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NEW FEATURES AND MODIFICATIONS IN TRAMO-SEATS

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TRAMO+, SEATS+, and TSW+:

1. BRIEF SUMMARY OF THE NEW FEATURES

1.1. Introduction

During the past decade, the intense and widespread use of TRAMO, SEATS, and TSW and, in particular, their use in production and in routine monitoring, implied the need for a minimum stability that made major changes undesirable. Changes and additions were incorporated to an eventual major revision of the programs, that extended from re-programming parts of the code, to important changes in the main procedures having to do with automatic model identification, the handling of regression variables, calendar variables, outliers, missing observations, the decomposition into unobserved components, inference and diagnostics, and with several additional facilities concerning input and output. The outcome of this work are the present versions; they are expected to remain stable over the next years.

Throughout these years, the code of TRAMO and SEATS has been made available on line to the X12-ARIMA and X13-ARIMA-SEATS developers (at the US Bureau of the Census), TRAMO as the basis of the automdl option in both programs, SEATS as an alternative to the X11-type filters in the later one. These codes have also been made available on line to the JDEMETRA+ developers at the National Bank of Belgium. Although an important part of TRAMO and SEATS has been incorporated to X13-ARIMA-SEATS and JDEMETRA+, there are parts however that have not, some due to the fact that updating inevitably takes time.

From the point of view of the programs' structure, the new programs have essentially respected the old ones. Thus most of the previous user instructions are still valid. This Note briefly lists the changes and differences that are relevant to the user and not self-evident; detailed information will soon be available. Description of parameters and facilities is also available on line when running TSW+ through the HELP facility or the F1 key. Although the programs are easy to use and reliable in automatic mode, until a complete manual is available, for a user not-familiar with the previous TRAMO, SEATS, or TSW, this note should be complemented with the user instructions of the old versions (Gómez and Maravall, 1996; Caporello and Maravall, 2001 and 2004), available on the Bank of Spain web site (see below).

An example of a relatively complete application of TSW+ to one series (the European Industrial Production Index) is presented in Maravall and Pérez (2012), and an example of an application of TSW to a set of 500 series is contained in Maravall (2009). A summary of the results of the automatic application to a set of simulated and real series is contained in Maravall et al. (2012a). Papers documenting the methodology and showing applications, the programs, and some related facilities and interfaces, are available on the Bank of Spain website (www.bde.es → Services → Professionals → Statistics and econometrics software).

1.2. Modifications to TRAMO

1.2.1. OUTLIERS

- **Seasonal outliers** can be added to the automatic outlier detection and correction. The seasonal outlier is a level shift that only operates on a particular period (e.g., month of December, fourth quarter of the year, ...).

Parameter: AIO = 0 (not default).

- When the **first observations contain too many outliers**, they can be automatically removed.

Parameter: DENSOUT = k (not default).

- The damping parameter of the **transitory outlier** may differ from 0.7 (the default value).

Parameter: DELTATC = k.

- The **default critical level** set for outlier significance has been slightly increased (parameter VA) and the automatic lowering of VA when the first pass of automatic model identification yields seriously autocorrelated residuals has been reduced.

Parameter PC = 0.12 by default.

$$VA = 3.3 \text{ if } NZ > 50$$

$$= 3.3 + 0.0025 (NZ - 50) \text{ if } 50 \leq NZ < 450$$

$$= 4.3 \text{ if } NZ > 450$$

1.2.2. MISSING OBSERVATIONS

When IFILT = 2 and missing values are estimated through regression (default case) the maximum number of them is 184. When missing values are estimated with the Fixed Point Smoother (ARIMA model is fixed) their number is only constrained by the number of actual observations.

When regression variables have missing values; they should be previously interpolated with, for example, an automatic run of TRAMO.

Flow and stock series can now be interpolated.

1.2.3. DATA TRANSFORMATION

The log/level pre-test is a likelihood-ratio test. The default value is now

FCT = 0.95 (to correct a bias detected in the test that favored levels).

1.2.4. REGRESSION VARIABLES

- **Initial values** for the estimation of ARMA parameters and of the coefficients of all regression variables (mean, trading day, Easter effect, and user supplied outliers and regression variables) can be entered.
Coefficients of all regression variables and ARMA parameters can be fixed. See parameters INIT, INITMU, INITTD, INITEE, INITREG.
- A **deterministic seasonal component** can be specified (IUSER = 4); no stochastic seasonality is extracted in this case. Not produced by AMI (it requires RSA = 0).
- **Ramp variables** can be specified (IUSER = 3).
- **Lagged values of regression variables** can be entered by the user (parameters IUSER = -1 and LAGS).
- If the **regression variable** entered by the user (IUSER = -1) does not cover the full in-sample + forecast period, it can be **automatically extended** (with RSA = 3 or 4 applied to the regression variable). Parameter PREDREG.

1.2.5. SHARED REGRESSORS

The **same regression variable** can be shared by many series.

The regression variable needs to start at the earliest date for which observations for some of the series are available.

In the window for each regression variable, two parameters; NYEAR and NPERIOD, indicate the starting period and year for the regression variable. The program selects the appropriate span for each series.

1.2.6. TRADING-DAY EFFECT

- **Automatic choice of the Trading Day effect specification.**

In prior versions of TRAMO, when Trading Day effect could be suspected, the user had to choose between a parsimonious specification for the pretest (with a single variable that reflected the number of working/non-working days in the period) and a 6 variable specification (that captured the day-of-week effect). Setting RSA = 4 (or ITRAD = -2), the one-variable specification was pre-tested; setting RSA = 5, (or ITRAD = -6, -7) the six-variable specification was pre-tested.

At present, the choice is automatically made by the program. Thus the option RSA = 5 has been removed, as well as the parameter values ITRAD = -6, -7. When RSA = 4, the two specifications are tried and the most significant one is selected (the F-values associated with the addition of the trading day variables to the regression are compared.) When none is significant, Trading Day effect is not included in the model.

- The Trading Day effect can now be estimated for **flow** as well as stock **series**. (Parameter SMPDAY).
- **Spectral tests** check for possible TD effect in the linearized series, reg-ARIMA model residuals, SA series, trend-cycle, and irregular component. Two spectral estimators are used: an AR(30) and a Tukey-type estimators.
- A new input parameter has been added:

PFTD: k , $0 < k < 1$, probability that a series with no TD effect is detected by the test as not having TD effect. By default = 0.99. (Evidence!!!)

Increasing k reduces the probability of detecting TD effect.

1.2.7. STOCHASTIC TRADING-DAY COMPONENT

- When the ARIMA model contains, in its regular AR polynomial, a complex root with an associated frequency approximately equal to the (theoretical) Trading-day frequency, the model-fit summary in TRAMO sends the message “close to TD.”
- In the previous case, a stochastic TD component can be estimated and removed from the SA series. This component follows an ARMA(2,2) model, with a pair of complex roots in the AR polynomial at the TD frequency (see Maravall and Pérez, 2011).

By default, the (stationary) stochastic TD will be estimated as a transitory component. For it to be considered a stochastic TD, the parameter STOCHTD should be made 1.

1.2.8. PRESENCE OF SEASONALITY TEST

Several tests are used to detect whether seasonality is present in the series. The tests are the following.

- A chi-square test based on **seasonal autocorrelation**, similar to the one in Pierce (1978);
- A chi-square **non-parametric test** similar to the Friedman test described in Kendall and Ord (1990);
- an **F-test** for significance of a set of seasonal dummy variables, similar to the one in Lytras, Feldpausch, and Bell (2007);
- a spectral test to detect peaks for the seasonal frequencies in the series spectrum. The results of two spectra estimators, namely,
 - a non-parametric **Tukey estimator** as in Jenkins and Watts (1968);
 - an **AR(30) estimator** similar to the one in X12-ARIMA,

are combined. These tests are applied at several stages.

When used on the original series at the beginning of the AMI procedure, they determine the starting point: if the series has seasonality, the Airline model is chosen; if there is no seasonality, the “IMA(1,1) + mean” model is used. When applied to the linearized series obtained from a first run of AMI, the results may cause a new round of AMI with different starting conditions. The tests are also used at some intermediate stages, in which case the model being considered at that point may be modified.

When applied to the reg-ARIMA model residuals, and to the SA series, trend-cycle, and irregular component, the tests are used as **diagnostics**: no seasonality should be found.

In order to reach a YES/NO decision concerning the **presence of seasonality**, the tests are aggregated into an “**Overall test**.” This test is meant to favor positive detection in borderline cases. Ultimately, the decision on whether or not the series contains seasonality that can be reliably extracted is made by SEATS, when decomposing the model produced by AMI. On occasion, SEATS may change this model although the presence/absence of seasonality will be respected (see below). Also, SEATS may detect that the seasonal effects produced by the AMI model are not significant, or that they are not worth removing (if, for example, they are too weak and unstable).

When the model that results from AMI has no admissible decomposition and is replaced by a decomposable one in SEATS, the presence/absence of seasonality will be preserved.

1.2.9.AUTOMATIC MODEL IDENTIFICATION, COMPARISON OF MODELS AND USE OF THE PRESENCE OF SEASONALITY TESTS.

A flow diagram summarizing the way AMI proceeds is given in the Appendix. (Diagram 1)

At several stages of AMI two models are compared. The comparison is based on the **BIC** criterion, the **number of outliers**, **residual correlation**, and **residual seasonal correlation**. By default, the model with minimum BIC is chosen, unless there are improvements in the other statistics considered and the BIC deterioration is moderate.

In particular, a comparison is introduced in the following cases.

When MO are present, TRAMO goes directly to a full AMI. When no observation is missing, a restricted Overall Seasonal Test on the (possibly log transformed) original series, that only considers the Q and NP test (OST1), provides starting models for the AMI procedure. If seasonality is detected, the Airline model is used, and the full AMI is applied. Otherwise, the “IMA(1,1) with mean” model is used, and AMI is restricted to an ARIMA with the seasonal orders (bp, bd, bq) made (0, 0, 0).

In both cases, the complete Overall Seasonal Test (with the F-test included,) (OST2), is applied to the linearized series that were produced by AMI.

In the majority of cases the tests OST1 and OST2 will be in agreement. When they are not, comparison of the results of OST1 and OST2 may lead to a new execution of AMI, perhaps under some constraints, as seen in the Appendix. The models obtained in the first and second AMI are compared.

Some checks are made on the selected model mostly to avoid cases where over- or under-differencing may be suspected. The check may, in some cases, change the AMI model.

Finally, when the parameter AMICOMP = 1 and the final model produced by AMI fails some important diagnostic, it is compared to the Airline model -as in the RSA = 1 or 2 options- when the model contains seasonality, or to the “IMA(1,1) + mean” when not. By default, this **benchmark comparison** is not enforced.

- **AMI: Threshold for unit root detection and identification of the differencing polynomial.**

The critical values for identification of unit roots in the routine that yields the differencing polynomial, $\delta(B)$, have been slightly increased. The default value for UB1, the parameter that detects unit roots when AR(1) AR_s(1) models are first tried, is 0.97.

The default value for UB2, that controls unit roots when ARMA(1,1) ARMA_s(1,1) model are estimated, is now equal to 0.91.

These values were set after an examination of the errors made by AMI in the identification of $\delta(B)$ in a set of 50000 series simulated with 50 different ARIMA models. (Described in the paper “Reliability of the TRAMO-SEATS Automatic Identification of Regression-ARIMA Models.”)

Note that, when the overall presence of seasonality test indicates that the series does not contain seasonality, the previous multiplicative models simplify into AR(1) and ARMA(1,1) models.

Once $\delta(B)$ has been applied to the series, an ARMA model is identified and estimated by MLE. It may happen that an AR root gets very close to 1 and it is considered preferable to make it 1 (i.e., transforming it into a difference). The parameter UBP sets the threshold for that transformation when the root is seasonal. By default, UBP = 0.96. The parameter UBPr sets the threshold for a regular root. By default, UBPr = 0.96.

When an a priori chosen model is entered, the maximum allowed for the modulus of an AR root is 0.99. Note that, when the model orders have been set a priori, TRAMO+ will always respect these orders. Thus real roots larger than 0.99 will be set equal to 0.99. It is now possible to fix the unit roots (if any) and perform AMI for the stationary part of the model.

The critical values for identification of unit roots in the routine that yields the differencing polynomial, $\delta(B)$, have been slightly increased. The default value for UB1, the parameter that detects unit roots when AR(1) AR_s(1) models are first tried, is 0.97.

1.2.10. RESIDUAL DIAGNOSTICS AND BACKCASTING

Besides the spectral tests for residual seasonality or calendar effect, two residual diagnostics have been added to the default option:

- **Stability test:** Divides the residuals in two halves. First, equality of means is tested with a t-test. If accepted, equality of the two variances is tested with an F-test.
- **Out-of-Sample F-test:** Having obtained a model, the last 1 ½ years of data (more if frequency is lower than quarterly) are removed and the model parameters are reestimated. One-period ahead out-of-sample forecasts are recursively computed, and an F-test is made on the equality of the out-of-sample forecast MSE and that of the in-sample residuals for the truncated series.
- It is now possible for AMI to produce backcasts of the series. Setting the parameter NPREDBACK = k, k backcasts will be computed (default = 0).

1.3. Modifications to SEATS

1.3.1. NON-ADMISSIBLE DECOMPOSITION

- When the AMB decomposition of the ARIMA model cannot yield components all of which have nonnegative spectra, the model cannot be decomposed and SEATS replaces it with a decomposable approximation.

For some sets of 2-parameter models, the regions of the parameter space that yield admissible decompositions have been obtained. If the orders of the “non-admissible model” belong to one of these sets, the model parameters are brought to a nearby point in the admissible-decomposition range.

When this is not the case, there are now two ways to obtain an approximation. One is the “old” SEATS way, that performs ad-hoc modifications to the model orders. These ad-hoc modifications have been drastically revised. The other, is as follows. Given that non-admissibility can be seen to be equivalent to a negative irregular variance in the partial fraction decomposition of the model, the irregular variance is forced to be zero, and the ARIMA model that results from summing the rest of the components (without the irregular one) is obtained. This new model is used to decompose the series.

Notice that this approximation preserves the forecast function of the TRAMO model, and hence the equality: (direct forecasting = indirect forecasting through the components) is preserved.

(See parameter NOADMISS.)

- The old ad-hoc procedure to replace the non-admissible decomposition model (case *NOADMISS* = 1) had a weakness: while the in-sample fit of the new model was reasonable most of the time, at least in what concerned the extraction of seasonality, the forecast of the series in SEATS (sum of the components forecasts) and the forecast of the series in TRAMO were not the same. If the model modification implied a change in the unit roots (∇ and/or ∇_s), the difference between the two forecasts could diverge.

This inconsistency has been corrected. The series forecast in TRAMO is respected, and the components forecasts have been modified accordingly: the difference between the two forecasts is decomposed into trend-cycle and seasonal components (perhaps also a transitory component), and these components are added to the components forecasts of the new model.

- The results of the SEATS approximation are tested for the presence of seasonality in the SA series, trend-cycle, and irregular component.

1.3.2. BUSINESS-CYCLE AND LONG-TERM TREND

An estimation of the business-cycle can now be obtained. It is computed by default for series with at least 10 years of data.

By default, the final trend-cycle component is decomposed into a **business-cycle component** and a **long-term trend** by means of a Hodrick-Prescott (HP)-type filter applied to the canonical trend-cycle extended with forecasts. (Hence both, the cycle and the long-term trend, will also be canonical and display a spectral zero for the π frequency.) The decomposition follows the AMB method of Kaiser and Maravall (2005).

Alternatively, the filter can be applied to the SA series or to the original series.

In all cases, the ARMA and ARIMA models for the business cycle and long-term trend are obtained from the convolution of the HP filter and the ARIMA filter implied by the model for the trend-cycle (or SA series/original series). Forecasts and confidence intervals are also provided. The business-cycle follows a stationary ARMA model, with the typical spectral shape of a cycle, namely, a skewed-to-the-right hill. The peak of the hill occurs at a cyclical frequency that depends on the so-called HP parameter and the series model.

Smoothness of the long-term trend can be controlled through the standard λ parameter of Hodrick and Prescott; alternatively one may enter the period associated with the frequency that splits the HP filter into a 50-50 allocation of the variance between the two components. Denote this period as the “period of

reference.” By default, the standard value $\lambda = 1600$ for quarterly series is respected, which implies a period of reference of very approximately 10 years. This period is preserved for non-quarterly data, which implies, for example, $\lambda = 133000$ for monthly series, and $\lambda = 6.85$ for annual data. Consistency of cycles under temporal aggregation is achieved as in Maravall and del Río (2007).

See parameters *HPCYCLE*, *HPLAN*, and *HPPER*.

1.3.3. MODEL CHANGED BY SEATS

As seen in the diagrams at the end of this document, TRAMO passes an ARIMA model to SEATS. Besides replacing models that do not accept an admissible decomposition, SEATS may perform some additional replacements:

By default the cases in which SEATS changes the TRAMO model are summarized in Flow Diagrams 1 to 5. The most frequent reason for a change of model is when the model that TRAMO passes to SEATS has no admissible decomposition, that is, when it is not possible for all components to have non-negative spectra for all frequencies. (In a set of 15000 series covering many concepts and many countries, with lengths between 60 and 360 observations, the percentage of models changed by SEATS was 5.1%; of these 4.8% were due to non-admissible decompositions.)

Diagram 2 shows the Main Flow Diagram for all model changes.

Diagram 3 details the particular cases when the change is not caused by non-admissibility but it is meant to improve stability of the SA series because seasonality is highly moving.

Diagram 3 describes the routine that decomposes the series into components.

Diagram 4 details the cases in which for some non-admissible model an ad-hoc replacement is directly available.

Diagram 5 shows the iterations of the general scheme for replacing a non-admissible model with an approximate one.

Other non-default values of some parameters (*POSBPHI*, *THLIM*, *BTHLIM*, *STATSEAS*) may change the TRAMO model (see the *HELP* facility). They are mostly aimed at increasing stability of the seasonal or trend-cycle estimators.

1.3.3.1. Multiplicative models with no seasonality

A seasonal AR polynomial in the seasonal multiplicative part of a model may not imply seasonality.

Simple examples are

- $(1 + 0.7 B^{12}) x_t = a_t$, or $(1 + 0.7 B^{12}) x_t = (1 + 0.3 B^{12}) a_t$,

with spectral peaks at intraseasonal frequencies (implying a two-year stationary cycle and its harmonics). SEATS will estimate a transitory component.

Even when the roots of the seasonal AR polynomial are associated with seasonal frequencies, the interaction with the seasonal MA polynomial may cancel any seasonal effect. An example is the model

$$\blacksquare (1 - 0.3 B^{12}) x_t = (1 - 0.8 B^{12}) a_t ,$$

with spectral peaks also at the same intraseasonal frequencies as in the previous examples, so that a transitory component is obtained.

1.3.3.2. Interaction between the AR and MA parameter

In general, in an ARMA(1,1) structure –regular or seasonal- with an MA parameter larger than the AR one (and both have the same signs), the spectral peaks are dominated by the MA roots. Thus, for example, the regular model

$$\blacksquare (1 - 0.3 B) x_t = (1 - 0.8 B) a_t ,$$

has a monotonically increasing spectrum, with a spectral peak for π . Although it displays a peak at the π -frequency, the component is highly stationary. If the Overall Test detects seasonality (unlikely) a seasonal component will be estimated; otherwise the component will be considered a transitory component.

1.3.3.3. Effect on forecasts when seats changes the model

When SEATS changes the model because no admissible decomposition has been found, if the parameter NOADMISS is equal to -1, the new model is obtained by adding white noise to the NA model. In this case, the forecasts of the series in TRAMO and in SEATS are the same; also the sum of the components forecasts is the same as the forecast of the series with the TRAMO model.

However, when the parameter NOADMISS is set equal to 1, or when the model passed by TRAMO is changed because of another reason (for example, a parameter ϕ_S may be made 0 if POSBHPI = 1 or -1 when STATSEAS = 1), the forecasts of the components obtained in SEATS with the new model will not add to the series forecast of the model passed by TRAMO. (The difference between the TRAMO and SEATS forecasts will be most noticeable when the unit roots, i.e., differences, are different for the two models.)

In these cases, a modification to the new model components forecasts is made. Let

f_{TC} = forecast of Trend-cycle obtained with the new model;

f_S = idem. for seasonal component,

f_C = idem. for transitory component,

f_{x_T} = forecast of series obtained with TRAMO model,

f_{x_S} = forecast of series obtained in SEATS as $(f_{TC} + f_S + f_C)$.

$d = f_{x_T} - f_{x_S}$: difference between the TRAMO and SEATS forecasts.

A trend is removed from d by means of a centered 13-term moving average, as in

$$r = d - MA(d) ,$$

where, for monthly series and period t ,

$$MA(d_t) = \frac{1}{2} (d_{t-6} + d_{t+6}) + \sum_{j=0}^5 (d_{t-j} + d_{t+j}) .$$

The filter, for the first values of d_t , requires last in-sample d_t 's; for the final values it requires some additional forecasts.

The trend-cycle forecasts become

$$p_t = p_t(\text{SEATS model}) + MA(d_t),$$

and, for the seasonal component:

$$s_t = s_t(\text{SEATS model}) + r_t .$$

The transitory component is left untouched. The forecasts of the series in TRAMO and the ones that results from aggregating the forecasts of the components in SEATS are the same.

1.3.4. INFERENCE IN SEATS

- Besides obtaining the **ARIMA models for each unobserved component** (SA series, trend-cycle, irregular, transitory, and stochastic TD components) complete ARIMA models are obtained for
 - The **historical (or final) estimator** and the associated estimation **standard error**;
 - The **concurrent (real-time) estimator**, and the **revision** this concurrent estimator will suffer.
- From these models, the **gain and phase function** of the asymmetric concurrent filter are obtained, that show the distortion in turning point detection implied by concurrent (and preliminary) estimation.
- The **seasonal-irregular ratios** are presented (both for seasonal and the seasonal irregular components or factors).

1.3.5. ANNUAL AVERAGES

The **annual averages** of the SA series can now match those of the original series using the Statistics Canada benchmarking method.

Alternatively, for monthly series, the difference between the two annual averages can be made zero by an ad-hoc window averaging method (BIAS = -1).

1.4. ADDITIONAL FACILITIES

(All are described in the HELP document).

1.4.1. CONFIGURATION

The config form permits the user to define the default system path of TSW+ from which the Series is loaded, and where to write the output: the graph-files, the standard TSW+ output-files and the user Saved files. In this way it is possible to change those parameters previously defined at installation-time.

1.4.2. INPUT/OUTPUT

- Many Excel formats are now accepted as input by TSW+.
- Output has been expanded. The amount of output produced is a function of the number of series that are jointly treated. (Parameter OUT)
- Output files can be produced in several formats: HTML (accessible AA), pdf, and text. Default: HTML.
- More graphs and graph facilities are now available. For example, they can be copied to the clipboard, or seen in several windows.
- It is possible to control which tables should appear in the output.

1.4.3. DATA-EXPORT

The purpose of the data-export system is to convert and deploy the data produced by a TSW+ execution for further use in other programs (such as Matlab or Excel). It grants flexibility in terms of “which” data is to be exported, and in “what” format.

1.4.4. ANALYSIS

The icon ANALYSIS provides the output of three Addins.

- **Problematic:** (multiple series applications) a utility that picks up problematic series following an application of TSW+ to a set of many time series. For each series, fifteen items are checked (among them, failed TRAMO diagnostics, models changed by SEATS, and number of outliers).
- **Group Outliers:** (multiple series applications) facilitates analysis of the full set of outliers detected by TSW+ in sets of many series.
- **Rates of growth:** presents a battery of growth rates and their forecasts (with associated SE) for the series, SA series, and trend-cycle component.

1.4.5. OTHER

- TSW+ incorporates an interface with the FAME database.
- TSW+ can now be run in batch mode.

2. DECOMPOSITION OF THE ARIMA MODEL

The basic decomposition of the ARIMA model and the derivation of the models for the components in SEATS+ broadly follows Burman (1980), Hillmer and Tiao (1982), Maravall (1995), Gómez and Maravall (2001), Bell and Martin (2004), and Findley (2012). As detailed below, some modifications have been introduced, among them, the introduction of possible additional stochastic components, the replacement of ARIMA models for which no admissible decomposition is available, and the treatment of models that require a departure from the standard decomposition algorithm. The new stochastic components are the stochastic trading day (if detected and if desired,) the business-cycle and the long-term trend. These last two, obtained by splitting the trend-cycle components, are estimated by default when the series is at least, 10 years long.

Let the ARIMA model to be decomposed be

$$\phi(B) x_t = \theta(B) a_t ,$$

and let the decomposition be

$$x_t = p_t + s_t + c_t + u_t ,$$

where p, s, c , and u denote the trend-cycle, seasonal, transitory, and irregular components, respectively. The decomposition is obtained from the identity

$$\frac{\theta(B)}{\phi(B)} a_t = \frac{\theta_p(B)}{\phi_p(B)} a_{pt} + \frac{\theta_s(B)}{\phi_s(B)} a_{st} + \frac{\theta_c(B)}{\phi_c(B)} a_{ct} + u_t ,$$

where each term in the r.h.s. provides the ARIMA model for a component.

Therefore, which components are present are determined from the factorization of the AR polynomial in the model for x_t .

2.1. Allocation of the AR roots to the components

The roots of $\phi(B)$ are assigned to the unobserved components as roots of the AR polynomial in the components' models. This allocation is as follows.

Let the total AR polynomial $\phi(B)$ of the ARIMA model be factorized as

$$\phi(B) = \varphi_r(B) \varphi_s(B^S) \nabla^d \nabla^{d_S} ,$$

where d_S can only be 0 or 1, $d < 3$, $\varphi_r(B)$ is the stationary regular polynomial in B , of order $p \leq 3$, and $\varphi_s(B^S)$ is the stationary seasonal polynomial in B^S , of order ≤ 1 .

Roots of $\nabla^d = 0$: Assigned to trend-cycle component.

Roots of ∇_S : Factorizing it as $\nabla_S = 0$, where

$$S = 1 + B + \dots + B^{S-1}$$

- the root of $\nabla = 0$ goes to the trend-cycle.
- the roots of $S = 0$ go to the seasonal component.

As for the stationary roots, by default, their allocation is as follows.

If $\phi_r(B) = 1 + \phi_1 B + \dots + \phi_p B^p$ and $\phi_s(B) = 1 + \phi_s B^s$, let $z = B^{-1}$ and consider the roots of the polynomials ($B^j = z^{-j}, j = 1, \dots, p$)

$$\phi_r(z) = z^p + \phi_1 z^{p-1} + \dots + \phi_p,$$

$$\phi_s(z) = z^s + \phi_s.$$

Roots of $\phi_r(z)$:

Real positive roots:

- If modulus $\geq k$, assigned to trend-cycle.
- If modulus $< k$, assigned to transitory component,

where k is the input parameter RMOD, by default, $k = 0.5$.

Real negative roots:

- If $s \neq 1$ and modulus $\geq k_s$, assigned to seasonal component (root implies a periodic component of period 2).
- If $s \neq 1$ and modulus $< k_s$, assigned to transitory component
- If $s = 1$ (annual data), assigned to transitory component.
- $k_s = 0.9$ if $\phi(B)$ does not contain any other seasonal root
= RMOD otherwise.

Complex roots:

Let ω denote the frequency of the root and m its amplitude.

If $\omega \in [\text{a seasonal frequency} \pm \varepsilon]$ and $m > k_s$, assigned to seasonal component.

- Otherwise, assigned to transitory component.

By default, ε is the input parameter EPSPHI, set to $\varepsilon = \pi/90$ rad.

- When the pair of complex conjugate roots occurs at the main trading-day frequency (e.g., 2.19 radians for monthly data), and STOCHTD = 1, the pair of roots is assigned to a stochastic trading-day component. This component will follow a canonical ARMA(2,2) model with the complex roots forming the AR polynomial. By default, STOCHTD = 0.

Roots of $\phi_S(z^S)$: $(1 + \phi_S B^S)$

- If $\phi_S < 0$,

Letting ϕ denote the real positive root of $(-\phi_S)^{\frac{1}{S}}$, the polynomial $\phi_S(z)$ can be rewritten as $(z - \phi)(z^{S-1} + \phi z^{S-2} + \phi^2 z^{S-3} + \dots + \phi^{S-1})$.

- when $BD = 1$, the AR root $(1 - \phi B)$ is assigned to the trend; the other $(s - 1)$ roots to the seasonal component.
- when $BD = 0$, the root is assigned to the seasonal when $\phi_S < -0.2$ and/or the overall test for seasonality indicates presence of seasonality. Otherwise it goes to the transitory component.
- If $\phi_S > 0$, roots are assigned to the transitory component. They induce spectral peaks for frequencies that are not seasonal and holes for seasonal ones; often, they produce non-invertibility.

Note:

There are some exceptions to the previous rules, in particular, when the series are stationary and the MA parameters are larger than the AR ones (in modulus). For example:

- the regular ARMA(1,1) model

$$(1 + 0.4 B) x_t = (1 + 0.8 B) a_t$$

generates a moderate peak for $\omega = 0$ that monotonically decreases, while

$$(1 - 0.4 B) x_t = (1 + 0.8 B) a_t$$

generates a moderate peak for the seasonal frequency $\omega = \pi$ and decreases monotonically.

- the seasonal ARMA(1,1)₁₂ model

$$(1 + 0.4 B^{12}) x_t = (1 - 0.8 B^{12}) a_t$$

generates moderate peaks for frequencies in the middle of intervals between two consecutive seasonal frequencies, and hence generates a transitory component; so does the model

$$(1 - 0.4 B^{12}) x_t = (1 - 0.8 B^{12}) a_t .$$

These cases, however, are unfrequent and tend to produce very weak components. (SA series may, on occasion, present these features which may induce non-admissibility and often yield transitory components.)

2.2. Models for the components

The AR polynomials of the component models, including differences, are derived from the AR polynomial in the model for x_t that SEATS+ is decomposing. The roots are assigned to the components as already described, and the factorization

$$\phi(B) = \phi_p(B) \phi_s(B) \phi_c(B)$$

is obtained, where $\phi_p(B)$, $\phi_s(B)$, and $\phi_c(B)$ are the AR polynomials with the trend, seasonal, and transitory roots, respectively. (The roots of the stochastic trading-day, when present, are a special case of the transitory component.) Let P and Q denote the orders of the polynomials $\phi(B)$ and $\theta(B)$ in the compact expression of the model for x_t .

For ARMA(P, Q) models with $P > 0$, SEATS proceeds as follows.

a) **Consider first the case $P \geq Q$.** A polynomial division of the spectrum (or pseudospectrum) of the model for x_t yields a first decomposition of the type

$$\frac{\theta(B)}{\phi(B)} a_t = \frac{\tilde{\theta}(B)}{\phi(B)} a_{1t} + e_t ,$$

where the order of $\tilde{\theta}(B)$ is $\min(Q, P - 1)$, and e_t is white-noise when $P = Q$, and 0 otherwise.

A partial fraction expansion of the spectrum of $[\tilde{\theta}(B)/\phi(B)] a_{1t}$ yields the decomposition

$$\frac{\tilde{\theta}(B)}{\phi(B)} a_{1t} = \frac{\tilde{\theta}_p(B)}{\phi_p(B)} \tilde{a}_{pt} + \frac{\tilde{\theta}_s(B)}{\phi_s(B)} \tilde{a}_{st} + \frac{\tilde{\theta}_c(B)}{\phi_c(B)} \tilde{a}_{ct} ,$$

where, letting $j = p, s, c$, we have $\text{order}(\tilde{\theta}_j) \leq \text{order}(\phi_j)$. If $\tilde{g}_j(\omega)$ denotes the spectrum of $[\tilde{\theta}_j(B)/\phi_j(B)] \tilde{a}_{jt}$, let

$$v_j = \min\{\tilde{g}_j(\omega): 0 \leq \omega \leq \pi\} ;$$

Imposing the canonical condition

$$g_j(\omega) = \tilde{g}_j(\omega) - v_j , \quad j = p, s, c,$$

and, for the irregular component, setting its variance equal to

$$v = v_1 + \sum_j v_j ,$$

the spectrum of the final components are obtained. To estimate a component, all that is needed is its spectrum (and the spectrum of the model for x_t) in order to apply the WK filter. The explicit ARIMA models associated with the components spectra are not used at the estimation stage. They are used, however, for diagnostic and inference. They are also helpful for interpretation of the component and of its forecast function. The models are obtained through the factorization of the components spectra. In compact form, they can be expressed as

$$\phi_p(B) p_t = \theta_p(B) a_{pt} , \quad a_{pt} \sim \text{w. n. } (0, V_p)$$

$$\phi_s(B) s_t = \theta_s(B) a_{st} , \quad a_{st} \sim \text{w. n. } (0, V_s)$$

$$\phi_c(B) c_t = \theta_c(B) a_{ct} , \quad a_{ct} \sim \text{w. n. } (0, V_c)$$

$$u_t = \text{w. n. } (0, V_u) , \quad V_u = v .$$

All components have balanced models, in the sense that the order of the AR polynomial equals that of the MA one.

b) **When** $(Q > P)$, the decomposition proceeds as follows.

A first decomposition is performed, whereby

$$\text{ARIMA}(P, Q) = \text{ARIMA}(P, P - 1) + \text{MA}(Q - P).$$

The first component falls under case a), and hence can be decomposed in the previous way. Let this decomposition be, in general,

$$\text{ARIMA}(P, P - 1) = p_t + s_t + c_t + u_t$$

where p_t , s_t , c_t and u_t denote the trend-cycle, seasonal, transitory, and irregular component. The $\text{MA}(Q-P)$ component, which represents stationary short-term deviations, is added to the transitory component after being made canonical. (The noise removed goes to the irregular.) The series is decomposed then, into a balanced trend-cycle model, a balanced seasonal model, a transitory model (with order $\text{MA} \geq \text{order AR}$), and a white-noise irregular. The first three components are made canonical (i.e., noise free): The MA polynomial in their models contains a unit root, hence the spectrum displays a zero.

When $P = 0$, decomposition of $\text{MA}(Q)$ yields a canonical $\text{MA}(Q)$ plus white noise.

3. MODELS FOR THE HISTORICAL AND PRELIMINARY ESTIMATOR, AND FOR THE REVISIONS. RATE OF CONVERGENCE

In the new version of SEATS, besides the models for the components, the historical estimators and the model for the associated estimation error, the ARIMA models for the concurrent preliminary estimator of

- the trend-cycle component,
- the SA series,
- the seasonal component,
- the transitory component,
- the irregular,

are derived, as well as the ARIMA model for the revision the preliminary estimators will undergo.

It is interesting to note that

- the historical estimator of the irregular,
- the error in the historical estimator,
- the revision in the concurrent estimator,

are all model in $F = B^{-1}$, and share as AR polynomial the MA polynomial $\theta(B)$ in the model for the observed series.

Further, the reciprocal of the root of $\theta(B)$ with the largest modulus determines the eventual speed of convergence of the concurrent estimator of the SA series to the historical one.

Thus a root $(1 - 0.9B)$, or $(1 - 0.9B^{12})$, will typically imply stable trend or seasonal component, that will take long to converge. A root $(1 - 0.2B^{12})$ will imply moving component and slow convergence.

4. QUALITY CHECKS

In TRAMO-SEATS two different types of quality are addressed:

- (1) Quality of the reg-ARIMA model in capturing the series
- (2) Quality of the decomposition, in particular concerning seasonal adjustment.

4.1 Final quality assessment of fitted model in TRAMO

The model fit is classified as GOOD, ACCEPTABLE, MILDLY POOR, and POOR, depending on the results of the 12 checks on Quality. This classification is, of course, arbitrary, and is aimed at orienting the user when many series are being treated, so that careful individual analysis is difficult if not prohibitive. Accordingly, 5% critical values (CV) in the tests are not appropriate (in 10000 series using the 5% CV on each of the 12 tests, many spurious failures could be expected!) When dealing with just a few series, individual analysis can be performed and the analyst can use his/her own criteria; TRAMO's assessment can then be seen as a benchmark reference.

The following table presents the CV of the tests that determine the quality of the model fit in TRAMO. They are expressed in %, thus 1 stands for a 1% test size. The test for the presence of seasonal autocorrelation in the residuals (SigSeas) is built on 4 tests (at the 1% size) following an ad-hoc rule that yields a Y/N answer, so that no CV is assigned. The test for Trading Day effect in residuals, built on 2 tests one of which uses an ad-hoc procedure, and the critical value for the number of outliers are also set with an ad-hoc procedure (one outlier in 20 months seems reasonable).

The set of CVs reflect a relevant fact: when the distribution is symmetric (Sk not significant at the 1% level,) kurtosis, and hence non-normality, do little damage to point estimators. They are more likely to affect inferences (e.g., the SE of the component estimator). We have observed that non-Normality is the main cause of model failure and, most often, due to high kurtosis (absolute value). Given that point estimation is (usually) the main concern, the tests N, Kur, and V-stab. have been made less restrictive.

A. CHECKS ON QUALITY OF MODEL FIT

Residual diagnostics

1. **t-mean:** zero mean (t).
2. **Q:** Lack of residual autocorrelation (χ^2).
3. **N:** Residual Normality (χ^2).
4. **Sk:** Residual skewness = 0 (t).
5. **Kur:** Residual kurtosis = 3 (t).
6. **Runs:** Residual signs are random (t).
7. **m-Stab:** Mean of first and second halves of residual series are equal (t).
8. **V-Stab:** Variance of first and second halves of residual series are equal (F).
9. **SigSeas:** No seasonality detected in residuals (see Detection of Seasonality below).
10. **TDres:** No TD effect detected in residuals (Spectral test).

Others:

11. **OofS:** Variance of out-of-sample forecast errors = Variance of in sample residuals (F).
12. **Out:** Number of detected outliers is not excessive (ad hoc).

B. DETECTION OF SEASONALITY

Performed on linearized series and on residuals.

1. **QS:** Lack of seasonal autocorrelation in residuals (χ^2).
2. **NP:** Non-parametric test (analysis of variance) (χ^2).
3. **F-test:** Significance of seasonal dummies (F).
4. **Spec:** Spectral test for the detection of peaks at seasonal frequencies.
Combines 2 tests:
 - 4.1 Seasonal peaks in AR(30) spectrum (ad hoc).
 - 4.2 Seasonal peaks in Tukey spectral estimator (F).
5. **Overall test:** Combines the previous tests.

TEST	GOOD	ACCEPTABLE	MILDLY POOR	POOR
1. t-mean	1	0.1	0.1	OTHERWISE
2. Q	1	0.5	0.1	
3. N	1	0.1	0.05	
4. Sk	1	0.5	0.1	
5. Kur	0.5	0.1	0.05	
6. Runs	1	0.5	0.1	
7. m-Stab	1	0.5	0.1	
8. V-Stab	0.5	0.1	0.05	
9. SigSeas	N	N	N/W	
10. TDres	N	N	--	
11.OofS	1	0.1	0.1	
12.Out	5%	6%	7%	

Two exceptions:

- a) If a series is classified as **POOR** and the only failed tests are:
Normality, and/or Kurtosis, and/or Variance-Stability, and: $N < 20$, $Kur < 5$, and $V\text{-Stab} < 4$,
⇒ Series classification is changed to MILDLY POOR.
- b) Similarly with series classified as **MILDLY POOR** only because N, and/or Kur, and/or V-Stab fail, if $N < 17$, $Kur < 4$, and $V\text{-Stab} < 3.5$,
⇒ Series re-classified as ACCEPTABLE.

4.2 QUALITY ASSESSMENT IN ARIMA-MODEL-BASED SEASONAL ADJUSTMENT

In standard seasonal adjustment with (possibly a limited set of) fixed filters, the quality of an adjustment is difficult to assess since seasonality, besides unobserved, is undefined. Quality of a measurement should be ultimately given by the size of the measurement error, yet this error is unavailable: we do not know what the seasonally adjusted series (or the seasonal component) should be compared to. Thus quality checks have mostly centered on features thought a priori to be undesirable, such as the presence of a large irregular, a weak trend, or a fast moving seasonal.

These checks can create problems. As a simple example, a monthly series that follows the model $x(t) = 0.6 x(t - 12) + a(t)$ will exhibit seasonal autocorrelation and spectral peaks for the seasonal frequencies, yet its seasonality is highly moving and likely to be rejected by the quality checks. If not removed, however, diagnostic test on the seasonally adjusted (SA) series (i.e., the original series) will indicate presence of seasonality.

Quality of an adjustment in the ARMA-model-based approach is addressed in a drastically different way. Assuming the model fits reasonably well the series, one can derive a model for the seasonal component (perhaps stable, perhaps moving), and the (model-dependent) Wiener-Kolmogorov filter yields the MMSE estimator of this component. Further, models can be derived for historical, preliminary, and concurrent estimators, as well as for their revisions and estimation error. This permits to perform standard statistical testing and inference (even if approximate).

4.3 SEASONALITY: QUALITY DIAGNOSTICS

1. There are two checks that may indicate **misspecification of the components models**. One compares the theoretical autocorrelation function of the stationary transformation of the component with that of its estimator. The second one does a similar comparison for the crosscovariance. Often, the misspecification is due to the replacement of a model with no admissible decomposition with a decomposable approximation. The check specifically considers the lag-1 and lag-12 autocorrelations, as well as the variance.
2. There is a check for the **presence of seasonality in the seasonally adjusted series**. Specifically the check considers the overall test on SA series. Spectral tests are applied on the irregular and trend components.

Checks 1 or 2 would lead to a rejection of the adjustment; another option should be tried.

Then several checks are made that attempt to capture undesired features of the seasonal adjustment. In all cases, Y means the undesirable feature has been detected; N means it has not and hence there is no problem

3. **“Small or Spurious”**: the seasonal component is negligible; the original and the SA series are practically indistinguishable. (Requires that $\text{SigD} < 10^{-4}$ and $\text{sigseas} = 1$, or $\text{sigD} < 10^{-3}$ and $\text{sigseas} = 0$.)

$\text{sigseas} = 0$ overall seasonal test did not detect seasonality
 $\text{sigseas} = 1$ overall seasonal test detected weak seasonality
 $\text{sigseas} = 2$ overall seasonal test detected clear seasonality

sigD:

When levels are used: $\sqrt{\frac{\text{Var}(\text{stochastic seasonal component})}{\text{var}(\text{linearized series})}}$

When logs are used: $\sqrt{\text{Var}(\text{stochastic seasonal component})}$

4. **“Highly stationary”**: the seasonality moves too fast (AR seasonal root > -0.2 or pure MA; no seasonal difference).
5. **“Not significant (Last year)”**: the seasonal component for last year are individually not significant.
Monthly data: No component has a value $t > 3$, and no more than 2 months have $t > 1.96$
Non-monthly data: no seasonal component has $t > 1.96$
6. **“Too many changes in sign of seasonal”**: for a given month, the seasonal component changes sign too often. (Uses Chi-square test; with the number of observations per year as degrees of freedom; at the 99% critical value; computed as the sum of squared t-values).
7. **“Unstable seasonality”**: SE of innovation in Seasonal Component > 0.99 SE of series innovation.
8. **“Unreliable estimator of seasonality”**: the SE of the concurrent estimator > 0.9 SE of series innovation.
9. **“Revisions are too large”**: the SE of the revision in the concurrent estimator > 0.9 SE of series innovation.
10. **“Bias in level of SA series too large”**. When logs are taken a bias effect is induced. (Measured as % of the average of the absolute value of the differences between the original and SA series too large when $\text{Bias} \geq 2$).

Seasonal adjustment of series is deemed of QUESTIONABLE INTEREST when checks 5 and 6 say Y, or checks 3, or 4, or 7, or 8 or 9 say Y.

When checks 5 and 6 say Y, seasonality is judged “Detected but not enough persistent”.

5. MODEL CHANGED BY SEATS: FLOW DIAGRAMS

Several flow diagrams of the changes that SEATS+ may do to the model passed by TRAMO+ are given below.

Diagram 2 shows the different places in SEATS+ where the model can be modified. The modification may occur before any attempt to decompose the model is made, or as a result of a decomposition that is non-admissible. In the later case, the model is replaced with a decomposable one.

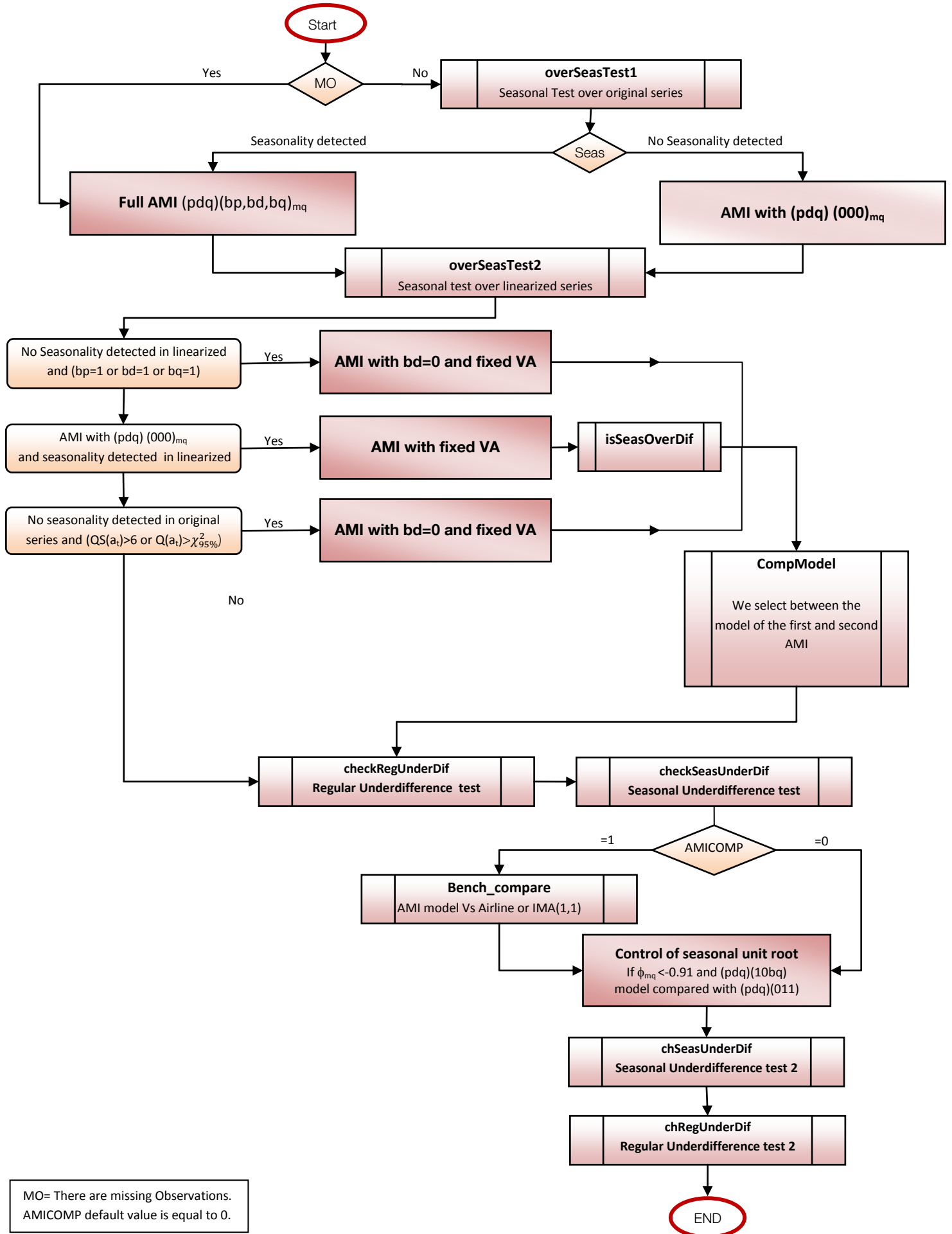
Diagram 3 details the changes that may be enforced prior to decompose the model. They affect the stationary polynomials (regular and seasonal). The changes may be due to awkward models that, due to the parameter interaction, need to be changed in order for the decomposition algorithm to make sense. They may also be aimed at reducing the number of stationary parameters (transforming them into unit roots or simply deleting them).

Diagram 4 shows the general flow of the algorithm to decompose the model, and of the steps to approximate the non-decomposable model with a decomposable one. One option is to add white noise to the series so that $\text{Var}(\text{irregular})$ becomes 0, and then to recompute the model. Other options are detailed in the following diagrams.

Diagram 5 details the model replacement when the model orders are among the set of orders for which the admissible parameter region is known.

Diagram 6 details the model replacement when the admissible parameter region is not known, and the ad-hoc replacement procedure is followed ($NOADMISS = 1$, default value). The full procedure may imply more than one iteration of the diagram.

Diagram 1: Automatic Model Identification



overSeasTest1

We consider there is seasonality if the QS test detects seasonality at 99%; or if non parametric criterion of seasonality and QS test detect seasonality at 95%

overSeasTest2

We returns the parameter OST_{XL} =number of tests that detect seasonality; crQS: the QS test detects seasonality at 99%; crFseas: the Fseas test detects seasonality at 99%. We consider there is seasonality if $OST_{XL}>1$ or crQS=Yes or crFseas=Yes

checkRegUnderDif

If $D<2, P>0, IMEAN=1$ and there is a real positive root of module greater than 0.9 the model is compared with $(P-1, D+1, q)$ (bp, bd, bq) [re-estimated] without mean, and we choose the best one.

checkSeasUnderDif

If $(p, d, q)(bp, 0, bq)_{MQ}$ and there is residual seasonality => we compare with the model $(p, d, q)(0, 1, 1)_{MQ}$ and use the best model.

Bench_compare

Using CompModel subroutine we choose between the input model and: an airline model if $OST_{XL}>0$ or an AMI(1,1)+mean model if $OST_{XL}=0$

isSeasOverDif

This check is only needed when overseasTest1 indicates presence of seasonality, the first AMI yields a $(p, d, q) (0, 0, 0)_{mq}$ model (M), and the second AMI produces a $(p, d, q) (0, 1, 1)_{mq}$ model (MM) with $\theta_{mq} < 0.70$. OverSeasTest2 is redone on the linearized series. If seasonality is detected, CompModel sets $M_o = MM$ otherwise $M_o = M$

chRegUnderDif (ACF test)

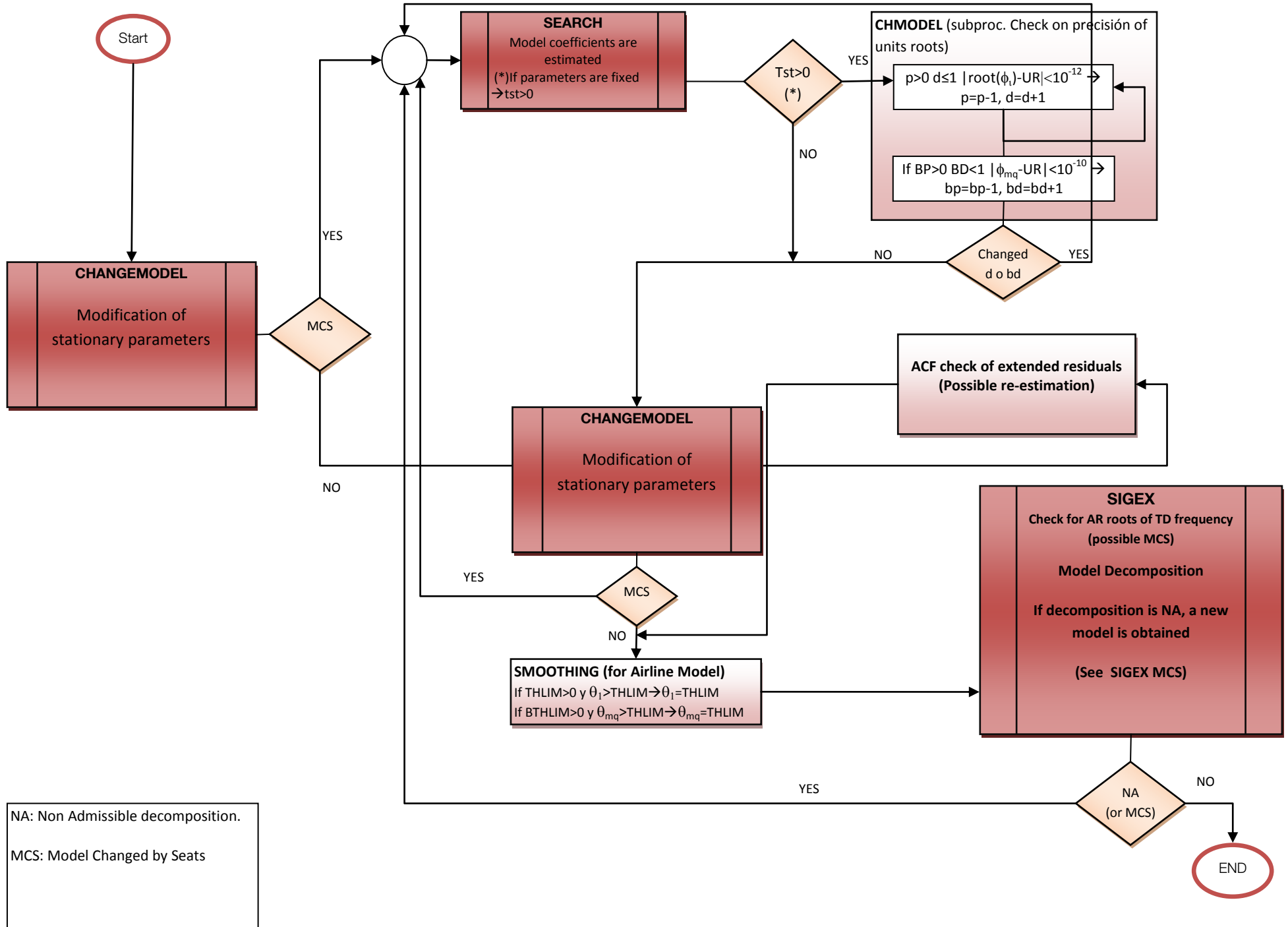
If $(p, d, q)(bp, bd, bq)_{MQ}$ fails Q-test at 95% and there are 17 autocorrelations>0 in the first 24 or at least min(9, mq) of the first 12 lags are positive then we compare with $(p, d+1, \min(q+1, 3))$ (bp, bdbq) if $d < 2$ or with $(\min(p+1, 3), d, q)$ (bp, bd, bq) + mean if $d=2$ and use the best model

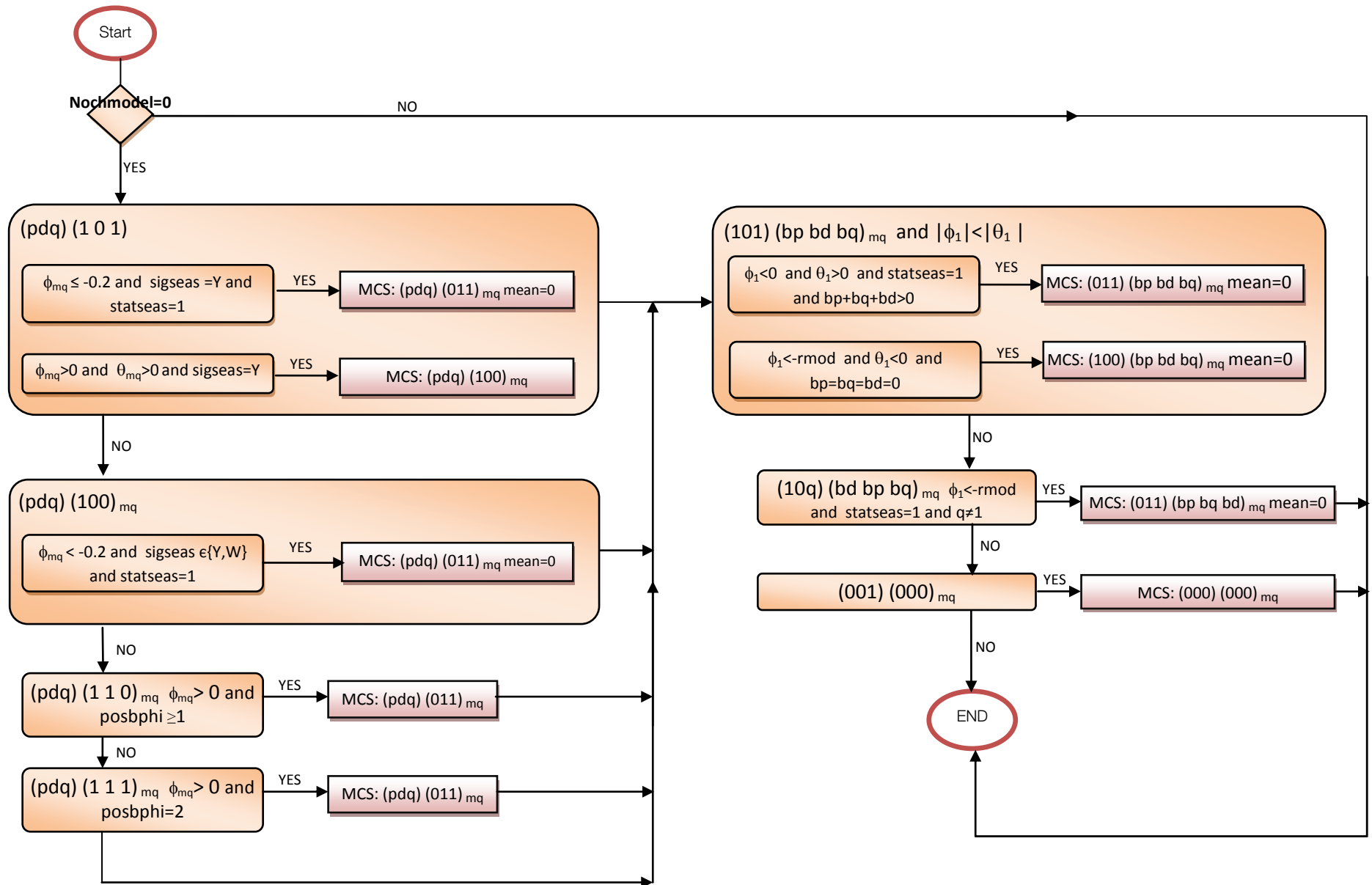
chSeasUnderDif

If $(p, d, q)(bp, 0, 0)_{MQ}$ and $OST_{XL} \geq 1$ and (bp>0 or EE>0 or TD>0) then we compare with $(p, d, q)(bp, 1, 1)_{MQ}$ without mean and use the best model.

Flow Diagram for Model Change in Seats. (Rel.933)

Diagram 2: Main Flow

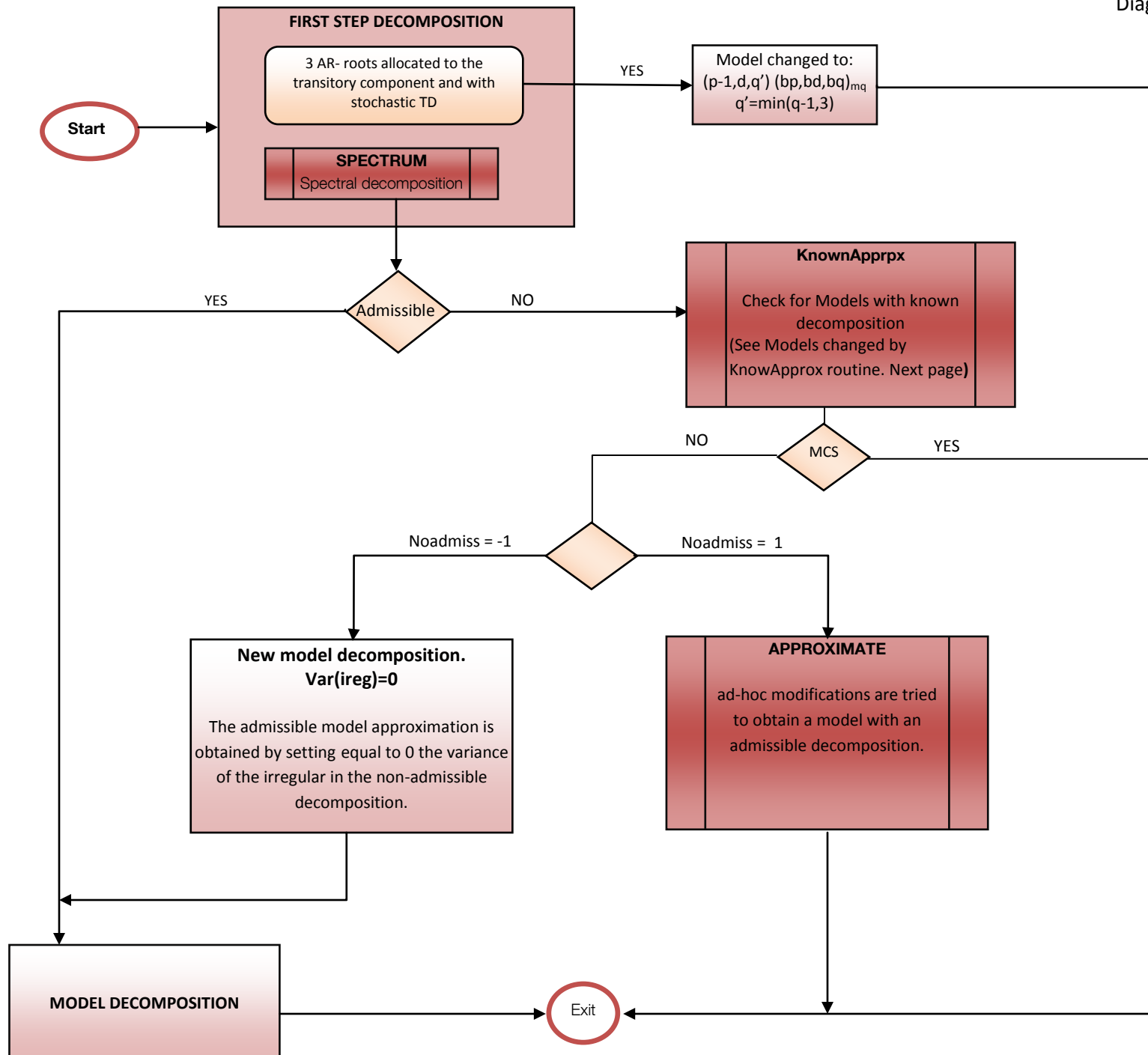


**Sigseas values:**

- 0: No evidence of seasonality in linerized series detected .
- 1: Weak evidence of seasonality in linerized series.
- 2: Strong evidence of seasonality in linerized series .

Default Parameters Values:

Posbphi = 0; statSeas=0



Flow Diagram for Model Change in Seats. (Rel.933)

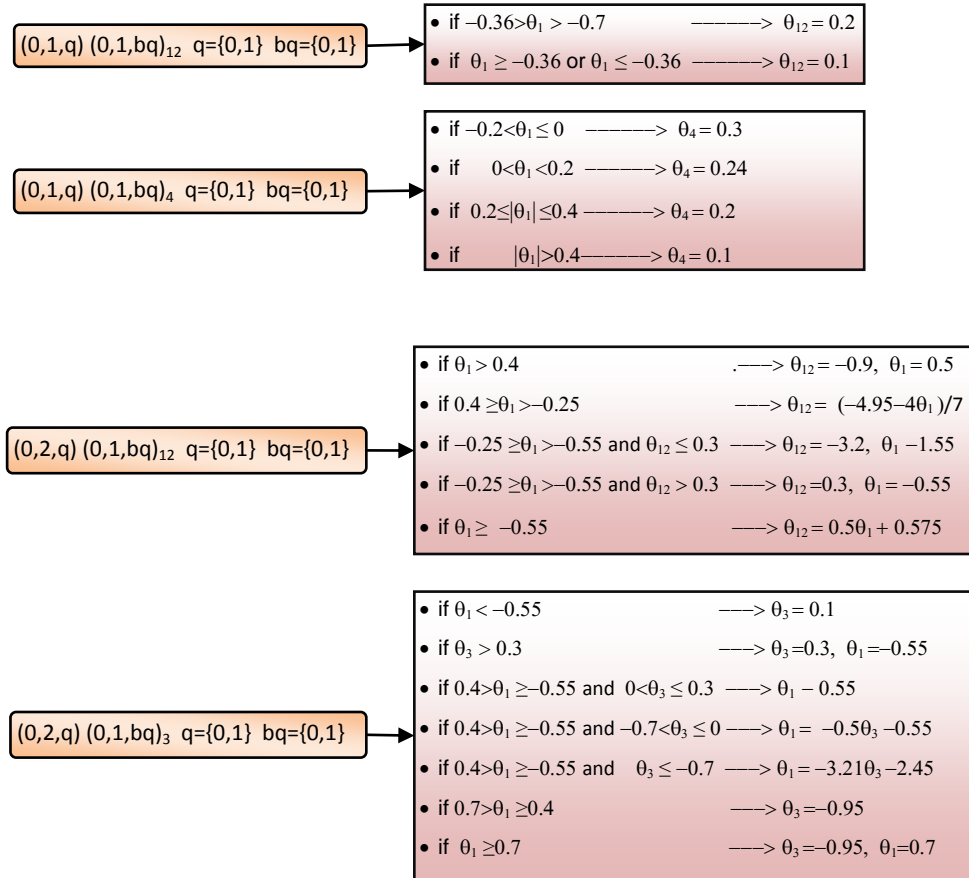


Diagram 5: models changed by KnownApprox

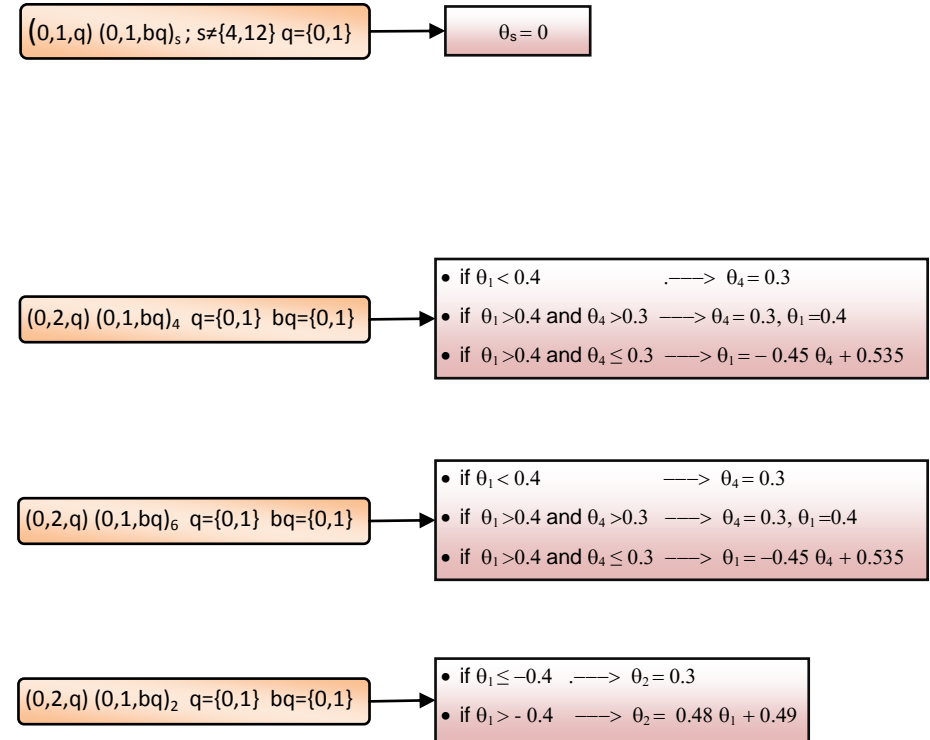


Diagram 6: Approximate routine MCS

