Modeling Construction Occupational Demand: Case of Hong Kong

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Abstract: Appropriate training can only be developed if training needs for specific skills are carefully identified. This paper, further to an aggregate model developed previously, aims to forecast the occupational share of the aggregate manpower demand for the construction industry of Hong Kong. The forecast, based on existing manpower statistics, is divided into two levels: broad occupations and detailed occupations. The broad occupational demand forecasting model is formulated using a time-series regression analysis to derive the relationship between the occupational share and the construction output cycle, technology, and various work-mix variables; whereas exponential smoothing technique is used to forecast the share of detailed occupations. This occupational demand estimation can provide solid information to facilitate manpower planning. It enables the policymakers to foresee the trends of occupational manpower demand and formulate policies and training and retraining programs tailored to deal effectively with the industry's human resource requirements in this critical sector of the economy. Although the study focuses on developing models for the Hong Kong construction labor market, the adopted methodology can be applied in other labor markets to develop such models for manpower planning.

DOI: 10.1061/(ASCE)CO.1943-7862.0000205

CE Database subject headings: Construction methods; Forecasting; Labor; Hong Kong.

Author keywords: Construction skills; Exponential smoothing; Regression; Forecasting; Manpower demand.

Introduction

Manpower forecasting has become an important management tool for balancing and structuring the skills of the workforce since the early 1960s (Gill 1996). Economists and educational planners endeavor to advise governments on avoiding imbalances between the supply and demand for skills, whether appearing as structural unemployment or skill shortages impeding economic growth. The forecasts of manpower demand and supply serve as critical guidelines to formulate active labor market policies relating to the provision of educational and training programs (Hughes 1991; Heijke 1994).

In construction, labor resources are valuable assets upon which the construction industry depends on [Chiang et al. 2004; Construction Industry Review Committee (CIRC) 2001]. However, the industry is going through a period of globalization and rapid culture changes accompanied by the introduction of new technologies and new ways of organizing construction activities. Powerful national and multinational clients will continue to influence the choice of these technologies through their demands for faster construction times (Agapiou 1996). As a result, the industry will continue to face increased competition in search of eligible recruits to train for these skills.

Researchers also reveal that the fluctuations in construction output tend to be enormously varied and the movements in skill demand can similarly be strong and rapid (Uwakweh and Maloney 1991; Rosenfeld and Warszawski 1993). In particular, the construction industry contains a large number of quite distinct occupations or skill categories. Supply shortages in any particular category can restrict output, reduce productivity, and result in sudden surge in wages and hence cost (Ball and Wood 1995); whereas oversupply will result in unemployment and is a squander of resources (Kao and Lee 1998). Appropriate training can only be developed if training needs are carefully identified (Agapiou 1996). Hence, it is necessary to realize the future requirements of labor resource, allowing interested parties in the industry to train and retrain workers to address the predicted skill imbalances.

Although the construction industry has long been interested in producing detailed forecasts of output and order (e.g., Tang et al. 1990; Goh 1998; Notman et al. 1998), relatively few published examples on employment projections can be found. Particularly, investigations on future manpower demand by occupations are rarely conducted. In addition, the reliability of the forecasting model in Hong Kong has proved to be unsatisfactory (Wong et al. 2005). It has become clear that a solid understanding of future skill needs for the development of the industry is in great demand.

Among the variety of methodologies, the "manpower requirements approach" is the dominant methodology of tackling the future manpower demand (Wong et al. 2004; Hopkins 2002). This approach first links the manpower requirements with the output of the industry and a number of corresponding variables in the rest of the economy, i.e., the growth of a certain industry will lead to

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Note. This manuscript was submitted on August 13, 2008; approved on February 12, 2010; published online on February 15, 2010. Discussion period open until February 1, 2011; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Construction Engineering and Management***, Vol. 136, No. 9, September 1, 2010. ©ASCE, ISSN 0733-9364/2010/9-991–1002/$25.00.

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Fig. 1. Total employed person in the construction industry of Hong Kong (1985 Q1–2008 Q4). Data source: general household survey, C&SD, and the HKSAR Government.

proportional growths of the manpower demand within this industry (Campbell 1997; Borghans and Willems 1998). Subsequently the occupational employment projections were developed based on past behavior of the occupational share. However, the projection models have not been validated rigorously.

Wong et al. (2007) has developed a model for forecasting aggregate manpower demand for the Hong Kong construction industry based on the Johansen cointegration procedure and error correction modeling technique. Briscoe and Wilson (1993), however, stressed that if the model forecasts are to be of value for effective employment planning, disaggregated projections are required. Once forecasts of the demand for all construction personnel have been derived, it is imperative to disaggregate the total projections into their skill components.

The aim of this paper is therefore, further to the aggregate model, to forecast the occupational construction manpower demand using time-series modeling techniques. Following this introductory section, the trends of construction employment in Hong Kong are discussed as appraising trends of employment and the structure of the local labor market is an important step to developing forecasting models. Previous methodologies for estimating occupational manpower demand are then reviewed and the framework for estimating the occupational demand is set up. It also evaluates the sources and availability of data. Subsequently, the empirical results of modeling the occupational share are presented, including a discussion on the diagnostic tests, predictability test of the developed forecasting models and the applications of the models. Conclusions are drawn in the last section.

Trends of Hong Kong Construction Employment

Fig. 1 shows the historical trends of the total number of employed persons in the construction industry of Hong Kong. Over the past 20 years, the construction employment has increased since the 1980s, reaching a peak of 315,100 in 1998 driven by the major infrastructure projects including the airport core project and extensive housing developments. The construction manpower demand then went into a nearly continuous decline to 257,400 in 2004 owing to the economic recession before rebounding slightly, an 18.3% drop from the peak. The share of the construction employment in total labor force had a narrow variation of between 7.5 and 10% over the last two decades. These figures indicate the significance of the construction industry in Hong Kong as a major employer.

Fig. 2 shows the trends of broad occupational shares for the period of 1993–2008 relative to overall construction employment. Despite the pace of technology and automation, the ratio of site operatives (including craft and related workers; plant and machine operators and assemblers; and elementary occupations) in the industry remains approximately 75% of the total construction employment in 2005. However, the share of crafted and related

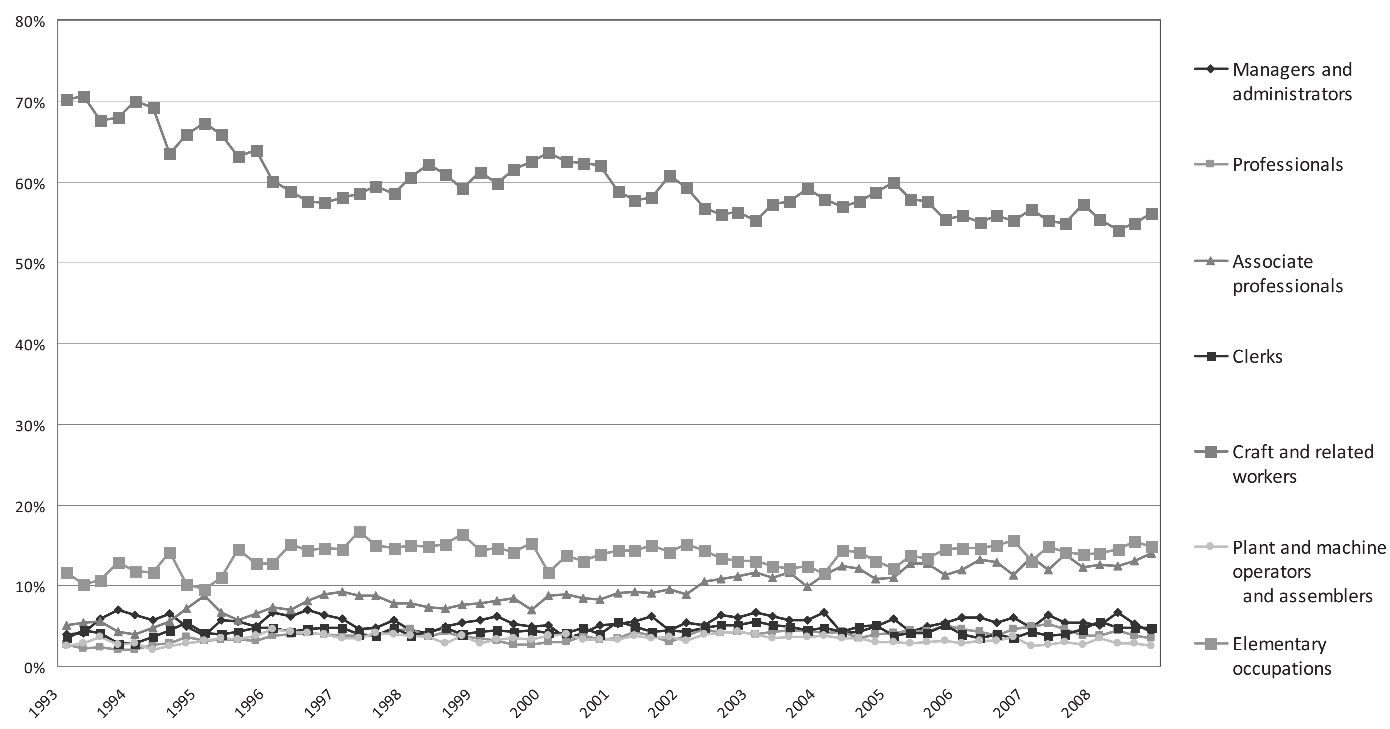

Fig. 2. Broad occupational shares (1993–2008)

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workers is declining steadily from 84.3% in 1993 to 73.4% in 2008. In contrast, the share of higher-level nonmanual occupations including managers, professional staff, as well as associate professionals has exhibited apparent growth over the past 15 years. The share increased from 12.2% in 1993 to 21.8% in 2008. The reasons for these patterns are possibly due to changes in technology, construction methods, complexity of projects, number of establishments, and the effect of regulations (Briscoe and Wilson 1993; Ganesan et al. 1996). An ideal forecasting model would take into account these trends in a full behavioral model to explain the mix of skills required.

Model Framework

Previous Models for Predicting Occupational Employment Shares

Fixed Coefficient Approach

The simplest approach to forecasting future occupational shares is to take the most recent available estimates and assume constancy. A variant on this approach would be to calculate the average percentage shares over the most recent 5 years or so, thus smoothing over the output cycle. The Building and Civil Engineering Industry Training Board of the Vocational Training Council (VTC) in Hong Kong disaggregated the estimated demand by principal jobs using the job structure revealed in the latest survey by assuming the manpower mix to remain reasonably constant over the project period (Wong 1996). Hopkins (2002) also applied this method to forecast the employment demand by occupation in Sri Lanka.

The fixed coefficient approach provides an easily understood basic method of projection (Briscoe and Wilson 1993). However, it fails to use the information available in the time-series data. The trend of the occupation therefore could not be captured. A cursory inspection of Fig. 2 suggests that some of these occupational shares exhibit long-term trend characteristics. Moreover, a number of studies on occupational trends of construction labor markets have established clear trend increases for nonmanual occupations and corresponding reductions for skilled manual trades (Ganesan et al. 1996; VTC 2003). Hence, it is important that the forecasts for future occupational shares take these factors into account.

Another method to estimate the occupational demand is linking the labor requirements to the size and sectoral composition of employment. For instance, Uwakweh and Maloney (1991) proposed a "multiplier approach" which is based on the premise that the industry will demand the same level of labor requirement per unit of construction output and follow a standard demand pattern in the planning horizon. Analogous to this forecasting approach, Rosenfeld and Warszawski (1993) and Chan et al. (2006) adopted this approach to forecast the occupational demand for the construction industry of Israel and Hong Kong, respectively.

Time Trend Models

A basic step toward refining the forecasting model is to test the series for the significance of a linear trend (Briscoe and Wilson 1993). The most primitive time trend forecasting model could be written as

$$P_s = \alpha + \beta(\text{TIME}) \qquad (1)$$

where P_s=percentage share for sth occupation ($s=1,2,3\ldots$). A constraint is applied to ensure that all the occupational shares sum to unity. A number of variants on this basic form are possible, such as an exponential relationship or a quadratic, where occupational share exhibits evidence of accelerating change.

The Institute for Employment Research (IER) in the United Kingdom applied this methodology to forecast occupational demand (Van Eijs 1994). The approach developed at the IER involves two stages. First, projections of the likely changes in industrial employment are made using the multisectoral dynamic macroeconomic model of the economy. Second, projections of the occupational structure within each industry are made based on extrapolations of past trends. These occupational coefficients are then combined with the projected levels of industrial employment to obtain projected levels of employment by occupation (Wilson 1994). The Ministry of Human Resources Development Canada (HRDC) also applied this method to develop an occupation-industry matrix for occupational forecasts in Canada (Smith 2002).

Recently, the models used have been more sophisticated, allowing for changing coefficients and responses to economic variables. An important step toward improving the time trend model is to allow for cyclical influences, as represented by changes in total construction output over the economic cycle. Undoubtedly, cyclically rising output levels could be expected to increase the share of some occupations at the expense of others. For instance, an increase in construction output might have effects, in terms of percentage change in employment demand among different occupations.

In addition to output fluctuations, another potential influence on occupational share is the mixture of the industry workload. It is generally recognized that some of the traditional manual skills are most in demand when output of new works is increasing. Equally, other skills such as managers and professional staff can be expected to increase their employment share when the percentage of new works, as opposed to repair and maintenance, is rising (Ganesan et al. 1996). It is useful to incorporate the effect of these variables

$$P_s = \alpha + \beta_1(\text{TIME}) + \beta_2(\text{OUTPUT}) + \beta_3(\text{MIX}) \qquad (2)$$

Eq. (2) represents potential refinements of the basic time trend approach provided by Eq. (1). In practice, the Research Centre for Education and the Labour Market (ROA) in The Netherlands uses explanatory models instead of extrapolation to forecast the occupational structure. Analogous to the forecasting approach adopted by the HRDC in Canada, the Bureau of Labor Statistic (BLS) in the United States also produces occupational demand forecasts based on an industry-occupation matrix showing the distribution of employment. However, the future change in occupational requirements is estimated by modeling technological change, wage level, changes to organizational patterns, and by making judgments on how the pattern will change in the future (BLS 2003). These models offer more flexibility in projecting occupational shares and thus more reliable forecasts. The increase in computer sophistication in the past two decades has even provided an unprecedented capability for long range forecasting.

Based on the previous specification for modeling the occupational demand, the proposed labor demand estimate for the

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Table 1. Comparison of the Manpower Survey in the Hong Kong Construction Industry

	C&SD (general household survey)	VTC manpower survey	C&SD (report of employment and vacancies at construction sites)
Frequency	Quarterly	Biennially	Quarterly
Coverage of the survey	Based on a sample of quarters selected scientifically from records of all permanent and temporary structures in Hong Kong. The survey covers about 98% of the total population of Hong Kong.	All persons employed by main contractors and subcontractors in construction sites and offices, except those engaged in accounting, administrative, and clerical jobs	All registered private sector sites; all public sector sites under the charge of Works Departments, Housing Department, and railway corporations. Construction projects for village-type houses, minor alternations, repairs, maintenance, and interior decoration of existing buildings are not included.
Labor types involved	Managers and administrators, professionals, associate professionals, clerks, craft and related workers, plant and machine operators and assemblers, and elementary occupations	Professional/technologist (20 detailed occupations), technician (22), tradesman/craftsman (78), semiskilled worker/general worker (9)	Craftsmen, semiskilled, and unskilled workers (33)
Occupational demand figures in 2007			
Managers and administrators	18,258	—	—
Professionals	11,135	14,327	—
Associate professionals	32,148	27,731	—
Craft and related workers	151,814	54,616	69,954
Plant and machine operators and assemblers	10,808		
Clerks	15,251	—	—
Elementary occupations	35,921	17,632	—
Total	275,336	114,306	69,954

construction industry of Hong Kong can be represented by the following function:

$$P_s = f(\text{TIME}, \text{COST}, \text{ARCH}, \text{CIV}, \text{SFPI}, \text{PUB}, \text{PRI}, \text{OTH}, \text{CEI}, \text{CU}) \quad (3)$$

where P_s=percentage share for labor demand of occupation s; TIME=time variable ($1=1993\text{ Q1}, 2=1993\text{ Q2}\cdots$); COST =total construction output in HK$ million; ARCH=construction output in erection of architectural superstructure; CIV =construction output in civil engineering construction; SFPI =construction output in site formation and clearance and piling and related foundation work; PUB=construction output at the public sector; PRI=construction output at the private sector; OTH=construction output at locations other than sites includes general trades (decoration, repair and maintenance) and special trades [carpentry, electrical and mechanical (E&M) fitting, plumbing, and gas work]; CEI=capital to employment index; and CU=capacity utilization index.

Data Sources and Availability

The demand of construction manpower series was compiled by summing the number of employed persons and the vacancy at a specific period. Quarterly employment data were collected from reports of the *General Household Survey* (GHS) issued by the Census and Statistics Department (C&SD) of the HKSAR Government. This employed population comprises all employed person in the construction industry. Vacancy figures were acquired from biennial *Manpower Survey Report on the Building and Civil Engineering Industry* issued by the VTC. In order to generate quarterly vacancy rate, the missing values were replaced using linear interpolation. The rates were subsequently combined to the corresponding employment level to derive the manpower demand series.

Due to the nature of the available data, two levels were involved in modeling the trend of occupational share: broad occupation group and detailed occupations. Employment figures by broad occupations can be obtained from the GHS reports. This series of data available covers seven broad occupations from the first quarter of 1993 to the fourth quarter of 2008, giving a total of 64 data points. The first 48 quarterly records were used for training and developing the model, while the remaining 16-quarter data (i.e., 4 years) served as in independent data set for testing and evaluating the ex-post forecasts. At the detailed occupational level, demand data can only be accessed in the aforementioned biennial VTC manpower survey reports, which are available from 1979 to 2007, covering 129 construction related occupations and giving 15 data points. Similarly, the latest two data points were used to verify the short- to medium-term predictability of the forecasting models. Forty-five occupations out of them are E&M construction job titles compiled by the Electrical and Mechanical Services Training Board of VTC since 2001. Hence, the data set provided by the VTC thus forms the basis for the detailed occupational share analysis of the construction industry. The *Quarterly Report of Employment and Vacancies at Construction Sites* issued by the C&SD also provides detailed occupation figures, but only limited to the manual site workers.

Large discrepancies of the employment figures among these surveys were detected as revealed in Table 1. The discrepancies exist mainly because GHS covers both employed persons work-

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ing in establishments and self-employed persons, whereas the VTC survey covers only those working in establishments technically related to construction work. On the other hand, the employment statistics in construction sites compiled by the C&SD exclude minor alternations, repairs, maintenance, and interior decoration works. By taking into account the properties of these series, the employment series extracted from GHS forms the basis for developing the specification of broad occupational demand functions; the VTC employment statistics are the prime source for share analysis at the detailed occupational level.

Because of these discrepancies, the detailed occupational analysis is confined to professional and associate professional occupational groups. This is also justified by the fact that it is more meaningful and valuable to provide medium-term forecasts of the manpower demand at these levels, since it takes years to properly train a skilled technician or professional. In this sense, the supply of technicians and professionals often cannot respond rapidly to demand increases, especially where such demand changes are unanticipated. In addition, skill mismatches in the higher occupational level are more costly than those in operative level. Nevertheless, more comprehensive forecasts should be made once data are available.

The regressors, except TIME and CEI, were transformed to natural logarithmic form as they displayed lognormal distributions. This also allows examining the log relationship between the occupational share and the independent variables. Data for gross value of construction work, at constant (2000) market prices, were extracted from the reports on the quarterly survey of construction output issued by the C&SD. CEI is a technology variable measured as the capital to labor ratio in the construction sector. The ROA in The Netherlands suggests that this variable represents the capital intensity of production for the sector, relating the volume of investment in equipment, transportation, and engineering work in the past 10 years (as a measure of the stock of capital goods), to the 5-year moving average of employment (as a measure of the "structural" workforce, controlled for business-cycle fluctuations) as shown Eq. (4). We also put the average capital to employment ratio to test the significance for explaining the occupational share represented by Eq. (5)

$$\mathrm{CEI}_t(\mathrm{ROA}) = \frac{\left[\sum_{h=-9}^{0} \mathrm{INV}_{t+h}\right]}{\left[\sum_{h=-2}^{2} \mathrm{EMP}_{t+h}/5\right]} \tag{4}$$

$$\mathrm{CEI}_t(\mathrm{AVG}) = \mathrm{INV}_t/\mathrm{EMP}_t \tag{5}$$

where INV_t=investments in the construction industry in time t and EMP_t=total number of employed person in the construction industry in time t.

The capacity utilization variable (CU) was also incorporated in the occupational model which indicates specific business-cycle effects in construction. The actual production in the sector must be related to the production capacity available. That variable is difficult to construct, however, because there are difficulties in determining a sector's capacity (Dekker et al. 1994). The solution has been found in a variable assumed to fluctuate in positive proportion to the degree of capacity utilization: the value added of the industry in a particular period. According to the C&SD, value added is equal to the gross construction output, minus (1) value of subcontract work rendered by fee subcontractors; (2) consumption of materials and supplies; fuels, electricity and water; and maintenance services; (3) rent, rates, and government rent for land and buildings; (4) rentals for hiring machinery and equipment; and (5) other operating expenses. The value added figures for deriving CEI and CU were obtained from the reports of Principal Statistics for all Building and Civil Engineering Establishments, issued by the C&SD.

Methodology

The starting point of modeling occupational demand is to establish the properties of the time series measuring industry employment (Briscoe and Wilson 1991). Examining the relationships among variables is preceded by tests for the stationarity and drift of the individual occupation series set in Eq. (6). The augmented Dickey-Fuller (ADF) unit root tests developed by Dickey and Fuller (1979) and extended by Said and Dickey (1984) were employed based on auxiliary regression

$$\Delta y_t = \alpha + \delta t + \gamma y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + u_t \tag{6}$$

The variable Δy_{t-i} expresses the lagged first differences, u_t adjusts the serial correlation errors and α, β, and γ=parameters to be estimated. This augmented specification was used to test for H_0:γ=0 in the autogressive (AR) process. If γ=0, then y_t is nonstationary. Under the alternative hypothesis of stationary γ is negative.

The specification in the ADF tests is determined by a "general to specific" procedure by initially estimating a regression with constant and trend, thus testing their significance. Additionally, a sufficient number of lagged first differences are included to remove any serial correlation in the residuals. In order to determine the number of lags in the regression, an initial lag length of eight is selected, and the eighth lag is tested using the Dickey-Fuller tau-statistics. If the lag is insignificant, the lag length is reduced successively until a significant lag length is obtained. Critical values simulated by MacKinnon (1991) were used for the unit root tests.

Disaggregated manpower demand by broad occupation was then modeled using multiple regression analyses (MLR). The MLR analysis is considered the most suitable technique to examine the causal relationships between the independent variables and the occupational share labor requirements (Kao and Lee 1998; Chatterjee and Hadi 1988). Lead and lag relationships between the dependent and independent variables were anticipated as individual occupational share is influenced by the past changes in the independent variables. Therefore, a maximum lag of four quarters was used as this was considered a long enough period for the influence of a change in a factor on the occupational share to be completed. The proposed model is in the form

$$\begin{aligned} P_s = {} & \alpha + \beta_1 \mathrm{TIME} + \beta_{i2} \sum_{i=0}^{4} \ln \mathrm{COST}_{t-i} + \beta_{i3} \sum_{i=0}^{4} \ln \mathrm{ARCH}_{t-i} \\ & + \beta_{i4} \sum_{i=0}^{4} \ln \mathrm{CIV}_{t-i} + \beta_{i5} \sum_{i=0}^{4} \ln \mathrm{SFPI}_{t-i} + \beta_{i6} \sum_{i=0}^{4} \ln \mathrm{PUB}_{t-i} \\ & + \beta_{i7} \sum_{i=0}^{4} \ln \mathrm{PRI}_{t-i} + \beta_{i8} \sum_{i=0}^{4} \ln \mathrm{OTH}_{t-i} + \beta_{i9} \sum_{i=0}^{4} \ln \mathrm{CEI}_{t-i} \\ & + \beta_{i10} \sum_{i=0}^{4} \ln \mathrm{CU}_{t-i} \end{aligned} \tag{7}$$

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Table 2. Models for Nonseasonal Linear Forms of ES

Description	Forecasts (for all $k>0$)	Smoothing method (by the following recursion)
Single smoothing	$\hat{y}_{T+k}=\hat{y}_T$	$\hat{y}_t=\alpha y_t+(1-\alpha)\hat{y}_{t-1}$ where $0<\alpha\leq 1$
Double smoothing	$\hat{y}_{T+k}=2S_T-D_T+\frac{\alpha}{1-\alpha}(S_T-D_T)k$	$S_t=\alpha y_t+(1-\alpha)S_{t-1}$ $D_t=\alpha S_t+(1-\alpha)D_{t-1}$ where $0<\alpha\leq 1$
HW (no seasonal)	$\hat{y}_{T+k}=a(T)+b(T)k$	$a(t)=\alpha y_t+(1-\alpha)[a(t-1)+b(t-1)]$ $b(t)=\beta[a(t)-a(t-1)]+(1-\beta)b(t-1)$ where $0<\alpha,\beta\leq 1$

Eq. (7) was estimated using stepwise regression analysis. The variables that enter and remain in the regression equation are determined by the stepwise regression criteria (probability of F to enter=0.10, probability of F to remove=0.15). Using this method, few variables were selected that meet the criteria. The equations were then reestimated using only the selected variables. This analysis allows, based on economic theory, specifying the economic relationships with the precise quantification of the lag distribution being best left to the data (Burridge et al. 1991).

Diagnostics tests of autocorrelation, normality, and heteroscedasticity were conducted to ensure the reliability of the models. If the error term is autocorrelated, the efficiency of the ordinary least-squares (OLS) parameter estimates is adversely affected and standard error estimates are biased (Pindyck and Rubinfeld 1998). Durbin-Watson (DW) statistics and their marginal probabilities were applied to diagnose autocorrelation. As quarterly data were used, the DW tests were performed for autocorrelation in the OLS residuals for orders 1 through 4. If the DW statistics are significant, autocorrelation correction is needed. Autoregressive error model was applied to correct for serial correlation. The stepwise autoregression method initially fits a model with five autoregressive lags order and then sequentially removes autoregressive parameters until all remaining autoregressive parameters have significant t-tests. The stepwise autoregressive process available in SAS (version 8.0) for PC is performed using the maximum likelihood estimation method.

Lagrange multiplier (LM) tests based on squared residuals were used to test for independence of the series, i.e., heteroscedasticity (McLeod and Li 1983). This kind of heteroscedasticity in time-series data was handled using AR conditional heteroscedasticity (ARCH) model proposed by Engle (1982). The LM test can help determine the order of the ARCH model appropriate for the data. Multicollinearity problem has been checked using the tolerance collinearity statistics among the independent variables in each of the regression model equations. The Jarque-Bera test was applied for examining normality (NORM) of the residuals (Jarque and Bera 1980). The model's predictive ability was also verified using Chow's second test (Chow 1960).

The coverage of the forecasts and the selection of forecasting methodologies depend heavily on the availability and nature of the data (Rosenfeld and Warszawski 1993). At the detailed occupational level, as only 13 biennial data points are available for the construction personnel engaged in the Building and Construction Industry, three nonseasonal exponential smoothing (ES) methods were applied. These include single ES (SES), double ES (DES) (Brown 1959), and Holt-Winter's no seasonal method (HW) (Holt 1957; Winters 1960), as shown in Table 2. For the E&M personnel working in construction sites, since only two data points are available, moving average was used for estimating their share.

ES is an effective way of forecasting when there are only a few observations on which to base the forecast (Bowerman and O'Connell 1993). ES method produces a time trend forecast, but in fitting the trend, the parameters are allowed to change gradually over time, and earlier observations are given exponentially declining weights. In general, ES methods have a proven record for generating sensible point forecasts (Gardner 1985; Makridakis and Hibon 2000). Each method in Table 2 contains a measurement equation that specifies how series values are built from unobserved components. The α and β are so-called smoothing parameters. These parameters were estimated by minimizing the sum of squared errors. The best method for estimating the detailed occupation share is chosen by comparing the root-mean-square error (RMSE).

Analysis of Occupational Trends in Construction

Broad Occupational Level

Following the approach described in the previous section, ADF tests were conducted to examine of the stationarity and the existence of trend of the construction broad occupational series for subsequent modeling. Table 3 reports the results of the unit root tests. It reveals that only the "associate professional" series show a significant positive trend. These statistics also indicate that, for "professional," "associate professional," "crafted and related workers," and "elementary occupations," a unit root can be rejected for the first difference but not the levels at the 5% significance level. Other broad occupations are stationary in level, i.e., integrated of the order zero. Hence, in order to develop a robust model, residuals tests should be carried out with caution especially where nonstationary variables are involved.

Table 4 reports the result of the model fitting process based on Eq. (7) for the seven broad occupations over the period 1993 Q1 to 2004 Q4. Initially, all error terms except the model for professional are positively correlated as indicated by the DW statistics. Autoregressive error model with autoregressive parameter (ν) was therefore applied to adjust for the estimated serial correlation. The results from the corrected best-fit run of multiple regression analysis for each occupation show reasonably good R^2 values and significant F statistics. The signs on output variables show no particular pattern as they are being used to explain occupational shares rather than absolute levels of industrial manpower demand.

The results of the LM tests suggest the presence of heteroscedasticity of the error variance for craft workers equation, which causes inefficient OLS estimations. The test for craft occupation is significant in the order 1, which indicates that first order ARCH model is needed to model the heteroscedasticity. The "AR(1)-ARCH(1)" short memory process model was therefore fit for the

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Table 3. ADF Unit Root Tests

Variable	Test statistics	Critical values	Variable	Test statistics	Critical values
P_{ma}	-3.7582 [C, 3][a]	-2.9286			
P_p	-2.5881 [C]	-2.9241	ΔP_p	-8.8958[a]	-1.9480
P_{ap}	-3.4664 [C, T]	-3.5066	ΔP_{ap}	-6.9990[a]	-1.9480
P_{cw}	-2.3649 [C]	-2.9241	ΔP_{cw}	-7.0158[a]	-1.9480
P_{po}	-3.7582 [C, 6][a]	-2.9339			
P_{ck}	-3.1655 [C, 4][a]	-2.9303			
P_{eo}	-2.6859 [C, 7]	-2.9358	ΔP_{eo}	-7.7884 [1][a]	-1.9481

Note: P_{ma}=share of managers and administrators; P_p=share of professionals; P_{ap}=share of associate professionals; P_{cw}=share of crafted and related workers; P_{po}=share of plant and machine operators and assemblers; P_{ck}=share of clerks; P_{eo}=share of elementary occupations; and Δ=first difference operator. The content of the brackets $[\cdot]$ denotes constant, trend, and the order of augmentation of the ADF test equation, respectively.

[a]Rejection of the null at the 5% significance level.

craft series as shown in the equation. Besides, all tolerance values are larger than 0.01, indicating no multicollinearity problem is posed. The normality tests are also not significant for all error terms of the derived regression equations, which is consistent with the hypothesis that the residuals from the estimated models are normally distributed. The results of the Chow's second test also verified that the models' predictability is robust and valid. This implies that the broad occupational share can be effectively explained by these regression equations which incorporate different combination of construction output cycle, time trend, technology, and work-mix variables.

Detailed Occupation

ES techniques were applied to further estimate the share of the detailed occupations in the professional and associate professional categories. Table 5 shows the parameter estimations of the three ES methods, covering 1979–2003, for each construction occupation. The best method for estimating the detailed occupation share is selected by comparing the RMSE. For example, the HW method gives the smallest RMSE for the occupational share of Building Service Engineer, the estimates of the smoothing parameters turned out to be $\alpha=0.0066$ and $\beta=0$. These results indicate the presence of a rather long memory of the past values, the zero value for β in this case means that the trend component is estimated as fixed and not changing. This estimated equation is a restricted version of model HW list in Table 2. In addition, it is interesting to find that some of the parameters are equal or close to one. This implies that the series is close to a random walk, where the most recent value is the best estimates of future values (Quantitative Micro Software, LLC 2000).

Predictability of the Developed Models

The predictive adequacy of the broad and detailed occupational share models was evaluated by comparing the forecasts with the actual occupational over the ex-post forecasting period, i.e., 2005–2008 as shown in Tables 6 and 7, respectively. The forecast

Table 4. Regression Equations Derived for the Share of Broad Occupations

Regression models	R^2	DW	NORM	CHOW
$P_{\mathrm{ma}}=0.8125^{\mathrm{a}}-0.0231\ \ln\mathrm{COST}^{\mathrm{c}}_{t-2}-0.0597\ \ln\mathrm{OTH}^{\mathrm{a}}_{t-3}+0.0015\ \ln\mathrm{CU}^{\mathrm{c}}_{t}+\nu_t$ $\nu_t=0.3427\nu^{\mathrm{b}}_{t-1}+\varepsilon_t$	0.4715	1.9058	0.0689 (0.9661)	1.48 (0.1935)
$P_p=-0.0145-0.0064\ \ln\mathrm{PUB}^{\mathrm{b}}_{t}+0.0140\ \ln\mathrm{CIV}^{\mathrm{a}}_{t-3}-0.9385\mathrm{CEI(AVG)}^{\mathrm{a}}_{t-3}$	0.7399	1.9067	0.7253 (0.6958)	1.47 (0.1959)
$P_{\mathrm{ap}}=0.1424+0.0282\ \ln\mathrm{COST}^{\mathrm{c}}_{t-4}-0.0291\ \ln\mathrm{ARCH}^{\mathrm{b}}_{t-4}-4.9464\mathrm{CEI(AVG)}^{\mathrm{a}}_{t}+\nu_t$ $\nu_t=0.0359\nu^{\mathrm{c}}_{t-1}+\varepsilon_t$	0.8868	1.8818	1.9875 (0.3702)	1.19 (0.3349)
$P_{\mathrm{cw}}=0.0367+0.0654\ \ln\mathrm{COST}^{\mathrm{c}}_{t}-0.00296\ \mathrm{TIME}^{\mathrm{b}}+\nu_t$ $\nu_t=0.9279\nu^{\mathrm{a}}_{t-1}+(0.000\,279-9.67\times 10^{-19}\varepsilon^{2}_{t-1})^{1/2}e_t$ $e_t\sim\mathrm{IN}(0,1)$	0.8260	1.7740	1.8025 (0.4061)	0.85 (0.6082)
$P_{\mathrm{po}}=-0.0802^{\mathrm{b}}+0.0053\ \ln\mathrm{CIV}^{\mathrm{b}}_{t-3}-0.7589\mathrm{CEI(AVG)}^{\mathrm{a}}_{t-1}+0.0084\ \ln\mathrm{PUB}^{\mathrm{b}}_{t}+\nu_t$ $\nu_t=0.2185\nu^{\mathrm{c}}_{t-1}+\varepsilon_t$	0.6342	1.9173	0.3658 (0.8329)	1.00 (0.4639)
$P_{\mathrm{ck}}=0.1914^{\mathrm{b}}-0.0196\ \ln\mathrm{COST}^{\mathrm{c}}_{t}+0.0092\ \ln\mathrm{SFPI}^{\mathrm{b}}_{t}-1.3371\mathrm{CEI(AVG)}^{\mathrm{a}}_{t}+\nu_t$ $\nu_t=0.1369\nu^{\mathrm{c}}_{t-1}+\varepsilon_t$	0.4857	1.9098	0.0504 (0.9751)	0.25 (0.9945)
$P_{\mathrm{eo}}=-0.4718^{\mathrm{a}}+0.0628\ \ln\mathrm{CU}^{\mathrm{a}}_{t-1}+\nu_t$ $\nu_t=-0.3391\nu^{\mathrm{b}}_{t-5}+\varepsilon_t$	0.5164	1.8025	0.4718 (0.7899)	0.95 (0.5116)

Note: DW=Durbin-Watson statistic; NORM=Jarque-Bera test for normality of the residuals; and CHOW=Chow's second test for predictive failure by splitting the data at fourth quarter 2002. Data in parentheses denote probability values.

[a]t-statistic significant at 0.01 level.

[b]t-statistic significant at 0.05 level.

[c]t-statistic significant at 0.1 level.

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Table 5. Comparison of the Nonseasonal ES Models

Professional					Associate professional				
		Constant					Constant		
Occupation	Method	α	β	RMSE	Occupation	Method	α	β	RMSE
Construction manager/builder	SES	0.9990	—	0.0465	Assistant safety officer/safety supervisor	SES	0.5700	—	0.0068
	DES	0.6120	—	0.0556		DES[a]	0.0010	—	0.0047
	HW[a]	0.9999	0.0001	0.0453		HW	0.0500	0.3501	0.0048
Civil engineer	SES	0.9990	—	0.0628	Civil/structural/geotechnical engineering technician	SES	0.7780	—	0.0408
	DES	0.2860	—	0.0663		DES[a]	0.0090	—	0.0342
	HW[a]	0.9999	0.0001	0.0549		HW	0.5101	0.0500	0.0394
Construction plant engineer	SES	0.9220	—	0.0014	Clerk of works/inspector of works/works supervisors	SES[a]	0.3000	—	0.0513
	DES	0.4340	—	0.0014		DES	0.2700	—	0.0536
	HW[a]	0.7900	0.1400	0.0014		HW	0.2400	0.9501	0.0558
Environmental engineer	SES	0.9990	—	0.0134	Construction plant technician	SES	0.7380	—	0.0028
	DES	0.5900	—	0.0144		DES	0.3800	—	0.0026
	HW[a]	0.9999	0.1400	0.0133		HW[a]	0.3100	1.0000	0.0024
Geotechnical engineer	SES	0.1460	—	0.0127	Construction purchaser/storekeeper	SES[a]	0.9620	—	0.0084
	DES[a]	0.0010	—	0.0113		DES	0.3060	—	0.0091
	HW	0.5700	0.1000	0.0161		HW	0.9600	0.0000	0.0084
Safety officer	SES	0.9990	—	0.0079	Estimator	SES[a]	0.1600	—	0.0279
	DES[a]	0.0010	—	0.0050		DES	0.2000	—	0.0292
	HW	0.6700	0.0000	0.0056		HW	0.1900	1.0000	0.0282
Structural engineer	SES[a]	0.5660	—	0.0272	Interior design technician	SES	0.3880	—	0.0084
	DES	0.3180	—	0.0291		DES	0.1440	—	0.0082
	HW	0.5800	0.2200	0.0297		HW[a]	0.1800	1.0000	0.0081
Town planner	SES[a]	0.0010	—	0.0090	Civil/structural/geotechnical design technician	SES[a]	0.0460	—	0.0366
	DES	0.4880	—	0.0098		DES	0.3040	—	0.0412
	HW	0.9600	0.0200	0.0091		HW	0.0600	0.0100	0.0372
Engineering geologist	SES	0.9990	—	0.0021	Laboratory technician (construction materials/soils)	SES[a]	0.0010	—	0.0098
	DES	0.5700	—	0.0022		DES	0.0010	—	0.0098
	HW[a]	0.9999	0.1500	0.0021		HW	0.0900	0.0000	0.0104
Quality assurance engineer	SES	0.9990	—	0.0062	Site agent	SES	0.6320	—	0.0160
	DES	0.8100	—	0.0051		DES[a]	0.3720	—	0.0129
	HW[a]	0.9999	0.5500	0.0050		HW	0.6200	0.2400	0.0130
Building services engineer	SES	0.7880	—	0.0188	Site foreman	SES	0.7280	—	0.0558
	DES	0.1520	—	0.0154		DES	0.4260	—	0.0411
	HW[a]	0.0066	0.0001	0.0136		HW[a]	0.2899	1.0000	0.0410
					Quality assurance engineer	SES	0.9990	—	0.0034
						DES	0.9990	—	0.0017
						HW[a]	1.0000	1.0000	0.0017
					Building services engineering/electrical engineer/mechanical engineer technician	SES	0.9340	—	0.0268
						DES	0.4760	—	0.0231
						HW[a]	0.9500	0.0000	0.0222

[a]Indicates best-fit model.

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Table 6. Evaluation of the Broad Occupational Share Forecasts

	2005			2006			2007			2008		
Occupations	Estimate	Actual	Diff. (%)	Estimate	Actual	Diff. (%)	Estimate	Actual	Diff. (%)	Estimate	Actual	Diff. (%)
Managers and administrators	4.73	5.23	−0.50	5.06	5.88	−0.82	5.02	5.47	−0.45	4.99	5.34	−0.35
Professionals	4.17	4.64	−0.47	3.97	4.36	−0.39	4.06	4.64	−0.58	4.16	3.91	0.25
Associate professionals	10.41	11.03	−0.62	10.65	12.32	−1.67	11.22	11.89	−0.67	11.83	12.04	−0.21
Craft and related workers	59.68	57.47	2.21	58.43	55.43	3.00	57.31	55.97	1.34	56.43	55.03	1.40
Plant and machine operators and assemblers	3.64	4.36	−0.72	3.67	3.79	−0.12	3.74	4.19	−0.45	3.83	4.97	−1.14
Clerks	4.51	3.98	0.53	4.59	4.16	0.43	4.69	3.76	0.93	4.80	3.92	0.88
Elementary occupations	12.86	13.25	−0.39	13.62	14.00	−0.38	13.96	13.98	−0.02	13.96	14.74	−0.78
Total	100	100		100	100		100	100		100	100	
		MAPE: 0.78%			MAPE: 0.97%			MAPE: 0.64%			MAPE: 0.72%	

Note: All occupational shares are constrained to sum to 100%.

values for the independent variables are based on log linear trend extrapolation. A constraint is applied to ensure that all the occupational shares sum to unity.

The mean absolute percentage error (MAPE) was used to quantitatively measure how closely the forecasted variable tracks the actual data. The prediction percentage error of the forecasting model at the broad occupational level is consistently less than 1% MAPE. At the detailed occupational level, although the forecasting errors for some occupations are nearly 4% due to the fluctuated demand for a particular trade, the overall MAPEs in 2005 and 2007 are reasonably low, ranging from 0.54 to 1.11%. Hence, the results of the diagnostic tests and the evaluation of forecasts verify that the developed occupational share models are adequately robust and reliable to forecast the short- to medium-term occupational share of the construction employment in Hong Kong.

The forecasting models could serve as a practical tool for policy makers in government and training institutions to assess the future manpower demand. Although the coverage of the forecasts at the detailed occupation level is confined to professionals and associate professionals, the occupational share can combine with the projected level of industrial manpower demand, to derive manpower demand by occupation. The manpower forecasts allow the industry to identify early imbalance for these occupations in the labor market for short to medium terms.

Conclusions

The construction industry in Hong Kong is recognized as an important industry that has consistently contributed to the spectacular economic growth of the territory [Construction Industry Review Committee (CIRC) 2001]. The industry enjoyed a boom in the 1990s, but it was badly hit by the recent economic downturn. Proper employment planning has become one of the critical factors for the recovery of the economy. Neugart and Schömann (2002) stressed that a successful policy must respond to shifts in the demand for skills and qualifications flexibly, and in due time. It is therefore essential for the construction industry to appreciate the complexity of the labor resource requirements in order to ensure an adequate supply of labor skills. Manpower forecasting is a powerful tool to help anticipate and respond swiftly to changing requirements in occupational labor markets, by minimizing structural unemployment or skill shortage (Wong et al. 2004).

This paper attempts to establish forecasting models for estimating the demand for specific skills of the Hong Kong construction industry. This research is a new attempt to improve the forecasts of manpower demand in two ways. First, the factors affecting occupational share were identified. Second, more importantly, these factors are incorporated effectively in the forecasting models and their lag relationships with the occupational share were considered. The information provided by such assessments is a key input into decisions to be made about the scale and content of immediate actions to adjust different education and training programs and strategies by government agencies, education provider companies, and trade unions (Agapiou et al. 1995). This study also compliments CIRC's recommendation to facilitate employment projection for reference by policy makers and the industry.

The broad occupational demand forecasting model is formulated from a separate set of regression equations which make the respective occupational shares a function of trend, output cycle, technology, and various work-mix variables; whereas ES technique was used to forecast the share of detailed occupations. These occupational share models, in association with the aggregated model developed previously, serve as a practical and robust tool to estimate the manpower required for the construction industry of Hong Kong for short to medium terms (i.e., 1–5 years). The labor demand estimation can provide solid information to facilitate manpower planning. It enables the policymakers to foresee the trend of manpower demand and formulate policies and training programs tailored to deal effectively with the industry's labor resource requirements in this critical sector of economy.

Since data were not available indicating the breakdown of labor demand on each occupational category, further investigation is therefore recommended to collect data and update the regression models once enough data points are collected for detailed estimations. In addition, qualitative information such as employers' view and expert knowledge are increasingly being incorporated in the forecasts, which can be complementary to the pure quantitative estimates. Although this paper focuses on developing models for the Hong Kong construction labor market, similar methodology can be applied in other labor markets to develop such models for manpower planning. The forecasts can be disaggregated by region and occupation in such markets, subject to the availability of indigenous data series.

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Table 7. Evaluation of the Detailed Occupational Share Forecasts

Professional

Occupations	2005 Estimate	2005 Actual	2005 Diff. (%)	2007 Estimate	2007 Actual	2007 Diff. (%)
Construction manager/builder	11.04	13.61	−2.57	12.26	11.07	1.19
Civil engineer	33.50	35.00	−1.50	28.55	30.10	−1.55
Construction plant engineer	0.59	0.51	0.08	0.69	1.94	−1.25
Environmental engineer	6.17	3.97	2.20	6.96	5.56	1.40
Geotechnical engineer	5.23	5.47	−0.24	4.80	7.09	−2.29
Safety officer	6.42	5.53	0.89	7.36	5.10	2.26
Structural engineer	13.20	12.21	0.99	12.95	14.93	−1.98
Town planner	4.03	4.55	−0.52	3.95	3.56	0.39
Engineering geologist	1.06	1.19	−0.13	1.25	1.22	0.03
Quality control/assurance engineer	4.44	3.91	0.53	6.02	4.33	1.69
Building services engineer	12.93	13.01	−0.08	13.84	14.50	−0.66
Control and instrumentation engineer	0.06	0.07	−0.01	0.06	0.00	0.06
Electrical engineer	0.44	0.15	0.29	0.43	0.25	0.18
Electronics engineer	0.04	0.05	−0.01	0.04	0.00	0.04
Lift engineer	0.14	0.24	−0.10	0.14	0.08	0.06
Mechanical engineer	0.09	0.04	0.05	0.09	0.10	−0.01
Refrigeration/air–conditioning/ventilation engineer	0.28	0.25	0.03	0.27	0.06	0.21
Fire services engineer	0.22	0.13	0.09	0.21	0.04	0.17
Engineering manager	0.13	0.12	0.01	0.13	0.08	0.05
Total	100.00	100.00		100.00	100.00	
		MAPE: 0.54%			MAPE: 0.82%	

Associate professional

Occupations	2005 Estimate	2005 Actual	2005 Diff. (%)	2007 Estimate	2007 Actual	2007 Diff. (%)
Assistant safety officer/safety supervisor	2.42	1.64	0.78	2.54	1.41	1.13
Civil/structural/geotechnical engineering technician	16.16	16.67	−0.51	17.40	18.37	−0.97
Clerk of works/inspector of works/works supervisors	26.96	25.06	1.90	24.63	26.69	−2.06
Construction plant technician	1.11	0.36	0.75	1.48	0.73	0.75
Construction purchaser/storekeeper	1.59	2.65	−1.06	1.45	1.90	−0.45
Estimator	3.35	4.61	−1.26	3.06	6.83	−3.77
Interior design technician	2.14	4.11	−1.97	2.83	5.32	−2.49
Site agent	4.65	5.24	−0.59	3.84	4.84	−1.00
Laboratory technician (construction materials/soils)	2.99	3.65	−0.66	2.74	4.23	−1.49
Civil/structural/geotechnical design technician	1.7	1.00	0.70	1.55	0.00	1.55
Site foreman	24.75	26.74	−1.99	24.18	22.65	1.53
Quality control assurance technician	2.47	0.91	1.56	3.48	0.88	2.60
Lift technician	0.39	0.20	0.19	0.36	0.04	0.32
Draughtsman	0.06	0.07	−0.01	0.06	0.03	0.03
Electrical instrument and meter technician	0.06	0.14	−0.08	0.05	0.02	0.03
Electronics technician	0.09	0.02	0.07	0.08	0.03	0.05
Building services engineering/electrical engineer/mechanical engineer technician	7.96	5.50	2.46	9.23	5.44	3.79
Telecommunication technician	0.06	0.06	0.00	0.06	0.00	0.06
Refrigeration/air-conditioning/ventilation technician	0.42	0.65	−0.23	0.38	0.25	0.13
supervisor	0.31	0.13	0.18	0.28	0.23	0.05
Fire services technician	0.34	0.58	−0.24	0.31	0.11	0.20
AV/TV service technician	0.01	0.00	0.01	0.01	0.00	0.01
	100.00	100.00		100.00	100.00	
		MAPE: 0.78%			MAPE: 1.11%	

Note: All occupational shares are constrained to sum to 100%.

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