Brief guide on adjustments to monthly raw data for demand of electricity

This brief paper has the chief goal of explaining the methodology used by Terna to adjust monthly raw data for demand of electricity. Time series' raw data are usually adjusted for a variety of reasons and depending on their use. Here the main purpose is to isolate and estimate calendar and temperature effects as well as the impact of the seasonal and trend-cycle components on monthly data.

To this end Terna resorts to the use of the Demetra+ software and the application of the TRAMO-SEATS procedure, which is also the procedure recommended by the "EES Guidelines for seasonal adjustments".

In previous publications Terna used two separate models to adjust for calendar/temperature effects on one side, and seasonal/trend-cycle components on the other.

With the use of Demetra+ instead, all effects and components are quantified within the same suite of models which has the benefit of greater robustness and comparability of results.

The paper delves first in a generalized description of the TRAMO-SEATS procedure to then conclude with a practical application to monthly demand data for the Italian electricity market.

A formulaic approach was intentionally avoided in favor of a greater readability for the wider audience. However, the second part of this paper, gives some numerical results from the application of the TRAMO-SEATS procedure which are intended for more advanced readers.

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Introduction

The aim of this paper is that of describing the methodology used by Terna to adjust the monthly raw data on demand for electricity. Said methodology addresses the problem of seasonality in the data as well as changes in temperatures and calendar days that often make data not entirely comparable.

The reason for adjusting raw data rests chiefly on the need to identify the underlying structural changes occurring in the electricity market that, as it happens, are blurred by non-recurring effects or other events that may distort the comparison of data that change over time.

One such instance occurs with changes in temperatures. For example, a very hot summer introduces a positive bias in demand for electricity as air conditioning systems absorb more power that would normally do under normal weather conditions. Like that, comparing two summers in two different years in terms of consumption levels, can become a difficult exercise and potentially leading to the wrong conclusions.

Raw and adjusted data are published by Terna in its Monthly Report and come in two forms: one is the publication of demand data adjusted by temperatures and calendar days; the other is the so-called ‘analisi congiunturale’ (cycle trend analysis – CTA).

In previous publications, Terna adopted two different models to account for different calendar days/temperatures on one side and for the CTA on the other. This paper instead introduces a new approach whereby only one model is used for both.

In essence, a TRAMO-SEATS procedure is implemented via the use of the Demetra+ software.

One of the main benefits of this new approach is that calendar days and temperatures adjustments to raw data are now calculated jointly with the destagionalization procedure which was not the case before.

This allows in our view for greater consistency amongst all data published by Terna while at the same time increasing the statistical significance of data itself.

This paper explains in broad terms the TRAMO-SEATS procedure and concludes with evidence from its application to electricity demand data for Italy.

In short, raw data on electricity demand generated within Terna’s proprietory database are first ‘transformed’ into logarithms and then data are furthered refined through the investigation and correction for calendar, temperature and one-off effects.

The TRAMO part of the procedure is devoted to determine the ‘best’ ARIMA model used to represent the time series (in essence the issue is to determine the most appropriate degree of the polynomial function of the ARIMA model). The ARIMA model thus chosen is then checked against a number of statistical test that the Demetra+ software runs.

With the SEATS procedure, the time series is further refined isolating the trend-cycle, the seasonal and the random components. Throughout this part of the procedure spectral analysis is also employed.

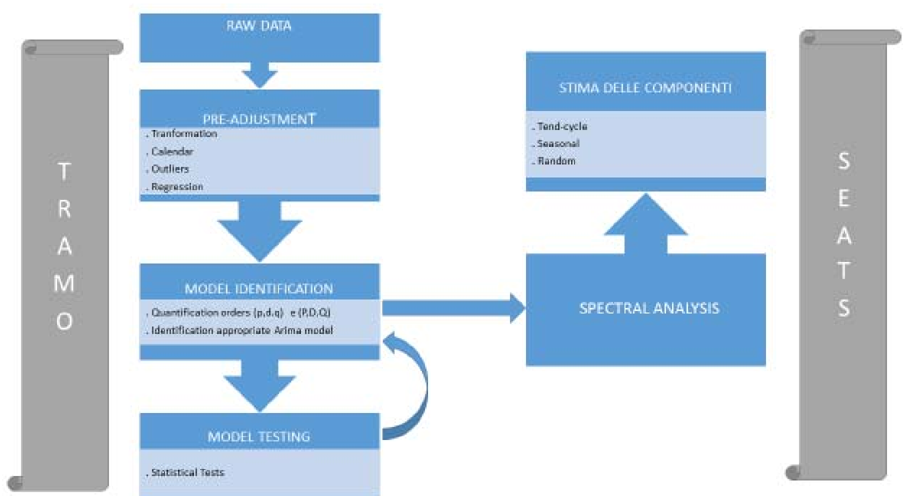
The TRAMO-SEATS procedure

The TRAMO-SEATS procedure is itself the combination of two procedures: TRAMO (Time Series Regression with ARIMA[1] Noise, Missing Observations and Outliers) and SEATS (Signal Extraction in ARIMA Time Series).

For reference, the TRAMO-SEATS procedure is that endorsed by the ESS[2] in its Guidelines[3] with regards to seasonal adjustments of raw data in time series analysis.

To explain these two procedures, we refer to Figure 1 that shows a simplified logic flow-chart and the steps that they entail.

Figure 1 – The Tramo-Seats procedure in brief



Source: Terna

The pre-adjustment phase

Before analyzing the two steps of TRAMO Procedure (TP) in Figure 1, it is worth noting that the analysis shall be run on the log transformed series which is typically the case for the analysis of time series for demand of electricity.

[1] ARIMA: AutoRegressive Integrated Moving Average
[2] ESS – European Statistical System
[3] Together with the less sophisticated X-11 ARIMA methodology

The reason is that the TP relies on ARIMA models which in turn require the series to be stationary (in terms of mean and variance), the latter being a prerequisite of the ARIMA model itself in a positive only series

The choice of the particular transform of the original series is called 'Transformation'.

This phase can be thought as a sort of 'pre-adjustment' to the raw data and it consists in identifying a number of deterministic effects (like calendars effects) and outliers.

Differences in calendar days

Different calendar days usually have a relevant effect on the time series under analysis, as is the case with demand of electricity. All else being equal, demand in months with more calendar days will typically be higher.

This is also true for differences in the number of working days within a given months as well as national festivities (such as Easter that changes from one year to another), bank holidays and leap years. Easter in particular can either be in March or April and this, of course, affects the seasonality of the time series.

That said, Demetra+ allows for treating these calendar differences automatically using built-in calendars which can also be customized to reflect national specificities.

Identifying the outliers

Moving to the 'outliers', these can be classified in three categories which the Demetra+ identifies automatically[4] and treats separately:

Additive Outlier (AO) – are one-off observations that are not repeated within the time horizon under analysis (but note that there can be more than one AO within a time series); an example of this can be the record high demand of electricity in July 2015 that reached 60.4GW as a consequence of the unusual and extremely high temperatures;

Transitory changes (TC) – is a temporary effect on the level of a series after a certain point in time; this for example is represented in the series as a sudden and abrupt change in the value of demand of electricity whereas this change is gradually 'absorbed' through time;

Level Shift (LS) – are those outliers that imply a step change in the mean level of the series under analysis. A level shift for example occurred with the recession of 2008 which not only implied a strong fall in the level of the Italian GDP but it also had an impact on demand of electricity as shown in Figure 2.

4 If required by the software's user

In other words, it is as if the mean of the series is 'reset' to a new level, after which the time series behaves as in the past. Post 2008 for example, both GDP and demand of electricity did show some recovery but this time starting from a lower base. Often, a simple eye inspection reveals the characteristic of the LS event.

Finally, Demetra+ allows for the introduction of 'User defined variables'[5], ie independent variables used for a regression based correction of the series under analysis. The correction is analogous to the one implemented, for instance, with respect to working days. In the present implementation this option was used in order to take into account the effect of deviations of temperatures from long term averages. A more detailed explanation of this is shown later in this paper when we discuss the model's specifications used by Terna.

Figure 2 – Demand of electricity in Italy 2000-2018

Source: Terna

The TRAMO procedure

With some simplifications, the TRAMO procedure can be thought of as being split in two steps: model identification and model testing.

Step 1 – Model identification

It is beyond the scope of this paper to run through a full discussion of the ARIMA model (and specifically of the two processes AR and MA[6]). It suffices her to say that the task of Step 1 the TRAMO Procedure is that of setting the order of the polynomials of the ARIMA model, both for the non-seasonal (p,d,q) and the seasonal part (P,D,Q) which in effect means to set the values for the P and D parameters. Demetra+ here offers two options:

5 'Regression' function in Demetra+

6 AR – Auto Regressive model; MA – Moving average model; ARIMA – AutoRegressive Integrated Moving Average model.

- An automatic identification of the model, whereby TRAMO compares a number of potentially suitable models and choses that that fits best the data via standard statistical criteria; or

- The user can chose its own identification of the model based on autocorrelation functions.

Step 2 – Model testing

The conclusion of Step 1 coincides with the choice by the TRAMO Procedure of an ARIMA model to be used for the purpose of the analysis. However, said model needs to be tested in order to verify whether it adequately reflects the behavior of the underlying data. To this end the TP carries out a number of statistical tests which are shown in the Terna's model section of this paper.

The SEATS procedure

Given the ARIMA model(s) identified by TRAMO, the SEATS Procedure (SP) separates the series into three different components, as mentioned earlier, the trend-cycle component, the seasonal component and the stochastic part.

The split into three components is common to most other technics used to adjust data for seasonal effects and is based on spectral analysis applied to the 'linearised' time series through, as mentioned, the application of logarithms.

More specifically:

The ***'trend-cycle'*** component includes those parts with lower frequency within the serie's spectrum, with the '*trend'* representing the long-term behavior of the data under analysis and with the 'cycle' being the deviation of observations from the trend; taking GDP as an example, this would represent periods of recession followed by periods of economic expansion.

The ***'seasonal component'*** is calculated subtracting the trend-cycle component from the time series; the peaks of the spectrum so recalculated are identified as the seasonal component of the series;

The ***random (or erratic) component*** made up of the so-called 'white noise', ie errors that are usually normally distributed.

One important part of the SEATS Procedure is that the deterministic effects in the Tramo part that were input in the model by the user are then attributed by SEATS to each of the three components of TRAMO just mentioned.

This last step in fact is important as it allows gauging the 'full size' of each component and its impact on the time series which are relevant for a good interpretation of the results.

Spectral analysis

Central to the analysis of seasonality or indeed any other effect that occurs with a 'certain regularity', is the spectral analysis.

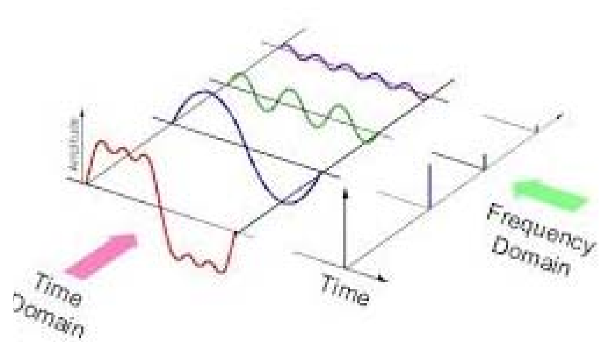
Economic data as well as data on consumption of electricity are presented as data 'spread over time' or more specifically time-series. Time is the independent variable and because of this time-series are also referred to as being presented in a time-domain.

However, for analysis purposes, it is often convenient to convert data expressed in a time-domain into a frequency-domain. As a result greater focus can be placed on the frequency with which certain events or phenomena appear within a given time frame.

Provided that the time series under analysis is stationary (a result that should be guaranteed by the fact that we are using logarithms instead of raw data), this can be expressed as a combination of cosine (or sine) functions. The latter are characterized with different periods (amount of time to complete a full cycle) and amplitude (max/min value during the cycle).

The tool used for the analysis of time series in frequency domain is called spectrum. Figure 3 shows how to move from the just described time-domain for a time series to a frequency-domain.

Figure 3 – From time- to frequency-domain



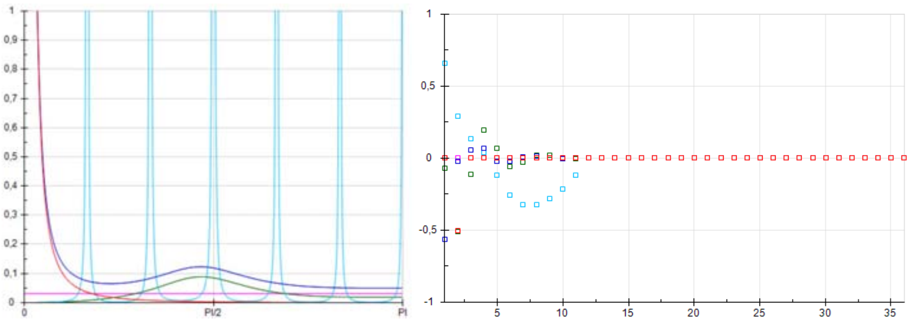
Source: Terna; Google

From the frequency-domain, a spectrum of frequency is then derived as shown in Figure 4 on the left.

The dark blue line shows the seasonal adjusted series spectra and this is the sum of trend-cycle component (in red), the transitory component (if present, in green) and the irregular component (pink). The seasonal component is also shown (light blue).

Figure 4 on the right shows the autocorrelation where all components of the spectrum show a (varying) degree of autocorrelation except for the irregular component which has no autocorrelation which is as it should be if the irregular component were to be random (stochastic).

Figure 4 – Example of spectrum (left) and ACF* (right)



Source: Demetra+, Terna; (*) ACF – Auto Correlation Function

TERNA'S MODEL

In this section of the paper we move to show how the TRAMO and SEATS procedure are used to analyse electricity demand data for Italy. The data we used in this implementation are for the period 1st January 1995 to the end of April 2018.

In practice, when the analysis is applied and the data published on a monthly basis, it is important to remember that the model is rolled forward to account for the new information that is made available in due course.

This has important implications for the values of demand adjusted that we publish (e.g. for temperature or calendar days). This is because the value of demand adjusted in one month is recalculated the following months, ie including the new information made available.

Data used and sources

As mentioned, the time series we use for the purpose of this paper rests on the raw data of electricity demand on a monthly basis going back to 1st January 1995 to the end of April 2018. Data are collected on a national basis and are produced directly by Terna.

We also use temperatures data as provided by the Servizio Metereologico dell'Aeronautica Militare which are supplied on a regional and daily basis. The span of the data is the same as that for demand of electricity.

For the calendar days we use as a basis that provided by the Demetra software which is then integrated with specific information related to Italian festivities and other bank holidays.

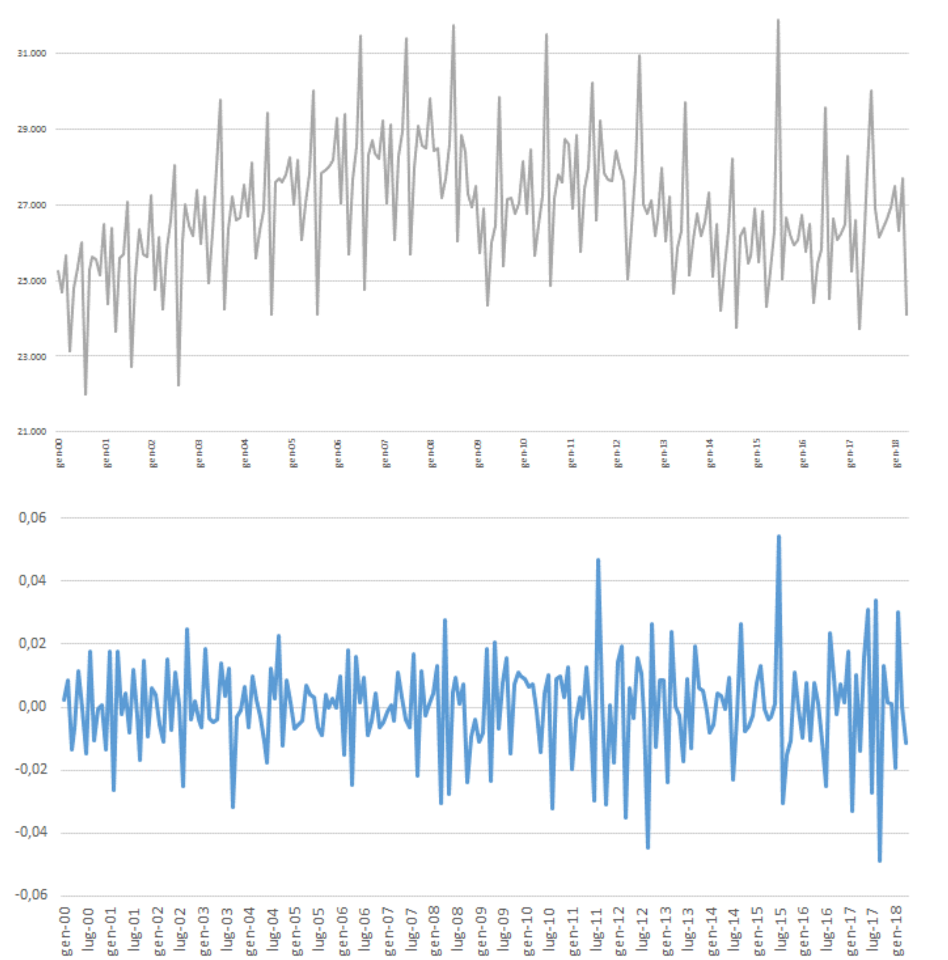
The pre-processing phase

The pre-processing phase is made of the three parts explained earlier, ie the transformation into logarithms, the setting up of a calendar for Italy and the analysis of outliers.

Transformation into logarithms

Raw data are ‘transformed’ to achieve stationarity of the time series with the use of logarithms. In Figure 5 we show first the series of raw data which, as it can be seen, can be quite unstable.

Figure 5 – Demand of electricity (TWh, above), and logarithm (YoY, below)



Source: Terna

The pure transformation into logarithm of the raw data would only change the ‘basis’ and the scale on the Y-axis, this is why in the lower part of Figure 5 we show the difference between the logarithms calculated on YoY demand[7]. It can be seen that in the latter case the time series is more ‘stable’ in that data swing around their mean value and this is 0.

7 YoY – year on year, which means the difference between demand in a month of a given year vs the demand in the same month of the previous year.

This transformation is also useful given that TRAMO-SEATS always accounts for seasonality on an additive basis rather than multiplicative, the latter would have been the case had the time series not been transformed into logarithms.

Figure 6 shows Demetra+ output for this first part of our analysis.

Figure 6 – Information data

Data transformation	
Estimation span: [1-1995 : 4-2018]	
Series has been log-transformed	
Model adequation	
Number of effective observations	267
Number of estimated parameters	26
Loglikelihood	788,2796
Transformation adjustment	-2714,8645
Adjusted loglikelihood	*-1926,5849*
Standard error of the regression (ML estimate)	0,0125
AIC	3905,1697
AICC	3911,0197
BIC	3998,4382
BIC (Tramo definition)	-8,2363
Hannan-Quinn	*3942,6351*

Source: Demetra+/Terna

Calendar effect

As to the calendar, Demetra+ offers some options for different calendar days, the default calendar is set to the Gregorian calendar although this can be modified to account for specific festivities or bank holidays of a given country.

For example, in the case of Italy adjustments need to be carried out for dates like 6th January (Epifania), 25th April (Festa della Liberazione), June 2nd (Festa della Repubblica) or 8th December (Immacolata Concezione) amongst the others.

The following figures show the results for a number of statistics calculated for the calendar days over the period under analysis starting from the Trading days to the leap-year and the impact of Easter.

In essence, within this pre-treatment phase, the model calculates whether the presence of one effect is statistically relevant, for example whether the leap-year has an impact on the time series in which case this is added as a regressor into the equation. The column Value returns the sensitivity of demand of electricity to changes in calendar days.

Figure 7 shows the result of the analysis. It is clear that different days have different impact on the time series (or we should say the absence or presence of one day more or less in the time series affect its value, in our case, demand of electricity).

It also worth noting that Saturdays and Sundays typically have a negative coefficient, this owing to the fact that low level of economic activities mean lower demand of electricity, hence that negative sign.

Figure 7 – Trading days

Parameter	Value	Std error	T-Stat	P-value
Monday	-0,03%	0,00	-0,18	0,86
Tuesday	0,14%	0,00	0,96	0,34
Wednesday	0,11%	0,00	0,74	0,46
Thursday	0,47%	0,00	3,28	0,00
Friday	0,29%	0,00	2,03	0,04
Saturday	-0,33%	0,00	-2,42	0,02
Sunday (derived)	*-0,65%*	*0,00*	*-4,99*	*0,00*

Join F-Test on trading days: F = 19,0191 [P-Value = 0,0000]

Source: Demetra+; Terna

By the same token Easter is characterized by a negative coefficient as its presence or not in a given month leads to lower consumption of electricity (Figure 8).

Figure 8 – Easter

Parameter	Value	Std error	T-Stat	P-value
easter [6]	-0,0082	0,003	-2,610	0,010

Source: Demetra+; Terna

And finally, leap years (Figure 9) usually display a positive sign as an additional day in the month of February necessarily brings about higher consumption of electricity, and in particular if the additional day is a working day.

Figure 9 – Leap year

Parameter	Value	Std error	T-Stat	P-value
leap year	0,0353	0,004	8,150	0,000

Source: Demetra+; Terna

Outliers

Demetra+ allows, via the command Outliers Detection, to automatically check for the presence of outliers in the series while also giving the option to select a specific outlier's research (Figure 10).

Figure 10 – Outliers

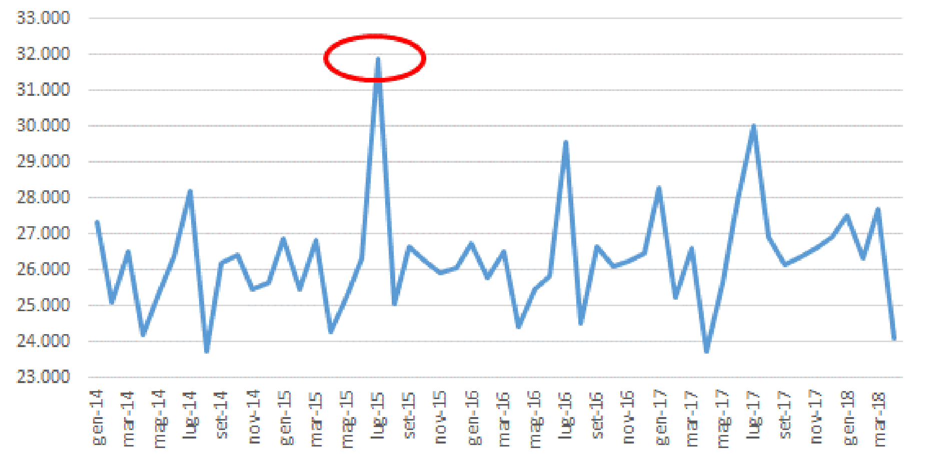
Parameter	Value	Std error	T-Stat	P-value
LS[10-2008]	-0,05	0,01	-5,25	0,00
TC[6-1999]	0,06	0,01	4,68	0,00
LS[1-2009]	-0,04	0,01	-3,87	0,00

Source: Demetra+; Terna

In our case, we search for all (three) types of outliers (LS – Level Shift, AO – Additive Outlier, TC – Transitory Changes) while leaving the critical value (hypothesis testing) at the default level.

Some of the outliers can be identified by simple eye-inspection and Figure 11 shows one such case. For good measure however, we look for all outliers through Demetra+, even in those instances where eye-inspection analysis would suffice.

Figure 11 – An example of outlier by eye-inspection (TWh)



Source: Terna

Implementation of the Tramo procedure

As illustrated earlier, the TRAMO procedure culminates with the identification of an appropriate ARIMA model which is then used by SEATS to adjust data for seasonality and other effects.

But before doing this, we adjust data for temperature effects. This is done directly via Demetra+ as it will be now be explained[8].

User-defined regression variables

In broad terms, Demetra+ allows the user to include a number of regression variables (called either *static* or *dynamic*) depending on the source of the data and how these are imported into the software.

In our case we have introduced 12 regression variables as depicted in Figure 12 where each regressor represents the “temperature anomaly” that is: the difference between the average temperature in one month vs the average of the temperature in the same months over the past ten years (each regressor is not zero in a given month and 0 in the other 11 months).

More specifically, the temperature anomaly in each month (both the current and that for the past years) is constructed as the difference between the average

[8] Note that temperature and calendar days adjustments are done at the same time.

temperature of that month and the average over different years of the average temperature of the same month.

The average temperature of a given month is the average of daily temperatures, the latter being in turn calculated as the daily average between max and min temperature. By construction, all other variables in the input matrix of Figure 12 are set to 0.

Figure 12 – Regression variables to account for differences in temperatures

	Jan	Feb	Mar	April	May	June	July	Aug	Sept	Oct	Nov	Dec
01/01/2016	**0,9**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/02/2016	0,0	**2,6**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/03/2016	0,0	0,0	**0,4**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/04/2016	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/05/2016	0,0	0,0	0,0	0,0	**-1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/06/2016	0,0	0,0	0,0	0,0	0,0	**-0,3**	0,0	0,0	0,0	0,0	0,0	0,0
01/07/2016	0,0	0,0	0,0	0,0	0,0	0,0	**0,4**	0,0	0,0	0,0	0,0	0,0
01/08/2016	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**-0,1**	0,0	0,0	0,0	0,0
01/09/2016	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,7**	0,0	0,0	0,0
01/10/2016	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**-0,4**	0,0	0,0
01/11/2016	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**-0,1**	0,0
01/12/2016	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**-0,1**
01/01/2017	**-2,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/02/2017	0,0	**1,8**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/03/2017	0,0	0,0	**1,7**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/04/2017	0,0	0,0	0,0	**-0,3**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/05/2017	0,0	0,0	0,0	0,0	**0,3**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/06/2017	0,0	0,0	0,0	0,0	0,0	**1,9**	0,0	0,0	0,0	0,0	0,0	0,0
01/07/2017	0,0	0,0	0,0	0,0	0,0	0,0	**0,5**	0,0	0,0	0,0	0,0	0,0
01/08/2017	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,8**	0,0	0,0	0,0	0,0
01/09/2017	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**-1,4**	0,0	0,0	0,0
01/10/2017	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**-0,2**	0,0	0,0
01/11/2017	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**-1,0**	0,0
01/12/2017	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**-0,9**
01/01/2018	**2,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/02/2018	0,0	**-1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/03/2018	0,0	0,0	**-0,5**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
01/04/2018	0,0	0,0	0,0	**1,5**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0

Source: Terna

Figure 13 shows results of the TRAMO-SEATS procedure following the application of the matrix in Figure 12 with the Column 'Value' displaying the sensitivity of demand of electricity to changes of temperatures in one month relative to its historical average.

As expected there is a negative correlation during winter months as higher temperatures reduce consumption of electricity, for example via a relatively lower need for heating.

In the summer the correlation becomes obviously positive as higher temperatures increase the use of air conditioning and hence demand of electricity. Note also that the coefficients (in absolute terms) are higher for summer than winter months as the impact of higher consumption of air conditioning is greater than that of heating given that most of heating needs in Italy are at present covered for by gas boilers.

Figure 13 – Demand's sensitivity to temperatures*

Parameter	Value	Std error	T-Stat	P-value
Var_1	-0,7%	0,0017	-3,8800	0,0001
Var_2	-0,8%	0,0015	-5,0900	0,0000
Var_3	-0,9%	0,0023	-4,1500	0,0000
Var_4	-0,3%	0,0023	-1,3800	0,1685
Var_5	0,3%	0,0018	1,3400	0,1800
Var_6	1,6%	0,0021	7,5700	0,0000
Var_7	2,3%	0,0021	10,9900	0,0000
Var_8	2,4%	0,0020	12,2200	0,0000
Var_9	0,7%	0,0019	3,8600	0,0001
Var_10	0,2%	0,0023	0,8300	0,4053
Var_11	-0,1%	0,0024	-0,5500	0,5826
Var_12	-0,4%	0,0024	-1,5200	0,1306

Source: Demetra+; Terna; (*) each var_ corresponds to a month in the year: for example var_1 is January, var_2 is February and so forth.

The calculations just shown constitute one of the main differences with the old methodology used by Terna. Previously the impact of temperatures was calculated via a separate model, whereas now it is all dealt within Demetra+ with the benefit of more statistically robust results and with greater comparability.

Model identification & statistical tests

With the model identification, the TRAMO procedure choses the ARIMA model that best fits the data with the quantification, amongst the others, of the order of the polynomials.

Demetra+ offers in this case two options, ie to automatically select the best ARIMA model or to allow the user to choose. In our case the 'Automatic modelling' option was chosen. The resulting specification of the ARIMA model is shown in Figure 14.

Figure 14 – Specification of the ARIMA model

Polynomials	
Regular AR	1
Seasonal AR	1
Regular MA	1 - 0,53378 B
Seasonal MA	1 - 0,54163 S

Source: Demetra+; Terna

The ARIMA model chosen is [(0,1,1)(0,1,1)] and in Figure 15 we show the results from the calculation of the coefficients of the regular (theta) e seasonal (btheta) moving average polynomial.

Figure 15 – Information data

Parameter	Value	Std error	T-Stat	P-value
Th(1)	-0,53	0,05	-10,18	0,00
BTh(1)	-0,54	0,06	-9,51	0,00

Source: Demetra+/Terna

Implementation of the SEATS Procedure

Once the ARIMA model is identified by TRAMO, SEATS proceeds with the calculation of the three components of trend-cycle, seasonality and a random component (irregular in Figure 17) to which here a fourth is added (SA).

The trend-cycle component includes those part of the time series with the lower frequency while the cycle component being the ‘deviations’ from the trend. Subtracting the trend-cycle component from the original series the seasonal component is then calculated leaving the erratic component as a residual. Figure 16 and Figure 17 portray the results.

Figure 16 – Decomposition

Model	
Non-stationary AR:	1 - B - B^12 + B^13
Stationary AR: 1	1,00
MA:	1 - 0,53378 B - 0,54163 B^12 + 0,28911 B^13
Innovation variance:	1,00
trend	
Non-stationary AR: 1 - 2 B + B^2	1 - 2 B + B^2
Stationary AR:	1
MA:	1 + 0,049629 B - 0,95037 B^2
Innovation variance:	0,03
seasonal	
Non-stationary AR:	1 + B + B^2 + B^3 + B^4 + B^5 + B^6 + B^7 + B^8 + B^9 + B^10 + B^11
Stationary AR:	1
MA:	1 + 1,2128 B + 1,1437 B^2 + 0,97895 B^3 + 0,73936 B^4 + 0,48722 B^5 + 0,24413 B^6 + 0,026595 B^7 - 0,14125 B^8 - 0,28607 B^9 - 0,37372 B^10 - 0,58942 B^11
Innovation variance:	0,05
irregular	
Non-stationary AR:	1
Stationary AR:	1
MA:	1
Innovation variance:	0,35

Source: Demetra+; Terna

Figure 17 – Components of the SEATS procedure

	Component	Estimator	Estimate	PValue
Trend	0,06	0,01	0,01	0,73
SA	2,16	1,66	1,60	0,75
Seasonal	0,31	0,05	0,05	0,70
Irregular	0,35	0,21	0,20	0,71

Source: Demetra+; Terna