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Modeling of Monthly Residential and Commercial Electricity Consumption Using Nonlinear Seasonal Models—The Case of Hong Kong

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Abstract: Accurate modeling and forecasting monthly electricity consumption are the keys to optimizing energy management and planning. This paper examines the seasonal characteristics of electricity consumption in Hong Kong—a subtropical city with 7 million people. Using the data from January 1970 to December 2014, two novel nonlinear seasonal models for electricity consumption in the residential and commercial sectors were obtained. The models show that the city's monthly residential and commercial electricity consumption patterns have different seasonal variations. Specifically, monthly residential electricity consumption (mainly for appliances and cooling in summer) has a quadratic relationship with monthly mean air temperature, while monthly commercial electricity consumption has a linear relationship with monthly mean air temperature. The nonlinear seasonal models were used to predict residential and commercial electricity consumption for the period January 2015–December 2016. The correlations between the predicted and actual values were 0.976 for residential electricity consumption and 0.962 for commercial electricity consumption, respectively. The root mean square percentage errors for the predicted monthly residential and commercial electricity consumption were 7.0% and 6.5%, respectively. The new nonlinear seasonal models can be applied to other subtropical urban areas, and recommendations on the reduction of commercial electricity consumption are given.

Keywords: modeling; forecasting; monthly electricity consumption; seasonal analysis; nonlinear model

1. Introduction

The modeling and forecasting of electricity consumption are crucial to a country's or city's energy management and planning, as well as to its economic development. Previous research has shown that the growth of energy consumption is related to the increase in population and economic growth of a country or city [1–7], and the demand for more electricity is expected to continue [4–6]. Hence, accurate forecasts of electricity consumption trends and variations are important, because they can help avoid power outages, waste of scarce energy resources, and overinvestment in capital equipment.

Niu et al. [6] studied the association between electricity consumption and human development level. With panel data collected from 50 countries for the period between 1990 and 2009, Niu et al. [6] reported that, generally, higher incomes lead to a greater demand in electricity and a higher level of human development. Kandananond [7] applied the autoregressive integrated moving average (ARIMA), artificial neural network (ANN), and multiple linear regression (MLR) to characterize annual electricity consumption in Thailand. Li et al. [8] explored the use of a least squares support vector machine (LSSVM) approach to modeling annual electricity consumption in China between 1978 and 2011. Li et al. [8] reported that the LSSVM model was able to reproduce China's annual electricity consumption (with the smallest percentage error in comparison with the generalized regression neural network and the MLR model). Chang et al. [9] developed and applied the weighted evolving fuzzy neural network for predicting monthly electricity demand in Taiwan. Suh and Chang [10] developed a residential energy consumption estimation model using ANN. Using datasets covering the characteristics of residential buildings, locations, and electricity usage for thirty apartment complexes in Korea, Suh and Chang [10] reported that the number of residential buildings, the number of households, the gross area, and the maintenance area significantly influence energy consumption of multi-family housing complexes. Lai et al. [4] studied Macao's monthly total electricity consumption during the period January 2000–December 2006. They reported that demographic, economic, and climatic factors such as population, the number of tourists, hotel room occupancy, and monthly mean air temperature affect electricity consumption (when monthly total electricity consumption is of the form of a power-of-two polynomial). Lai et al. [4] also compared the predictions of MLR, ANN, and wavelet-ANN models. Although ANN models were able to predict electricity consumption slightly better, they did not provide insight into how each factor affects the monthly total electricity consumption [4]. To et al. [5] reported that Hong Kong's annual total electricity consumption increased from 4451 million kWh (i.e., 16,023 TJ) in 1970 to 41,862 million kWh (i.e., 150,704 TJ) in 2010, while Hong Kong's population increased from 4.0 million to 7.1 million during the same period. To et al. [5] indicated that the increase in electricity consumption was partly influenced by population growth, but more significantly influenced by changes in the structure of the economy over the period 1970–2010. They also showed that Hong Kong's annual total electricity consumption has followed a logistic growth pattern during the past four decades.

Monthly electricity consumption shows a distinct seasonal pattern [4,9,11]. Apadula et al. [11] studied the effect of meteorological factors such as temperature, wind speed, relative humidity, and cloud cover on monthly electricity consumption in Italy. They identified that temperature is the most significant predictor of monthly electricity consumption in Italy. Rossi et al. [12] and Morini et al. [13] indicated that the characteristics of urban areas, including the lack of vegetation, the absorption of solar radiation by road and building surfaces, anthropogenic heat fluxes from building energy use, and the blockage of wind by buildings exacerbate urban heat island effect, causing an increase in energy consumption for summer cooling. Rossi et al. [12] reported that electricity consumption in the city of Rome increased from 8450 TJ in 1962, to 19,100 TJ in 1982, then to 59,000 TJ in 2008. Rossi et al. [12] showed that higher ambient temperature in urban areas causes a more frequent replacement of LED lamps for street lighting, resulting in an increase of carbon footprint. Morini et al. [13] showed that retro-reflective materials can reduce the energy trapped within the urban canopy when they are applied as coatings on building surfaces, while De Santoli et al. [14] showed that a hybrid heating system with a photovoltaics array and a two-stage electric heat pump can reduce electricity consumption quite significantly. Santamouris et al. [15] and Kapsomenakis et al. [16] studied the influence of urban climate on the energy consumption of buildings in Greece. Kapsomenakis et al. [16] showed that the increase in air temperature considerably increased the total energy consumption of the building sector, because the energy demand for cooling was much greater than that for heating. Zhu et al. [17] indicated that electricity consumption exhibits nonlinear characteristics, such as seasonality and nonlinear increasing trends. They proposed a seasonal hybrid procedure for forecasting electricity consumption in China. Lam [18] and Lam et al. [19] found that electricity consumption increased rapidly during the summer months in Hong Kong, and that the electricity consumption of air conditioning alone accounted for more than 50% of the total amount of electricity consumption in the city's residential and commercial sectors. In Hong Kong, residential electricity consumption is the total electricity use by all households, while commercial electricity consumption is the total electricity use by commercial entities such as commercial buildings, hotels, shopping centers, markets, shops, etc. However, Lam et al. [19] did not develop seasonal models for electricity consumption. The same seasonal phenomenon was reported by Chua et al. [20] for other subtropical regions. As a result, there is a lack of literature on nonlinear, statistical, seasonal analysis of Hong Kong's electricity consumption using long-term monthly data. As understanding the seasonal patterns of electricity consumption can enable the government, building owners, managers, and operators to manage their utilities more efficiently, the objectives of this paper are: (i) to identify the trends and seasonal patterns of monthly electricity consumption in Hong Kong's residential and commercial sectors from January 1970 to December 2014; (ii) to develop nonlinear seasonal (or mixed) models that take long-term logistic growth and the seasonality of residential and commercial electricity consumption into consideration; and (iii) to validate nonlinear seasonal models using monthly electricity consumption data from January 2015 to December 2016.

The structure of the rest of this paper is as follows: first, the next section presents the methodology, including the normalized electricity consumption values, 4-parameter logistic model, coefficient of determination, a generalized nonlinear seasonal model for electricity consumption, and error analysis; second, the results and analysis are presented; and finally, the paper ends with conclusions and recommendations.

2. Method

In this paper, the values of monthly electricity consumption were normalized by annual electricity consumption data to reveal the seasonal characteristics of the data during the past forty six years. The trend was determined using a 4-parameter logistic growth model. Other mathematical tools/approaches, including coefficient of determination and error analysis, were used to determine the fit between the predicted values and actual values. Details of the methods are given as below.

2.1. Normalized Monthly Electricity Consumption Values

Radar diagrams were used to show the seasonal variations of residential and commercial electricity consumption data. Moreover, the patterns of seasonal variations were determined using normalized monthly electricity consumption, as shown in Equation (1):

$$Elec_{i,t}^{normalized} = \frac{Elec_{i,t}}{\sum\limits_{j=1}^{12} Elec_{j,t}} \times 100\% \tag{1}$$

where $Elec_{i,t}$ is electricity consumption in TJ and $Elec_{i,t}^{normalized}$ is normalized electricity consumption in the i month of the year t in percent.

2.2. Seasonal Time-Series Data

Human activities vary from time to time and they depend on economic, social, and climatic conditions. Hence, it is common that the output of an economy exhibits seasonal variation. For example, economists have found that the total manufacturing output and a country's GDP have strong seasonal characteristics [21,22]. Similarly, the consumption of resources such as electricity, total energy, water, and other raw materials has strong seasonal characteristics [7,17,23,24]. In order to understand the underlying trend of a data set that is affected by seasonal variation, economists [21,22] suggest that a seasonal time series has three components, namely the trend, the seasonal component, and the error term (or residual). Hence, monthly electricity consumption can be expressed as:

$$Elec_{i,t} = TElec_{i,t} + SElec_{i,t} + \varepsilon_{i,t} \tag{2}$$

where $TElec_{i,t}$ is the trend of electricity consumption, $SElec_{i,t}$ is the seasonal component, and $\varepsilon_{i,t}$ is the error term (or residual) in the i month of the year t.

2.3. Four-Paramter Logistic Model for the Trend

Researchers including biologists, sociologists, and economists have illustrated that the population of a species, the adoption of innovations, or the growth of an economy depends on how well the species, innovations, or economic structure adapts to the environment and the availability of remaining resources or opportunities [25–27]. The population/innovations/economy initially has a slow rate of growth, followed by a rapid rate of growth and a leveling off at the saturation level; as a result, growth normally follows an S-shaped curve, also known as the logistic growth curve. To and Lee [28] reviewed the diffusion of the ISO14001 environmental management system and identified that the diffusion of ISO14001 follows logistic growth at global, regional, and country-specific levels. Lai and To [29] applied the logistic model to characterize the growth of Internet users in China and predicted, accurately, that the number of Internet users in China would exceed 670 million in 2015. To and Lee [28] showed that the diffusion of an innovation can be expressed as:

$$N(t) = \frac{N_{saturation}}{1 + e^{-\tau(t - Year_{mid})}} \tag{3}$$

where $N(t)$ is the adoption of the innovation at a specific time (for example, year t), $N_{saturation}$ is the saturation level of the innovation, τ is the growth rate, and $Year_{mid}$ is the year with the highest rate of growth when annual data are used.

Electricity is a utility due to population growth, diffusion of new ideas (such as electrification), and an increase in the use of electric and electronic appliances (innovations). Hence, it is not unexpected that the electricity consumption of a city follows a logistic growth pattern. To et al. [5] showed that Hong Kong's total electricity consumption follows a logistic growth pattern. In this study, we used the monthly data and demonstrated that the following 4-parameter logistic curve would be able to fit the trend component of monthly electricity consumption data well:

$$Elec(t) = Elec_{initial} + \frac{Elec_{increase}}{1 + e^{-\tau(t - t_{mid})}} \tag{4}$$

where $Elec(t)$ is the amount of electricity consumption at time t, $Elec_{initial}$ is the initial value, $Elec_{increase}$ is the total net increase in $Elec$, τ is a growth constant, and $Year_{mid}$ is the time (i.e., month-year) having the maximum rate of growth.

2.4. Generalized Seasonal Model of Residential/Commercial Electricity Consumption

Lam [18] and Lam et al. [19] showed that Hong Kong's monthly residential/commercial electricity consumption has exhibited seasonal variation. As the seasonal patterns of residential electricity consumption and commercial electricity consumption may not be the same, a generalized seasonal model is proposed as follows:

$$R(\text{or}C)Elec_{i,t} = \left(R(\text{or}C)Elec_{initial} + \frac{R(\text{or}C)Elec_{increase}}{1 + e^{-\tau_{R(\text{or}C)}(t - t_{mid})}} \right)(1 + f(T_i)) \tag{5}$$

where $R(\text{or } C)Elec_{i,t}$ is the amount of monthly electricity consumption in the ith month of the year t, $R(\text{or } C)Elec_{initial}$ is the initial value, $R(\text{or } C)Elec_{increase}$ is the net increase in $R(\text{or } C)Elec$, $\tau_{R(\text{or } C)}$ is a growth constant, t_{mid} is the time (i.e., month-year) having the maximum rate of growth, and $f(T_i)$ is a function of mean air temperature T in the ith month.

2.5. Coefficient of Determination and Error Analysis

The coefficient of determination, r^2, has been widely used to indicate how well the collected data fit a mathematical model. Specifically, it provides a measure indicating if the collected data are adequately predicted by the model, i.e., the proportion of total variance explained by the model.

The value of r^2 is always between 0 and 1. The explanation power of the model is strong when the value of r^2 is close to 1. The value of r^2 was calculated by the following equation:

$$r^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{6}$$

where SSR is the sum of squared regression, SSE is the sum of squared error, and SST is the sum of the squared total. In addition, the mean absolute error (MAE) and two scale invariant measures of accuracy—the mean absolute percentage error (MAPE) and the root mean square percentage error (RMSPE)—were also used to assess model performance [3].

2.6. Data Sources

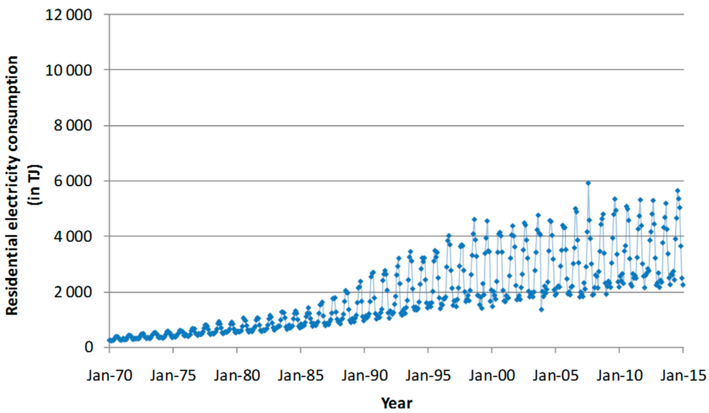
Monthly residential electricity consumption and monthly commercial electricity consumption data for the period January 1970–December 2016 were obtained from the Hong Kong Census and Statistics Department [30]. The values of monthly mean air temperature were obtained from the Hong Kong Observatory [31].

3. Results and Analysis

Following the classification of the Hong Kong Census and Statistics Department [30], the electricity consumption of Hong Kong is divided into residential electricity consumption, commercial electricity consumption, industrial electricity consumption, and the electricity used by public services, such as street lighting [30]. In 1970, the ratio between residential, commercial, industrial, and public electricity consumption was 20.8:37.6:41.1:0.5. The ratio changed to 20.1:46.7: 32.8:0.4 in 1985, and then to 24.7:61.5:13.6:0.2 in 2000. In 2014, the ratio was 27.5:65.1:7.2:0.2. After Hong Kong transformed from a manufacturing-based city in the 1970s to one of the world's finance and tourism centers in the 2000s [5], electricity consumption has been dominated by residential and commercial activities. In this study, monthly residential and commercial electricity consumption data for the period January 1970–December 2014 were used to derive nonlinear seasonal models, while monthly residential and commercial electricity consumption data for the period January 2015–December 2016 were used to validate the then developed models.

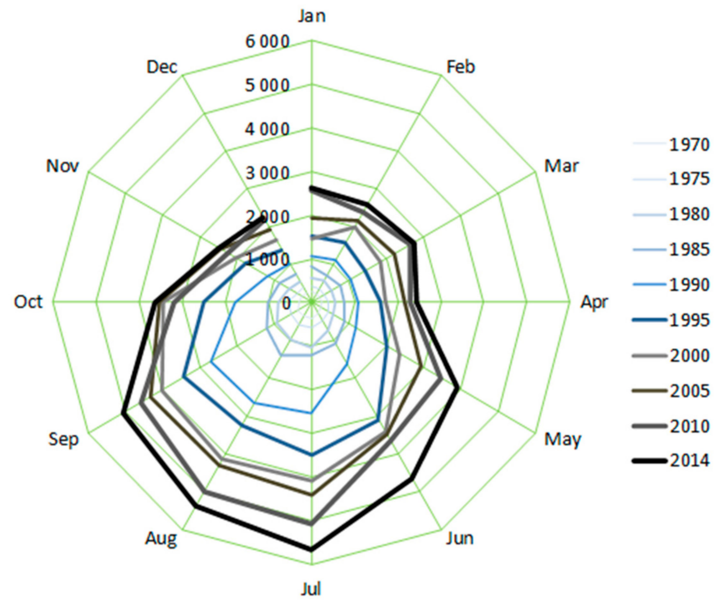
3.1. Monthly Residential Electricity Consumption and Its Seasonal Variation

Figure 1a shows Hong Kong's monthly residential electricity consumption from January 1970 to December 2014 while Figure 1b shows the associated radar diagram. Figure 1a,b illustrates that residential electricity consumption exhibited very strong seasonal variation during the period 1970–2014. Figure 2 shows Hong Kong's monthly mean air temperature from January 1970 to December 2014.



(**a**)

Figure 1. *Cont.*



(**b**)

Figure 1. (**a**) Monthly residential electricity consumption for the period 1970:01–2014:12; and (**b**) Radar diagram of monthly residential electricity consumption.

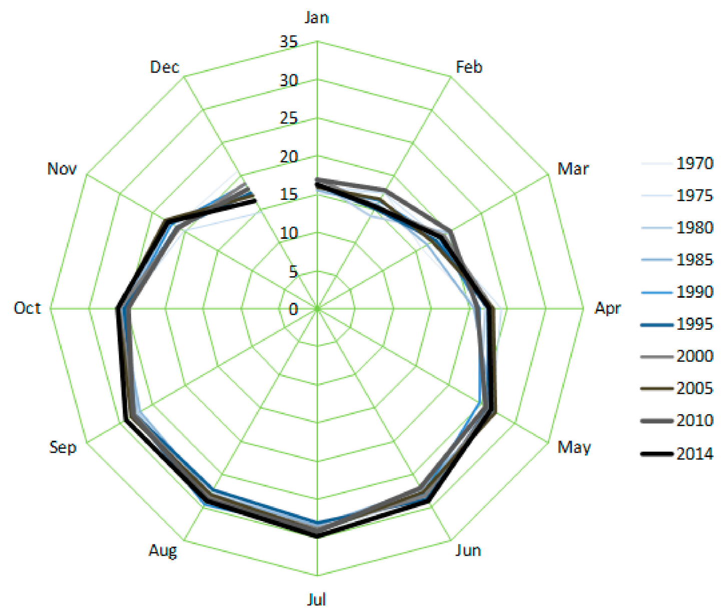


Figure 2. Radar diagram of monthly mean air temperature for the period 1970–2014.

Equation (1) was applied to obtain normalized monthly residential electricity consumption. Figure 3 shows the box-plot of normalized monthly residential electricity consumption in percent. It illustrates that normalized monthly residential electricity consumption was the minimum in December (mean = 5.91%, SD = 0.66%) and reached the maximum in August (mean = 12.41%, SD =1.05%). Hence, it was confirmed that more than 50% of the total amount of electricity consumption was spent in air-conditioning in residential units, as reported by Lam [18]. Nevertheless, the mean values of the normalized residential electricity consumption between December and March (i.e., the winter months in Hong Kong) were not significantly different at the 0.05 level, using analysis of variance.

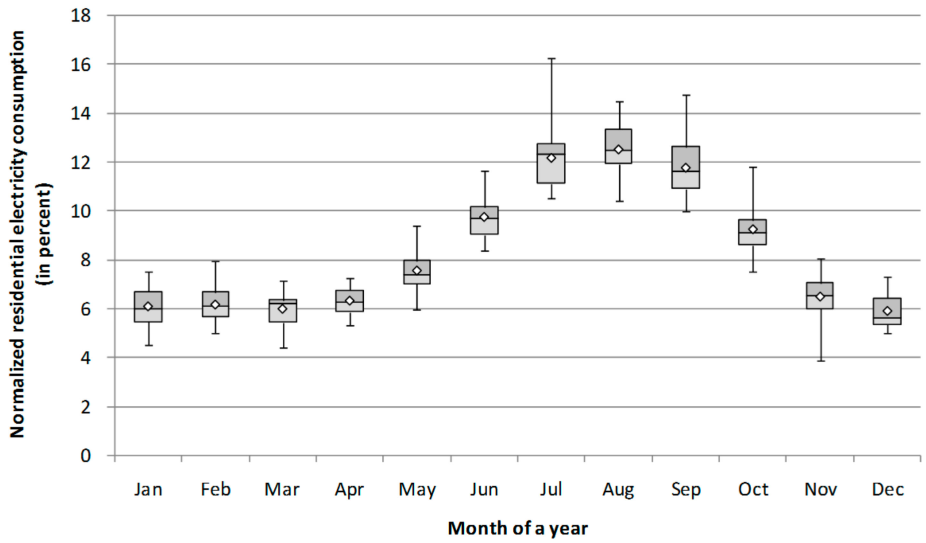


Figure 3. The box-plot of normalized monthly residential electricity consumption during the period 1970–2014.

Figure 4 shows mean values of normalized monthly residential electricity consumption (as a function of mean values of monthly mean air temperature of Hong Kong) from 1970 to 2014. A quadratic function was fitted to the data and the coefficient of determination r^2 was 0.928. MAE was 0.50%. Based on the coefficients of the quadratic function, it was found that monthly residential electricity consumption would reach a minimum at 19.25 °C—a temperature close to the mean of monthly mean air temperature in March (19.0 °C). It can be understood, because people may turn on electric heaters at temperatures below 19 °C, such as in December to February (about 16–17 °C), while people will turn on air conditioners between May and October, in which the mean air temperature is above 25 °C.

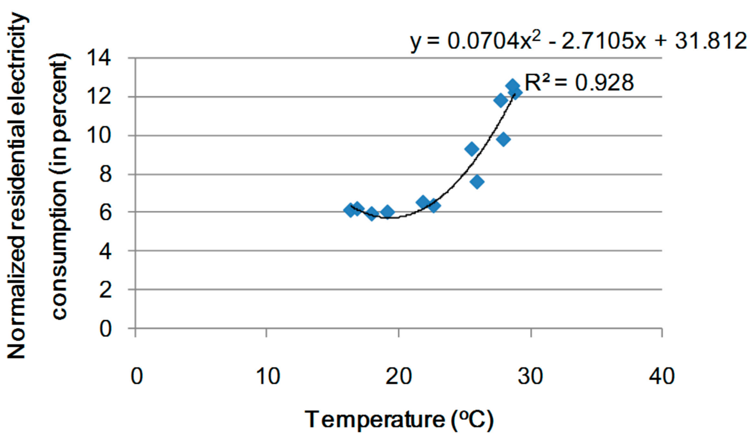


Figure 4. Mean values of normalized monthly residential electricity consumption as a function of mean values of monthly mean air temperature during the period 1970–2014.

In order to explore whether seasonal variation of residential electricity consumption was repeatable, monthly residential electricity consumption was plotted as a function of monthly mean air temperature of each year between 1970 and 2014. All the resulting 45 plots showed a quadratic relationship between residential electricity consumption and temperature. The quadratic function for each year was used to obtain the characteristic equation of monthly residential electricity consumption, as below:

$$RElect_{i,t} = RElec_t^{Trend} + \beta_t (T_{i,t} - T_{\text{min. use of elect.}})^2 \tag{7}$$

where $RElec_{i,t}$ is residential electricity consumption, $RElec_t{}^{Trend}$ is its trend component, $T_{i,t}$ is the mean air temperature in the i month of the year t, β_t is the coefficient of the year t, and $T_{\text{min. use of elect.}}$ is the temperature at which the consumption of electricity reached the minimum.

Figure 5 shows the values of $T_{\text{min. use of elect.}}$, β_t and $RElec_t{}^{Trend}$ from 1970 to 2014. It shows that $T_{\text{min. use of elect.}}$ ranged from 17.19 °C to 20.18 °C (mean = 18.73 °C, SD = 0.70 °C), β_t increased from 0.919 in 1970 to 28.85 in 2014, and $RElec_t{}^{Trend}$ increased from 225.9 TJ to 2279.8 TJ during the same period. The ratio between β_t and $RElec_t{}^{Trend}$ was nearly constant, at 0.0123 after 1987.

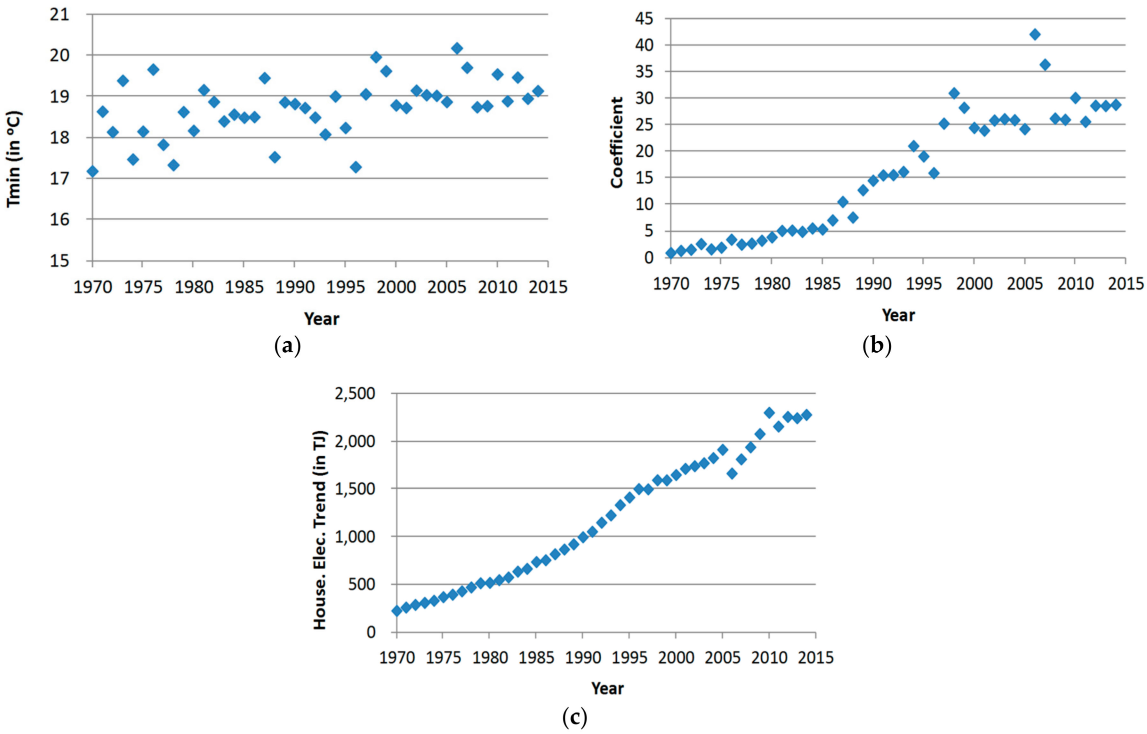


Figure 5. Estimates of model parameters for residential electricity consumption: (**a**) temperature at which the consumption was at a minimum; (**b**) coefficient; and (**c**) trend component.

A nonlinear algorithm was applied to the trend component [32]. It was found that the logistic function shown in Equation (8) fitted the trend of residential electricity consumption well:

$$RElec_t^{Trend} = 110 + \frac{2210}{1 + e^{-0.129(t - 1992{:}06)}} \tag{8}$$

where the time having the highest growth rate was June 1992. By combining this logistic function with Equation (7), we obtained the seasonal model of monthly residential electricity consumption, as follows:

$$RElec_{i,t} = \left(110 + \frac{2210}{1 + e^{-0.129(t - 1992{:}06)}}\right)\left(1 + 0.0123(T_i - 19.25)^2\right) \tag{9}$$

Figure 6 shows the actual monthly residential electricity consumption against the predicted monthly residential electricity consumption, from January 1970 to December 2014. It shows that the seasonal model given in Equation (9) regenerated the actual monthly residential electricity consumption values accurately. The r^2 value was 0.958, *MAE* was 195 TJ, MAPE was 10.6%, and RMSPE was 13.6%.

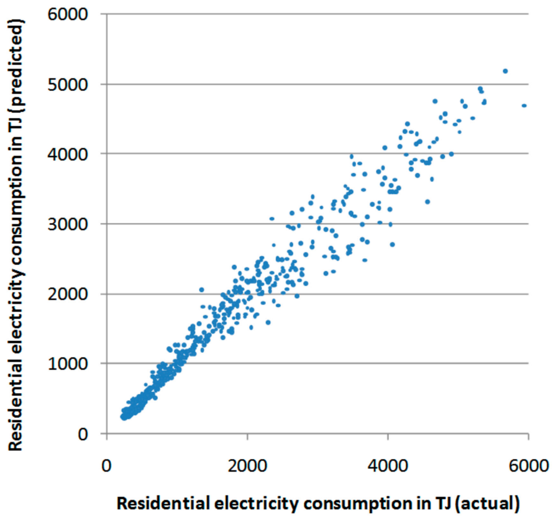


Figure 6. Residential electricity consumption—actual vs. predicted, using Equation (9).

Out-of-Sample Prediction

The Hong Kong Census and Statistics Department and the Hong Kong Observatory have recently published electricity consumption and mean air temperature of Hong Kong between January 2015 and December 2016. The seasonal model shown in Equation (9) was used to predict residential electricity consumption in 2015 and 2016. Figure 7 presents the actual and predicted monthly residential electricity consumption from January 2015 to December 2016. It shows that the seasonal model predicted residential electricity consumption accurately. The correlation between the predicted and actual values was 0.976. The MAE, MAPE, and RMSPE values were 205 TJ, 5.6%, and 7.0%, respectively. When the predicted monthly residential electricity consumption values were summed, the predicted total residential electricity consumption values were found to be 41,596 TJ for 2015 and 41,392 TJ for 2016, respectively. These predicted values were 772 TJ (or 1.8%) less than the actual residential electrical consumption (at 42,368 TJ for 2015) and 1726 TJ (or 4.0%) less than the actual electricity consumption (at 43,118 TJ for 2016).

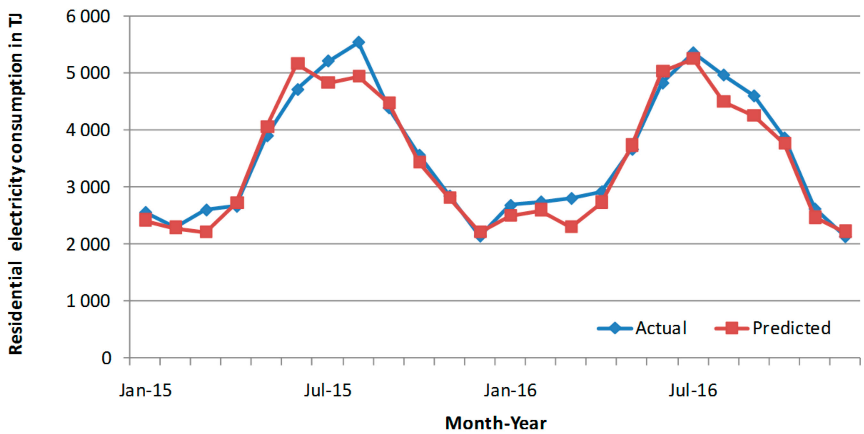
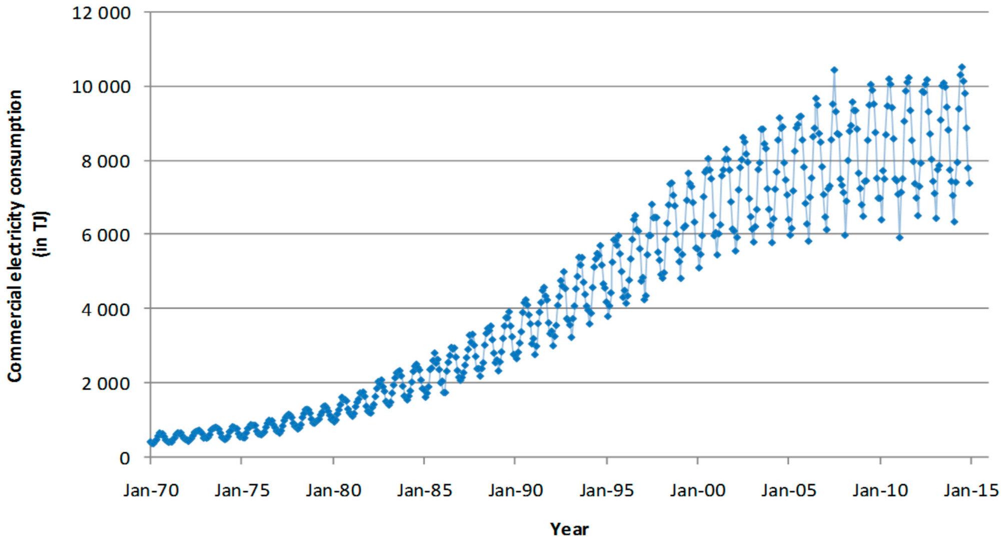


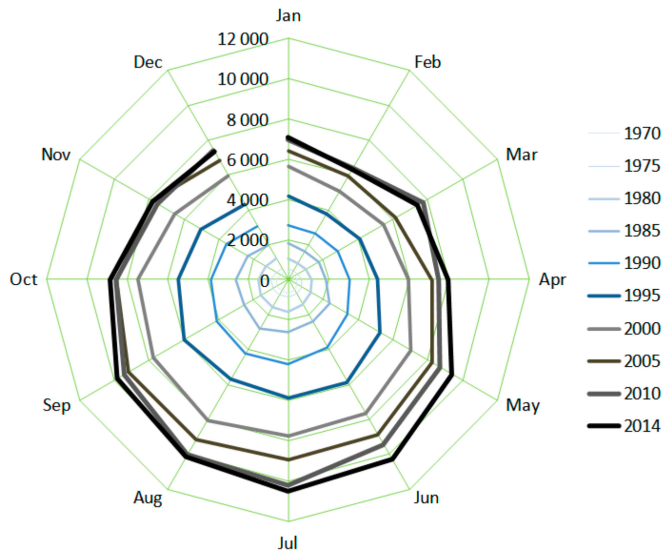
Figure 7. Residential electricity consumption during the period January 2015–December 2016.

3.2. Monthly Commercial Electricity Consumption and Its Seasonal Variation

Figure 8a shows Hong Kong's monthly commercial electricity consumption from January 1970 to December 2014, while Figure 8b shows the associated radar diagram. Figure 8a,b illustrates that commercial electricity consumption exhibited very strong seasonal variation during the period 1970–2014.



(**a**)



(**b**)

Figure 8. (**a**) Monthly commercial electricity consumption for the period 1970:01 to 2014:12; and (**b**) Radar diagram of monthly commercial electricity consumption.

Equation (1) was applied to obtain normalized monthly commercial electricity consumption. Figure 9 shows the box-plot of normalized monthly commercial electricity consumption in percent. It illustrates that normalized monthly commercial electricity consumption was at a minimum in December (mean = 6.28%, SD = 0.22%), and reached the maximum in July (mean = 10.04%, SD =0.28%).

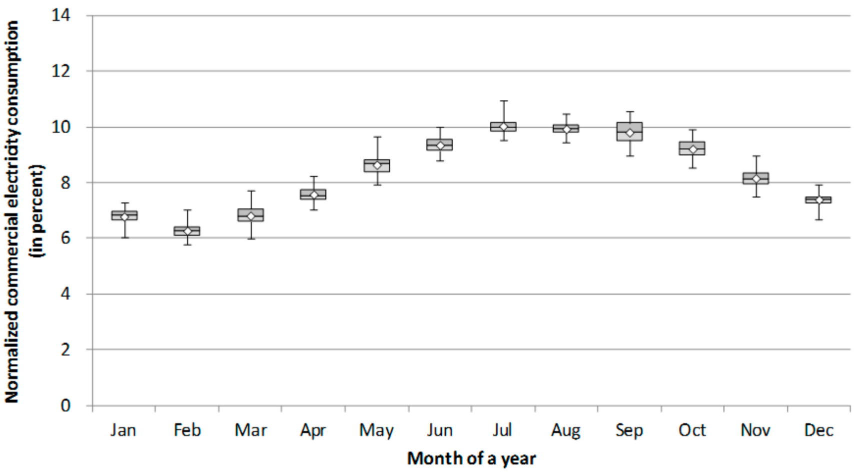


Figure 9. Box-plot of normalized monthly commercial electricity consumption during the period 1970–2014.

Figure 10 shows mean values of normalized monthly commercial electricity consumption, as a function of mean values of the monthly mean air temperature of Hong Kong, from 1970 to 2014. With such data, a linear function was developed, for which the coefficient of determination r^2 was 0.928 and MAE was 0.32%. Unlike residential users, commercial buildings normally operate ventilation systems continuously to supply fresh air to users and will switch on chillers frequently during hot summer days. Hence, the cooling loads of commercial ventilation and air-conditioning systems change linearly with mean air temperature.

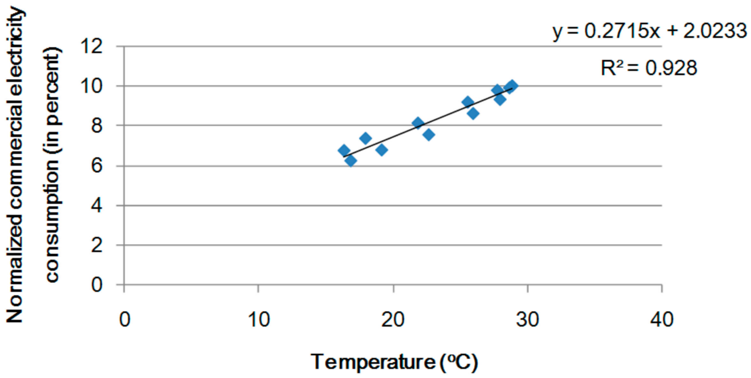


Figure 10. Mean values of normalized monthly commercial electricity consumption, as a function of mean values of monthly mean air temperature, during the period 1970–2014.

In order to explore whether the seasonal variation of commercial electricity consumption was repeatable, monthly commercial electricity consumption was plotted as a function of monthly mean air temperature of each year between 1970 and 2014. All the resulting 45 plots showed a linear relationship between commercial electricity consumption and temperature. The linear function for each year was used to obtain a characteristic equation of monthly commercial electricity consumption, as below:

$$CElect_{i,t} = CElec_{i,t}^{Trend} + \gamma_t T_{i,t} \tag{10}$$

where $CElec_{i,t}$ is commercial electricity consumption, $CElec_{i,t}^{Trend}$ is its trend component, $T_{i,t}$ is the mean air temperature in the i month of the year t, and γ_t is the coefficient of the year t.

Figure 11a shows the values of $CElec_{i,t}^{Trend}$ and Figure 11b shows γ_t from 1970 to 2014. It was found that $CElec_{i,t}^{Trend}$ increased from 75.5 TJ to 2743.7 TJ, and γ_t increased from 18.57 TJ/°C to 248.7 TJ/°C during the same period. The data shown in Figure 11a,b followed roughly a logistic growth pattern. The ratio between γ_t and $CElec_{i,t}^{Trend}$ was quite a constant at 0.109 after 1983.

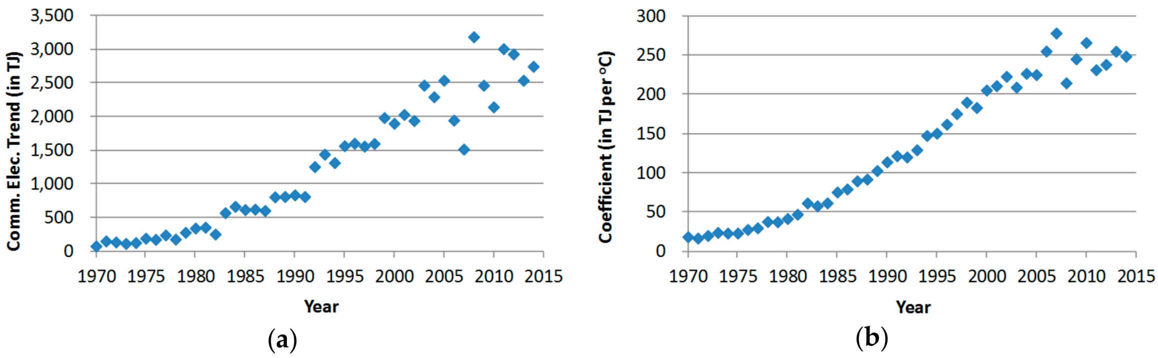


Figure 11. Estimates of model parameters for residential electricity consumption: (**a**) trend component; and (**b**) coefficient.

A nonlinear algorithm was applied to the trend component [32]. It was found that the logistic function shown in Equation (11) fitted the trend of commercial electricity consumption well:

$$CElec_t^{Trend} = 10 + \frac{2650}{1 + e^{-0.129(t-1995:01)}} \tag{11}$$

where the time having the highest growth rate was January 1995. By combining this logistic function with Equation (10), the seasonal model of monthly commercial electricity consumption was obtained as follows:

$$CElec_{i,t} = \left(10 + \frac{2650}{1 + e^{-0.129(t-1995:01)}}\right)(1 + 0.109T_i) \tag{12}$$

Figure 12 shows the actual monthly commercial electricity consumption against the predicted monthly residential electricity consumption from January 1970 to December 2014. It shows that the seasonal model given in Equation (12) regenerated the actual monthly commercial electricity consumption values accurately. The r^2 value was 0.992, MAE was 195 TJ, MAPE was 5.7%, and RMSPE was 7.2%.

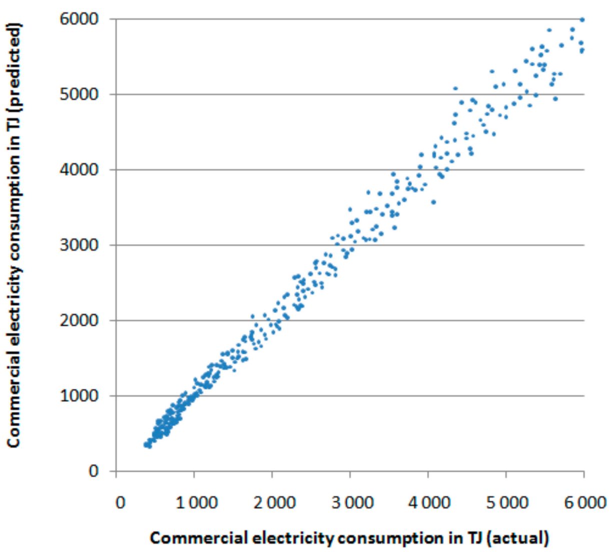


Figure 12. Commercial electricity consumption—actual vs. predicted, using Equation (12).

Out-of-Sample Prediction

The seasonal model shown in Equation (12) was used to predict commercial electricity consumption in 2015 and 2016. Figure 13 presents the actual and predicted monthly commercial electricity consumption between January 2015 and December 2016. This figure shows that the seasonal model predicted commercial electricity consumption accurately. The correlation between the predicted and actual values was 0.962. The MAE, MAPE, and RMSPE values were 448 TJ, 5.4%, and 6.5%, respectively. When the predicted monthly commercial electricity consumption values were summed, the predicted total commercial electricity consumption values were 108,786 TJ for 2015 and 107,830 TJ for 2016, respectively. The predicted values were 4891 TJ (or 4.7%) higher than the actual commercial electrical consumption (at 103,895 TJ for 2015 and 4093 TJ (or 3.9%) higher than the actual commercial electrical consumption (at 103,737 TJ) for 2016, respectively).

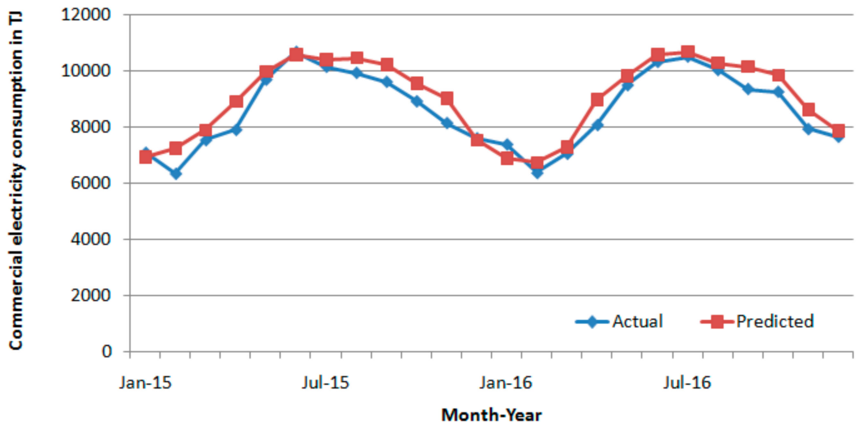


Figure 13. Commercial electricity consumption during the period January 2015–December 2016.

Table 1 Summarizes nonlinear seasonal models for Hong Kong's monthly residential and electricity consumption.

Table 1. Non-seasonal models of Hong Kong's monthly electricity consumption.

Sector	Nonlinear Seasonal Model	Relationship with Monthly Mean Air Temperature
Residential	$RElec_{i,t} = \left(110 + \frac{2210}{1+e^{-0.129(t-1992:06)}}\right)\left(1 + 0.0123(T_i - 19.25)^2\right)$	Quadratic
Commercial	$CElec_{i,t} = \left(10 + \frac{2650}{1+e^{-0.129(t-1995:01)}}\right)(1 + 0.109T_i)$	Linear

4. Conclusions

This paper explores Hong Kong's residential and commercial electricity consumption using monthly electricity consumption data between January 1970 and December 2014. The findings indicate that Hong Kong's residential electricity consumption reaches its minimum in the winter months, i.e., between December and March, while consumption reaches its maximum in August (a summer month) at about 100% more than that of the winter month. Further analysis reveals that residential electricity consumption has a quadratic relationship with monthly mean air temperature. This finding is similar to what was reported by Lai et al. [4] in Macao. In the past, Fung et al. [33] reported that Hong Kong's total electricity consumption was of the power-of-two polynomial form between 1990 and 2002, but Fung et al. [33] did not go further to explore Hong Kong's electricity consumption in the residential and commercial sectors. Moreover, our results show that commercial electricity consumption has its minimum in February, while consumption reaches its maximum in July or August (at about 60% more than that in February). Further analysis reveals that commercial electricity consumption has a linear relationship with monthly mean air temperature. It is because commercial buildings demand good ventilation throughout the year, while the cooling load of chillers normally increases with mean air temperature. This new finding indicates that tenants or owners of commercial buildings should find ways to reduce ventilation loads, such as adopting heat recovery ventilation systems [34], stratified air distribution systems [35], or passive and advanced cooling techniques [36]. The new nonlinear seasonal models of residential and commercial electricity consumption (Equations (9) and (12)) can be applied to other subtropical urban areas that cover a large number of megacities such as Guangzhou, Shanghai, Taipei, New Delhi, Tokyo, Nagoya, Dallas/Fort Worth, Philadelphia, Sao Paulo, Buenos Aires, etc. [37].

Electricity consumption creates a significant environmental burden because Hong Kong's power plants burn fossil fuels, such as coal and natural gas, to generate electricity. The emission factor of Hong Kong's power plants was 824 g CO_2-eq per kWh electricity [5], similar to the figure reported by Yu et al. [38] in mainland China. In particular, commercial buildings consume about two-thirds of the electricity in Hong Kong. On top of the amount of electricity used for ventilation, the cooling load alone in the summer time contributes to about 37% of commercial electricity consumption. Hence, building owners and managers of commercial firms should encourage occupants and employees to save electricity by creating environmental awareness [39], and adopting new energy-saving technologies including smart grids [34–36,40]. In addition, the government should work with the building management sector in energy policy design and goal setting [41].

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