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A technical analysis approach to tourism demand forecasting

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Tourism demand forecasts are of great economic value both for the public and private sector. Any information concerning the future evolution of tourism flows, is of great importance to hoteliers, tour operators and other industries concerned with tourism or transportation, in order to adjust their policy and corporate finance. In the last few decades, numerous researchers have studied international tourism demand and a wide range of the available forecasting techniques have been tested. Major focus has been given to econometric studies that involve the use of least squares regression to estimate the quantitative relationship between tourism demand and its determinants. However, econometric models usually fail to outperform simple time series extrapolative models. This article introduces a new approach to tourism demand forecasting via incorporating technical analysis techniques. The proposed model is evaluated versus a range of classic univariate time series methods in terms of forecasting and directional accuracy.

I. Introduction

According to the World Tourism Organisation (WTO), many countries find tourism to be a very important source of foreign currency earnings and employment. Tourism is one of the largest and fastest-growing business sectors of the world economy. Its economic significance is well illustrated by the fact that in 1999 nearly 12% of the global GDP came from tourism. The promotion of tourism projects involves substantial sums of money. To be successful, an entrepreneur in the field must be equipped with the appropriate tools in order to analyse and interpret available data (Cho, 2003). Accurate forecasts of tourism demand are prerequisite to the decision-making process in the tourism organizations of the private or public sector (Goh and Law, 2002).

In the current study, a method that introduces technical analysis (TA) techniques in tourism demand forecasting is presented. The proposed model uses the Wilder's (1978) relative strength indicator (RSI), a momentum indicator that is widely used in TA (Pring, 2002), and builds a system of rules based on it, in order to forecast tourism demand. The model is evaluated in terms of MAPE (Makridakis *et al*., 1998) and directional accuracy

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(Witt and Witt, 1995) versus six classical forecasting approaches.

II. Tourism Demand Forecasting

Tourism demand is usually measured in terms of the number of tourist visits from an origin country to a destination country, in terms of tourist nights spent in the destination country or in terms of tourist expenditures by visitors from an origin country in the destination country. Data generally used are annual, cross-sectional or pooled data (Witt and Witt, 1995).

As do business-forecasting methods so do tourism methods fall into two major categories: quantitative and qualitative. Quantitative methods that have been applied to tourism demand include econometric and time-series methods. Time-series methods include naïve 1-no change, naive2-constant growth, exponential smoothing, univariate Box–Jenkins, autoregression and decomposition (Witt and Witt, 1995). Spatial models (particularly gravity models) have also been used in tourism forecasting. Research on qualitative methods has centered on Delphi method (Rowe and Wright, 1999).

In the existing literature, the majority of articles which are concerned with tourism demand forecasting, are econometric studies that involve the use of least squares regression to estimate the quantitative relationship between tourism demand and its determinants. Typically, the models refer to tourism flows from specific origin to specific destination countries. Thus, a multitude of explanatory variables has been used, related to income of origin country, cost of transportation and prices for each destination, exchange rates between the two countries, marketing and special events. However, least squares regression models that explain international tourism demand have been shown to generate less accurate forecasts than the naïve – 'no change' model (Witt and Witt, 1995). Even econometric models that involve recent methodological developments in particular in the areas of diagnostic checking, cointegration and error correction models still fail to outperform the 'no change' model, which provides some support by Daws (Daws *et al.*, 1994) that 'there is little evidence that the intensive concern with such issues have led to more than a marginal improvement in accuracy' (Kulendran and Witt, 2001). The failure of econometric forecasting to outperform single extrapolative models has been noted in the general forecasting literature (Daws *et al.*, 1994; Witt and Witt, 1995). The relative poor performance of least squares regression models may be a result of various factors since: historical data are not often available, tourism demand can be volatile and is sensitive to catastrophic influences, tourism behaviour is complex and finally there is a wide choice of forecast variables. On the other hand, econometric models can be used to increase our understanding of relationships between and among variables.

Time series methods use pattern in data over the past to extrapolate future values. These models are often more accurate than econometric models, less costly and time consuming to construct. Findings show that simplicity and ease of use are not the only advantages of extrapolative methods. In terms of out-of-sample forecasting accuracy, they often outperform econometric models (Daws *et al.*, 1994; Witt and Witt, 1995, Song and Witt, 2000). Especially Box–Jenkins (ARIMA) models have performed particularly well in tourism data (Kulendran and Witt, 2001; Lim and McAleer, 2002).

III. Technical Analysis Momentum Indicators – RSI

Principles of TA are widely used in favour of the investors or traders that incorporate these principles into an overall investment strategy (Pring, 2002). The technical approach to investment is essentially a reflection of the idea that prices move in trends, which are determined by the changing attitudes of investors toward a variety of economic, monetary, political and psychological forces. The art of technical analysis is to identify trend changes at an early stage and to maintain an investment posture until the weight of the evidence indicates that the trend has reversed.

Momentum indicators

Momentum indicators can warn of latent strength or weakness in the indicator or price being monitored, often well ahead of the final turning point. When a market evolution is taking place, momentum indicators are useful in detecting the *overbought* or *oversold* levels of the price or indicator and defining the exact time to penetrate the underline trend.

Momentum indicators logic is opposite to that of moving-average indicators. The later assume that an 'upward movement will continue' while the former consider that it 'will soon move downwards'. The indicators calculate not the price or indicator changes, but the rate at which they change and they are capable of identifying the loss of momentum before it is indicated so by the price index, that is, the fact that a market is ready to move towards the opposite direction.

A major use of these indicators is the detection of divergences. A divergence happens when the momentum index fails to confirm the highs or lows of the price index. If the price index moves to one direction but the accompanying movement in the momentum index is a much slower one, this pattern suggests that the price index is tired of moving in the direction of the prevailing trend.

*Relative strength indicator (*RSI*)*

The *RSI* was introduced by Wilder (1978). It is a momentum indicator that measures the relative internal strength of a market against itself. The formula of the *RSI* is:

$$RSI = 100 - \frac{100}{1 + RS}$$

where $RS =$ the average of x day's up closes divided by the average of x day's down closes. The indicator fluctuates in a constant range between 0 and 100. Overbought line is drawn at the 70 levels while oversold line is drawn at 30 levels. The most significant and secure signal that *RSI* can give is that of divergence, which Wilder call as 'failure swing'.

IV. Proposed Model

The concept of using *RSI* indicator in tourism demand forecasting is justified from the fact that tourism markets behave more or less like stock markets. When a country's inbound tourism has become highly developed, a number of growing factors affect the country's demand for tourism. Tourism industry tends to rely on its success and as a result, services come behind quality while prices stand on the same or higher levels. On the contrary, the competitive countries improve their services and offer better prices in order to gain the lost market's share. Besides, tourists that like the country and visit it repeatedly contributing to tourism demand, nevertheless being lead by the power of convention and risk aversion, are likely sooner or later to seek for different travelling experiences. So volumes of inbound tourism behave similar to a stock price being in the overbought levels. In the same way when a constant downward trend in a country's inbound tourism is established, tourism industry awakes, improves tourism infrastructures and services, offers reasonable prices and finally makes its product more attractive. In this case tourism demand behaves similar to a stock price being in the oversold levels.

Tourism technical analysis system (TTAS)

The proposed time series model TTAS, is based on the concept of constructing two new equal-weighted time series, the long trend line (*LTL*) that follows the long-term behaviour of the original time series and the short trend line (*STL*), a line that identifies the short-term behaviour of the original time series. The extrapolations of these two new time series will lead after equal-weighted combination to the final point forecasts of TTAS model. The *LTL* line is extrapolated via the linear trend curve method. The *STL* line is extrapolated following a system of rules based on the *RSI* indicator.

The model is basically oriented for yearly data, thus no seasonal adjustment is applied. The model has been scheduled for tourist flows data, optimized and validated for forecasting horizons up to two years ahead.

The steps followed are:

Step 0 (construction of the trend lines).
The time series is constructed from n yearly observations Y_i, $i = 1, 2, \ldots, n$. It is considered that each observation Y_i is an equal-weighted combination of LTL_i and STL_i where LTL_i is the i-th point of the regression line fitted to the data while STL_i is derived from the formula: $Y_i = (LTL_i + STL_i)/2$.
Step 1 (extrapolation).
The *LTL* line is extrapolated via the Linear Regression theory (least squares method, Makridakis *et al.*, 1998). The *STL* line is extrapolated via a method that uses a system of rules based on RSI as described in the following section.
Step 2 (combination).
The forecasts produced from the extrapolation of the two trend lines, *LTL* and *STL*, are combined with equal weights.

An example of the outcomes of the model, that is the two trend lines with the one-step-ahead forecasts and the simple combination of these forecasts (that produces the final forecast) is shown in Fig. 1.

Rule based STL *extrapolation*

The following system of rules, attempts to interpret the behaviour of *STL* in accordance with *RSI*, i.e. what *RSI* values indicate for the next *STL* value, when RSI_t and RSI_{t-1} are in the same or different zones, or RSI_t moves near the overbought or oversold levels line. It also treats the situation when RSI_t moves to the upper area of overbought or the lowest area of oversold levels, while the situation of a dip, i.e. a strong fall in *RSI* or *STL* is examined, as markets tend to be very sensitive in high reductions of tourism volumes. Under certain conditions,

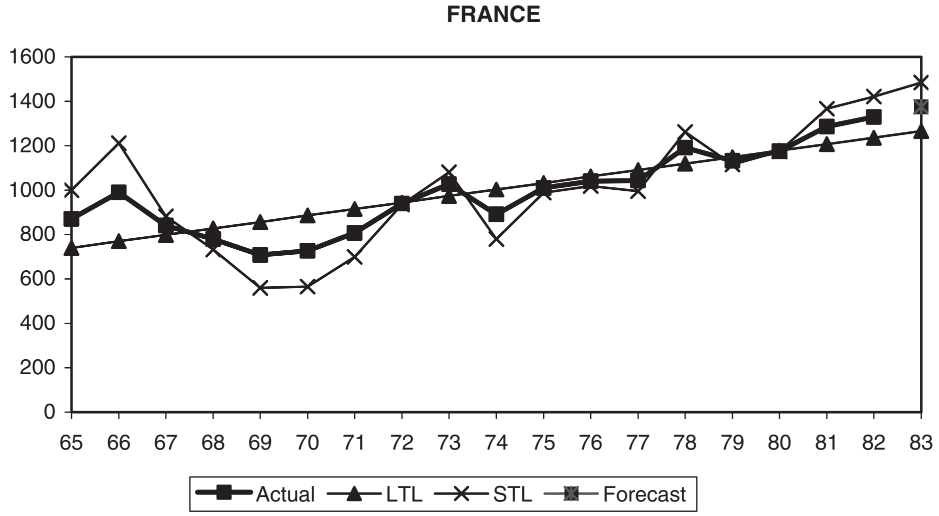

Fig. 1. France tourism market (years 1965–1982)

Table 1. Out of sample MAPE on France, Germany, UK and USA data, MAPE

	Origin country			
Forecasting method	France	Germany	UK	USA
Forecasting horizon 1				
Naïve 1	9.06(2)	5.80(2)	12.73(2)	11.94(2)
Naïve 2	12.76(5)	10.55(7)	15.73(3)	14.10(4)
Exponential smoothing	9.38(3)	7.29(4)	16.72(5)	12.95(3)
Gompertz	13.41(6)	9.07(6)	24.12(7)	16.48(6)
Trend curve analysis	12.54(4)	8.33(5)	22.12(6)	20.93(7)
Autoregression	13.45(7)	5.96(3)	15.81(4)	15.03(5)
TTAS	7.29(1)	5.41(1)	11.80(1)	10.95(1)
Forecasting horizon 2				
Naïve 1	10.08(3)	7.59(2)	18.24(2)	19.43(4)
Naïve 2	22.13(7)	20.77(7)	29.42(5)	17.34(3)
Exponential smoothing	10.22(4)	12.17(5)	23.24(4)	20.48(5)
Gompertz	15.46(5)	13.03(6)	30.45(7)	21.19(6)
Trend curve analysis	17.41(6)	10.61(3)	30.04(6)	29.56(7)
Autoregression	10.04(2)	6.10(1)	16.75(1)	10.73(1)
TTAS	9.18(1)	10.75(4)	19.69(3)	16.86(2)

a strong *RSI* variation, or a failure swing event will cause an inversion in *STL* direction. A measure of *STL* variance is added or subtracted to STL_t in order to get STL_{t+1}.

The proposed algorithm examines the following cases (flowchart 1):

- Dip event
- *RSI* resistance area levels – support levels
- overbought zone ($70 < RSI < 100$)
- normal zone ($30 < RSI < 70$)
- oversold zone ($0 < RSI < 30$)

In order to extrapolate *STL* and produce the point forecast STL_{t+1} for each of the five cases/zones under examination, a set of rules has to be applied. As an example, the set of rules for the *RSI* resistance area levels–support levels case is described in the Appendix. (The description of the whole set of rules is considered out of the scope of this article.)

V. Evaluation

In this article the proposed model was tested versus six classic tourism demand time series forecasting models (Witt and Witt, 1995; Burger *et al.*, 2001; Kulendran and Witt, 2001). Mean absolute percentage error (MAPE) was used to measure out

Table 2. Out of sample directional change accuracy on France, Germany, UK and USA data, direction change error

Forecasting method	Origin country France	Germany	UK	USA	All origins
Forecasting Horizon 1					
Naïve 1	50(4=)	50(4=)	50(4)	50(2=)	200(4)
Naïve 2	39(7)	39(7)	67(2)	50(2=)	195(5)
Exponential smoothing	67(1=)	50(4=)	70(1)	43(5)	230(2)
Gompertz	50(4=)	61(2)	33(7)	42(6)	186(6)
Trend curve analysis	50(4=)	50(4=)	47(6)	33(7)	180(7)
Autoregression	60(3)	67(1)	49(5)	44(4)	220(3)
TTAS	67(1=)	56(3)	57(3)	67(1)	247(1)

of sample forecasting accuracy for horizons 1 and 2 years (Makridakis *et al*., 1998; Law, 2000; Kulendran and Witt, 2001). Directional change accuracy is also measured, for forecasting horizon 1 via direction change error (i.e. if the actual change is positive while the actual change is negative, Witt and Witt [1992]). The results are presented in Tables 1 and 2.

The results, as presented in Table 1, show that the proposed model produced the most accurate (lowest MAPE) tourism demand forecasts for one-year time horizon, while for two-year time horizon ranked second after autoregression method. The proposed model also yields the most accurate forecasts, in average (all origins), of directional changes (Table 2).

VI. Conclusion

The methodology proposed in this article is evaluated for application in the popular tourism demand time series methods. The model provides the most accurate forecasts, when accuracy is measured in terms of the magnitude or forecasting error (MAPE) while in terms of direction change error it performs with a reasonable level of accuracy.

The model innovatively introduces the technical analysis logic into tourism demand forecasting, presenting an alternative way of thinking of the tourism product when the subject is modelling and forecasting. It uses only 10 periods of historical data of a single time series in order to forecast, over-passing the problem of data availability that limits the performance of econometric models.

Our prospect is to upgrade the method and incorporate the ability to treat with one-off events. The evaluation results make the proposed model rather attractive and by all means worth expanding.

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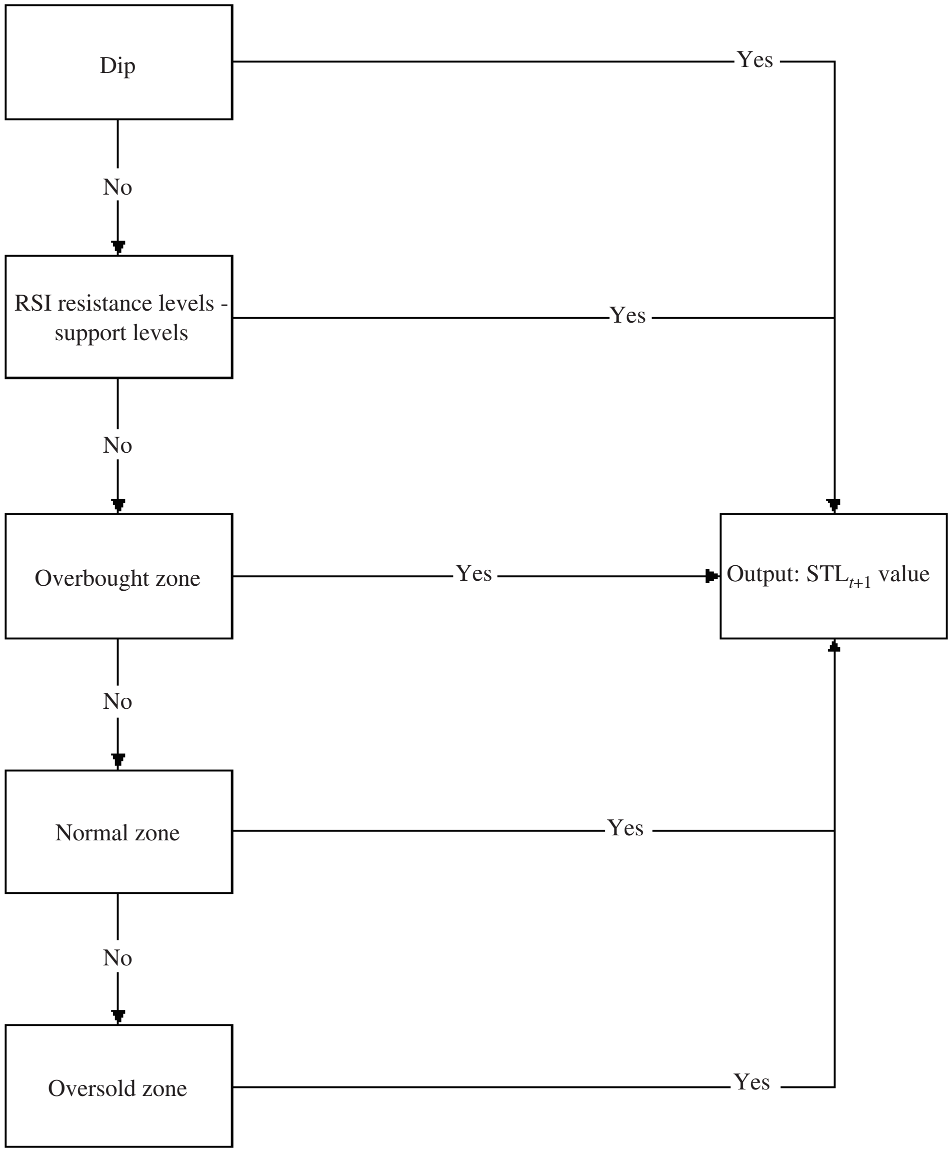
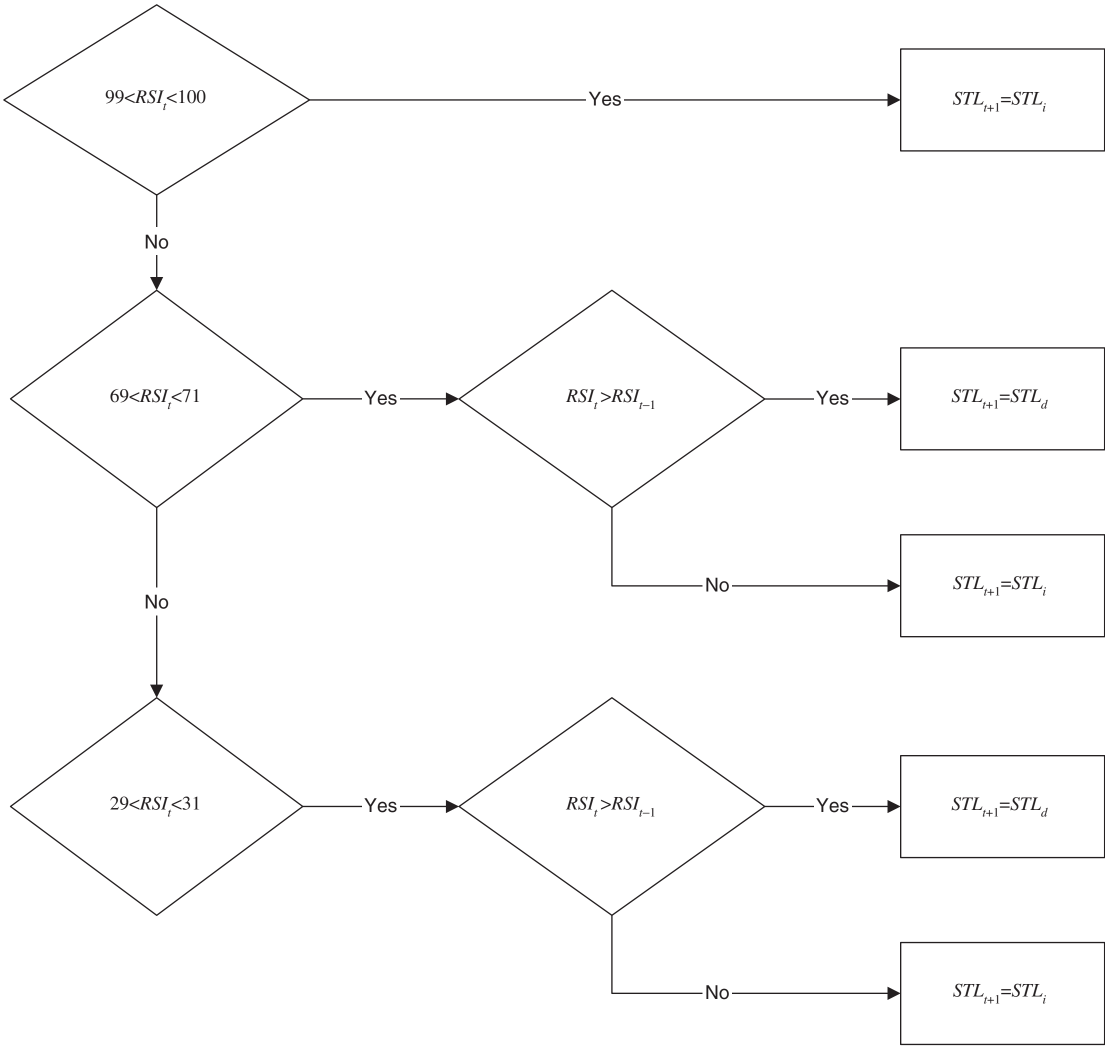
Appendix



Flowchart 1. TTAS, *STL* extrapolation algorithm



Notation:

RSI_t : Value of RSI at period t

STL_t : Value of STL at period t

$$STL_d = \max(STL_t - SDS/2,\ STL_{\min}),\ STL_t > STL_{\min}$$
$$= STL_t - SDS/2,\ STL_t < STL_{\min}$$

$$STL_i = \min(STL_t + SDS/2,\ STL_{\max}),\ STL_t < STL_{\max}$$
$$= STL_t + SDS/2,\ STL_t > STL_{\max}$$

Flowchart 2. *RSI* resistance area levels – support levels, *STL* extrapolation rules