*Journal of Information & Optimization Sciences*
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
DOI : 10.47974/JIOS-2050

# Developing a hybrid forecasting system for International hotel revenue : The case of Taiwan

Yi-Hui Liang
*Department of Information Management*
*I-SHOU University*
*1, Section 1, Hsueh-Chen Road*
*Ta-Hsu Hsiang*
*Kaohsiung County*
*Taiwan (R.O.C.)*

**Abstract**

The hotel industry has grown rapidly over the past decade, placing higher demands on managers to outperform their competitors in the industry. Planning and allocating sufficient resources to hotel operations, investments, finance and marketing requires accurate forecasts. This study proposes an approach to predict international hotel revenue in Taiwan. First, the SARIMA model is used to predict the number of occupied rooms and average room price. Next, genetic algorithm technology is used to establish an artificial intelligence neural network model for hotel revenue prediction. The hospitality industry can benefit from the suggested approach.

***Subject Classification (2020):*** *62R07.*

**Keywords:** *Forecasting, Hotel, Revenue, SARIMA, Neural network, Genetic algorithms.*

## 1. Introduction

Hotel revenue management is commonly used to help hotels set room rates and allocations. Forecasting is the basis of revenue management, and good forecast quality leads to higher profits and revenue [1]. Furthermore, Cetin, Demirçiftçi, and Bilgihan [2] pointed out that revenue management requires technical assistance such as optimization algorithms, data exploration and forecasting tools.

*ORCID-ID:* **0000-0001-9440-8274**

*E-mail:* **german@isu.edu.tw**

Law [3] proposed a neural network method for predicting room occupancy rates. Optimization algorithms include genetic algorithm (GA) and cuckoo search, etc. GA is an optimization algorithm related to genetic evolution. For example, Barman et al. [4] applied GA for personalized query recommendation system. Kapoor and Dey [5] proposed GA based decision support systems for predicting stock prices. Sukanya and Thangaiah [6] combined GA and cuckoo search for frequent itemsets mining. The advancement of artificial intelligence technology has promoted the development of neural network intelligent prediction methods. Incorporate optimization techniques such as GA that can be used to optimize the parameters of neural network architectures [7]. Zhang et al. [8] also suggested that future research could input data into a support vector neural network model with optimization techniques to

**Table 1**

**Forecasting approaches in hotel revenue management**

| Author | Topic |
|---|---|
| Kaya *et al*. [14] | A prediction model is proposed that uses demand data and additional features gained from K-means clustering results to predict hotel demand through a long-term attention short-term memory model. The results are shown to improve forecasting performance. |
| Xu, Xiao, and Gursoy [15] | Maximize hotel profits using optimal pricing and sustainability strategies. The results show that a number of external factors affect the development of optimal pricing and sustainability strategies. |
| Zhang *et al*. [8] | EEMD was introduced and individual hotels were selected to validate the performance of the combined EEMD and ARIMA methods. The results show that this method is more accurate than the ARIMA method in predicting hotel occupancy. |
| Schwartz *et al*. [13] | Forecasted occupancy rates from hotel competition settings are added as inputs to single hotel forecasts, and a novel recursive approach is used. Results show that integrating competing set predictions using genetic algorithms and simple linear regression models improves predictive power. |
| Pereira [16] | A model is proposed that can solve the complex problem of seasonality, including non-integer seasonality and multiple seasonal periods for forecasting hotel occupancy rates. The results show that the triangle model performs better than most other compared models. |

*Contd...*

| | |
|---|---|
| Oses, Gerrikagoitia, and Alzua [17] | A prediction model is proposed to predict the average hotel occupancy rate of a destination based on hotel room rates provided online. The results show that prices can change to reflect actual demand and occupancy. |
| Haensel and Koole [18] | A dynamic update method is proposed to predict the cumulative booking curve and booking quantity of hotel booking data. The results show an improvement in predictive power. |
| Zakhary *et al*. [19] | A method is proposed to predict occupancy and arrival rates using Monte Carlo simulation. This method is suitable for future scenarios using probabilistic estimation. |
| Guadix *et al.* [20] | A decision support system is proposed that includes a set of demand forecasting methods, combines deterministic and stochastic mathematical programming models, and maximizes hotel revenue. |
| Lim [21] | Some methods are proposed to predict the number of guest nights per month. The results show that the ARMA and Holt-Winters exponential smoothing approaches are more accurate than other compared time series approaches. |
| Yüksel [22] | A model is proposed for forecasting hotel demand using monthly data and compare the results with those of MA, some exponential smoothing, and ARIMA approaches and suggest that the most appropriate method to maximize forecast accuracy is to combine quantitative and qualitative method for prediction. |
| Weatherford and Kimes [23] | Explore multiple hotel revenue forecasting methods using Choice Hotels and Marriott Hotels. The results show that arrival forecasts are a key input to hotel revenue management systems and show that pick-up and regression methods provide more accurate forecasts using Choice hotel data. However, after preliminary analysis, and through in-depth analysis of Marriott Hotels, the results show that pickup, MA, and exponential smoothing approaches are the most robust. |
| Law [24] | Forecasting hotel spending in Hong Kong using neural network, Naïve I, Naïve II, multiple regression, MA, autoregressive, and some exponential smoothing approaches. The results show that neural network and autoregressive approaches outperform other approaches. |
| Law [3] | A neural network method for predicting room occupancy rates is proposed. |

predict tourism revenue and hotel room occupancy rates. In addition, many studies further combine neural networks with optimization technology and seasonal autoregressive integrated moving average (SARIMA) models, such as in forecasting annual energy cost budgets [9].

Therefore, the study proposes a prediction approach for international hotels in Taiwan. First, use the SARIMA model to predict the number of occupied rooms and average room price. Next, construct an AI neural network model with optimization technology to predict hotel revenue, in which GA is used as the optimization technology.

## Literature overview

Over the past three decades, hotel revenue management practices have made significant and rapid progress and are now considered a dominant part of hotel marketing and operations strategies [10]. Forecasting volumes related to hotel operations is important for hotel revenue management systems [11].

For tourism and hotel demand modeling, Wu, Song, and Shen [12] reviewed the latest papers on from 2007 to 2015 and recommended the introduction of more sophisticated methods in this research area. Many studies have explored and compared different revenue forecasting methods. These quantitative approaches include time series, AI, and combination methods. Time series approaches include moving averages (MA), exponential smoothing, ARIMA, and SARIMA approaches. AI methods include neural networks, mathematical programming, Monte Carlo simulation, etc. Combination methods mainly combine time series methods and AI methods, such as [8] and [13]. Table 1 lists past studies using different methods for hotel revenue management forecasting.

## Research Method

This study first used the SARIMA or ARIMA model for conducting preliminary time series analysis. If the collected data show significant seasonality, the SARIMA model is used. Otherwise, use the ARIMA model.

The ARIMA model is illustrated as follows:

$$(1-\phi_1 L-\cdots-\phi_p L^P)(1-L)^d y_t = C+(1-\theta_1 L-\cdots-\theta_q L^q)\varepsilon_t$$

where $\phi$ and $\theta$ represent AR and MA parameters, respectively.

An ARIMA model order is expressed by $ARIMA(P,D,Q)$. AR order is P; MA order is Q, and difference order is D.

The SARIMA model, which comprises seasonal components, is illustrated as follows:

$$(1-\phi_1 L-\cdots-\phi_p L^P)(1-\Phi_1 L^s-\cdots-\Phi_p L^{PS})(1-L)^d(1-l^s)^D y_t$$
$$=C+(1-\theta_1 L-\cdots-\theta_q L^q)(1-\Theta_1 L^s-\cdots-\Theta_Q L^{QS})\varepsilon_t$$

where $s$ is a seasonal cycle , and $\Phi$ and $\Theta$ are seasonal AR and MA parameters.

A SARIMA model order is represented by $SARIMA(P,D,Q)*(p,d,q)_s$. For the seasonal component, s is the seasonal cycle; AR order is p; MA order is q, and difference order is d.

Analytical hotel room occupancy and room rate results generated through preliminary time series analysis were then fed into a neural network model used to predict future revenue. This study selected GA as the optimization technology, and GA is used to optimize the learning parameters and the number of hidden layer neurons in the model structure. The optimization procedure of GA is described as follows [7]:

**Step 1:** Chromosomes are used to express the parameters of neural network structures.

**Step 2:** Generate initial population.

**Step 3:** Training Cycle:

Begins the training cycle, which is nested within the population evolution cycle. Once the learning count reaches a predetermined value, training stops. Through the evolution cycle, MSE is selected as the fitness function to score fitness to promote the evolution of the network. Networks with poorer fitness scores will withdraw from the population, while networks with higher fitness scores will be selected for breeding. Crossover is the most striking stage in genetic algorithms. Crossing indicates mating between individuals. Mutations introduce random modifications. Mutations occur to maintain diversity within the population and prevent premature convergence. Executing the above procedure produces the next generation.

**Step 4:** Return to step 3 until the training reaches the predetermined stopping condition.

Figure 1 illustrates the flow of the GA.

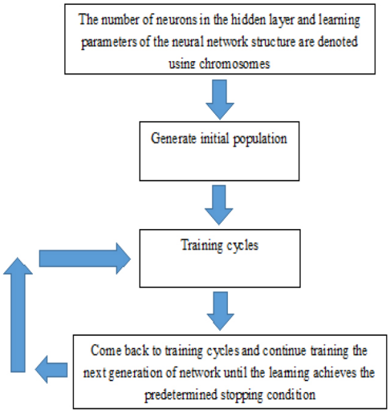



**Figure 1**

**The procedures of GA**

Finally, use this model to predict hotel revenue.
This study named this proposed approach the RPGANN approach.
Forecast accuracy is measured using MAD, RMSE and MAPE.

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|Z_t - \hat{Z}_t\right|$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Z_t - \hat{Z}_t)^2}$$

$$\text{MAPE} = \frac{1}{n}\frac{\sum_{i=1}^{n}\left|Z_t - \hat{Z}_t\right|}{Z_t}$$

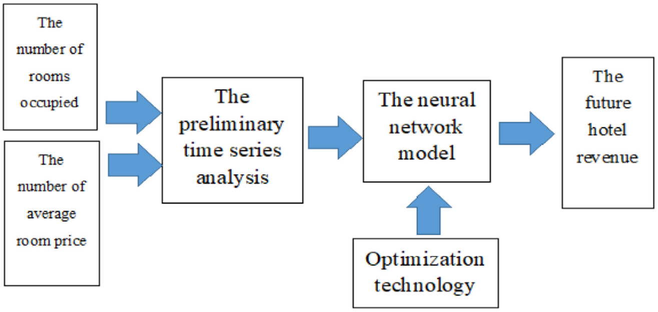



**Figure 2**

**The RPGANN approach**

where *n* represents the number, and $Z_t$ and $\hat{Z}_t$ represents the actual and the predicted number of value of the hotel's revenue at time *t*.

Figure 2 shows the proposed approach.

## Empirical Results

This study proposes a new prediction method. First, data on international hotels in Taiwan (including number of rooms, number of occupied rooms, occupancy rate, and average room rate) were collected from open information provided by Taiwan's Ministry of Transportation and Communications, and their relationship with revenue from international hotels in Taiwan was explored. Through regression analysis, the study found that two variables (including number of rooms and average room rate) are most related to hotel revenue. The adjusted correlations between room occupancy and average room rates and revenue are 0.6990 and 0.7304 respectively.

The research object is a large international hotel located in Kaohsiung City, southern Taiwan. The hotel is one of the top large five-star international hotels in Taiwan. The empirical data for this study selected monthly data from May 2010 to August 2015. Started in May 2010 because the hotel opened on this date. The deadline is August 2015 because the government-funded program ends on this date. In Taiwan, international hotels' revenue mainly comes from catering revenue and room revenue. Sometimes, food and beverage revenue will be greater than room revenue. The above three series of training sets use data from May 2010 to April 2014, and the test set uses data from May 2014 to August 2015. The training set includes 48 observations, and the test set includes 16 observations.

The number of rooms occupied and average room price reveal seasonality after the analysis. For the number of rooms occupied, the $SARIMA\ (1,0,0) * (1,0,0)_{12}$ model is adopted for analysis. For the average

**Table 2**

**The results for the number of rooms occupied**

| | coefficient | Std. | t value | probability |
|---|---|---|---|---|
| $c$ | 7830.001 | 5761.896 | 1.358928 | 0.1811 |
| $\phi_1$ | 0.910256 | 0.060045 | 15.15952 | 0.0000 |
| $\Phi_1$ | 0.629828 | 0.138318 | 4.553481 | 0.0000 |
| AIC value | 17.94317 | | | |

room price, $SARIMA\ (0,0,2) * (1,0,0)_{12}$ is adopted for analysis. Tables 2 and 3 show the results.

**Table 3**

**The results for the average room price**

| | coefficient | Std. | t value | probability |
|---|---|---|---|---|
| $c$ | 3362.240 | 285.5208 | 11.77581 | 0.0000 |
| $\theta_1$ | 0.559600 | 0.122874 | 4.554251 | 0.0000 |
| $\theta_2$ | 0.874290 | 0.080795 | 10.82108 | 0.0000 |
| $\Phi_1$ | 0.514650 | 0.135996 | 3.784306 | 0.0005 |
| AIC value | 15.39352 | | | |

The neural network software NeuralSolutions is used for analysis, and the analysis results of the number of occupied rooms and average room price are used as input data for the neural network model structure. Then, the neural model with GA is used to obtain the predicted value of hotel revenue. Table 4 show the results.

**Table 4**

**The results of the proposed forecasting method**

| Date | the forecasts of the number of rooms occupied | the forecasts of the average room price | the forecasts of the hotel revenue |
|---|---|---|---|
| May-14 | 12130.07276 | 3035.647424 | 73810176.30 |
| Jun-14 | 11269.37333 | 3721.819721 | 79558434.59 |
| Jul-14 | 15390.08885 | 4426.679352 | 112411795.7 |
| Aug-14 | 16312.02753 | 4164.560388 | 113409757.2 |
| Sep-14 | 11006.52987 | 3189.536859 | 70089027.04 |
| Oct-14 | 11649.19083 | 3231.630217 | 74186350.64 |
| Nov-14 | 10461.61371 | 2868.165770 | 62292173.43 |
| Dec-14 | 10120.65840 | 3913.201046 | 76269047.97 |
| Jan-15 | 10371.01319 | 3332.179922 | 68825473.90 |
| Feb-15 | 9670.719586 | 3937.219333 | 74209788.43 |
| Mar-15 | 10305.37621 | 3021.537238 | 63771625.12 |
| Apr-15 | 9820.614738 | 3582.560331 | 69650444.42 |

*Contd...*

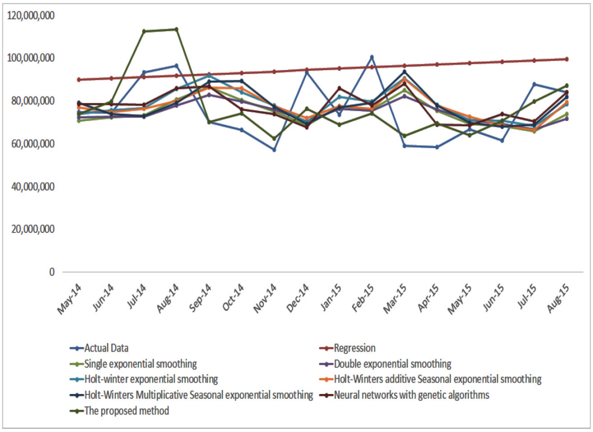
| | | | |
|---|---|---|---|
| May-15 | 10524.00377 | 2956.549033 | 63965465.25 |
| Jun-15 | 9983.150492 | 3602.635716 | 70829381.94 |
| Jul-15 | 10353.09720 | 4066.321250 | 79837518.25 |
| Aug-15 | 11715.82768 | 4062.061978 | 87110667.67 |

Simple exponential smoothing method, double exponential smoothing method, Holt-Winter exponential smoothing methods and the neural network model with GA alone are also used to predict future hotel revenue. Table 5 and Figure 3 show the results.

**Table 5**

**The results of different methods**

| | MAD | MAPE | RMSE |
|---|---|---|---|
| Regression | 20068659.00 | 0.304179000 | 23857574.44 |
| Single exponential smoothing | 14254041.17 | 0.189703955 | 16381111.42 |
| Double exponential smoothing | 14077687.02 | 0.186557968 | 16101923.08 |
| Holt-winter exponential smoothing | 14469573.55 | 0.199790062 | 16807575.13 |
| Holt-winters additive seasonal exponential smoothing | 14424982.58 | 0.197009661 | 16919166.26 |
| Holt-winters multiplicative seasonal exponential smoothing | 14869297.28 | 0.203655975 | 17761496.51 |
| The neural network model with GA | 12988559.00 | 0.175692063 | 15287498.54 |
| The proposed RPGANN approach | 8887296.659 | 0.110666374 | 11414811.28 |




**Figures 3**

**The results of different methods**

Through the measurement of MAD, RMSE and MAPE, the results confirmed the superiority of the proposed RPGANN approach.

**Implications and Conclusions**

Forecast accuracy significantly affects the revenue generated by a revenue management system [25]. Empirical evidence confirms the superiority of the proposed RPGANN method in predictive capabilities. More accurate forecasts benefit the international hotel's competitiveness.

However, this study has some limitations. First, there is the problem of too few samples, which limits the conclusions. Due to project funding, the sample size used was limited. But if you consider that the covid-19 epidemic has caused a devastating blow to the entire Taiwan International Hotel for several years. The problem is that valid samples cannot be collected. The number of samples is bound to hinder the collection of more useful data. Secondly, the proposed RPGANN approach cannot consider the impact of external variables such as COVID-19.

Future research can be directed towards using newer AI technology or more useful variables to predict hotel revenue to obtain more accurate prediction results.

**Acknowledgement**

Thanks to the support of the ministry of Science and Technology, R.O.C. no. 103-2410-H-214-012-

**References**

[1] L. Kouprouchina, P. van der Rest, J., and Z. Schwartz. On revenue management and the use of occupancy forecasting error measures. *International Journal of Hospitality Management*, vol. 41, pp. 104-114 (2014).

[2] G. Cetin, T. Demirçiftçi, and A. Bilgihan. Meeting revenue management challenges: Knowledge, skills and abilities. *International Journal of Hospitality Management*, vol. 57, pp. 132-142 (2016).

[3] R. Law. Room occupancy rate forecasting: a neural network approach. *International Journal of Contemporary Hospitality Management*, vol. 10, no. 6, pp. 234-239 (1998).

[4] D. Barman, R. Sarkar, A. Tudu, and N. Chowdhury. Personalized query recommendation system: A genetic algorithm approach. *Journal of Interdisciplinary Mathematics*, vol. 23, no. 2, pp. 523-535 (2020).

[5] V. Kapoor, and S. Dey. A genetic algorithm based decision support system for forecasting security prices in stock index. *Journal of Information and Optimization Sciences*, vol. 43, no. 8, pp. 2153–2166 (2022).

[6] N. S. Sukanya and P. R. Thangaiah. An integrated cuckoo search-genetic algorithm for mining frequent itemsets. *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 25, no. 3, pp. 671-690 (2022).

[7] J. A. Bullinaria. Using evolution to improve neural network learning: pitfalls and solutions. *Neural Computing and Applications*, vol. 16, no. 3, pp. 209-226 (2007).

[8] G. Zhang, J. Wu, B. Pan, J. Li, M. Ma, M. Zhang, and J. Wang. Improving daily occupancy forecasting accuracy for hotels based on EEMD-ARIMA model. *Tourism Economics*, vol. 23, no. 7, pp. 1496-1514 (2017).

[9] K. Jeong, C. Koo, and T. Hong. An estimation model for determining the annual energy cost budget in educational facilities using SARIMA (seasonal autoregressive integrated moving average) and ANN (artificial neural network). *Energy*, vol. 71, pp. 71-79 (2014).

[10] R. G. Cross, J. A. Higbie, and Z. N. Cross. Milestones in the application of analytical pricing and revenue management, *Journal of Revenue and Pricing Management*, vol. 10, no. 1, pp. 8-18 (2011).

[11] K. Talluri, and G. Van Ryzin. Revenue management under a general discrete choice model of consumer behavior. *Management Science*, vol. 50, no. 1, pp. 15-33 (2004).

[12] D. C. Wu, H. Song, and S. Shen. New developments in tourism and hotel demand modeling and forecasting. *International Journal of Contemporary Hospitality Management*, vol. 29, no. 1, pp. 507-529 (2017).

[13] Z. Schwartz, M. Uysal, T. Webb, and M. Altin. Hotel daily occupancy forecasting with competitive sets: a recursive algorithm. *International Journal of Contemporary Hospitality Management*, vol. 28, no. 2, pp. 267-285 (2016).

[14] K. Kaya, Y. Yılmaz, Y. Yaslan, Ş. G. Öğüdücü, and F. Çıngı. Demand forecasting model using hotel clustering findings for hospitality industry. *Information Processing & Management*, vol. *59, no.* 1, pp. 102816 (2022).

[15] X. Xu, G. Xiao, and D. Gursoy. Maximizing profits through optimal pricing and sustainability strategies: A joint optimization approach. *Journal of Hospitality Marketing & Management*, vol. 26, no. 4, pp. 395-415 (2017).

[16] L. N. Pereira. An introduction to helpful forecasting methods for hotel revenue management. *International Journal of Hospitality Management*, vol. 58, pp. 13-23 (2016).

[17] N. Oses, J. K. Gerrikagoitia, and A. Alzua. Modelling and prediction of a destination's monthly average daily rate and occupancy rate based on hotel room prices offered online. *Tourism Economics*, vol. 22, no. 6, pp. 1380-1403 (2016).

[18] A. Haensel, and G. Koole. Booking horizon forecasting with dynamic updating: A case study of hotel reservation data. *International Journal of Forecasting*, vol. 27, no. 3, pp. 942-960 (2011).

[19] A. Zakhary, A. F. Atiya., H. El-Shishiny, and N. E. Gayar. Forecasting hotel arrivals and occupancy using Monte Carlo simulation. *Journal of Revenue and Pricing Management*, vol. 10, pp. 344-366 (2011).

[20] J. Guadix, P. Cortés, L. Onieva, and J. Muñuzuri. Technology revenue management system for customer groups in hotels. *Journal of Business Research*, vol. 63, no. 5, pp. 519-527 (2010).

[21] W. M. Lim. Alternative models framing UK independent hoteliers' adoption of technology. *International Journal of Contemporary Hospitality Management*, vol. 21, no. 5, pp. 610-618 (2009).

[22] S. Yüksel. An integrated forecasting approach to hotel demand. *Mathematical and Computer Modelling*, vol. 46, no. 7-8, pp. 1063-1070 (2007).

[23] L. R. Weatherford, S. E. Kimes, and D. A. Scott, D. A. Forecasting for hotel revenue management: Testing aggregation against disaggregation. *The Cornell Hotel and Restaurant Administration Quarterly*, vol. 42, no. 4, pp. 53-64 (2001).

[24] R. Law. Demand for hotel spending by visitors to Hong Kong: A study of various forecasting techniques. *Journal of Hospitality & Leisure Marketing*, vol. 6, no. 4, pp. 17-29 (1999).

[25] L. R. Weatherford, S. E. Kimes, and D. A. Scott. Forecasting for hotel revenue management: Testing aggregation against disaggregation. *Cornell hotel and restaurant administration quarterly*, vol. 42, no. 4, 53-64 (2001).

*Received December, 2024*