To Cite:
Zhang, G., Wu, J., Pan, B., Li, J., Ma, M., & Wang, J. (accepted). Improving daily occupancy forecasting accuracy for hotels based on EEMD-ARIMA model. To appear in *Tourism Economics*.

IMPROVING DAILY OCCUPANCY FORECASTING ACCURACY FOR HOTELS BASED ON EEMD-ARIMA MODEL

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March 21, 2017

Acknowledgements

This research is partially supported by a grant from the National Natural Science Foundation of China (Grant # 41428101). We want to thank the anonymous company that provided the valuable data. Dr. Qing Zhu of the International Business School of Shaanxi Normal University offered tremendous help in research methodology.

Short Title: Improving Hotel Forecasting with EEMD-ARIMA Model

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Abstract

Predicting daily occupancy is extremely important for the revenue management of individual hotels. However, daily occupancy can fluctuate widely and is difficult to forecast accurately based on existing forecasting methods. In this paper, Ensemble Empirical Mode Decomposition (EEMD)—a novel method—is introduced, and an individual hotel is chosen to test the effectiveness of EEMD in combination with an autoregressive integrated moving average (ARIMA). Result shows that this novel method, EEMD-ARIMA, can improve forecasting accuracy better than the popular ARIMA method, especially for short-term forecasting.

Keywords: forecasting; occupancy; individual hotels; EEMD; ARIMA

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Introduction

Accurate forecasting plays an important role in human society, ranging from dealing with natural disasters to the development of economies. Accurate forecasting can help individuals or organizations allocate resources optimally (Song and Li, 2008). Private businesses and local governments can use accurate forecasting to make decisions on guiding traffic, designing better infrastructure, adjusting prices, and formulating policies (Song and Li, 2008). This also applies to the tourism industry. For tourism businesses, accurate forecasting can help them reduce the costs of excess capacity or unfilled demand due to the perishable nature of tourism products (Archer, 1987; Frechtling, 2001; Xie, 2010). Indeed, revenue cannot be realized from a product that is unsold the following day.

Moreover, accurate forecasting of tourism demand has been one of the most important fields in tourism economics over the past few decades (Song et al., 2012; Witt and Witt, 1995). Tourism forecasting research has gone through several methodological developments, and numerous models have been proposed, including time series models and multivariate models. However, as an increasing number of methods were employed in tourism demand forecasting, researchers started to compare and discuss the best-performing

models (Schwartz, 1999; Weatherford and Kimes, 2003; Zakhary et al., 2011). However, after extensive studies, no consensus has been reached (Peng et al., 2014). Based on empirical evidence, no single model can consistently outperform others on all occasions (Peng et al., 2014; Schwartz and Hiemstra, 1997). Different methods suit different contexts, and the latest research tends to combine different methods with the purpose of improving forecasting accuracy (Li et al., 2006; Shen et al., 2011; Wong et al., 2007). For example, Chen KH (2011) combined linear and non-linear models, while Shen et al. (2011) used six linear combination methods; Chan et al. (2010) employed programming approaches to determine the weights of combination; and Song et al. (2013) combined statistical and judgmental approaches to improve forecasts. All these empirical studies generally provide evidence of favorable outcomes by combining forecasting methods.

In general, the improvement of forecasting accuracy between these combined methods is similar. In fact, some researchers believe model complexity does not necessarily improve forecasting accuracy (Lim et al., 2009; Pan et al., 2012), and, as Kouprioucha et al. (2014) noted, the future of forecasting performance is possibly leading to a more comprehensive forecasting evaluation framework. Therefore, in order to improve forecasting accuracy significantly, it is necessary to uncover the origin of forecasting errors. In the field of tourism demand forecasting, indicators such as tourist volumes and

occupancy rates fluctuate wildly with no obvious regularity. This is due to the fact that the factors influencing tourism demand fluctuate themselves. If the irregularity of tourism demand data can be reduced, or irregular fluctuations can be converted to regular patterns, it would be easier to capture the rules for a forecasting model. This would lead to an improvement in forecasting accuracy. The present work mainly focuses on combining two different methods—ARIMA and a novel method, named EEMD—to improve forecasting accuracy.

Theoretical background

In hotel revenue management practices, accurate forecasts can facilitate decision making on pricing for an individual property or a group of hotels (Yang et al., 2014). The amount of revenue generated from a hotel often depends on its ability to utilize its capacity efficiently; therefore, knowing how many guests would arrive in the coming days is very useful (Heo et al., 2013). This makes high quality forecasting of guest arrivals and occupancy rates a key aspect for hotel revenue management (Kouprioucchina et al., 2014; Weatherford and Kimes, 2003). As Talluri and Van Ryzin (2004: 407) observed: "A revenue management system requires forecasts of quantities such as demand, price sensitivity, and cancellation probabilities, and its performance depends critically on the quality of these forecasts." Despite the importance of occupancy forecasting, research in the field is still lacking (Heo et al., 2013).

The literature has been rather undeveloped before the 2000s, with a few notable published studies after 2000 (Weatherford et al., 2001; Zakhary et al., 2011).

Multivariate Models

Multivariate models might be among the most used in tourism demand forecasting. For example, Jeffrey and Barden (2000) induced a stepwise regression analysis with nine variables to forecast the occupancy peak and trough of chain or group hotels. Also, a similar multivariate model can be seen in Yüksel's (2007) study, which combined 25 variables to forecast the monthly occupancy of a five-star hotel. Concentrating on tourism data only, Zakharya et al. (2011) forecasted a hotel occupancy rate with many variables such as reservation arrivals, cancellations, length of stay, no-shows, group reservations, seasonality, trends and so on. Conversely, Chen MH (2011) measured the forecasting ability of a single variable—crisis events—to hotel occupancy.

Time Series Models

In addition to multivariate models, time series models are another important method for forecasting hotel occupancy (Gunter and Önder, 2015; Weatherford and Kimes, 2003; Zakharya et al., 2011). Specifically, one form of the time series model is the (seasonal) autoregressive (integrated)

moving-average model ((S)AR(I)MA). In addition, novel time series models have also emerged in tourism demand forecasting, such as error trend seasonal or exponential smoothing (ETS) (Hyndman et al., 2002, 2008); cointegration and error correction (Halïcïoglu et al., 2010; Song et al., 2011b); the vector autoregressive method (VAR); autoregressive distributed lag (ADL) (Song et al., 2013); the time-varying parameter (TVP) (Song et al., 2011a); an exponentially weighted moving average (E(W)MA) combined with the Holt-Winters method (Aghazadeh, 2007); and autoregressive mixed data sampling (AR-MIDAS) (Bangwayo-Skeete and Skeete, 2015). All of them have performed well in forecasting future tourism demand under certain scenarios.

Many researchers have tried to forecast the average occupancy of hotels in different areas, countries, regions, cities, and even for some specific hotels. For example, Andrew, Cranage and Lee (1990) employed time series and exponential smoothing methods to forecast the monthly occupancy of a major city-center hotel. They found that both methods function very well and produce a very low mean sum of squared residuals; moreover, they stated that the Box-Jenkins approach outperforms exponential smoothing. Later, Law and Au (1999) published work focused on regional occupancy rate, and he validated the value of the neural network approach to forecast annual hotel occupancy in Hong Kong. He compared the accuracy of the neural network approach with with multiple regressions, and concluded that the

neural network method performed the best among the three methods. Post-2000, Choi (2003) identified the leading economic indicators that can affect the US hotel industry, then built a model based on those indicators and used the novel indicator system model to forecast hotel demand in the United States.

In addition, Schwartz and Hiemstra (1997) proposed a method to forecast daily occupancy based on previous booking curves. Other researchers updated a special version of the ESM method (the Holt-Winters method) to forecast daily hotel room demand in a particular property (Rajopadhye et al., 1999). In order to forecast a series of occupancies of Norwegian guests in Swedish hotels, the authors concluded that models based on differenced series were preferred when measured by goodness-of-fit. In Yüksel's (2007) work, the analytical hierarchy process (AHP) was employed to adjust the forecast of ESM models, which integrated quantitative and qualitative methods, and obtained a lower error rate between real and forecast values. In comparison, Kouprioucchina et al. (2014) utilized system forecasting (prepared via the computer) and manual forecasting (prepared by hotel managers) to investigate a better method. Interestingly, no single method has outperformed others in all cases. Although the time series method usually performs the best, it failed to do so in Italy, where pick-up models achieved the best results (Ellero and Pellegrini, 2014). Therefore, we need more real-life cases and the

investigation of diverse methods to fit different data series in distinct regions. In summary, the studies focusing on occupancy forecasting are displayed in Table 1.

---------- Insert Table 1 Here ----------

In the past, annual, quarterly, or monthly data was often used in tourism demand forecasting, as well as hotel demand forecasting (Song and Li, 2008; Table 1). However, forecasting with daily data is the most crucial approach due to fierce market competition in the hospitality industry. Compared to other indicators, such as international tourist arrivals, the occupancy of hotels is more relevant to the industry (Pan et al., 2012). Therefore, in this paper, we have selected daily hotel occupancy as the dependent variable. As noted by Weatherford et al. (2001), hotels should forecast occupancy in high frequency in order to fulfill the needs of revenue management. Consequently, this paper would attempt to improve the forecasting the daily occupancy of an individual hotel, with the assistance of a new and unique method known as ensemble empirical model decomposition (EEMD). This paper is organized as follows: the next section is an introduction to EEMD; the following one shows the data and forecasting results calculated by EEMD and ARIMA; and the last section summarizes the paper and discusses the results as well as the new method.

Ensemble Empirical Mode Decomposition

EEMD is derived from empirical mode decomposition (EMD) (Wu and Huang, 2009). EMD was proposed by Huang et al. (1998) and is considered a major breakthrough in linear and stable analysis based on Fourier transformation, which won the NASA Government Invention of the Year in 2003 (NASA, 2003). The method is proficient in dealing with non-stationary data by identifying the different scales of volatility in the origin wave and decomposing it into a series of new waves; the new wave is called an intrinsic mode function (IMF), and the IMF with the lowest frequency represents the trend of the data series. Owing to the self-adaptive nature of IMF, its frequency and Hilbert spectrum can be calculated by Hilbert transformation.

The application of EMD for the analysis of wave $x(t)$ should satisfy three pre-conditions:

(1) Oscillating and periodic patterns are repeated;

(2) The local mean is zero and the signal is symmetric to its local mean;

(3) One cycle of oscillation should comprise the following: the sinusoidal function should start at zero, end at zero, and pass through zero between two crossings. Alternately, it should start at the local maximum and terminate at consecutive local maxima, passing through two zeros and the local minimum.

When the original signal meets the requirements given above, EMD can be

used to systematically decompose the signal. In short, the EMD decomposition is a screening process of the vibration mode. The basic principle of EMD is to use the cubic spline function to fit the partial maximum and minimum values. By doing so, one can confirm the instantaneous equilibrium position of the signal. Consequently, several IMFs and a residual that satisfy some particular criteria can be extracted, and finally, the original signal is decomposed. The unique advantage of EMD is that IMFs can highlight partial characteristics, and the residual can reveal the internal trend of the original signal. By analyzing the IMFs, the characteristics of the origin signal information can emerge.

Since IMF is an important indicator in EMD, Huang et al. (1998) defined how an oscillating wave can be considered as IMF. It should satisfy two conditions:

(1) The number of extrema and the number of zero crossing must differ only by one;

(2) The local average is zero, meaning that the mean of the upper envelope and lower envelope is zero.

Specifically, the process of EMD analysis is as follows:

(1) Identify the local extrema, including the maximum and minimum;

(2) Connect all of the local maxima to form a new signal with a cubic spline function as the upper envelope $U_1(t)$; similarly, all of the local

minima forms the lower envelope $L_1(t)$.

(3) Calculate the mean curve of the upper and lower envelope $M_1(t)$

$$M_1(t) = \frac{1}{2}[U_1(t) - L_1(t)]$$

(4) Calculate a signal $S_{1,1}(t)$ by $X(t)$ minus $M_1(t)$

$$S_{1,1}(t) = x(t) - M_1(t)$$

(5) Check the residue $S_{1,1}(t)$ to make sure it satisfies the two conditions of IMF in the previous statements, and, if so, we obtain the first IMF_1, and, if not, repeat the process from (1) to (5) while $S_{1,1}(t)$ is taken as the new signal until the residue satisfies the two properties. However, in practice, the actual meaning would be lost if the process is to be repeated several times, which would make the IMF an amplitude constant frequency modulation signal. Therefore, Peng et al. (2005) noted that the standard deviation of the adjacent signals $S_{1,k-1}(t)$ and $S_{1,k}(t)$ can be used as stopping criterion (the experience value is 0.2-0.3). When the standard deviation (SD) meets the threshold value, the screening process would stop, and the IMF is abstracted;

(6) Separate the residue $R_1(t)$ from $x(t)$

$$R_1(t) = x(t) - IMF_1$$

However, $R_1(t)$ may contain some IMFs with a longer period, and therefore another sifting is needed for $R_1(t)$. More IMFs would be separated, namely IMF_2, IMF_3, IMF_4 … IMF_n and $R_2(t)$, $R_3(t)$, $R_4(t)$… $R_n(t)$.

The entire process can be represented as follows:

$$\begin{cases} R_1(t) = x(t) - IMF_1 \\ R_2(t) = R_1(t) - IMF_2 \\ \cdots\cdots \\ R_{n-1}(t) = R_{n-2} - IMF_{n-1} \\ R_n(t) = R_{n-1} - IMF_n \end{cases}$$

When the residue $R_n(t)$ is a constant or a monotonic function, the process ends, and, at the same time, the latent trend of the signal can be judged by $R_n(t)$, which is also known as trends function.

Now the signal is decomposed into IMF_1, IMF_2, IMF_3 … IMF_n and $R_n(t)$

$$x(t) = \sum_{j=1}^{n} IMF_j + R_n(t).$$

As a self-adaptive signal analysis method, EMD has been successfully adopted in various fields. However, many problems exist. The most serious one is model mixing (also termed modal aliasing). This happens when either: (1) one IMF mixes two different models with distinct cycles; or (2) two or more IMFs contain the same model with one cycle.

To deal with this limitation, Huang and Wu (2008) upgraded EMD to EEMD, which can deal with illusive components or mode mixing and overlap effectively (Huang et al., 2009; Wu et al., 2007, 2009; Wu and Huang, 2004). Further, the decomposition of signals by EEMD is better than that of EMD (Wu and Huang, 2009). Consequently, IMFs would be more distinct and reliable. EEMD is essentially a method to handle signals with white noise and is known as noise assisted data analysis. The method is the opposite of noise

reduction, where white noises $w(t)$ would be added to the original signal $x(t)$ to form a new signal $X(t)$.

$$X(t) = x(t) + w(t)$$

$w(t)$ is a small white Gaussian noise that obeys normal distribution:

$$\xi_n = \frac{\xi}{\sqrt{N}}$$

In the formula above, N is the total number of noise series; ξ is the amplitude of the white Gaussian noise; and ξ_n is the standard deviation, which is calculated from the refactoring signal and original signals. In other words, ξ_n is the deviation between input signal and the corresponding result that is obtained from the refactoring IMF components. $X(t)$ is the decomposing signal, and many white Gaussian noises are added to $x(t)$ to simulate the observation:

$$X_i(t) = x(t) + w_i(t)$$

Then the new signal $X_i(t)$ is decomposed, we obtain a group of IMFs and residual components:

$$X_i(t) = \sum_{j=1}^{n} IMF_{ij} + R_{nj}(t)$$

According to the zero-mean features of the white Gaussian noises' uniform distribution, we count the average of all the IMFs in order to offset the impact of the white Gaussian noise. At the same time, the modal aliasing problem can be solved (Wu et al., 2009).

$$IMF_i = \frac{1}{n}\sum_{j=1}^{n} IMF_{ij}$$

$$R_n(t) = \frac{1}{n}\sum_{j=1}^{n} R_{nj}$$

In the process, the amplitude of added white noise is limited, rather than infinite or infinitesimal. Wu et al. (2009) pointed out that the amplitude of noise has little effect on the decomposition result, and the application of EEMD has no subjectivity and is also self-adaptive. With the intention of ensuring that the IMFs are closer to the real signal, a sufficient number of noise series should be added to the decomposition process. Moreover, the amplitude of noise should be as small as possible, so the error can be reduced.

$$T = \frac{N_1}{N_2}$$

In the formula above, T denotes the period, N_1 denotes the number of original data, and N_2 denotes the number of maximums or minimums. In this paper, we choose the number of maximums as N_2.

As a novel method to deal with non-stationary data, EEMD has been applied to the natural and social sciences for forecasting purposes. In astronomy, Monjoly et al. (2016) attempted to conduct hourly forecasting of global solar radiation with EEMD and significantly improved solar forecast accuracy; in meteorology, Qi et al. (2016) combined EEMD and SVR (support vector regression) to forecast monthly rainfall; while Zang et al. (2016) forecasted the short-term wind power interval with the combination of EEMD, a runs test (RT), and a relevance vector machine (RVM). In the context of the rapid

development of high-speed rail (HSR) in China, Jiang et al. (2014) adopted EEMD and combined it with a grey support vector machine (GSVM) to forecast the daily ridership of the Wuhan-Guangzhou HSR, and found that the forecasting error was much lower than the other two existing forecasting approaches (a support vector machine and autoregressive integrated moving average). Other studies have also adopted the EEMD method (Basha et al., 2015; Li et al., 2008; Plakandaras et al., 2014; Tang et al., 2012). All of them proved that EEMD has distinct advantages in dealing with time series data and integrating with existing forecasting methods.

Tourism researchers have also adopted EMD for tourism demand forecasting. Cao et al. (2016) adopted EMD and wavelet decomposition methods to analyse the characteristics of multi-scale fluctuations and calculate tourism efficiency in Chinese national scenic areas. Moreover, Lai et al. (2013) integrated EMD and support vector regression (SVR) for forecasting international tourist arrivals to Taiwan, and Shabri (2015) forecasted tourism demand with the Group Method of Data Handling (GMDH) and ARIMA. He added EMD in the process and showed that both of the proposed models—EMD-GMDH and EMD-ARIMA—were better than traditional single methods. Wang (2015) combined EMD with ARMA and also demonstrated the superior performance of the new model.

However, the improved model of EEMD has not been widely adopted in tourism research with a few exceptions. When forecasting tourist arrivals from Singapore to Malaysia, Shabri (2016) blended a Least Square Support Vector Machine (LSSVM) and EEMD, and indicated that EEMD can efficiently improve prediction accuracy. In this paper, EEMD will be combined with a popular and useful method, ARIMA, to forecast the occupancy rate of an individual hotel, with the purpose of improving forecasting accuracy.

Data resource

The daily occupancy data in this study is provided by a leading revenue management software company offering pricing solutions for hotels and gaming casino resorts as well as apartments.

Figure 1 shows the annual fluctuation of occupancy in the test hotel (LMN), from July 12, 2007 to August 14, 2014. The daily occupancy fluctuates with no apparent patterns. The only observable regularity is that the occupancy declines first and rises later—twice in December every year.

---------- Insert Figure 1 here ----------

Hotel occupancy forecasting with EEMD-ARIMA

First, we need to set up a few parameters to instruct the model on how to decompose the data. According to past studies (Wu et al., 2009), the number

of IMFs is set to 10 since the real occupancy data has 2591 data points; the standard deviation of white noise is set to 0.2, and the number of integrations is 100. The results of the EEMD are displayed in Figure 2; the first sub-plot named signal is the real occupancy, followed by IMF_1 to IMF_{10}, and the last one is the residue, also termed "trend." Figure 2 shows that the randomness is decreasing from signal to trend, and, in turn, patterns emerge at higher levels of aggregation.

---------- Insert Figure 2 here ----------

---------- Insert Table 2 here ----------

---------- Insert Table 3 here ----------

In total, the IMFs and trend decomposed by EEMD can explain 75.5% of the variance of occupancy. This is because of the nonlinear wave added in the original data series (Peel et al., 2005). The fluctuation period of IMF1 is about 3 days, which contributes the most to the variance explanation and accounts for 26.3% and 34.9% of the original and decomposed data, and it has the widest oscillation. The oscillation was obvious from July 2007 to May 2009, during the early stages of hotel operations. After operating for 600 days, the oscillation decreased, but the amplitude increased, suggesting that the hotel's occupancy began to stabilize.

The fluctuation period of IMF2 is 7 days, which explains the second-most variance to the model, which accounts for 18.9% of the origin variance and 25.0% of the decomposed data. Similar to IMF1, IMF2 also experienced two stages: an oscillation stage followed by a different amplitude stage. The difference is that the later oscillations of IMF2 became more drastic, and the degree of fluctuation was even more than those during the hotel's initial operations. The fluctuation period of IMF3 is about 14 days, and interestingly, IMF3 contributes the fourth-most to the result while IMF4 with a period of 29 days contributes the third-most, suggesting that the period of 29 days was more significant than the 14 days' cycle.

The variance contribution rate of IMF5 to IMF10 is small: the total being 4.3%, and the period ranging from 63 days to 1,296 days. This suggests that these IMFs are low-frequency, long periods, slow fluctuating, and have a limited effect on explanatory power for hotel occupancy. In other words, a long period has little effect on hotel occupancy forecasting, which also implies that the factors influencing occupancy are complicated. As stated by Huang et al. (2003), the trend term reveals the latent trajectory of the origin data. In the case of LMN, it decreases at first and then keeps increasing from 1,000 days onward because, as the trend evolves to a steady-state growth, the occupancy of LMN keeps increasing in the foreseeable future.

The correlation coefficient between the IMFs showed that the IMFs and the trend term as well as the real occupancy have significantly positive correlations (see Table 3), with the exception of IMF10. This suggests that the decomposition is effective, of which the correlation coefficients of IMF1 to IMF4, with the real hotel occupancy data, are more than 0.4, and therefore moderately significant positive correlations. The correlation coefficients between IMF5 to IMF10 for the trend and real occupancy are small, which suggests they are significant but weak correlations. The results of correlation coefficients are consistent with the analysis of variance contribution rates, suggesting that short-period cycles of less than a month are more meaningful.

Forecasting with EEMD-ARIMA

According to the analysis above, the forecasting steps are set to four periods within a month: 3 days, 7 days, 14 days, and 29 days. These correspond to the major period of hotel operations: half a week, a week, two weeks and four weeks. The origin data is divided into a training set and a testing set (see Table 4). Each of the four training sets is decomposed by EEMD, and the most popular forecasting method—ARIMA—is adopted as the benchmark. The top rows in Table 4 and Table 5 represent the original ARIMA models. The IMFs and trends are modeled and forecasted separately and integrated later; the forecasting results of ARIMA and EEMD-ARIMA are compared to determine if the new method can indeed improve the forecasting accuracy. The related

statistical indices can be seen in Table 5 and Table 6.

---------- Insert Table 4 here ----------

Figures 3 through 6 compare the forecast results, which show that the EEMD-ARIMA method clearly outperforms the individual ARIMA over three or seven days. Besides, the former can follow the directional change of real occupancy better than ARIMA method. However, the forecasts made by EEMD-ARIMA do not function very well beyond 7 days, as the forecast occupancy would keep increasing or decreasing. Further, the forecasting error becomes progressively larger. This indicates that EEMD-ARIMA may not be suitable for direct forecast of long-term occupancy rates.

---------- Insert Table 5 here ----------

---------- Insert Table 6 here ----------

---------- Insert Figure 3 here ----------

---------- Insert Figure 4 here ----------

---------- Insert Figure 5 here ----------

---------- Insert Figure 6 here ----------

From the analysis above, it seems that direct application of EEMD-ARIMA is not suitable for long-term forecasting. Thus, we introduce the rolling forecasting method. As an example, we take the next 30 days' forecasts, which

can be divided into 10 three-day periods. The first three days' occupancy is forecasted and then added to the training set in order to forecast occupancy for the next three days, and so on. The forecast results can be seen in Figure 7; the rolling forecasting method that divides longer periods into shorter periods achieved better results with both ARIMA and EEMD-ARIMA. Further, EEMD-ARIMA outperforms ARIMA again. It is important to note that, since ARIMA is not proficient in capturing turning points, a sudden decrease or increase in real occupancy will result in a significant error in the forecasts. On the other hand, EEMD-ARIMA outperforms ARIMA in capturing the turning points in the data series.

---------- Insert Figure 7 here ----------

---------- Insert Table 7 here ----------

Conclusions

Individual hotels are basic business units of the hospitality industry, occupancy rate is a key indicator in hotel performance, and thus its forecasting is crucial for revenue management. Forecasting for a single hotel on a daily basis is especially difficult due to complex and erratic fluctuations (Jeffrey and Barden, 2000). We introduce a novel method, EEMD, to reduce the fluctuation and capture the regularities in the patterns of hotel occupancy. Eventually, a forecasting model integrated by EEMD-ARIMA has been presented.

The comparison between forecasting results of ARIMA and EEMD-ARIMA shows that the novel model performs better especially for short-term forecasts, whether measured by diagnostic parameters or the ability to predict turning points. This unique method can effectively handle data fluctuation by decomposing the complicated occupancy data into a set of relative regular waves. Therefore, an EEMD-ARIMA model is appropriate to forecast daily occupancy for individual hotels.

The practical implications of this study rest on its application in individual hotels. There is a lack of studies focusing on daily occupancy forecasting for single properties. EEMD is proficient in dealing with non-stationary and fluctuating data and has been popular in other disciplines. After the exploratory and empirical testing, we found that the introduction of EEMD can bring more accurate daily forecasting. This provides a more efficient and accurate way for individual properties in forecasting daily occupancy.

For an individual hotel, the within-week occupancy pattern can be complex and erratic, since its patterns will depend on the range and type of markets served. National holidays, local school holidays, occasional sporting events, one-off exhibitions or tourism promotions, unforeseen events, and even extreme weather conditions can produce day-to-day variations in occupancy rates. However, our results show that consistent patterns underlie this

complexity (Lomanno, 1995). It is towards the identification of these consistent and aggregate patterns, along with their effects in the daily occupancy of individual hotels, that this study contributes to literature.

However, one limitation of this model is its complexity. Parsimonious models are usually preferred in forecasting (Makridakis and Hibon, 2000). The complexity of EEMD-ARIMA will make it hard to explain to laypeople and thus limit its adoption and usage. In addition, this model could be improved further. The EEMD method does not have a satisfactory solution to deal with the ending effect due to EEMD envelopes. Since it's unlikely that the IMFs' ends are all at their maximum or minimum values, the upper and lower envelope would radiate at both ends, which would consequently affect IMFs and trends, and the forecasts would deviate from the actual trends. For example, when the current occupancy is a local extrema, the next forecasting step would increase or decrease as well. The ending effect has little influence on short-term forecasts, but it would exert great influence over long-term forecasts. This explains why the results of the 14-day or 29-day period's direct forecasting are poor in Figure 5 and Figure 6. Further, the forecasting model cannot determine the turning point automatically, and, therefore, it is necessary to add human intervention or divide long-term forecasting into short periods to obtain accurate occupancy results. Future studies should examine these problems.

References

Aghazadeh SM (2007) Revenue forecasting models for hotel management. *Journal of Business Forecasting* 26: 33–37.

Andrew WP, Cranage DA and Lee CK (1990) Forecasting hotel occupancy rates with time series models: an empirical analysis. *Hospitality Research Journal* 14(2): 173-182.

Archer BH (1987) Demand forecasting and estimation. In: Ritchie JRB and Goeldner CR (eds) *Travel, tourism and hospitality research*. New York, USA: Wiley, pp.77–85.

Athanasopoulos G, Hyndman JR, Song H and Wu CD (2011) The tourism forecasting competition. *International Journal of Forecasting* 27(3): 822-844.

Bangwayo-Skeete PF and Skeete RW (2015) Can google data improve the forecasting performance of tourist arrivals? Mixed-data sampling approach. *Tourism Management* 46: 454–464.

Basha G, Ouarda TBMJ and Marpu PR (2015) Long-term projections of temperature, precipitation and soil moisture using non-stationary oscillation processes over the UAG region. *International Journal of Climatology* 35(15): 4606-4618.

Brännäs K, Hellström J and Nordström J (2002) A new approach to modelling and forecasting monthly guest nights in hotels. *International Journal of Forecasting*, 18(1): 19-30.

Cao F, Huang Z, Jin C and Xu M (2016) Influence of Chinese economic fluctuations on tourism efficiency in national scenic areas. *Tourism Economics*: 22(5): 884-907.

Chan CK, Witt SF, Lee YCE and Song H (2010) Tourism forecast combination using

the CUSUM technique. *Tourism Management* 31(6): 891-897.

Chen KY (2011) Combining linear and nonlinear model in forecasting tourism demand. *Expert Systems with Applications* 38(8): 10368-10376.

Chen MH (2011) The response of hotel performance to international tourism development and crisis events. *International Journal of Hospitality Management* 30(1): 200-212.

Choi JG (2003) Developing an economic indicator system (a forecasting technique) for the hotel industry. *International Journal of Hospitality Management* 22(2): 147-159.

Ellero A and Pellegrini P (2014) Are traditional forecasting models suitable for hotels in Italian cities? *International Journal of Contemporary Hospitality Management* 26(3): 383-400.

Frechtling DC (2001) *Forecasting Tourism Demand: Methods & Strategies*. Oxford, UK: Butterworth Heinemann.

Gunter U and Önder I (2015) Forecasting international city tourism demand for Paris: accuracy of uni- and multivariate models employing monthly data. *Tourism Management* 46: 123-135.

Halicioglu F, Blake A and Cortés-Jiménez I (2010) An econometric analysis of the aggregate outbound tourism demand of Turkey. *Tourism Economics* 16(1): 83-97.

Heo CY, Lee S, Mattila A and Hu C (2013) Restaurant revenue management: Do perceived capacity scarcity and price differences matter? *International Journal of Hospitality Management* 35(5): 316-326.

Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, Yen NC, Tung, CC and Liu HH (1998) The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. In: *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences* 454(1971), pp.903-995. The Royal Society.

Huang NE, Shen Z and Long SR (2003) A new view of nonlinear water waves: the Hilbert spectrum. *Annual Review of Fluid Mechanics* 31(1): 417-457.

Huang NE and Wu Z (2008) A review on Hilbert-Huang transform: method and its applications to geophysical studies. *Reviews of Geophysics* 46(2): 1-23.

Huang NE, Wu Z, Long SR, Kenneth CA, Chen X and Blank K (2009) On instantaneous frequency. *Advances in Adaptive Data Analysis* 1(2): 177-229.

Hyndman RJ, Koehler AB, Ord KJ and Snyder RD (2008) Forecasting with exponential smoothing: The state space approach. *Springer* 26(1): 204-205.

Hyndman RJ, Koehler AB, Snyder RD and Grose S (2002) A state space framework for automatic forecasting using exponential smoothing methods. *International Journal of Forecasting* 18(3): 439-454.

Jeffrey D and Barden RDR (2000) An analysis of daily occupancy performance: a basis for effective hotel marketing. *International Journal of Contemporary Hospitality Management* 12(3): 179-189.

Jiang X, Zhang L and Chen X (2014) Short-term forecasting of high-speed rail demand: a hybrid approach combining ensemble empirical mode decomposition and gray support vector machine with real-world applications in China. *Transportation*

Research Part C Emerging Technologies, 44: 110–127.

Kouprioucha L, Rest JPVD and Schwartz Z (2014) On revenue management and the use of occupancy forecasting error measures. *International Journal of Hospitality Management* 41: 104-114.

Lai MC, Yeh CC and Shieh LF (2013) A hybrid model by empirical mode decomposition and support vector regression for tourist arrivals forecasting. *Journal of Testing & Evaluation 41*(3): 351-358.

Law R and Au N (1999) A neural network model to forecast Japanese demand for travel to Hong Kong. *Tourism Management, 20*(1), 89-97.

Li G, Song H and Witt SF (2006) Time varying parameter and fixed parameter linear aids: an application to tourism demand forecasting. *International Journal of Forecasting* 22(1): 57-71.

Li YY, Niu DX, Qi JX and Liu D (2008) A novel hybrid power load forecasting method based on ensemble empirical mode decomposition. *Power System Technology 32*(8): 58-62.

Lim C, Chang C and McAleer M (2009) Forecasting h(m)otel guest nights in New Zealand. *International Journal of Hospitality Management* 28(2): 228-235.

Lomanno MV (1995) Examining worldwide trends. *Hotel & Motel Management* 210(21): 15.

Monjoly S, André M, Calif R and Soubdhan T (2016) Hourly forecasting of global solar radiation based on multiscale decomposition methods: a hybrid approach. *Energy* 119: 288–298.

Makridakis S and Hibon M (2000) The M3-Competition: results, conclusions and implications. *International journal of forecasting* 16(4): 451-476.

NASA. (2003). NASA selects commercial & government inventions of the year. Available at: https://www.nasa.gov/home/hqnews/2003/mar/HP_news_03120.html. Accessed January 15, 2016

Pan B, Chenguang Wu D and Song HY (2012) Forecasting hotel room demand using search engine data. *Journal of Hospitality & Tourism Technology* 3(3): 196-210.

Peel MC, Amirthanathan GE, Pegram GGS, McMahon TA and Chiew HS (2005) Issues with the application of empirical mode decomposition[C]. In: *MODSIM 2005 international congress on modelling and simulation, modelling and simulation society of Australia and New Zealand* (ed RM Argent), pp.1681-1687.

Peng B, Song H and Crouch GI (2014) A meta-analysis of international tourism demand forecasting and implications for practice. *Tourism Management* 45: 181-193.

Peng ZK, Tse PW and Chu FL (2005) An improved Hilbert–Huang transform and its application in vibration signal analysis. *Journal of Sound & Vibration* 286(1–2): 187-205.

Plakandaras V, Gupta R, Gogas P and Papadimitriou T (2014) Forecasting the U.S. real house price index. *Economic Modelling 45*: 259-267.

Qi O, Lu W, Xin X, Zhang Y, Cheng W and Yu T (2016) Monthly rainfall forecasting using EEMD-SVR based on phase-space reconstruction. *Water Resources Management* 30(7): 2311-2325.

Rajopadhye M, Ghalia M B, Wang PP, Baker T and Eister CV (1999) Forecasting

uncertain hotel room demand. *Information Sciences* 132(1–4): 1-11.

Schwartz Z (1999) Monitoring the accuracy of multiple occupancy forecasts. *Fiu Hospitality Review* 17 *(1–2)*: 29-42.

Schwartz Z and Hiemstra S (1997) Improving the accuracy of hotel reservations forecasting: curves similarity approach. *Journal of Travel Research* 36(1): 3-14.

Shabri A (2015) A novel hybrid ensemble learning paradigm for tourism forecasting. In: AIP Conference Proceedings (eds MS Mohamad, WNS Wan Yusoff, NAZ Md Noar, R Zakaria and MR Ab Hamid, 1643(1), pp.192-200. AIP.

Shabri A (2016) A hybrid of EEMD and LSSVM-PSO model for tourist demand forecasting. *Indian Journal of Science and Technology* 36(9): 1-6.

Shen SJ, Li G and Song H (2011) Combination forecasts of international tourism demand. *Annals of Tourism Research* 38(1): 72-89.

Song H, Dwyer L, Li G and Cao Z (2012) Tourism economics research: a review and assessment. *Annals of Tourism* Research 39(3): 1653-1682.

Song H, Gao BZ and Lin VS (2013) Combining statistical and judgmental forecasts via a web-based tourism demand forecasting system. *International Journal of Forecasting* 29(2): 295-310.

Song H and Li G (2008) Tourism demand modelling and forecasting—a review of recent research. *Tourism Management* 29(2): 203-220.

Song H, Li G, Witt SF and Athanasopoulos G (2011a) Forecasting tourist arrivals using time-varying parameter structural time series models. *International Journal of Forecasting* 27(3): 855-869.

Song H, Lin S, Witt SF and Zhang X (2011b) Impact of financial/economic crisis on demand for hotel rooms in Hong Kong. *Tourism Management* 32(1): 172-186.

Talluri KT and Van Ryzin GJ (2005) *The Theory and Practice of Revenue Management*. Springer Netherlands.

Tang L, Yu L, Wang S, Li J and Wang S (2012) A novel hybrid ensemble learning paradigm for nuclear energy consumption forecasting. *Applied Energy 93*(5): 432-443.

Wang Y (2015) The tourism demand of nonlinear combination forecasting based on time series method and WNN. *International Journal of u- and e- Service, Science and Technology* 8(3): 301-310.

Weatherford LR and Kimes SE (2003) A comparison of forecasting methods for hotel revenue management. *International Journal of Forecasting* 19(3): 401-415.

Weatherford LR, Kimes SE and Scott DA (2001) Forecasting for hotel revenue management: testing aggregation against disaggregation. *Cornell Hotel & Restaurant Administration Quarterly* 42(4): 53-64.

Witt SF and Witt CA (1995) Forecasting tourism demand: a review of empirical research. *International Journal of Forecasting* 11(3): 447-475.

Wong KKF, Song H, Witt SF and Wu DC (2007) Tourism forecasting: to combine or not to combine?. *Tourism* Management 28(4): 1068-1078.

Wu Z and Huang NE (2009) Ensemble empirical mode decomposition: a noise-assisted data analysis method. *Advances in Adaptive Data Analysis* 1(1): 1-41.

Wu Z and Huang NE (2004) A study of the characteristics of white noise using the

empirical mode decomposition method. *Proceedings of the Royal Society A Mathematical Physical & Engineering Sciences* 460: 1597-1611.

Wu Z, Huang NE and Chen XY (2009) The multi-dimensional ensemble empirical mode decomposition method. *Advances in Adaptive Data Analysis* 1(3): 339-372.

Wu Z, Huang NE, Long SR and Peng CK (2007) On the trend, detrending, and variability of nonlinear and nonstationary time series. *Proceedings of the National Academy of Sciences of the United States of America* 104(38): 14889-14894.

Xie Y J (2010) *Tourism Studies*, 3rd ed. Beijing, China: China Travel & Tourism Press.

Yang Y, Pan B and Song HY (2014) Predicting hotel demand using destination marketing organization's web traffic data. *Journal of Travel Research* 53: 433-447.

Yüksel S (2007) An integrated forecasting approach to hotel demand. *Mathematical & Computer Modelling* 46(7-8): 1063-1070.

Zakhary A, Atiya AF, El-Shishiny H and Gayar NE (2011) Forecasting hotel arrivals and occupancy using Monte Carlo simulation. *Journal of Revenue & Pricing Management* 10(4): 344-366.

Zang H, Fan L, Guo M, Wei Z, Sun G and Zhang L (2016) Short-term wind power interval forecasting based on an EEMD-RT-RVM model. Advances in Meteorology, 2016(3): 1-10.

Tables and Figures

Table 1. Summary of studies on hotel demand forecasting

Author(s)	Data type	Research area	Main methodology
William et al. (1990)	Monthly	Individual hotel, USA	Time series model
Schwartz and Hiemstra (1997)	Daily	3 hotels, USA	Curves similarity model
Law (1998)	Annual	Hong Kong, PRC	Neural network
Jeffrey and Barden (2000)	Daily	91 hotels, England	Stepwise regression analysis
Rajopadhye et al. (2001)	Daily	Individual hotel, USA	Exponential smoothing model
Brännäs et al. (2002)	Monthly	Swedish	Time series model
Choi (2003)	Annual	USA	Economic indicator system
Weatherford and Kimes (2003)	Daily	International hotel group	Time series model Exponential smoothing model
Yüksel (2007)	Monthly	Individual hotel, Turkey	Time series model Analytic hierarchy process
Lim et al. (2009)	Monthly	New Zealand	Exponential smoothing model Time series model
Zakhary et al. (2011)	Daily/ Weekly	Individual hotel, Egypt	Monte Carlo simulation
Song et al. (2011b)	Quarterly	Hong Kong, PRC	Error correction method
Pan et al. (2012)	Weekly	Charleston, USA	Time series model
Yang et al. (2014)	Weekly	Charleston, USA	Time series model
Ellero and Pellegrini (2014)	Daily	5 hotels, Italy	Pick-up models Time series model
Kouprioucha et al. (2014)	Daily	Hotel group, Netherlands	System and manual

Table 2. Analysis of IMFs and TREND Based on EEMD

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	Trend
Percentage of variance before decomposition (%)	26.32	18.85	7.88	7.99	4.27	2.71	2.09	1.20	1.45	0.17	2.54
Percentage of variance after decomposition (%)	34.88	24.98	10.44	10.59	5.66	3.59	2.77	1.58	1.92	0.22	3.37
Period (days)	3.2	7.0	13.7	28.8	64.8	117.8	235.5	431.8	1295.5	2591.0	

Table 3. Correlation Test Between IMFs, Trend, and Real Occupancy

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	Trend
P-value	.591**	.575**	.429**	.408**	.358**	.312**	.153**	.188**	.175**	.008	.127**

*the significant level of p-value is 0.05 (two-tailed);

**The significant level of p-value is 0.01 (two-tailed).

Table 4. The Size of Each Forecast Data Series

	3d	7d	14d	29d
Training set	2588	2584	2577	2562
Testing set	3	7	14	29

Table 5. Adopted Structure and Parameters of ARIMA for 3- and 7-day Forecasts

Model	Stationary Test	ARIMA (p, d, q)	Adjusted R^2	R^2	RMSE	MAPE		MAE	Normalized BIC	
						3d	7d		3d	7d
signal	1	(1,0,14)	.444	.444	.178	27.934	27.957	.142	-3.435	-3.434
IMF1	1	(0,0,8)	.234	.234	.107	423.965	424.269	.087	-4.449	-4.448
IMF2	1	(3,0,6)	.963	.963	.020	101.546	101.672	.015	-7.820	-7.819
IMF3	0	(0,2,8)	.962	.999	.002	293.956	294.593	.002	-12.074	-12.073
IMF4	0	(1,4,8)	.637	1.000	.000	.650	.651	.000	-17.589	-17.587
IMF5	0	(1,4,13)	.761	1.000	.000	.033	.033	.000	-24.431	-24.430
IMF6	0	(2,4,1)	.867	1.000	.000	.005	.005	.000	-30.960	-30.958
IMF7	0	(1,5,8)	.159	1.000	.000	.000		.000	-35.944	-35.942
IMF8	0	(0,5,4)	.782	1.000	.000	.000			-39.941	-39.940
IMF9	0	(3,3,7)	.935	1.000	.000	.001		.000	-39.417	-39.415
IMF10	0	(2,3,6)	.781	1.000	.000	.010		.000	-39.097	-39.095
Trend	0	(2,2,2)	.484	1.000	.000	.000		.000	-42.549	-42.549

Table 6. Adopted Structure and Parameters of ARIMA for 14- and 29-day Forecasts

Model	Stationary Test		ARIMA (p,d,q)		Adjusted R^2		R^2		RMSE		MAPE		MAE		Normalized BIC	
	14d	29d	14d	29d	14d	29d	14d	29d	14d	29d	14d	29d	14d	29d	14d	29d
signal	1		(1,0,13)	(1,0,14)	.421	.444	.421	.444	.182	.178	28.735	28.032	.146	.142	-3.392	-3.431
IMF1	1		(0,0,8)		.233	.231	.233	.231	.107		424.435	426.315	.087		-4.447	-4.446
IMF2	1		(3,0,8)		.933	.962	.933	.962	.027	.020	105.905	101.179	.020	.016	-7.215	-7.792
IMF3	0	1	(0,2,8)	(2,0,8)	.890	.999	.996	.999	.004	.002	173.292	209.551	.003	.001	-11.026	-12.639
IMF4	0		(1,4,8)		.637		1.000		.000		.653	.656	.000		-17.584	-17.583
IMF5	0		(1,4,13)		.761		1.000		.000		.033		.000		-24.427	-24.422
IMF6	0		(2,4,1)		.867		1.000		.000		.005		.000		-30.956	-30.950
IMF7	0		(1,5,8)		.159	.158	1.000		.000		.000		.000		-35.940	-35.934
IMF8	0		(0,5,4)		.782		1.000		.000		.000		.000		-39.941	-39.938
IMF9	0		(3,3,7)		.935		1.000		.000		.001		.000		-39.413	-39.407
IMF10	0		(2,3,6)		.781		1.000		.000		.010	.011	.000		-39.093	-39.087
Trend	0		(2,2,2)		.482		1.000		.000		.000		.000		-42.547	-42.546

Table 7. Forecasting Error Measures of the 3 Periods

	RMSE			MAPE			MAE		
	3d	7d	30d	3d	7d	30d	3d	7d	30d
ARIMA	0.194	0.196	0.057	18.713	18.496	18.930	0.171	0.167	0.138
EEMD-ARIMA	0.113	0.114	0.039	12.549	11.593	11.507	0.088	0.093	0.077

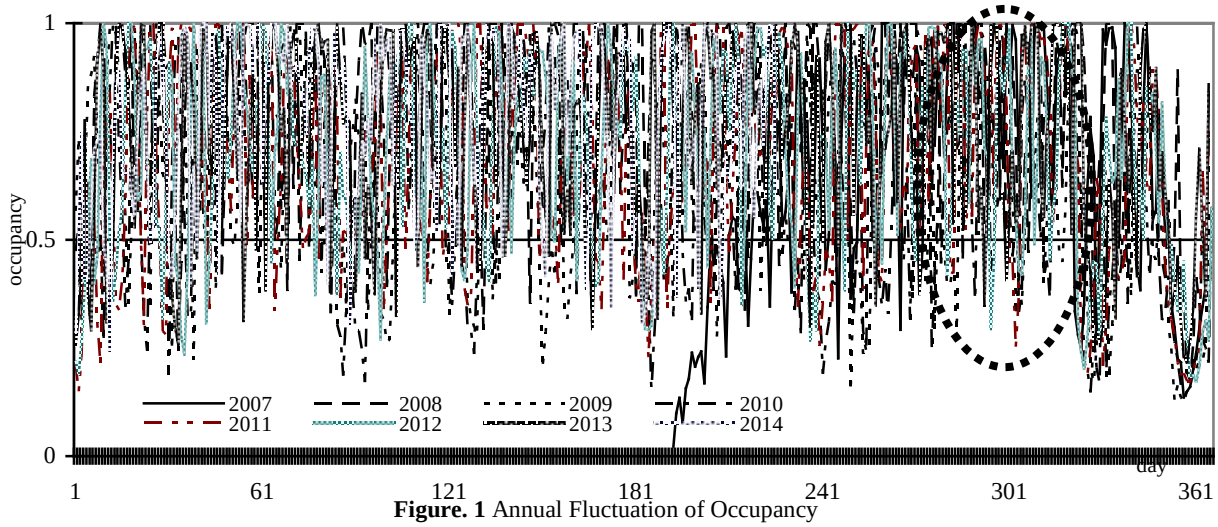
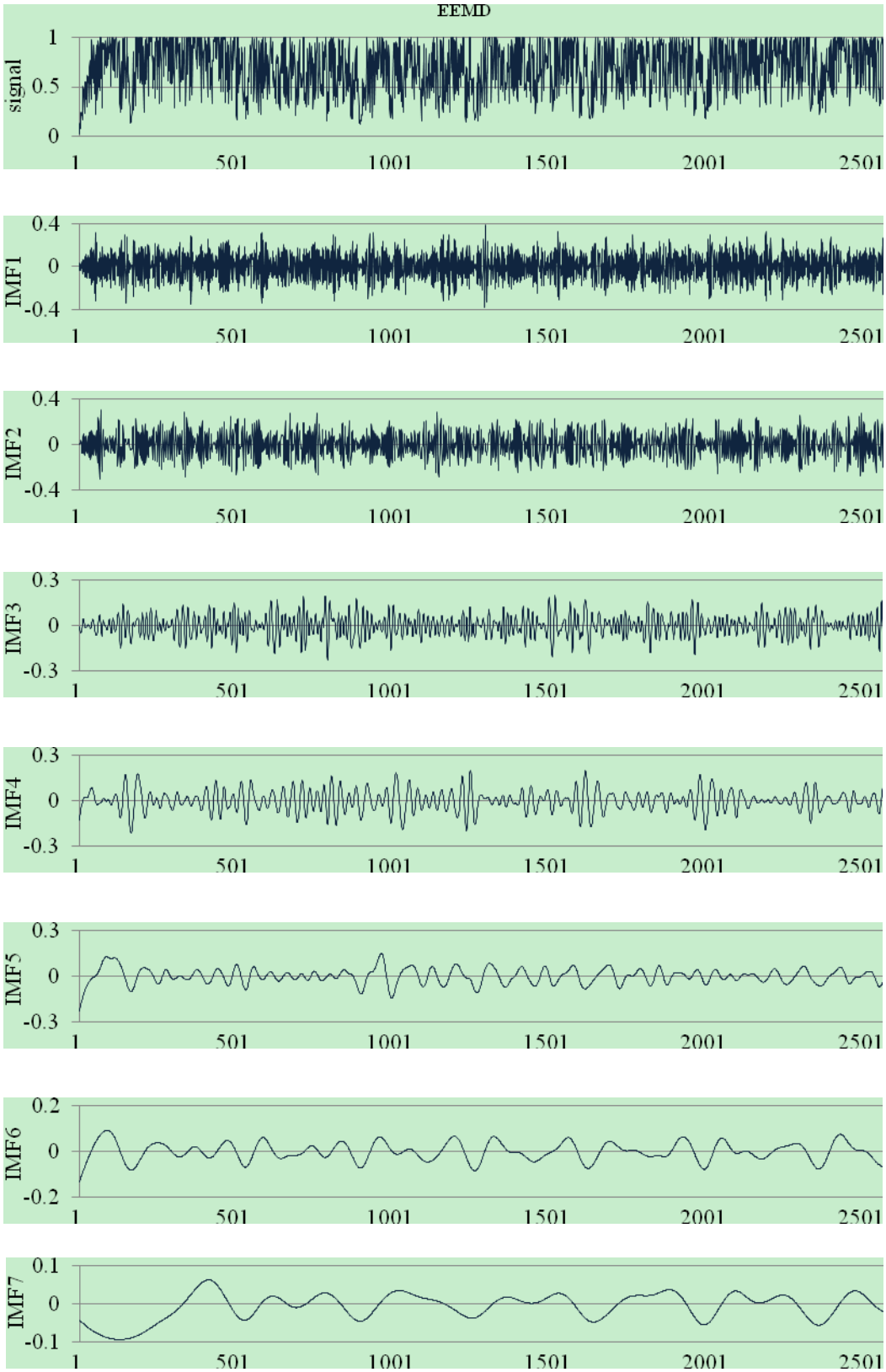


Figure. 1 Annual Fluctuation of Occupancy


EEMD
signal
1
0.5
0
IMF1
0.4
0
-0.4
IMF2
0.4
0
-0.4
IMF3
0.3
0
-0.3
IMF4
0.3
0
-0.3
IMF5
0.3
0
-0.3
IMF6
0.2
0
-0.2
IMF7
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1
501
1001
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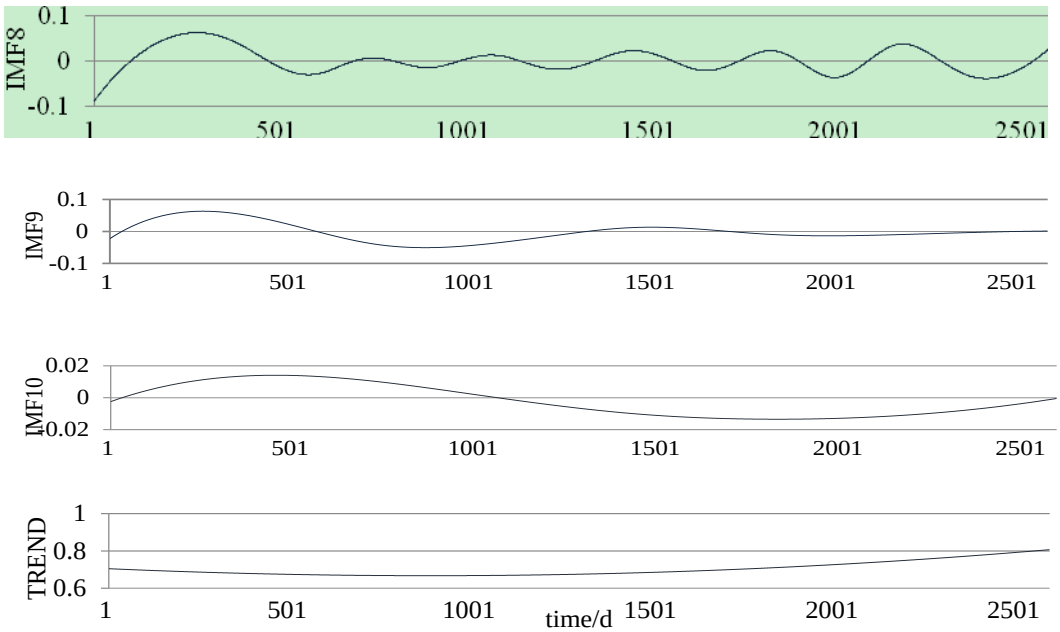

Figure 2. Ensemble Empirical Mode Decomposition of Occupancy Rate

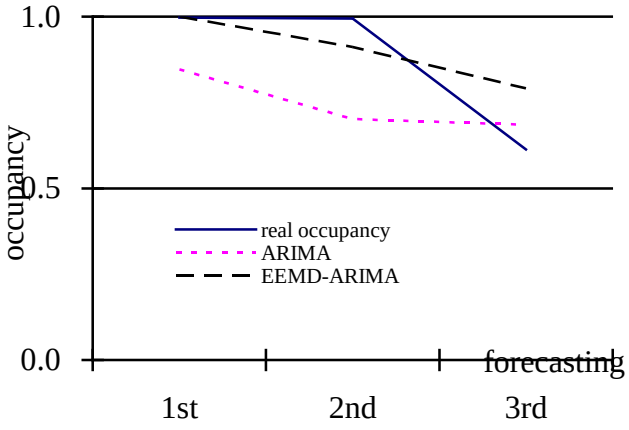

Figure 3. Comparison of Forecasting (3 days)

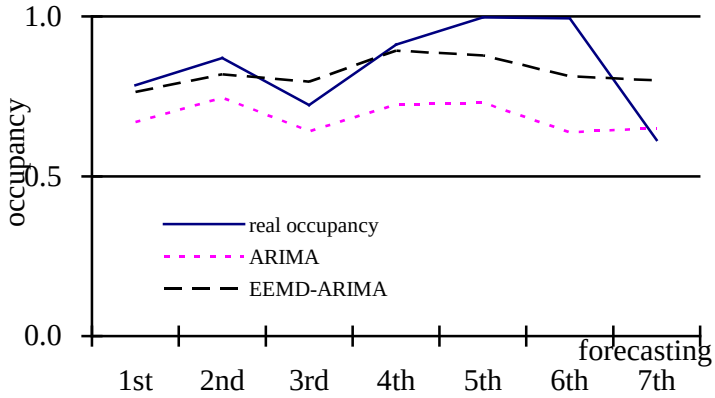

Figure 4. Comparison of Forecasting (7 days)

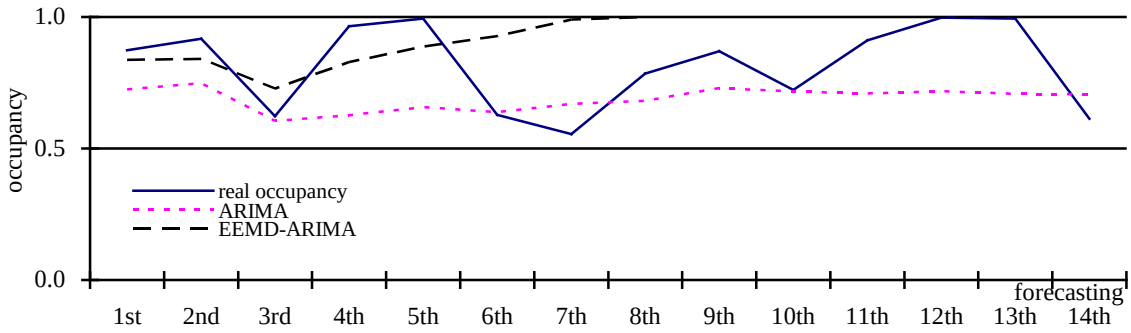

Figure 5. Comparison of Forecasting（14 days）

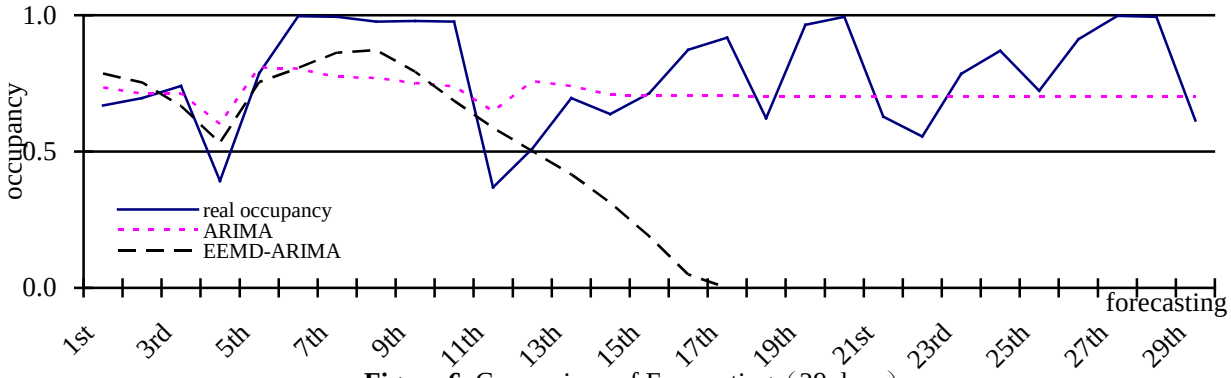

Figure 6. Comparison of Forecasting（29 days）

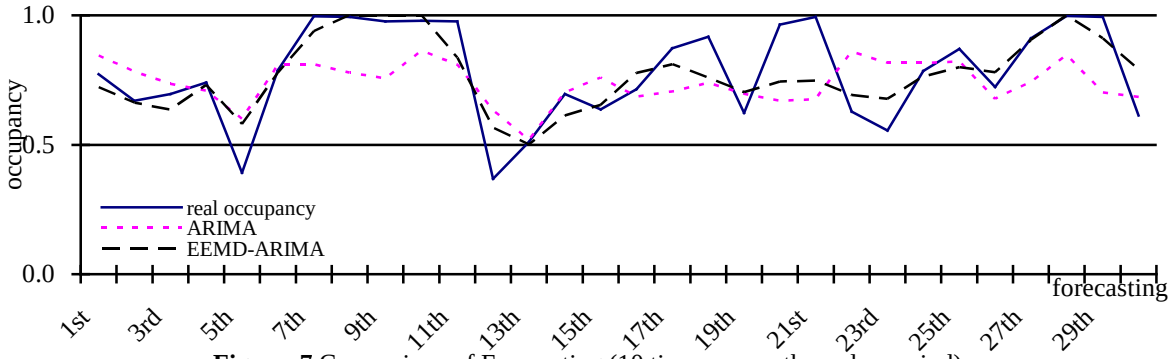

Figure. 7 Comparison of Forecasting (10 times over a three-day period)