

Transformation and trend–seasonal decomposition

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Abstract

Many time series, particularly monthly economic and official time series, are both non-linear and seasonal. In practice simple power transformations are often used to transform such series to additive linear models and standard trend–seasonal decomposition procedures are then applied for various purposes including seasonal adjustment, trend extraction and forecasting.

This paper considers the effects of trend–seasonal decomposition on transformed time series which are then transformed back to provide seasonal and trend components in the original scale of the data. It is shown that this approach leads to ambiguities in the resulting decomposition which result in systematic biases to these components. These effects are particularly evident when there is significant variation about the trend, due to either or both of the seasonal and irregular components.

A new trend–seasonal decomposition is proposed which is largely free of these biases. Results are illustrated by simulation and with reference to NZ official time series.

Keywords: Trend–seasonal decomposition; seasonal adjustment; trend estimation; transformation; bias correction.

1 Introduction

Many time series, particularly monthly economic and official time series, are both non-linear and seasonal. In practice simple power transformations are often used to transform such series to additive linear models and standard trend–seasonal decomposition procedures are then applied for various purposes including seasonal adjustment, trend extraction and forecasting. Accurate identification of trends from seasonal data is important if only to determine important trend parameters such as direction, level and rate of change, or for the purpose of comparison between series. In the development that follows we restrict attention to monthly time series with annual seasonality although our results and observations apply more generally.

A broad class of non-linear seasonal time series models widely used in practice is given

by the additive model

$$\phi(Y_t) = T_t + S_t + \epsilon_t \tag{1}$$

where Y_t denotes the original series, $\phi(y)$ a suitable transformation, T_t and S_t the trend and seasonal components and the so-called irregular component ϵ_t denotes noise. The latter is assumed to be stationary with mean zero (often white noise), and all three components in the additive decomposition are assumed to be independent. Other components such as a calendar component can also be added. To further identify the components in (1) additional constraints are needed. These include local smoothness constraints for the trend and the year to year evolution of the seasonal. Furthermore, the seasonal component is assumed to approximately sum to zero over any twelve month period so that

$$\sum_{j=0}^{11} S_{t-j} \approx 0. \tag{2}$$

These constraints are sufficient to ensure that the trend T_t runs through the middle of the transformed data over any twelve month period.

The most widespread transformations used are the identity $\phi(y) = y$ for the simple additive model and the logarithm $\phi(y) = \log y$ for data whose components are multiplicative. The trend–seasonal decomposition procedure SABL (Cleveland et al (1978)) augments these by considering the class of power transformations defined by

$$\phi(y) = \begin{cases} y^p & (p > 0) \\ \log y & (p = 0) \\ -y^p & (p < 0) \end{cases} . \tag{3}$$

It is assumed that a value of p can be found which makes the decomposition (1) hold, at least to a first approximation. In practice, p is chosen so that there is no interaction between the trend and seasonal components in (1). However the trend–seasonal decomposition procedures used by most official statistical agencies in the world are X–11–ARIMA (Dagum (1980)) and X–12–ARIMA (Findley et al (1988)). These are based on the original X–11 procedure (Shiskin et al (1967)) which has its own multiplicative model which is different from (1) with $\phi(y) = \log y$. A useful reference to seasonal models such as (1) and trend–seasonal decomposition procedures in general is given in the survey article Cleveland (1983).

Consider the case where Y_t follows (1) with $\phi(y)$ not the identity transformation. To seasonally adjust Y_t it is common practice to seasonally adjust the transformed series $\phi(Y_t)$ by removing the seasonal component and then transforming back into the original scale of the observations. Seasonally adjusted trends can also be obtained by back–transforming the trend of the transformed series. However this approach can lead to ambiguities in terms of definition of trend and seasonal, particularly where there is significant variation about the trend, due to either or both of the seasonal or irregular components.

An example is given in Figure 1 which shows the number of visitor arrivals to New Zealand by month over the period January 1980 to December 1991. Three trends are superimposed: the trend estimated by the X–11 multiplicative model and two SABL

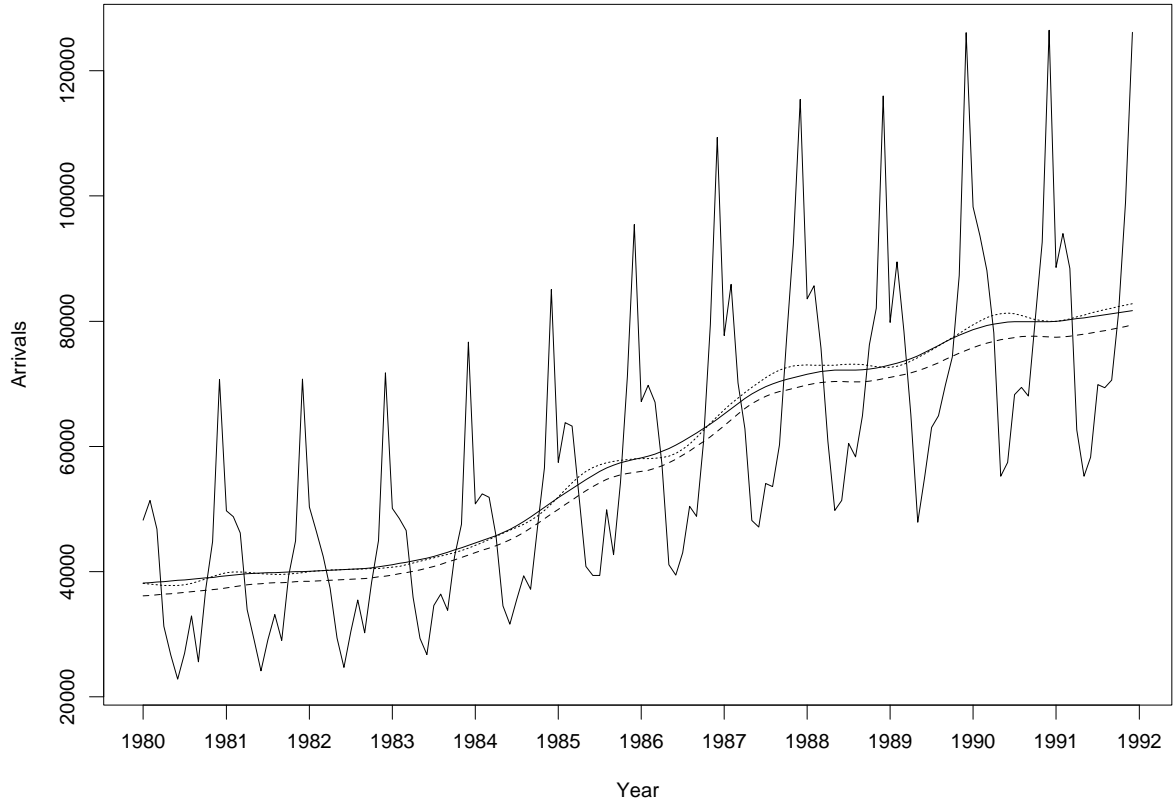


Figure 1: Visitor arrivals to New Zealand by month. Three trends are superimposed: the trend estimated by the X-11 multiplicative model (dotted line) and two SABL trends, one of the untransformed data (solid line) and the other the exponential of the trend of the logarithms of the data (dashed line)

trends, one of the untransformed data and the other, the exponential of the trend of the logarithms of the data. Despite the fact that X-11 trends are locally quadratic and SABL trends are locally linear, both the X-11 and SABL trends of the original data are much the same. However there is a significant difference between these and the exponential of the trend of the logarithms of visitor arrivals. This difference, essentially the difference between the arithmetic and geometric means, was first systematically discussed in the literature by Young (1968). His correction formulae for the multiplicative model are closely related to the more general formulae proposed here.

The reason why the X-11 multiplicative trend yields much the same trend as the SABL trend from the original visitor data is discussed in Section 2. However the important point to note is the following. If an additive model is fitted to the transformed data using (1) and then the inverse transform applied, the trend, seasonal and seasonally adjusted series obtained are not independent of the transformation chosen. Systematic differences exist between them. In many cases the differences are slight. However in cases where there is significant variability about the trend due to either or both of the seasonal or irregular, the difference can be sizeable. For the New Zealand Visitor Arrivals data given in Figure 1, the difference between the two SABL trends during June 1988 is 1839 arrivals or 2.5%.

The above discussion highlights the importance of defining appropriate trend and seasonal components in the case where $\phi(y)$ is not the identity transformation. The standard requirement that is built in to both the additive and multiplicative X-11 models is that (moving) annual totals of seasonally adjusted and unadjusted series should be essentially the same. We shall refer to this as the *seasonal balance constraint*. This is an economic requirement which ensures that the process of seasonal adjustment is essentially one of redistribution of seasonal variation so that, on an annual basis, observed totals (wealth, credits, debits, numbers of visitor arrivals etc) are neither created nor destroyed. Although this is a natural economic requirement, for transformed series following (1) it conflicts with (2) except in the additive case $\phi(y) = y$. In Section 3 we use the seasonal balance constraint to define appropriate trend and seasonal components for the original series Y_t .

2 X-11 Models

Before developing appropriate definitions of trend, seasonal and irregular for models such as (1) where $\phi(y) \neq y$, it is instructive to review the X-11 multiplicative model.

X-11 was initially developed by Shiskin et al (1967). Despite many new developments in seasonal time series models, it remains the most popular method of seasonal adjustment and forms the basis of X-11-ARIMA (Dagum (1980)) and X-12-ARIMA (Findley et al (1988)) used by the majority of the world's official statistical agencies. The additive version of X-11 is as given in (1) with $\phi(y) = y$. However the multiplicative version of X-11 is essentially based on the model

$$Y_t = T_t(1 + S_t)(1 + \epsilon_t) \quad (4)$$

where the seasonal factor S_t satisfies (2) and $E(\epsilon_t) = 0$. Applying the logarithm transformation to (4) yields a model which is approximately the same as (1) with $\phi(y) = \log y$ provided that S_t and ϵ_t are small. If either or both of the seasonal or irregular are sizeable then differences emerge as is evidenced in Fig. 1. In particular the two seasonal constraints differ with one requiring the moving annual arithmetic mean, the other the moving annual geometric mean, of the seasonals to be approximately zero.

The model (4) can also be written in additive form as

$$Y_t = T_t + T_t S_t + T_t(1 + S_t)\epsilon_t. \quad (5)$$

Provided that the trend is smooth, (2) ensures that the seasonal component $T_t S_t$ will approximately sum to zero over any twelve month period. This model is similar to that proposed by Durbin and Murphy (1975), but has heteroskedastic multiplicative errors rather than additive homoskedastic errors.

The additive form (5) helps to explain the non-linear X-11 model fitting procedure. Broadly speaking, the trend T_t is first estimated by filtering (5) with a linear low-pass filter that also removes the seasonal $T_t S_t$. The resulting trend estimate is then divided through (5) and the seasonal component $1 + S_t$ extracted using simple linear filters. This is then divided into (4) to obtain a seasonally adjusted series. Further smoothing iterations are

carried out together with various procedures to down-weight outliers, adjust for calendar effects etc. Thus it can be argued that the X-11 procedure expresses a multiplicative model as an additive model and fits accordingly. This has the advantage of ensuring that the seasonal balance constraint is satisfied and is the reason why, in Figure 1, the X-11 multiplicative trend of the NZ visitor arrivals series is much the same as the SABL trend from the untransformed data.

3 A new trend–seasonal decomposition

Following the example of the X-11 model (5), the general strategy we adopt is to express Y_t in additive form with trend, seasonal and irregular defined as functions of the corresponding components in the transformed series. The derived trend, seasonal and seasonally adjusted series are then constructed from the estimates of the components in the transformed series. This approach is implicit in the X-11 multiplicative procedure. It has the virtue of separating the model fitting, which takes place with the transformed series, from the additive trend–seasonal decomposition of the original series Y_t which is constructed so that the seasonal balance constraint remains approximately true.

Before constructing an additive decomposition for Y_t , we first need to make some basic assumptions about the trend, seasonal and irregular components given in (1). We shall assume that all three components are independent and that the trend T_t follows a deterministic or stochastic model which is locally smooth. For example X-11 and SABL assume that T_t follows a local low-order deterministic polynomial model in t within a moving window of consecutive monthly observations. On the other hand Akaike (1980), Gersch and Kitagawa (1983), Harvey (1989) and many others assume global stochastic models for T_t of the form

$$\Delta^p T_t = \eta_t$$

where η_t is white noise and Δ is the backwards difference operator satisfying $\Delta X_t = X_t - X_{t-1}$. Typically $p = 1$ or 2 and the variance of η_t is taken small enough to ensure that T_t is smooth. The irregular component ϵ_t is assumed to be a zero-mean stationary time series.

We shall assume that the evolving seasonal component can always be represented as

$$S_t = \sum_{j=1}^6 \{ \alpha_j(t) \cos t\lambda_j + \beta_j(t) \sin t\lambda_j \} \quad (6)$$

where $\lambda_j = 2\pi j/12$ and $\beta_6(t) = 0$. The zero frequency component corresponding to $\lambda_0 = 0$ has been omitted from (6) to ensure that S_t measures departures from the trend T_t which describes the instantaneous local level of $\phi(Y_t)$ at time t . As a consequence this representation automatically satisfies (2) since $\sum_{j=0}^{11} S_{t-j}$ will be approximately zero provided that the $\alpha_j(t)$ and $\beta_j(t)$ are sufficiently smooth. Note that it will rarely be the case that $\sum_{j=0}^{11} S_{t-j}$ is identically zero. This will only be true when S_t is strictly periodic and the $\alpha_j(t)$, $\beta_j(t)$ are constants. If, as is commonly the case, the $\alpha_j(t)$, $\beta_j(t)$ are evolving slowly over time then S_t will also evolve slowly and $\sum_{j=0}^{11} S_{t-j}$ will have the appearance of

a stationary time series with small variance. However, in the case where the $\alpha_j(t)$, $\beta_j(t)$ are evolving linearly in t , then $\sum_{j=0}^{11} S_{t-j}$ may also exhibit a seasonal pattern which, in turn, will need to approximately sum to zero over any twelve month period. In this case (2) will need to be replaced by $\sum_{j=0}^{11} \sum_{k=0}^{11} S_{t-j-k} \approx 0$.

The model (6) is implicitly used by X-11 and SABL where the $\alpha_j(t)$, $\beta_j(t)$ are assumed to be constant or linear in t within an appropriately defined moving window. The mixed model proposed by Durbin and Murphy (1975) also fits this framework. In terms of stochastic seasonal models, (6) is the same as the model proposed by Hannan (1967) (see also Ng and Young (1990)) where $\alpha_j(t)$, $\beta_j(t)$ follow the stochastic trend models

$$\Delta\alpha_j(t) = \eta_j(t), \quad \Delta\beta_j(t) = \xi_j(t) \quad (7)$$

and the white noise processes $\eta_j(t)$ ($j = 1, \dots, 6$) and $\xi_j(t)$ ($j = 1, \dots, 5$) are mutually independent with $E(\eta_j(t)^2) = E(\xi_j(t)^2) = \sigma_j^2$. In fact this stochastic seasonal model is more general than might first appear. Dongfeng et al (1997) show, among other results, that Hannan's model is stochastically equivalent to the model proposed by Harvey (1989) where

$$S_t = \sum_{j=1}^6 u_j(t)$$

and

$$\begin{pmatrix} u_j(t) \\ v_j(t) \end{pmatrix} = \begin{pmatrix} \cos \lambda_j & \sin \lambda_j \\ -\sin \lambda_j & \cos \lambda_j \end{pmatrix} \begin{pmatrix} u_j(t-1) \\ v_j(t-1) \end{pmatrix} + \begin{pmatrix} \eta_j(t) \\ \xi_j(t) \end{pmatrix}$$

with the $\eta_j(t)$, $\xi_j(t)$ defined as in (7). (This result was also informally communicated to the first author by W.R. Bell (US Census Bureau) at an earlier date.) This seasonal model is used in the structural time series modelling procedure STAMP (Koopman et al (1995)) and the seasonal decomposition procedure MING (Bruce and Jurke (1996)). Moreover, if the $\eta_j(t)$, $\xi_j(t)$ are replaced by carefully chosen stationary processes, then (6) can be shown to encompass the stochastic seasonal model

$$\sum_{j=0}^{11} S_{t-j} = \eta_t$$

where η_t is stationary. The case where η_t is white noise is commonly used (see Gersch and Kitagawa (1983), Harvey (1989) for example). If η_t is an AR(1) process then the seasonal model is equivalent to that used in BAYSEA (Akaike (1980)). The generality of (6) and the properties of such stochastic seasonal models is the subject of ongoing research with some results already reported in Dongfeng et al (1997). It is sufficient for our purposes here that we assume that S_t admits the instantaneous Fourier representation (6) with the $\alpha_j(t)$, $\beta_j(t)$ evolving slowly over time.

To handle both (1) and (4), we now consider

$$Y_t = g(T_t, S_t, \epsilon_t) \quad (8)$$

where the components T_t , S_t , ϵ_t are as defined above and $g(x, s, e)$ is either $\phi^{-1}(x + s + e)$ with $\phi(y)$ given by (3) or the X-11 model $x(1 + s)(1 + e)$ given by (4). More generally

$g(x, s, e)$ could be any well-behaved function of its arguments. We write Y_t in the additive form

$$Y_t = T_t^* + S_t^* + \epsilon_t^* \quad (9)$$

where T_t^* , S_t^* , ϵ_t^* are yet to be defined trend, seasonal and irregular components. Proceeding constructively we define $M_t = T_t^* + S_t^*$ as

$$M_t = E\{g(T_t, S_t, \epsilon_t) | \mathbf{T}, \mathbf{S}\} \quad (10)$$

where \mathbf{T} and \mathbf{S} denote the processes $\{T_t; t = 0, \pm 1, \dots\}$ and $\{S_t; t = 0, \pm 1, \dots\}$ respectively. This additively decomposes Y_t into a systematic component M_t and an irregular component

$$\epsilon_t^* = Y_t - M_t \quad (11)$$

where ϵ_t^* has zero mean and is uncorrelated with M_t .

Now M_t is an evolving trend and seasonal pattern that is a function $M(x, s)$ of T_t and S_t which, from (6), can be written as

$$M_t = M(T_t, S_t) = M\left(T_t, \sum_{j=1}^6 \{\alpha_j(t) \cos t\lambda_j + \beta_j(t) \sin t\lambda_j\}\right).$$

However any function of an (instantaneous) Fourier representation will create a new (additive) Fourier representation of the form (6) with new coefficients $\alpha_j(t)$, $\beta_j(t)$ and, in particular, an additional zero frequency ($\lambda_0 = 0$) or local level component with $\beta_0(t) = 0$, but $\alpha_0(t)$ not necessarily zero. For example, if $M(x, s) = (x + s)^2$ then

$$M(T_t, S_t) = \left(\sum_{j=0}^6 \{\alpha_j(t) \cos t\lambda_j + \beta_j(t) \sin t\lambda_j\}\right)^2 = \sum_{j=0}^6 \{a_j(t) \cos t\lambda_j + b_j(t) \sin t\lambda_j\}$$

where $\alpha_0(t) = T_t$, $\beta_0(t) = 0$ and

$$a_0(t) = \alpha_0(t)^2 + \sum_{j=1}^5 \{\alpha_j(t)^2 + \beta_j(t)^2\} + \alpha_6(t)^2, \quad b_0(t) = 0.$$

This can be verified by direct algebra or by using the formula for the Fourier coefficients which, for $\lambda_0 = 0$ gives

$$a_0(t) = \frac{1}{12} \sum_{k=0}^{11} \left(\sum_{j=0}^6 \{\alpha_j(t) \cos(t-k)\lambda_j + \beta_j(t) \sin(t-k)\lambda_j\}\right)^2.$$

These arguments lead us us to define the instantaneous local level of Y_t at time t as

$$T_t^* = E\left\{\frac{1}{12} \sum_{k=0}^{11} M\left(T_t, \sum_{j=1}^6 \{\alpha_j(t) \cos(t-k)\lambda_j + \beta_j(t) \sin(t-k)\lambda_j\}\right) | \mathbf{T}, \mathbf{S}\right\} \quad (12)$$

where the conditional expectation ensures that T_t^* is a function of T_t and \mathbf{S} . The conditional expectation is needed in general since the second argument of M is not S_{t-k}

unless the $\alpha_j(t)$, $\beta_j(t)$ are locally constants. However the conditional expectation will not be necessary in the special case where the $\alpha_j(t)$, $\beta_j(t)$ are exactly directly from the transformed series. The seasonal component S_t^* is now defined by subtraction as

$$S_t^* = M_t - T_t^*. \quad (13)$$

In the special case of the identity transformation where $g(x, s, e) = x + s + e$ we have $M(x, s) = x + s$ and

$$T_t^* = T_t, \quad S_t^* = S_t, \quad \epsilon_t^* = \epsilon_t.$$

For the X-11 case where $g(x, s, e) = x(1 + s)(1 + e)$ we have $M(x, s) = x(1 + s)$ and

$$T_t^* = T_t, \quad S_t^* = T_t S_t, \quad \epsilon_t^* = T_t(1 + S_t)\epsilon_t.$$

This leads to the following definition.

Definition 1 *Let Y_t follow the model specified by (8). Then the trend T_t^* , the seasonal S_t^* and the irregular ϵ_t^* in the additive decomposition (9) of Y_t are defined by (10), (11), (12) and (13). In particular, the identity transformation model (1) with $p = 0$ and the X-11 model (5) have this additive form.*

This defines the required trend–seasonal decomposition. Given any particular model for Y_t of the form (8), one could derive precise formulae for T_t^* , S_t^* and ϵ_t^* as functions of T_t , S_t and ϵ_t . Then these functions and the estimated trend, seasonal and irregular of the transformed series could be used to provide estimates of the trend, seasonal and irregular for the original series. Although of interest, this approach has not been followed here. Rather we shall adopt a simpler strategy of approximating these functions with simple non–parametric linear filters of functions of the component series.

3.1 Approximate decompositions

We now consider approximating T_t^* and S_t^* by

$$\hat{T}_t^* = \sum_k c_k M(T_t, S_{t-k}) \quad (14)$$

$$\hat{S}_t^* = M_t - \hat{T}_t^* \quad (15)$$

where the c_k are the coefficients of a linear trend filter L_S that satisfies

$$L_S(X_t) = \sum_k c_k X_{t-k} \quad \left(\sum_k c_k = 1 \right) \quad (16)$$

and L_S also filters out fixed annual seasonal patterns. If the $\alpha_j(t)$, $\beta_j(t)$ are locally constant then this filter is just the simple one–sided 12 month moving average. However, to allow for evolution in the $\alpha_j(t)$, $\beta_j(t)$, other linear filters based on the simple 12 month moving average might better be employed in practice. These include the standard 12 month (13 point) centred moving average or the triangular 23 point moving average where the non zero c_k are given by

$$c_k = \frac{12 - |k|}{144} \quad (k = 0, \pm 1, \dots, \pm 11).$$

In particular, the latter filter results if the $\alpha_j(t)$, $\beta_j(t)$ are locally linear. Then it is not hard to show that

$$T_t^* = \frac{1}{12} \sum_{k=0}^{11} M(T_t, (1 - \frac{k}{12})S_{t-k} + \frac{k}{12}S_{t+12-k})$$

which, using linear interpolation, should be well approximated by

$$\frac{1}{12} \sum_{k=0}^{11} ((1 - \frac{k}{12})M(T_t, S_{t-k}) + \frac{k}{12}M(T_t, S_{t+12-k})) = \sum_{k=-11}^{11} \frac{12 - |k|}{144} M(T_t, S_{t-k}).$$

The quality of this approximation is dependent on the smoothness of $M(x, s)$ and the closeness of the values of S_t for the same month in successive years. However it might be expected that these would be quite reasonable approximations in practice. Finally we note that (12) is identically zero when $M(x, s)$ is proportional to s , regardless of the law of evolution for the $\alpha_j(t)$, $\beta_j(t)$. This leads to the convention that $L_S(S_t)$ is set to zero when evaluating \hat{T}_t^* . These approximations and definitions are now used to define suitable non-parametric approximations of T_t^* and S_t^* .

Result 2 *Let Y_t follow the model specified by (8) with additive decomposition given by Definition 1. Then the expressions (14) and (11) provide an approximate non-parametric additive decomposition of Y_t in cases other than the identity transformation model (1) with $p = 0$ and the X-11 model (5).*

Consider, for example, (1) and the cases $p = 0$ and $p = 0.5$. For the multiplicative case $\phi(y) = \log y$ and

$$M_t = \psi(1)e^{T_t + S_t}, \quad \hat{T}_t^* = \psi(1)e^{T_t}L_S(e^{S_t}), \quad \hat{S}_t^* = \psi(1)e^{T_t}(e^{S_t} - L_S(e^{S_t}))$$

with $\psi(s)$ denoting the moment generating function of ϵ_t . In the case of Gaussian errors $\psi(1) = \exp \frac{1}{2}\sigma^2$ where $\sigma^2 = E\epsilon_t^2$. In the case of the square-root transform ($p = 0.5$) we have

$$M_t = (T_t + S_t)^2 + \sigma^2, \quad \hat{T}_t^* = T_t^2 + L_S(S_t^2) + \sigma^2, \quad \hat{S}_t^* = 2T_tS_t + S_t^2 - L_S(S_t^2).$$

The functional dependence of \hat{T}_t^* and \hat{S}_t^* on T_t and S_t can now be utilised to construct estimates. In the simplest case this means replacing T_t and S_t in (14) by their estimates obtained from the transformed data using standard trend-seasonal decomposition procedures. The unknown ϵ_t parameters in M_t are estimated from the estimated irregular of the transformed data. Depending on the nature of the data, these particular estimates could be simple moment estimates or robust estimates that take proper account of outliers. In the multiplicative case this procedure yields formulae that are closely related to those advocated by Young (1968). For parametric Gaussian models such as those advocated by Akaike (1980), Gersch and Kitagawa (1983), Harvey (1989), Ng and Young (1990), Maravall (1995) among many others, better estimates of M_t and \hat{T}_t^* can be obtained directly by determining

$$E\{M_t|\text{data}\}, \quad E\{\hat{T}_t^*|\text{data}\} \tag{17}$$

using the relevant conditional densities determined from the Kalman filter and smoother. Using this technology, confidence limits can also be constructed.

Now consider the case where Y_t follows (1) and $\phi(y)$ is given by (3) or, more generally, by some other well-behaved function. In this case computationally simpler approximate procedures can be used provided S_t and ϵ_t are small.

Result 3 *Let Y_t follow the model specified by (1) where $\phi(y)$ is some well-behaved function. Then T_t^* , S_t^* , ϵ_t^* of Definition 1 can be approximated by the simpler forms \tilde{T}_t^* , \tilde{S}_t^* , $\tilde{\epsilon}_t^*$ respectively where*

$$\begin{aligned}\tilde{T}_t^* &= \phi^{-1}(T_t + \frac{1}{2}\gamma(T_t)(L_S(S_t^2) + \sigma^2)) \\ \tilde{S}_t^* &= \phi^{-1}(T_t + S_t + \frac{1}{2}\gamma(T_t)\sigma^2) - \tilde{T}_t^* \\ \tilde{\epsilon}_t^* &= Y_t - \tilde{T}_t^* - \tilde{S}_t^*\end{aligned}\tag{18}$$

provided S_t and ϵ_t are small. Here

$$\gamma(x) = -\phi^{(2)}(\phi^{-1}(x))/(\phi^{(1)}(\phi^{-1}(x)))^2$$

and $\phi^{(j)}(y)$ denotes the j th derivative of $\phi(y)$. When $\phi(y)$ is given by the power transformation (3)

$$\gamma(x) = \begin{cases} 1 & (p = 0) \\ (p^{-1} - 1)/x & (p \neq 0) \end{cases} .\tag{19}$$

The approximations given by Result 3 make simple additive adjustments to the trend of the transformed data and then back-transform. Alternative approximations can also be devised which make additive adjustments in the original scale of the observations yielding the following result.

Result 4 *Let Y_t follow the model specified by (1) where $\phi(y)$ is some well-behaved function. Then T_t^* , S_t^* , ϵ_t^* of Definition 1 can be approximated by the simpler forms \bar{T}_t^* , \bar{S}_t^* , $\bar{\epsilon}_t^*$ respectively where*

$$\begin{aligned}\bar{T}_t^* &= \phi^{-1}(T_t)(1 + \frac{1}{2}\delta(T_t)\gamma(T_t)(L_S(S_t^2) + \sigma^2)) \\ \bar{S}_t^* &= \phi^{-1}(T_t)\delta(T_t)(S_t + \frac{1}{2}\gamma(T_t)(S_t^2 - L_S(S_t^2))) \\ \bar{\epsilon}_t^* &= Y_t - \bar{T}_t^* - \bar{S}_t^*\end{aligned}\tag{20}$$

provided S_t and ϵ_t are small. Here

$$\delta(x) = \frac{d}{dx} \log \phi^{-1}(x)$$

and $\gamma(x)$ is as given in Result 3. When $\phi(y)$ is given by the power transformation (3)

$$\delta(x) = \begin{cases} 1 & (p = 0) \\ p^{-1}/x & (p \neq 0) \end{cases} .\tag{21}$$

Note that in the case of (3) and the identity transformation $p = 1$ the components given by Results 3 and 4 are identical with those of Definition 1. In the multiplicative case where $\phi(y) = \log y$

$$\tilde{T}_t^* = e^{T_t + \frac{1}{2}(L_S(S_t^2) + \sigma^2)}, \quad \tilde{S}_t^* = e^{T_t + \frac{1}{2}\sigma^2} (e^{S_t} - e^{\frac{1}{2}L_S(S_t^2)})$$

and

$$\bar{T}_t^* = e^{T_t} (1 + \frac{1}{2}(L_S(S_t^2) + \sigma^2)), \quad \bar{S}_t^* = e^{T_t} (S_t + \frac{1}{2}(S_t^2 - L_S(S_t^2))).$$

If $\phi(y)$ is the square-root transform (3) with $p = 0.5$ then

$$\tilde{T}_t^* = (T_t + \frac{1}{2}(L_S(S_t^2) + \sigma^2)/T_t)^2, \quad \tilde{S}_t^* = (T_t + S_t + \frac{1}{2}\sigma^2/T_t)^2 - (\tilde{T}_t^*)^2$$

and

$$\bar{T}_t^* = T_t^2 + L_S(S_t^2) + \sigma^2 = \hat{T}_t^*, \quad \bar{S}_t^* = 2T_t S_t + S_t^2 - L_S(S_t^2) = \hat{S}_t^*.$$

In the next section the relative performance of these various procedures is investigated by analysis of simulated and real data.

In practice the above will need to be modified to handle calendar and holiday effects, and to incorporate robust estimation procedures to cope with outliers. The latter is directly addressed by estimating M_t using the robustness weights derived when processing the transformed data. Calendar and holiday effects are typically modelled by adding in an extra fixed effects regression component to the right-hand side of (1). The regressors include month length, numbers of each type of week-day in the month and dummy variables for holidays. A similar development to that leading to Definition 1 could be undertaken to define appropriate additive components in the original scale of the observations. When mean corrected, these effects will typically be sufficiently small that they do not influence the definitions of trend and seasonal given by Definition 1, at least to first order. Thus, in practice, calendar and holiday effects can be safely removed from the transformed data prior to forming the required components given by (14), (18) or (20).

4 Numerical studies

In keeping with Thomson and Ozaki (1992) the analysis and simulations undertaken in this section are based on a selection of New Zealand official series over the 12 year period 1980 – 1991. The series considered are short-term visitor arrivals, merchandise trade exports and merchandise trade imports.

We first consider the trends and seasonally adjusted series obtained from the New Zealand Visitor arrivals data using (1) with $p = 0$ and $p = 0.5$. The former is the more natural transformation although arguments can be advanced for both; indeed the power transformation chosen by SABL was (3) with $p = 0.25$, a compromise between the two alternatives. The effects of the corrections given in Section 3 are illustrated in Table 1 where the mean trend bias gives the mean of the differences between the X-11 trend and each of the trends given by $\phi^{-1}(T_t)$, (14), (18) and (20). Since X-11 fits the additive decomposition model

Adjustment Method	Mean Trend Bias		Seasonal Balance	
	$p = 0$	$p = 0.5$	$p = 0$	$p = 0.5$
No correction	-2040	-1181	1957	985
Equation (14)	-47	-186	1	1
Equation (18)	-99	-186	53	-4
Equation (20)	-133	-181	1	1

Table 1: Visitor arrivals to New Zealand by month; trends and seasonally adjusted series obtained using (1) with logarithm and square root transformations. The mean trend bias (by comparison to X-11) and the mean seasonal balance bias from zero are given for the corrected and uncorrected series.

(5) directly without any correction, its trend has been used as the basis for comparison. The mean seasonal balance bias measures the mean difference between the centred 12 month (13 point) moving averages of the original and seasonally adjusted series. Here the trend T_t and other components have been estimated from the transformed series $\phi(Y_t)$ using SABL. All measurements are in the original scale of the observations and the calculations have been carried out for the various corrected and uncorrected series over the central 10 year period to avoid complications with filter end effects.

The results in Table 1 indicate that, in the case of strong seasonality, the corrections are a marked improvement over the usual procedure of no correction. There is little to pick between the direct adjustment (14) and its approximations. As might be expected, the unadjusted trend obtained using the square root transformation is better than that obtained using the logarithm transformation. Moreover the corrected trend using the logarithm transformation appears to be better than the corrected trend using the square root transformation. However both corrected trends approximate the X-11 trend reasonably well irrespective of the transformation adopted. Thus the correction procedure results in trends that are, to a large extent, invariant with respect to the transformation chosen

We now consider analyses of three different types of simulated series whose key parameters are given in Table 2. For each type of series, 20 independent realisations of 12 years duration were generated using (1) with power p given by Table 2. The trends were deterministic linear or quadratic functions of time, the seasonal components were fixed non-evolutionary annual cycles, and the irregular components were Gaussian white noise. All components were generated for the transformed series which were then transformed back into the original scale of the observations. The model parameters were chosen following an analysis of the actual series concerned. However these analyses were used as a guide only and the parameters adopted provide, at best, an overly simplistic description of the series concerned.

The key parameters given in Table 2 are CV, the average coefficient of variation in the original scale of the observations, and SI, the seasonal to irregular ratio $\text{RMS}(S_t)/\sigma$ in the transformed scale. Here σ^2 is the (constant) variance of the irregular component and $\text{RMS}(S_t)$ is the root mean square of the seasonal pattern over any 12 month period. Simulated exports and imports have a relatively high variability about the mean level of

Simulated Series	p	CV	SI
Visitor Arrivals	0.0	0.05	5
Exports	0.5	0.10	2
Imports	0.0	0.10	1

Table 2: Key parameters for series simulated using (1) with power p , coefficient of variation CV and seasonal to irregular ratio SI.

approximately 10%. Moreover, simulated exports have seasonal amplitudes approximately twice the size of the irregular whereas simulated imports have seasonal amplitudes of approximately the same size as the irregular. Thus, compared to visitor arrivals, simulated exports and imports represent situations where the use of correction formulae should be more marginal.

The results are summarised in Figure 2. Here the standardised trend bias at a given point in time t is defined as $\Delta\bar{T}_t/(s_{\Delta T}/\sqrt{20})$ where $\Delta\bar{T}_t$ and $s_{\Delta T}^2$ are the sample mean and variance respectively of the differences between the 20 individual trend estimates (with and without correction) and the true trend T_t^* . The latter is defined by (12) and evaluated for the true T_t , S_t and σ . The standardised seasonal balance bias is defined similarly as $\Delta\bar{S}_t/(s_{\Delta S}/\sqrt{20})$ where $\Delta\bar{S}_t$ and $s_{\Delta S}^2$ are the sample mean and variance respectively of the differences between the 20 individual centred 12 month (13 point) moving averages of the original series and their seasonally adjusted forms. Thus the mean trend or seasonal balance bias at any given time point has been measured in units of its own standard deviation. As before, the results displayed relate to the central 10 year period of the series to avoid possible end effect complications. Only the results for the correction procedure (14) have been displayed in Figure 2 since the other procedures (18) and (20) produce much the same results. The choice of correction procedure can thus be based on other criteria such as theoretical considerations and computational convenience.

The results are self evident; the greater the variation about the trend the greater the gains obtained from using the correction formulae. Even in the case of exports and imports where the seasonal and irregular amplitudes are of modest size, there are still significant gains to be had. These remarks apply to both trend and seasonal balance biases.

In the case of the corrected trends, there remains a small downwards bias. This is most likely due to the fact that T_t^* has been estimated from (14) with T_t , S_t and σ^2 replaced by estimates from the decomposition of the transformed data. For parametric Gaussian based models this problem might be alleviated to some extent by using (17) and the Kalman filter. For models such as X-11 which are already in the appropriate additive form, no correction formulae are needed and direct fitting of the components should be largely free of trend bias. Procedures that directly fit the X-11 model include X-11-ARIMA, X-12-ARIMA or the parametric procedures of Ozaki and Thomson (2002). However, in general, further corrections will be needed to eliminate estimation bias. This is beyond the scope of the current paper. Finally note that the correction procedures do not appear to increase the variability of the trend estimates; indeed, if anything there might be a slight reduction in variability.

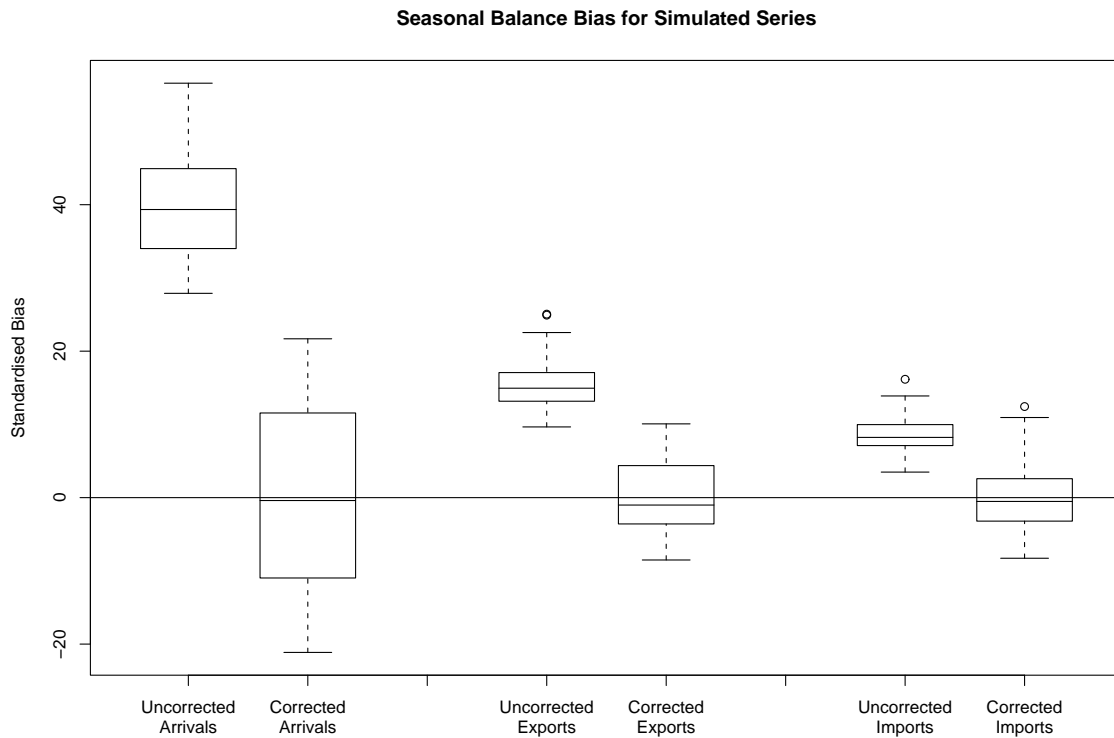
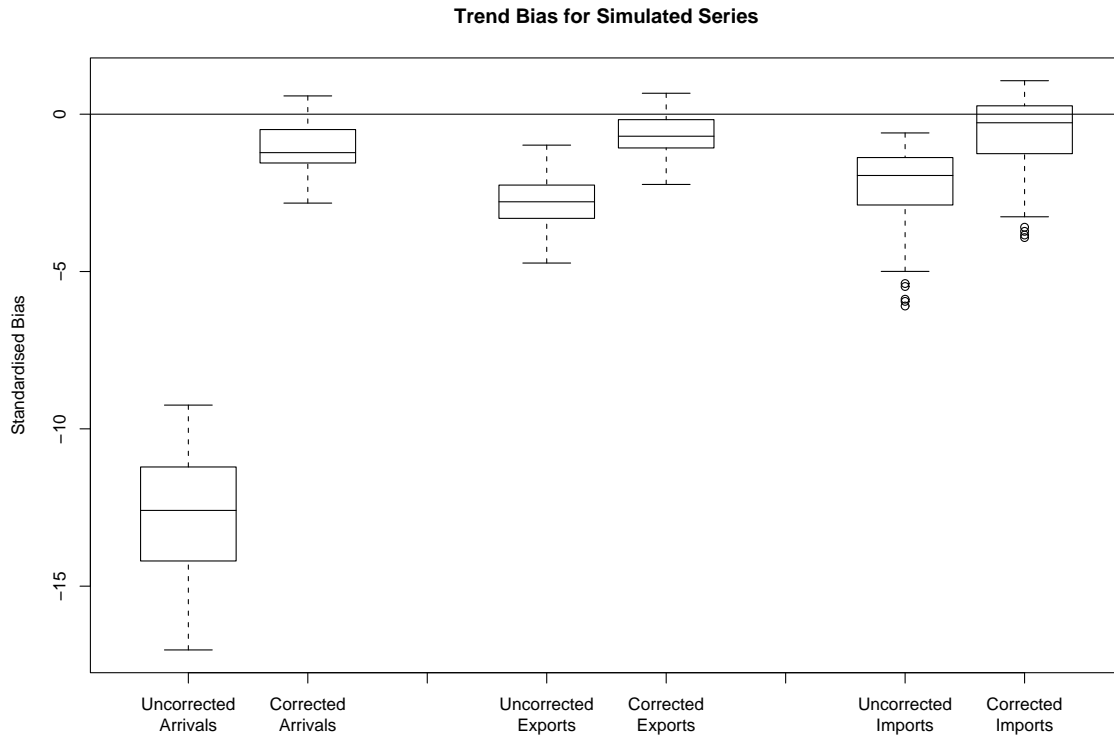


Figure 2: Simulated visitor arrivals, exports, imports and balance of exports less imports; trend and seasonal balance biases. In each case boxplots of standardised trend biases from the true trend and standardised seasonal balance biases from zero are given for the uncorrected series and series corrected using (19).

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