

6-520-12A: PLANING AND CONTROL OF LOGISTICS SYSTEMS

Session 2: Forecasting

Multiplicative decomposition

Exercise: building a model in Excel

Set up: download the template workbook

Download the "E.Forecasting_exercises.xlsx" file from ZoneCours and open it in Excel. Select sheet "Decomposition". Figure 1 shows the initial state of the model.

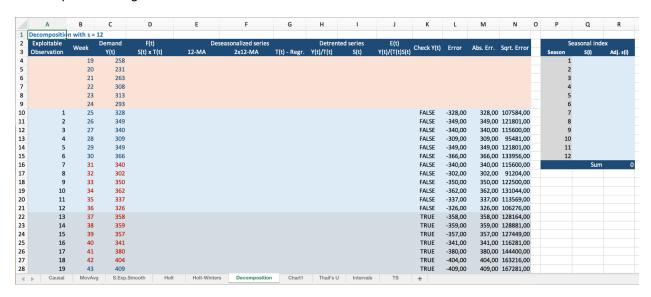


Figure 1: the E.Forecasting exercises.xlsx/Decomposition spreadsheet

Step 1: understanding the data

Our dataset contains demand information for 36 periods (weeks). The demand has a seasonal pattern (cycle) that repeats every 12 periods (weeks in our case). A brief description of the three columns holding the data follows.

A | Exploitable Observation: as the name suggests, this column contains an index for exploitable observations. Indeed, for a reason that you will understand later, the data for the first 6 and the last 6 periods is not exploitable for forecasting. This is the reason why the index starts at row 10 (week 25) and ends at row 33 (week 48).

B | Week: this column holds the identifier of the periods (weeks). The data on this column is for reference only, we will not use it on our computations.

C | Demand: as the name suggests, this column contains de observed demand **Y(t)** for each period (week). The blue and red colors help identifying observations belonging to the same demand cycle. Figure 2 shows a plot of the demand. For graphical convenience we use a line graph instead of an XY plot.

3000, chemin de la Côte-Sainte-Catherine, Montréal (Québec) Canada H3T 2A7 **Téléphone : 514 340-6716** Télécopie : 514 340-6834 www.hec.ca/gol www.hec.ca/chaine

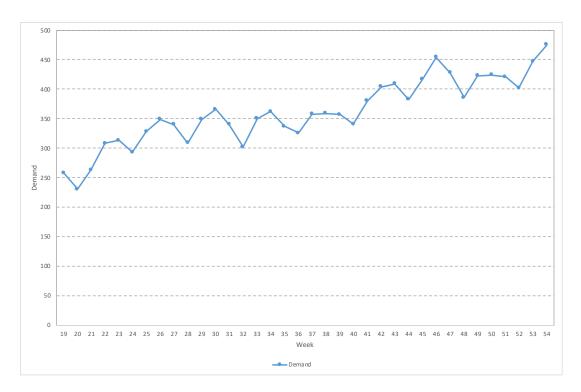


Figure 2: Demand observed in the past 36 weeks

Step 2: isolate the trend-cycle component of the demand (i.e., "deseasonalize" the series)

There are several techniques that can be applied to isolate the trend-cycle component of the demand. In our example, we will apply what is commonly known as moving average smoothing. In a nutshell, this technique consists in estimating the trend-cycle component at period at period t, by computing a moving average (MA) of order t (where t is equal to length of the demand cycle). More precisely, the trend-cycle component at period t, denoted, t is computed as follows:

$$\widehat{T}(t) = \frac{1}{m} \sum_{j=-k}^{k} Y(t+j)$$

where m=2k+1. This moving average is usually referred to as a m-MA. In our particular case, the demand cycle has 12 seasons. Therefore, we should use a m-MA with m=12 and k=6.5. The latter means that we need to center our MA around the "imaginary" season 6.5. To achieve this goal we will apply what is known as a 2×12 -MA, that is, a MA of order 2 applied to a MA of order 12. A more thorough discussion on centered moving averages is out of the scope of this tutorial. We refer students interested on this topic to Chapter 6, Section 6.2 in [1].

First, we will compute in Column D a 12-MA centered in season 6. Go to Cell D9 and insert the formula =AVERAGE(C4:C15) as shown in Figure 3a. Then, drag the formula down to cell D34. Next, we will compute in Column E a 2-MA centered in Season 7. Go to Cell E10 and insert the formula =AVERAGE(D9:D10) as shwon in Figure 3b. Then, drag the fomula down to Cell E34. What we obtain in Column E is $\hat{T}(t)$, a 12-MA centered in season 6.5. This "deseasonalized" series represents the isolated trend-cycle component of the demand. Figure 4 shows the original demand its trend-cycle component.

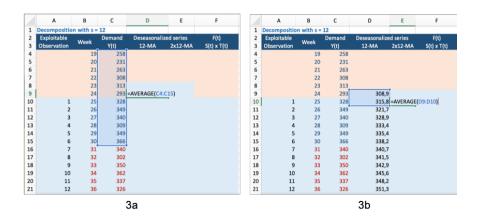


Figure 3: Isolating the trend-cycle component of the demand



Figure 4: Demand and its isolated trend-cycle component $\hat{T}(t)$

Step 3: computing the seasonal indices

Now we are going to "detrend" the series so we can compute the seasonal indices (also known as seasonal factors or relatives). Since we are assuming a multiplicative model, the seasonal component of the demand at period t is equal to: $\hat{S}(t) = Y(t)/\hat{T}(t)$, where $\hat{T}(t)$ is the tread-cycle component we found in Step 2.

Go to Cell F10 and insert the formula: =C10/E10 as shown in Figure 5. Then, drag the formula down to cell F34.

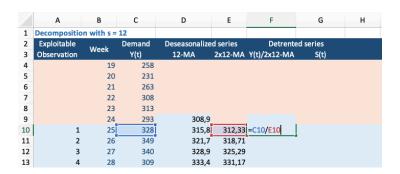


Figure 5: "detrendeing" the series

To compute the seasonal indices, we average the seasonal component of the observed demand for similar seasons. For instance, week 19 and week 31 correspond to the same season (Season 1) in the demand cycle. The index for Season 1 is then be $\frac{\hat{S}(19)+\hat{S}(31)}{2}=\frac{1.05+1.01}{2}$, which is the average of the values in cells F10 and F22.

To average the seasonal components we will use the secondary table in Range P2:R16. Go to Cell Q4 and insert the formula =AVERAGE(F10;F22) as shown in Figure 6. Then, drag the formula down to cell Q15. Note that the values in Range Q4:Q15 should add to 12 (the number of seasons in the demand cycle). In our case, however, the they add up to 12.08. To correct this issue, we adjust the seasonal index for each season as follows. Go to Cell R4 and insert the following formula: =Q4/AVERAGE(\$Q\$4:\$Q\$15). Then, drag the formula down to Cell R15. Note that the sum in Cell R16 now equals exactly 12.

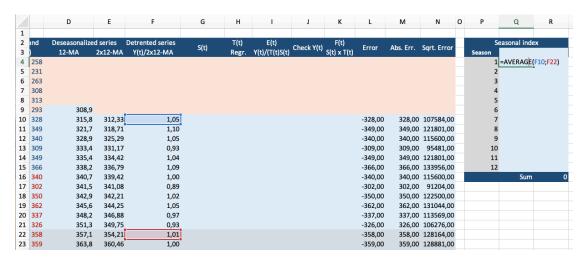


Figure 6: computing the seasonal indices

Now we are going to "import" the newly calculated season indices to our main table (model). Go to Cell G10 and insert the following formula =R4. Then drag the formula down to Cell G21. The current state of the main table is shown in Figure 7. Repeat the operation starting at Cell G22. Note that observations belonging to the same season should have the same value in Column G. For instance, cells G1 and G13 should both have the same value (i.e., 1.05), so should cells G2 and G14 (i.e., 1,10).

Exploitable		Demand	Deseasonalized series		Detrented series		T(t)
Observation	Week	Y(t)	12-MA	2x12-MA	Y(t)/2x12-MA	S(t)	Regr.
	19	258					
	20	231					
	21	263					
	22	308					
	23	313					
	24	293	308,9				
1	25	328	315,8	312,33	1,05	1,02	
2	26	349	321,7	318,71	1,10	1,04	
3	27	340	328,9	325,29	1,05	1,00	
4	28	309	333,4	331,17	0,93	0,92	
5	29	349	335,4	334,42	1,04	1,01	
6	30	366	338,2	336,79	1,09	1,06	
7	31	340	340,7	339,42	1,00	1,02	
8	32	302	341,5	341,08	0,89	0,92	
9	33	350	342,9	342,21	1,02	1,02	
10	34	362	345,6	344,25	1,05	1,07	
11	35	337	348,2	346,88	0,97	1,00	
12	36	326	351,3	349,75	0,93	0,92	
13	37	358	357,1	354,21	1,01		
14	38	359	363,8	360,46	1,00		

Figure 7: computing the seasonal indices

Step 4: forecasting the trend-cycle component T(t)

We are going to forecast the trend-component of the demand using a linear regression built using the deseasonalized series (i.e., the trend-cycle component of the observed demand). There are several ways to run a linear regression in Excel (see for instance [2] for a tutorial). We are going to use the SLOPE() and INTERSECT() built-in functions. Remember that a linear model has the form f(x) = bx + a. The first function computes parameter b while the second computes parameter a. For both functions, the first parameter is the range holding the values of the independent variable a and the second parameter is the range holding the values of the dependent variable a.

Insert formula =SLOPE(\$£\$10:\$£\$33;\$A\$10:\$A\$33)*A10+INTERCEPT(\$£\$10:\$£\$33;\$A\$10:\$A\$33) into Cell H10 as shown in Figure 8. Note that this formula simultaneously computes the linear model and predicts the trend-cycle component for the period in Cell A10 (period 1 in this case). Next, drag the formula down to Cell H33. Figure 9 reflects the current state of the main table.

Optional remark: It is worth noting that our choice of the tool employed to run the linear regression may have an impact in the computational performance of the model. As a matter of fact, every time the spreadsheet is refreshed, Excel recomputes functions SLOPE() and INTERSECT() for every row. This basically means recomputing several times the same linear. In our example, this is not a perceivable issue, because the time series contains only a few tens of observations. However, if you are working with larger datasets, you may experience a degradation in the time needed to refresh the spreadsheet. A good alternative to solve this problem would be to run the linear regression only once on a separate sheet and "hard code" the value of the b and a coefficients in the formulas of Column H. For instance, in our case the linear model fitted to the deseasonalized series is: f(x) = 4.43x + 279.67. We could then write into Cell H10 the formula =4.43*A10+279.67 and drag the formula down to Cell H33. The reason why we favor our initial approach, is to have a model that is automatically updated if the demand data changes, rather than one that uses hard-coded values that must be recalculated "by hand" and then updated in the formulas. The latter is typically a source of errors, because users tend to forget to recompute and update those values.

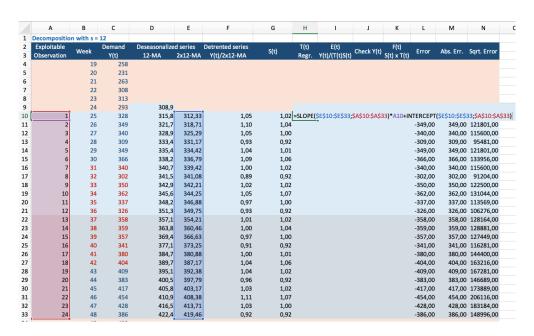


Figure 8: forecasting the trend-cycle component

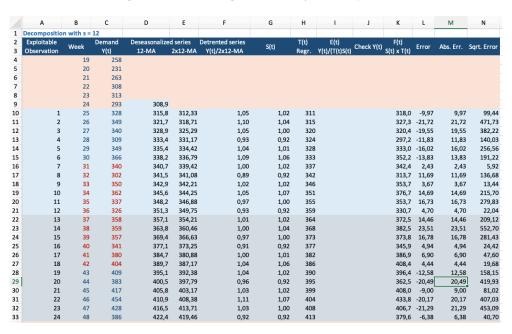


Figure 9: state of the table after forecasting the trend-cycle component

Step 5: forecasting

In theory we need to forecast not only the trend-cycle component but also the seasonal component. However, as Hyndman and Athanasopoulos point out (Section 6.8, Chapter 6 in [1]) "it is usually assumed that the seasonal component is unchanging, or changing extremely slowly" so we can forecast it using the naïve method. The latter simply means using the last available observed value (the values estimated in Step 3).

Recall that in the multiplicative decomposition model, the forecast is given by $F(t) = T(t) \times S(t)$. Therefore, we only need to multiply the values in Column G and H to obtain our forecast. Go to Cell I10 and insert the following formula: =H10*G10. Drag the formula down to Cell J33. Figure 10 shows the forecast along with the observed demand, the isolated trend-cycle component (i.e., deseasonalized series), and the forecasted trend-cycle component.

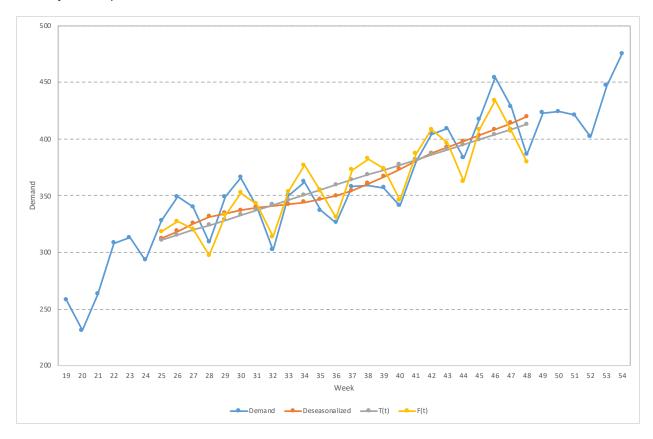


Figure 10: Demand, Isolated trend-cycle component, forecasted trend-cycle component, and forecast

Step 6: estimating the error E(t) component

Recall that the objective of a forecasting method is to predict the systematic component of a demand (see Step 5) and estimate the random component. Recall also that in the multiplicative decomposition model, the random or error component is given by $E(t) = \frac{Y(t)}{T(t) \times S(t)}$. We can then estimate the random component of the future demand by dividing the observed demand by our forecast.

Go to Cell I10 and insert the formula =C10/(H10*G10). Drag the formula down to Cell I33. Figure 11 shows the final state of the model. Column L computes, for the forecast, the single error, Column M the absolute error, and Column N the squared error.

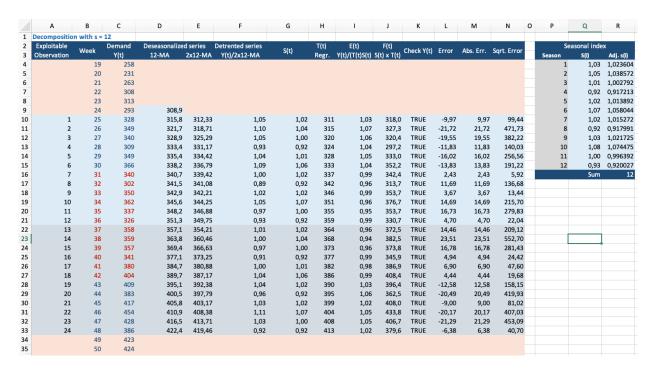


Figure 11: Demand, Isolated trend-cycle component, forecasted trend-cycle component, and forecast

References:

[1] Rob J Hyndman and George Athanasopoulos. Forecasting: Principles and Practice 2nd Edition. OTexts. Available as open content at: https://otexts.com/fpp2/.

[2] https://www.ablebits.com/office-addins-blog/2018/08/01/linear-regression-analysis-excel/. Last Accessed: 01/19/2019