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A neural network model to forecast Japanese demand for travel to Hong Kong

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Abstract

Apart from simple guesswork, time-series and regression techniques have largely dominated forecasting models for international tourism demand. This paper presents a new approach that uses a supervised feed-forward neural network model to forecast 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. Officially published annual data in the period of 1967 to 1996 were used to build the neural network. Estimated Japanese arrivals were compared with actual published Japanese arrivals. Experimental results showed that using the neural network model to forecast Japanese arrivals outperforms multiple regression, naïve, moving average, and exponent smoothing. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords: Japanese tourist arrivals; Neural networks; Tourism demand forecasting; Hong Kong

1. Introduction

During the past 30 years, the Japanese economy has experienced significant growth. According to Japanese official publications, the Gross Domestic Expenditure per capita, when translated to real values, increased from US$1,237.91 in 1967 to US$34,232.76 in 1996 (Statistics Bureau Prime Minister's Office of Japan, 1977–1997; Statistics Bureau Management & Coordination Agency, 1996–1997). An outcome of this extensive growth in national income in Japan is the increased number of outbound tourists. In the period 1967 to 1996, the number of Japanese visitors to Hong Kong increased 28 times (Hong Kong Tourist Association, 1967–1997). This represents an annual average of approximately 20% of total number of tourists in Hong Kong. Fig. 1 shows the number of Japanese tourist arrivals in Hong Kong during the period 1967–1996. Naturally, the tourism related sectors in Hong Kong benefit significantly from the arrivals of Japanese visitors. In 1996, total tourism receipts in Hong Kong reached US$10.93 billions.

It is not possible to stock the unfilled airline seats, unoccupied hotel rooms, or unused concert hall seats. Due to the perishable nature of the tourism industry, the need for accurate forecasts is crucial. Hence, researchers, practitioners, and policy makers have long recognized the necessity of accurate forecasts for tourism demand (usually measured in the number of tourist arrivals) (Sheldon & Var, 1985). Accurate forecasts would help managers and investors make operational, tactical and strategic decisions. Examples of operational decisions include scheduling and staffing; tactical decisions relate to the preparation of tour brochures, and strategic decisions are to do with hotel investments. Similarly, government bodies need accurate forecasts about tourism demand in order to plan for tourism infrastructure such as accommodation site planning, and transportation development.

In spite of the consensus on the need for accurate forecasting, and a clear understanding of the benefits of accurate forecasts, there is no standard supplier of tourism forecasts (Witt & Witt, 1995). Also, there does not exist a single forecasting model that outweighs all other forecasting models in term of forecasting accuracy. Previous studies of forecasting demand for tourism have been primarily based on time-series models and

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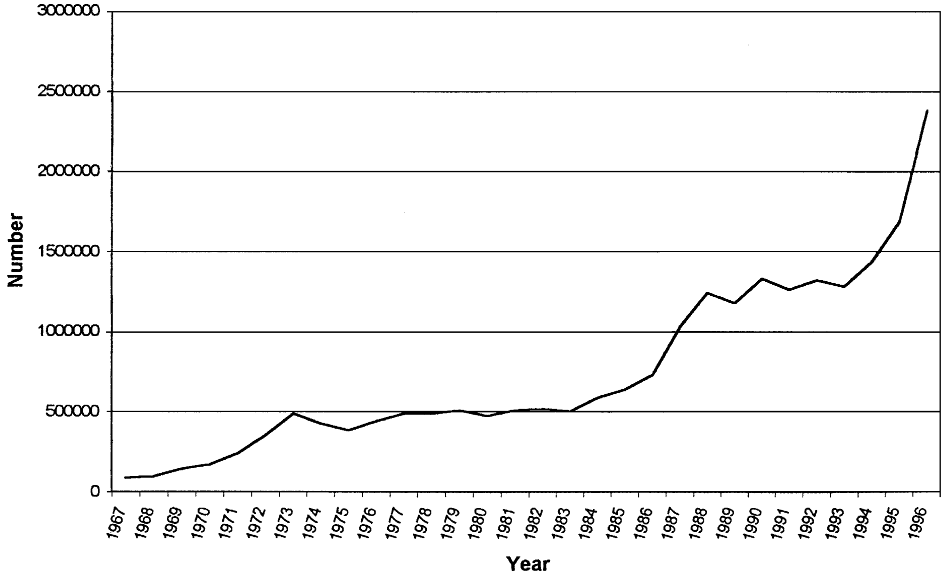

Fig. 1. Number of Japanese visitors in Hong Kong from 1967 to 1996.

regression models (Wong, 1997). Making no assumptions about other factors, time-series forecasting models use historical data of a variable to predict values in the future. Time-series models are often able to achieve good forecasting results (Andrew et al., 1990; Martin & Witt, 1989). On the other hand, regression models (also known as econometric models) identify the independent variables that could significantly affect the values of a dependent variable and then model the relationship of the dependent variable and independent variables.

The primary objective of this research was to investigate the feasibility of incorporating a neural network model (also known as an artificial neural network), which is computer software that simulates the human intelligence to deduce or *learn* from a data set, to forecast Japanese demand for travel to Hong Kong. The neural network model built for this research, if successful, could benefit managers in the Hong Kong tourism industry, as well as the Hong Kong Government, in allowing for more accurate planning for service provision for Japanese tourists, a major source of Hong Kong's international tourist arrivals.

The remaining sections of this paper are organized as follows. First, there is an overview section that examines the theoretical foundation of neural networks. This section, in particular, analyzes the use of neural network models as a forecasting tool for business applications. Based on the theoretical analysis, a neural network is developed to forecast Japanese demand for travel to Hong Kong. Actual data from official publications in Hong Kong and Japan are used for the neural network development. The model development process is described in the next section. An experiment section then follows to present the empirical results of forecasting. The quality of forecasting results is measured in mean absolute percentage error, acceptable output percentage, and normalized correlation coefficient. The results forecast by the neural network model are then compared with the corresponding values obtained from some commonly used econometric and time-series models for international tourism demand. These other models for comparison include multiple regression, naïve, moving average (3), and exponential smoothing (0.3). An analysis section is then presented, which analyzes the research findings and the applicability of neural network models to forecast Japanese demand travel to Hong Kong. Finally, a conclusion section outlines the significance of this research and suggests future research possibilities.

2. Neural network models

A neural network consists of an input layer, an output layer, and usually one or more hidden layers. Each of these layers contains nodes, and these nodes are connected to nodes at adjacent layer(s). Fig. 2 demonstrates a simplified neural network with three layers.

Each node in a neural network is a processing unit that contains a weight and a summation function. A weight (w) returns a mathematical value for the relative strength of connections to transfer data from one layer to another layer; whereas a summation function (y) computes the weighted sum of all input elements entering a processing unit. In Fig. 2, each node in the hidden layer computes y_j ($j = 1, 2, 3$) in the following way:

$$y_j = \sum_{i=1}^{2} x_i w_{ji}.$$

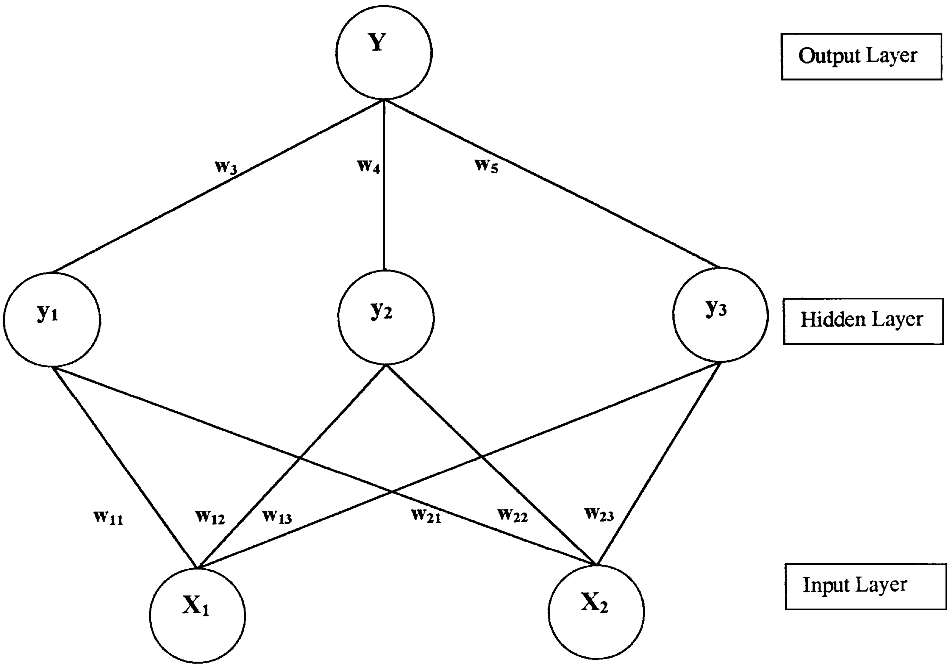

Fig. 2. A neural network model.

Also, a *sigmoid function* (y_T) in the following form is used to transform the output so that it falls into an acceptable range. This transformation is done before the output reaches the next level. The purpose of a *sigmoid function* is to prevent the output value from being too large, as the value of y_T must fall between 0 and 1:

$$y_T = \frac{1}{1 + e^{-y}}.$$

Finally, Y in node of the output layer in Fig. 2 is obtained by the following summation function:

$$Y = \sum_{i=1}^{3} y_{Ti} w_i.$$

Nodes in the input layer represent independent variables of the problem. For instance, to determine a person's credit rating, a financial institution needs information about that person's income level, education background, and home ownership status as the essential input variables. The hidden layer is used to add an internal representation of handling non-linear data. The output of a neural network is the solution to a problem. To demonstrate, a numeric value from the output node is used to represent the credit rating of an individual loan applicant.

A supervised feed-forward neural network learns from training data to discover patterns representing input and output variables. Usually, the process of learning involves the following stages.

(i) Assign random numbers to the weights.

(ii) For every element in the training set (a set of sample observations used to develop the pattern or relationship among the observations), calculate output using the summation functions embedded in the nodes.

(iii) Compare computed output with observed values.

(iv) Adjust the weights and repeat steps (ii) and (iii) if the result from step (iii) is not less than a threshold value.

(v) Repeat the above steps for other elements in the training set.

A neural network can best be described as an intelligent computer system that mimics the processing capabilities of the human brain (Law, 1996). Neural networks are an information technology that is capable of representing knowledge based on massive parallel processing (rapid processing of a large amount of information concurrently) and pattern recognition based on past experience or examples. The pattern recognition ability of a neural network makes it a good alternative classification and forecasting tool in business applications. In addition, a neural network is expected to be superior to traditional statistical methods in forecasting because a neural network is better able to recognize the high-level features, such as the serial correlation, if any, of a training set. Furthermore, a neural network has been demonstrated to outperform standard statistical models in forecasting with a small-sized training set and a high level of white noise (random errors in the samples) (Pattie & Snyder, 1996). This feature was particularly useful for forecasting the Japanese tourist arrivals in this research, as the number of samples in the training set was relatively small due to data unavailability. An additional advantage of applying a neural network to forecasting is that a neural network can capture the non-linearity of samples in the training set (Wang & Sun, 1996). The non-linear factor handling ability makes a neural network different from time-series models. Pattie and Snyder claimed, with substantiation, that using a neural network to forecast non-linear tourist behavior could achieve a lower mean absolute percentage error, lower cumulative relative absolute error, and lower root mean square error than linear trend, exponential smoothing, Box-Jenkins, or the naïve extrapolation models (Pattie & Snyder, 1996). Similarly, Mazanec demonstrated that a neural network is superior to discriminant analysis function in classifying tourists into market segments based on a set of non-linear demographic, socio-economic, and behavioral variables (Mazanec, 1992). However, there are also some drawbacks with the use of neural networks. For instances, the looser linkage to theory and the inability to yield useful parameters of independent variables' impact on a dependent variable (such as elasticity) are weaknesses of neural networks, as compared to regression models. Furthermore, a neural network, like regression, requires forecasts of the independent variables to generate forecasts of the dependent variable.

3. Methodology

3.1. Data

Secondary sources of data were used in this research. The selection of data for the neural network was based on data availability, the reliability of data sources, and the measurability of variables in the modeling process. Table 1, containing relevant data for forecasting Japanese demand for travel to Hong Kong in the period of 1967 to 1996, was set up from the following sources.

- *Japan Statistical Yearbook*, 1977–1997 published by the Statistics Bureau Prime Minister's Office of Japan (1977–1997);

Table 1
An overview of Japanese tourist arrivals in Hong Kong

Year	Service price in Hong Kong relative to Japan	Average hotel rate in Hong Kong (US$)	Foreign exchange rate (¥/US$)	Population in japan (1000)	Marketing expenses in promotional Hong Kong (US$)	Gross domestic expenditure per capita in japan (US$)	Number of visitors
1967	1.15	141.50	361.90	100 196	879 961	1 237.91	85 512
1968	1.12	155.05	357.70	101 331	1 315 195	1 467.71	96 387
1969	1.10	176.17	357.80	102 536	1 275 507	1 702.07	143 746
1970	1.09	189.40	357.60	103 720	1 348 986	1 979.87	168 473
1971	1.06	189.48	314.80	105 145	1 455 308	2 426.94	237 950
1972	1.08	185.41	302.00	107 595	1 733 809	2 854.30	349 212
1973	1.14	167.00	280.00	109 104	1 827 120	3 696.43	486 677
1974	1.01	160.24	300.10	110 573	1 939 102	4 061.98	423 098
1975	0.95	151.81	305.20	111 940	1 592 844	4 357.80	382 740
1976	0.90	150.50	292.80	113 094	1 838 513	5 047.81	437 931
1977	0.88	162.40	240.00	114 165	2 768 517	6 795.83	485 495
1978	0.89	186.16	194.60	115 190	2 590 579	9 146.97	487 250
1979	0.97	220.15	239.70	116 155	2 268 932	7 976.64	508 011
1980	1.00	247.22	203.00	117 060	2 171 039	10 133.00	472 182
1981	1.11	246.61	219.90	117 902	2 323 436	9 972.71	507 960
1982	1.21	240.00	235.00	118 728	2 283 280	9 719.15	515 697
1983	1.31	246.24	232.20	119 536	2 300 954	10 172.27	502 175
1984	1.40	268.67	251.10	120 305	3 005 080	9 968.14	584 013
1985	1.42	304.51	200.50	121 049	2 770 805	13 226.93	635 767
1986	1.49	310.90	159.10	121 660	4 060 536	17 360.15	727 219
1987	1.58	327.74	123.50	122 239	5 007 499	23 206.48	1 033 525
1988	1.70	362.76	125.85	122 745	4 613 568	24 251.09	1 240 470
1989	1.85	344.59	143.45	123 205	4 500 844	22 662.95	1 176 189
1990	1.94	292.57	134.40	123 611	6 451 593	25 922.62	1 331 677
1991	2.14	242.44	125.20	124 043	4 670 739	29 592.65	1 259 837
1992	2.31	222.94	124.75	124 452	5 287 735	30 436.87	1 324 399
1993	2.49	228.52	111.85	124 764	5 376 281	34 108.18	1 280 905
1994	2.72	256.47	99.74	125 034	4 988 267	38 460.00	1 440 632
1995	2.99	268.60	102.83	125 569	5 725 266	37 420.99	1 691 283
1996	3.17	277.53	116.00	125 864	6 048 504	34 232.76	2 382 890

- *Statistical Handbook of Japan*, 1996–1997 published by the Statistics Bureau Management and Coordination Agency, Government of Japan (1996–1997);
- *Statistical Survey of Japan's Economy*, 1976–1986 published by the Economic and Foreign Affairs Research Association of Japan (1976–1986);
- *A Statistical Review of Tourism*, 1976–1997 published by the Hong Kong Tourist Association (1967–1997);
- *Hong Kong Tourist Association Annual Report*, 1967–1997 published by the Hong Kong Tourist Association (1976–1997); and
- *Commissioner of Inland Revenue Annual Review*, 1967–1996 published by the Hong Kong Government (Hong Kong Statistics Department, 1967–1996).

In this research, all monetary values are measured in US$ due to the currency peg between the US$ and the HK$. Japanese demand for travel to Hong Kong, measured by the number of Japanese tourist arrivals, can be stated as

$$Y = f(\mathrm{SP}, \mathrm{FER}, \mathrm{Pop}, \mathrm{Mkt}, \mathrm{GDE}, \mathrm{AHR}),$$

where Y is the number of Japanese tourist arrivals in Hong Kong, SP the service price in Hong Kong relative to Japan, FER the foreign exchange rate (¥/US$), Pop the population in Japan, Mkt the marketing expenses to promote Hong Kong's tourism industry, GDE the real gross domestic expenditure per person in Japan, and AHR the average hotel rate in Hong Kong.

Previous studies have suggested that the exogenous variables in econometric forecasting models for international tourism demand comprise mainly: the population and income of the origin country, the cost of living in the destination country, currency foreign exchange rate, marketing expenditure on promotional activities in the destination country, and relative prices for tourist services in destination country (Lim, 1997). Transportation costs have been used as an exogenous variable in some studies of forecasting international tourism demand (Carey, 1991; Witt & Witt, 1995), but, transportation costs were omitted in this study due to data unavailability. In fact, Qu and Lam claimed that "transportation cost was generally not a significant or major determinant in tourism demand" (Qu & Lam, 1997), so in this study, Qu and Lam's findings were generalized to Japanese arrivals in Hong Kong. Additionally, since the majority of Japanese visitors to Hong Kong came on tours that were paid for by their employers (Hong Kong Tourist Association, 1976–1997), the exogenous variable SP can basically be used as a relative index to represent all traveling costs, including transportation costs for Japanese visitors to Hong Kong.

In this study, due to data unavailability, AHR was used as a proxy for the cost of living for tourists in Hong Kong, and Mkt was used as a proxy for marketing expenses to promote Hong Kong's tourist industry. Similarly, GDE was used as a proxy for the Japanese income level, and SP was used as a proxy variable for the relative prices for purchases. In Table 1, all monetary figures were in US$ and in real values relative to 1980. The marketing expenditures for tourism promotion in 1974, 1978, 1983, and 1990 were adjusted to deal with the discrepancies found in the Hong Kong Tourist Association's publications. As in previous studies performed by Morley (1993) and Carey (1991), SP for year i was calculated in the following way:

$$\mathrm{SP}_i = \frac{\mathrm{CPI}_i(\text{Hong Kong})/\mathrm{CPI}_{1980}(\text{Hong Kong})}{\mathrm{CPI}_i(\text{Japan})/\mathrm{CPI}_{1980}(\text{Japan})}.$$

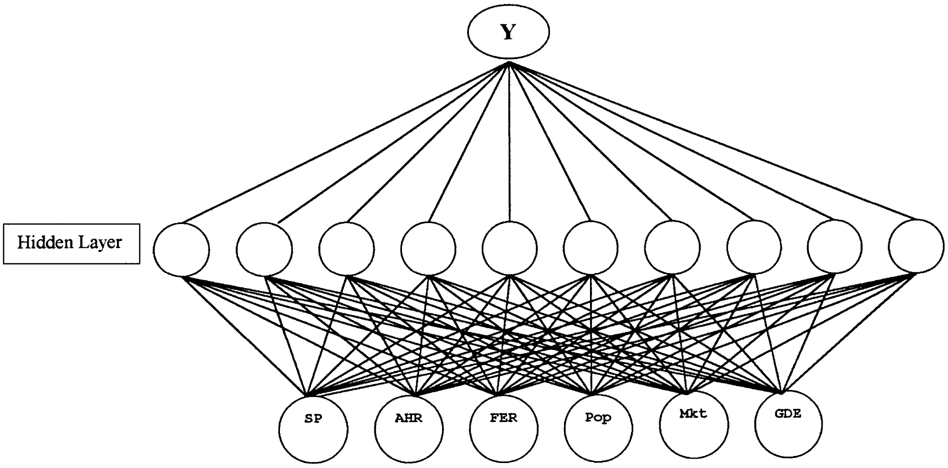

Fig. 3. A demand neural network model for travel by Japanese tourists to Hong Kong.

3.2. A neural network model to forecast Japanese demand for travel to Hong Kong

This research establishes a neural network to model Japanese demand for travel to Hong Kong. To date, there exists no published article that makes such an attempt. This study adopts the data from Table 1 for network training and testing. Among the 30 sample entries, 20 were randomly selected to form the training set, while the rest were used for accuracy testing (validation). The six nodes in the input layer contained the following variables:

SP; AHR; FER; Pop; Mkt; GDE.

The output variable used in this research was Y, representing the number of Japanese tourist arrivals in Hong Kong in a given year. Fig. 3 shows the neural network, with a hidden layer of 10 nodes, which was used in this research to determine the number of Japanese tourist arrivals in Hong Kong.

A computer program was developed using AiNet version 1.1 for the neural network model exhibited in Fig. 3. There were six input nodes (independent variables) and one output node (dependent variable). There is no standard formula to calculate the number of nodes needed in the hidden layer (Wang & Sun, 1996). In this research, 10 nodes were used for fast convergence and stable performance. Empirical findings are presented in the next section.

4. Empirical results

Four other forecasting models, namely multiple regression, naïve, moving average (3), single exponential smoothing (0.3) were employed to forecast Japanese tourist arrivals based on the same testing set as the neural network model. These four models are some of the common models in tourism demand forecasting (Carey, 1991; Lim, 1997; Witt & Witt, 1995; Wong, 1997). Widely adopted in international tourist arrival demand forecasting, multiple regression models attempt to identify the relevant variables and estimate the relationship between the independent variables and the dependent variable in terms of parameters. A naïve model forecasts the value of a variable at time t using the value of the variable at time $t-1$, i.e. $F_t = V_{t-1}$. Similarly, a moving average (3) forecasting model calculates the value of V at time t by $F_t = (V_{t-1} + V_{t-2} + V_{t-3})/3$. Lastly, an exponential smoothing (0.3) model forecasts the value of V at time t by $F_t = F_{t-1}(0.3) + V_{t-1}(0.7)$, where F_{t-1} is the forecasted value of V at time $t-1$. The naïve model, moving average model, and exponent smoothing model are time-series based, and make no assumptions about the dependence relationship and are relatively easy to implement. Athiyaman and Robertson (1992) found that these time-series models generate relatively accurate forecasts for international tourism demand when annual data are used.

Table 2 shows the empirical findings of the five different forecasting models, and Fig. 4 provides a graphical presentation of these findings.

Accuracy measurement of the five different forecasting models is based on mean absolute percentage error (MAPE), acceptable output percentage (**Z**) (within a $\pm 15\%$ range), and normalized correlation coefficient (**r**). MAPE is a relative measurement used for comparison across the testing data because it is easy to interpret, independent of scale, reliable and valid. **Z** is used as a relative measurement for acceptance level. As a reference point for optimal experimental outcome, **Z** was set for $\pm 15\%$ in this research. **r** measures the closeness of the observed and estimated Japanese tourist arrivals. Each of these measurements is defined next:

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n} |X_i - Y_i|/Y_i}{n} * 100\%,$$

$$\mathbf{Z} = \frac{\sum_{i=1}^{n} j}{n} * 100\% \ \text{ for } \begin{cases} j = 1 & \text{if } \dfrac{|X_i - Y_i|}{Y_i} \dots \leqslant 0.15, \\ j = 0 & \text{otherwise,} \end{cases}$$

Table 2
Experimental results of forecasting Japanese demand for travel to Hong Kong

Year	Actual number of visitors	Neural network	Naïve	Moving average	Exponential smoothing	Multiple regression
1	168 473	139 388	143 746	108 548	128 178	76 202
2	237 950	208 801	168 473	136 202	156 385	250 464
3	349 212	354 247	237 950	183 390	213 480	393 388
4	486 677	421 785	349 212	251 878	308 493	580 383
5	382 740	428 112	423 098	419 662	426 135	257 037
6	472 182	509 941	508 011	493 585	499 999	373 802
7	1 033 525	1 066 340	727 219	649 000	692 987	869 320
8	1 240 470	1 122 840	1 033 525	798 837	931 363	789 277
9	1 280 905	1 414 250	1 324 399	1 305 304	1 307 067	1 489 225
10	1 440 632	1 710 490	1 280 905	1 288 380	1 288 754	1 389 741

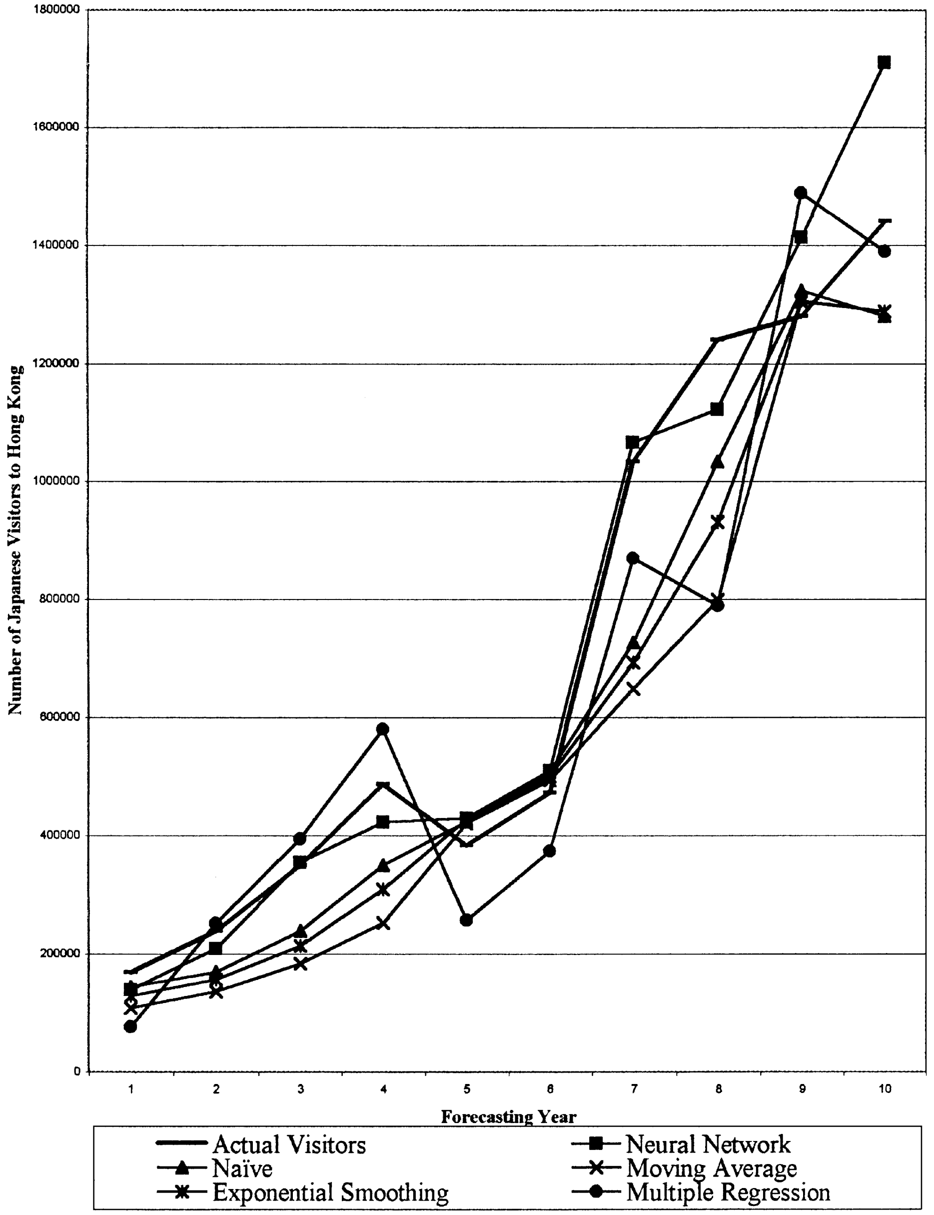

Fig. 4. Graphical presentation of different forecasting methods.

$$r = \frac{\sum_{i=1}^{n}(X_i * Y_i)}{\sqrt{\sum_{i=1}^{n}(X_i)^2 * \sum_{i=1}^{n}(Y_i)^2}},$$

where X_i and Y_i represent the estimated and actual Japanese tourist arrivals for $i = 1, \ldots, 10$, respectively. In this research, $n = 10$. Values of MAPE, **Z**, and r are presented in Table 3.

Data in Table 4, representing the relative percentage error of the five forecasting models, were used to test for the statistical significance between the group means. Four non-parametric Mann–Whitney U tests were conducted, and the values of the U statistic are presented in Table 5.

5. Analysis

Experimental results in Table 3 reveal that the number of Japanese arrivals estimated by a neural network is very close to the actual values. In other words, the forecasting output from a neural network is accurate, with a relatively small amount of error. The low MAPE indicates that the deviations between the discrepancies between the predicted values derived by the neural network and the actual values are very small. Within a 15% discrepancy range, a neural network succeeds in achieving 80% of output in the acceptable range. Additionally, the normalized correlation coefficient for the neural

Table 3
An accuracy comparison in sample for different forecasting models

Forecasting model	MAPE	Z	r
Neural network	10.59	80	0.9851
Naïve	18.29	50	0.9712
Multiple regression	21.77	30	0.9330
Exponential smoothing	22.14	40	0.9605
Moving average (3)	27.35	40	0.9382

Table 5
Tests for differences in the relative percentage error

Mann–Whitney U test	Mann–Whitney U value[a]
Neural network vs. multiple regression	23
Neural network vs. exponential smoothing (0.3)	27
Neural network vs. moving average (3)	28
Neural network vs. naïve	30

[a] All U values are significant at $\alpha = 0.05$.

Table 4
Relative percentage errors in the validation samples

Year	Neural network (%)	Naïve (%)	Moving average (%)	Exponential smoothing (%)	Multiple regression (%)
1	17.26	14.68	35.57	23.92	54.77
2	12.25	29.20	42.76	34.28	5.26
3	1.44	31.86	47.49	38.87	12.65
4	13.33	28.25	48.25	36.61	19.25
5	11.86	10.54	9.65	11.34	32.84
6	8.00	7.59	4.53	5.89	20.84
7	3.18	29.64	37.21	32.95	15.89
8	9.48	16.68	35.60	24.92	36.37
9	10.41	3.40	1.91	2.04	16.26
10	18.73	11.09	10.57	10.54	3.53
MAPE	10.59	18.29	27.35	22.136	21.77

network is the highest with a value of almost 1. This demonstrates the close relationship between the estimated results and the actual tourism data.

As indicated in Table 3, a neural network outperforms the multiple regression model, naïve model, moving average (3) model, and exponential smoothing (0.3) model in forecasting accuracy. Forecasting accuracy is based on MAPE, acceptable output range, and normalized correlation coefficient. As well, the non-parametric Mann–Whitney U statistic values as indicated in Table 5 were all significant at the 0.05 level of a one-tail test, meaning that a neural network significantly outperforms the other models in forecasting Japanese tourist arrivals in Hong Kong.

6. Conclusions

This paper has described the process of modeling Japanese demand for travel to Hong Kong, using a neural network model. Data used to build the neural network were obtained from official publications in Hong Kong and Japan. These data were randomly separated into a training data set to build the neural network, and a testing data set to examine the level of forecasting accuracy. Input nodes of the neural network held exogenous variables for factors that influence Japanese tourists' demand for travel to Hong Kong. The output node consisted of the Japanese demand for travel to Hong Kong. The output of the neural network model has demonstrated forecasting efficiency when compared with officially published data. Experimental results demonstrated that the forecasting efficiency of a neural network is superior to that of multiple regression, naïve, moving average (3) and exponential smoothing (0.3). This indicates the feasibility of applying a neural network model to practical international tourism demand forecasting. Forecasting for tourism demand is a major requirement of planning (Athiyaman, 1992). In addition to the commonly used time series and regression tourism demand forecasting models, practitioners and policy makers may confidently apply neural network models as an alternative. To decide which forecasting method to use, the general conclusion that can be drawn from this research seems to be that if values of independent variables are known or can be estimated accurately, then neural networks will give the best results. When impacts of independent variables for policy issues need to be measured, regression models are more useful, and if independent variables are not available, time series models offer the best forecasts.

This research was a first attempt to model Japanese demand for travel to Hong Kong. This research, albeit limited in scope due to data unavailability, could be useful to the Hong Kong hotel industry. It is expected that as there are more parameters, a neural network should fit better than regression models. At present, the tourism industry in Hong Kong is facing serious challenges. Tourist arrivals dropped 35% after the political hand-over (Poole, 1997). This could be explained as a "post-hand-over slump" phenomenon. Then, the Asian financial crisis hit. This, in turn, seriously reduced the number of visitors that Hong Kong most wanted to attract – the emerging Asian middle class. Next, bird flu made Hong Kong famous for the worst possible reason. These factors, in addition to the fact that Hong Kong is seen by many as over-crowded and over-expensive, could seriously affect the number of future international tourist arrivals in Hong Kong. So an accurate forecast from neural network models could certainly help industry practitioners and official policy makers improve their planning and decision making.

A possibility for future research could be to include some qualitative exogenous variables in the neural network model for forecasting Japanese demand for travel to Hong Kong. For instance, it is reasonable to believe that government policies and weather conditions play an important role in determining annual/seasonal tourist arrivals, leading to a notable change in demand for tourism. However, these qualitative factors are dynamic in a continuous way. A major challenge for including qualitative factors would be to provide a commonly acceptable measurement for these factors.

Finally, due to the unavailability of seasonal data for most of the variables, only annual data were used in this research. Another potential area for future research could be to build a neural network model for tourism demand forecasting using seasonal data. It would be interesting to investigate whether the accuracy rate for forecasting international tourism demand using neural network models still holds for seasonal data.

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