. Each year, Singapore welcomes approximately 340,000 visitors from India. Recognising the potential of India as a major source of tourist arrivals, the STB has set up operations in Mumbai in 1993, in 2001 a marketing representative was appointed in New Delhi to service the North Asian market and in 2002 a Chennai representative was established to ensure that the South Indian markets will be serviced.

The visitor arrivals (from 1999 to 2001) and the forecast arrivals (from 2002 to 2004) for USA, Japan, China, India, UK, and Australia by Turner and Witt (2001) are shown in Table 1.7.

Table 1.7
Forecast Arrivals of USA, Japan, China, India, UK and Australia from (2002 to 2004)

Country	1999	2000	2001	2002	2003	2004
USA	351,459	385,585	343,805	*342,132*	*366,330*	*406,730*
Japan	860,662	929,895	755,766	*897,551*	*936,400*	*946,570*
China	372,881	434,335	497,397	*487,990*	*552,790*	*584,110*
India	288,383	346,356	339,812	*350,029*	*354,865*	*362,260*
UK	401,474	444,976	460,018	*427,462*	*474,055*	*503,560*
Australia	466,067	510,347	550,681	*562,130*	*583,480*	*601,800*

The main purpose of visit to Singapore is classified into four categories: Holiday, Business, Business & Pleasure, In Transit, and Others. As shown in Table 1.8, Holiday travel is the dominant purpose of visit at about half of total volume. Business travel also makes up a significant proportion of travel at 16%.

Table 1.8

Percentage Distribution of Visitor Arrivals by Purpose of Visit

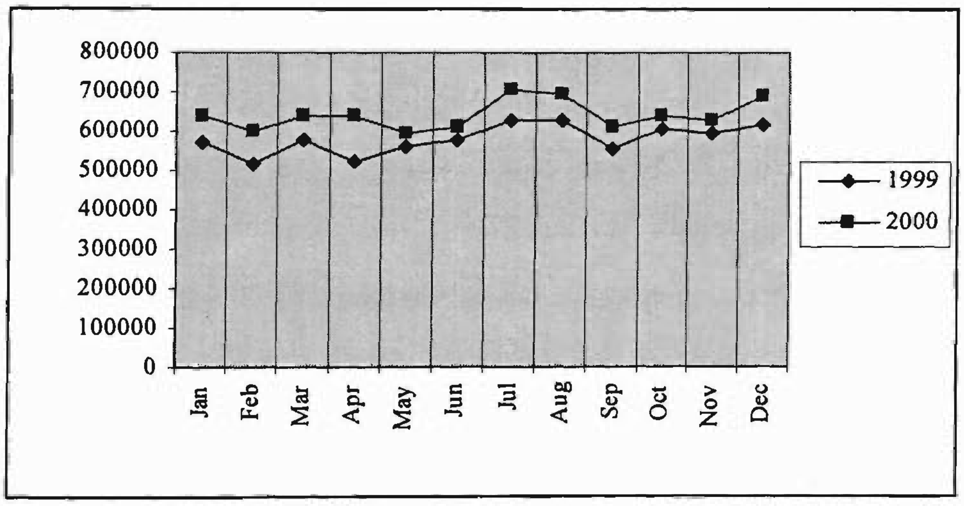
PURPOSE OF VISIT	1998	1999	2000
Holiday	45%	49%	48%
Business	16%	16%	16%
Business & Pleasure	3%	3%	3%
In Transit	10%	10%	10%
Others	26%	22%	15%

Figure 1.1 shows the seasonality of arrivals into Singapore for the years 1999 and 2000. The peak arrival months are mostly in the second half of the year, particularly in July and August. March, October and December are also popular months for travel into Singapore (STB, 2001).

July, August and December were the peak months of travel for visitors from Asia who in all, accounted for over 65% of arrivals to Singapore. Peak months of travel for visitors from Europe are concentrated in the latter part of the year – in August, October and November. The peak month of travel for visitors from the Americas is usually in March. For the Oceania markets where Australia is represented, September and October are the peak months of travel.

Figure 1.1

Seasonality of Arrivals into Singapore for 1999 and 2000



1.5.5 Tourism Development

Tourism is regarded by Singapore as an important mechanism for its economic growth as discussed above. As such, the country's National Tourist Organisation (NTO) known as the Singapore Tourist Promotion Board (STPB) was established in 1964, with a mission to promote tourism and establish Singapore as a premier destination with universal appeal. The STBP changed its name to the Singapore Tourism Board (STB) in 1998 and currently the STB has regional offices in Bombay, Chicago, Frankfurt, Hong Kong, London, Los Angeles, New York, Osaka, Paris, Perth, Seoul, Sydney, Taipei, Tokyo, Toronto and Zurich. Besides the STB, the Economic Development Board (EDB), the national airline (Singapore Airlines), hotels, travel and tour agencies, as well as the Singapore public have played an increasingly active role in promoting tourism in the country.

Marketing efforts by the STB over the years have focused on trade and consumer activities aimed at increasing the number of tourist arrivals, the average length of stay, and tourist expenditure in Singapore. These tourism marketing activities or campaigns include: (a) International advertising - where major advertising campaigns were undertaken in ASEAN, Australia, Taiwan, UK, US, Japan using both the print and the broadcast media; (b) Consumer promotions - here the STB led sales missions and joint promotions with airlines into countries such as Australia, Korea, the Middle East countries, and Thailand; (c) Participation in major international travel trade fairs - this was conducted to raise Singapore's profile among international tour wholesalers and operators; including participation regularly in the ASEAN Tourism Forum (ATF), World Travel Mart (WTM) and the Pacific Asia Travel Association (PATA) Travel Mart; (d) Active media relations and publicity - whereby the international press is kept informed of new tourism developments in Singapore through a public relations programme consisting of seminars, publications and other relevant media education programmes; (e) Promotion of cultural and sporting events (Weiler and Hall, 1992) - the STB also promoted many cultural and local festivities such as the annual Chinese Lunar New Year, Singapore's National Day celebrations, and Christmas light-up. In promoting Singapore's reputation as an international sporting venue, spectacular sporting events such as the Singapore Powerboat Grand Prix, Singapore Super Tennis Tournament, Singapore World Invitational Dragon Boat Race and the Dunhill World Cup Qualifying Round have been organised in the country by the STB.

Other than the above tourism marketing initiatives which serve to 'pull' visitors to Singapore, the STB has adopted a forward-looking and strategic approach in promoting Singapore as a premier tourist destination, with universal appeal, as well as a venue and leading hub for meetings, conventions, exhibitions, incentive travel and other tourism-related services. This was intended to allow Singapore to not only capture new growth opportunities, such as those offered by the more affluent Asian economies, but also to better meet the increased competition in the international tourism market, with its limited land and labour resources.

The three major strategies for growth implemented by the STB since its inception to promote the country as a tourist destination are:

(1) a 1 billion “Tourism Product Development Plan” in 1986 (STPB 1986) which called for the conservation and revitalisation of historic districts such as Chinatown, Little India, Arab Street, Boat and Clark Quays; the upgrading of Raffles Hotel; the development of resorts on Sentosa Island,

(2) The Strategic Plan for Growth from 1993 to 1995 to further promote tourism in Singapore (STPB, 1993) with the objectives and strategies listed in Table 1.9.

Table 1.9

Strategic Plan for Growth (1993 to 1995)

<u>OBJECTIVES:</u>

1. To boost tourism receipts by 10% per annum from $7.8 billion Singapore dollars in 1991 to $11.4 billion by end 1995.
2. To achieve an annual target of 25 million visitor-days by end 1995, by achieving an annual target of 6.8 million visitors by end 1995 and maintaining the 1992 average length of stay of 3.7 days.
3. To improve Singapore's position to the 6th top convention city in the world.
4. To establish Singapore as a venue with world-class special events.
5. To establish Singapore as the major cruise hub in the Asia-Pacific region.
6. To enhance the quality of the tourism experience.

<u>STRATEGIES:</u>

1. Increasing Singapore's share in existing key markets.
2. Forging Strategic alliances with airlines, national tourism organisations and industry members.
3. Capturing niche market segments.
4. Tapping new markets.
5. Intensifying convention promotion.
6. Developing world-class events.
7. Taking new directions in product development.
8. Improving services.

(3) the "Tourism 21 Vision" national tourism master plan launched in 1996 (STPB 1996) designed to position Singapore as a Tourism Capital, where Singapore is not only a memorable tourist destination with plenty to see and do, but also a tourism business centre and a tourism hub (STPB 1996). In the words of the Tourism 21 strategy document:

'Singapore is a vibrant, multicultural and progressive Asian city, located in the heart of one of the world's most exciting and fast-growing tourism and economic regions. In other words, it embodies the essence of 'New Asia'... After all Singapore, with its progressiveness, sophistication and unique multi-cultural Asian identity, can be said to be an expression of the modern Asian dynamism that marks the entire region – the island is a place where tradition and modernity, East and West meet and intermingle comfortably (p. 25).'

According to this strategy, as a Tourist Destination, Singapore must be a centre of attraction in its own right. As a Tourism Business Centre, Singapore must be in a position to attract the very best tourism businesses to take a stake in Singapore. As a Tourism Hub, Singapore must assume the position of a switching node; a springboard for visitors venturing into the region and vice versa as well as a headquarter for tourism-related businesses in the region. Broadly, the six distinctive strategic thrusts of Tourism 21 are as follows:

(1) Redefine tourism with new tourism products such as business centre, hub and New Asia,
(2) Reformulate products to be sophisticated to cater to demanding tourists with thematic developments, hardware and software harnessed in technology,
(3) Develop tourism as an Industry involving a cluster of industries (Porter 1990) with a creative, productive and service-oriented workforce,
(4) Configure new tourism space in terms of Singapore's own facilities and regional resort and selected destinations which are unlimited,
(5) Partnering for success involves public, private sectors on a win-win concept, and,
(6) Championing tourism with STPB being renamed to STB with wider powers and capabilities.

In conjunction with these thrusts, the image of Singapore as a vibrant cultural scene, cosmopolitan and dynamic is projected using the New Asia-Singapore Brand introduced in 1996. However, Henderson (2000) found in her survey that there is still a lack of awareness amongst both its tourists and locals of the New Asia-Singapore brand and concluded that devising and implementing meaningful brands remains a challenge for destination marketers. Kotler et al. (1996), Ward (1998) and Buhalis (2000) highlighted that destination marketing has become increasingly important. In addition, the creation of the right destination image through branding is a challenging task (Echtner and Ritchie 1991; Chon 1992; Waitt 1996; Morgan and Pritchard 1998).

A second aspect of the Tourism 21 master plan comes under the slogan "Tourism Unlimited" and the thrust is to develop and expand Singapore's role as a business and investment centre for the Asia Pacific Region. STB (1996) highlighted that with the successful implementation of the Tourism 21 vision, Singapore aims by the year 2005 to welcome its 10 millionth visitor and to receive S$16 billion in tourism receipts. This seems achievable judging by the successes that Singapore has received in recent times. In 2002, Singapore was voted the Favourite Business City in the world in an annual readership poll conducted by Business Traveller Asia Pacific (BTAP). Singapore was ahead of more than 30 cities to take the top spot in the Favourite Business City category with Hong Kong in second place and London, third. Singapore also swept the polls in other categories. Singapore Airlines won six awards including the Best Airline in the World, and the Best Asian Airline. Changi Airport won for the Best Airport and Best Duty Free categories. In 2001, thousands of travellers in Asia and Europe have also voted for Singapore as their Best Business Destination. This was the unanimous result of three separate readership polls conducted by Time Magazine, Business Traveller Asia Pacific (BTAP) and Business Traveller UK (BTUK). For the year 2001, about 19% of total visitor arrivals to Singapore were business travellers. Also in April 2001, Singapore was awarded the Destination of the Year. This award was presented at the end of the annual PATA Travel Mart. In March 2001, at the ITB 2001 (Internationale Tourismus Börse), a major travel trade event held annually in Berlin, the Singapore Tourism Board (STB) was awarded the Best Marketing Effort recognising STB has succeeded in putting across its tourism products and services in a clear, creative and consistent manner. For a third year running, the Singapore Tourism Board has been named the "Best National Tourist Organisation" at the prestigious 1998 Travel Awards; in 1998 STB also won the same award organised by the Miller Freeman Group.

It can be seen that tourism development initiatives by the STB over the years have resulted in tourism growth and an economic contribution to Singapore. The tourism strategies for growth developed and implemented by the STB indicate a high level of commitment by the STB and its management to strategic planning. Key strategic frameworks for tourism are discussed by Porter (1980), Gilberts (1990), Poon (1993), and Tribe (1997). The need and the effectiveness of the strategy development and implementation procedures adopted by the NTO are highlighted by Athiyaman and Robertson (1995) and Soteriou and Roberts (1998). Ooi (2002) concluded that STB in additional to taking initiatives, it's success and tourism plans are well supported by the government policies and valuable resources and this has contributed to STB success.

In summary, the factors that have contributed in the success and growth of Singapore's' tourism industry are as follows:

a) High level investment by government and the private sector, which resulted in good transportation, telecommunications and financial infrastructure.

b) The variety of admission-charging tourist attractions and public places of interest.

c) The availability of a wide range of excellent value-for-money accommodation facilities to suit the needs of various types of visitors.

d) The social and political stability of a modern city.

e) The positive and welcoming attitudes of a well-trained English speaking workforce serving the tourism industry created by both its culture and education and training system.

f) The accessibility of Singapore especially by air, land and sea due to its open-skies policy and its strategic location at the 'crossroads of the world' acting as a regional hub and gateway to the Asia- Pacific region. It is also an important stopover point for long-haul travellers. The opening of Changi International Airport Terminal 1 in 1981 and Terminal 2 in 1990 has provided greater accessibility to international visitors.

g) A clean, green and safe city with an all-year round warm and pleasant tropical climate.

h) An excellent venue for social and business meetings and functions because of its clean, safe and efficient reputation internationally.

i) A shopping and food paradise. Singapore offers good shopping facilities and good service with shoppers being protected by consumer protection and licensing policies.

j) A unique blend of Asian traditions and culture with Asian visitors feeling at home and Westerners intrigued by its multicultural society.

k) The high level of awareness of Singapore created by government participation in trade missions, sales missions and promotional campaigns in selling Singapore as a tourist destination.

l) Rapid economic growth of the Pacific Rim region leading to a corresponding increase in personal disposable incomes and consumerism.

The growing importance of tourism and growing maturity of Singapore as a tourist destination pose a great challenge to Singapore. Given its small size and lack of natural resources and attractions, it will be increasingly difficult for Singapore to sustain high levels of growth in visitor arrivals and tourism receipts or earnings. In addition, as the regional countries develop and open their markets, Singapore will also have to contend with intensifying competition. The question that is now raised is whether it is possible to use practical time-series models to further advance the planning of tourism development in Singapore.

CHAPTER 2 LITERATURE REVIEW

Introduction

This chapter reviews the various qualitative and quantitative forecasting methods that have been applied to tourism demand forecasting. Section 1 reviews qualitative forecasting methods that include surveys, jury of executive opinion and the Delphi method. In Section 2 quantitative forecasting methods are reviewed and are subdivided into causal and time-series methods. Causal methods include regression analysis and error correction models. The quantitative time series methods reviewed include the naïve method, moving average, exponential smoothing, Box-Jenkins, structural time-series models, and Neural Network models.

Tourism demand modelling and forecasting have been well discussed by Song and Witt (2000), and reviews of empirical research have been done by Bar On (1979), Uysal and Crompton (1985), Sheldon and Turgut (1985), Calantone et al. (1987), Witt (1989a, 1989b), Crouch and Shaw (1990), Crouch et al. (1992), Crouch (1994), Witt (1994), Witt and Witt (1995), Lim (1997), Song et al. (1999). Tourism forecasting methods can be divided into (a) qualitative, and (b) quantitative methods which in turn can be subdivided into non-causal quantitative techniques and causal quantitative techniques.

Regardless of the type of forecasting method used, the usefulness of any tourism demand forecasting model is really determined by the accuracy of the tourism forecasts that it can generate, as measured by comparison to actual tourism flows (Mahmoud 1984).

Frechtling (1996, 2001) provides a useful distinction between a forecasting method and a forecasting model as follows:

"A forecasting method is simply a systematic way of organising information from the past to infer the occurrence of an event in the future. 'Systematic' means following a distinct set of procedures in a prescribed sequence .

A forecasting model is one expression of a forecasting method. More specifically, it is a simplified representation of reality, comprising of a set of relationships, historical information on these relationships, and procedures to project these relationships into the future." (1996, p.19).

Figure 2.1 shows the list of forecasting methods that are reviewed in this chapter under the qualitative and quantitative classification headings.

Figure 2.1

Types of forecasting methods

A. Qualitative

1. **Jury of executive opinion**
2. **Delphi method**
3. **Surveys**

B. Quantitative

1. **Causal methods**
   - **a. Regression analysis**
   - **b. Error Correction Model**
   - **c. Multivariate Structural Model**
2. **Time-series methods**
   - **a. Naïve**
   - **b. Simple Moving Average**
   - **c. Decomposition**
   - **d. Exponential smoothing**
   - **e. Box-Jenkins Approach**
   - **f. Basic Structural Model**
   - **g. Neural Networks**

2.1 Qualitative Forecasting Methods

Qualitative forecasting methods, also called 'judgemental methods' or 'subjective forecasting' rely on managerial or expert judgement without using specific models. Therefore, different individuals using the same qualitative method may arrive at widely different forecasts. However, these methods are useful when there is a lack of historical data or when the historical data are not reliable predictors of the future.

2.1.1 Jury of Executive Opinion

In this approach, forecasts are made by a group of executives on the basis of experience, hunches, or facts about the situation. This approach is aimed at generating as much debate and interchange of ideas as possible in order to reach a consensus on the forecast. The advantages of this technique are: (1) simplicity, (2) it does not require much historical data, and (3) the most experienced executives can be brought together to make the forecasts. The disadvantages include: (1) it requires costly executive time, (2) the lack of consistency in the generated forecasts, (3) the 'bandwagon' effect where participants are reluctant to state views at odds with a developing consensus, and (4) the most forceful or senior executive's opinion might carry the most weight, which might lead to a poor forecast.

Example Application

Moutinho and Witt (1995) adopted a consensus approach method that permits full discussion among the experts, in forecasting and ranking the importance and impact of possible future developments in science and technology affecting tourism. The results show that the experts expect advances in science and technology to have major impacts on tourism development during the period up to 2030. This approach was useful as it supports the clarification of reasoning for proposed developments.

2.1.2 Delphi Method

The Delphi method (Brown 1968; Robinson 1979; Taylor and Judd 1989; Rowe et al. 1991; Moeller and Shafer 1994; Rowe and Wright 1999) which was developed by the RAND Corporation, has been widely applied to tourism forecasting.

The Delphi method is conducted through a sequence of steps. On the first round, each participant of the panel provides a written response to the questions asked. Responses are fed back to the panel, and each participant is then asked to reconsider his or her previous answers and to respond to the questions again. This procedure is repeated for four to six rounds until sufficient convergence is achieved from the collective knowledge of the participants (Robinson 1979). Thus, the estimates from the last round are used as the forecasts. The Delphi method has attracted the most attention of the several qualitative methods because all estimates from the panel of experts are treated anonymously. Anonymity eliminates the influence of the supposed greatest authority, as well as the 'bandwagon or herd effect' that is so common in the 'jury of executive' opinion method (Frechtling 1996). However, the feedback process of the Delphi method is criticised as having a tendency to force convergence toward the group centre, which has sometimes been referred to as 'pool ignorance' (Schroeder 1982). This method also requires a substantial amount of time from beginning to the end, resulting in panel attrition. Seely et al. (1980) highlighted that the most important potential weakness of the Delphi method is not asking pertinent questions, while Taylor and Judd (1989) consider the most important step is choosing the respondents.

Example Applications

Kaynak and Macaulay (1984) use the Delphi technique to gather data on tourism research, on future impacts of tourism and to strengthen a regional data base, all of which are intended to act as an effective policy-making tool in solving management and planning problems in the tourism and hospitality industry of Nova Scotia, Canada to the year 2000. The questions were posed to 150 judges, and after two rounds, 44 completed questionnaires were returned.

Liu (1988) used the Delphi forecasting technique to forecast tourism to Hawaii, particularly Oahu, by the year 2000. Local experts and travel agents were questioned on visitor arrivals and percentage of domestic arrivals to Hawaii, market share, visitor-to-resident ratio, maximum visitor accommodation and desirable growth rates, and probable scenarios for Oahu tourism. The results show few significant differences in responses among the groups, and confirmed expectations about convergence and consistency of managerial responses with statistical projections and existing trends.

Yong, Keng and Leng (1989) used the Delphi method to project the future of Singapore's tourism industry from 2 different panels, one consisting of people from the local tourist industry and the other consisting of an international group of business executives. The conclusions highlighted (a) positive future trends that include: 1. increased purchasing power for leisure and travel services for individuals from developed countries, 2. better access to travel information, 3. fewer constraints for cross-border travel movements, and 4. higher pressure for regional collaboration in tourism-related activities; and (b) negative trends which include the imposition of more stringent exit taxes and a decrease in business travellers.

Miller (2001) presented the results of a two round Delphi study conducted into expert opinion on the development of indicators for sustainable tourism. The results of this dephi survey show considerable disagreement over 'sustainability' and where the borders of the concept exist.

2.1.3 Surveys

The two survey approaches in qualitative forecasting are: (1) national or regional surveys of tour operators, travel agencies, and airlines, and (2) surveys of visitors or potential visitors as to whether they anticipate a trip to the tourism destination areas. The analysis of these surveys often provides valuable insights into emerging tourism trends in the short to medium term. However, the survey approach is time consuming and expensive and the conclusions drawn can be biased or incorrect due to (a) sampling errors, (b) non-response errors, and (c) response errors.

In summary, qualitative forecasting methods have more value applied to medium- and long-range forecasting, and are considered to be less rigorous than the quantitative forecasting methods. However, they are appropriate where data is insufficient or unreliable for the application of quantitative forecasting methods (Archer 1987; Var and Lee 1993). Sheldon and Turgut (1985) in their review of empirical research on tourism forecasting concluded expert-opinion methods are useful when data are unavailable. Another key advantage of qualitative methods is that they do not require high-level statistical skills to conduct forecasting. Sanders and Manrodt (1994) found that companies still relied heavily on judgmental methods, even though the knowledge of quantitative methods seemed to be improving. In another study by Frank and McCollough (1992) it was found that judgement (82% of the respondents) was most widely used followed by the quantitative methods such as moving averages and exponential smoothing to obtain forecasts.

2.2 Quantitative Forecasting Methods

The basic divisions of the quantitative forecasting methods are causal and time-series forecasting.

2.2.1 Causal Methods

2.2.1.1 Regression analysis

The linear regression method is one of the major approaches to causal modelling in tourism demand forecasting (Frechtling 1996). The general form is given as:

$Y_t \quad = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_n x_n + e$

where:

Y = the dependent of forecast variable,

α = intercept constant,

β = slope coefficients,

x = independent, or explanatory, variables,

n = number of explanatory (independent) variable,

e = error term.

The regression line is a linear time trend regression of the data series that minimises the sum of the squared vertical departures (i.e. residuals) of the data from the regression line; hence the technique is called 'least squares regression' or 'ordinary least squares regression' (OLS) (Greene 1997).

Regression models include simple regression and multiple regression. In simple regression, there is only one explanatory variable affecting the dependent or forecast variable. Mathematically, it is expressed as:

$Y_t \quad = \beta_0 + \beta_1 x_t + e_t$

where:

Y_t = dependent or forecast variable,

β_0 = intercept constant estimated by least squares regression,

β_1 = slope coefficient estimated by least squares regression,

x_t = explanatory (independent) variable,

e_t = error term.

With simple regression, a 'misspecification' problem can occur and this can be due to one or more relevant explanatory variables being excluded from the simple regression equation. As such, the multiple (or 'multivariate') regression model with two or more explanatory variables is more commonly used and is expressed as:

$$Y = \beta_0 + \beta_1 b_1 + \beta_2 x_2 + \beta_n x_n + e$$

where:

Y = dependent or forecast variable,

β_0 = intercept constant estimated by least squares regression,

β_1 = slope coefficient estimated by least squares regression,

x = explanatory (independent) variables,

n = number of explanatory variables,

e = error term.

The possible explanatory variables or determinants of tourism demand (Morley 1991 1996; Witt and Witt 1992; Frechtling 1996; Lim 1999; Song and Witt 2000) include the following:

(a) Population

- It is expected that the level of inbound tourists into the destination country depends upon the population of the tourist generating countries. Therefore, population can be used as an explanatory variable. Although, excluding the population variable is not likely to affect the model significantly, as population changes in the tourist generating countries are normally small over the short to medium term. The main argument for not having population as a separate variable is that it may cause multicollinearity problems. Population can also act as a surrogate variable for time change reflecting tourism growth rates that are common over time but not 'caused' by population change. In this way, a population variable can act as 'spurious' independent variable,

(b) Income

- The real per capita income of visitors from the tourist generating country is normally used as an explanatory variable (Crouch 1992). Income is an important explanatory variable in nearly all forecasting demand studies and is a direct and current determinant of the capacity of individuals within a given market to afford travel,

(c) Expenditure on the tour or price

- The expenditure on the tour can be included as an explanatory variable in regression analysis; and it consists of two components: (i) travel cost to the destination, and (ii) cost of living for the tourist in the destination (Martin and Witt 1987).

Travel costs could be air fares between the origin and destination, ferry fares, and/or petrol cost (based on the distances travelled) for surface travel. However, travel cost as a demand determinant is often excluded from the models due to potential multicollinearity problems, and the difficulty in obtaining this data (Uysal and Crompton 1984).

The consumer price index (CPI) in a country is usually taken as a reasonable proxy for the cost of living for the tourist in the destination. As Kliman (1981) highlighted where 'the data do not represent the underlying variables as accurately as one would like ... there are some instances in which only rough approximations to the theoretically correct constructs are possible'. Gray (1966) commented that 'prices are seldom completely known in advance by travellers so that the price level foreseen by the potential traveller will depend predominantly upon the rate of exchange of his domestic and [the destination currency]'. Thus a reasonable proxy for the cost of tourism is the exchange rate adjusted consumer price index. Using exchange rate on its own is not an acceptable proxy as consumers could be misled; as a favourable exchange rate could be counterbalanced by a relatively high inflation rate. For all-inclusive tours, both the travel cost element and the tourists' cost of living element are often added into a single cost variable as a determinant (Witt 1983).

(d) Substitute prices

- Prices of substitutes may be important determinants of demand in causal models. Gray (1966, p.86) highlighted that: '...there is a high elasticity of tourism demand substitution among countries so that higher than expected prices in one country may result in a change of destination rather than a decision to forgo overseas travel'. Thus both the tourists' travel costs (White 1985; Martin and Witt 1988a; Rosenwseig 1988) and tourists' living costs at the destination are just as likely to cause substitution possibilities thereby influencing the demand for tourism to a destination. From the review studies, it is found that substitute tourists' living costs are used more often than substitute travel costs (Gray 1966; Kliman 1981; Papadopoulous and Witt 1985).

(e) Dummy variables

- These are included in the regression model to allow for the effect of 'one-off' events. These variables take the value 1 when the event occurs and 0 otherwise. Thus the impact of events such as the oil crises and mega-events such as the Olympic Games can be incorporated as dummy variables (Witt and Martin 1987c; Smeral et al. 1992). Dummy variables can also be used to accommodate the effects of seasonality (Chadee and Mieczkowski 1987) when quarterly data are used in tourism model estimation. Additionally, for multi-destination models, dummy variables are used to represent destination 'attractiveness' (Witt 1980a) with the assumption that the relative attractiveness of the destinations remains the same over the time period considered. In reality this is not necessarily true or possible.

(f) Trend

- A trend variable representing the steady change in the popularity of a destination country over the time period considered can be included in the tourism demand model. Therefore this variable captures time-dependent effects of all the other independent determinants that have not been explicitly incorporated in the model, such as demographic changes in the origins.

(g) Marketing expenditure

- The marketing expenditure of national tourist organisations, used specifically for the promotion of the country as a tourist destination, is expected to have a significant effect on the level of international tourism demand. Promotional activities that include media advertising and public relations are often used to create interest and persuade potential visitors to travel to the particular country. However, there are problems associated with: (i) obtaining the relevant data, (ii) defining the relationship of this particular variable due to the distribution effect of advertising over time (that is, the advertising in a given period is likely to influence not only the immediate period but also subsequent periods), and (iii) assessing the effectiveness of a given level of advertising expenditure on tourism demand, as it often varies across media. Empirical studies that have included some form of marketing variable, in their tourism demand models include those by Barry and O'Hagan (1972), Uysal and Crompton (1984), O'Hagan and Harrison (1984) and Papadopoulous and Witt (1985).

(h) Lagged dependent variable

- A lagged dependent variable can be included in the tourism demand function to bring in the effect of: (a) habit persistence, that is, a visitor would tend to return to a particular destination in future if the visitor likes the place; there is less uncertainty associated with touring that destination again as compared to travelling to a new and foreign environment, and (b) supply constraints (Smith and Toms 1967; Witt and Martin 1987a).

Other than determining the causal variables, it is the responsibility of the forecaster to define the mathematical relationship or functional form (linear, nonlinear, additive, or multiplicative) of the tourism demand model. The log-linear form has been more popular due to its association with elasticities and superior empirical results compared with the corresponding linear functional form (Artus 1970; Barry and O'Hagan 1972; Uysal and Crompton 1984; Witt 1987a; Johnson and Ashworth 1990; Crouch 1994). Other functional forms include the semi-log (O'Hagan and Harrison 1984; White 1985), the Probit and Logit models (Witt, 1983), and a non-linear, diffusion form (Morley 1998, 2000). Morley (1991) highlighted a wrong functional form can have a significant impact on the model estimated. Song and Witt (1995) highlighted that 'For tourism demand forecasters, correctly identifying the determinants of tourism demand and appropriately specifying the tourism demand models are crucial for the generation of accurate forecasts of future tourism demand.'

In regression models, once this estimated mathematical relationship and the explanatory variables are established, forecasts into the future are obtained. As mentioned, the forecasting model parameter estimates are generated using the ordinary least squares (OLS) estimation method (Morley 1997); sometimes this method is augmented by the Cochrane-Orcutt procedure if autocorrelated residuals are identified. The OLS estimator for the parameter of an explanatory variable in a regression model is a constant and the best linear unbiased estimator of the parameter if the error term, e, satisfies the following basic assumptions:

1. Zero mean: $E(e) = 0$.
2. Homoskedasticity or constant variance: $E(e^2) = \sigma_e^2$.
3. Nonautocorrelation: $E(e_t e_k) = 0$ for $t \neq k$.
4. Uncorrelated with explanatory variable x_t : $E(x_t\, e_t) = 0$.

The strength of the relationship between the forecast (dependent variable) and the causal explanatory variables is calculated using the coefficient of determination, R^2. That is, R^2, is the proportion of the total variation in the observed values of the dependent variable that is explained by the overall regression model. Values of R^2 close to 1 indicate a close agreement between the model and data, while values close to 0 indicate a poor fit. To avoid the trap of only trying to find a model that maximises R^2, a 'good' regression model is selected based upon the following properties (Farnum and Stanton 1989):

(1) it should be a simple model with a reasonable number of predictor variables,

(2) it should have a statistically significant overall F-value, showing the usefulness of the entire set of predictor variables,

(3) it should have statistically significant partial t-values for each of the predictor variables. The partial-t values test whether the variable adds significantly to a model already containing the remaining predictor variables,

(4) a high R^2 value should be obtained from the model.

It has been recognised that certain problems can arise using the regression forecasting methods above: (a) it requires considerable user understanding in order to determine the causal structure, (b) it is generally more expensive and more complex through the inclusion of more explanatory variables, (c) more importantly, the dependence on predictor variables which are often themselves estimated or unavailable at the point of estimation, (d) the accuracy of the forecasts is highly affected and dependent on the accuracy of the predictor variables, and, (e) low levels of achieved accuracy despite high R^2 measures often occur. Generally, 'satisfactory' or 'acceptable' causal tourism demand models can be identified using criteria based on: (i) Durbin-Watson (DW) statistic - indicating no autocorrelation at the 5% significance level, (ii) 'correct' signs for the predictor variable coefficients, and (iii) F statistic - indicating that the equation is significantly different from zero at the 5% level. The 'best estimated' model is then identified from these acceptable models by comparing their coefficient of determination (R^2) and the statistical significance of the coefficients using t statistics. However, this assessment can be misleading as the appropriateness of the independent variables in the estimated model may change over the forecast time period, and this can lead to a decline in the accuracy of the model. One test for the stability of the forecasting model is the Chow predictive failure test described in Song and Witt (2000) and Frechtling (2001). As Witt and Witt (1990) highlighted: 'Conditions such as a high goodness of fit and a large proportion of statistically significant coefficients do not appear to be sufficient to ensure a high level of forecast accuracy'.

In addition, with the regression forecasting technique, care is needed to deal with the following problems:

(a) Heteroscedasticity; which implies that the residuals do not maintain constant variance throughout the time series.

(b) Multicollinearity; which refers to the correlation among explanatory variables (Fujii and Mak 1980). This was 'the most common methodological problem encountered' as highlighted by Crouch (1994) in his review of 85 tourism demand forecasting models.

(c) Autocorrelation of the error terms or residuals that can lead to an inappropriate model (Cook and Weisberg 1982). In regression models, error terms or residuals are assumed to be an independent white noise sequence with zero mean which has constant variance, independence, and normality assumptions. The presence of autocorrelated residuals may be detected by using residual plots and the Durbin-Watson statistic d test (Durbin and Watson 1951). Values close to 0 indicate positive autocorrelation, values close to 4 indicate negative correlation, and values close to 2 indicate independent error terms.

(d) Spurious relationships, which occur when statistical evidence points to the existence of a relationship between variables where, in fact, none exists and are another serious problem found in regression models (Granger and Newbold 1974; Skene 1995; Morris et al. 1995). In particular, many tourism demand variables are non-stationary and using the traditional regression model and obtaining a high R^2 can lead to a false conclusion that these variables are actually related when they are not. This problem of a spurious relationship has led to the use of co-integration analysis designed to overcome the problems of stationarity and these issues are discussed further below.

Morley (1991) highlighted that it is unlikely "that the widespread use of multiple regression for estimating tourism demand functions will diminish, given its widely perceived advantages over other ways of forecasting demand". However, he highlighted that while problems of heteroscedasticity, multicollinearity, and autocorrelation are well recognized by modelers, questions of model specification are less widely understood. Misspecification of the multiple regression model, such as failure to include an important explanatory variable or a wrong functional form, can have significant impacts on the model estimated. He concluded that more complex or general functional forms yield better models than more simple functions, such as the commonly used log-linear model.

Example Applications

Choy (1984) examines the accuracy and efficiency of forecasting techniques by applying time series regression to forecasting visitor arrivals. Past studies have shown that simpler time series techniques perform as well or better than complex forecasting models. An assessment of visitor forecasts developed at regional, destination and individual market levels suggests that time series regression performs well in producing annual forecasts of visitors which can serve as a baseline for evaluating the net benefits, if any, from applying more complex techniques. He highlighted that tourism managers should appreciate the usefulness of simpler formal methods in developing forecasts of visitors.

Witt and Martin (1987b) explored the inclusion of marketing variables in international tourism demand models, as National Tourist Organizations often spend considerable sums in foreign countries on promoting the particular country as a tourist destination. However, marketing activity is seldom incorporated as an explanatory variable in models of the demand for international tourism. It was highlighted where marketing is used to explain international tourism demand, caution must be exercised in interpreting the empirical results; poor results cannot be used to reach sensible conclusions, and when good results are obtained the full implications of the estimated coefficients need to be explored.

Smeral, Witt and Witt (1992) specified a complete system of econometric demand equations to generate forecasts of tourism imports and exports for various major geographical areas. The forecasts are presented for the period 1991 to 2000 under three alternative assumptions: (1) there is no change in the external environment (baseline scenario), (2) the completion of the single internal market of the European Community takes place, and (3) the liberalization and general creation of market economies in Eastern Europe. A comparison of the latter two scenarios with the baseline scenario was made to explore the effects of these changes on the tourism demand forecasts.

Crouch et al.'s (1992) study estimated the impact of the international marketing activities of the Australian Tourist Commission (ATC) on the number of tourist arrivals into Australia. Multivariate regression analysis was employed in order to estimate the elasticities of demand from five origin countries (USA, Japan, New Zealand, UK and FR Germany) using a set of determinants that include both total ATC marketing expenditure and advertising-only expenditure. The results suggested that international marketing activities of the ATC have a significant role in influencing inbound tourism to Australia from these countries. The best estimates of the marketing elasticities for the USA, Japan, New Zealand, the UK and FR Germany were +0.11, +0.20, +0.25, +0.14, and +0.23 respectively.

Chan (1993) employed a regression model that comprises a linear term in time and a sine function in time to fit the monthly total tourist arrival data in Singapore. Because of the seasonal fluctuation in the data, deseasonalised data was used in fitting the model. This regression model was compared with the naïve 1 model, naïve 2 model, a simple linear regression time series model, and an ARIMA (2,1,2) model using the mean absolute percentage errors (MAPEs) generated in forecasting the monthly tourist arrivals from January 1989 to July 1990. The result indicated that the sine wave time series regression model was the best forecasting model with a MAPE of 2.56%.

Crouch (1994), through his survey of the practices of past empirical studies of international tourism demand, highlighted the methodologies employed vary in a number of ways. Ordinary least-squares (OLS) multivariable regression analysis was identified as the most widely used approach. In terms of the functional form of the model, it was found that there appears to be almost universal agreement that the multiplicative (i.e., log-linear) form is superior to the additive (i.e., linear) form. In addition, it was found that the most common methodological problem encountered has been the difficulty of separating the effect of certain determinants as a result of multicollinearity. He concluded the selection of the most suitable approach will depend upon the circumstances and objectives of the study being planned, and it would be wrong to blindly adopt any one approach without first judging its limitations and assumptions.

Witt and Witt (1995) provided a review of empirical research of forecasting tourism demand studies and found that the vast majority of such studies are concerned with econometric modelling/forecasting with emphasis placed on empirical comparisons of the accuracy of tourism forecasts generated by different techniques. They highlighted considerable scope exists for improving the model specification techniques employed in econometric forecasting (Allen and Fildes 2001) of tourism demand.

Qu and Lam's (1997) study was to determine what exogenous variables best explained the travel demand for Mainland Chinese tourists to Hong Kong. A 12 year (1984-1995) annual time series data set of 'Mainland Chinese tourist arrivals', 'China disposable income per capita', 'consumer price indices in Hong Kong and China' and 'exchange rates' was used to develop a travel demand model. Seven exogenous variables were selected for the model. The OLS multiple regression analysis was performed to identify the 'best' subset of seven exogenous variables to determine the demand model. The results showed that travel demand for Mainland Chinese tourists to Hong Kong could be explained by 'disposable income per capita' and 'relaxation of visa requirements'.

Aki (1998) examined the relationship between tourism demand for Turkey and national income of the tourist generating country at constant prices, and relative prices (prices in the host country divided by prices in the tourist generating country) using a double-logarithmic functional form of the regression model. The results indicated a positive relationship between tourist arrivals and national income for the tourist generating countries, and a negative relationship between tourist arrivals and relative prices.

Kulendran and Wilson (2000) attempted to identify those economic variables that are most important in influencing business trips to Australia from four of Australia's most important travel and trade partners. They found that the importance of the economic variables varies from country to country, although overall openness to trade and origin country real income are important variables explaining business travel to Australia from these origin countries.

2.2.1.2 Error Correction Models

In a stationary time series the mean, variance and covariance will not change through time. If the time series analysed is non-stationary, using a regression model with the assumption of stationarity would give misleading results (the spurious regression problem). For a non-stationary time series, the ordinary least squares coefficients do not generally follow a normal distribution and the validity of tests such as the t test are in doubt. Moreover, the F test for the overall contribution of the independent variables is also invalid, as the F distribution does not hold. Nelson and Plosser (1982) indeed found non-stationarity in many macroeconomic variables and these would lead to spurious inferences when using them in formulating the models.

The cointegration technique developed by Engle and Granger (1987), together with the error correction mechanism is the proposed solution to the spurious regression problem when non-stationary time series are used in tourism demand modelling. Song and Witt (2001) provided a detailed description on cointegration and ECM. In summary, the use of cointegration raises the level of complexity in tourism demand modelling with the need to: (1) identify the order of integration using tests such as the Dickey and Fuller (DF) and Augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1981), and the Hylleberg, Engle, Granger and Yoo (HEGY) (1990) test; (2) test for cointegration, (3) estimate the ECM using either the Engle-Granger two stage, the Wickens-Breusch one-stage (Wickens and Breusch 1988) or the ADLM (Pesaran and Shin 1995) procedures.

In terms of forecasting accuracy performance, ECMs have been shown to perform well more for medium and long forecast horizons by Engle and Yoo (1987) and Hofman and Rasche (1996). Clements and Hendry (1995) showed that the sample size and representation of data are of great importance for forecasting performance improvement. Applications of cointegration and ECM for tourism forecasting include Kulendran (1996), Kulendran and King (1997), Lathiras and Siriopoulous (1998), Kim and Song (1998), Song et al. (2000), Kulendran and Witt (2001).

Example Applications

Lathiras and Siriopoulous (1988) was the first study to forecast demand for tourism using a cointegrated approach. In the study, tourist arrivals to Greece from six important generating countries were considered: the UK, Germany, Italy, France, the USA, and Holland using a total of 36 years' data from 1960 to 1995. As the economic determinants of tourism demand were integrated to the order of one, cointegration analysis and ECM methodology were applied to estimate the short- and long-run demand for tourism. They concluded that although past empirical studies do not indicate clearly that ECMs outperform regression models in forecasting, their results have shown that the estimated short-run demand models have good forecasting power.

Kulendran and King (1997) compared a range of forecasting models in the context of predicting quarterly tourist flows into Australia from the major tourist markets of USA, Japan, UK and New Zealand. Models considered included the error-correction model, the autoregressive model, the autoregressive integrated moving average model, the basic structural model and a regression based time series model. They found that the forecast horizon and country of origin are important parameters for the forecasting performance of various time series models.

Song et al. (2000) explored UK demand for outbound tourism to 12 destinations using error correction models. Ex post forecasts over a period of 6 years are generated from the ECM models and the results compared with those of a naive model, an AR(1) model, an ARMA (p,q) model, and a VAR model. The forecasting performance criteria show that the ECM model has the best overall forecasting performance for UK outbound tourism, although the improvement is not statistically significant at 5%.

2.2.1.3 Multivariate Structural Model

The single multivariate regression model assumes the only causality is from each explanatory variable to the forecasting variable, and does not capture feedback and cross-dependencies that might be present estimating the model. As such, structural models which are systems of interdependent equations including time elements and economic measures have been developed to more fully represent the interdependencies of variables in the real world (Frechtling 2001). As such these models in their basic form (refer to section 2.2.2.6) are time-series models and are discussed in the section ahead referring to time-series methods.

Key limitations of the multivariate structural models are: (a) its complexity, (b) vulnerability to the 'specification problem', (c) there is no standard way to build these models, and (d) it requires a large amount of input data. An extension of the structural modelling concept is the use of Structural Equation Modelling (SEM) which is also regression based (Reisinger and Turner 1999).

Example applications

González and Moral (1995) analysed the external demand for Spanish tourist services using Structural Time Series Models. The estimated structural model includes as explanatory variables an income index, two price indexes (one with respect to client countries and another with respect to competitor countries), a stochastic trend, representing the changes in tourist tastes, and a stochastic seasonal component. The results show that both price indexes are the more relevant of the variables that determine tourist demand and that the contribution of the trend component has been decisive in the rapid rates of growth of the tourist sector during recent years. The forecasting performance of the estimated structural model compares well with the forecasting performance of two alternative dynamic models, the transfer function and error correction models.

Turner, Reisinger and Witt (1998) examined tourist flows disaggregated into holidays, business visits and visits to friends and relatives (VFR) for each origin country-destination country pair in order to discover whether the various demand determinants had differential impacts depending upon the purpose of visit under consideration using structural equation modelling (SEM) as distinct from the multivariate structural model. The findings of the study suggested that simultaneously modelling on all three flow types using SEM had considerable potential in both widening the variety of explanatory variables that might be used, and also providing a clearer exposition of the difference among types of tourism demand in terms of their individual determinants.

Turner and Witt (2001) analysed the factors influencing international inbound tourism demand to New Zealand from Australia, Japan, UK, and the USA also using structural equation modelling. The tourist flows were disaggregated into holidays, business visits and visits to friends and relatives (VFR). The empirical results show that international trade plays a major role in influencing business tourism demand, retail sales are the major influence on the demand for foreign holidays, and new private car registrations were the major determinant of VFR tourism demand. Again this approach was used primarily to attempt to broaden the types of economic determinant variables that could be used.

2.2.2 Time Series Forecasting Methods

A time series refers to observations on a variable that occurs in a time sequence. A time series is deterministic if it can be predicted exactly. Most time series are stochastic in that the future is only partly determined by past values. A time-series forecasting model predicts future values of a time series solely on the basis of the past values of the time series (Makridakis et al. 1983; Newbold and Bos 1990; Wei 1990; Mills 1991; Morley 1993; Frechtling 1996; Makridakis et al. 1998). The basic strategy in time series forecasting is:

(a) To identify a data pattern based on the historical time series. This can be done by dividing the time series into data components, such as average level, trend, seasonality, cycle, and residuals,

(b) Make forecasts by extrapolating the data pattern.

Thus, time series forecasting methods as an extrapolative method is not concerned with causal factors when extrapolating the forecast estimates, unless specific interruptions in the time series can be related to specific events that have occurred. In this latter case, the time series model can be adjusted in its level by measurement of the specific event. For example, in order to take into account the impact of discrete external factors that could affect the forecast variable, intervention models (Box and Tiao 1975) and leading indicator models (Turner et al. 1997a) have been introduced.

Frechtling (1996, 2001) highlighted five patterns in a tourism time series: (a) seasonality, (b) stationarity, (c) linear trend, (d) non-linear trend, and (c) stepped series. Tourist arrivals which typically exhibit seasonal, trend and irregular data components have therefore made time series forecasting methods a reasonable forecasting choice (Sheldon and Turgut 1985; Uysal and Crompton 1985; Calontone et al. 1987; Martin and Witt 1989; Turner and Kulendran 1993; Turner et al. 1995a, 1995b; Gonzalez and Moral 1996; Turner et al. 1997a, 1997b; Chan et al. 1999; Greenidge 2001; Lim and McAleer 2001; Lim and McAleer 2002).

Different time-series forecasting methods employed in tourism demand forecasting include the following:

2.2.2.1 Naïve Forecasting Method

In the naïve or no-change forecasting method, the forecast value is equal to the actual value of the last period value. Mathematically,

$$F_t = A_{t-1}$$

where:

F = forecast value,

A = actual value.

This simplest forecasting method can be used as a benchmark in comparing with other forecasting methods. Though simple, the naïve model can outperform more complex forecasting models for tourism demand as highlighted by Witt and Witt (1992, 1995). Two other versions of the naïve method are: (1) 'Naïve 2' model where the forecast value is the current value multiplied by the growth rate between the current value and the previous value, (2) 'Seasonal naïve' where in a seasonal context, the one-period-ahead forecast value is equal to the value of the same period in the previous year (Turner and Witt 2001).

2.2.2.2 Simple Moving Average Method

In this method, a given number of periods N is selected for the averaging process in attempting to obtain a better forecast for the next period. The simple moving average model is given as follows:

$$F_t = (A_{t-1} + A_{t-2} + \ldots + A_{t-n})/n$$

where:

F = forecast value,

A = actual value,

n = number of averaging periods.

As a general principle, the longer the averaging period, the slower the response to demand changes. Therefore, a longer period has the advantage of providing stability in the forecast but the disadvantage of responding more slowly to real changes in the demand level. Thus, the appropriate trade-off between stability and response of the forecast must be made by selecting the average length n.

In the simple moving average method, all the past values used in the averaging all have the same influence on the forecast value. To make the moving average respond more rapidly to changes in demand, relatively more weight (w) is placed on recent demand than on earlier demand. This is known as the weighted moving average approach and is computed as follows:

$$F_t \quad = (w_1 A_{t-1} + w_2 A_{t-2} + . . . + w_n A_{t-n})/n \quad .$$

The advantage of the moving average method is its forecast simplicity. Disadvantages of the weighted moving average method include: (a) the need to carry the entire demand history for n periods for computation, and (b) the response of the weighted moving average cannot be easily changed without changing each of the weights.

In summary, the moving-average method is one of the simplest methods of time-series forecasting and assumes that the time series has only a level component and a random component; that is no seasonal pattern, trend, or cycle components are present in the time series data. In the results of a questionnaire survey by Martin and Witt (1988b), it was indicated that the moving-average was the most popular technique for short-term forecasting (less than one year ahead).

2.2.2.3 Decomposition Model

The classical decomposition approach decomposes a time series into four components: trend, cycle, seasonal, and an irregular component. Therefore, a time series can be represented as:

$x_t = T_t \times C_t \times S_t \times I_t$ or

$x_t = T_t + C_t + S_t + I_t$

where:

x represents the actual value in the time series,

T represents the trend component,

C represents the seasonal component,

S represents the seasonal component,

I represents the irregular component.

Thus the principle is to (1) identify these components and develop forecasts for each using methods such as the moving average and regression, and (2) recombine the individual forecasts to generate the final forecast.

The Census X11 model developed for the US Bureau of the Census (Shiskin 1967) is an example of the decomposition method. The X-11 program is used to deseasonalise quarterly or monthly data thereby producing detailed analyses of seasonal factors, and trend-cycle and irregular variations. The main disadvantage of X-11 is its inflexibility, as the same procedure is essentially applied irrespective of the properties of the time series.

2.2.2.4 Exponential Smoothing Methods

Intermediate extrapolative forecasting methods (Frechtling 1966, 2001) include: (1) simple exponential smoothing, (2) double exponential smoothing, and (3) autoregression. The single exponential smoothing method (Brown 1963; Gardner 1985) equation is given as follows:

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

where:

F = forecast value,

α = a smoothing constant between 0 and 1,

A = actual value.

From the equation, it can be seen that the higher the value of the smoothing constant, the more weight it gives to the last value. A lower smoothing constant implies more weight is given to all the values previous to the last value. Thus, the objective is to obtain the smoothing constant value that will minimize the forecasting error measure.

The single exponential smoothing forecasting method is applicable to stationary time series with no seasonality. Thus, it cannot always be applied directly for tourism arrival forecasting because of the seasonal effects that are present in a tourist arrival data series. Differencing is used to derive stationary and to pre-process the seasonal data series before using the single exponential forecasting to generate the forecast values.

The double exponential smoothing method (Brown 1963) was developed for trended time series, but its disadvantage is that is cannot deal with seasonality that is common in tourism data series.

The triple exponential smoothing (Holt 1957; Winters 1960) method was developed for a seasonal time series with trend. The model is based on three equations (Makridakis et al. 1998); one for level, one for trend and one for seasonality.

$$L_t = \alpha (A_t / S_{t-s}) + (1 - \alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \beta (L_t - L_{t-1}) + (1 - \beta) T_{t-1}$$

$$S_t = \gamma (A_t / L_t) + (1 - \gamma) S_{t-s}$$

where:

L = level of the series,

α = level smoothing constant between 0 and 1,

A = actual value,

s = number of seasonal periods in a year,

T = trend of the series,

β = seasonal smoothing constant between 0 and 1,

S = seasonal component,

γ = seasonal smoothing constant between 0 and 1, t = some time period,

h = number of time periods ahead to forecast.

Upon the determination of the values of the three smoothing constants, α, β and γ the forecast for m periods ahead is computed using the following equation:

$$F_{t+h} = (L_t + h\,T_t)\,S_{t-s+h}$$

where:

h = number of time periods ahead to forecast.

The values of the three smoothing constants are calculated generally by the forecasting system or statistical program internally and are chosen based on the minimum absolute percentage error (MAPE) or mean square error (MSE) criterion (discussed later in chapter 4).

In general, exponential smoothing methods are found to be most effective when the components describing the time series are changing slowly over time (Bowerman and O'Connell 1993).

Example Applications

Martin and Witt (1989) tested the accuracy of selected forecasting models (naïve 1, naïve 2, exponential smoothing, trend curve analysis, Gompertz, autoregression, and econometric) for outbound tourism from France, Germany, the United Kingdom, and the United States to six of their main destinations. The results reveal that the simple naïve no-change extrapolation model generally generates the most accurate one-year-ahead tourism demand forecasts with lower mean absolute percentage errors (MAPEs).

Witt et al. (1992) applied the Holt-Winters, Naïve 1 and Naïve 2 models to generate domestic forecasts of visitor arrivals in Las Vegas. The study shows that the Holt-Winters exponential smoothing method generates forecasts with lower error magnitudes (MAPE) than both the naive models for domestic tourism demand forecasting in Las Vegas. This supported the suggestion that the Holt-Winters model is particularly appropriate for data series where trend and seasonality components are present.

Athiyaman and Robertson (1992) use the following time-series forecasting techniques to generate forecasts of international tourist arrivals from Thailand to Hong Kong: 1. naive, 2. moving average, 3. single exponential smoothing, 4. linear moving average, 5. Brown's one-parameter linear exponential smoothing, 6. Holt's 2-parameter linear exponential smoothing, and 7. Winter's 3-parameter exponential smoothing. Their results confirm that simple techniques may be just as accurate and often more time- and cost-effective than more complex ones.

Sheldon (1993) examined the accuracy of six different forecasting techniques (time series and econometric causal models) to forecast annual tourism expenditures in the United States by tourists from six origin countries (Canada, Japan, United Kingdom, West Germany, France and Italy) for the years 1970 to 1986. The results show that the accuracy of the forecasts, using MAPE, differs depending on the country being forecast, but the no-change model and Brown's double exponential smoothing are, overall, the two most accurate methods for forecasting international tourism expenditures.

Witt, Witt and Wilson (1994) examined the forecasting of quarterly outbound tourist flows from the UK to four countries (Austria, Greece, Italy and Spain). The forecasting models (naïve 1, naïve 2, exponential smoothing, trend curve analysis, Gompertz, autoregression, and ARIMA) were estimated over the period 1971 to 1987, and used to forecast tourist flows for each quarter of 1988 and 1989. The forecasting accuracy of the models were performed using MAPEs, and it was found that the ARIMA forecasting model was the best performing model reflecting the suitability of ARIMA for forecasting seasonal data as conducted in this study.

Witt and Witt (1995) reviewed the empirical research on forecasting tourism demand and concluded that no single forecasting method performs consistently best across different situations, but autoregression, exponential smoothing and econometrics are worthy of consideration as alternatives to the no change model.

Lim and McAleer (2001) estimated various exponential smoothing models over the period 1975 to 1999 to forecast quarterly tourist arrivals to Australia from Hong Kong, Malaysia, and Singapore. Using the root mean squared error criterion as a measure of forecast accuracy, they found that the Holt-Winters Additive and Multiplicative Seasonal models outperform the Single, Double, and the Holt-Winters Non-Seasonal exponential smoothing models for the one-quarter-ahead forecasts for the period 1988 to 2000. They also concluded there is a need to be concerned about seasonality in forecasting of international tourism demand for Australia.

2.2.2.5 Box-Jenkins Method

The Box-Jenkins process (Box and Jenkins 1976; Vandaele 1983; Box et al. 1994) uses the autoregression and moving average methods to suggest the most appropriate form of a forecasting model (Frechtling 1996). The acronym ARMA is used to indicate the autoregressive and moving average combined method. These basic forms of Box-Jenkins models are outlined below:

(a) autoregressive (AR) models which are regressions on themselves. A pth-order autoregressive process, AR(p), is written as:

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \ldots + \phi_p Z_{t-p} + a_t$$

where:

Z_t = forecast value,

P = the number of autoregressive parameters of the model.

(b) moving average (MA) models which express that the forecast variable depends on the previous values of its error term or white noise. MA models were first considered by Slutsky (1927) and Wold (1938). A qth-order moving average process, MA(q), is written as:

$$Z_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q}$$

where:

q = the number of moving average parameters.

(c) mixed autoregressive-moving average (ARMA) models, when the series is partly autoregressive and partly moving average. An autoregressive moving average process of orders p an q respectively, ARMA(p,q), is written as:

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots + \phi_p Z_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} .$$

A time series is known as stationary when its mean and variance do not change over time. As ARMA models can only handle stationary time series, a non-stationary time series would first be transformed to become approximately stationary by applying operations such as differencing. However, care is needed not to overdifference as this can introduce unnecessary correlations into a model. If differencing is required to achieve stationarity, then the series is eventually integrated before forecasting. In this case, an I (for integrated) is added to ARMA model resulting in the autoregressive/integrated/moving average or ARIMA model.

Mathematically, a nonseasonal stationary model resulting from d differencing, i.e., ARIMA (p,d,q) is written as:

$$Z_t - Z_{t-1} = \phi_1 (Z_{t-1} - Z_{t-2}) + \phi_2 (Z_{t-2} - Z_{t-3}) + \dots + \phi_p (Z_{t-p}) + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} ,$$

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q}$$

where:

$$Y_t = Z_t - Z_{t-1} ,$$

$$Y_t - \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - \dots - \phi_p Y_{t-p} = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} .$$

Using the backshift operator B, which is defined such that any variable that it multiplies has its time subscript shifted back by the power of B (Pankratz, p. 115). That is:

$$B^k Y_t = Y_{t-k}$$

$$Y_t - \phi_1 B^1 Y_t - \phi_2 B^2 Y_t - \ldots - \phi_p B^p Y_t = a_t - \theta_1 B^1 a_t - \theta_2 B^2 a_t - \ldots - \theta_q B^q a_t$$

$$Y_t (1 - \phi_1 B^1 - \phi_2 B^2 - \ldots - \phi_p B^p) = a_t(1 - \theta_1 B^1 - \theta_2 B^2 - \ldots - \theta_q B^q)$$

Defining : $\phi(B) = (1 - \phi_1 B^1 - \phi_2 B^2 - \ldots - \phi_p B^p)$

which is a AR characteristic polynomial evaluated at B,

$\theta(B) = (1 - \theta_1 B^1 - \theta_2 B^2 - \ldots - \theta_q B^q)$

which is a MA characteristic polynomial evaluated at B,

$\nabla^d Z_t = (1-B)^d Z_t$

where d is the level of differencing to achieve stationarity for the data series.

the ARIMA (p,d,q) model can be expressed in a compact notation:

$$\phi(B) \nabla^d Z_t = \theta(B) a_t \quad .$$

A seasonal stationary ARIMA model is represented by the ARIMA (P,D,Q)s model where s denotes the known seasonal period, and D denotes the seasonal differencing, that is calculating the change from the last corresponding season ($Z_t - Z_{t-s}$) is performed.

$$Z_t - Z_{t-s} = \Phi_1 (Z_{t-s} - Z_{t-2s}) + \Phi_2 (Z_{t-2s} - Z_{t-3s}) + \ldots + \Phi_P (Z_{t-Ps}) + a_t - \Theta_1 a_{t-s} - \Theta_2 a_{t-2s} - \ldots - \Theta_Q a_{t-Qs} ,$$

$$Y_t = \Phi_1 Y_{t-s} + \Phi_2 Y_{t-2s} + \ldots + \Phi_P Y_{t-Ps} + a_t - \Theta_1 a_{t-s} - \Theta_2 a_{t-2s} - \ldots - \Theta_Q a_{t-Qs}$$

where:

$Y_t = Z_t - Z_{t-s}$,

$$Y_t - \Phi_1 Y_{t-s} - \Phi_2 Y_{t-2s} - \dots - \Phi_P Y_{t-Ps} = a_t - \Theta_1 a_{t-s} - \Theta_2 a_{t-2s} - \dots - \Theta_Q a_{t-Qs} .$$

Using the backshift operator B :

$$B^s Y_t = Y_{t-s} ,$$

$$Y_t - \Phi_1 B^s Y_t - \Phi_2 B^{2s} Y_t - \dots - \Phi_P B^{Ps} Y_t = a_t - \Theta_1 B^s a_t - \Theta_2 B^{2s} a_t - \dots - \Theta_Q B^{Qs} a_t ,$$

$$Y_t (1 - \Phi_1 B^s - \Phi_2 B^{2s} - \dots - \Phi_P B^{Ps}) = a_t(1 - \Theta_1 B^s - \Theta_2 B^{2s} - \dots - \Theta_Q B^{Qs}) .$$

Defining : $\Phi(B) = (1 - \Phi_1 B^s - \Phi_2 B^{2s} - \dots - \Phi_P B^{Ps})$

which is a AR characteristic polynomial evaluated at B,

$\Theta(B) = (1 - \Theta_1 B^s - \Theta_2 B^{2s} - \dots - \Theta_Q B^{Qs})$

which is a MA characteristic polynomial evaluated at B,

$\nabla_s^D Z_t = (1-B^s)^D Z_t$

where D is the degree of seasonal differencing,

the seasonal ARIMA (P,D,Q)s model can be expressed in compact notation as :

$$\Phi(B) \nabla_s^D Z_t = \Theta(B) a_t .$$

Many tourism arrival data series contain both seasonal and nonseasonal patterns. The seasonal component has its own autoregressive and moving average parameters with orders P and Q in addition to the non-seasonal component parameters with orders p and q. Seasonal differences D, and regular difference d, are used to reduce the series to stationary. The mixed seasonal ARIMA model is written as ARIMA $(p,d,q)(P,D,Q)^s$ where s is the seasonal order and can be expressed as:

$$\phi(B) \Phi(B) \nabla^d \nabla_s^D Z_t = \theta(B) \Theta(B) a_t$$

where:

$\phi(B)$ = polynomial non-seasonal AR operator of order p,

$\Phi(B)$ = polynomial non-seasonal MA operator of order q,

$\theta(B)$ = polynomial seasonal AR operator of order P,

$\Theta(B)$ = polynomial seasonal MA operator of order Q, and

$\nabla^d \nabla_s^D$ = differencing operators.

The Box-Jenkins modelling methodology, shown in Figure 2.1, has the following five stages (Frechtling 1996, 2001):

(1) Preparation

- the data series is first examined for stationarity and seasonality. Seasonality in the series can be determined by using the autocorrelated coefficients. The data is then pre-processed to achieve mean and variance stationarity.

(2) Model identification

- the data series estimated autocorrelation and partial autocorrelation coefficients are displayed graphically using the estimated autocorrelation function (acf) and partial autocorrelation function (pacf). An estimated autocorrelation function (acf) shows the correlation between ordered pairs from a time series, separated by various time spans; and an estimated partial autocorrelation function (pacf) which shows the correlation between ordered pairs from a time series, separated by various time spans, with the effects of intervening observations accounted for.

To identify a tentative model with the values of *p,d* and *q*, a visual examination and comparison is then made between the theoretical and estimated acf's and pacf's, with the objective of finding a model that is parsimonious and statistically adequate. A time-dependent process has a theoretical acf and pacf and the estimated acf's and pacf's are found by applying the autocorrelation coefficient statistic and Yule-Walker equations (Pankratz, 1983). Estimated acf's and pacf's never match theoretical acf's and pacf's exactly due to sampling error. The decision matrix for identifying the appropriate form of the ARMA model using the acf and pacf is shown in Table 2.1

$\Phi(B)$ = polynomial non-seasonal MA operator of order q,

$\theta(B)$ = polynomial seasonal AR operator of order P,

$\Theta(B)$ = polynomial seasonal MA operator of order Q, and

$\nabla^d \nabla_s^D$ = differencing operators.

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To identify a tentative model with the values of *p,d* and *q*, a visual examination and comparison is then made between the theoretical and estimated acf's and pacf's, with the objective of finding a model that is parsimonious and statistically adequate. A time-dependent process has a theoretical acf and pacf and the estimated acf's and pacf's are found by applying the autocorrelation coefficient statistic and Yule-Walker equations (Pankratz, 1983). Estimated acf's and pacf's never match theoretical acf's and pacf's exactly due to sampling error. The decision matrix for identifying the appropriate form of the ARMA model using the acf and pacf is shown in Table 2.1

Table 2.1

ARMA models decision matrix

Model (order)	Autocorrelations (acf)	Partial Autocorrelations (pacf)
AR (p)	Tail off toward zero	Cuts off to zero after lag p
MA (q)	Cuts off to zero after lag q	Tails off toward zero
ARMA (1,1)	Tails off towards zero	Tails off towards zero

(3) Model estimation

- the tentative ARMA model parameters (ϕ and θ) are then estimated based on the iterative maximum likelihood (ML) process (Norden, 1972). The final values of ϕ and θ are based on their combination to minimise the sum of the squared errors.

(4) Diagnostic checking

- Once the tentative model has been estimated, a residual analysis diagnostic check can be made of the model. The fitted residuals should be white noise ; that is it should have a mean of zero, a constant covariance, and be uncorrelated with each other over time. These assumptions can be examined by visual examination of the residuals plot in the diagnostic checking process. Also, the Box-Pierce Q statistic and the modified Box-Pierce (or Ljung-Box) Q* statistic can be applied to check that there are no significant autocorrelations in the fitted model's error terms. If the t-tests on the estimated parameters show that they are significantly different from zero, and the fitted residuals are white noise, then the model is deemed to be adequate. Should the model fail the diagnostic checks, the cycle is repeated until a satisfactory model is found. When final model selection is needed from various competing possible models, the Akaike information criterion (AIC) (Akaike, 1973, 1974, 1979) and Schwartz Baynesian criterion (SBC) can be used to aid in selecting the most appropriate model. Ideally, the AIC and SBC should be as small as possible.

(5) Forecasting

- The fitted model is used to forecast future values of time series. Once the forecasts are obtained, transformation of the values back to into the term of the original series is taken, if necessary.

Characteristics of a good ARMA or ARIMA model (Pankratz, 1983) are that (a) it is parsimonious, i.e. the model uses a small number of parameters or coefficients to explain the available data, (b) it is stationary, (c) it is invertible, (d) it has high quality estimated coefficients, (e) it has uncorrelated residuals, (f) it fits the available data satisfactorily, that is, it has acceptable root-mean-squared error (RMSE) and mean absolute percent error (MAPE) values, and (g) it produces accurate forecasts.

Advantages of ARIMA models are: (a) ARIMA models are based on a solid foundation of classical probability theory and mathematical statistics (Pankratz 1983), (b) Versatility of the ARIMA models for various types of time series. For example, exponential smoothing methods can handle only time series with deterministic trend in which the average level of the series grows or declines according to some specific function in time. However, many time series display stochastic trends, i.e. trends with variable rates of growth. Both deterministic and/or stochastic trend can be modelled using ARIMA models (Farnum and Stanton 1989), and (c) Unified, theoretically sound approach to forecasting. That is, the Box-Jenkins methodology provides a systematic approach to model selection, utilising all the information available in the sample acf and pacf.

Disadvantages of the Box-Jenkins method are: (a) the method is fairly complicated and considerable expertise is required in specifying a suitable model using the sample and partial autocorrelation functions, particularly in small samples, (b) difficulties of interpretation, and (c) attempts to select ARIMA models by an automatic procedure, such as the AIC can lead to worse results (Harvey and Todd 1983). Consequently, statistical packages which purport to offer automatic ARIMA selection are severely limited, (d) the method requires about at least 50 observations as the minimum amount of data in the time series (Box and Jenkins 1976), and (e) it does not necessarily guarantee better forecasts than simpler forecasting techniques.

Box-Jenkins models are best used in short-term forecasting (Kress and Synder 1988) as they place emphasis on the recent past data rather than the distant past. Frechtling (1996) highlighted that the Box-Jenkins approach is appropriate for forecasting horizons of 12 to 18 months.

Intervention models can be used when exceptional, external events affect the variable to be forecast. External events such as war, recession, or advertising campaigns known as 'interventions' (Thury 1988; Box and Tiao 1975; Montgomery and Weatherby 1980; Liu and Lin 1991) often influence would-be travellers to forgo travel that in turn affect international tourism flows and arrivals. Intervention analysis is therefore implemented to estimate the impact of such interventions that are likely to influence the behaviour of a time series and can be used to extend univariate ARIMA and Structural Models (SM). Interventions are modelled either as (a) pulse variables, where the intervention disturbs the time series for a short period, or as (b) step variables, where the intervention introduces a one-time shift in the level of the time series pattern. These effects can be incorporated into the ARIMA and SM models by using deterministic dummy variables with values of 1 or 0. A model that is modified to take into account interventions is likely to produce a more reliable forecast. As Funke (1992) highlighted, if there is an expected change due to an event, intervention models outperform univariate ARIMA models both in model fitting and forecasting.

Example Applications

Turner et al. (1995a) compared the forecasting performance of the ARIMA model and the Winters exponential smoothing method against each other and the naïve model. The models were fitted to quarterly international tourist flow data to New Zealand, from June 1978 to September 1992. Forecasting performance was compared between eleven different countries and world regions with Holiday travel, Business travel and VFR travel. They concluded that the Winters and ARIMA methods outperform the naïve model. In addition, where the data series has a regular trend and seasonality, the Winters model performs better than the ARIMA model. However, when there is no highly significant trend and seasonality, the ARIMA forecasting model performs better.

Dharmaratne (1995) estimated ARIMA models for forecasting long-stay annual visitors arrivals in Barbados with data from 1956-87 and from 1956-91, to facilitate testing of the long-term (5-year) and short-term (2-year) forecasting ability of the models. The accuracy of the ex post forecasts were compared using MAPE. It was found that the ARIMA (2, 1, 1) model provides excellent forecasts for both the long-term and short-term forecasts of tourist arrivals in Barbados. Therefore, he concluded that customized forecasting model building may be highly rewarding as the value of a forecasting model depends on the accuracy of out-of-sample forecasts that can be generated from the model.

Chu (1998a) performed the forecasting of annual total tourist arrivals into Singapore using seasonal and non-seasonal ARIMA models. Data from July 1977 to December 1988 were used to forecast the tourist arrivals for the following 19 months (January 1989 to July 1990). The empirical results showed that the ARIMA (3, 1, 0) (0, 1, 0) forecasting model turned out to be relatively accurate among several other forecasting methods including a nonlinear sine wave time-series regression model. Chu concluded that although the proposed ARIMA model needed a reasonable amount of data to implement, the gain in forecasting accuracy over the naïve model was worth the effort.

Chu (1998b) examined forecasting models using monthly international tourist arrivals data in 10 countries (Taiwan, Japan, Hong Kong, South Korea, Singapore, the Philippines, Indonesia, Thailand, New Zealand, and Australia). The models are fitted to the arrivals in these countries between January 1975 and December 1994. Tourist arrival forecasts were made from January 1995 to June 1996. The forecasting accuracy was compared based on the smallest MAPE value, and it was found to differ between countries. Overall, the seasonal-non-seasonal ARIMA models were found to be the most accurate forecasting method in nine out of ten countries. Holt-Winters were found to perform marginally better than the ARIMA model for New Zealand arrivals.

Chan, Hui and Yuen (1999) highlighted that most forecasting models for tourist arrivals were constructed under the assumption of only minor changes in the environment; and the performance of forecasting models in situations of sudden, drastic environmental change(s) has not been given much attention. Using the Gulf War as an example of sudden environmental change, the study explored the relative performance of different forecasting models which include: (1) ARIMA (p,d,q) model, (2) exponential smoothing, (3) naive I, (4) naive II, and (5) trend curve analysis. Six sets of data were used that included total tourist arrivals in Singapore as well as arrivals from the United States, Japan, United Kingdom, Germany, and Australia. For each of the five forecasting techniques, the mean absolute percentage error (MAPE) was the criterion used to measure the accuracy of the forecasting model. The findings showed that in terms of forecasting accuracy, the naive II model performs better than other techniques in this study.

Lim and McAleer (2002) estimated various Autoregressive Moving Average (ARMA) models over the period 1975(1) to 1996(12) for monthly tourist arrivals to Australia from Hong Kong, Malaysia and Singapore. The Akaike Information Criterion and the Schwartz Baynesian Criterion was used to select the best fitting ARMA model to obtain post-sample forecasts. They found that the fitted seasonal ARIMA models outperform the non-seasonal ARMA models. In particularly, the fitted ARIMA (0,1,1) model for the seasonally adjusted data series performed better than the non-seasonally adjusted ARMA (12,2) model for Singapore monthly tourist arrivals to Australia.

Goh and Law (2002) applied ARIMA models with interventions in forecasting tourism demand using ten arrival series for Hong Kong. The forecasts obtained using these intervention models captured stochastic nonstationary seasonality and interventions, were found to have the highest accuracy compared with other time series models.

2.2.2.6 Basic Structural Time Series Models

Basic Structural time series models (Engle 1978; Nerlove et. al. 1979; Kitagawa 1981; Harvey 1989) are models that are formulated directly in terms of components such as trend, seasonality and cycle. Structural time series models therefore offer clear interpretations through the decomposition into components (Kendall and Ord 1990). This decomposition ability of structural models is a major attraction for time series forecasting.

The Basic Structural Model (BSM) was introduced by Harvey and Todd (1983) with non-stationarity being handled directly without the need for explicit differencing operations. The BSM according to Harvey and Todd "is a univariate time series model consisting of a slowly changing trend component, a slowly changing seasonal component, and a random irregular component". Statistically, the treatment of the BSM model can be performed by casting it into the state space form (SSF) so that the Kalman filter (Kalman 1960; Kalman and Bucy 1961; Meinhold and Singpurwalla 1983) can be used to evaluate the likelihood function. This formulation consists of the observation equation and the state equation. The observation equation relates the observed variables to the elements of the state vector, which for the basic structural model in an additive form is given as:

$$Y_t = \mu_t + \gamma_t + \psi_\tau + \nu_\tau + \varepsilon_t$$

where:

$\mu_{t,}$, γ_t, ψ_τ, ν_τ and ε_t represent a local linear trend, seasonal, cyclical, first-order autoregressive component and irregular components.

The state equations describe the evolution of the unobserved state vector, which in this case consist of the trend and seasonal component, written as:

level: $\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t$

slope: $\beta_t = \beta_{t-1} + \zeta_t$

seasonality : $\gamma_t = \sum_{j=1}^{s-1} \gamma_{t-j} + \omega_t$

where:

ε_t , η_t , ζ_t and ω_t = mutually uncorrelated white noise disturbances with variances σ_ε^2 , σ_η^2 , σ_ζ^2 and σ_ω^2, and

μ_t = the stochastic trend component with level and slope determined by random walks.

Once the model is in SSF, the model can be estimated using the following procedure (Cuthbertson et al. 1992):

(a) apply the Kalman filter to the SSF equations to yield a set of recursive equations (the prediction and updating equations), that is the Kalman filter recursively calculates for the optimal estimator of the state vector upon given all the currently available information (i.e., new observations); these are then applied to update the state,

(b) use the recursive equations to generate the minimum mean square error (MMSE) estimates of the unobserved state vector, the one-step prediction errors and their variance, given observations on Y_t,

(c) apply the one-step prediction errors and their variance as inputs into the prediction error decomposition of the likelihood functions,

(d) maximise the likelihood functions in computing for the unknown estimates of the parameters for the estimated BSM model,

(e) extrapolate these parameter estimates into the future for predictions.

The basic goodness of fit measure in a time series model is the prediction error variance (p.e.v.) which is the variance of the one-step ahead prediction errors in the steady state. For the goodness of fit criteria, the coefficient of determination, R^2, that is often found in regression analysis is not used. The reason being that any model that can pick up the upward or downward trend of a time series would have an R^2 close to unity. That is, this statistic is of little value, except when the time series is close to or stationary. Harvey (1989, p. 268) proposed two coefficients of determination, R^2_S and R^2_D, which are useful for non-stationary time series data. Mathematically, for nonseasonal observation, R^2_D may be used, where :

$$R^2_D \quad = \quad 1 - [\, SSE/ \sum (\Delta y_t - \overline{\Delta y})^2 \,]$$

where:

SSE = the residual sum of squares for a univariate time series model,

Δy_t = the first difference of y_t, and

$\overline{\Delta y}$ = the mean of the first differences of y_t.

For monthly or quarterly observations with seasonal effects, R^2_S is suggested as the goodness-of-fit criterion, and is expressed as:

$$R^2_S \quad = \quad 1 - [SSE/SSDSM]$$

where:

SSDSM = the sum of squares of first differences around the seasonal means.

Any model with negative R^2_S and R^2_D values are rejected.

Example Applications

Turner et al. (1995b) compared the forecasting performance of the Autoregressive Integrated Moving Average (ARIMA) model and the Basic Structural Model (BSM) with Intervention Variables. The ARIMA and BSM models are fitted to quarterly tourist flows into Australia and New Zealand, from the USA, Japan, and the UK. The model estimation period was from 1978 (June) to 1993 (September), and eight quarters (December 1991 to September 1993) were used as the post-sample period to assess the forecasting performance of the models. It was found that the BSM model showed a consistently high performance against the ARIMA model. In addition the forecast errors were reduced when intervention variables (such as special events) were added to the models. They highlighted that tourism practitioners will find it worthwhile to look at BSM modelling in the future.

Turner and Witt (2001) analysed forecasting of inbound tourism to New Zealand from Australia, Japan, the UK and the USA disaggregated by purpose of visit using both the Basic Structural Model (BSM) and the multivariate structural time series model. The structural time series models were estimated over the 2nd quarter 1978 to 4th quarter 1995, leaving a post-estimation period of eleven quarters from 1st quarter 1996 to 3rd quarter 1998 for forecasting performance assessment. The respective forecasting accuracy of the models is compared using MAPEs. The findings are that the structural time series model is reasonably accurate and outperformed the seasonal naïve model; and the multivariate structural time series model does not generate more accurate forecasts than the BSM model. They concluded that the structural time series model can reduce overall forecast error by 2% to 3% against the seasonal naïve model and this was important, because this has not been found to be case for causal based models.

Greenidge (2001) utilized Structural Time Series Modeling to explain and forecast tourist arrivals to Barbados from its major generating markets and found these models offered valuable insights into the stylized facts of tourism behavior and provided reliable out-of-sample forecasts.

2.2.2.7 Neural Networks

The application of Artificial Neural Networks (ANNs) in forecasting as an alternative to traditional statistical methods have been well reviewed by Hill et al. (1994), Warner and Misra (1996), and Zhang et al. (1998). Denton (1995) highlighted that the Neural Network offers an alternative to multiple regression for performing causal forecasts. In particular, under less than ideal conditions, Neural Networks do a better job. That is, the Neural Network forecasting method eliminates the ambiguities present in selecting the appropriate independent variables needed in defining a multiple regression model. This is important as performing a statistical regression with a mis-specified model can result in biased and inconsistent parameter estimates. In Hill et al. (1996) study, time series forecasts produced by Neural Networks are compared with forecasts from 6 statistical time series methods generated in a major forecasting competition (Makridakis et al. 1982). The traditional method forecasts are estimated by experts in the particular techniques. It was found that across monthly and quarterly time series, the Neural Networks did significantly better than traditional methods. Refenes et al. (1994) also highlight that traditional statistical techniques for forecasting have reached their limitations in applications with non-linearities in the data set, such as stock indices.

ANN Overview

The artificial Neural Network (ANN) (Simpson 1990; Carling 1992; Haykin 1994; Rojas 1996; Taylor 1998) consists of a number of processing elements, normally arranged in layers. Each processing element is linked to elements in the previous layer by connections that have an adaptable strength or weight. The adaptation of these weights is performed by a learning algorithm. It is this adaptation of these weights that gives the Neural Network its capability to learn by example thereby capturing the functional relationships within the data (White 1989; Koster et al. 1990; Ripley 1993; Cheng and Titterington 1994). ANN has been mathematically shown to be a universal approximator of functions and their derivatives (Cybenko 1989; Hornik et al. 1989; White et al. 1992). Unlike traditional statistical methods, ANN do not require assumptions about the form or distribution of the data to analyze it, and are more tolerant of imperfect data, and therefore estimate nonlinear functions well (Lapedes and Farber 1987; Gorr 1994; Hill and Remus 1992, 1994; Zhang 1998) and discontinuous functions (Wasserman 1989; Marquez et al. 1991). After the network has been trained and validated, the model may be applied to suitable neural computations such as prediction, classification, time-series forecasting or data segmentation.

ANN models have two learning methods, supervised and unsupervised. Time-series forecasting neural computation involves the use of a class of neural models known as supervised Neural Networks. These networks require both inputs and targets. The learning algorithm modifies the network weights so that the model learns the mapping from input to target. The different supervised artificial Neural Networks known for time-series forecasting are Multi-Layer Perceptron, Radial Basis Function, and Bayesian Neural Network. An overview of the architecture, activation function, and training algorithm for these Neural Networks is discussed below.

The Multi-Layer Perceptron

The MLP is perhaps the most popular network architecture in use (Rumelhart and McClelland 1986; Haykin 1994; Bishop 1995). The MLP is a Neural Network that is based on the original Simple Perceptron model but with additional hidden layers of neurons between the input and output layers. This hidden layer vastly increases the learning power of the MLP. The inputs to each processing element, or nodes, are usually fully connected to the outputs of the previous layer. Typically, the incoming signals to a node are combined by summing their weighted values. This is represented mathematically as:

$$netj = \sum_{i=1}^{n} xi\ wij$$

where:

netj = the resultant combined input to node j,

xi = the output from node i, and,

n = the number of impinging connections.

The learning algorithm modifies the weights associated with each processing element such that the system minimizes the error between the target output and the network's actual output. The number of nodes is directly related to the complexity of the system being modelled. The most widely use MLP Neural Network training or learning algorithm is back propagation (Rumelhart et al. 1986; Patterson 1996; Haykin 1994; Fauset 1994). The backpropagation algorithm was first developed by Werbos (1974) and has been actively adopted for use with Neural Networks. In the backpropagation training algorithm, there is a forward pass through the Neural Network to determine the network's current outputs, followed by a backward pass to determine, based on the difference between these outputs and the correct ones, how the weights should be changed. Training begins with arbitrary values for the weights. In each iteration, called epoch, the network adjusts the weights in the direction that reduces the error. As the iterative process continues, the weights gradually converge to an optimal set of values.

The method of determining the amount of change is known as the learning law. Two commonly used learning laws are Steepest Descent and Conjugate Gradient. For Steepest Descent, at the completion of a pass, all the nodes change their weights based on the accumulative derivatives of the error with respect to each weight. These weight changes move the weight in the direction in which the error declines most quickly. The Conjugate Gradient method (Bishop 1995) also called 'backpropagation with momentum' is one of the second-order methods of deciding weight change. Second-order methods involve calculating an approximation of the second derivative of the error with respect to a weight and using this quantity, in conjunction with the first derivative, to decide the amount of the weight change.

There are also heuristic modifications of back propagation which work well for some problem domains, such as quick propagation (Fahlman 1989) and Delta-Bar-Delta (Jacobs 1988). In most cases, they are not significantly better than back propagation, and sometimes they are worse (relative performance is application-dependent). They also require more control parameters than any of the other algorithms, which makes them more difficult to use.

During the forward pass through the MLP, each node output is computed from its inputs based on several possible 'activation' or 'transfer' functions such as sigmoid, linear, and hyperbolic tangent (tanh). Mathematically,

Sigmoid: $f(net) = 1/1 + \exp(-net)$.

Tanh: $f(net) = [\exp(net) - \exp(-net)] / [\exp(net) + \exp(-net)]$

Where:

f(net) = the node output using the transfer function,

net = the resultant combined inputs to the node,

exp = the constant with value of about 2.71828.

MLP models generally use a sigmoid activation function, with continuous activations, mostly chosen from [0, 1] or [-1, 1].

Important issues in Multilayer Perceptrons (MLP) design include the specification of the number of hidden nodes and the learning algorithm for the network (Haykin 1994; Bishop 1995). If there are too many hidden nodes for the problem, the network can become too specific or over-trained. Funahashi (1989) has shown mathematically that only one hidden layer is needed to model a network to fit and function optimally; and Hecht-Nelson (1989) show that there need be no more than 2n+1 hidden layer nodes, for n input nodes. Therefore, developing an MLP requires a certain degree of experimentation. The error of a particular configuration of the MLP network can be determined by running all the training cases through the network, and comparing the actual output generated with the desired or target outputs. The differences are combined together by an error function to give the network error. The most common error functions are the sum squared error (used for regression problems), where the individual errors of output units on each case are squared and summed together, and the cross entropy functions (used for maximum likelihood classification).

The Radial Basis Function

Another model used in time-series forecasting is the Radial Basis Function network, or RBF (Broomhead and Lowe 1989; Moody and Darkin 1989; Leonard et al. 1992; Haykin 1994). It is a supervised, feed-forward Neural Network with one hidden layer of artificial neurons. RBF is also used for supervised learning, but uses different activation functions than multilayer perceptrons. The advantages of RBF models are that they can model any nonlinear function using a single hidden layer, which removes some design-decisions about numbers of layers, and the training is much more rapid than with the MLP since they train in one stage rather than using an iterative process.

In the RBF network the outputs that form the hidden layer are treated as a measure of how far away the data are from a centre. The transfer functions of the nodes are nonlinear. The transfer function used is known as the Radial Basis Functions, which is a linear combination of nonlinear basis functions.

The most common transfer functions used in Radial Basis Functions are radial spline, Gaussian, Quadratic, and Inverse Quadratic.

The Baynesian Network

Lastly but not least, the Bayesian Network (BAYN) is a modified MLP network for time-series forecasting designed to avoid over-fitting. The Bayesian network applies Bayes Theorem to the MLP. The Bayesian theory adds an extra term to the error measure that reduces the impact of noise on the network.

Performance measures

The method for validating the performance of a Neural Network in time-series forecasting is based on the measurements of the residuals; that is the differences between the output of the Neural Network model and the actual values in the time series. These different measures of accuracy in forecasting (Makridakis et al. 1983, 1998) are: MSE, RMSE, and MAPE. They will be discussed further in next chapter. In addition, Adya and Collopy (1998) highlighted how effectively a Neural Network technique was compared with other forecasting methods and how well the Neural Network technique was implemented, is a key area to consider before concluding on the effectiveness of Neural Networks for forecasting and prediction.

ANN Modelling Issues

Zhang et al. (1998) has reviewed the main ANN modelling issues which include: (1) the network architecture, which include determining the number of input nodes, the number of hidden layers and hidden nodes, and the number of output nodes; (2) the activation function, and (3) the training algorithm, (4) the training sample and test sample, and (5) performance measures. Similarly, Walczak (2001) highlighted several design factors that can significantly impact on the accuracy of Neural Network forecasts. These factors include selection of input variables, architecture of the network, and quantity of training data.

Another issue with the use of Neural Networks comes essentially from their power as a universal approximator. In general, a complex (in terms of numbers of hidden layers) network will be able to fit any data set perfectly. When this happens, over-fitting occurs, that is the Neural Network will offer good explanatory power within their training sample but they may breakdown completely out of the sample. Thus, it is an art to achieve a sufficiently good fit without over-fitting.

Also the question of whether the data should be deseasonalized first for time series forecasting using Neural Networks was raised by Nelson et al. (1999). Their findings using forecasts for 68 monthly time series from the M-competition (Makridakis et al. 1982) indicated that when there was seasonality in the time series, forecasts from Neural Networks estimated on deseasonalized data were significantly more accurate than the forecasts produced by Neural Networks that were estimated using data which were not deseasonalized. They highlighted that the mixed results from past studies of

ANN forecasting accuracy may be due to inconsistent handling of seasonality. It cannot be assumed that the Neural Network model can build seasonal effects into its learning process.

In summary, there is no formal systematic ANN model building approach (Qi and Zhang 2001). For instance, there is no standard formula for calculating the number of layer and nodes needed in the hidden layer (Lippman 1987; Gorr et al. 1994; Turban 1995; Jeng and Fesenmaier 1996). In particular, the problem of network "tuning" remains: parameters of the backpropagation algorithm as well as the Neural Network design need to be adjusted for optimal performance. Therefore, there is no one single ANN configuration that is suitable for all applications; and a process of trial and error is needed to find the right parameters for an ANN forecasting model.

Example Applications

Neural Networks has been used in many business areas (Widrow et al. 1994; Ansuj et al. 1996; Wong et al. 2000; Smith and Gupta 2002). One major application of Neural Networks is in financial forecasting (Refenes 1995; Qi 1996; Cheng et al. 1997; Fadlalla and Lin 2001). Some of these studies are highlighted below.

Chiang et al. (1996) applied a backpropagation artificial Neural Network to forecast the end-of-year net asset value (NAV) of mutual funds. The results of the forecasting are compared to those of traditional econometric techniques (linear and nonlinear regression analysis), and it was shown that Neural Networks significantly outperform regression models in situations with limited data availability.

Zhang and Hu (1998) in their application of Neural Network forecasting of the British pound/US dollar exchange rate highlighted that researchers often overlook the effect of Neural Network parameters on the performance of Neural Network forecasting. They found that Neural Networks outperform linear models, particularly when the forecast horizon is short. In addition, the number of input nodes has a greater impact on performance than the number of hidden nodes, while a larger number of observations do reduce forecast errors.

Aiken (1999) presented the findings of Consumer Price Index (CPI) forecasts from an artificial Neural Network using leading economic indicator data in the USA. The results show that the Neural Network predicts the level of the CPI with a high degree of accuracy.

Yao and Tan (2000) in their forecasting of the option prices of Nikkei 225 index futures using backpropagation Neural Networks found that different results in terms of accuracy are achieved by grouping the data differently. The results suggested that for volatile markets a Neural Network option pricing model outperforms the traditional Black-Scholes model. However, the Black-Scholes model is still good for pricing at-the-money options.

Moshiri and Cameron's (2000) study compared the performance of Back Propagation Artificial Neural Network (BPN) models with the traditional approaches to forecasting the inflation rate. The traditional models included a structural reduced-form model, an ARIMA model, a vector autoregressive model, and a Bayesian vector autoregression model. Each model is compared with a hybrid BPN model that uses the same set of variables. Dynamic forecasts are compared for three different horizons: one, three and twelve months ahead. The results show the hybrid BPN models are able to forecast as well as all the traditional methods, and to outperform them in some cases.

Tkacz (2001) in his Neural Network forecasting of Canadian GDP growth found that Neural Networks yield statistically lower forecast errors for the year-over-year growth rate of real GDP relative to linear and univariate models. However, such forecast improvements are less notable when forecasting quarterly real GDP growth.
More recently, Neural Networks have been applied to tourism demand forecasting.

Pattie and Snyder (1996) utilised a Neural Network to forecast over-night backcountry stays in US national parks. Comparison of classical time series forecasting techniques, namely (1) simple regression, (2) single exponential smoothing, (3) Holt-Winters exponential smoothing, (4) ARIMA model, (5) Census II decomposition, and (6) naïve or 'random walk' with a backpropagation Neural Network model was made.

The models are estimated using monthly data from 1979 to 1989 with forecasts made for the 12 periods of 1990. The widely used unit-free measure MAPE was used as a measure of forecasting accuracy comparison. They found that the Census II decomposition (MAPE of 1.9%) and the Neural Network (MAPE of 2.7%) are the most accurate models. These results indicated that the Neural Network model is a valid alternative to classical forecasting techniques in tourism forecasting.

Fernando et al. (1999) used Neural Networks to forecast monthly tourist arrivals to Japan from the USA. Univariate forecasts were made for total tourism for the two disaggregated categories of tourist and business travel. Multivariate forecasts were made using the same data, combined with national indicators of the tourist's country of origin. The national indicators used are income, imports and exports. They found that the univariate and multivariate Neural Network forecasts generated were very close to the actual arrivals. They concluded that the multivariate forecasts did not provide improved forecasting accuracy to the univariate forecast of total arrivals and this may be due to the very steady pattern in the data for tourist arrivals.

Uysal and Roubi (1999) compare the use of ANN against multiple regression in tourism demand analysis. The study uses Canadian tourism expenditures in the US as a measure of demand. The variables selected for explaining the dependent variable include (1) per capita income of Canada in real terms, (2) consumer price index ratio in real terms between Canada and the US multiplied by the exchange rate ratio between Canada and the US, (3) lagged Canadian tourist expenditures in the US, (4) yearly quarter dummies. The relative comparison of the two approaches with regard to model prediction accuracy is based on the mean absolute percentage error (MAPE). The ANN approach resulted in a MAPE of 3.2% compared to 4.1% for the estimated regression model. The results of the study provide evidence to suggest that the ANN model is useful in identifying existing data patterns that may not be revealed by multiple regression, and demonstrated the usefulness of ANNs in tourism demand studies.

Law and Au (1999) use a supervised feed-forward Neural Network causal model to forecast annual Japanese tourist arrivals in Hong Kong. The input layer of the Neural

Network contains six nodes: Service Price, Average Hotel Rate, Foreign Exchange Rate, Population, Marketing Expenses, and Gross Domestic Expenditure. The single node in the output layer of the Neural Network represents the Japanese demand for travel to Hong Kong. Accuracy comparison was based on MAPE and the results showed that the Neural Network model outperforms the multiple regression, naïve, moving average, and exponential smoothing methods in forecasting the Japanese arrivals into Hong Kong.

Law (2000) highlighted in his tourism demand forecasting of Taiwanese tourist arrivals in Hong Kong the importance of incorporating the backpropagation learning process in the ANN causal model. The study adopts the first 25 observations (i.e. 1966 to 1991) for training the ANN. Forecasts were then made from 1992 to 1996. Five other forecasting methods, namely multiple regression, naïve, moving average, Holt's two-parameter exponential method, and a feed-forward ANN were used as comparison for forecasting accuracy. The results indicated that utilising the backpropagation ANN causal model outperforms regression models, time-series models, and feed-forward networks in terms of forecasting accuracy with an exceptionally low MAPE of 2.8%.

Burger et al.'s (2001) study uses monthly time series data of tourist arrivals from the US to Durban, South Africa over the time period 1982 to 1998 in an attempt to create models that can predict the expected number of tourist arrivals over defined future periods. A variety of techniques are employed, namely naïve, moving average, decomposition, single exponential smoothing, ARIMA, multiple regression, genetic regression and Neural Networks. He found that the Neural Network time series model performed best with the lowest MAPE (5.1%). They suggested that the Neural Network be used in time series forecasting as the innate model complexity is far better able to handle non-linear behaviour.

Tsaur et al. (2002) employed artificial Neural Networks (ANNs) for analyzing the guest loyalty toward international tourist hotels and found that ANNs models demonstrate satisfactory model fitting performance. Their comparative analysis between ANNs and logistic regression models concluded that ANNs outperforms regression models in overall model-fitting.

The above studies indicate the feasibility of applying Neural Network causal and time-series models to practical tourism demand forecasting. Zhang et al. (1998) noted 'the unique characteristics of ANNs – adaptability, nonlinearity, arbitrary function mapping – make them quite suitable and useful for forecasting tasks. Overall, ANNs give satisfactory performance in forecasting'. In addition, Remus and O'Connor (2001) highlighted that Neural Networks performed best when used for discontinuous monthly and quarterly data for time series forecasting.

The next chapter covers the tourism forecasting strategy for forecasting inbound tourist arrivals into Singapore from Australia, China, India, Japan, UK and USA. The selection of the forecasting models and the forecasting accuracy comparison approach used in this study are discussed.

CHAPTER 3 FORECASTING PROCESS

Introduction

This chapter discusses the tourism forecasting process used in this study.

3.1 The Forecasting Process

The forecasting process used in this study is based on four sequential major phases, namely (1) design, (2) specification, (3) implementation, and (4) evaluation as discussed by Frechtling (2001, 1996). The various issues under each phase are discussed below:

3.1.1 Design

This phase involves determining the user or industry need, data availability and makes a choice of the forecasting method for this study.

(a) The Industry Need

The aim is to identify tourism arrivals forecasting models that are practical for industry use in a whole variety of business activity from medium to large sized firms. The issue of cost is highly relevant for complex quantitative causal models because these models require constant surveillance and updating. In particular, the cost of skilled personnel to run the quantitative causal models can be extremely high and beyond the reach of most companies and government agencies. Consequently, the choice is limited in the first instance to time-series methods.

In addition, practical tourism industry forecasting has largely moved to a focus on short-term forecasting. This is up to 3 years ahead with emphasis on the first two years ahead. The reason relates partly to recent world travel instability and partly to the now industry accepted view that long-term forecasts are both inaccurate and less useful in a world subject to increasing competition and chaos. For instance, competition between suppliers of the tourism product leads to rapid market demand shifts relating to fashion, safety, price, and the emerging and not yet known growth markets of China and India.

(b) Data availability

The selection of a forecasting method is often constrained by available data. With causal and econometric models, data on the predictor variables might just not be available within the timeframe of practical industry forecasting cost and time constraints. Also, more sophisticated methods using the time-series Box-Jenkins model require about sixty data points (Turner et al. 1995b).

The time series of the tourist arrivals data for this study was acquired from the STB electronically and the 'Statistical Report on Visitor Arrivals to Singapore' a publication of the STB. The Singapore Tourism Board compiles statistics based on the information collected from the disembarkation/embarkation cards filled out by visitors entering the country. All visitors are classified by country of residence. The accuracy of the data pertaining to the characteristics of visitors therefore depends on how accurately the visitors had filled out these cards.

The data used in this study are the quarterly disaggregated tourist flows (Holiday, Business, and Total) visitor arrivals into Singapore from six major tourist generating markets, namely: Australia, China, India, Japan, UK, and USA. The data is available for 68 quarters from 1985 Quarter 1 to 2001 Quarter 4 for US, UK, Australia, Japan and India, which represents a total of 68 quarters of which 60 quarters are use for model estimation and the last eight quarters is used to forecasting performance comparison. Tourist flows data for

China are collected from 1995Q1 to 2001Q4 which provides 28 quarters in total of which the last eight quarters is used for forecasting comparison ex ante. Given the shorter series there is a constraint on the methods that can be used for forecasting arrivals to China.

The time series data pattern for each of the disaggregated quarterly tourist flows from each of the six major tourist generating markets to Singapore (Australia, China, India, Japan, UK, and USA) are shown in Appendix A.

(c) Resource availability

The computer statistical programs that are adopted for the time-series models in this research are:

1. GB STAT for the Holt-Winters forecasting model.
2. Structural Time Series Analyser, Modeller and Predictor (STAMP) for the Basic Structural Model. STAMP is a menu-driven program for automatically fitting univariate time-series models.
3. SPSS Neural Connection 2.0 for the Neural Network time series forecasting model.

Each of these programs is readily available to industry and relatively inexpensive

(d) Selection of forecasting method

The selection of the forecasting methods is based on the purpose of this study that is to test the short-term forecasting accuracy of the modern time-series methods of BSM and Neural Networks. The BSM and Neural Networks are chosen based on the following reasons:

(i) As objective data is available, the study will adopt quantitative methods instead of the subjective qualitative methods (Mahmoud 1984).

(ii) The forecast horizon is not more than 2 years and as such time-series methods are considered suitable for this study. Frechtling (2001) highlighted that time-series or extrapolative methods have often proved less successful only in providing accurate long-range forecasts than quantitative causal methods.

(iii) With quantitative time series methods, it has been found that the complex time series forecasting methods are not necessarily more accurate than simple extrapolative methods. It has been concluded in studies, that between the quantitative causal and time-series methods, and between the time series methods themselves there was no one 'best' method (Makridakis 1986; Makridakis et al. 1998). For example, Martin and Witt (1989) found that forecasts from causal econometric models are relatively less accurate than several univariate models. Among the univariate forecasting methods, Van Doorn (1984) in his examination of inbound tourism to the Netherlands found that the ARIMA forecasts are more accurate than the exponential smoothing forecasts. In contrast, empirical results obtained by Geurts and Ibrahim (1975), who examined inbound tourism to Hawaii found that the univariate ARIMA model and exponential smoothing method performed equally well. In another study of inbound tourism to Hawaii (Geurts 1982), it was found that exponential smoothing outperforms univariate ARIMA methodology. Thus, the more sophisticated univariate autoregressive integrated moving average (ARIMA) time series method does not necessarily produce a more accurate forecast than simpler and older methods, such as exponential smoothing methods. As the relatively modern ARIMA model has already been extensively tested for tourism forecasting it is not included here. It would also have a problem in that it cannot be applied to the important China flow data due to the shorter series available for analysis.

(iv) Additionally, it is only recently that the techniques of Structural time series models (BSM) and Neural Networks have been applied to tourist arrivals forecasting with mixed results as reviewed in Chapter 2. The general conclusion for tourism data is that Neural Networks outperform regression (Muzaffer and Roubi 1999) and time-series methods although the BSM model has yet to be tested. Thus, these modern time series methods are selected to further extend the research study in this area of tourism demand forecasting.

The structural time series models are still limited by their underlying assumption of linearity though they have a firm statistical base. However, Neural Networks are non-linear models that can be trained to map past values of a time series, and thereby extract hidden structure and relationships governing the data. As Hall (1994) highlighted the potential power of non-linear techniques is enormous and they may well be the main area of development in forecasting in coming decades.

In the case of Neural Networks the models have been used for long-term forecasting and they have been assumed to be less useful for short-term tourist arrivals forecasting, given the seasonal nature of tourist flows it is also unclear how Neural Networks are best applied to trended seasonal tourist measures. Furthermore, most work has focussed upon the MLP Neural Network model and the value of the more recent RBF and Bayesian Neural Network models requires further study.

The Holt-Winters models are also calculated as a base model for comparison. This method is a suitable seasonal model that could reasonably be applied (from past studies) to offer an acceptable level of forecasting accuracy. The Holt-Winters method is the most sophisticated model from among the simpler time-series methods discussed earlier. Moreover, because its parameters can be calculated by trial and error the model can be automatically generated by computer, requiring little operator expertise. It is worth noting here that the nature of data does vary slightly between the disaggregated series. The Business flows are less seasonal than the Holiday flows. However, the Business flows do contain some seasonality and it would not be correct to just use a Holt model on this somewhat less seasonal data. The decision has been made therefore to use the Winters model on all the series even though the degree of seasonal effect varies between the series. The Chinese data is probably the most difficult series in this regard as the first part of the series is non-seasonal and the more recent data is seasonal and this is compounded by the data having a shorter time-span. However, this does not mean that the Winters model cannot handle the series as well as a non seasonal model such as Holt's model.

In addition, the naïve process (naïve 1 model) is calculated as a basic benchmark to compare model performance against the use of no model at all. That is, simply using the previous period's known arrival numbers as the naïve forecast.

3.1.2 Specification

The objective of this phase is to determine the relationships that should be measured in the appropriate forecasting model and to select the appropriate model. The BSM and the Multi-Layer Perceptron (MLP), Radial Basis Function (RBF) and Bayesian (BAY) Neural Network models are selected because they are the currently known models supported by commercial software. There are some other methods, for example the use of fuzzy logic (Fernando et al. 1999) that use only private software tools at this time.

3.1.3 Implementation

In this phase, the selected models are used to generate forecasts. The Naïve, Holt-Winters exponential smoothing, BSM, and Neural Network model (MLP, RBF, BAY) forecasts are generated and presented in Chapter 4.

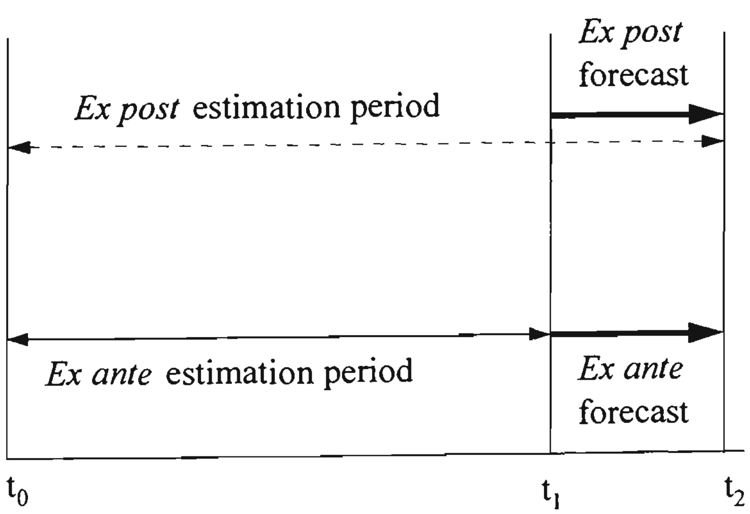
3.1.4 Evaluation

The evaluation phase includes: (i) monitoring forecast accuracy, (ii) determining the causes for deviations by comparing the forecasts against actual values, and (iii) deciding whether to generate a new forecast from the existing model or, alternatively, develop a new model.

The two common approaches used in producing a forecast are ex post and ex ante forecasting (Song and Witt 2000) as shown in Figure 3.1.

Figure 3.1

Ex ante/ex post forecasts.



Witt and Witt (1992) point out that: "the latter [ex ante] approach most nearly resembles the position that forecasters face in reality." Armstrong (2001) also supported the use of ex-ante tests for evaluating forecasting accuracy. For this reason, the forecasts in this study are estimated based on the ex ante method, with the estimation period 1985 Quarter 1 to 1999 Quarter 4 and the forecast period 2000 Quarter 1 to 2001 Quarter 4. A single 'best forecast' model for each origin-Singapore pair is therefore chosen on the basis of minimum forecast error. The choice of which is discussed in Chapter 4.

The forecasting horizon has been selected, as discussed before, to be short-term. Therefore, the performance of the models is compared for only two years ahead (8 quarters). In order to test the capacity of the forecast models fully, direct forecasts for the whole two years ahead are compared against the shorter time frames of one quarter ahead per forecast and one year ahead forecasts (4 quarters).

The next chapter discusses the implementation and evaluation of the selected time series forecasting models for each disaggregated quarterly tourist flow from the six major tourist generating markets to Singapore (Australia, China, India, Japan, UK, and USA) using the Winters, BSM and Neural Network models. The empirical results and the findings obtained are presented and discussed.

CHAPTER 4 EMPIRICAL RESULTS

Introduction

This chapter presents the empirical results of the time-series forecasting performance analysis compared on the basis of the selected forecasting performance measures. Firstly, the various forecasting performance measures are discussed. Next, forecasting results obtained from each of the forecasting models are given.

4.1 Forecasting Performance Evaluation

While the cost of forecasting must be balanced against the accuracy obtained, the most important forecast performance criterion is the accuracy of the prediction that is generated by the forecasting method or model as compared to the actual observation. As highlighted by Klein (1984), "the forecast ... accuracy is the bottom line for the professional forecaster". Carbone and Armstrong (1982) also concluded that forecasting accuracy is the most important forecasting performance criterion, relative to other criteria such as ease of interpretation, cost/time, and ease of use/implementation. In another survey by Witt and Witt (1992) carried out at the 'Tourism in the 1990s" conference held in London in November 1986, the results found that 'accuracy' is the most important forecast performance evaluation criterion. More recently, Yokum and Armstrong (1995) summarised the selection criteria for selecting a forecasting method that had been examined in earlier surveys by Carbone and Armstrong (1982), Mahmoud et al. (1986), Mentzer and Cox (1984) and Sanders and Mandrodt (1994), and found that forecasting accuracy is still the most important criteria.

4.1.1 Forecasting Accuracy Measures

The various types of forecasting accuracy measures (Mahmoud, 1984; Mahmoud, 1990) include: (a) Mean absolute deviation (MAD) or mean absolute error (MAE) which is the average of the absolute values of the forecast errors with all errors assigned equal weights, (b) Mean square error (MSE) where large errors are given additional weight, (c) Root mean squared error (RMSE) which is the square root of the average of the squared values of the errors, (d) Mean absolute percentage error (MAPE) which is the average of the absolute values of the percentage errors. These four common measures each have advantages and limitations (Makridakis 1983; Makridakis et al. 1998) and are shown mathematically in Table 4.1 where e_t is the forecast error in period t (i.e., F_t - A_t), A_t is the actual observation at time t, and F_t denotes the forecast at time t.

Table 4.1

Forecasting Error Measures

MAD	$1/n \sum_{t=1}^{n} \mid e_t \mid$
MSE	$1/n \sum_{t=1}^{n} (e_t)^2$
MAPE	$1/n \sum_{t=1}^{n} \mid e_t / A_t \mid \cdot 100$
RMSE	$\surd$ MSE

However, Makridakis et al. (1983) highlighted that, 'one of the difficulties in dealing with the criterion of accuracy in forecasting situations is the absence of a single universally accepted measure of accuracy'. From a theoretical standpoint, the best accuracy measure must be robust from one situation to another and not be unduly influenced by outliers. From a practical point of view, it must make sense, be easily understood, and convey as much information about accuracy (or errors) as possible.

Witt and Witt (1992) summarises the use of the various forecasting accuracy measures used by researchers that include MAD, MSE, RMSE, MAPE and concluded: 'there are two clear winners: MAPE and RMSE. Many of the authors do not discuss the measures that they use but simply employ them'. Additionally:

> "The MAPE ... First, being less affected than squared measures by extreme errors, it becomes a good relative measure for comparison among techniques. Secondly, is independent of scale, enabling a comparison to be made between different time series" (Lawrence et al. 1985, p. 28),

> "MAPE being a relative dimensionless measure incorporates the best characteristics among the various accuracy criteria" (Makridakis 1993, p. 527),

> "Both [MAPE and RMSE] of these accuracy criteria are measured in unit-free terms; they are independent of scale, and hence it is possible to compare data series of tourist flows which are of widely differing sizes or stated in different units" (Witt et al. 1992, p. 37).

However, Armstrong (2001) highlighted that given RMSE is based on squaring forecast errors, it is unreliable, especially if the data contains mistakes or outliers, and it should not be used for comparison across series. While Carbone and Armstrong (1982) found that RMSE was the most popular in their survey in 1981, Mentzer and Kahn (1995) in contrast over a decade later found that MAPE has become the most commonly used measure (52%) while only 10% used RMSE. The unreliability of RMSE as a forecasting measure is also highlighted in the findings of Armstrong and Collopy (1992).

As the disaggregated tourist flow volumes vary considerably among the different purpose of visits (Holiday, Business and Total) for a given origin country, it is necessary to use a unit-free measure for comparing forecasting accuracy. The use of unit-independent measures allows forecasting comparison not only between models but also across countries (units) as highlighted by Song and Witt (2001). Hence, MAPE is selected for forecasting accuracy comparison purposes in this study.

4.2 Forecasting Implementation and Evaluation

This section discusses the forecasting implementation and evaluation for the selected Naïve model, Holt-Winters exponential smoothing model, Basic structural model, and the MLP, RBF, and BAYN Neural Network models. A summary of the forecasting framework for the selected forecasting models is given in Table 4.2. This table captures the various issues in the forecasting process as discussed in Chapter 3.

Table 4.2

Forecasting Framework

Data Series	Quarterly Holiday, Business and Total Tourist Arrivals into Singapore
Origin Countries	Australia, US, UK, Japan, China and India
Forecasting Models	Naïve, Winters, BSM, Neural Networks (MLP, RBF, BAYN)
Estimation Period	1985Q1 to 1999Q4
Post-estimation period	2000Q1 to 2001Q4
Forecasting Horizon	Direct 8 quarter forecasts, One-quarter ahead forecast, Four-quarter ahead forecast
Forecast Accuracy Measure	MAPE

4.2.1 Naïve Model

(a) Forecasting Implementation

The forecasting implementation using the naïve model is performed for the direct eight-step-forecasts, one-step-ahead forecasts, and four-step-ahead forecasts as a seasonal naïve model. For the one-step-ahead forecasts, the quarterly seasonal naïve values are the corresponding quarterly seasonal values from the previous year. For the four-step-ahead forecast, the first value forecast (2000 Q4) is the fourth quarter ahead in time from the fourth quarter 1999. The seasonal naïve values for 2000 Q4 to 2001 Q3 are the corresponding values from 1999Q4 to 2000Q3. Table 4.3 shows the forecasting implementation of the naïve model.

Table 4.3

Forecasting implementation of the naïve model

		8 Step Direct Naïve Forecast	1 step ahead Naïve Forecast	4 step Ahead Naïve Forecast
1985 Q1 to 1999Q4				
2000Q1	=>	1999Q4	1999Q1	
2000Q2	=>	2000Q1	1999Q2	
2000Q3	=>	2000Q2	1999Q3	
2000Q4	=>	2000Q3	1999Q4	
2001Q1	=>	2000Q4	2000Q1	2000Q1
2001Q2	=>	2001Q1	2000Q2	2000Q2
2001Q3	=>	2001Q2	2000Q3	2000Q3
2001Q4	=>	2001Q3	2000Q4	2000Q4

(b) Forecasting Evaluation

The direct, one step ahead, four step ahead forecasts and Mean Average Percentage Errors (MAPEs) calculated for each of the Australia, China, India, Japan, UK, and USA tourist flows are provided in Appendix B. A summary of the MAPE values for each of the disaggregated Australia, China, India, Japan, UK, and USA tourist flows are shown in Table 4.4.

Table 4.4

Summary of Naïve Forecast MAPEs

	Direct forecast	1-Step-ahead	4-Step-ahead
Aus Holiday	10.45%	9.26%	8.74%
Aus Business	11.83%	10.82%	8.87%
Aus Total	10.30%	9.13%	9.55%
Average	10.86%	9.74%	9.05%
China Holiday	12.11%	9.94%	9.98%
China Business	13.90%	11.50%	3.75%
China Total	16.04%	13.32%	12.31%
Average	14.02%	11.59%	8.68%
India Holiday	18.67%	15.18%	7.94%
India Business	14.97%	12.32%	4.97%
India Total	13.32%	11.23%	6.33%
Average	15.65%	12.91%	6.41%
Japan Holiday	14.97%	25.97%	44.98%
Japan Business	12.80%	14.54%	18.13%
Japan Total	13.29%	19.95%	32.46%
Average	13.69%	20.15%	31.86%
UK Holiday	11.10%	9.63%	7.11%
UK Business	9.28%	9.20%	8.42%
UK Total	9.14%	8.23%	6.65%
Average	9.84%	9.02%	7.39%
USA Holiday	10.94%	11.58%	13.64%
USA Business	17.40%	20.52%	28.04%
USA Total	10.24%	11.32%	13.79%
Average	**12.86%**	**14.47%**	**18.49%**
Overall	**12.82%**	**12.98%**	**13.65%**
Overall Average 13.15%			

4.2.2 Winters Forecasting

(a) Forecasting Implementation

The forecasting implementation using the Holt-Winters exponential smoothing model is performed for the direct eight-step-forecasts, one-step-ahead forecasts, and four-step-ahead forecasts as shown in Table 4.5.

Table 4.5

Forecasting implementation of the Winters model

Actual		8 Step Direct Winters Forecast	1 step ahead Winters Forecast	4 step ahead Winters Forecast
1985 Q1		↑	↑	
to		Model Estimation	Model Estimation	
1999Q4		↓		
2000Q1	=>	1999Q4	↓	
2000Q2	=>	2000Q1	2000Q2	
2000Q3	=>	2000Q2	2000Q3	
2000Q4	=>	2000Q3	2000Q4	
2001Q1	=>	2000Q4	2001Q1	2001Q1
2001Q2	=>	2001Q1	2001Q2	2001Q2
2001Q3	=>	2001Q2	2001Q3	2001Q3
2001Q4	=>	2001Q3	2001Q4	2001Q4

Table 4.6 presents the empirical results for one example of a one-step-ahead forecast of the Winters Model - Holiday flow forecast from UK to Singapore. In here, the number of Holiday arrivals from the UK in the 62nd Quarter (2001Q2) is generated, the value being 45961.

Table 4.6

Winters exponential smoothing forecasting model example: UK Holiday tourism to Singapore

--Winter's Trend & Seasonal Forecast Model--

Time Period	Actual Value	Forecasted Value	Forecasting Error	Percentage Error
1	25766	36483.925947	-10717.925947	-41.597167
2	18938	27257.353616	-8319.353616	-43.92942
3	23050	32432.554999	-9382.554999	-40.705228
4	26365	35773.580743	-9408.580743	-35.685874
5	31532	27316.366539	4215.633461	13.369382
6	21321	20092.183501	1228.816499	5.763409
7	24524	24440.330747	83.669253	.341173
8	29435	27924.359929	1510.640071	5.132122
9	36405	33010.102723	3394.897277	9.32536
10	27042	22362.615431	4679.384569	17.304136
11	31628	25768.435254	5859.564746	18.526511
12	38078	30892.404828	7185.595172	18.870726
13	49360	38086.140012	11273.859988	22.840073
14	35778	28187.541212	7590.458788	21.215436
15	43487	32923.971715	10563.028285	24.290083
16	50958	39597.614991	11360.385009	22.293624
17	56978	51202.142052	5775.857948	10.136997
18	40093	37070.86676	3022.13324	7.537808
19	46469	44949.780461	1519.219539	3.269318
20	55607	52635.625707	2971.374293	5.343526
21	58563	58989.213039	-426.213039	-.727786
22	43978	41494.821055	2483.178945	5.646412
23	49221	48090.257425	1130.742575	2.297277
24	53175	57455.283173	-4280.283173	-8.049428
25	49039	60583.233667	-11544.233667	-23.540924
26	35712	45403.505552	-9691.505552	-27.137952
27	42599	50845.195491	-8246.195491	-19.357721
28	48178	55050.337798	-6872.337798	-14.264473
29	51327	50958.820239	368.179761	.717322
30	44815	37125.987927	7689.012073	17.157229
31	49071	44197.160673	4873.839327	9.932219
32	50392	49935.505427	456.494573	.905887
33	54583	53035.97856	1547.02144	2.834255
34	44447	46119.657456	-1672.657456	-3.763263
35	46480	50594.240038	-4114.240038	-8.851635
36	50546	52080.573332	-1534.573332	-3.035994
37	49229	56353.527099	-7124.527099	-14.472216
38	39079	45911.937345	-6832.937345	-17.484934
39	49499	48048.824759	1450.175241	2.929706
40	47889	52177.275901	-4288.275901	-8.954616

41	42598	50953.672263	-8355.672263	-19.615175
42	33674	40477.593917	-6803.593917	-20.204294
43	44778	51018.496497	-6240.496497	-13.936524
44	44575	49494.308235	-4919.308235	-11.036025
45	44735	44155.072589	579.927411	1.296362
46	36661	34924.869643	1736.130357	4.735633
47	43456	46347.898395	-2891.898395	-6.654774
48	49915	46108.689233	3806.310767	7.625585
49	55529	46153.121381	9375.878619	16.884652
50	37903	37801.669642	101.330358	.267341
51	40760	44941.047604	-4181.047604	-10.257722
52	40411	51426.946299	-11015.946299	-27.259772
53	52097	57033.369581	-4936.369581	-9.475343
54	40122	39080.936289	1041.063711	2.594745
55	49875	42147.249302	7727.750698	15.494237
56	55664	41938.417749	13725.582251	24.657916
57	64012	53778.906995	10233.093005	15.98621
58	44721	41291.154568	3429.845432	7.669429
59	63519	51166.472593	12352.527407	19.44698
60	67756	56982.669481	10773.330519	15.900187
61	72183	65674.500428	6508.499572	9.016665
62		**45961.197162**		

Summary Statistics

Mean Square Error (MSE) = 44390755.402126
Mean Absolute Deviation (MAD) = 5531.560003
Alpha = .175
Beta = .975
Gamma = 0
Initial Intercept Estimate = 32006.059016
Initial Slope Estimate = 393.025066

Seasonal Adjustments
1. = 1.126079
2. = .831217
3. = .977322
4. = 1.065382

The software program GB-STAT automatically provides optimised estimates (alpha, beta, and gamma) that minimize forecast error for the forecast.

(b) Forecasting Evaluation

The forecasts and the Mean Average Percentage Errors (MAPEs) are then calculated for each of the Australia, China, India, Japan, UK, and USA tourist flows and are presented in Appendix C. A summary of the MAPEs for the Australia, China, India, Japan, UK, and USA tourist flows is shown in Table 4.7.

Table 4.7

Summary of Winter's Forecast MAPEs

	Direct forecast	1-Step-Ahead	4-Step-Ahead
Aus Holiday	7.89%	9.99%	9.45%
Aus Business	10.78%	9.20%	9.04%
Aus Total	15.30%	11.03%	9.07%
Average	11.32%	10.07%	9.19%
China Holiday	8.28%	8.16%	8.76%
China Business	13.98%	10.33%	4.72%
China Total	10.45%	8.07%	8.22%
Average	10.90%	8.85%	7.23%
India Holiday	16.00%	15.14%	5.52%
India Business	25.53%	12.35%	5.59%
India Total	10.87%	11.35%	7.20%
Average	17.47%	12.95%	6.10%
Japan Holiday	19.05%	26.05%	47.85%
Japan Business	11.71%	13.38%	20.19%
Japan Total	14.85%	19.91%	36.19%
Average	15.20%	19.78%	34.74%
UK Holiday	8.87%	8.66%	7.34%
UK Business	6.90%	7.32%	12.48%
UK Total	7.08%	6.90%	7.12%
Average	7.62%	7.63%	8.98%
USA Holiday	11.82%	10.69%	12.56%
USA Business	10.78%	17.69%	34.50%
USA Total	7.50%	10.68%	16.41%
Average	**10.03%**	**13.02%**	**21.16%**
Overall	**12.09%**	**12.05%**	**14.57%**
Overall Average 12.90%			

4.2.3 BSM Forecasting

(a) Forecasting Implementation

The forecasting implementation using the Basic structural model is performed for the direct eight-step-forecasts, one-step-ahead forecasts, and four-step-ahead forecasts as shown in Table 4.8.

Table 4.8

Forecasting implementation of the BSM model

Actual		**8 Step Direct BSM Forecast**	**1 step ahead BSM Forecast**	**4 step ahead BSM Forecast**
1985 Q1		↑	↑	
to		Model Estimation	Model Estimation	
1991Q4		↓		
2000Q1	=>	1991Q4	↓	
2000Q2	=>	2000Q1	2000Q2	
2000Q3	=>	2000Q2	2000Q3	
2000Q4	=>	2000Q3	2000Q4	
2001Q1	=>	2000Q4	2001Q1	2001Q1
2001Q2	=>	2001Q1	2001Q2	2001Q2
2001Q3	=>	2001Q2	2001Q3	2001Q3
2001Q4	=>	2001Q3	2001Q4	2001Q4

Table 4.9 presents the empirical results for one example of a one-step-ahead forecast using the BSM Model - Business travel flow from Australia to Singapore.

Table 4.9

BSM forecasting model example: Australia Business Travel to Singapore

```
Aus_Busin = Trend + 1 Cycle(s) + Trigo seasonal + Irregular

Estimation report
Model with  7 hyperparameters ( 2 restrictions).
Parameter estimation sample is 1985. 1 - 1999. 4. (T =   60).
Log-likelihood kernel is 2.662589.
Very strong convergence in  25 iterations.
( likelihood cvg 1.077454e-013
  gradient cvg   3.751133e-007
  parameter cvg  5.610296e-008 )

Eq 12 : Diagnostic summary report.

Estimation sample is 1985. 1 - 1999. 4. (T =   60, n =   55).
Log-Likelihood is 159.755 (-2 LogL = -319.511).
Prediction error variance is 0.002214178

       Summary statistics
             Aus_Busin
Std.Error    0.047055
Normality       1.265
H( 18)          1.651
r( 1)       -0.041365
r(12)         0.10640
DW              2.012
Q(12, 6)        5.895
Rsý           0.36953

Eq 12 : Estimated coefficients of final state vector.

Variable      Coefficient       R.m.s.e.        t-value
Lvl               9.8375       0.0242686        405.36  [ 0.0000] **
Slp            0.0198502      0.00278754        7.1211  [ 0.0000] **
Cyl_ 1         0.0186340       0.0171186
Cyl_ 2       -0.00492498       0.0181365
Sea_ 1        -0.0485977       0.0137398        -3.537  [ 0.0008] **
Sea_ 2        -0.0429572       0.0142696       -3.0104  [ 0.0039] **
Sea_ 3        -0.0192732       0.0110214       -1.7487  [ 0.0859]

Eq 12 : Cycle analysis for Cyl.
The amplitude of the cycle is 0.01927389.

Eq 12 : Seasonal analysis (at end of period).

Seasonal Chiý( 3) test is 30.5828  [0.0000] **.

               Seas  1    Seas  2    Seas  3    Seas  4
Value       -0.023684   0.029324   0.062230  -0.067871


Goodness-of-fit results for Aus_Busin
Prediction error variance (p.e.v)            0.002214
Prediction error mean deviation (m.d)        0.001764
Ratio p.e.v. / m.d in squares (ñ 1.0)        1.002963
Coefficient of determination       Rý        0.981986
... based on differences           RDý       0.716826
... based on diff around seas mean RSý       0.369527
Information criterion of Akaike    AIC      -5.746207
... of Schwartz (Bayes)            BIC      -5.362244
```

This model contains a trend component, one cycle, seasonal coefficients, and an irregular component. The prediction error variance is low and its square root is presented as the "Std Error". The normality test statistic is the Bowman-Shenton statistic based on third and fourth moments of the residuals, with a Chi-square distribution and 2 degrees of freedom. The critical 5% value is 5.99 and needs to be exceeded to consider rejecting the model.

H is the heteroskedasticity test statistic, treated as having an F distribution with 18, 18 degrees of freedom in this example (critical 5% value is 2.23). A low 'H' value indicates a decrease in variance over time and a high value indicates an increase. The r values give the autocorrelations at given lags. The DW statistic is the standard Durbin Watson test, and Q is the Box-Ljung statistic based here on 12 autocorrelations, tested against the Chi-square distribution with six degrees of freedom in this example (critical 5% value is 12.59). The Rsy statistic compares the model fit against a random walk with fixed seasonal dummies and as such is a measure of goodness of fit.

In the final state vector, the t value is the coefficient divided by the root mean square error, with 1.96 the critical value for 5% statistical significance. The seasonal effects are jointly tested for significance and the resulting statistic is denoted "Seasonal Chiy". The probability value is the probability of a Chi-square at s=3, exceeding the value of the test statistic. The seasonal effect is highly significant here. The final estimate of the seasonal effect for each season is also provided.

The goodness-of-fit relates to the generalised least squares residuals. The prediction error variance (p.e.v.) is the variance of the residuals, and the mean deviation of the residuals is also given. The ratio of the p.e.v. and m.d. should approximate unity in a correctly specified model. Ry is the equivalent of a regression R square, and RDy should not be negative. Model comparison are best made using the AIC and BIC statistics; the lower the value the better the model.

(b) Forecasting Evaluation

The forecasts and the Mean Average Percentage Errors (MAPEs) are then calculated for each of the Australia, China, India, Japan, UK, and USA tourist flows. A summary of the MAPEs for the Australia, China, India, Japan, UK, and USA tourist flows is shown in Table 4.10.

Overall the MAPE is 11.5% for the direct forecast, 8.55% for 1-step-ahead and 9.90% for 4-step-ahead forecasts. The forecasts are good in that they outperform the naïve forecasts and Holt-Winters exponential smoothing forecasts.

Table 4.10

Summary of Basic Structural Model Forecast MAPEs

	Direct forecast	**1-Step-Ahead**	**4-Step-Ahead**
Aus Holiday	13.59%	5.89%	6.49%
Aus Business	7.28%	5.77%	7.14%
Aus Total	15.99%	11.72%	3.58%
Average	12.29%	7.79%	5.73%
China Holiday	7.18%	5.56%	5.16%
China Business	8.46%	5.67%	4.03%
China Total	10.93%	10.82%	6.94%
Average	8.86%	7.35%	5.38%
India Holiday	17.85%	12.01%	9.03%
India Business	10.43%	5.49%	4.95%
India Total	10.96%	6.92%	5.04%
Average	13.08%	8.14%	6.34%
Japan Holiday	19.05%	16.58%	30.79%
Japan Business	12.20%	9.57%	15.69%
Japan Total	16.18%	14.33%	24.37%
Average	15.81%	13.50%	23.62%
UK Holiday	7.93%	5.56%	4.77%
UK Business	5.65%	4.26%	6.78%
UK Total	5.02%	5.16%	5.70%
Average	6.20%	4.99%	5.75%
USA Holiday	13.23%	9.66%	10.70%
USA Business	15.54%	10.85%	16.11%
USA Total	9.51%	8.15%	10.85%
Average	**12.76%**	**9.55%**	**12.56%**
Overall	**11.50%**	**8.55%**	**9.90%**
Overall Average 9.98%			

4.2.4 Neural Network Forecasting

(a) Forecasting Implementation

Given that Neural Networks are universal approximators of functions (Cybenko 1989) one might expect that they could model seasonal patterns. However, Kolarik and Rudorfer (1994) and Wheelwright and Makridakis (1985) have found Neural Networks have difficulty modelling seasonal patterns. Nelson et al. (1999) tested this issue and established that for time series with seasonality, the MAPE for Neural Networks based on deseasonalised data was significantly more accurate than Neural Networks based on non-deseasonalised data. Further post-hoc testing was also performed to establish that this finding was valid across the functional form, the number of historical data points and the type of forecasting horizon. These results suggest deseasonalising may benefit forecast accuracy just as with statistical methods. Consequently, a test is conducted here whereby the results are given for both a seasonal and deseasonalised series.

Neural models can have two learning methods 'supervised' and 'unsupervised'. Only a supervised method can be used for time-series analysis where 'targets' (actual values) can be used to train the models. An 'unsupervised' model has an internal comparison process between sets of data and is best used for clustering analysis. In SPSS the Kohonen Network is provided as an 'unsupervised' model and is not used here. The three models MLP, RBF and Bayesian are 'supervised' models suitable for forecasting.

There are also two directions of flow that the learning process can take 'forward' and 'backward'. Forward flow passes from one node to the next with information sent only from the preceding node to adjust the layer calculations. Backward flow receives preceding information and compares it with the output before adjusting the layer calculations.

The MLP method is a backward flow process. From initial random weights a forward pass of the original data is applied to a training pattern in the first hidden layer and the nodes are calculated. The outputs from the nodes are transferred via the selected function to the next layer and a signal sent to the output layer.

The difference between the calculated and actual values in the output layer is measured and a backward pass via the selected function adjusts the connections (beginning at the output layer backwards) so that a closer match is made in the output layer.

The RBF model is a feed forward process with only one hidden layer. At the first forward pass a centre is used to measure the distance from each data point and this measure is passed to the hidden layer. The function used to adjust the nodes is a non-linear combination of functions termed a Radial Basis Function.

The Bayesian model is similar to the MLP but uses Bayes Theorem in the calculation of the error in the output layer which removes the need to use a validation data set and speeds up calculation.

The different Neural Network model architecture for the MLP and RBF models to be tested in this study are shown in Table 4.11.

Table 4.11

MLP and RBF Neural Network model parameters

Neural Network Model	Parameters
MLP	Learning Algorithm: a) Conjugate Gradient b) Steepest Descent Functions: a) Tanh b) Sigmoid c) Linear
RBF	Functions: a) Gaussian b) Inverse Quadratic c) Quadratic d) Spline

The resulting Neural Networks models are:

1) MLP conjugate gradient Tanh
2) MLP conjugate gradient Sigmoid
3) MLP conjugate gradient Linear
4) MLP steepest descent Tanh
5) MLP steepest descent Sigmoid
6) MLP steepest descent Linear
7) RBF Gaussian
8) RBF Inverse Quadratic
9) RBF Quadratic
10) RBF Spline
11) Bayesian

The Bayesian Neural Network model has no function selection.

Parameter selection is a complex issue. The parameters are largely focussed upon the number of nodes, the number of hidden layers and differ between the three network models.

These parameters are best selected by trial and error automatically in the software and are not reported separately in this study. The reasons for this need some discussion. For the MLP models the choice of the number of layers is between one or two, although selecting a second layer often does not improve forecast accuracy. In the case of this analysis no series was improved by having more than one layer and this is a finding discussed later. However, because only one layer was used there is no point in specifying the number of layers in the model tables.

For the MLP the number of nodes in a layer is also selected automatically. Increasing the number of nodes will improve the accuracy of the MLP model gradually until 100% fit is achieved on the training data. However, this is because each new unit starts to represent individual features in the data, and it is possible to over-fit the model and begin to decrease forecasting accuracy through adding more nodes, as the nodes begin to represent noise in the data. SPSS uses an automatic convergence criteria to avoid the over-fitting problem. As such the number of nodes derived is of little practical information and is not reported.

For the Radial Basis Function model parameter selection focuses upon the number of centres (nodes). Again this is best selected by trial and error automatically based upon 5 centres as a start running up to 50 at intervals of 5. As with the MLP model the number of centres provides no practical information when selected automatically and there is no reason to try and select them manually because of the risk of over-fitting. The positioning of the centres also needs to be decided and it is possible to select particular data points such as outliers. However, a reason is needed for doing this, and no reason exists in this study with this type of data. Consequently, selection is random through the series as recommended by the SPSS Neural Connections software manual.

It needs to be noted that Euclidean error distance was used to calculate the Radial Basis model because this is the most accurate parameter to use (refer to the SPSS Neural Connection Manual).

For the Bayesian Network model parameter selection focuses upon the weights for the parameter groups and given the input data is a time-series (automatically normalized) of arrivals the paramount basis for deciding is to reduce noise in the series. This is best done by again selecting an automatic process (Automatic Relevance Detection) so that the number of groups is dependent on the number of nodes in the input layer. The number of nodes selected is also automatic for the same reasons given above for the MLP model. Also like the MLP model the number of layers could be one or two, but of the working models, only one layer is selected by the model.

A further parameter for the Bayesian model is the number of models. Because the training begins from a randomly selected set of parameter values the accuracy of calculations (when compared in the output layer) can vary depending upon the start selected. Consequently it is possible to run several models with different starting points and then have two different decision rules to select the best model. The choice is Most Likely Models and the Committee Decision. Although initial testing attempted to test the difference in the decision rules, the Bayesian model did not work for the time-series in this study, and rule selection became irrelevant.

The forecasting implementation using the Neural Network model is performed in two stages for the seasonal data series and deseasonalised data series.

Stage 1: In this stage, each of the eleven Neural Network models as highlighted above are used to perform the eight-quarter Direct forecast for each of the disaggregated data series. Appendix B provides the RMSE values of the MLP and RBF models for the non-deseasonalised data, while Appendix C provides the RMSE values of the MLP and RBF models for deseasonalised data. The RMSE forecasting accuracy comparison is used as this error measure (as conventionally RMSE and not MAPE is used for neural model selection in the software) to compare across the MLP, RBF, and BAY Neural Network models with the same data series.

Table 4.12 provides a summary of the best MLP, RBF and Bayesian models for each deseasonalised data series with their respective RMSE values; the overall best model is then selected as shown in the last column. Similarly, Table 4.13 provides a summary of the best MLP, RBF and Bayesian models for each non-deseasonalised data series with their respective RMSE values; the overall best model is then selected as shown in the last column. The Bayesian model did not work on the sample data. However, there is no reason as to why this occurred. In many cases the model could not be calculated at all and when calculated the model did not provide accurate forecasts.

Table 4.12

Overall Best Performing Neural Network models – Seasonal Data

Data Series	Best MLP RMSE	Best RBF RMSE	BAYN RMSE	Best Performing Neural Network Model
Aus Holiday	6472	**5396**	NA	**RBF Inverse Quadratic**
Aus Business	**1660**	1944	1706	**MLP Steepest Descent Sigmoid**
Aus Total	9781	**8757**	NA	**RBF Inverse Quadratic**
UK Holiday	12035	**11744**	NA	**RBF Quadratic**
UK Business	**1044**	1367	NA	**MLP Conjugate Gradient Tanh**
UK Total	16484	**15507**	NA	**RBF Quadratic**
USA Holiday	**4615**	4657	317768	**MLP Conjugate Gradient Sigmoid**
USA Business	**3047**	3562	125943	**MLP Conjugate Gradient Sigmoid**
USA Total	**8901**	9386	104974	**MLP Conjugate Gradient Sigmoid**
Japan Holiday	31108	**29536**	NA	**RBF Spline**
Japan Business	**3246**	3357	NA	**MLP Conjugate Gradient Tanh**
Japan Total	**33308**	35116	NA	**MLP Conjugate Gradient Tanh**
India Holiday	**10848**	24157	14376	**MLP Conjugate Gradient Linear**
India Business	**1168**	1225	1209	**MLP Conjugate Gradient Tanh**
India Total	**16520**	26209	19497	**MLP Conjugate Gradient Linear**
China Holiday	**9249**	15986	NA	**MLP Conjugate Gradient Linear**
China Business	**658**	1002	1277	**MLP Conjugate Gradient Linear**
China Total	**9820**	12938	10499	**MLP Conjugate Gradient Linear**

Table 4.13

Overall Best Performing Neural Network models – Deseasonalised Data

Data Series	Best MLP RMSE	Best RBF RMSE	BAYN RMSE	Best Performing Neural Network Model
Aus Holiday	5098	**5006**	NA	**RBF Inverse Quadratic**
Aus Business	**1609**	1800	NA	**MLP Conjugate Gradient Sigmoid**
Aus Total	18916	**18668**	NA	**RBF Inverse Quadratic**
UK Holiday	**7590**	8114	NA	**MLP Conjugate Gradient Sigmoid**
UK Business	**870**	1078	NA	**MLP Conjugate Gradient Sigmoid**
UK Total	**9401**	10102	NA	**MLP Conjugate Gradient Sigmoid**
USA Holiday	3352	**3208**	NA	**RBF Inverse Quadratic**
USA Business	**3166**	3303	NA	**MLP Conjugate Gradient Sigmoid**
USA Total	7473	**7462**	NA	**RBF Inverse Quadratic**
Japan Holiday	**25172**	25675	NA	**MLP Conjugate Gradient Sigmoid**
Japan Business	**3204**	3223	NA	**MLP Conjugate Gradient Sigmoid**
Japan Total	**30024**	32138	NA	**MLP Conjugate Gradient Sigmoid**
India Holiday	**7156**	7521	NA	**MLP Conjugate Gradient Sigmoid**
India Business	**1170**	1427	NA	**MLP Conjugate Gradient Sigmoid**
India Total	**9280**	9448	NA	**MLP Conjugate Gradient Sigmoid**
China Holiday	7290	8309	NA	**MLP Conjugate Gradient Linear**
China Business	639	1636	NA	**MLP Conjugate Gradient Linear**
China Total	9850	12843	NA	**MLP Conjugate Gradient Linear**

Stage 2: Here, the best performing models that were selected from the seasonalised and deseasonalised tourist data flows from stage 1 are used to conduct the one-step-ahead forecast and four-step-ahead forecasts. The multistepping and single-stepping forecasting method used to generate these forecasts is shown in Table 4.14.

Table 4.14

Forecasting implementation of the Neural Network models

Actual		**8 Step Direct Neural Network Forecast (Selected from MLP, RBF, BAYN models)**	**1 step Ahead Neural Network Forecast (Using the best Neural Network model)**	**4 step ahead Neural Network Forecast**
1985 Q1		↑	↑	
to		Model Estimation	Model Estimation	
1991Q4		↓		
2000Q1	=>	1991Q4	↓	
2000Q2	=>	2000Q1	2000Q2*	
2000Q3	=>	2000Q2	2000Q3*	
2000Q4	=>	2000Q3	2000Q4*	
2001Q1	=>	2000Q4	2001Q1*	2001Q1*
2001Q2	=>	2001Q1	2001Q2*	2001Q2*
2001Q3	=>	2001Q2	2001Q3*	2001Q3*
2001Q4	=>	2001Q3	2001Q4*	2001Q4*

With Neural Network forecasting, the network is trained over a given training set and a validation set that is used to evaluate the generalisation capabilities of the learned model.

A summary of the MAPEs for the Australia, China, India, Japan, UK, and USA are shown in Table 4.15 and 4.16 for the deseasonalised and seasonal data series respectively.

Table 4.15

Summary of Neural Network Forecast MAPEs - Deseasonalised Data

	Direct forecast	1 Step	4 Step
Aus Holiday	6.46%	6.66%	6.65%
Aus Business	6.52%	7.71%	7.76%
Aus Total	10.34%	11.01%	7.20%
Average	7.77%	8.46%	7.20%
China Holiday	9.73%	9.99%	8.94%
China Business	6.47%	6.32%	7.32%
China Total	8.14%	7.91%	7.42%
Average	8.11%	8.07%	7.90%
India Holiday	19.33%	22.80%	18.19%
India Business	5.64%	6.22%	7.13%
India Total	8.96%	9.86%	7.17%
Average	11.31%	12.96%	10.83%
Japan Holiday	17.40%	20.72%	39.28%
Japan Business	8.07%	11.13%	18.91%
Japan Total	12.58%	15.81%	29.27%
Average	12.68%	15.89%	29.16%
UK Holiday	9.15%	9.21%	10.57%
UK Business	5.36%	5.45%	6.37%
UK Total	7.00%	7.13%	8.62%
Average	7.17%	7.26%	8.52%
USA Holiday	9.86%	11.27%	11.68%
USA Business	10.45%	12.99%	20.22%
USA Total	6.90%	11.72%	17.50%
Average	9.07%	11.99%	16.47%
Overall	9.35%	10.77%	13.34%
Overall Average 11.16%			

Table 4.16

Summary of Neural Network Forecast MAPEs – Seasonal Data

	Direct forecast	1 Step	4 Step
Aus Holiday	7.04%	6.97%	6.44%
Aus Business	5.83%	5.64%	7.04%
Aus Total	4.93%	5.38%	4.45%
Average	5.93%	6.00%	5.97%
China Holiday	11.55%	12.52%	10.13%
China Business	5.80%	5.72%	5.60%
China Total	6.84%	7.48%	7.14%
Average	8.06%	8.57%	7.62%
India Holiday	22.91%	27.89%	21.94%
India Business	6.05%	6.79%	4.97%
India Total	14.29%	14.41%	12.43%
Average	14.42%	16.36%	13.11%
Japan Holiday	22.84%	20.24%	31.33%
Japan Business	8.31%	9.01%	14.01%
Japan Total	16.03%	18.20%	24.05%
Average	15.73%	15.82%	23.13%
UK Holiday	13.93%	17.03%	21.32%
UK Business	7.08%	7.28%	10.05%
UK Total	11.17%	13.26%	16.23%
Average	10.73%	12.52%	15.86%
USA Holiday	14.62%	15.81%	22.56%
USA Business	9.88%	10.33%	15.17%
USA Total	8.16%	8.43%	12.58%
Average	10.88%	11.52%	16.77%
Overall	10.96%	11.80%	13.75%
Overall Average 12.17%			

4.3 Forecasting Accuracy Comparison

Table 4.17 shows the forecasting performance accuracy comparisons of the Naïve, Winters, BSM, and Neural Network forecasting methods..

Table 4.17

Forecasting Accuracy Comparison of Naïve, Winters, BSM and Neural Network Models using MAPE

Origin Country		Direct forecast	1 Step ahead forecast	4 Step ahead forecast
Aus Holiday	Naïve	10.45%	9.26%	8.74%
	Winters	7.89%	9.99%	9.45%
	BSM	13.59%	**5.89%**	6.49%
	Neural Network – Seasonal	7.04%	6.97%	**6.44%**
	Neural Network - Deseasonalised	**6.46%**	6.66%	6.65%
Aus Business	Naïve	11.83%	10.82%	8.87%
	Winters	10.78%	9.20%	9.04%
	BSM	7.28%	**5.77%**	7.14%
	Neural Network – Seasonal	**5.83%**	5.64%	**7.04%**
	Neural Network - Deseasonalised	6.52%	7.71%	7.76%
Aus Total	Naïve	10.30%	9.13%	9.55%
	Winters	15.30%	11.03%	9.07%
	BSM	15.99%	11.72%	**3.58%**
	Neural Network – Seasonal	**4.93%**	**5.38%**	4.45%
	Neural Network - Deseasonalised	10.34%	11.01%	7.20%
Aus Average	Naïve	10.86%	9.74%	9.05%
	Winters	11.32%	10.07%	9.19%
	BSM	12.29%	7.79%	**5.73%**
	Neural Network - Seasonal	5.93%	**6.00%**	5.97%
	Neural Network - Deseasonalised	7.77%	8.46%	7.20%
China Holiday	Naïve	12.11%	9.94%	9.98%
	Winters	8.28%	8.16%	8.76%
	BSM	**7.18%**	**5.56%**	**5.16%**
	Neural Network – Seasonal	11.55%	12.52%	10.13%
	Neural Network - Deseasonalised	9.73%	9.99%	8.94%

China Business	Naïve	13.90%	11.50%	3.75%
	Winters	13.98%	10.33%	4.72%
	BSM	8.46%	**5.67%**	**4.03%**
	Neural Network – Seasonal	**5.80%**	5.72%	5.60%
	Neural Network - Deseasonalised	6.47%	6.32%	7.32%
China Total	Naïve	16.04%	13.32%	12.31%
	Winters	10.45%	8.07%	8.22%
	BSM	10.93%	10.82%	**6.94%**
	Neural Network - Seasonal	**6.84%**	**7.48%**	7.14%
	Neural Network - Deseasonalised	8.14%	7.91%	7.42%
China Average	Naïve	14.02%	11.59%	8.68%
	Winters	10.90%	8.85%	7.23%
	BSM	8.86%	**7.35%**	**5.38%**
	Neural Network - Seasonal	**8.06%**	8.57%	7.62%
	Neural Network - Deseasonalised	8.11%	8.07%	7.90%
India Holiday	Naïve	18.67%	15.18%	7.94%
	Winters	**16.00%**	15.14%	**5.52%**
	BSM	17.85%	**12.01%**	9.03%
	Neural Network - Seasonal	22.91%	27.89%	21.94%
	Neural Network - Deseasonalised	19.33%	22.80%	18.19%
India Business	Naïve	14.97%	12.32%	4.97%
	Winters	25.53%	12.35%	5.59%
	BSM	10.43%	**5.49%**	**4.95%**
	Neural Network - Seasonal	6.05%	6.79%	4.97%
	Neural Network - Deseasonalised	**5.64%**	6.22%	7.13%
India Total	Naïve	13.32%	11.23%	6.33%
	Winters	10.87%	11.35%	7.20%
	BSM	10.96%	**6.92%**	**5.04%**
	Neural Network - Seasonal	14.29%	14.41%	12.43%
	Neural Network - Deseasonalised	**8.96%**	9.86%	7.17%
India Average	Naïve	15.65%	12.91%	6.41%
	Winters	17.47%	12.95%	**6.10%**
	BSM	13.08%	**8.14%**	6.34%
	Neural Network - Seasonal	14.42%	16.36%	13.11%
	Neural Network - Deseasonalised	**11.31%**	12.96%	10.83%
Japan Holiday	Naïve	**14.97%**	25.97%	44.98%
	Winters	19.05%	26.05%	47.85%
	BSM	19.05%	**16.58%**	**30.79%**
	Neural Network - Seasonal	22.84%	20.24%	31.33%
	Neural Network - Deseasonalised	17.40%	20.72%	39.28%

Japan Business	Naïve	12.80%	14.54%	18.13%
	Winters	11.71%	13.38%	20.19%
	BSM	12.20%	9.57%	15.69%
	Neural Network - Seasonal	8.31%	**9.01%**	**14.01%**
	Neural Network - Deseasonalised	**8.07%**	11.13%	18.91%
Japan Total	Naïve	13.29%	19.95%	32.46%
	Winters	14.85%	19.91%	36.19%
	BSM	16.18%	**14.33%**	24.37%
	Neural Network - Seasonal	16.03%	18.20%	**24.05%**
	Neural Network - Deseasonalised	**12.58%**	15.81%	29.27%
Japan Average	Naïve	13.69%	20.15%	31.86%
	Winters	15.20%	19.78%	34.74%
	BSM	15.81%	**13.50%**	23.62%
	Neural Network - Seasonal	15.73%	15.82%	**23.13%**
	Neural Network - Deseasonalised	**12.68%**	15.89%	29.16%
UK Holiday	Naïve	11.10%	9.63%	7.11%
	Winters	8.87%	8.66%	7.34%
	BSM	**7.93%**	**5.56%**	**4.77%**
	Neural Network - Seasonal	13.93%	17.03%	21.32%
	Neural Network - Deseasonalised	9.15%	9.21%	10.57%
UK Business	Naïve	9.28%	9.20%	8.42%
	Winters	6.90%	7.32%	12.48%
	BSM	5.65%	**4.26%**	6.78%
	Neural Network - Seasonal	7.08%	7.28%	10.05%
	Neural Network - Deseasonalised	**5.36%**	5.45%	**6.37%**
UK Total	Naïve	9.14%	8.23%	6.65%
	Winters	7.08%	6.90%	7.12%
	BSM	**5.02%**	**5.16%**	**5.70%**
	Neural Network - Seasonal	11.17%	13.26%	16.23%
	Neural Network - Deseasonalised	7.00%	7.13%	8.62%
UK Average	Naïve	9.84%	9.02%	7.39%
	Winters	7.62%	7.63%	8.98%
	BSM	**6.20%**	**4.99%**	**5.75%**
	Neural Network - Seasonal	10.73%	12.52%	15.86%
	Neural Network - Deseasonalised	7.17%	7.26%	8.52%
USA Holiday	Naïve	10.94%	11.58%	13.64%
	Winters	11.82%	10.69%	12.56%
	BSM	13.23%	**9.66%**	**10.70%**
	Neural Network - Seasonal	14.62%	15.81%	22.56%
	Neural Network - Deseasonalised	**9.86%**	11.27%	11.68%

USA Business	Naïve	17.40%	20.52%	28.04%
	Winters	10.78%	17.69%	34.50%
	BSM	15.54%	10.85%	16.11%
	Neural Network - Seasonal	**9.88%**	**10.33%**	**15.17%**
	Neural Network - Deseasonalised	10.45%	12.99%	20.22%
USA Total	Naïve	10.24%	11.32%	13.79%
	Winters	7.50%	10.68%	16.41%
	BSM	9.51%	**8.15%**	**10.85%**
	Neural Network - Seasonal	8.16%	8.43%	12.58%
	Neural Network - Deseasonalised	**6.90%**	11.72%	17.50%
USA Average	Naïve	12.86%	14.47%	18.49%
	Winters	10.03%	13.02%	21.16%
	BSM	12.76%	**9.55%**	**12.56%**
	Neural Network - Seasonal	10.88%	11.52%	16.77%
	Neural Network - Deseasonalised	**9.07%**	11.99%	16.47%
Overall Average	**Naïve**	**12.82%**	**12.98%**	**13.65%**
	Winters	**12.09%**	**12.05%**	**14.57%**
	BSM	**11.50%**	**8.55%**	**9.90%**
	Neural Network - Seasonal	**10.96%**	**11.80%**	**13.75%**
	Neural Network - Deseasonalised	**9.35%**	**10.77%**	**13.34%**

Overall Average of Direct, 1-step-ahead and 4-step ahead forecasts:

Naïve	**13.15%**
Winters	**12.90%**
BSM	**9.98%**
Neural Network – Seasonal	**12.17%**
Neural Network – Deseasonalised	**11.16%**

The following findings are concluded upon from the empirical results above :

1) Are the modern time series models better than traditional simpler forecasting Holt-Winters and naïve models?

From Table 4.17, overall average BSM MAPE (9.98%) and Neural Network model MAPE with deseasonalised data (11.16%) are lower than those for the Holt-Winters (12.90%) and naïve model (13.15%). Based on the MAPE, the BSM model is the more accurate model with lowest MAPE value. Statistically, the BSM is significantly lower (t=3.56, 0.012) at 95% than the naïve and Winters models (t=2.44, 0.035). However, the deseasonalised Neural Network model MAPE is not significantly lower (t=1.67, 0.09) than the naïve model, and the Winters model (t=1.21, 0.145).

Consequently, the study findings suggest that the Basic structural time series model and Neural Network model forecast more accurately than the traditional simpler extrapolative forecasting Holt-Winters and naïve models.

2) Do any of the models perform better over different forecasting horizons?

With the Direct forecast, it can be seen from Table 4.17, the deseasonalised Neural Network forecasting model (MAPE 9.35%) outperforms the seasonal Neural Network model (MAPE 10.96%), BSM (MAPE 11.50%), Winters (MAPE 12.09%), and naïve model (MAPE 12.82%). Statistically, the deseasonalised neural model is significantly lower (t=2.78, 0.01) at 95% than the naïve model. However, it is not significantly lower than the seasonal Neural Network (t=0.91, 0.19), BSM (t=1.30, 0.11) or Winters (t=1.59, 0.07) models.

With the 1-step-ahead forecasts, the BSM forecasting model (MAPE 8.55%) outperforms the deseasonalised neural model (MAPE 10.77%), the seasonal neural model (MAPE 11.80), the Winters (MAPE 12.05%), and the naïve model (MAPE 12.98%). Statistically, the BSM is significantly lower (t=2.19, 0.03) at 95% than the naïve model, but not for the Winters (t=1.64, 0.07), seasonal Neural Network (t=1.61, 0.07) or deseasonalised Neural Network (t=1.23, 0.12) models.

With the 4-step-ahead forecasts, the BSM forecasting model (MAPE 9.90%) outperforms the deseasonalised Neural Network (MAPE 13.34%), seasonal Neural Network (MAPE 13.75%), Winters (MAPE 14.57%), and naïve model (MAPE 13.65%). Statistically, the BSM is not significantly lower (t=0.74, 0.24) at 95% than the naïve model, Winters (t=0.85, 0.21), seasonal Neural Network (t=0.98, 0.18) or deseasonalised Neural Network (t=0.76, 0.23) models.

This overall result suggests that the BSM model is more accurate for forecasting short-term quarterly tourist flows up to one year ahead than the Neural Network model or the simpler models. However, for two years ahead the neural model is superior to the BSM model.

3) Did any particular model perform better for different types of tourist flows (that is, Holiday, Business and Total flows)?

The Holiday, Business, and Total flow overall average MAPEs for the Direct, 1-step-ahead and 4-step-ahead forecast are shown in Table 4.18, 4.19 and 4.20 respectively.

Table 4.18

Summary of Holiday Flow MAPEs

Origin Country		Direct forecast	1 Step	4 Step
Aus Holiday	Naïve	10.45%	9.26%	8.74%
	Winters	7.89%	9.99%	9.45%
	BSM	13.59%	5.89%	6.49%
	Neural Network - Seasonal	7.04%	6.97%	6.44%
	Neural Network - Deseasonalised	6.46%	6.66%	6.65%
China Holiday	Naïve	12.11%	9.94%	9.98%
	Winters	8.28%	8.16%	8.76%
	BSM	7.18%	5.56%	5.16%
	Neural Network - Seasonal	11.55%	12.52%	10.13%
	Neural Network - Deseasonalised	9.73%	9.99%	8.94%
India Holiday	Naïve	18.67%	15.18%	7.94%
	Winters	16.00%	15.14%	5.52%
	BSM	17.85%	12.01%	9.03%
	Neural Network - Seasonal	22.91%	27.89%	21.94%
	Neural Network - Deseasonalised	19.33%	22.80%	18.19%
Japan Holiday	Naïve	14.97%	25.97%	44.98%
	Winters	19.05%	26.05%	47.85%
	BSM	19.05%	16.58%	30.79%
	Neural Network - Seasonal	22.84%	20.24%	31.33%
	Neural Network - Deseasonalised	17.40%	20.72%	39.28%
UK Holiday	Naïve	11.10%	9.63%	7.11%
	Winters	8.87%	8.66%	7.34%
	BSM	7.93%	5.56%	4.77%
	Neural Network - Seasonal	13.93%	17.03%	21.32%
	Neural Network - Deseasonalised	9.15%	9.21%	10.57%
USA Holiday	Naïve	10.94%	11.58%	13.64%
	Winters	11.82%	10.69%	12.56%
	BSM	13.23%	9.66%	10.70%
	Neural Network - Seasonal	14.62%	15.81%	22.56%
	Neural Network - Deseasonalised	9.86%	11.27%	11.68%
Overall	Naïve	13.04%	13.59%	15.40%
	Winters	12.00%	13.12%	15.25%
	BSM	13.14%	9.21%	11.16%
	Neural Network - Seasonal	15.48%	16.74%	18.95%
	Neural Network - Deseasonalised	11.99%	13.44%	15.88%

Overall Holiday Average:	
Naïve	**14.01%**
Winters	**13.45%**
BSM	**11.17%**
Neural Network - Seasonal	**17.06%**
Neural Network - Deseasonalised	**13.77%**

Table 4.19

Summary of Business Flow MAPEs

Origin Country		Direct forecast	1 Step	4 Step
Aus Business	Naïve	11.83%	10.82%	8.87%
	Winters	10.78%	9.20%	9.04%
	BSM	7.28%	5.77%	7.14%
	Neural Network - Seasonal	5.83%	5.64%	7.04%
	Neural Network - Deseasonalised	6.52%	7.71%	7.76%
China Business	Naïve	13.90%	11.50%	3.75%
	Winters	13.98%	10.33%	4.72%
	BSM	8.46%	5.67%	4.03%
	Neural Network - Seasonal	5.80%	5.72%	5.60%
	Neural Network - Deseasonalised	6.47%	6.32%	7.32%
India Business	Naïve	14.97%	12.32%	4.97%
	Winters	25.53%	12.35%	5.59%
	BSM	10.43%	5.49%	4.95%
	Neural Network - Seasonal	6.05%	6.79%	4.97%
	Neural Network - Deseasonalised	5.64%	6.22%	7.13%
Japan Business	Naïve	12.80%	14.54%	18.13%
	Winters	11.71%	13.38%	20.19%
	BSM	12.20%	9.57%	15.69%
	Neural Network - Seasonal	8.31%	9.01%	14.01%
	Neural Network - Deseasonalised	8.07%	11.13%	18.91%
UK Business	Naïve	9.28%	9.20%	8.42%
	Winters	6.90%	7.32%	12.48%
	BSM	5.65%	4.26%	6.78%
	Neural Network - Seasonal	7.08%	7.28%	10.05%
	Neural Network - Deseasonalised	5.36%	5.45%	6.37%
USA Business	Naïve	17.40%	20.52%	28.04%
	Winters	10.78%	17.69%	34.50%
	BSM	15.54%	10.85%	16.11%
	Neural Network - Seasonal	9.88%	10.33%	15.17%
	Neural Network - Deseasonalised	10.45%	12.99%	20.22%
Overall	Naïve	13.36%	13.15%	12.03%
	Winters	13.28%	11.71%	14.42%
	BSM	9.93%	6.94%	9.12%
	Neural Network - Seasonal	7.16%	7.46%	9.47%
	Neural Network - Deseasonalised	7.09%	8.30%	11.28%
Overall Business Average:				
Naïve	**12.85%**			
Winters	**13.14%**			
BSM	**8.66%**			
Neural Network - Seasonal	**8.03%**			
Neural Network - Deseasonalised	**8.89%**			

Table 4.20

Summary of Total Flow MAPEs

Origin Country		**Direct forecast**	**1 Step**	**4 Step**
Aus Total	Naïve	10.30%	9.13%	9.55%
	Winters	15.30%	11.03%	9.07%
	BSM	15.99%	11.72%	3.58%
	Neural Network - Seasonal	4.93%	5.38%	4.45%
	Neural Network - Deseasonalised	10.34%	11.01%	7.20%
China Total	Naïve	16.04%	13.32%	12.31%
	Winters	10.45%	8.07%	8.22%
	BSM	10.93%	10.82%	6.94%
	Neural Network - Seasonal	6.84%	7.48%	7.14%
	Neural Network - Deseasonalised	8.14%	7.91%	7.42%
India Total	Naïve	13.32%	11.23%	6.33%
	Winters	10.87%	11.35%	7.20%
	BSM	10.96%	6.92%	5.04%
	Neural Network - Seasonal	14.29%	14.41%	12.43%
	Neural Network - Deseasonalised	8.96%	9.86%	7.17%
Japan Total	Naïve	13.29%	19.95%	32.46%
	Winters	14.85%	19.91%	36.19%
	BSM	16.18%	14.33%	24.37%
	Neural Network - Seasonal	16.03%	18.20%	24.05%
	Neural Network - Deseasonalised	12.58%	15.81%	29.27%
UK Total	Naïve	9.14%	8.23%	6.65%
	Winters	7.08%	6.90%	7.12%
	BSM	5.02%	5.16%	5.70%
	Neural Network - Seasonal	11.17%	13.26%	16.23%
	Neural Network - Deseasonalised	7.00%	7.13%	8.62%
USA Total	Naïve	10.24%	11.32%	13.79%
	Winters	7.50%	10.68%	16.41%
	BSM	9.51%	8.15%	10.85%
	Neural Network - Seasonal	8.16%	8.43%	12.58%
	Neural Network - Deseasonalised	6.90%	11.72%	17.50%
Overall	Naïve	12.06%	12.20%	13.52%
	Winters	11.01%	11.32%	14.04%
	BSM	11.43%	9.52%	9.41%
	Neural Network - Seasonal	10.24%	11.19%	12.81%
	Neural Network - Deseasonalised	8.99%	10.57%	12.86%

Overall Total Average:	
Naïve	**12.59%**
Winters	**12.12%**
BSM	**10.12%**
Neural Network - Seasonal	**11.41%**
Neural Network - Deseasonalised	**10.81%**

Overall, for Holiday flows and Total flows (as shown in Table 4.18) the BSM model was more accurate, than the other models, with a MAPE of 11.17% and 10.12% respectively. Statistically, the BSM is significantly lower than the seasonal Neural Network (t=3.87, 0.01) and the naïve (t=0.10, 0.05) models. However, the BSM model is not significantly more accurate than the Winters (t=1.54, 0.09) or deseasonalised Neural Network (t=1.62, 0.09) models.

Overall for Business flows, the seasonal Neural Network model was more accurate with a MAPE of 8.03%. Statistically, the model is significantly lower at 95% than the naïve model (t=5.77, 0.002) and Winters model (t=4.77, 0.004). However, it is not significantly lower than the BSM model (t=0.55, 0.31) or the deseasonalised Neural Network model (t=0.60, 0.29).

Overall for Total flows, the BSM was more accurate with a MAPE of 10.12%. Statistically, the model is significantly lower (t=3.08, 0.02) at 95% than the naïve model. However, it is not significantly lower than the Winters model (t=1.72, 0.08), seasonal Neural Network model (t=1.29, 0.13) or the deseasonalised Neural Network model (t=0.52, 0.31).

In examining the holiday, business and total flows forecasting accuracy compared for each of the forecasting horizons (Direct, 1-step-ahead, and 4-step-ahead), the following results are found:

1) Holiday flows
   a) Direct forecast
   The deseasonalised Neural Network model was more accurate (MAPE 11.99%). Statistically, the model is not significantly more accurate at 95% than the naïve model (t=0.42, 0.34), Winters model (t=0.001, 0.5), seasonal Neural Network (t=1.05, 0.16) or BSM model (t=0.39, 0.35).

   b) 1-step-ahead forecast
   The BSM model was more accurate (MAPE 9.21%). Statistically, the model is significantly more accurate than the seasonal Neural Network model (t=2.20, 0.03).

However, it is not significantly more accurate at 95% than the naïve model (t=1.37, 0.1), Winters model (t=1.17, 0.13), or deseasonalised Neural Network model (t=1.29, 0.11).

c) 4-step-ahead forecast

The BSM model was more accurate (MAPE 11.16%). Statistically, the model is not significantly more accurate at 95% than the naïve model (t=0.58, 0.29), Winters model (t=0.53, 0.30), seasonal Neural Network (t=1.42, 0.09) or deseasonalised Neural Network model (t=0.74, 0.23).

2) Business flows

d) Direct forecast

The deseasonalised Neural Network model was more accurate (MAPE 7.09%). Statistically, the model is significantly more accurate at 95% than the naïve model (t=4.57, 0.0005), Winters model (t=2.26, 0.02), BSM model (t=1.71, 0.06), and seasonal Neural Network (t=0.07, 0.47).

e) 1-step-ahead forecast

The BSM model was more accurate (MAPE 6.94%). Statistically, the model is significantly more accurate at 95% than the naïve model (t=3.18, 0.01), Winters model (t=2.60, 0.01), seasonal Neural Network model (t=0.40, 0.35), and deseasonalised Neural Network model (t=0.83, 0.21).

f) 4-step-ahead forecast

The BSM model was more accurate (MAPE 9.12%). Statistically, the model is not significantly more accurate at 95% than the naïve model (t=0.66, 0.26), Winters model (t=1.04, 0.16), seasonal Neural Network model (t=0.13, 0.45), and deseasonalised Neural Network model (t=0.63, 0.27).

3) Total flows

g) Direct forecast

The deseasonalised Neural Network model was more accurate (MAPE 8.99%). Statistically, the model is significantly more accurate at 95% than the naïve model (t=2.21, 0.03). However, it is not significantly more accurate than the Winters model (t=1.20, 0.12), BSM model (t=1.26, 0.12), and seasonal Neural Network model (t=0.63, 0.27).

h) 1-step-ahead forecast

The BSM model was more accurate (MAPE 9.52%). Statistically, the model is not significantly more accurate at 95% than the naïve model (t=1.21, 0.13), Winters model (t=0.78, 0.28), seasonal Neural Network model (t=0.69, 0.25) or deseasonalised Neural Network model (t=0.56, 0.29).

i) 4-step-ahead forecast

The BSM model was more accurate (MAPE 9.41%). Statistically, the model is not significantly more accurate at 95% than the naïve model (t=0.81, 0.22), Winters model (t=0.82, 0.22), seasonal Neural Network model (t=0.80, 0.22) or deseasonalised Neural Network model (t=0.71, 0.25).

This suggests that the Neural Networks with deseasonalised data were more accurate across all flows for the Direct forecasts; while the BSM was more accurate across all flows for the 1-step-ahead and 4-step-ahead forecasts. However, there was no difference between the different data series disaggregated by purpose of visit in regard to particular forecasting models.

4) Does disaggregation of the Total flows improve forecast accuracy?

Table 4.21 shows the overall average MAPEs for the best flows for each type of travel.

Table 4.21

Overall Average MAPEs for Holiday, Business and Total Flows

	Holiday	Business	Total
Naïve	14.01%	12.85%	12.59%
Winters	13.45%	13.14%	12.12%
BSM	**11.17%**	8.66%	**10.12%**
Neural Network - Seasonal	17.06%	**8.03%**	11.41%
Neural Network - Deseasonalised	13.77%	8.89%	10.81%

For business flows (8.03%) it appears that higher forecasting accuracy is achieved relative to accuracy for total flows (10.12%). However, this is not statistically significant difference (t=1.31, 0.13). For holiday flows the forecasting accuracy is lower than for total flows.

Also the forecast horizon has no particular impact on improving the accuracy of the disaggregated business flows with Direct flows (t=1.61, 0.07), 1 step flows (t=1.48, 0.08) and 4 step flows (t=0.08, 0.47) all significantly lower than their equivalent total flows.

5) Was any particular model more suited for forecasting tourist arrivals into Singapore from particular tourist generating countries (Australia, China, India, Japan, UK and USA)?

From each of the country average MAPE values in Table 4.17, the following conclusions can be made for each country:

a) Australia - The Neural Network model with seasonalised data was the most accurate model (MAPE 5.93%), and the BSM was the best model for the 1-step-ahead and 4-step-ahead forecasts with MAPE values of 6.00% and 5.73%.

b) China - The Neural Network model with seasonalised data was the most accurate model (MAPE 8.06%), and the BSM was the best model for the 1-step-ahead and 4-step-ahead forecasts with MAPE values of 7.35% and 5.38%.

c) India - The Neural Network model with deseasonalised data was the most accurate model (MAPE 11.31%), and the BSM was the best model for the 1-step-ahead forecasts with a MAPE of 8.14%, while the Holt-Winters was the best model for the 4-step-ahead forecasts with a MAPE of 6.10%.

d) Japan - The Neural Network model with deseasonalised data was the most accurate model (MAPE 12.86%), and the BSM was the best model for the 1-step-ahead forecasts with MAPE 13.5%. For the 4-step-ahead forecasts, the Neural Network model with seasonal data was best model with a MAPE of 23.13%.

e) UK - The BSM was the most accurate model over the three forecasting horizons with MAPEs of 6.20%, 4.99% and 5.75% respectively.

f) USA - The Neural Network model with deseasonalised data was the most accurate model (MAPE 9.07%), and the BSM was the most accurate model for the 1-step-ahead and 4-step-ahead forecasts with MAPE values of 9.55% and 12.56%.

Only for the UK was the BSM selected as the most accurate model across all the forecasting horizons. Consequently, there is no evidence of particular models being suited to particular countries. The overall results for most countries supports the previous finding that Neural Network models and BSM models are the most accurate with the Neural Network model working better over longer forecasting horizon and the BSM model working better over a shorter forecasting horizon.

6) Did deseasonalising the data improve the forecasting accuracy of the Neural Network models?

A summary of the Neural Network forecasting performance with seasonal and deseasonalised data is shown in Table 4.22.

Table 4.22

Summary of overall average MAPEs for the Neural Network models with seasonal and deseasonalised data

	Direct forecast	1-step-ahead forecast	4-step-ahead forecast
Neural Network - Seasonal	10.96%	11.80%	13.75%
Neural Network - Deseasonalised	9.35%	10.77%	13.34%

The results suggests that the Neural Network models using deseasonalised data perform better than the Neural Network models using seasonal data in all of the three forecasting horizons examined. However, the differences are not statistically significant with the Direct difference (t=0.92, 0.19), 1 step difference (t=0.47, 0.32) and 4 step difference (t=0.09, 0.46) all insignificant at 95%.

The conclusion here is that deseasonalising the data improves the forecasting accuracy of Neural Network models when forecasting seasonal tourism arrivals data. However, the improvement cannot be said to be statistically significant.

7) Which Neural Network model architecture was most suitable for tourist arrival forecasting?

From Tables 4.12 and 4.13, it was found that the MLP Conjugate Gradient model was the best performing Neural Network model for 26 data series out of the 36 seasonal and deseasonalised data series. In particular, the MLP Conjugate Gradient Sigmoid model was the selected as the best model for 14 data series. This has been the most commonly used model in previous tourism forecasting and is found to be the best default model. However, for some series alternative models do improve forecast accuracy so that just using an MLP Conjugate Gradient model for lower cost will mean possibly achieving lower accuracy.

8) Do different Neural Network model activation functions have an affect on the forecasting accuracy of the model?

Appendices B and C give the RMSE values and particular functions used for the different Neural Network models. The RMSE results indicate that different functions are associated with particular Neural Network model architecture and can have a significant effect on the forecasting performance of the model.

Therefore attention must be given to testing and selecting the most appropriate functions before applying Neural Network models for tourist arrivals forecasting. This weakens the ease of applying neural models and therefore increases the cost of using neural models in industry.

9) Do different Neural Network model parameters have an affect on the forecasting accuracy of the model?

From an analysis of the data in this study it appears that the number of hidden layers will almost always be one. However, this question is not a problem for practical industry forecasting as the software can test out by trial and error for the necessary number of layers. Similarly the number of nodes is best left to trial and error and selecting the number of nodes may be dangerous in industry situations as over-fitting of the data may suggest a very good model that is not relevant for forecasting ahead because of adding in the noise of the original series.

The various parameters discussed under model implementation for the Neural models are all best selected by trial and error.

The final conclusions to this study are discussed in the next chapter.

CHAPTER 5 CONCLUSIONS, IMPLICATIONS AND FUTURE RESEARCH

5.1 Conclusions

Practical modern time series models, namely Winters, BSM and Neural Networks have been used to model the aggregated and disaggregated tourist flows (Australia, China, Japan, India, UK, and US) into Singapore.

Empirical results in this study show that the relative performance of a particular forecasting model varies for each of the tourist flows. There is no single model that is 'best' for all the origin-Singapore pairs. It was found that the more sophisticated BSM model and Neural Network time series models are more accurate forecasting models for the total or disaggregated inbound tourists into Singapore in all the short-term forecasting horizons used in this study.

The failure of the Winters and naïve methods to forecast arrivals accurately for most of the tourist flows into Singapore seems to suggest that we can discount the ability of these simpler methods for forecasting quarterly seasonal inbound tourists, in favour of the more sophisticated BSM and Neural Network techniques.

The BSM and Neural Network models are more complicated models than the Winter's forecasting method. But with the advent of sophisticated programs, these models can be applied for tourism forecasting to obtain more accurate forecasts in industrial environments, at relatively low cost in manpower and data requirements.

In summary the following findings are concluded from the empirical results discussed above:

1) Modern Time Series models such as the Basic structural time series models and Neural Network models forecast tourism arrivals more accurately than traditional simpler extrapolative forecasting Holt-Winters and naïve models.

2) The overall results support the conclusion that Neural Network models are useful for forecasting short-term quarterly tourist flows data, but Neural Networks perform better over longer time periods (in this case two years ahead) compared with one year or one quarter ahead horizons where the BSM is more accurate.

3) No particular model works best for disaggregated data.

4) It is not clear that disaggregating the data improves the accuracy of forecasts

5) No particular model is best for forecasting arrivals from any particular country.

6) Deseasonalising the data improves the forecasting accuracy of Neural Network models.

7) The MLP Conjugate Gradient model stands out as the most accurate neural model. However, other models may also work better for particular series.

8) The appropriate selection of the Neural Network model and its associated functions is important and will improve the forecasting accuracy of a particular Neural Network architecture type (MLP and Radial Basis Function).

The findings are highly consistent with previous research (the exception being the comparison to BSM that has not been done before) that suggest Neural Network models work better over longer time horizons, are best run using deseasonalised data and that they outperform the simpler time-series methods (eg. Naïve and Winters). The finding that the Neural Network operates well over the short-term for tourism series is a new finding. It is also a new finding that the BSM is the overall best modern time series model and particularly so over short time-frames. The BSM model has not been compared with Neural Network modelling before.

Furthermore, previous studies in tourism demand forecasting have not examined the issue of the Neural function in sufficient depth. Previous studies have primarily used the sigmoid function or not stated the function used. This study has found that such an approach is a reasonable default method, but that other functions sometimes outperform the sigmoid function and need to be considered to obtain the most accurate forecast possible.

In regard to the Gradient function it is noticeable in the findings (refer to Table 4.13) that for the particularly short China series the linear gradient function worked better than the generally selected sigmoid function. So it is possible that the length of the series may affect functional choice and this would need to be an issue in future research.

In regard to the original objectives of this study is can be concluded that the study has identified the relative performance of the modern time-series forecasting models and assessed the most relevant structure of neural models for tourism forecasting.

5.2 Practical Contributions

This study makes new, significant and practical contributions to tourism demand forecasting.

(1) this study has shown that the newer BSM and neural techniques are capable of producing high levels of forecasting accuracy around 10% error and outperform simpler forms of time-series models.

(2) the suitability and usefulness of Neural Networks for short term forecasting is confirmed for use by management and decision makers.

(3) for Neural Network modelling, it has been shown that deseasonalisation of the data can improve short-term forecasting accuracy.

(4) it is found that the neural MLP models have outperformed the neural RBF networks in most instances in this study, and Bayesian model did not work satisfactorily.

(5) it has been found that the MLP Conjugate Gradient model is the preferred Neural Network model for short-term tourist arrival forecasting.

(6) it is shown there is a need to test and select the appropriate Neural Network model functions before applying any MLP or Radial Basis model.

5.3 Recommendations for Future Research

The results suggest three possible directions for future research.

The question can firstly be raised as to whether the findings can be replicated with arrival series to other countries. The Singapore series tends to be a relatively non-seasonal series in that the variations between travel seasons are less than in most markets. This arises because Singapore is located so close to the equator that weather variations are not marked. In this regard the finding that the data should be deseasonalised for input into Neural models is particularly significant and suggests this would be essential in highly seasonal markets. The question of whether the particular model findings here would be similar in other markets with different series cannot be answered, and must be left the subject of further research.

Secondly, future researchers could consider expanding tourism demand forecasting with the use of Neural Networks and fuzzy logic models. The most important reason for combining fuzzy systems with Neural Networks is their learning capability as highlighted by Nauck et al. (1997) and they can aid ANNs in extracting the features of time series data and potentially generate more accurate forecasts (Zhang, 1998).

Thirdly, although it is apparent from the literature that it is unlikely that regression methods will outperform neural and BSM models in the short-term, and that deseasonalising the neural data input is worthwhile; further studies into these issues are needed for different tourism data series, to further confirm these findings. Other issues also remain with the Neural forecasting process. It is unclear why the Bayesian model would not accurately forecast or even calculate out on the sample data, and this requires further investigation. Also more work needs to be done on the functional form of the Neural models.

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