Adaptive Approach and Seasonal Technique for Universal Data Forecasting

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Abstract

The main component of observation data includes both trend and seasonal effects. The represented equation of forecasting model like ARIMA seems to have more explained parameters when we need more accuracy in time series prediction. To apply these elaborate and beautifully crafted techniques we require an advanced level of knowledge and sophistication only available from specialists. However, it is more suitable for anyone who does not familiar with complex forecasting models can use a simple equation like applied exponential smoothing model for forecasting. We propose a simple suitable model that can be applied to most kinds of data observation types with good prediction outcome. The proposed model can be applied to a simple spreadsheet calculation which yields good short term prediction with low error rate.

Keyword : time series, exponential smoothing forecast, prediction, adaptive approach, seasonal technique

1. Introduction

During the past 30 years, the forecasting field has expanded significantly. A number of forecasting methods, including some sophisticated models have been developed [1]. Practically, forecasting methods such as single exponential smoothing, double exponential smoothing, and simple moving average are selected and implemented to acquire accuracy based on slow or fast moving by using appropriate exponential smoothing factors with adaptability of the forecasting method [2].

Usually, we can apply exponential smoothing and moving average methods for short-term forecasting whereas double exponential smoothing method additionally provides some estimation and accounting for an upward or downward trend to adjust the next-period forecast. These time series prediction methods are also powerful tools to model long-term stable observations [3]. Many time series actually encountered in industry, business, and economics exhibit non-stationary behavior and in particular do not vary about a fixed mean. This is why the number of parameters in the transfer function tends to be quite large when fitting actual time series [4]. This can make estimation of parameters cumbersome and inexact.

Another attractive time series model is Autoregressive Integrated Moving Average (ARIMA) introduced by G. Box and G. Jenkins in the early 1970s [13]. This time series analysis is attractive because it can capture complex arrival patterns, including those that are stationary, non-stationary, and seasonal (periodic) ones [5]. Box-Jenkins approach is elegant in theory but has been of little practical use in business because of its complexity and limited increase in accuracy over less sophisticated methods [1]. To evaluate all of these factors simultaneously in a specific situation to select appropriate models is not easy, even for the expert in the field. ARIMA models can describe temporal patterns but provide little insight on spatial access patterns. Other research [5] applied Markov model that is an effective technique for representing spatial access patterns.

These elaborate and beautifully crafted techniques require an advanced level of knowledge, labor-intensive tasks, and sophistication only available from specialists [1],[3],[6]. Artificial intelligences are alternative good techniques that can be applied to forecasting by using of prior distributed data learning. The main methods are Bayesian, neural networks, and fuzzy models.

Bayesian method assumes that past data follow a particular probability distribution [2]. By knowing this prior distribution, the prediction is immediately available, and the method can forecast next-period of a part by a simple formula. It may be effective in forecasting the erratic demand for the slow moving parts; however, it requires a substantially larger inventory investment than do the two exponential smoothing methods. The empirical evidence that has been reported suggests that explanatory models do not provide significantly more accurate forecasts than the time series models, even though the former are much more complex and expensive [1].

Neural networks are very efficient models for daily index forecasts although it takes some time initially to set up the right network structures. The artificial neural network forecasting is generally superior to time series but it occasionally produces some very wild forecasting values [3].

Fuzzy models are particularly well suited for modeling human decision making. These often rely on common sense and use vague and ambiguous terms while making decision. Although, most fuzzy applications are popular in control and engineering, and even larger potential exist in business and finance [12]. These areas are based on human intuition, common sense and experience, rather than on the availability and precision of data. These provide a means of coping with the soft criteria and fuzzy data that are often used in business and finance models.

Intelligent hybrid models are the methods that combine at least two intelligent technologies and give synergetic

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advantage. For example, an intelligent hybrid model composed of an artificial neural network combined with a modified genetic algorithm was able to classify a random- walk-like-model time series [7]. Clustering techniques that attempt to group similar data points are other combined techniques that are a very well studied problem. However, information about errors associated with data, traditional clustering methods are inadequate [8]. Another example, the neuro-genetic stock prediction system based on financial correlation among companies proposed in [9]. This algorithm showed significantly better performance than the "buy-and-hold" strategy and a recurrent neural network using only the input variables of the target company as input nodes [9]. In addition, feed-forward neural network and cosine radial basis function neural network approaches yield better generalization capability and lower prediction error compared to those neural network approaches [10].

The successful impact of forecasting is tied directly to the one's need, understanding and involvement for forecasts. However, few people are familiar with the wide range of forecasting techniques like ARIMA and beyond the intelligent hybrid [1].

In this paper, we propose a simple suitable forecasting model, based on exponential smoothing and adaptive approach. The proposed model can be applied to most kinds of data observation types. One can apply in simple spreadsheet and receive good short term prediction with low error outcome.
The remainder of this paper are organized as follows. In Section II, we give details of the focused methods and our proposed methods. Section III illustrates the simulation results and discussion. Finally, concluding remarks is given in Section IV.

2. The Focused Method

ARIMA's classification models [5] are attractive and nice model. These are several of suitable models to describe data prediction. However, if we need more accurate prediction in advance, then these are too complex to use. So, our models are developed based on simple models: exponential smoothing and adaptive approaches. Then, we selected Pegels' model [11] as our benchmark.

2.1 Exponential Smoothing Forecast

Exponential smoothing makes use of a smoothing constant, which is the percentage of the forecast affected by the most recent observation. This is an extension to the moving average model by weighted moving average. The weight assigned to observations is by-product of the particular moving average. The past *k*-period is observation the weight equal to 1/*k* for all *k* data point. This is implied that it is an exponentially decreasing weight. The basic equation is known as single exponential smoothing (SES) as follow:

$$F_{t+1} = \alpha_t Y_t + (1-\alpha_t) F_t \qquad (1)$$

where α is a constant between 0 and 1; F_t is a forecast value in time period *t*; and Y_t is a real data observation in time period *t*.

This model is an improvement than simple mean moving average model because the latest observation value has more effect on the next predicted values. It is also a good fitting with observed data that have significant trends. However, if we need more precision with low prediction error with the type of seasonal observations, the model in equation (1) is not acceptable for forecasting.

2.2 Exponential Smoothing Forecast Using Seasonal Factors

In many situations, most real observations such as sale volume have more trends with seasonal period patterns. The model applying seasonal factors with exponential smoothing model is better as it yields lower prediction error outcomes. The combined equations are illustrated as follow:

$$F_{t+1} = (S_t + G_t) C_{t+1,N} \qquad (2)$$

$$St = \alpha (D_t / C_{t,N}) + (1-\alpha)(S_{t-1} + G_{t-1}) \qquad (3)$$

$$G_t = \beta (S_t - S_{t-1}) + (1-\beta) G_{t-1} \qquad (4)$$

$$C_t = \gamma (D_t / S_t) + (1-\gamma) C_{t,N} \qquad (5)$$

where G_t is one period trend estimate; D_t is latest data point; C_t is seasonal factor; $C_{t+1,N}$ is the latest period of seasonal factors being used in the next period; α, β, γ are smoothing constant; and N is seasonal period.

Using seasonal model with trend applied to exponential smoothing model with non-seasonal observation data gives prominent of predicted value at each time period as shown in Fig.1. This can be demonstrated in equation (2) with N =12 (season 12) yielding prominent prediction at time period 13 when it is compared with nearest neighbors. The bigger value of *N*, the higher prominent value of prediction. We have observed that small value, such as 4, will result better smoothing of prediction.

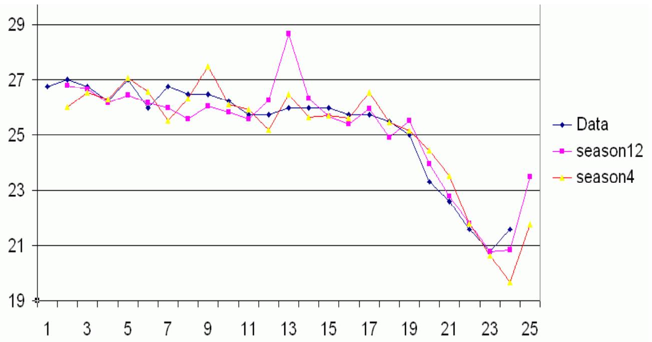

Fig. 1. Effects of prominent of predicted value at each time period N+1

2.3 Pegels' Classification

In referring to Pegels' classification in [11], the authors have provided a simple but useful framework, two-way classification which is the combination of trends and seasonal.

This classification can support both non-seasonal and seasonal observation data and is divided into nine sub-models according to additive (linear) or multiplicative (non-linear) models based on the following equation:

$$L_t = \alpha P_t + (1-\alpha) Q_t \tag{6}$$

$$b_t = \beta R_t + (1-\beta) b_{t-1} \tag{7}$$

$$S_t = \gamma T_t + (1-\gamma) S_{t-s} \tag{8}$$

where P, Q, R, and T vary according to the cells of Table 1.

Table 1. Pegels' Formula for Calculation and Forecasting

Trend	Seasonal Component 1 (no seasonal effect)	2 (additive seasonal)	3 (multiplicative seasonal)
A (no trend effect)	$P_t = Y_t$ $Q_t = L_{t-1}$ $F_{t+m} = L_t$	$P_t = Y_t - S_{t-s}$ $Q_t = L_{t-1}$ $T_t = Y_t - L_t$ $F_{t+m} = L_t + S_{t+m-s}$	$P_t = Y_t / S_{t-s}$ $Q_t = L_{t-1}$ $T_t = Y_t / L_t$ $F_{t+m} = L_t S_{t+m-s}$
B (additive trend)	$P_t = Y_t$ $Q_t = L_{t-1} + b_{t-1}$ $R_t = L_t - L_{t-1}$ $F_{t+m} = L_t + mb_t$	$P_t = Y_t - S_{t-s}$ $Q_t = L_{t-1} + b_{t-1}$ $R_t = L_t - L_{t-1}$ $T_t = Y_t - L_t$ $F_{t+m} = L_t + mb_t + S_{t+m-s}$	$P_t = Y_t / S_{t-s}$ $Q_t = L_{t-1} + b_{t-1}$ $R_t = L_t - L_{t-1}$ $T_t = Y_t / L_t$ $F_{t+m} = (L_t + mb_t) S_{t+m-s}$
C (multiplicative)	$P_t = Y_t$ $Q_t = L_{t-1} b_{t-1}$ $R_t = L_t / L_{t-1}$ $F_{t+m} = L_t b_t^m$	$P_t = Y_t - S_{t-s}$ $Q_t = L_{t-1} b_{t-1}$ $R_t = L_t / L_{t-1}$ $T_t = Y_t - L_t$ $F_{t+m} = L_t b_t^m + S_{t+m-s}$	$P_t = Y_t - S_{t-s}$ $Q_t = L_{t-1} b_{t-1}$ $R_t = L_t / L_{t-1}$ $T_t = Y_t / L_t$ $F_{t+m} = L_t b_t^m S_{t+m-s}$

One of all nine Pegels' exponential smoothing models that give low prediction error is selected as the equation representing observation data. We use Pegels' classification models as our reference to compare with our models because Pegels' models are a simple but useful framework for discussion.

In our results and discussion section we use:

- A-1 as Pegels' no trend and no seasonal effect. This model is equivalent to SES when α is closed to 1 and gives the same result as ARIMA(0,1,1).
- A-2 as additive seasonal effect without trend.
- A-3 as multiplicative seasonal effect without trend.
- B-1 as an additive trend without seasonal effect. This model is equivalent to ARIMA(0,2,2).
- B-2 as an additive trend and additive seasonal effect. This model is equivalent to ARIMA(0,1,s+1)(0,1,0). The only number of parameters are different. B-2 uses 3 parameters but ARIMA use s+1 parameters.
- B-3 as an additive trend and multiplicative seasonal effect. This model has no equivalent to ARIMA model.
- C-1 as a multiplicative trend without seasonal effect.
- C-2 as a multiplicative trend and additive seasonal effect.
- C-3 as a multiplicative trend and multiplicative seasonal effect.

2.4 Adaptive Approach

An adaptive-response-rate single exponential smoothing (ARRSES) may have advantages over SES in that it allows the value of α to be modified as changes in the pattern of data occurred. The model of ARRSES, in equation (9), is similar to SES in equation (1) except α replaced by α_t.

$$F_{t+1} = \alpha_t Y_t + (1-\alpha_t) F_t \tag{9}$$

where $\alpha_{t+1} = \left|\frac{A_t}{M_t}\right|$; smoothing error $A_t = \beta E_t + (1-\beta) A_{t-1}$; absolute smoothing error $M_t = \beta |E_t| + (1-\beta) M_{t-1}$; $E_t = Y_t - F_t$; and β is between 0 and 1. If value is closed to 1 its characteristic is similar to naïve model.

3. The Proposed Model

Our proposed models are adapted from exponential smoothing forecast using seasonal factors. With refference to equation (4), we add constants found in equation (12). Also we apply equations (2), (3), and (5) to equations (10), (11), and (15), respectively, for ease in explanation. The advantage of seasonal factor is that it gives low error rate for exponential smoothing forecast prediction. Our proposed models also gives prominent predicted value at each time period of $N+1$ with non-seasonal observation data. So, we modify $C_{t+1,N}$ in equation (14) and (15) and use an adaptive approach to dynamically change C_t in order to adjust seasonal type. Our model can be used with non-seasonal data type. However, we found that equation (14) is suitable for non-seasonal observation data and the equation (15) gives better prediction to seasonal data type.

$$F_{t+1} = (S_t + G_t) \cdot C_{t+1,N} \tag{10}$$

$$F_{t+1} = \alpha \cdot (D_t / C_{t,N}) + (1-\alpha) \cdot (S_{t-1} + G_{t-1}) \tag{11}$$

$$G_t = \beta \cdot (S_t - S_{t-1}) + \delta \cdot (1-\beta) \cdot G_{t-1} \tag{12}$$

$$C_t = \gamma \cdot (D_t / S_t) + (1-\gamma) \cdot C_{t,N} \tag{13}$$

Our model I: linear

$$C_{t+1,N} = C_{t-1-N} + (C_t - C_{t+1-N}) - \frac{1}{N} \cdot SD(C_t \ldots C_{t+1-N}) \tag{14}$$

Our model II: non-linear

$$C_{t+1,N} = C_{t-1-N} + (C_t - C_{t+1-N}) \cdot SD(C_t \ldots C_{t+1-N}) \tag{15}$$

where $\gamma_{t+1} = \left|\frac{A_t}{M_t}\right|$; $A_t = \nu E_t + (1-\nu) A_{t-1}$; $M_t = \nu |E_t| + (1-\nu) M_{t-1}$; and $E_t = Y_t - F_t$.

G_t is one-period trend estimate; D_t is the latest data point;

C_t is seasonal factors; $\alpha, \beta, \gamma, \nu, \delta$ are smoothing constants; N is seasonal period which is a positive integer larger than 1; and $SD(.)$ is standard deviation function.

4. Results and Discussion

For benchmarking our model, we performed simulation studies. In our experiments, we selected Pegels' models and naïve model for prediction comparisons. We selected the standard statistical measurements: MAE, MSE, MAPE and U-Theil for our benchmark. To see the outcomes with different kinds of observations we tested the proposed models with 5 groups of data: two for seasonal types and three for non-seasonal types.

From subsection C of section II, we used Pegel's models with seasonal effect equal to 4 (N=4). Our models in equations (10), (13), (14), and (15) was set $N = 12$ since it is optimal.

Both Pegels' and our proposed models used the same initial values for statistical error testing during the time period 10 and 24.

In the first test, we used observation data with growth rate trend and seasonal effect = 4. The results are shown in Fig. 2 and Table I. The winning model is Pegel B-3 with parameters $(\alpha, \beta, \gamma) = (0.82, 0.05, 0)$ because of resonance seasonal effects with observation. Nevertheless, in our model, both type I with $(\alpha, \beta, \gamma, \delta)$ = (0.6,0.6,0.1.0.2) and type II with $(\alpha, \beta, \gamma, \delta)$ = (0.9,0.9,0.9,0.4), respectively, give low error prediction compared with naïve model, a standard reference model. Type II is also good match for acceptatance.

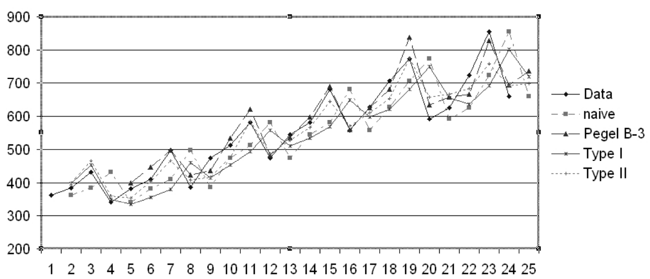

Fig. 2. Forecast comparing with observated data which growth trend and seasonal effect N = 4

Table 2. Statistic of Error Measurement Results From Fig.2

	MAE	MSE	MAPE	U-Theil
naïve model	93.33333	10844.27	14.90862	1
Pegel B-3	20.69283	583.0444	3.142316	0.247803
Our type I	79.60159	8986.838	11.98782	0.931655
Our type II	30.65027	2183.477	5.134932	0.585335

In the second test, we changed observation data to seasonal effect with N = 12. The testing results are shown in Fig.3 and table 3. Type II with parameters $(\alpha, \beta, \gamma, \delta)$ = (0.9,0.9,0.6,0.4) give most optimized prediction because of seasonal effect resonance.

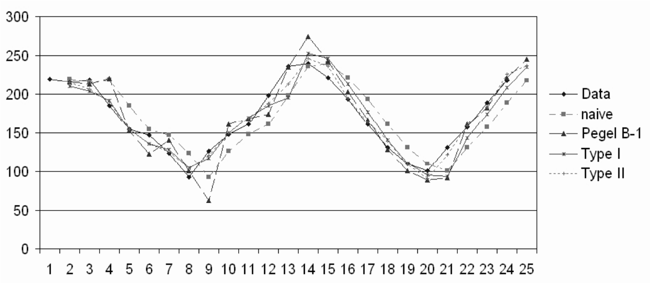

Fig. 3. Forecast comparing with observation data type of seasonal effect, N=12

Table 3. Statistic of Error Measurement Results from Fig.3

	MAE	MSE	MAPE	U-Theil
naïve model	24.4	692	14.73767	1
Pegel B-1	12.93333	294.4	7.899996	0.74743
Our type I	14.99736	348.5556	8.556208	0.776128
Our type II	7.529237	90.8981	4.332804	0.346101

In Figs. 2 and 3, it is obvious that type II model is trend with seasonal pattern. In addition, Type I give better results than naïve model.

When fluctuating and declining trends were applied, the bast model were Pegels B-1 (α, β) = (0.8,0.15) and type I $(\alpha, \beta, \gamma, \delta)$ =(0.9,0.1,0.9.0.1), as shown in Fig. 4 and table 4. These two models yield nearly the same results, even though type I shows a little bit better.

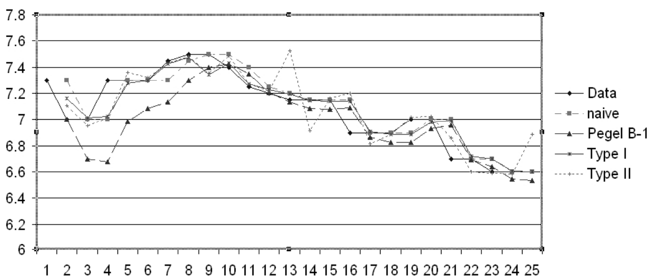

Fig. 4. Forecast comparing with observated data which has fluctuations and decline trends

Table 4. Statistic of Error Measurement Results from Fig. 4

	MAE	MSE	MAPE	U-Theil
naïve model	0.073333	0.014	1.057239	1
Pegel B-1	0.079177	0.011227	1.143977	0.921107
Our type I	0.063317	0.011223	0.923015	0.920528
Our type II	0.097887	0.022447	1.398824	1.272304

Another example of testing results is shown in Fig. 5 and table 5. This comparison emphasizes that our model type I $(\alpha, \beta, \gamma, \delta)$ = (0.9,0.9,0.9.0.6) is optimal model. Whereas C-1 (α, β) = (0.9,0.9) and our type II model $(\alpha, \beta, \gamma, \delta)$ = (0.9,0.9,0.2.0.4) have the same results and closed to naïve model.

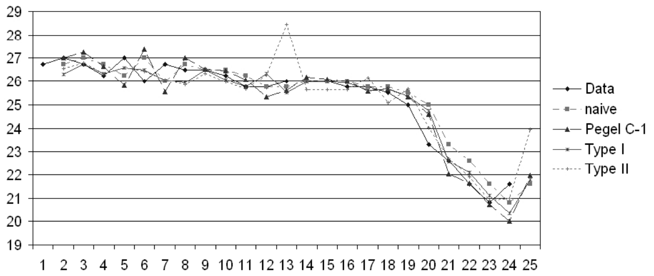

Fig. 5. Forecast comparing with observated data which has higher slope and tailing

Table 5. Statistic of Error Measurement Results from Fig.5

	MAE	MSE	MAPE	U-Theil
naïve model	0.466667	0.427333	2.025327	1
Pegel C-1	0.494288	0.445379	2.112849	1.070838
Our type I	0.383703	0.325943	1.637114	0.887519
Our type II	0.501614	0.565896	2.018574	1.072704

The last example is shown in Fig.6 and table VI. Type II $(\alpha, \beta, \gamma, \delta)$ = (0.7,0.7,0.1,0.6) is a little better than type I = (0.8,0.6,0.1,0.5) because the observed time series rapidly changes both falling and increasing in slope and type II is applied from non-linear. Type I has also conformance with the non-seasonal observation. Whereas C-1 is the best from nine models of Pegels' classification models. In this case, C-1 gives the result not better than naïve model.

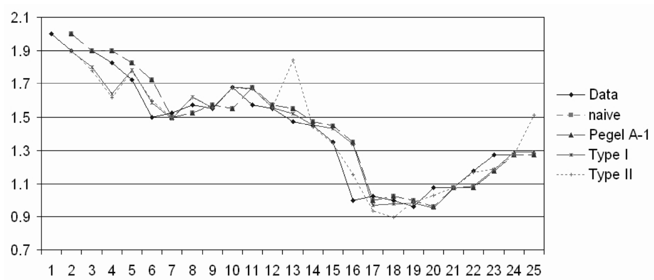

Fig. 6. Forecast comparing with observation data type of dramatic falling and increasing

Table 6. Statistic of Error Measurement Results from Fig. 6

	MAE	MSE	MAPE	U-Theil
naïve model	0.080333	0.013405	6.719882	1
Pegel C-1	0.08034	0.013408	6.720176	1.000113
Our type I	0.066379	0.011154	5.828194	0.962264
Our type II	0.067406	0.01321	5.505751	0.94727

After we tested our models with real observation data, we found that the seasonal exponential smoothing model combined with adaptive approach model has good responses to all data types. Our model type I is more suitable for non-seasonal observations but type II gives good prediction with seasonal data.

The type I model has dramatic improvement on the models in subsection B of section II when applied to non-seasonal data because the seasonal factor $C_{t+1,N}$ in equation (14) is adjusted by differential value $\left(C_t - C_{t+1-N}\right)$ and reduced the deviation value $SD(C_t \ldots C_{t+1-N})$ by factor of N. This also combined with the effect from the smoothing constant δ in equation (12). The result of our models can be applied to most types of data with least effect of parameters. This is a nice model that can reduce the complicated task like ARIMA and Pegels' classification, from ten models with hundreds of values obtained [3] and nine models with ten values obtained, respectively to only two models with five values obtained, in our proposed models. So, we can reduce labor-intensive tasks yet receive acceptable prediction results.

5. Conclusion

In time series prediction, the forecasting model like ARIMA seem to have many complicated parameters when we need more accuracy in time series prediction. To apply these elaborate and beautifully crafted techniques we require advanced knowledge only available from specialists. However, it is more suitable if one who is not familiar with complex forecasting models can use a simple equation like applied exponential smoothing model for forecasting. In this paper we propose an algorithm based on an adaptive approach and seasonal technique, which is dedicated to time series prediction. The proposed method can deal with both trend and seasonal effects. Our approach is a simple model that can be applied to most kinds of data with good prediction outcome. The proposed model can be applied to time series prediction by calculating in a simple spreadsheet which yields good short term prediction with low error rate.

For our future work, we will implement fuzzy temporal concepts to be applied to the prediction time series. It is also questionable that how the dynamic and highly-nonlinear behavior of the time series can be resolved. This would be future investigation.

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