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Developing a Polynomial-Fourier Series Model for Building's Electricity Consumption Forecasting

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Abstract

Electricity consumption in various types of buildings can be seen in terms of long-term trends, periodic activities and irregular activities, and can vary according to a range of time frames, from seasonal to hourly, making it difficult to construct models to accurately predict electricity consumption. A Polynomial-Fourier series (P-FS) model is developed to analyze long-term consumption trends and the periodic activities ascribed to use by middle management and technical engineers. Relying on limited data inputs and mathematical iterations, the proposed P-FS model can quantify values of data due to long-term trends and periodical activities.

Keywords
Electricity consumption prediction, Polynomial-Fourier series, long-term trends

1. Introduction
Energy use is a key issue in the operation of buildings, with electricity usage varying hourly and seasonally in response to a range of factors including user activity and weather, thus it is of fundamental importance to have an accurate model for predicting electricity demand in buildings (Chen et al. 2009). The key factor in determining a building's electricity consumption is the activities of its users, which can be periodical (e.g., seasonally-determined heating or cooling, or low usage during weekends or holidays) or irregular (e.g., installation of new electrical fixtures or power failures). Electricity usage for most buildings is also subject to gradual long-term trends, such as climate change.

Various methods have been proposed for estimating electricity consumption and performance in various types of buildings (Lam and Hui 1996, Korjenic and Bednar 2012, Yan et al. 2012, Maile et al. 2012). The Fourier series (FS) has been used to analyze structural vibration (Hall 2006, Penny et al. 2012) and many other events such as sea levels (Wu et al. 2011, Wu et al. 2012). FS also has been partially used to forecast electricity demand (González-Romera and Jaramillo-Morán 2008).

In this work, a combination of polynomial and Fourier series named the polynomial-Fourier series model (P-FS), is developed to analyze electricity consumption in a building in which consumption is largely determined by the activities of its users. Raw data for electricity consumption of the buildings were collected for analysis. The P-FS model accounts for long-term trends using a polynomial of time and periodical activities by a Fourier series. Each data set is separated into two parts. The first part is analyzed using the P-FS model while the second part is used to check the accuracy of the analysis.

2. Polynomial-Fourier Series
If a function of time is fitted by a polynomial of time, the error between them is

$$f(t) - \sum_{m=0}^{M} P_m t^m \quad (1)$$

where *f(t)* is the function, *t* is time, *M* is the highest order of the polynomial, and P_m is a coefficient of each term. Calculating P_m requires a set of data for *f(t)*, and the sum of the square of error, SSE_P, is

$$SSE_P = \sum_{i=1}^{I} [\, f(t_i) - \sum_{m=0}^{M} P_m t_i^m \,]^2 \quad (2)$$

where t_i is the *t* for the *i*-th data, *I* is the number of data, and $f(t_i)$ is the *i*-th data of *f(t)* corresponding to t_i. Number of data cannot be smaller the number of the coefficients, P_m. Based on the algorithm of least square curve fitting, SSE_P is minimized by taking P_m as variables to achieve the best fit.

$$0 = \frac{\partial SSE_P}{\partial P_w} = 2t_i^w \sum_{i=1}^{I} [\, f(t_i) - \sum_{m=0}^{M} P_m t_i^m \,] \quad (3)$$

where *w* is an index varying from 0 to *M*. As a result, *M* + 1 equations can be obtained and solved simultaneously to derive P_w. Notably, when *w* = 0, Eq. (3) becomes

$$0 = \sum_{i=1}^{I} [\, f(t_i) - \sum_{m=0}^{M} P_m t_i^m \,] \quad (4)$$

Eq. (4) ensures that

$$0 = \frac{\sum_{i=1}^{I} [\, f(t_i) - \sum_{m=0}^{M} P_m t_i^m \,]}{I} \quad (5)$$

The right hand side of Eq. (5) is the average of the errors between the data and the values calculated by the polynomial, which is verified to be zero. Assume that Eq. (1) is a periodic function with a period *T*, which is the data sampling duration, and expressed as a Fourier series.

$$f(t) - \sum_{m=0}^{M} P_m t^m = a_0 + \sum_{n=1}^{\infty} [\, a_n \cos(\frac{2n\pi}{T} t) + b_n \sin(\frac{2n\pi}{T} t)] \quad (6)$$

where a_0, a_n and b_n are coefficients of the Fourier series.

$$a_0 = \frac{1}{T} \int_0^T [\, f(t) - \sum_{m=0}^{M} P_m t^m \,] dt \quad (7)$$

$$a_n = \frac{2}{T} \int_0^T [\, f(t) - \sum_{m=0}^{M} P_m t^m \,] \cos(\frac{2n\pi}{T} t) dt \quad (8)$$

$$b_n = \frac{2}{T} \int_0^T [\, f(t) - \sum_{m=0}^{M} P_m t^m \,] \sin(\frac{2n\pi}{T} t) dt \quad (9)$$

For discrete data, integrations in Eqs. (7-9) should be replaced by numerical summations.

$$a_0 = \frac{1}{T}\sum_{i=1}^{I}[\, f(t_i) - \sum_{m=0}^{M} P_m t_i^m \,]\, \Delta t \tag{10}$$

$$a_n = \frac{2}{T}\sum_{i=1}^{I}[\, f(t_i) - \sum_{m=0}^{M} P_m t_i^m \,]\, cos(\frac{2n\pi}{T} t_i)\Delta t \tag{11}$$

$$b_n = \frac{2}{T}\sum_{i=1}^{I}[\, f(t_i) - \sum_{m=0}^{M} P_m t_i^m \,]\, sin(\frac{2n\pi}{T} t_i)\Delta t \tag{12}$$

where Δt is the data sampling period. Divide T by Δt to obtain number of data, I, and Eq. (10) becomes the right hand side of Eq. (5) which is zero, meaning that a_0 is cancelled out.

Let

$$A_n = \sqrt{a_n^2 + b_n^2} \tag{13}$$

$$T_n = \frac{T}{n} \tag{14}$$

$$\theta_n = \begin{cases} arctan(\frac{a_n}{b_n}), & a_n \ge 0, \quad b_n > 0 \\ \frac{\pi}{2}, & a_n > 0, \quad b_n = 0 \\ \pi + arctan(\frac{a_n}{b_n}), & b_n < 0 \\ -\frac{1}{2}\pi, & a_n < 0, \quad b_n = 0 \\ arctan(\frac{a_n}{b_n}), & a_n < 0, \quad b_n > 0 \\ undefined, & a_n = 0, \quad b_n = 0 \end{cases} \tag{15}$$

and Eq. (6) becomes

$$f(t) - \sum_{m=0}^{M} P_m t^m = \sum_{n=1}^{\infty} A_n \, sin(\frac{2\pi}{T_n} t + \theta_n) \tag{16}$$

In Eq. (16), the Fourier series takes the form of a sinusoid with parameters amplitude A_n, period T_n and phase angle θ_n (Maile et al. 2012). A sinusoid with parameters A_n, T_n and θ_n, is shown in Figure 1. Taking infinite terms for the series in Eq. (16) is not practical in reality. Modify and rearrange Eq. (16) as

$$f(t) = \sum_{m=0}^{M} P_m t^m + \sum_{n=1}^{N} A_n \, sin(\frac{2\pi}{T_n} t + \theta_n) \tag{17}$$

where N is the number of the sinusoid terms. Equation (17) is the P-FS model for analyzing and predicting data.

3. A Case Study

3.1. Analysis

The electricity consumption of the library at the National Yunlin University of Science & Technology (NYUST) in Taiwan is analyzed using the P-FS model. The data sample includes total electricity consumption for 48 consecutive months from January 2008 to December 2011 (Table 1). The 36 data points from January 2008 to December 2010 are analyzed and the result is used to predict the values of the following 12 months starting January 2011, which are compared with the last 12 data points to confirm prediction accuracy using the P-FS model.

We first determine M and fit the polynomial to the first 36 data points by adjusting the coefficients based on least square curve fitting. Obviously, increasing M can reduce the SSE_P between the first 36 data and those calculated from the polynomial, $SSE_{P1\text{-}36}$, but not the SSE_P between the last 12 data points and those calculated from the polynomial, $SSE_{P37\text{-}48}$. Table 2 shows the polynomial, $SSE_{P1\text{-}36}$ and $SSE_{P37\text{-}48}$ after least square curve fitting for different values of M. $SSE_{P1\text{-}36}$ reduces monotonically as M increases, but the lowest value of $SSE_{P37\text{-}48}$ occurs when M = 1 standing for the best prediction for the last 12 data points. When M = 2, $SSE_{P37\text{-}48}$ increases slightly, but increases significantly when M = 3. Accordingly, let M = 1

$$\sum_{m=0}^{1} P_m t^m = P_0 + P_1 t, \quad P_0 = 1.673 \times 10^2 \, MW \cdot h, P_1 = -4.611 \times 10^{-1} \, MW \cdot h/month \tag{18}$$

The polynomial stands for the long-term trend of the data.

Table 1: Electricity consumption of the library of NYUST

t, *month*	*f(t)*, MW·h	*t*, *month*	*f(t)*, MW·h	*t*, *month*	*f(t)*, MW·h	*t*, *month*	*f(t)*, MW·h
1	158.400	13	93.067	25	140.977	37	88.434
2	90.720	14	115.026	26	72.759	38	55.804
3	171.000	15	159.238	27	170.213	39	138.988
4	204.480	16	170.436	28	160.737	40	139.981
5	224.640	17	199.881	29	198.679	41	159.979
6	249.840	18	199.708	30	181.104	42	162.364
7	111.600	19	133.114	31	121.133	43	94.441
8	101.160	20	118.410	32	119.711	44	105.812
9	169.200	21	147.661	33	152.389	45	142.055
10	246.240	22	182.459	34	194.617	46	199.190
11	195.182	23	165.151	35	172.241	47	164.057
12	144.124	24	134.692	36	146.778	48	145.544

Table 2: Polynomials, $SSE_{P1\text{-}36}$ and $SSE_{P37\text{-}48}$ for different M based on data of Table 1

M	Polynomial, MW·h (t, month)	$SSE_{P1\text{-}36}$, $(MW \cdot h)^2$	$SSE_{P37\text{-}48}$, $(MW \cdot h)^2$
0	1.588×10^2	6.221×10^4	2.538×10^4
1	$1.673 \times 10^2 - 4.611 \times 10^{-1} t$	6.138×10^4	2.088×10^4
2	$1.743 \times 10^2 - 1.567t + 2.988 \times 10^{-2} t^2$	6.108×10^4	2.597×10^4
3	$1.550 \times 10^2 + 4.304t - 3.614 \times 10^{-1} t^2 + 7.050 \times 10^{-3} t^3$	5.970×10^4	13.69×10^4

After the polynomial is decided, calculate errors between each data point and those calculated from the polynomial.

$$f(t) = P_0 + P_1 t \tag{19}$$

Assume Eq. (19) is a periodic function with a period T = 36 months which is the sampling duration of the data for analysis. Express Eq. (19) as a Fourier series, and calculate its parameters from Eqs. (11-15).

Equation (14) indicates that when n = 1, $T_n = T$ which is the maximum of T_n. On the other hand, every sinusoid has three parameters, A_n, T_n and θ_n. At least three data points are required to describe a sinusoid. In this case, the data sampling period is one month meaning that three months is the minimum requirement for calculating the three parameters, and 3 = T_n = $T/12$ = 36/12. As a result, n should be in between 1 and 12. All a_n, b_n, A_n, T_n and θ_n calculated are listed in Table 3.

Table 3: Original parameters of Fourier series based on data of Table 1

n	a_n, MW·h	b_n, MW·h	A_n, MW·h	T_n, month	θ_n
1	5.4483	5.2691	7.5794	36.000	0.802
2	0.0616	1.9370	1.9380	18.000	0.032
3	-13.2647	-3.8733	13.8186	12.000	4.428
4	2.0973	0.4169	2.1383	9.000	1.375
5	-6.0011	-2.1382	6.3707	7.200	4.370
6	9.0834	-45.9603	46.8493	6.000	2.946
7	10.0107	-1.5843	10.1353	5.143	1.728
8	1.7885	10.8631	11.0094	4.500	0.163
9	-12.4247	4.3178	13.1536	4.000	-1.236
10	2.3731	-3.3869	4.1355	3.600	2.530

We then plot the spectrum of A_n versus T_n as shown in Figure 1. If only the sinusoid term with the biggest amplitude is picked up for rebuilding the data, Eq. (17) becomes

$$f(t) = P_0 + P_1 t + A_6 \sin\left(\frac{2\pi}{T_6} t + \theta_6\right) \tag{20}$$

Minimize the sum of the square of error between the first 36 data points and those calculated by Eq. (20), $SSE_{1\text{-}36}$, by readjusting P_0, P_1, A_6, T_6 and θ_6. As a result,

$$\begin{cases} P_0 = 1.750 \times 10^2\, MW \cdot h, \quad P_1 = -8.697 \times 10^{-1}\, MW \cdot h / month \\ A_6 = 48.006\, MW \cdot h, \quad T_6 = 5.951\, month, \quad \theta_6 = 2.799 \\ SSE_{1-36} = 2.086 \times 10^4 (MW \cdot h)^2, \quad SSE_{37-48} = 5.841 \times 10^3 (MW \cdot h)^2 \end{cases} \tag{21}$$

where $SSE_{37\text{-}48}$ is the sum of the square of error between the last 12 data points and the calculated ones.

If two of the sinusoid terms with the two largest amplitudes are chosen to rebuild the data, Eq. (17) becomes

$$f(t) = P_0 + P_1 t + A_6 \sin\left(\frac{2\pi}{T_6} t + \theta_6\right) + A_3 \sin\left(\frac{2\pi}{T_3} t + \theta_3\right) \tag{22}$$

Minimize $SSE_{1\text{-}36}$ by readjusting P_0, P_1 and all A_n, T_n and θ_n in Eq. (22). As a result,

$$\begin{cases} P_0 = 1.751 \times 10^2\, MW \cdot h, \quad P_1 = -9.021 \times 10^{-1}\, MW \cdot h / month \\ A_6 = 47.781\, MW \cdot h, \quad T_6 = 5.965\, month, \quad \theta_6 = 2.829 \\ A_3 = 14.062\, MW \cdot h, \quad T_3 = 12.379\, month, \quad \theta_3 = 4.636 \\ SSE_{1-36} = 1.745 \times 10^4 (MW \cdot h)^2, \quad SSE_{37-48} = 4.275 \times 10^3 (MW \cdot h)^2 \end{cases} \tag{23}$$

If three of the sinusoid terms with the three largest amplitudes are chosen to rebuild the data, Eq. (17) becomes

$$f(t) = P_0 + \mathrm{P}_1 \mathrm{t} + \mathrm{A}_6 \sin\left(\frac{2\pi}{\mathrm{T}_6} t + \theta_6\right) + \mathrm{A}_3 \sin\left(\frac{2\pi}{\mathrm{T}_3} t + \theta_3\right) + \mathrm{A}_{12} \sin\left(\frac{2\pi}{\mathrm{T}_{12}} t + \theta_{12}\right) \tag{24}$$

Minimize $SSE_{1\text{-}36}$ by readjusting P_0, P_1 and all A_n, T_n and θ_n in Eq. (24). As a result,

$$\begin{cases} P_0 = 1.757\times 10^2\, MW\cdot h, \quad P_1 = -9.368\times 10^{-1}\, MW\cdot h/month \\ A_6 = 47.941 MW\cdot h, \quad T_6 = 5.957 month, \quad \theta_6 = 2.804 \\ A_3 = 14.121 MW\cdot h, \quad T_3 = 12.399 month, \quad \theta_3 = 4.657 \\ A_{12} = 12.930 MW\cdot h, \quad T_{12} = 2.991 month, \quad \theta_{12} = 0.989 \\ SSE_{1-36} = 1.445\times 10^4 (MW\cdot h)^2, \quad SSE_{37-48} = 2.820\times 10^3 (MW\cdot h)^2 \end{cases} \tag{25}$$

If four of the sinusoid terms with the four largest amplitudes are chosen to rebuild the data, Eq. (17) becomes

$$\begin{aligned} f(t) = P_0 + \mathrm{P_1 t} + \mathrm{A_6}\sin\left(\frac{2\pi}{\mathrm{T_6}}t + \theta_6\right) + \mathrm{A_3}\sin\left(\frac{2\pi}{\mathrm{T_3}}t + \theta_3\right) + \mathrm{A_{12}}\sin\left(\frac{2\pi}{\mathrm{T_{12}}}t + \theta_{12}\right) \\ + \mathrm{A_9}\sin\left(\frac{2\pi}{\mathrm{T_9}}t + \theta_9\right) \end{aligned} \tag{26}$$

Minimize $SSE_{1\text{-}36}$ by readjusting P_0, P_1 and all A_n, T_n and θ_n in Eq. (26). As a result,

$$\begin{cases} P_0 = 1.746\times 10^2\,\mathrm{MW\cdot h}, \quad \mathrm{P_1} = -8.885\times 10^{-1}\,\mathrm{M}W\cdot h/month \\ A_6 = 47.529\,\mathrm{MW\cdot h}, \quad \mathrm{T_6} = 5.970\mathrm{month}, \quad \theta_6 = 2.871 \\ A_3 = 14.751\,\mathrm{MW\cdot h}, \quad \mathrm{T_3} = 12.320\mathrm{month}, \quad \theta_3 = 4.604 \\ A_{12} = 13.790\,\mathrm{MW\cdot h}, \quad \mathrm{T_{12}} = 2.978\mathrm{month}, \quad \theta_{12} = 0.860 \\ A_9 = 13.024\,\mathrm{MW\cdot h}, \quad \mathrm{T_9} = 4.103\mathrm{month}, \quad \theta_9 = -0.827 \\ SSE_{1-36} = 1.151\times 10^4 (\mathrm{MW\cdot h})^2, \quad SSE_{37-48} = 3.403\times 10^3 (\mathrm{MW\cdot h})^2 \end{cases} \tag{27}$$

If five of the sinusoid terms with the five largest amplitudes are picked up for rebuilding the data, Eq. (17) becomes

$$\begin{aligned} f(t) = P_0 + P_1 t + A_6 \sin\left(\frac{2\pi}{T_6}t + \theta_6\right) + A_3 \sin\left(\frac{2\pi}{T_3}t + \theta_3\right) + A_{12} \sin\left(\frac{2\pi}{T_{12}}t + \theta_{12}\right) \\ + A_9 \sin\left(\frac{2\pi}{T_9}t + \theta_9\right) + A_7 \sin\left(\frac{2\pi}{T_7}t + \theta_7\right) \end{aligned} \tag{28}$$

Minimize $SSE_{1\text{-}36}$ by readjusting P_0, P_1 and all A_n, T_n and θ_n in Eq. (28). As a result,

$$\begin{cases} P_0 = 1.770 \times 10^2 \,\mathrm{MW \cdot h}, \quad \mathrm{P}_1 = \text{-}9.930 \times 10^{-1} \,\mathrm{M}W \cdot h / month \\ A_6 = 52.108 \,\mathrm{MW \cdot h}, \quad \mathrm{T}_6 = 5.850 \mathrm{month}, \quad \theta_6 = 2.399 \\ A_3 = 13.236 \,\mathrm{MW \cdot h}, \quad \mathrm{T}_3 = 12.622 \mathrm{mont\,h}, \quad \theta_3 = 4.887 \\ A_{12} = 12.577 \,\mathrm{MW \cdot h}, \quad \mathrm{T}_{12} = 2.993 \mathrm{month}, \quad \theta_{12} = 1.030 \\ A_9 = 11.537 \,\mathrm{MW \cdot h}, \quad \mathrm{T}_9 = 3.904 \mathrm{month}, \quad \theta_9 = -1.904 \\ A_7 = 19.175 \,\mathrm{MW \cdot h}, \quad \mathrm{T}_7 = 5.215 \mathrm{month}, \quad \theta_7 = 2.515 \\ SSE_{1-36} = 8.724 \times 10^4 (\mathrm{MW \cdot h})^2, \quad SSE_{37-48} = 1.031 \times 10^4 (\mathrm{MW \cdot h})^2 \end{cases} \tag{29}$$

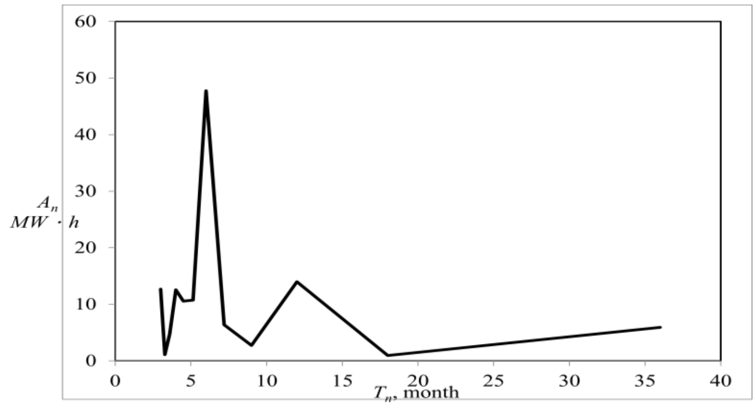

Figure 1: Original spectrum of data of Table 3

3.2. Discussion

In determining the terms of the polynomial, the best prediction for the last 12 data does not occur when the best fit of the first 36 data occur. A similar phenomenon is found in determining the terms of the Fourier series. Figure 2 plots SSE_{1-36} and SSE_{37-48} versus the number of sinusoid terms, and clearly shows that SSE_{1-36} decreases monotonically when number of terms increases, while the minimum SSE_{37-48} occurs when the three sinusoids with the three largest amplitudes are chosen to rebuild the data. As shown in Figure 3, Eq. (24) with the coefficients of Eq. (25) yields the best prediction for the last 12 data points. It seems that reasonable errors should be retained when fitting the P-FS model to the analyzed data to yield the best prediction, because the analysis does not account for irregular activities. Minimizing *SSE* in the fitting process can easily be done by increasing the number of terms in the model, but this will spoil the model's predictive value. Figure 4 shows errors between the calculated values of Eq. (24) with the coefficients of Eq. (25) and the data. The mean absolute percentage of error for the 48 data is 10.4% which seems to represent the percentage of fluctuation due to irregular activities that are not accounted for by the P-FS model. This error is reasonable should reasonably exist and not be forced down by increasing the number of terms in the P-FS model. This is the most important finding of this work.

Surprisingly, the real data at t = 40 is 34 MW·h less than the predicted value (see the circled areas in Figures 3 and 4), which is the most significant prediction error for the last 12 data points. It was later found non-routine major maintenance for the library's air conditioning system occurred at t = 40, causing the system to be shut down for several days during the month, which is a typical type of irregular activity. Another major function of the P-FS model is that it can identify and quantify the impact of significant individual irregular activities.

The three sinusoids chosen for the Fourier series with the amplitudes of 5.957, 12.399 and 2.991 stand for the electricity consumption due to three periodic activities. The first term has the biggest amplitude and a period of roughly six months, clearly representing events related to the two-semester academic schedule. The second term has a period of roughly 12 months, apparently representing annual activities. At the university, each academic semester lasts about four months, with a summer break lasting about three months, and a winter break lasting about one month. The two semesters and two holidays (winter and summer) interact to produce the final item in Eq. (24), which has a period of roughly one season. Equation (24) with the coefficients of Eq. (25) can easily be used to predict the electricity consumption of the coming months.

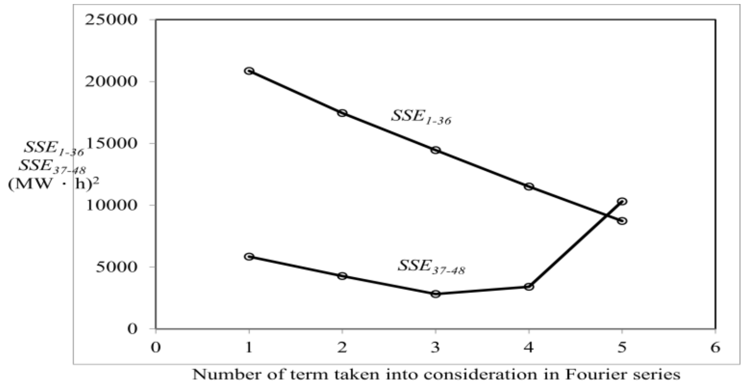

Figure 2: SSE_{1-36} and SSE_{37-48} for data of Table 3 versus number of terms taken into analysis in Fourier series

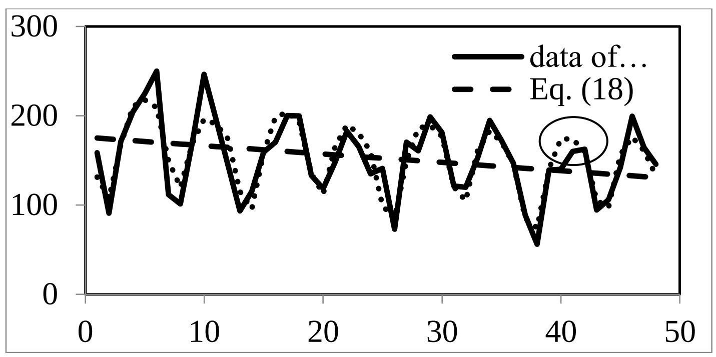

Figure 3: Electricity consumption of the library of Yuntech

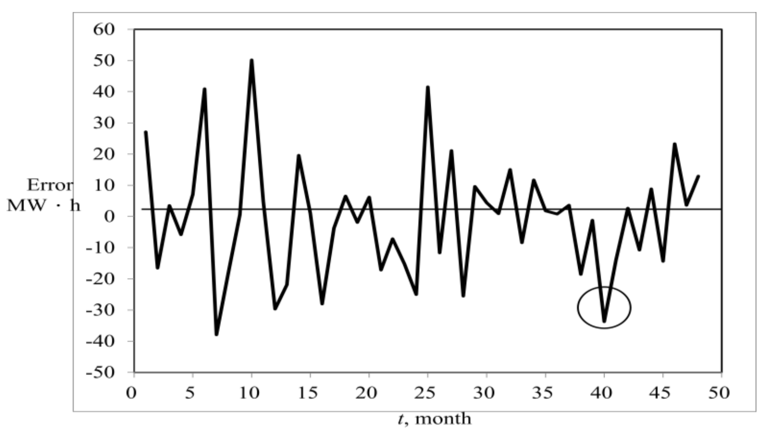

Figure 4: Errors between data of Table 3 and values calculated by Eq. (25)

4. Conclusions

A P-FS model is proposed to analyze and predict electricity consumption of various types of buildings in terms of long-term trends and periodic usage patterns. P-FS only requires limited data input and mathematical iterations to quantify data values due to long-term trends and periodic activities. The P-FS model generalizes the regular behavior of the data to yield a mathematical model to predict future electricity consumption. Irregular behavior can cause the data to deviate from the predicted values. One of the major functions of the P-FS model is to identify the value of data fluctuations due to significant irregular activities. Another major function of the P-FS model is that the meaning of each sinusoid term can be addressed.

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Biography

Cho-Liang Tsai is currently a professor in the department of Construction Engineering at National Yunlin University of Science and Technology, Taiwan. Dr. Tsai holds a Ph.D. from Northwestern University, USA. His research interests include theoretical and applied mechanics, construction materials, experimental mechanics and data analysis.

Wei Tong Chen is a Professor and the Chairman of the Dept of Construction Engineering at YunTech, Taiwan. He received his PhD from University of Florida in U.S.A. Professor Chen is the chief editor of Value Management Journal and Journal of Property Management. A certified AVS of the SAVE International, Professor Chen serves the publishing committee of the Construction Management Association of Taiwan and the Engineering Management committee of the Chinese Institute of Civil and Hydraulic Engineering. Professor Chen offers value engineering courses at graduate school. He is now principally involved in innovative project performance measurement, construction management, construction safety, property management, and value engineering application with an active interest in research. He published more than 150 papers in construction management and property management in last 10 years.

Chin-Shiang Chang is a middle level engineer with the Department of Labor, the Yunlin County Government, Taiwan. He holds a Bachelor of Science degree in Construction Engineering and a Master of Science degree in Construction and Property Management from National Yunlin University of Science & Technology. He has been working as a supervisor of workers’ safety of construction projects in Yunlin County, Taiwan.