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Nonparametric Transfer Function Models with Localized Temporal Effect

by

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ABSTRACT

The transfer function model is postulated as a semiparametric function of the inputs in addition to the autocorrelation structure. The effect of an input series x_t to the output series y_t is formulated as a nonparametric regression while some localized temporal effects such as seasonality, trend and structural changes present in the output series is accounted by a mixed effects model. The semiparametric additive model is then estimated via the backfitting algorithm.
Simulation study shows that the procedure provides robust estimates for the transfer function especially for short time series. This provides a viable alternative to the traditional transfer function model that requires large number of time points to estimate a number of parameters. Furthermore, in the presence of seasonality or structural change, the procedure is generally more robust than the maximum likelihood estimation of a transfer function.

Keywords: transfer function model, semiparametric model, backfitting, mixed models

1. Introduction

Some time series data exhibit dynamic behavior that often invalidates results of univariate time series analysis. Given a single output time series denoted by $\{y_t\}$, variation can be explained by the past values (autocorrelation) and the present and past values of an input series $\{x_t\}$. As an example, daily water consumption can be affected by consumption pattern in the past and the present weather conditions. Past weather conditions may also contribute in terms of the inherent autocorrelation structure.
Box et al. (1994) discussed a function that relates the output and the input series along with the autocorrelations of both the output and input series given by

$$y_t = v(B)x_t + n_t. \tag{1}$$

Equation (1) is called transfer function model. The filter $v(B)=\sum_{j=-\infty}^{\infty} v_j B^j$ is called the transfer function and n_t is the noise process independent of the input function. The output series is a linear function of the current and past values of the input series. The coefficients of the transfer function, $\{v_j\}$ are called the impulse response weights. Box et al. (1994) also presented a procedure in estimating the model. The procedure involves two preliminary steps: first is to identify the transfer function followed by the identification of the noise model. Once the transfer function and the noise process are specified, maximum likelihood estimation is used to estimate the parameters.
There are some limitations in the transfer function model in equation (1). While the infinite-ordered linear process can approximate both linear and non-linear functions, the model is saturated with parameters. The input and output series must be also be bivariate stationary. Furthermore, an inherent feature of the untransformed input and output series is that they must have certain degree of cointegration (Granger 1981 as cited in Granger and Engle, 2003).
Some models were introduced to address these problems in the transfer function model. Gao (2007) presented models that used mixed modeling in order to address nonlinearity of the series. Partially linear autoregressive models was also introduced

where the current value of the output y_t is a linear function of its past values and a nonlinear function on $\{x_t\}$ or y_t is a linear function of $\{x_t\}$ and a nonlinear function of its past values, see (Tjøstheim et.al., 2007; Li and Racine, 2006; Gao et.al., 2009) for further details. While these models addressed some of the limitations of the transfer function model, they are still vulnerable to random movements which cannot be explained by either x_t or past values of y_t, therefore the error series may still deviate from a white noise. Hidalgo (1992) proposed a linear input and nonparametric (using kernels) error model. Truong and Stone (1994) considered nonparametric input and linear autoregressive error model. These semiparametric methods handle the error series well but still impose stationarity restrictions and other assumption in the models.

We propose a semiparametric form of the transfer function model that is flexible enough to capture both linear and nonlinear features of the input and output series. With the inclusion of random effects, the proposed model can also accommodate nonstationarity, seasonality and structural change without going through the prewhitening methods required in transfer function modeling algorithm.

2. Transfer Function Models

Suppose there are two time series $\{x_t\}$ and $\{y_t\}$ gathered at the same time interval and frequency, these two series are linked by some dynamic system. Box et al. (1994) as cited in Wei (2006) proposed a method to model such dynamism through transfer function models. The transfer function model is given in equation (1). Due to the fact that the input and noise processes can be assumed to follow autoregressive moving average (ARMA) models, the transfer function model is also called as ARIMAX model.

The basic steps of transfer function modeling are as follows (Wei, 2006; Box et al., 1994):

1. *Pre-whiten the input series.* Transfer function models require both the input and the output series to be stationary. This step includes the traditional way of modeling time series: inspect the autocorrelation functions (ACF) and partial autocorrelation functions (PACF) for possible differencing and determining the order of the ARIMA model, then investigating the behavior of the noise series as diagnostic checking. The prewhitened input series is denoted by the following model:

$$\alpha_t = \frac{\phi_x(B)}{\theta_x(B)} x_t. \qquad (2)$$

   α_t is a white noise process with mean zero and variance σ^2_α.

2. *Transform the output series using the prewhitened input series as the filter.* The output series will then be filtered using the prewhitened input series defined in step 1. The transformed output series is denoted by the following model:

$$\beta_t = \frac{\phi_x(B)}{\theta_x(B)} y_t. \qquad (3)$$

3. *Calculate the sample cross correlation function (CCF) between α_t and β_t and estimate the transfer function.* The CCF, via significant correlations between the input and the output series determines which lags of the input series are significantly influencing the current output value. The sample CCF therefore is vital in estimating the impulse responses and consequently, the transfer function. It is important to note that both input and output series must be prewhitened in order to have meaningful interpretations of the CCF. If the input and output series have a rigid dependence structure, then when the output series is filtered through the estimated model of the input, then it is also prewhitened.

4. *Estimate the noise series and combine it with the function in step 4 to have the estimated transfer function model.* In transfer function modeling, the noise process is not limited to a white noise process. That is, the noise process can still be modeled by say, an ARMA(1,1) process.

5. *Do diagnostic checking.* Examine the residuals and check if the residuals are indeed white noise and independent of the input series $\{x_t\}$. Once this is satisfied, then the model is considered adequate.

The transfer function model can be viewed as a regression model on time series data. The dependent variable is the output series and the independent variables are the current and past values of the input series. The impulse response weights are the regression coefficients, which quantifies the value of information from the current and past values of the input to the output.
Nonlinearity and seasonality is addressed by the prewhitening processes through differencing. However, shocks and interventions happen in time. Box et al. (1994) discusses techniques in intervention analysis that can handle such time points in transfer function modeling.

3. Backfitting and Mixed Models

The backfitting procedure was proposed by Buja et al. (1989) as an iterative algorithm which uses smoothing techniques in building nonparametric regression models. Hastie and Tibshirani (1990) discussed the steps in implementing backfitting:

1. *Initialize values*. Let $\hat{\alpha} = \bar{Y}$ and $f_j = f_j^{(0)}, j = 1,2,\ldots,p$.
2. *Iterative smoothing*. For repeated *j=1,2,…,p*, the smooth of x_j is obtained by smoothing the residuals on x_j. That is,
   $$\tilde{f}_j = smooth_j\left(y - \alpha - \textstyle\sum_{k \neq j} f_k \,|\, x_j\right).$$
3. *Repeat*. Step *2* is done continuously until the individual functions don't change. The resulting estimated model is additive:

$$\hat{y} = \hat{\alpha} + \sum_{j=1}^{p} \hat{f}_j\left(x_j\right) + \varepsilon. \tag{4}$$

The additive model has been used effectively in time series. Dominici et al. (2002) used generalized additive models in their analysis of air pollution and health time series. Barrios and Vargas (2007) postulated an additive model used in forecasting multicollinear time series. Sheike (2001) presented a nonparametric survival model based on generalized additive modeling. Asymptotic optimality of the backfitting algorithm has been established by Mammen et al. (1997) and Opsomer (2000). Hastie and Tibshirani (1995) further stated that the additive model can replace an additive decomposition of the time series model into its linear and nonlinear components.

The additive model gives a higher level of flexibility on the postulated model since the form of the function of the input series need not be specified and the effects of each input series to the output series can be investigated individually.

The additive model can effectively capture the dependence structure between the input and the output time series. However, if some features in y_t which are not present in x_t (e.g. seasonality and structural change), the noise structure would consist of pure noise at some points and meaningful localized structures at some points. This will consequently induce clustering behavior among time points where these behaviors has been localized. Demidenko (2004) argued that when dealing with clustered data, one can use the mixed effects model:

$$y_{ij} = \alpha_i + \beta x_{ij} + \varepsilon_{ij}. \quad (5)$$

The first term α_i is the i^{th} cluster effect, the second term βx_{ij} is the effect of the j^{th} observation in the i^{th} cluster.

4. The Postulated Model and Estimation Procedures

We propose the following model as an alternative to the transfer function model:

$$y_t = \gamma_t + \lambda_t = \sum_{i=1}^{p} g(x_{it}) + L_t + \varepsilon_t, \ ,$$

$$L_t = \sum_{j=1}^{s} L_{jt} + \eta_{jt}. \quad (6)$$

Where:

$\{y_t\}$	=	output series
$\{x_{it}\}$	=	ith input series
$\{\varepsilon_t\}$	=	the error series
p	=	number of input variables
t	=	number of time series points
$g_i(x_{it})$	=	the smooth of y_t on x_{it}
L_t	=	localized temporal effect
s	=	number of clusters
η_{jt}	=	random variation within the jth cluster

We decompose the output series into two components, the basic output component (summarizing the contributions of the inputs) and the localized temporal component λ_t. The basic output is explained by the additive nonparametric function $g(x_{it})$, that account for the dependence between the input and the output series. No rigid assumptions on the dependence of the input and output series will be imposed. This will also skip the tedious process of identifying the impulse response function specially for transfer functions with more than one input variable. The input and output series need not be stationary processes. Since the input and output series are not governed by regularization constraints, some information on the output series will not be manifested by the input series, leading to the initial error process to manifest such. Any perturbations in the output not associated with the input (e.g. seasonality and structural changes) will be captured by the localized temporal component λ_t. In the absence of these components, the noise term will manifest such perturbations as random shocks. This component is captured by the localized temporal effect L_t. The localized temporal effect is a mixed model and will handle other features of the time series such as seasonality, deterministic trend and structural changes not associated with the input series. The noise process is assumed to have a zero mean and finite variance.
The following iterative procedure is used in estimating the model:

Step1: Smooth the output series based on the input series. Using some smoothing algorithms, e.g., cubic smoothing splines, estimate the smooth function *$g(x_t)$.* This is the nonparametric approximation on the dependencies link between the input and the output series. The initial additive model is as follows:

$$y_t - \sum_{i=1}^{p} g\left(x_{it}\right) = \delta_t \tag{7}$$

The innovation process δ_t is still not yet white noise since it still contains the localized temporal component.
The estimate of g in the equation above minimizes the penalized sum of squared errors:

$$\sum_{t=1}^{T} \left\{y_t - f\left(x_t\right)\right\}^2 + \lambda \int_a^b \left\{g''\left(x\right)\right\}^2 dx. \tag{8}$$

Step 2: Compute the residuals:

$$e_t = y_t - \hat{g}\left(x_t\right) \tag{9}$$

This is a realization of the innovation process δ_t. The residuals e_t contain information on the temporal dependencies left out in the output series that is not associated with the input series.

Step 3: Estimate the localized temporal component with a mixed model from the residuals in Step 2. Treating the perturbations as producing clustering effect, the residuals are considered as clustered data and the mixed model proposed by Demidenko (2004) is used. The initial error series are divided into previously identified clusters. A priori clustering can be identified from time plots or other sources of information like documentation of data generation.

The estimation procedure takes advantage of the fact that the components of equation (6) are additive. Hence, nonparametric regression and mixed model are imbedded into the backfitting algorithm to estimate the semiparametric model in equation (6).

5. Simulation Studies

Different scenarios accounting for different possible perturbations and characteristics of time series data were simulated. In the simulation, each scenario is replicated to 100 datasets.

Since transfer function models are very sensitive to the length of the time series, four different lengths of the time series are considered. For the very short time series, 36 time points were generated, 60 time points for small sample, 180 for medium length, and 360 for a longer time series.

The output series y_t is generated into two phases. First is to simulate the dependency of the output on the input series. The scenarios considered under this step are stationarity of the input, form of the transfer function and the presence of a second correlated input variable. Next is to add the localized temporal effect in the output series. The localized temporal effects considered are seasonality, an increasing trend and structural change at the end of the output time series.

The scenarios can be seen all at once from the model:

$$y_t = \frac{\sum_{i=0}^{s} \omega_i B^i}{\left(1 - \sum_{j=1}^{r} \delta_j B^j\right)} B^b x_t + L_t + \varepsilon_t,\ \ L_{jt} = \sum_{j=1}^{s} L_{jt} + \eta_{jt}, \tag{10}$$

where $\varepsilon_t \sim N(0,1)$ and $\eta_{jt} \sim N(0,0.75)$.

In simulating the input series, two scenarios were considered, a stationary AR(1) process and a near nonstationary AR(1) process:

$$(1 - 0.5B)(x_t - 20) = a_t \text{ where } a_t \sim N(0,1), \tag{11}$$

$$(1 - 0.99B)(x_t - 20) = a_t \text{ where } a_t \sim N(0,1). \tag{12}$$

Both the stationary and nonstationary series have mean 20. The goal here is to assess the performance of the proposed model under the nonstationary and nonlinear (or stochastic trend) conditions.

In Model (10), the coefficient of x_t is the transfer function which will simulate the dependencies between the input and the output series. Denote B as the backshift operator. There are 3 parameters in the transfer function. The first parameter is *b*, the delay parameter that indicate the time lag until the input affects the output. The order of the numerator polynomial is *s*, where *s+1* is the number of input series time points affecting y_t. Lastly, *r* is the order of the denominator polynomial representing the number of autoregressive time points affecting the output series. Two transfer functions are being considered:

$$\left(0.25 + 0.5B^1 + 0.25B^2\right)x_{t-1} \tag{13}$$

$$\frac{\left(0.125 + 0.25B^1 + 0.125B^2\right)}{\left(1 - 0.5B^1\right)}x_{t-1} \tag{14}$$

For both transfer functions, a delay parameter *b=1* is used. Both transfer functions are also affected by two input time series. The difference is that in the second transfer function, the output y_t is affected by one autoregressive time point.

In the case of multiple input series, the Wei (2006) noted that these input series must be uncorrelated so that modeling with a single input series can be extended and applied with no difficulty. Problem arises when the two input series are correlated. One scenario will investigate the consequence of correlation existing between the two input series, i.e., simulate another time series x_2 which is correlated with x_1. This is obtained by the following:

$$x_2 = 0.3x_1 + e_{x_1} \text{ where } e_{x_1} \sim N(0,3). \tag{15}$$

After simulating the dependency structure between the input and the output series, localized temporal effects are added to the output series. The seven levels of localized temporal components will be treated as clusters not observed in the input series but present in the output series. Note that the clusters here are not necessarily contiguous time points, rather packets of time points which exhibit similar patterns (structures and dependencies).

These localized temporal effects will be accounted by the following model:

$$L_t = \sum_{j=1}^{s} L_{jt} + \eta_{jt} \text{ where } \eta_{jt} \sim N(0,0.75). \tag{16}$$

In the Equation (16) above, there are *s* clusters. Note that this temporal effect will represent the component in the output series that is not associated with the input series. Hence, the temporal effect will represent significant data perturbations with respect to the output series only.

Seasonality as a temporal effect is simulated by dividing the *T* time points into cycles, each of length *l*. The r^{th} point in each seasonal cycle is the point wherein the seasonality spikes appear, with all other time points generated as a white noise. For the trend, temporal effect can be visualized by a ladder going up. The total number of time points *T* is divided into steps of length *l*. The first cluster step is generated from a white noise. The next cluster is obtained by adding a constant to the mean of the previous cluster along with noise. The form of the structural change is also an autoregressive series of order 1.

$$\left(1 - 0.75B\right)\left(x_t - 25\right) = a_t \text{ where } a_t \sim N(0,1). \tag{17}$$

Combinations of these localized temporal effects are also investigated. In summary, we considered the following scenarios:

Table 1. Different Scenarios for the Output Series

Scenario	Description and Rationale	Notation and number of levels	Level values	Level Descriptions
Time points	Robustness of model across time	*t*: 4 levels	*t=30*	Very small
			t=60	Small
			t=180	Medium
			t=360	Large
Input series stationarity	Nonstationarity and nonlinearity of the series	$x_{t:}$ 2 levels	x_t: stationary time series	Stationary
			x_t: nonstationary time series	Nonstationary
Transfer Function	Models dependency of the output with the input series	$\frac{\sum_{i=0}^{s}\omega_i B^i}{(1-\sum_{j=1}^{r}\omega_j B^j)} x_{t-1}$: 2 levels	*(r,s,b)=(0,2,1)*	Finite lags
			(r,s,b)=(1,2,1)	Exponentially decaying lags
Adding a correlated 2nd input variable	Tests the postulated model for multiple correlated input series	x_1+x_2: 2 levels	$x_2 = 0$ *(single input)*	
			x_2 *moderately correlated with* x_1	
Localized Temporal Effect	Cluster effects not present in input series	L_t: 7 scenarios	L_t: Seasonality	Annual seasonality
			L_t: Step function deterministic trend	Annual ladder increase in output series
			L_t: Structural change – end	10% structurally different from input series at the end
			L_t: Seasonality and Step Function	
			L_t: Seasonality and structural change	
			L_t: Step function and structural change	
			L_t: Seasonality, step function and structural change	

6. Results and Discussions

The predictive ability of the model is evaluated using the mean absolute prediction erros (MAPE). MAPE per scenario are computed for both the transfer function (parametric) and the proposed semiparametric version of the transfer function.

From Table 2, the average MAPE of the postulated model for very short time series is lower than that of the parametric model. Table 3 gives the average MAPE for both the parametric and the semiparametric model for the different forms of the input series across time points. Except for the average MAPE for scenarios with two moderately correlated inputs series, all the average MAPE in the postulated procedure are lower when there are 36 time points. That is, simulation results show that whereas the parametric procedure performs poorly for series with short time series, the semiparametric procedure is robust for short time series. As the length of time series increases, the parametric procedure gives better estimates while the postulated procedure yield comparable estimates as well.

Table 4 presents the MAPE per localized temporal effect across different time points. Except for the presence of a trend, the postulated model has consistently produced lower MAPE than the parametric procedure. Again, as the length of the time series increases, the performance of the parametric procedure improves. For output series with structural change, the postulated model yield lower MAPE across all time series lengths. There are also a number of scenarios with seasonality wherein the postulated model produced lower MAPE than its parametric countepart.

Furthermore, even though the MAPE are smaller for the parametric transfer function procedure for long time series, the difference between their MAPE are not considerably large. That is, the postulated model still produces comparable estimates and is robust across the different lengths of time series.

For short time series, the postulated model yield lower MAPEs for 31 of 56 scenarios. The postulated model has consistently perfomed well in estimating the second form of the transfer function model. Majority of the time series with seasonality were modeled better by the semiparametric procedure.

When there are 60 time points, the postulated model produced better estimates than the parametric procedure for majority of the scenarios with an exponentially decaying transfer function. Note also that 24 of the 56 scenarios with 60 time points are modeled better by the semiparametric procedure.

Even though the semiparametric model produced better estimates only for 16 out of 56 scenarios for time series data with 180 data points, it has consistently produced better estimates for data with seasonality or structural change.

For longer time serie, the semiparametric procedue produced lower MAPE's only in 13 out of 56 scenarios, 12 of which are for scenarios where seasonality, structual change or both are present.

It is also worthy to note the limitations of the parametric transfer function model. First, in all cases of localized temporal effects, the crosscorrelation function can only identify correctly the delay lag of the input series less than 50% of the time. Except possibly for the presence of seasonality, when localized temporal effects are present in the output series, the cross correlation function fails to specify a correct form of the transfer function. And even if a delay parameter is consistently specified, the specification is incorrect.

The postulated model, being a nonparametric one mitigates the tedious process of identifying the model form, and therefore avoiding the problem of misspecification.

Convergence in estimation is also an issue for the parametric method. For data sets with a finite lag form of transfer function, estimation in 99.80% of the datasets converged. However, for an exponentially decaying form of the transfer function, the estimation procedure converged only in 75.75% of the datasets.

For the semiparametric transfer function procedure, even though it invokes two highly iterative procedures, the backfitting algorithm for the estimation of the additive model and the mixed modeling procedure, none of the datasets come out with nonconconvergent estimation procedure.

Table 2. Mean Absolute Percentage Errors across Time Points

Method	36 Time Points	60 Time Points	180 Time Points	360 Time Points
ARIMA	9.82992	16.65544	8.88494	10.16917
GAM-Mixed	9.19555	17.17574	10.23115	13.78936
Difference	0.63437	-0.52030	-1.34621	-3.62019

Table 3. Mean Absolute Percentage Errors of the Models
for the Different Scenarios across Time Points

	36 Time Points		60 Time Points			180 Time Points		360 Time Points	
Method	Stationary	Nonstationary	Stationary	Nonstationary	Method	Stationary	Nonstationary	Stationary	Nonstationary
ARIMA	6.87535	14.16584	6.79417	32.62984	ARIMA	5.82068	14.34268	5.53185	17.80004
GAM-Mixed	6.45370	13.67491	6.87414	34.33247	GAM-Mixed	6.62885	16.11554	6.19186	26.05563
Difference	0.42165	0.49094	-0.07997	-1.70263	Difference	-0.80817	-1.77286	-0.66001	-8.25559
Method	Finite Lags	Exponentially Decaying Lags	Finite Lags	Exponentially Decaying Lags	Method	Finite Lags	Exponentially Decaying Lags	Finite Lags	Exponentially Decaying Lags
ARIMA	11.77300	7.88684	26.12344	7.18744	ARIMA	12.32316	5.92116	14.87507	5.46326
GAM-Mixed	11.41788	6.97322	27.57637	6.77511	GAM-Mixed	13.66234	6.79995	20.73880	6.83991
Difference	0.35512	0.91361	-1.45293	0.41233	Difference	-1.33919	-0.87879	-5.86373	-1.37665
Method	One Input	2 Correlated Inputs	One Input	2 Correlated Inputs	Method	One Input	2 Correlated Inputs	One Input	2 Correlated Inputs
ARIMA	9.76484	9.89500	23.17117	10.13971	ARIMA	8.35110	9.89322	11.55198	8.78635
GAM-Mixed	8.37146	10.01965	23.52504	10.82644	GAM-Mixed	9.07457	11.38772	15.27443	12.30428
Difference	1.39339	-0.12465	-0.35388	-0.68673	Difference	-0.72348	-1.49450	-3.72245	-3.51793

Table 4. Mean Absolute Percentage Errors of the Models
for the Different Localized Temporal Effects across Time Points

	Seasonality	Ladder Trend	Structural Change	Season + Ladder	Season + SC	Ladder + SC	All
36 Time Points							
ARIMA	10.78124	9.37489	11.93047	11.19944	10.00243	7.32241	8.19856
GAM-Mixed	10.53586	10.34550	8.12783	10.15862	8.35691	8.37720	8.46695
Difference	0.24538	-0.97061	3.80263	1.04082	1.64551	-1.05478	-0.26839
60 Time Points							
ARIMA	10.24794	9.54316	58.22568	10.60476	12.96061	7.01479	7.99113
GAM-Mixed	11.99423	12.40215	57.38382	11.13905	10.59880	8.45572	8.25642
Difference	-1.74629	-2.85899	0.84186	-0.53429	2.36182	-1.44093	-0.26529
180 Time Points							
ARIMA	17.05131	7.42948	11.71852	8.09481	7.12726	6.00667	6.42706
GAM-Mixed	16.81357	10.39271	8.73840	10.55917	8.43798	8.66955	8.00664
Difference	0.23774	-2.96323	2.98012	-2.46437	-1.31072	-2.66288	-1.57958
360 Time Points							
ARIMA	26.71893	6.20442	9.13981	11.21365	6.74314	5.09813	6.06609
GAM-Mixed	35.72079	9.98540	8.31374	17.72307	8.52897	7.82954	8.42397
Difference	-9.00185	-3.78099	0.82607	-6.50942	-1.78583	-2.73141	-2.35788

7. Conclusions

For time series with localized temporal effects, the parametric transfer function procedure may not be reliable due to the following reasons: first, the parametric procedure requires a rigid dependence structure between the input and output variables. Second, the parametric procedure becomes unstable for datasets with very short time series. Furthermore, the parametric procedure is vulnerable to incorrectly specifying the transfer function form, particularly the order of the delay parameter. Lastly, the estimation procedure for the parametric transfer function model may not converge, especially for short time series data.

The postulated model is robust with respect to the length time series. For short series, the semiparametric model yield better predictive ability than the traditional procedure. As the length of time series becomes increases, the MAPE for the parametric procedure declines but still the semiparametric procedure produced comparable results. Further, the postulated model produced lower MAPE than the parametric model when seasonality or structural change is present in the output time series.

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