Forecasting Occupancy Levels: A Problem for Management Forecasters

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Accurately forecasting occupancy levels is an essential planning ingredient in the process of developing a forecast of total annual revenue in managing an institution of higher education. Literature suggests that applied time series analysis is preferable to causal models for this application. The problem is that time series methods may not be optimal for forecasting total occupancy level due to the presence of measurement error in the historical occupancy data. Song and Chissom (1993b, 1994) developed a time series method based on Fuzzy Logic Set Theory (Zadeh, 1965), which they report to be robust in the presence of this type of uncertainty. We compare six general time series methods and the fuzzy method of Song and Chissom across two direct and two derived forecasting strategies. We also compare six time series methods and the "fuzzy" across direct and composite forecasting. We evaluate these combinations of method and strategy based on the criteria of accuracy and economy. The results indicate that the fuzzy time series method in conjunction with a direct forecasting strategy is preferable to all other combinations of method and strategy evaluated for forecasting each semesters total occupancy level.

Significant changes in the economic and demographic environments of public institutions of higher education increase the difficulty of forecasting of their total annual revenue (Zuniga, 1997). Rather than forecast total annual revenue directly, administrators combine the revenue forecasts for each of the revenue centers within the institution to obtain the institution's total annual revenue forecast, (Caruthers and Wentworth, 1997). These revenue centers, in descending order of contribution, are Tuition and Fees (27.5%), Auxiliary Services (25.0%), State and Local Government (24.5%), Federal Government (11.0%), Endowments/gifts (8.5%) and Other (3.5%), (Hauptman, 1997). Recent data not discussed here indicate a continued decline in the public support of higher education.

Administrators facing the pressure to fulfill student demand for housing, have adopted sophisticated quantitative forecasting models to improve the accuracy of their forecasts (Layzell, 1997). To date, nearly all of the research in this area focused on developing methods for forecasting enrollment levels. These levels are necessary to calculate the revenue forecast for tuition and fees, which are the institution's largest revenue center (Brinkman,1997).

In contrast, research focusing on the development of methods for forecasting occupancy levels are nonexistent. These levels, however, are necessary to predict the revenue forecast for room and board. Revenue from room and board is 75.5% of the revenue from auxiliary services or 18.5% of an institution's total annual revenue (Hauptman, 1997). In light of an institution's objective to accurately forecast its total annual revenue, the need to accurately forecast each semester's residence hall occupancy level is clear and is similar to occupancy levels of for-profit enterprises.

The objective of this paper is to offer practical guidelines when followed by *budget planners* so they may obtain accurate forecasts of their institution's fall and spring semesters' total occupancy level. The relevant body of literature indicates that, for reasons of economy and accuracy, time series forecasting methods are preferable to other forecasting methods for this application. This will be investigated further in this paper.

Unfortunately, due to the manner in which *management* predicts and records occupancy levels, historical occupancy data contain considerable measurement error. In addition, general time series forecasting methods may not be robust enough to produce a sufficiently accurate forecast when this type of uncertainty is present (Song and Chissom, 1993). The authors propose to use "fuzzy set theory" (Zadeh, 1965) introduced by Song and Chissom (1993b), to produce better results for university management.

This paper studies and compares six general time series methods (Chan, 2002) and the Song and Chissom (1994) fuzzy time series methods across two direct and two derived forecasting strategies. The dynamic artificial neural network models for forecasting time series events (Zhang, 2003; Ghiassi et al., 2005) are ignored since dynamic modeling of this type presents a different architecture and is not directly comparable to the fuzzy method that is the focus of attention in this study. By directly modeling the direct strategies, the original total occupancy time-series to obtain the total occupancy forecast for the fall and spring semesters. In the derived strategies, freshmen, sophomores, junior and senior occupancy forecasts are combined to form the total occupancy forecast for each semester are evaluated. In total, we evaluate fifty-six combinations of method and strategy for forecasting total occupancy level for each semester for goodness-of-fit. The measures of fit used are *Mean Absolute Deviation* (MAD), *Mean Absolute Percentage Error* (MAPE) and *Root Mean Square Error* (RMSE) (Jarrett, 1991; Shumway and Stoffer, 2000). The authors hypothesize that due to the presence of measurement error, the fuzzy time series method, strategy aside, produces the most accurate forecast.

We organize the remainder of this paper as follows: The Background section highlights the similarity between occupancy and enrollment data, and reviews the quantitative and combination methods used to forecast the latter. The Methodology section discusses the data collection process; the four competing strategy alternatives for obtaining a total occupancy forecast for each semester; a review of the general time series methods use and a review of the measures used to assess goodness-of-fit. The Results section presents in two tables, evidence indicating that the fuzzy time series method in combination with a direct forecasting strategy provides the most accurate forecasts of each semester's total occupancy level. We include a subjective assessment of the economy of each combination. The Discussion section reviews the efficacy of the direct forecasting approach as well as an evaluation of the fuzzy time series method. We include some suggestions for future research.

The results section presents in two tables, evidence indicating that the fuzzy time series method in combination with a direct forecasting strategy provides the most accurate forecasts of each semester's total occupancy level. A subjective assessment of the economy of each combination is included. The discussion section reviews the efficacy of the direct forecasting approach as well as an evaluation of the fuzzy time series method. Suggestions for future research are also included in this section of the paper.

Background

There is significant similarity between the dynamics and characteristics of occupancy data and those of enrollment data within a given institution. Occupancy level, like enrollment level, fluctuates throughout a given semester. Often the department notified of changes in these levels is different than the one recording or the one reporting these levels. As such, it is likely that an institution's reported historical occupancy level and its enrollment level have measurement error. Due to these similarities between occupancy data and enrollment data, previous research on forecasting enrollment levels is used as the relevant body of literature for this study on forecasting occupancy level.

Methods

The methods examined fall into one of two groups: curve fitting techniques (time series methods) or causal (explanatory, structural and econometric) models. Curve fitting techniques rely on patterns in the behavior of enrollment itself to produce a forecast, whereas causal models rely on the relationship between the predictors of enrollment and enrollment itself to produce the forecast (Brinkman, 1997). Causal modeling by far dominates the research on forecasting enrollment within institutions of higher education.

Recent research covering the use of quantitative methods includes the following. Hoenack and Weiler (1979) developed a complex causal model for long-term enrollment forecasting. They focused on the examination of the relationship between demands for higher education, and price and labor market variables. Sally (1979) argued that short-term forecasts are more important for budgetary purposes than are long-term forecasts, and showed how to distinguish the influence of cyclical, seasonal and trend effects.

Gardener (1981) utilizing a double exponential smoothing model examined the effects which alternative weighting factors had on enrollment forecasts. Weiler (1984; 1987a) demonstrated how to design and use econometric enrollment demand models. Weiler (1987b) used an econometric technique for dealing with supply constrained graduate enrollments at public universities. Pope and Evans (1985), Chatman (1986), and Paulsen (1989) all showed how to provide regularly updated monthly forecasts of the next term's enrollment. Pfitsner (1987) explained how to use a Box-Jenkins procedure for producing a short-term enrollment forecast. Mixon (1993) and Mixon and Hsing (1994) use econometric techniques to forecast out-of-state enrollments. Bingham (1993) demonstrates how one predicts enrollment within the framework of marketing theory. Song and Chissom (1993b and 1994) introduced a time series method based on Fuzzy Set Theory (Zadeh, 1965) for forecasting enrollments. These authors proposed this model to address uncertainty in the form of "fuzziness" in the historical observations of enrollment data. These authors drew a distinction between uncertainties in the form of fuzziness and uncertainty because of white noise. In the latter case, they concluded that white noise results from random factors and can be handled by traditional stochastic models. In the former case, they concluded that fuzziness results from non-random factors such as measurement error and can only be handled by fuzzy models. In their study, they compared their fuzzy method to time series linear regression on a single series of enrollment data. They evaluated their method using the forecast error measures (MAD) and (MAPE).

Several results come from prior research on the use of quantitative forecasting methods. Specifically, curve fitting or time series methods appear to be more appropriate for short-term forecasts, particularly when one uses the forecast for budgetary purposes. In contrast, past research indicates that causal methods are more appropriate for long-term forecasts. Further, the curve fitting techniques are more economical then the causal techniques as they require only historical observations on enrollment itself to produce a forecast. Mahmoud (1984, pg. 139) has stated with respect to quantitative forecasting methods: "time series methods are almost always better than explanatory variable models'. The fuzzy time series method appears to offer the dual benefits of economy and robustness to measurement error.

Combination Methods

Research on the use of combination forecasting methods for enrollment forecasting is quite limited. Nunley (1981) discusses how to use a combination of quantitative forecasting techniques along with a qualitative consultative approach to predict enrollment. Weissman (1994) provides an example of a hybrid approach in which one uses regression routines to develop statistical relationships between services area populations and enrollments in various academic disciplines. These forecasts are adjusted by administrators in each discipline as they consider various factors, including supply, which may affect enrollment.

Although the number of studies exploring the use of combination forecasting methods is small, in practice, these methods may be the most frequently used. As an example, at the University of Rhode Island, the institution serving as the subject of this study, administrators regularly adjust forecasts of enrollment level and occupancy level based on their intuition. On this point however, Makridakis (1979, pg. 97) concludes, "modifying the results of a quantitative forecast with a judgmental component tends to reduce the accuracy of the forecasts and adds to their costs".

Forecasting Strategies

The forecasting literature indicates one can use alternative strategies to obtain forecasted values when employing time series methods, specific forecasting method aside. One such strategy is to obtain forecasted values by directly modeling the time series of interest (Box, Jenkins and Reinsel, 1994). We used this direct strategy exclusively in the research on forecasting methods discussed above. A second strategy, when applicable, is to forecast the sub-aggregate series of the time series of interest. One combines these sub-aggregate forecasts to form a derived forecast for the series of interest (Wei and Abraham, 1981; Weatherby, 1984; Lütkepohl, 1984). This second strategy, in principle, is the one used by administrators to obtain the total annual revenue forecast for four-year public higher education institutions. A third strategy is to directly model the time series of interest with several methods, and to use the mean of these forecasts as the final forecast for the time series (Bunn, 1979; Theil, 1954).

Method

Data Collection

We obtained the residence occupancy data from the Department of Housing, the Registrar's Office, and the Bursar's Office at the University of Rhode Island. As there is no single measure of occupancy level for an academic year, historical occupancy data was obtained and recorded separately for the fall and the spring semesters for the academic years 1986-1997. This was a sufficiently lengthy period to avoid problems associated with a spike or some other data intervention.

Data collection establishes October 16th as the occupancy level date for the fall semester and February 23rd for the spring semester. These dates are also suitable for calculating total revenue for each semester. However, due to inaccuracies in the occupancy records and the absence of a recording date for some observations, there is a substantial probability that measurement error is present.

The specific time series used in this study are total occupancy level, as well as freshman, sophomore, junior and senior occupancy levels for the fall and spring semesters for the years 1986-1997. This provided ten time series of occupancy data with twelve observations each. We created an additional five time series by combining each category's fall and spring semester occupancy time series into a single time series with twenty-four observations.

Forecasting Strategies

Both direct and derived forecasting strategies were examined. When these two strategies were implemented, two direct and two derived alternatives result for obtaining each semester's total occupancy forecast. These four possibilities are (1a) directly model the fall and spring semester total occupancy time series finding (t+1) for each semester. (1b) directly model the combined fall/spring semester total occupancy time series finding (t+l) and (t+2) for the fall and spring semesters respectively. (2a) directly model the fall and spring semesters freshman, sophomore, junior and senior occupancy time series' finding (t+l) for each semester. Then combine the class forecasts for each semester to obtain the derived total occupancy forecast for each semester; (2b) directly model the combined fall/spring semester freshman, sophomore, junior and senior occupancy time series' finding (t+l) and (t+2) for the fall and spring semester respectively. Then combine the class forecasts for each semester to find the derived total occupancy forecast for each semester. Alternative (la) implies that each semester's historical total occupancy level is the best predictor of its future total occupancy level. Alternative (1b) implies that each semester's historical total occupancy level plays a role in predicting the future total occupancy level of the other semester. Alternatives (2a) and (2b) suggest that the process of combining the class forecasts into a forecast of total occupancy level serves to minimize overall forecast error.

Data Analysis: General Time Series Methods

Six general time series forecasting methods were used. They are: Moving Average (MA), Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), Brown's Method (BLE), Holt's Two-parameter Linear Exponential Smoothing (HLES) and Times Series Linear Regression (TSLR). The purpose is to find the benefits from the fuzzy method using the aforementioned benchmark methods to learn lessons for future forecasting activities (see Armstrong and Pagell, 2003) where they argue that one cannot evaluate all techniques under all principles). Time series methods were engaged because they represent methods ranging in sophistication from simple to complex and because they include both methods with and without trend adjustments. To ensure sufficient rigor, every parameter setting or combination of parameter settings for fit in each of the above methods was evaluated. Due to their limitations, we did not employ the first three general time series methods in the evaluation of approach (1b) and (2b) were not employed.

Data Analysis: Fuzzy Time Series Methods

Fuzzy time series methods to evaluate all four-strategy alternatives outlined above were examined[1].

Evaluation Methods

In this study, the recommendation of Krajewski and Ritzman (1994), regarding the magnitude of the weights used in time series methods were followed. Specifically, if

[1]An in-depth example, with appropriate descriptions, of the fuzzy time series method combined with strategy alternative (1a) are available from the authors @DelCampo@mgt.unm.edu.

weights exceed (.5), an alternative method was employed. The magnitude of the model weights aside, the selection of the appropriate time series method was based on the fit of the method to the time series, with the fit being measured as forecast error. Decisions on goodness-of-fit were based on achieving the objectives of minimizing MAD and MAPE (as was the case in the Song and Chissom (1993b) study). RMSE was also included because of its wide use and statistical properties.

Results

The objective of this study was to identify the combination of a forecasting strategy and a time series method which provided the most accurate forecast of each semester's total occupancy level. Tables 1 and 2 present the forecast errors for the model of best fit within each of the four strategies alternatives evaluated in this study for the fall and spring semesters respectively. In each table, the forecasting strategy and method combination, are listed in descending order.

Table 1: *Forecast errors for model of best fit within each of four strategy alternatives evaluated (Fall Semester)*

Approach		Method		Forecast Error	
			MAD	MAPE	RMSE
Direct Independent	(la)	Fuzzy	113.91	2.93%	161.95
Derived Independent	(2a)	TSIR	134.77	3.57%	167.05
Derived Combined	(2b)	TSIR	149.55	4.06%	184.23
Direct Combined	(lb)	TSIR	149.86	4.08%	183.3

Table 2: *Forecast errors for model of best fit within each of four strategy alternatives evaluated (Spring Semester)*

Approach		Method		Forecast Error	
			MAD	MAPE	RMSE
Direct Independent	(la)	Fuzzy	87.73	2.42%	138.65
Derived Independent	(2a)	Fuzzy	115.27	3.38%	144.26
Derived Combined	(2b)	BIE	139.69	3.87%	171.31
Direct Combined	(lb)	TSLR	149.86	4.08%	183.3

These results suggest that alternative (la) in conjunction with the fuzzy time series method, provides the most accurate forecast of each semester's total occupancy level. In addition, while the fuzzy method is more time consuming to setup initially than are the general time series methods, the fuzzy method (la) combination is very economical to implement. The derived strategy (2a) in conjunction with TSLR for the fall semester, and fuzzy time series for the spring semester ranks second in accuracy.

However, due to the use of the derived strategy these combinations are not very economical. Alternative (2b) in combination with TSLR for the fall semester and BLE for the spring semester ranks third in accuracy. Due to the derived strategy, however, these combinations are not very economical. Alternative (1b) in combination with TSLR ranks forth in accuracy for both semesters. This combination is, however, the most economical of the combinations evaluated[2, 3].

Discussion

The need to accurately forecast residence halls' occupancy levels in public institutions of higher education has become increasing important as budget planners strive to produce a more accurate forecast of their institution's total annual revenue. This study presents a comprehensive review of common forecasting strategies and time series forecasting methods which the literature suggests are appropriate for forecasting residence occupancy level. Included in this review is the relatively unknown fuzzy time series method of Song and Chissom (1993a), a method they proposed as a solution to the problem of measurement error in the historical observations of a time regardless of the source of the time series.

The results of this research indicate that directly modeling each semester's total occupancy time series with the fuzzy time series method provides a more accurate forecast of each semester's total occupancy level than do any of the alternative combinations evaluated. This combination of strategy alternative and method is relatively economical and all calculations can easily be performed in an Excel spreadsheet.

The success of the direct forecasting strategy (1a) in this application indicates that each semester's historical total occupancy level is the best predictor of each semester's future total occupancy level. Correctly identifying this relationship is an important step in obtaining an accurate forecast.

The accuracy of the fuzzy method is due to two factors. The first is the model's robustness, which is established in Step 4 of the fuzzy forecasting procedure. In this step, a probability is assigned to each fuzzy set representing the degree of membership of a given historical observation to that fuzzy set. In essence, this step creates an interval around the observed occupancy value which is likely to capture the true occupancy value in fuzzy teffi1s. As such, the influence of measurement error is muted. In the Song and Chissom (1993b) study, these authors observed that increasing or decreasing observed values by as much as 5% had no influence on the forecasted values.

The second factor contributing to the fuzzy method's accuracy is the Rfinal matrix calculated in Step 7. The Rfinal matrix summarizes the relationships between the historical observations of occupancy level, just as beta does in the TSLR method or the level or trend component does in the simpler time series methods. The difference, however, is that the Rfinal matrix appears to retain more unique information about the relationships between historical observations than do the single summary measures.

A shortcoming of the fuzzy time series method is the subjective nature of the decisions made in steps 1, 2 and 4 of the fuzzy forecasting procedure. Developing more objective criteria for steps 1, 2 and 4 in the procedure represents an excellent

[2]Charts presenting the observed vs. the Fuzzy forecast values of total occupancy level for each semester are available from the authors @DelCampo@mgt.unm.edu.

[3]Twenty four tables presenting the forecast error measures for all of the combinations and all of the time series evaluated in this study are available from the authors @DelCampo@mgt.unm.edu.

opportunity for additional research to advance the fuzzy time series method. There are also opportunities for additional research on forecasting occupancy level. Assuming continued use of qualitative or judgment forecasting methods by higher education budget planners to obtain each semester's total occupancy level, an experiment to compare methods and add to the relevant research in this area. Relative to quantitative methods, the addition of the results from more advanced time series methods and long memory modeling of occupancy data would serve to extend the results of this study. Most important, management and budget planners can relieve themselves of the burden of terribly inaccurate and confusing forecast information.

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