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A hybrid dynamic and fuzzy time series model for mid-term power load forecasting

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ABSTRACT

A new hybrid model for forecasting the electric power load several months ahead is proposed. To allow for distinct responses from individual load sectors, this hybrid model, which combines dynamic (i.e., air temperature dependency of power load) and fuzzy time series approaches, is applied separately to the household, public, service, and industrial sectors. The hybrid model is tested using actual load data from the Seoul metropolitan area, and its predictions are compared with those from two typical dynamic models. Our investigation shows that, in the case of four-month forecasting, the proposed model gives the actual monthly power load of every sector with only less than 3% absolute error and satisfactory reduction of forecasting errors compared to other models from previous studies.

Introduction

Electric power load forecasting is essential for sustainable energy management and economic operation of power plants. Various methods have been proposed for the accurate prediction of power loads on hourly, monthly, and yearly temporal scales, from simple regression models to complex artificial neural network models. In particular, mid-term load forecasting concerns power requirements for up to a few months ahead and focuses on predicting the peak monthly power load or monthly variations. Mid-term load forecasting is important in the scheduling of power plant maintenance, energy conservation and hydrothermal regulation and has been studied extensively for improving our forecasting skills [e.g., 1–5,7–9]. The prediction of loads over this timescale is particularly vital in fast growing mega-cities, where the rate of increase in the demand for power exceeds that of the power supply because of a population explosion and fast economic growth, thus endangering their sustainability. For example, in Asia, power consumption patterns have changed dramatically with government policies. As a result, the economic management of power loads is vulnerable to climate change, such as abnormally cold winter seasons, which are becoming more frequent. There is an urgent need to predict power loads several months ahead so that there is sufficient time to prepare alternatives in the event of a power shortage. Indeed, there was a large-scale blackout in Korea in 2011, and this power failure was partially attributable to the combination of errors in short- and mid-term power load forecasting [6].

It is well known that many factors influence the electric power load, and their relationships are highly nonlinear. By considering such relationships, previous studies have proposed useful methods for power load forecasting. Notably, the power load is significantly affected by changes in weather conditions and therefore, most previous studies especially on short-term load forecasting (i.e., forecasting hourly and daily load peaks) have attempted to account for this sensitivity [9–12]. In case of short-term load forecasting, meteorological conditions on the following day, such as air temperature, humidity, wind, and illumination, are available from the weather forecast. In contrast to short-term load forecasting, weather forecasts of air temperature and humidity on monthly timescales are uncertain for the purpose of the mid-term power load forecasting and so not reliable for mid-term load forecasting in general. Furthermore, there are also practical difficulties over time periods of a few months because of the propagation of forecasting errors [9,13–15]. Accordingly, we need a different strategy to predict the load a few months in advance.

In this study, we propose a simple hybrid model that combines a dynamic model for the temperature sensitivity of the power load with a fuzzy time series approach to forecast the power load a few months ahead. To evaluate the proposed hybrid model, we construct two typical stochastic models, the Koyck model and the autoregressive integrated moving average (ARIMA), and compare their performance using power load data from the Seoul metropolitan area.

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Model construction

Koyck model

Because of the persistency of the power load and its meteorological driving variables, such as air temperature, we must consider a time lag when forecasting the power load. Distributed lag models use a regression equation to predict a dependent variable from an independent variable and the time-lagged independent variable. The distributed-lag model can involve an infinite number of lagged variables and the effect of the regression is distributed over time. Koyck model based on the so-called Koyck transformation is the one of the popular distributed-lag model. We explain the core of the Koyck model since the details are well documented in many papers and pertinent details on the Koyck model can be found in Appendix A.

The general form of a linear distributed lag model with a single explanatory variable X is:

$$Y_t = \alpha_0 + \sum_{i=1}^{\infty}\beta_{i,1}X_{t-i} + \sum_{i=1}^{\infty}\beta_{i,2}X_{t-i}^2 + u_t \quad (1)$$

where X_t is an independent variable (air temperature in this study) and u_t is a normally distributed and serially independent random variable with a mean of zero. In Eq. (1), $\beta_{i,k}(k = 1,2)$ is the lag coefficient of X_{t-i}^k and X_{t-i}^2 is explicitly included in the distributed lag model to incorporate the quadratic sensitivity of the load to air temperature.

Because the predictor Y_t is written in terms of the lagged value of itself, the Koyck model is called a dynamic model. This model has been used in many economic time series. In this study, the air temperature at time $t\,(T_t)$ is applied as an independent variable in the Koyck model. All coefficients are estimated statistically using the real power load and the observed air temperature.

ARIMA model

ARIMA is a widely used time-series approach. It is a linear model that represent both stationary and non-stationary data. ARIMA uses historical time series patterns and therefore, does not require the dependent variable; instead, time series information is used to generate the series itself. ARIMA is relatively simple and has been applied to forecast electricity loads and prices in previous studies [17–20]. Therefore, we explain the core of the ARIMA model here and further information can be found in [21,22].

The general ARIMA model is formulated as follows:

$$\Phi(B)\Delta^d Y_t = \theta(B)\epsilon_t \quad (2)$$

where Δ is the difference operator and B is a time lag operator. ϵ_t is a random error term with zero mean and constant variance σ^2 (i.e., a white noise process).

The ARIMA model includes an autoregression part (AR), an integration part (I), and a moving average part (MA). The non-seasonal ARIMA model is referred as ARIMA(p,d,q) where p, d, and q are integers in the autoregressive, non-seasonal difference, and moving average parts of the model, respectively. Below, we will concisely explain the procedure for building an appropriate ARIMA model.

For robust forecasting, this study expands the non-seasonal ARIMA to consider seasonal variabilities in the load. This seasonal ARIMA model consists of non-seasonal parameters (p,d,q) and seasonal parameters (P,D,Q). The parameters of the seasonal ARIMA model are in a similar way to those for the non-seasonal ARIMA model.

Hybrid model

Power load demand is correlated to many factors. Not only meteorological conditions, but also socio-economic states make impacts on power load demand at the same time and these driving variables can be correlated with one another on a nonlinear way. In such conditions, using a linear relationship estimated from traditional statistics based on the identical and independent variables will cause uncertainties in the load forecasts. To overcome these issues, we propose a hybrid model that combines a dynamic model with a fuzzy time series. In the dynamical model, primary meteorological relationship with the power load is considered and uncertainties resulted from other socioeconomic factors and inter-variable dependencies is incorporated into a fuzzy time series.

Dynamic model

First our hybrid approach begins from a dynamic model based on the relationship between power load and air temperature. By incorporating the primary quadratic sensitivity of the load with respect to air temperature, the dynamic model is formulated as

$$Y_t = \alpha + \beta Y_{t-s} + \gamma T_{t-1} + \delta T_{t-1}^2 + \epsilon_t$$
$$t = 1,2,\ldots,n \quad (3)$$

where s is an auto-dependent time lag. Eq. (3) is a dynamic model because it considers the temporal behavior of past values. In our case, t-test says that the dynamic model used in the hybrid model (i.e., Eq. (3)) is appropriate.

Fuzzy time series

Traditional time series analysis is based on the classification of data in chronological order, with many data points needed to ensure that a time series includes seasonal variations. However, fuzzy time series, consisting of fuzzy sets and a fuzzy boundary, require neither linearity nor a large number of data points [23]. Because of these advantages, fuzzy time series analysis has been applied to various research area, such as stock prices, temperatures, and precipitation.

As pointed out above, it is not always easy to determine which independent variables explain the residual (i.e., the difference between the actual load and the values forecast by the dynamic model). This is because of the complex nonlinear relationships between the load and its controlling factors. Our new hybrid approach attempts to account for the residual using fuzzy time series. Before constructing the fuzzy time series, we define several terms.

Definition 1. Let U be the universe of discourse with $U = \{u_1, u_2, \ldots, u_n\}$ where u_i are possible linguistic values of U. A fuzzy set of fuzzy variables A_i of U is defined by

$$A_i = f_{A_i}(u_1)/u_1 + f_{A_i}(u_2)/u_2 + \cdots + f_{A_i}(u_n)/u_n \quad (4)$$

where f_{A_i} is the membership function of the fuzzy set A_i, such that $f_{A_i}: U \to [0,1]$, and $f_{A_i}(u_j)$ indicates the grade of membership of u_j in A_i. Throughout this paper, the indexes i and j will be used to indicate current and past values, respectively.

Definition 2. The fuzzy time series $\{F(t) : t = 0,1,\ldots\}$ is defined as the collection of $f_{A_i}(t)$.

Definition 3. We can express $F(t-1) \to F(t)$ if there is a fuzzy relation $R(t,t-1)$ satisfying $F(t) = F(t-1) \circ R(t,t-1)$. Here, $\circ$ is the maximum and minimum composition operator [24] and R indicates a fuzzy relationship between fuzzy time series [25]. In particular, if $F(t-\lambda),\ldots,F(t-2),F(t-1) \to F(t)$, then it is said that there is a λth-order fuzzy relationship, and $A_{i\lambda}$ is defined as $F(t-\lambda)$.

Using the fuzzy time series, the procedure for forecasting the residual is as follows.

Step (1) *Determination of the universal set:* Universal set U is defined as $[D_{min} - c_1, D_{max} + c_2]$ and a finite closed interval of U is determined. Here, D_{min} and D_{max} are the minimum and maximum values, respectively and c_1 and c_2 are positive real numbers for simplifying these end points. Table 1 shows the values used in the proposed hybrid model.

Step (2) *Determination of the closed interval:* It is known that the prediction of a fuzzy time series depends on the length and number of a closed interval. Several methods for choosing their proper values have been suggested [25–28]. In this study, following [29], the universal set is divided by the same interval length that is producing the best accuracy in the hybrid model.

Step (3) *Definition of membership degree:* To construct the fuzzified time series A_i, the membership degree in the i^{th} time period (u_i) is defined as:

$$\begin{aligned} A_1 &= \frac{1}{u_1} + \frac{0.5}{u_2} \\ A_i &= \frac{0.5}{u_{i-1}} + \frac{1}{u_i} + \frac{0.5}{u_{i+1}} \quad i = 1, \ldots, n-1 \\ A_n &= \frac{0.5}{u_{n-1}} + \frac{1}{u_n} \end{aligned} \tag{5}$$

Step (4) *Construction of fuzzy logical relationships:* A fuzzy logical relation is defined as the transition of the state at time $t-1$ to the state at time t. This is expressed as $A_i \rightarrow \{A_j : j = 1, \ldots, k\}$, where A_i and A_j are the states at t and $t-1$, respectively.

Step (5) *Calculation of predictive values:* Predictive values of the λ's order are estimated as follows:
(1) If $A_{i\lambda}, A_{i(\lambda-1)}, \ldots A_{i2}, A_{i1} \rightarrow A_j$, then the predictive value is the midpoint of u_j, m_j because the current state A_j has the maximum functional value of membership.
(2) If $A_{i\lambda}, A_{i(\lambda-1)}, \ldots A_{i2}, A_{i1} \rightarrow A_{j1}, A_{j2}, \ldots, A_{jl} (l \geqslant 2)$, then the predictive value is $\bar{m}_j = \frac{1}{l}\sum_{k=1}^{l} m_{jk}$. In this case, $A_{j1}, A_{j2}, \ldots, A_{jl}$ has the maximum functional value of membership at $u_{j1}, u_{j2}, \ldots, u_{jl}$ and its midpoint is defined as $m_{j1}, m_{j2}, \ldots, m_{jl}$.
(3) If $A_{i\lambda}, A_{i(\lambda-1)}, \ldots A_{i2}, A_{i1} \rightarrow$ empty, then the predictive value is $\bar{m}_j = \sum_{k=1}^{\lambda} w_k m_{ik} / \sum_{k=1}^{\lambda} w_k$. Here w_k is a weighting factor that is set to 1 in this study.

More detailed information on fuzzy time series can be found in [29,25,28,24].

Model evaluation

The three models predicted upcoming 4 months power load continuously for 14 months from December 2009 to January 2011. The accuracy of the power load values forecast by the three models described in this section was compared on the basis of the index of agreement (d) suggested by [30] and the mean absolute percentage error (MAPE). These are computed as follows:

$$d = 1 - \left[\frac{\sum (P_i - O_i)^2}{\sum \left(|P_i - \overline{O}_i| + |O - \overline{O}_i| \right)^2} \right], \quad 0 \leqslant d \leqslant 1 \tag{6}$$

$$MAPE(\%) = \frac{1}{N} \sum_{i=1}^{N} \left\| \frac{P_i - O_i}{O_i} \right\| \times 100$$

where N is the total number of data and O_i, and P_i are the observed and predicted loads, respectively. $\overline{O_i}$ is the mean value of the observed load. The metric d quantifies the relative contribution of systematic error to random error and has a value of 1 in a perfect model [30].

Results

Fig. 1 shows the monthly variations of electricity consumption for household, public, service, and industrial purposes in Seoul, South Korea between 2000 and 2011. The power load except for the industrial power load increases linearly with seasonal fluctuations above and below the overall trend line. Peak values occur in the same period of each year, indicating the strong auto-dependency of the data. It is also noteworthy that there are bimodal peaks in the annual cycle during the summer and winter seasons, suggesting a significant quadratic correlation between the load and air temperature. Indeed, our statistical analysis of the orthogonal polynomials shows that air temperature variation can account for approximately 84.3%, 83.2%, 86.1%, and 72.7% of the power load variations for household, public, service, and industrial purposes, respectively.

Unlike other sectors, the industrial power load shows an overall decline. This is because of the local government policy to transfer industrial factories to suburban areas. The sensitivity of power load to air temperature is relatively weak in this sector. Table 2 shows the coefficients used in the dynamic model for a hybrid approach (i.e., Eq. (3)) estimated by the ordinary least squares method. Annual variations in the load are clearly shown in Fig. 1, and so the auto-dependent time lag is estimated to be 12 months (see Table 3).

To evaluate the performance of the three models, the actual monthly load data for Seoul and the observed air temperatures from January 2000 to October 2010 were used. After training the three models, they were applied to forecast the load four months ahead. In particular, the proposed models gave separate forecasts for the household, public, service and industry sector.

Table 1 shows the residual that cannot be explained by the dynamic model described in Eq. (3). To construct the fuzzy time series, the universal set was determined by these residuals, and the data was divided into 24, 10, 13, and 9 categories from 10,000, 5000, 40,000, and 7500 MW h for the household, public, service, and industrial loads, respectively (Table 1).

Fig. 2 illustrates the index of agreement (d) of the three models. It is clear that the Koyck model, which considers air temperature and time lags only, exhibits poor performance, with $d < 0.5$, compared to ARIMA and the hybrid model. This poor agreement from the Koyck model indicates that even though the load seems to be closely related to air temperature and time lag, these two variables are not enough to improve our load forecasting. We speculate that such a pattern results both from other atmospheric conditions such as humidity and wind and the non-meteorological conditions such as government regulations, that make load prediction challenging.

The hybrid approach and ARIMA provide superior forecasting ability in terms of the absolute error. The hybrid model gives only less than 3% error of 4-month load forecasting for 14 months (Fig. 3). In particular, compared to ARIMA, the hybrid model is noticeably better at reproducing the observed peaks in the load (Fig. 4). In particular, the hybrid model gives almost perfect results ($d > 0.9$) for the household, public and service sectors (Fig. 2),

Table 1
The residual after application of the dynamic model and the constants used in the fuzzy time series.

Sector (MW h)	Minimum	Maximum	Universal set U
Household	−104633.73	121668.28	[−110,000, 130,000]
Public	−19977.75	24516.88	[−25,000, 25,000]
Service	−262213.40	217364.76	[−270,000, 250,000]
Industrial	−26658.74	39537.58	[−27,000, 40,500]

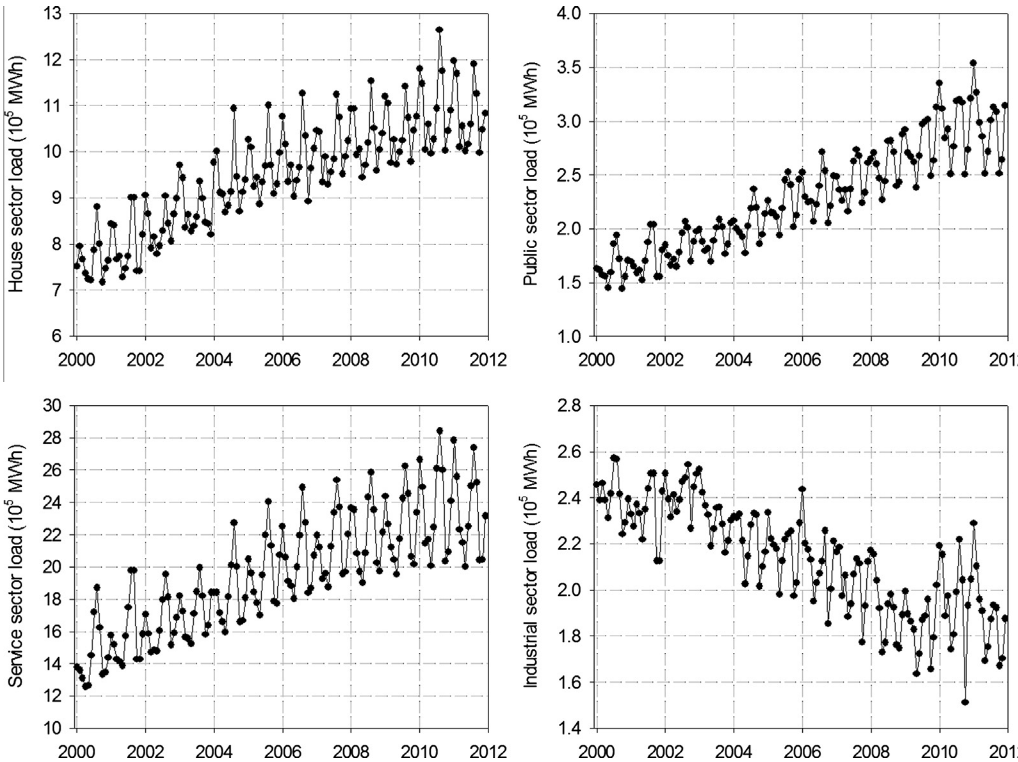

Fig. 1. Monthly variations of electricity consumption in Seoul metropolitan area from 2000 to 2011. (unit: 10^5 MW h).

Table 2
Parameter estimates for the dynamical model of Eq. (3).

Variable	Household	Public	Service	Industrial
α	113029.72	3908.3	213569.38	30394.00
β	0.92006	1.05209	0.94879	0.85202
γ	−2358.29	−603.81	−9103.54	−994.33
δ	94.95	23.32	351.61	38.40
Adjusted R^2	0.9082	0.9581	0.9525	0.7673

Table 3
Mean absolute percentage error (MAPE) (%) of consecutive 4-month ahead forecasting during 14 months.

Models	Household	Public	Service	Industrial
Koyck	9.4	13.8	13.8	12.0
ARIMA	3.9	2.9	2.9	5.4
Hybrid	2.6	2.6	3.1	5.1

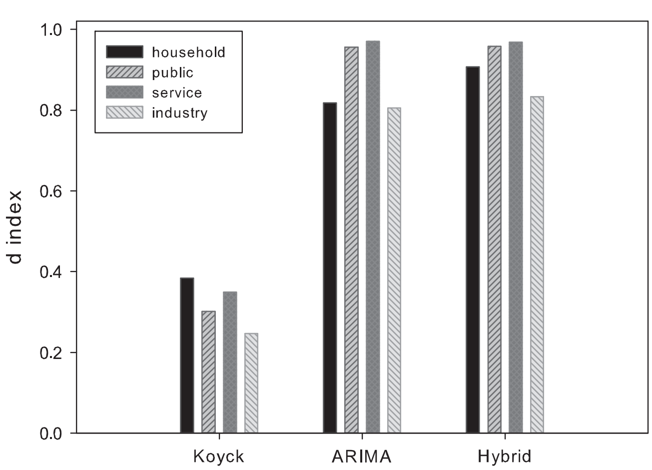

Fig. 2. Index of agreement (d) of the three models for consecutive 4-month ahead forecasting during 14 months from December 2009.

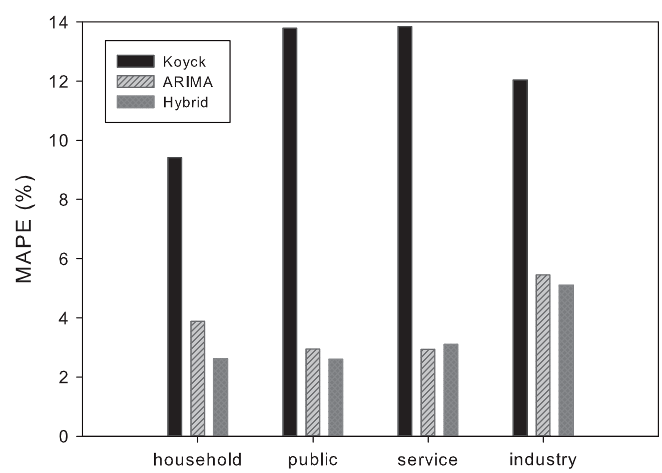

Fig. 3. MAPE (%) of consecutive 4-month ahead forecasting from the three models during 14 months.

compared to ARIMA. This result of large d index indicate that the proposed hybrid model produces a notable reduction on the prediction error and temporal variability of the power load, and this method can provide reliable information with a decision maker accordingly. Such small error of the proposed hybrid model is quite satisfactory compared to other models proposed earlier in the previous studies [e.g. 1,2].

It is also noteworthy that ARIMA exhibits comparable accuracy to that of the hybrid model. ARIMA does not require any additional meteorological information, because it forecasts the load based solely on the auto-dependent processes. Accordingly, this suggests that ARIMA could be an alternative tool for load forecasting when there is either no air temperature data or significant uncertainties in the observed air temperature data so long as there is a strong auto-dependency in the data.

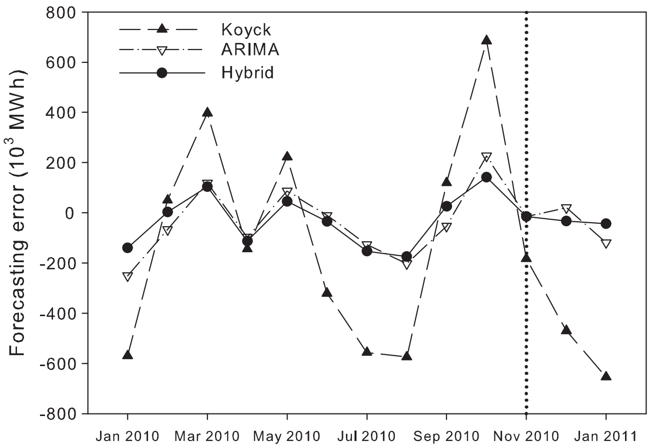

Fig. 4. One example of load forecasting from the three models. In this example, each model forecasted power load for three months from November 2011.

Conclusion

In this study, we developed a hybrid model based on dynamic and fuzzy time series for mid-term load forecasting and then evaluated the performance of this model by applying them to actual load data of Seoul metropolitan area, South Korea with a typical dynamic model, the Koyck model and ARIMA model. The proposed hybrid model and the Koyck model incorporated a quadratic sensitivity to air temperature. The proposed hybrid model provided the better forecasts than the Koyck and ARIMA models. Noticeably, the index of agreement d of the hybrid model was close to 1, and the MAPE of the total load forecast was less than 3% for consecutive four-month load forecasting. This suggests that compared to other models proposed by previous studies, the proposed hybrid model produces a substantial reduction on the forecasting error and its temporal variability and can be a useful tool for mid-term forecasting alongside observed air temperature data.

It was also noticeable that ARIMA reproduced the actual load data for Seoul with an MAPE of less than 3%. This implies that auto-dependent processes are dominant in power load of Seoul metropolitan area, the greatest portion of which comes from the service sector. Accordingly, ARIMA can be applied as an alternative mid-term load forecasting when there are significant uncertainties in the observed air temperature or such data are not available.

The main advantages of the proposed hybrid model are that (1) it eliminates the need for the statistical analysis of non-weather factors, and (2) it can easily be extended to a more complex model by incorporating a multivariate statistical analysis of other independent factors. Our study emphasizes that constructing a forecasting model based on the demand from individual sectors is preferable, because each displays a different response to weather conditions, economic situations, and government policy. Most of the power load is consumed in urban areas, and urban heat islands combined with global warming increase the power load substantially to compensate for this temperature rise. Therefore, the application of our proposed model to the Seoul metropolitan area will be a useful tool for urban management policy makers.

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Appendix A. Koyck model

A linear distributed lag model with a single explanatory variable X is:

$$Y_t = \alpha_0 + \sum_{i=1}^{\infty}\beta_{i,1}X_{t-i} + \sum_{i=1}^{\infty}\beta_{i,2}X_{t-i}^2 + u_t \tag{A.1}$$

where X_t is an independent variable (air temperature in this study) and u_t is a normally distributed and serially independent random variable with a mean of zero. In Eq. (A.1), $\beta_{i,k}(k = 1,2)$ is the lag coefficient of X_{t-i}^k and X_{t-i}^2 is explicitly included in the distributed lag model to incorporate the quadratic sensitivity of the load to air temperature.

It is known that the distributed lag model described in Eq. (A.1) becomes problematic if (i) the lags in the same variable are significantly correlated, or (ii) the sample size is so small that the use of multiple lags erodes the degree of freedom. By assuming that all βs in an infinitely distributed lag model have the same sign and decrease exponentially with time [16], illustrated that these general pitfalls of the distributed lag model can be avoided. That is:

$$\beta_{i,k} = \beta_{1,k}\lambda^i, \quad \forall i, with\ 0 < \lambda < 1 \tag{A.2}$$

where λ is the rate of decay, and a measure of how rapidly the effects of the independent variable are lost with time. Values close to 1 indicate that the variable had a significant effect on the dependent variable in the past, and λ values close to 0 imply that the defining variable rapidly lost its effect on the dependent variable.

It then follows that

$$Y_t = \alpha_0 + \beta_{1,1}\sum_{i=1}^{\infty}\lambda^{i-1}X_{t-i} + \beta_{1,2}\sum_{i=1}^{\infty}\lambda^{i-1}X_{t-i}^2 + u_t \tag{A.3}$$

Lagging and multiplying Eq. (A.3) by λ gives

$$\lambda Y_{t-1} = \lambda\alpha_0 + \beta_{1,1}\sum_{i=1}^{\infty}\lambda^{i}X_{t-i-1} + \beta_{1,2}\sum_{i=1}^{\infty}\lambda^{i}X_{t-i-1}^2 + \lambda u_{t-1} \tag{A.4}$$

and then subtracting Eq. (A.4) from (A.3) gives

$$Y_t - \lambda Y_{t-1} = \alpha_0(1-\lambda) + \beta_{1,1}X_{t-1} + \beta_{1,2}X_{t-1}^2 + u_t - \lambda u_{t-1} \tag{A.5}$$

Arranging Eq. (5) in terms of Y_t, we obtain the Koyck model for the predictor Y_t as

$$Y_t = \alpha + \beta_{0,1}X_{t-1} + \beta_{0,2}X_{t-1}^2 + \lambda Y_{t-1} + \epsilon_t \tag{A.6}$$

where $\alpha = \alpha_0(1-\lambda)$ and $\epsilon_t = u_t - \lambda u_{t-1}$.

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