Forecasting demand for qualified labour in the South African hotel industry

by

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As South Africa's popularity as a tourist destination increases its need for skilled human capital subsequently increases. The study of skills development and human capital in all sectors of the economy has long been topical as a means to support organisational progression that can eventually lead to economic growth. Estimates suggest that tourism and hospitality employs at least 10 per cent of the global workforce and consequently proves to be a sector that cannot be readily ignored. Included in most of the literature on skills development in the tourism sector is the notion of inadequate skills and capacity. However, due to the complex and consumption-based nature of the tourism sector, and the general scarcity of sector-related information, data on both demand and supply of skills are few and of a qualitative rather than a quantitative nature. This research addresses this gap and aims to forecast the demand for qualified labour in the South African hotel industry. The research methodology is twofold; firstly, hotel turnover is forecasted using univariate forecasting methods and data available from Statistics South Africa; secondly, a questionnaire was distributed to hotels to obtain information on current and expected turnover, current job levels and current qualification requirements from which employment elasticities can be determined (similar to research by the HRSC (1999)). Linking elasticity with turnover forecasts presents an estimate of the future demand for qualified labour in the hotel industry. In addition, qualitative adjustments are made based on information obtained through the survey.

JEL Codes: C53 - Forecasting Models; Simulation Methods; J23 - Labor Demand; L83 - Sports; Gambling; Restaurants; Recreation; Tourism

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1. Introduction

Tourism is the largest and fastest growing industry in the world. Recent figures estimate the contribution of tourism to the world economy at 10% and every 1 out of 11 persons are employed in the industry (WTTC, 2015a). Also in South Africa, tourism is estimated to contribute 3% directly to the GDP, with 4.5% of all persons employed working in this industry. Through indirect linkages with other industries, the contribution to South Africa's GDP is estimated at 9.4% (WTTC, 2015b).

South Africa's popularity as a tourist destination has increased over the years as well as its need for skilled human capital. The study of skills development and human capital in all sectors of the economy has long been topical as a means to support organisational progression that can eventually lead to economic growth. Estimates suggest that tourism and hospitality employs at least 10 per cent of the global workforce (Baum, 2002:344) and consequently proves to be a sector that cannot be readily ignored.

However, according to Saayman (2013:17), preliminary investigations have shown that poor service in the tourism industry is predominant and this can be attributed to a lack of training and inadequate supply of skilled workers especially in South Africa. This in turn is affecting the level of service provided to tourists, and inadvertently reducing South Africa's level of competitiveness as a tourist destination.

Kaplan (2004:218) found that there is a need for an integrated approach to skills development for this sector in order to realise the full benefits that tourism can offer an economy as a whole. Included in most of the literature on skills development in the tourism sector is the notion of inadequate skills and capacity. However, due to the complex and consumption-based nature of the tourism sector, and the general scarcity of sector-related information, data on both demand and supply of skills are few.

Most importantly, data on the specific educational qualifications that are demanded at different occupational levels in tourism is hard to find. This is confirmed in the report by WTO and ILO (2014) which emphasised that employment in tourism is generally inadequately and insufficiently researched. Current research has concentrated on growing the transparency of labour market developments for the various parties who are interested in a good match between education and the labour market, rather than on a comprehensive planning of required facilities in this field. The present paper will give a quantitative analysis of the educational qualifications that are demanded in the South African accommodation sector according to the National Qualifications Framework (NQF) and the Adult Basic Education and Training (ABET).

The main aim of this research is to analyse the demand for skilled labour, and more specifically the different levels of qualified labour that are required in the tourism accommodation sector in South Africa, and provide a forecast of future output and employment requirements in the this sector. The accommodation sector was chosen because of its centrality to the tourism sector is such that a relatively substantial amount of revenue comes from accommodation compared to other tourism sectors.

The remainder of this article is organised as follows: Section 2 reviews the literature on skills and the labour market in the tourism accommodation sector in South Africa. Section 3 involves a discussion of the data and methodology used in this study. A presentation of the results and empirical findings will be done in section 4 and lastly section 5 draws conclusions about the qualifications that are demanded in the tourism accommodation sector and recommendations thereof.

2. South Africa's tourism labour market

The inception of South Africa as a democratic nation in 1994 formally ended the long-run effects of biased policies and legislation that had a negative impact on the structure and efficiency of the employment sector (Rospabé, 2002:185). The apartheid fabric was such that there was racial segregation in all aspects including employment.

Employment restructuring was progressed by legislative measures in order to redress the inequalities among different racial groups and gender. The measures included the Labour Relations Act of 1995, the Employment Equity Act (EEA) and the Skills Development Act of 1998, and the Promotion of Equality Act and Broad-Based Black Economic Empowerment Act (BBBEE) of 2003 (Horwitz, 2013:2435).

Nevertheless today the country is still struggling with a high unemployment rate of 25 per cent, reported by SARB (2014:2). Recurring levels of unemployment in any economy give unfavourable economic and social costs. Horwitz (2013:2435) suggested that South Africa's high unemployment is mainly because of a labour market paradox of an oversupply of low skilled labour and a shortage of appropriate skills in all sectors of the economy including tourism.

The tourism industry is labour intensive and dynamic in nature as such that if labour is adequately supplied, the industry can realise more economic growth from this sector. In recent years the industry has become so competitive that if tourists and the employees are not satisfied, they will go elsewhere. This is why it is paramount for South Africa to be equipped with workers who have the appropriate qualifications to work in the different levels of employment in the hotel industry, and produce quality service that will set it apart from other tourist destinations in the world.

2.1 Demand and supply of labour in hotels

The level of demand for hotel accommodation services can be seen to change over a 24 hour cycle, a weekly demand pattern (varying between a 'four-day market' and a 'three-day market'), a seasonal pattern (varying between off-season and on-season) and market volatility in response to external forces. Table 1 shows the typical hotel demand variability that inadvertently affects the demand for labour to work in hotels.

Table 1: Hotel Demand Variability

	Examples of hotel demand variability
Daily	Morning rush hour, guest check-out and evening check-in; peak demands for restaurant services during meal time: breakfast (7-10a.m), lunch (12-2p.m) and dinner (7-10p.m).
Weekly	High occupancy during mid-week for business hotels, but low in weekends. More restaurant reservations at the weekend.
Seasonal	Winter closure of beach resorts. High occupancy rate in ski chalets during the winter.
Ad hoc	Flight cancellation leading to unpredictable demand for hotel rooms and meal services. 'Chance' guest bookings.

(Source: Nickson, 2013:79)

Throughout the day, each department and each group of employees in the department are faced with different peaks of demand for their services. The 'four-day market' hotel has a high peak from Monday to Thursday nights, and suffers a drop in occupancy during the weekends (Guerrier & Lockwood, 1989:60). Consequently the 'three-day market' hotel experiences a high peak during the weekends and a low occupancy from Monday to Thursday.

Accommodation demand also depends on local, domestic and international factors and events that are occurring at a particular time. All these different factors affect the need for labour at different times, and since the hotel industry is labour intensive as mentioned before, these also cause the demand for labour to fluctuate in response to these factors.

Since the hospitality industry is labour intensive, employers have tried to minimise the labour costs by flooding their hotels with "marginal workers" on the basis of casual part-time workers. Such workers are reported to be women, young people, students, migrant workers and ethnic minorities, who are fitted into low-skill jobs with relatively low pay (Nickson, 2013:79).

Therefore the supply of labour in hotels has generally attracted workers who desire an income and not necessarily because they have a passion for the industry. Recent research shows that the hospitality sector is one of the least desired career choices (Coughlan, Moolman & Haarhoff, 2013:98). The reasons for this are not hard to find with the industry's characteristic low wages; casual, seasonal and temporary employment contracts and long erratic working hours that make it hard for employees to settle in the hospitality work environment. This lack of passion for the industry may also be resulting in incompetent delivery of service, as workers are unwilling to practice professionalism (Horwitz, 2013:2442).

Nevertheless the dynamic nature of the industry allows employees to benefit from the wide range of remuneration, high labour turnover, seasonality and temporary positions. Such working positions are specifically attractive for the low skilled job seekers, unemployed youth, minority groups, foreigners and part-time job seekers such as students and women with family responsibilities (UNWTO & ILO, 2014).

While employment creation and facilitation of labour market participation are important in decreasing the unemployment rate, the actual allocation of vacant jobs among the unemployed is determined by the matching of job seekers and recruiting firms (Schöer *et al.*, 2014:2). In other words the available labour should at least have the minimum qualifications to work the jobs on offer. The next section will discuss the methodology used to forecast the qualifications demanded in hotels.

3. Method

There are four different methods for forecasting tourism labour demand and these include: market signalling approach, top-down forecasting methods, time series forecasting and the bottom-up coefficient approach. The top-down approach involves identifying the output of the industry and linking it with the labour needs in that industry and to the developments of the rest of the economy (Wong *et al.*, 2004:46). This model assumes that the realised growth in a particular industry will result in proportional growths in the demand for each occupation in that industry and is useful because it allows for long term labour demand predictions.

However empirical evidence shows that it does not allow for changes in business environment, job turnover and occupational mobility.

The labour market signalling methods are based on 'market signals' such as changes in relative wages, employment rates by skills, training among other things. These signals are then used to identify job opportunities as well as skills gaps so as to emphasise the benefits of investing in specific skills (Wong *et al.*, 2004:49), and these models are used when data is insufficient to build a time series model.

This study will employ the time series forecasting method together with the bottom-up model. These two approaches will be discussed in a brief in the next sub sections.

3.1 Time series methods

Box, Jenkins and Reinsel (2008:1) describe a time series as a series of observations that are taken successively over time. This is achieved by substituting the structural limits essential for decreasing the sampling error and improving forecasts, with limits that are determined by the data. These methods are either univariate (a single variable is forecasted based on its past observations) or multivariate (a forecast of several variables).
Time-series methods are advantageous for short-run forecasts because they require relatively less time and energy than causal methods in the short-run (Chu, 1998:598). However they do not explore the reasons that cause a change in labour requirements and structures.

i. The simplest of all the time series methods of forecasting are the naïve methods which provide a benchmark for comparison of all other methods of forecasting. These assume that the past will repeat itself and any trends, seasonality or cycles are either reflected in the previous period's demand or do not exist. For the seasonal Naïve method, Athanasopoulos *et al*. (2011:828) records that all forecasts for seasonal data is equal to the most recent observations of the corresponding season. Therefore the equation becomes:

$$\hat{y}_{(t+h|t)} = y_t + h - km \ldots\ldots, k = \lceil (h-1)/m \rceil + 1 \qquad \text{(Eq. 1)}$$

where $\hat{y}_{(t+h|t)}$ denotes the h-step ahead forecast based on all of the data up to time t, y_t is the last observed value and m is the seasonal period.

ii. An ARIMA time-series model consists of three broad components, a non-seasonal Autoregressive (AR) component, the Integrated (I) component as well as a non-seasonal Moving Average (MA) component. Since ARIMA models comprise different variations, they are regarded as a family of models courtesy of Box and Jenkins (1976) who developed a strategy that guides the researchers in selecting the appropriate model out of a varied family of models.

The SARIMA technique includes identification, estimation and diagnostic checking. The SARIMA model with seasonal difference *(D*) is composed of both seasonal and non-seasonal parts namely: the seasonal part which has its own autoregressive and moving average parameters with orders (*P)* and (*Q)*, and the non-seasonal part with orders *p* and *q* (Kulendran & Wong, 2005:163). In this model the capitalized letters correspond to the seasonal components of the model.

According to Goh & Law (2002:502) the seasonal ARIMA model can be represented by ARIMA (p, d, q)(P, D, Q)$_{\mathbf{s}}$:

$$\boldsymbol{\phi}_p(\boldsymbol{B})\boldsymbol{\varphi}_p(\boldsymbol{B}^s)\boldsymbol{\nabla}^{\mathbf{d}}\boldsymbol{\nabla}_s^{\mathbf{D}}\mathbf{y}_{\mathbf{t}} = \boldsymbol{\theta}_{\mathbf{q}}(\mathbf{B})\boldsymbol{\Theta}_{\mathbf{Q}}(\mathbf{B}^s)\boldsymbol{\varepsilon}_{\mathbf{t}}, \qquad \text{(Eq. 2)}$$

where B is the backward shift operator,$\phi_p(B)$, $\theta_q(B)$, $\varphi_p(B^s)$, and $\Theta_Q(B^s)$ are polynomial in B or B^s of non-seasonal and seasonal orders p, q, P, and Q respectively, and ε_t is the white noise term (Kulendran & Wong, 2005:164). The *s* indicates the order of periodicity or seasonality, φ*p*(*B*) is the non-seasonal AR operator, Φ*P*(*Bs*) is the seasonal AR operator, θ*q*(*B*) is the non-seasonal MA operator, Θ*Q*(*Bs*) is the seasonal MA operator, ∇*d* is the non-seasonal differencing operator and ∇*Ds* is the seasonal differencing operator (Shen, Li & Song, 2009:695).

iii. The exponential smoothing was chosen because it has proven to be an effective model in past studies. It involves forecasting from a rapidly increasing weighted average of previous observations and it seeks to isolate trends or seasonality from irregular variation (Cho, 2003:324). This is done by way of giving the latest observations more weight than the earlier observations. The forecast is derived as a weighted average of previous observations, with the weights declining geometrically as follows:

$$P\ (X_{T+1}) = \alpha\ (X_T + \beta X_{T-1} + \beta^2 X_{T-2} + \cdots + \beta^j X_{T-j}) \qquad \text{(Eq. 3)}$$

where $0 < \beta < 1$ (Carnot, Koen & Tissot, 2005:86).

In other words, the weighting is exponentially decaying with the most recent data getting the most weight and those further back receiving progressively less weight (Goh & Law, 2002:502). According to Billah, King, Snyder and Koehler (2006:239) these models have three simple variations which are commonly used: simple exponential smoothing; trend-corrected exponential smoothing; and Holt–Winters' method.

iv. In addition to the above methods, simple techniques were chosen because they are easy to execute and understand. This includes the Basic Structural Model (BSM) which is based on the assumption that a time series model is composed of a structure that is the summation of a stochastic trend, seasonal, irregular components and an error term (Zhou-Grundy & Turner, 2014:2) and applied in most tourism forecasting studies. By consisting of a trend, seasonal and an irregular component, the BSM has the advantage of allowing an instantaneous interpretation and it thus works as a natural vehicle for making forecasts (Harvey & Peters, 1990:89).

Assume y_t is the observed variable, the basic structural model has the form:

$$y_t = \mu_t + \gamma_t + \epsilon_t, \quad t = 1 \qquad \text{(Eq. 4)}$$

where μ_t is the trend, γ_t is the seasonal component and ϵ_t is the irregular component.

The process generating the trend is of the form:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t, \quad t = 1, \ldots, T \qquad \text{(Eq. 5)}$$

and

$$\beta_t = \beta_{t-1} + \zeta_t, \quad t = 1, \ldots, T \qquad \text{(Eq. 6)}$$

where η_t and ζ_t are normally distributed independent white noise processes with zero means and variances σ_η^2 and σ_ζ^2, respectively. The essential feature of this model is that it is a local approximation to a linear trend. The level and slope both change slowly over time according to a random walk mechanism.

The process generating the seasonal component is:

$$\gamma_t = -\sum_{j-1}^{s-1} \gamma_{t-j} + \omega_t, \quad t = 1, \ldots, T \quad \text{j = 1} \qquad \text{(Eq. 7)}$$

where ω_T ~ NID$(0, \sigma_\omega^2)$, and s is the number of seasons in the year. The seasonal pattern changes slowly through a mechanism that makes sure that the total of the seasonal components over any s consecutive time periods has an anticipated value of zero and a variance that remains constant over time (Harvey & Todd, 1983:300).

3.2 Bottom-up approach

This method employs a labour multiplier approach by assuming that each job assignment will demand a constant level of labour requirement per unit of assignment expenditure and follow a standard demand pattern (Wong *et al.*, 2004:45). The data collected from each assignment will be used to link the supply of labour for an assignment and number of days worked with its past expenditure and used to predict the estimated labour demand by occupation as shown in equations 1 and 2 below.

$$L_{sx}^{J} = \frac{D_{sx}^{J}}{E_{x}^{J}} \qquad \text{(Eq. 8)}$$

$$L_{S}^{D} = \sum_{x} E_{x(est)} \qquad \text{(Eq. 9)}$$

where,

L_{sx}^{J} is the labour multiplier of trade s at stage x of the assignment type j;

L_{S}^{D} is the total labour demand of trade s for a particular hotel assignment;

D_{sx}^{J} is the number of days worked of trade s at stage x of the assignment type j;

E_{x}^{J} is the assignment expenditure at stage x of the project type j.

$E_{x(est)}$ is the estimated project expenditure at stage x.

While this method is mainly used for project-based forecasting, it is similar to the approach applied by the Human Science Research Council (HSRC) in determining labour demand for South Africa (see HSRC, 1999).

This method uses fixed coefficients that are derived by using current employment levels at different job levels and linking these with current output. The disadvantage of the bottom-up approach is that it relies on fixed coefficients and past employment data and future output estimates that might not be readily available (Wong *et al.*, 2004:45).

3.3 Data sources and variables used

Two levels of analysis were completed, namely determining the elasticity of demand for various qualifications in the hotel accommodation sector and then forecasting demand in the hotel accommodation sector.

The variable that was used for the time series forecasting methods (discussed below) was income from accommodation, (hotels to be specific), in South Africa. The data was extracted from the Statistics South Africa (StatsSA) database as monthly income from hotel accommodation, deflated using the CPI for restaurants and hotels, and converted into logarithms over the period September 2004 to January 2015.

Employment data from 1970 to 2014 including statistics on the skilled, semi-skilled and unskilled labour in the hospitality sector (catering and accommodation) was also extracted from the Quantec database. A visual plot of the changing demand for different skills in this industry is shown below. It is evident that the demand for skilled labour is showing an increasing trend, while the demand for highly skilled labour remains relatively flat. The demand for semi- and unskilled labour also shows some stagnation. The employment data, together with real output and labour productivity, are subsequently used to determine the labour elasticities in this sector.

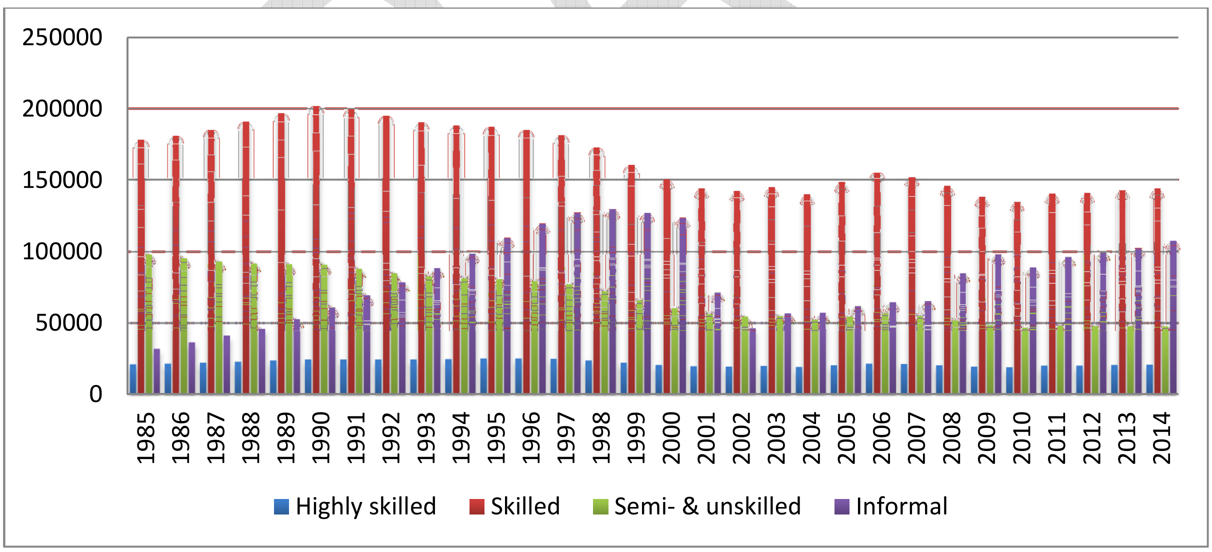

Figure 1: Employment according to skill level in the hospitality industry of SA
(Source of data: Quantec)

While the analysis is mainly based on the data obtained from StatsSA and the Quantec database, the relevant occupations and resulting qualifications are assessed using information obtained from both primary sources as well as CATHSSETA. Data was collected through a web-based survey, where a questionnaire was administered to a stratified sample of star graded hotels in South Africa. The data gathered from the questionnaires provided information about current and expected minimum education requirements according to occupation as well as the lack of qualified labour.

4. Preliminary results

This research follows a combination of the bottom-up approach and time-series forecasting. Firstly, the labour elasticities are derived using aggregate data from 1970-2014 for the hospitality industry (obtained from the Quantec database).

The labour elasticity is then applied to forecasted values of real hotel income, obtained from Statistics South Africa as a monthly series (starting September 2004 until December 2014). These forecasts are obtained using the following time-series methods:

- Naïve forecast (as baseline).
- SARIMA.
- Holt-Winters.
- Unobserved components model (or BSM).

To determine which forecasts are the most efficient, the dataset was divided into a development sample – ranging from 2004M09 to 2012M12 – and a subsequent forecast sample (from 2013M01 to 2014M12). The models were developed using the development sample data and forecasts were obtained for the following 24 months. To measure the accuracy of the forecasts, the forecasted values are compared to the actual values, using the mean average percentage error (MAPE). The model with the lowest MAPE over the 24 months is then used to forecast real income up to 2019.

The MAPE is measured as follows:

$$\text{mean}\ (|p_t|) \qquad \text{(Eq. 10)}$$

where $p_t = 100\, e_t / y_t$. The MAPE is good because they are scale independent, and are mostly used to compare forecast performance across different data sets. However percentage errors are reported to have the disadvantage of being infinite or undefined if y_t= 0 for any t in the period of interest, and having an exceptionally skewed distribution when any value of y_t is close to zero (Hyndman, 2006:44).

4.1 The labour elasticities

According to Hamermesh (1993), the labour demand function is based on minimisation of firm cost. Therefore the demand for labour is a function of the real wage (W), the sales of a firm (Y) and other relevant control factors. To determine labour elasticities that apply to hospitality industry, the following generalised form of the demand function was considered (Babecky et al., 2010):

$\ln L_t^i = \beta_0 + \beta_1 \ln\left(\frac{1}{A_t}\right) + \beta_2 \ln Y_t + \beta_3 \ln W_t + \varepsilon_t$, with $i = s, u$ (Eq. 11)

where $\frac{1}{A_t}$ is the inverse of productivity.

The data were obtained from the Quantec database that distinguishes between highly-skilled, skilled and unskilled (including semi-skilled) labour. For the purposes of this analysis, skilled labour includes both skilled and highly skilled labour input. Real hospitality output (or sales) is also recorded since 1970 and labour productivity is also recorded. The real wage bill is also available, but only at aggregate level (i.e. there is not a distinction between skilled and unskilled wages). The wage rate is determined by dividing the wage bill by the number of workers (both skilled and unskilled). Real output of the hospitality sector is also available since 1970.

Before estimating the models, the data were inspected for their unit root properties using both the augmented Dickey-Fuller and the Phillips Perron tests. According to both these tests, all the variables are I(1) and therefore needs to be differenced in order to obtain stationarity. The data were also inspected for cointegration using the Johansen cointegration test, but no cointegrating vectors were found. Therefore the following model was estimated:

$\Delta \ln L_t^i = \beta_0 + \beta_1 \Delta \ln\left(\frac{1}{A_t}\right) + \beta_2 \Delta \ln Y_t + \beta_3 \Delta \ln W_t + \varepsilon_t$, with $i = s, u$ (Eq. 12)

In each equation, three dummy variables were added to control for structural breaks in the data; these were for 2010 (both models), 2005 (both models), 2008 (unskilled labour) and 2001 (skilled labour). In order to obtain well-behaved error terms, autoregressive terms had to be included to control for autocorrelation. Given this, the errors of both the models for skilled and unskilled labour have normally distributed error terms, with no serial correlation. In none of the equations the wage rate was significant, and this we ascribe to the aggregation of data. The final models therefore exclude the wage rate, since an exclusion of the variable led to improved information criteria and a higher adjusted R-squared. The results of the estimations are shown in the Table below, and it is evident that the labour elasticity for skilled labour is 0.166 and significant. However, the labour elasticity for unskilled labour is only 0.136 and it is only significantly at a 10% level of significance.

Table 2: Regression results – labour coefficients

	Skilled labour	Unskilled labour
constant	-0.055 (0.082)	-0.014** (0.006)
Δln(1/At)	0.339*** (0.054)	0.233*** (0.077)
ΔlnY	0.166*** (0.055)	0.136* (0.076)
DUM2010	0.034** (0.015)	0.055** (0.023)
DUM2005	0.047*** (0.010)	0.039** (0.015)
DUM2001 / DUM2008	0.059*** (0.020)	-0.022 (0.018)
Adj R-squared	*0.718*	*0.653*
AIC	*-4.796*	*-4.688*
SIC	*-4.420*	*-4.358*

4.2 Forecasting hotel income and labour demand

Real hotel income was modelled and forecasted for 24 months. The naïve model, or no change model, provided the benchmark forecast. The models was developed using data from September 2004 to December 2012. The SARIMA model fitted was the typical airline model found to be superior in tourism data, i.e. a SARIMA(0,1,1)(0,1,1) model.

The BSM is estimated using STAMP 8.0 in the OxMetrics program. The strength of the STAMP is that a large range of models can be analysed including univariate and multivariate models (Mendelssohn, 2011:1). Using the linearlised series we find very strong convergence for the BSM, which include a stochastic level and deterministic seasonal component, as well as three irregular components, coinciding with the years 2005 and 2010.

Table 3: Comparison of the accuracy of the forecasting models

	Average MAPE			
	1 month	**6 month**	**12 months**	**24 months**
Naïve	2.736	5.535	5.047	4.751
SARIMA (0,1,1)(0,1,1)	1.372	3.869	4.492	3.335
Holt-Winters (Additive)	1.591	1.954	2.955	3.581
Holt-Winters (Multiplicative)	1.644	1.969	2.963	3.609
BSM	1.746	2.469	3.671	4.524

The forecasting results are compared in Table 3 using the mean average percentage error. It is evident that all the models fitted are better than the baseline naïve model. Over a 1-month period, the SARIMA model outperforms the Holt-Winters models, and this is also true for the 24 months. The Holt-Winters (additive) model is superior over the 6- and 12-month period. There is, however, little difference between the various models, but since the SARIMA almost reaches 5% error and the Holt-winters methods never exceed a 4% error, the forecasts were rather performed using the Holt-Winters additive method.

Applying the Holt Winters method to the real income of hotel data and forecasting until 2019, the forecasts obtained are shown in Table 4. Based on the labour elasticities shown in Table 2, the percentage changes in skilled and unskilled labour demand were determined and are also shown in Table 4. Based on historical data, real income of hotels is expected to increase by 5% in 2015, while the income is expected to be almost 15% higher in 2019 than in 2014.

Based on these changes, the demand for skilled labour is expected to increase by approximately 1% in 2015 and compared to 2014, 2.5% more skilled labourers will be demanded by 2019. The increase in demand for unskilled labour is slightly less, with only a 0.7% increase in 2015 and a 2% increase between 2014 and 2019. It is important to note that this increase in labour demand is only that due to an increase in sales – it does not take into account replacement demand due to retirement or job rotation, or current vacancies that exist.

Table 4: Forecasted changes in hotel income, skilled and unskilled labour

Year	**Y^f (Rm)**	**% change in Y**	**Ls^f**	**% change in L^s**	**Lu^f**	**% change in L^u**
2014	23 592		164 683		47 804	
2015	24 787	5.064%	166 069	0.842%	48 135	0.692%
2016	25 347	7.440%	166 720	1.237%	48 290	1.017%
2017	25 921	9.870%	167 386	1.641%	48 449	1.350%
2018	26 507	12.355%	168 066	2.054%	48 612	1.690%
2019	27 106	14.897%	168 762	2.477%	48 778	2.037%

4.3 What types of qualifications are demanded?

The results above show a clear increase in demand for skilled labour, but exactly what types of qualifications are demanded by hotels? To shed light on this question, results from the questionnaire were used and enhanced by information obtained from CATHSSETA.

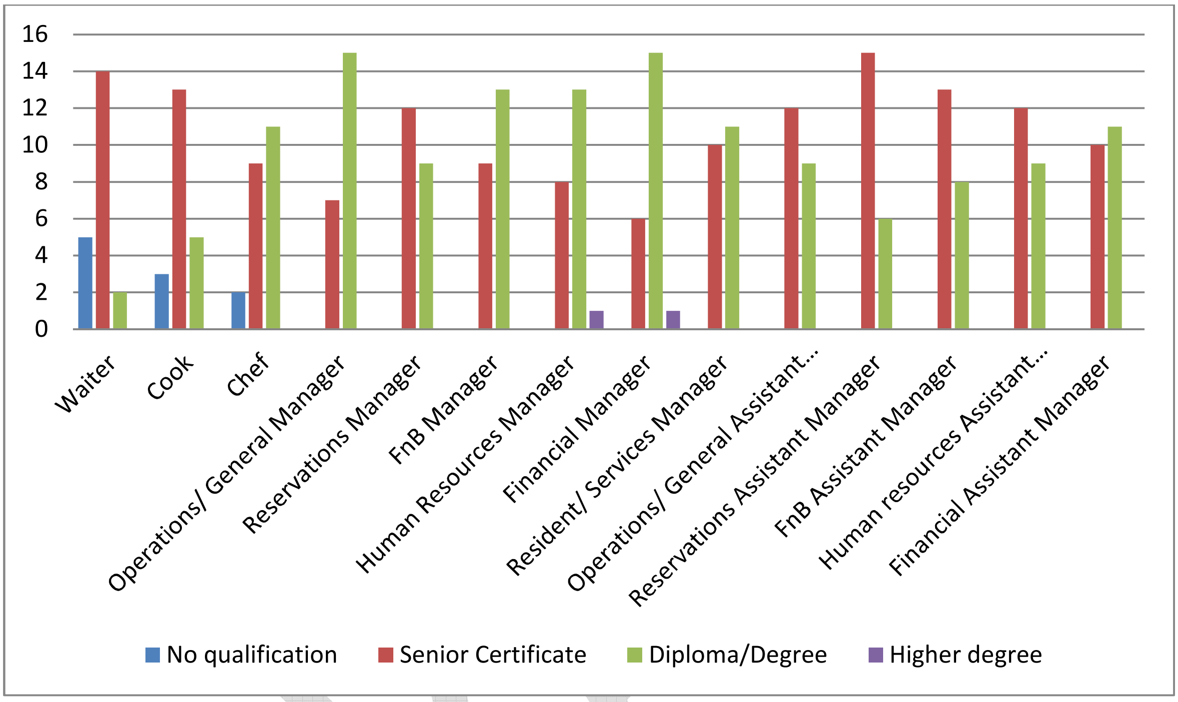

Figure 2: Qualification requirements according to job level

Based on the questionnaire distributed, the minimum qualifications required for different occupations in a hotel are shown in Figure 2. It is evident that all manager occupations require at least a senior certificate, and more often require at least a diploma or degree. The chef occupation is another where the qualification requirement is generally higher. Assistant managers, cooks and waiters are the only occupation where the qualification requirement is less – i.e. biased towards semi- and unskilled labour. It is also noteworthy that higher degrees are only required for financial and human resource managers.

This is largely echoed by the CATHSSETA data (CATHSSETA, 2014). All management occupations in the hospitality sector require qualifications of NQF level 6, with the chef occupation requiring NQF level 4 qualifications. The critically scarce occupations, according to CATHSSETA (2014) include chefs, hotel managers, restaurant managers, general managers and operations managers. In fact, current vacancies in these occupations are 3% and 2.1% for chefs and managers respectively. In addition, 2.8% and 2.4% of chefs and managers will retire within 5 years.

5. Conclusion

The aim of this paper was to analyse the demand for skilled labour, and more specifically the different levels of qualified labour that are required in the tourism accommodation industry in South Africa, and provide a forecast of future output and employment requirements in the this industry. The increase in the importance of tourism and the relative labour-intensity of accommodation as a key part of the tourism offering in a country, is the reason why this is an important question to investigate. Coupled with the fact that while unskilled unemployment in South Africa hovers above 40%, skilled unemployment is less than 6%, the focussed on the demand for skilled labour remains paramount in the South African context.

The main challenge faced in this research is the fact that data is not readily available, leaving one with the task to sensibly combine different data sources. The approach to forecast labour demand followed in this research was that of a bottom-up coefficients approach combined with time-series forecasts. The coefficients were based on data from Quantec for the hospitality industry and both skilled and unskilled labour demand equations were estimated in order to derive labour elasticities.

Three approaches to time-series forecasts were followed, namely the seasonal ARIMA approach, the Holt-Winters exponential smoothing approach and the unobserved components approach. These methods were compared to the baseline naïve forecast results using the MAPE. The data for forecasting was real hotel income (or output), obtained from Statistics South Africa. The comparison showed that the Holt-Winters methods and the SARIMA are more accurate than the naïve and BSM forecasts. Using the Holt-Winters method, hotel income (or output) was forecasted to 2019.

By applying the labour elasticities to the forecasted output, it is forecasted that the demand for skilled labour will increase by 2.5% over the next 5 years. The typical skills required are those of managers (i.e. hotel and restaurant managers) as well as qualified chefs. Current information on vacancies and retirements in these occupations show a further 5.8% of chefs are required and 4.5% managers.

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