Inferential Active Disturbance Rejection Control of a Distillation Column using Dynamic Principal Component Regression Models

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Keywords: Distillation Column, Composition Control, Inferential Control, Active Disturbance Rejection Control, Principal Component Regression, Estimator.

Abstract: This paper presents a multivariable inferential active disturbance rejection control (ADRC) method for product composition control in distillation columns. The proposed control strategy integrates ADRC with inferential feedback control. In order to overcome long time delay of gas chromatography in measuring product compositions, static and dynamic estimators for product compositions have been developed. The top and bottom product compositions are estimated using multiple tray temperatures. In order to overcome the colinearity issue in tray temperatures, principal component regression is used to build the estimator. The proposed technique is applied to a simulated methanol-water separation column. It is shown that the proposed control strategy gives good setpoint tracking and disturbance rejection control performance.

1 INTRODUCTION

Distillation is the most common and important operation for purification and separation in industry. According to Humphrey (1995) the United States has around 40,000 distillation columns in operation that handle more than 90% of purification and separation processes. The capital investment for these distillation systems is estimated to be around 8 billion US dollars. Referring to the data by Mix et al. (1978), Soave and Feliu (2002) state that distillation columns accounts approximately 3% of the total world energy consumption which is equivalent to about 2.87×10^{18} J of energy per year. Unfortunately, this enormous amount of energy is consumed in providing heat to convert liquid to vapour and condense the vapour back to the liquid at the condenser.

With the growing environmental concern and rising energy awareness, there is a need to reduce the energy consumption in manufacturing industries. Reducing the energy consumption of distillation systems can be very effective in product cost reduction because distillation can produce more than 50% of both capital and plant operating costs in a typical chemical plant which can have a significant impact on the overall plant profitability (Kiss and Bildea, 2011). Therefore, extensive studies have been carried out in recent years through the overall system integration and new distillation design with high energy efficiency. A suitable integration of distillation columns with the total process leads to substantial energy savings but the scope for this is usually limited (Linnhoff, 1988). Therefore, synthesis and design of new energy efficient distillation systems and development of advanced distillation control systems are both significant to improve distillation technologies. As a result, advanced and efficient control techniques are required to reduce the energy consumption and to meet the product compositions specifications. Strong loop interactions exist between composition loops that make distillation product composition control a difficult task. Likewise, composition analyzers usually introduce long time delay which affects the achievable control performance.

In order to address these issues in distillation column control, this paper presents an inferential active disturbance rejection control (ADRC) method which integrates ADRC with inferential control. Multiple tray temperatures are used to estimate the top and bottom product compositions. Since tray temperatures are typically highly correlated, multiple linear regressions would in this case not be effective due to ill conditioning of the regression data matrix. In order to overcome the colinearity issue among tray temperatures, principal component regression (PCR) is used to build the estimator

Al Kalbani F. and Zhang J..
Inferential Active Disturbance Rejection Control of a Distillation Column using Dynamic Principal Component Regression Models.
DOI: 10.5220/0005516703580364
In *Proceedings of the 12th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2015), pages 358-364
ISBN: 978-989-758-122-9

models. Both static and dynamic PCR models are developed. In dynamic PCR models, tray temperature measurements at the current and past sampling times are used as model inputs in order to account for dynamic relationship between tray temperatures and product compositions. To the authors' knowledge, the integration of ADRC and dynamic inferential control has not been reported in the literature.

This paper is organised in five sections. Section 2 presents an overview of ADRC and inferential control. Section 3 presents the development of static and dynamic estimator using PCR. The inferential feedback control of distillation compositions based on these software sensors is represented in Section 4. Finally, the last section draws some concluding remarks.

2 OVERVIEW OF ADRC AND INFERENTIAL CONTROL

Disturbances and uncertainties are the main issues in control system synthesis especially in engineering applications. Dealing with disturbances and uncertainties has attracted the attention of engineers and scientists. There have been many control methods suggested for dealing with uncertainties such as adaptive control, robust control, variable structure control, intelligent control, etc. However, due to their dependence and complexity on advanced analytical methodologies, these methods have certain limitations in engineering applications.

PID control is still widely used in process control because of its simplicity and robustness. The main limitations of PID control are the error computation, noise degradation due to the derivative control, oversimplification and the loss of performance in the control law in the form of linear weighted sum and complication associated to the integral control.

2.1 Overview of ADRC

ADRC, derived the essence from PID control and observer, was pioneered over ten years ago by Jingqing Han (Han, 2009). The basic principle of ADRC is that it uses the extended state observer (ESO) to estimate the existing total disturbances, and cancel it or remove it from the system. The main advantage of ADRC is the disturbance rejection (Gao et al, 2011). Fig. 1 shows the structure of ADRC, which consists of three main components: transient profile generator (TPG), non-linear weighted sum (NWS), and ESO.

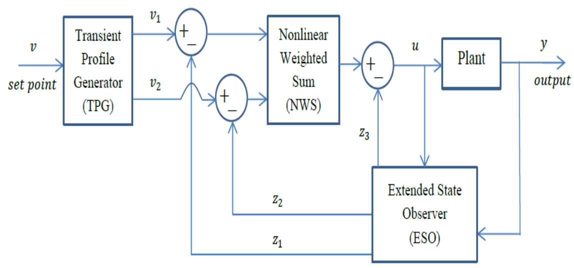

Figure 1: Structure of ADRC.

A. Transient Profile Generator
The control signal with TPG can rapidly track the setpoint signal without overshoot with strong adaptability and robustness (Wang and Miao, 2010). TPG can smooth out sudden changes in setpoints.

B. Non-linear Weighted Sum of Control Errors
Over-simplification of PID control law is the major limitation of the conventional PID controller that consists of present, predictive and accumulative errors. This over-simplification ignores other complex parameters that can make the PID control performance more robust to the error signal. As a result, Han (2009) presented an alternative non-linear function which depends on the magnitude of error signal to produce the control signal.

C. Extended State Observer
The main idea of ESO is to online estimate the variables that are usually inapproachable instrumentation-wise such as internal non-linear dynamics, external disturbance and model errors. Then, the undesired disturbances are then effectively compensated in the control effort. ADRC can successfully drive the controlled output signal to its required value if the ESO has a precise estimation for the internal non-linear dynamics, external disturbances and model error of the plant (Xia et al, 2007).

2.2 Overview of Inferential Control

In the product composition control in distillation columns, it is really challenging to get reliable and accurate product composition measurements without long time delay in the sampling and analysis process. Numerous composition analysers such as gas chromatography regularly introduce significant time delays. The overall time delay in composition measurements normally between 10 to 20 minutes (Mejdell and Skogested, 1991). Such amount of time delay substantially reduces the achievable performance of composition controllers. Moreover, the reliability of the composition analysers is usually quit low and incurs high maintenance cost. Therefore, in distillation composition control, it is a usual practice to indirectly control product compositions by controlling tray temperatures or utilize the secondary tray temperature measurements to estimate and control the product compositions. Compared with composition measurements, temperature measurements are more economic, reliable and virtually without any measurements time delays.

The estimator based inferential feedback control structure for product composition control in a binary distillation column is depicted in Fig. 2. The estimated variable is used instead of the measured variable to overcome the long measurement delay. The manipulated variables for composition control are the reflux rate (L) and steam flow rate to the reboiler (V). A sample of variable X (tray temperature) is taken continuously and sent it to estimator to estimate the output $Y(s)$ (product composition) and generate signal Y_M as a feedback signal. The feedback controller can be any such as a multi-loop controller or a multivariable controller.

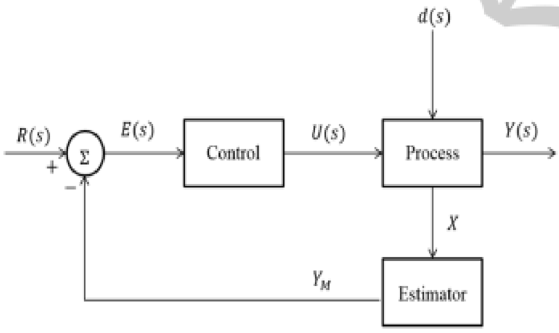

Figure 2: Inferential feedback control.

3 PCR MODEL BASED SOFTWARE SENSORS

The distillation columns presented in this paper is comprehensive non-linear simulation of a methanol-water separation column. A non-linear tray by tray mechanistic model has been developed using mass and energy balances. The following assumptions are made: constant liquid holdup, negligible vapour holdup and perfect mixing in each stage. The nominal operation data for this specific column are given in Table 1.

The nominal operating point considered in this study is the top composition at 93% and the bottom composition at 7%. To generate data for building PCR inferential estimation models, series of random disturbances were added. Fig. 3 shows the top and bottom product compositions in the generated data. Fig. 4 shows the corresponding tray temperature data. It can be realized that correlation exists among tray temperature measurements.

Table 1: Nominal distillation column operation data.

Variables	Nominal values
Top concentration (y_1)	93 % methanol
Bottom concentration (y_2)	7 % methanol
Top product rate (D)	9.13 g/s
Bottom product rate (B)	9.1 g/s
Reflux flow rate (u_1)	10.108 g/s
Steam flow rate (u_2)	13.814 g/s
Feed concentration (d_1)	50.12 %
Feed flow rate (d_2)	18.23 g/s
No. of trays	10

3.1 Static PCR Model

In the static model, the product compositions at time t are estimated from tray temperatures at time t. The model can be defined in the following form:

$$y(t) = \theta_1 T_1(t) + \theta_2 T_2(t) + \cdots + \theta_{10} T_{10}(t) \quad (1)$$

where y represents the product compositions, T_1 to T_{10} denote the tray temperatures from tray 1 to tray 10 respectively, θ_1 to θ_{10} are model parameters corresponding to tray temperatures, and t indicates the discrete time.

The data were scaled to zero mean and unit variance before model building to allow data with different ranges to be used within the same model. Then, the data is divided into training data set (samples 1 to 1189) and the testing data set (samples 1190 to 1982). PCR models with different numbers of principal components were developed on the training data and tested on the testing data.

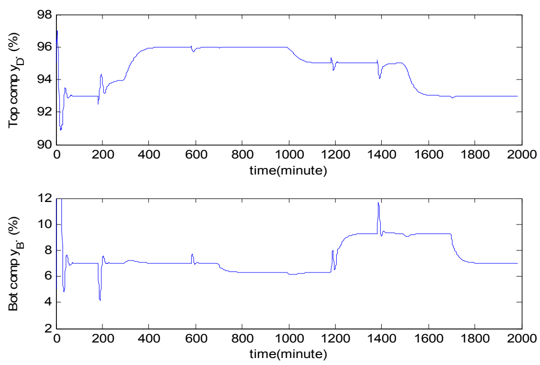

Figure 3: Top and Bottom product compositions.

Fig. 5 represents the sum of squared errors (SSE) of PCR models with different number of principal components on the training and testing data. The number of principal components is determined based on the minimum value of SSE on the testing data. The PCR model with the lowest SSE on the testing data is considered as having the appropriate number of principal components.

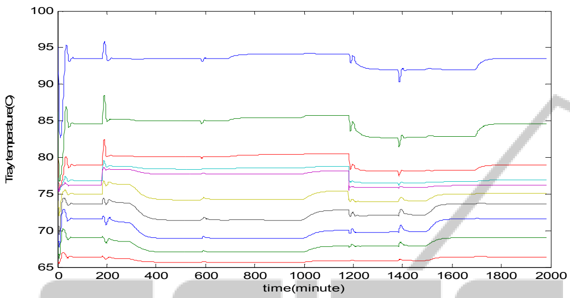

Figure 4: Tray temperatures.

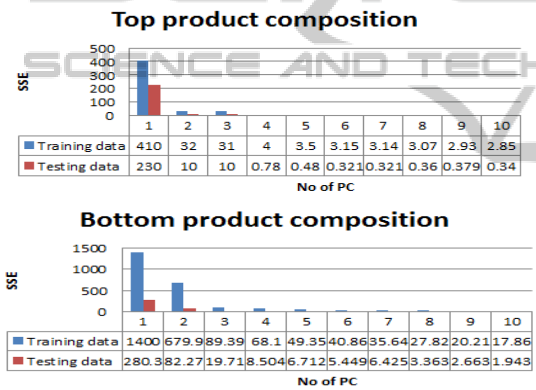

Figure 5: SSE of different PCR models.

It can be seen from Fig. 5 that 6 principal components offers the best performance for the top composition on the testing data and 10 principal components give the best performance for the bottom composition. Hence, the suitable numbers of principal components for the top and bottom compositions were specified as 6 and 10 respectively. The SSE on the testing data is 0.34 for the top composition and 1.943 for the bottom composition.

3.2 Dynamic PCR Model

The accuracy of inferential estimation could be further enhanced and improved if a dynamic PCR module is developed. Seven dynamic models with different orders were developed. As an example, the first order dynamic PCR model is of the following form:

$$y(t) = \theta_{1.1}T_1(t) + \theta_{1.2}T_2(t-1) + \theta_{2.1}T_2(t) + \theta_{2.2}T_2(t-1) \cdots + \theta_{10.1}T_{10}(t) + \theta_{10.2}T_{10}(t-1) \quad (2)$$

Data partition and data scaling are the same as in building the static PCR model. By taking the least SSE, the appropriate numbers of principal components can be determined. Table 2 presents the numbers of principal components and the SSE on the testing data of these dynamic PCR models.

Table 2: Number of principal components and SSE on testing data of different dynamic PCR models.

Model orders		SSE	No. of principal components
1	Top composition	0.662	11
	Bot composition	13.04	11
2	Top composition	0.361	14
	Bot composition	9.958	7
3	Top composition	0.045	32
	Bot composition	2.970	7
4	Top composition	0.140	50
	Bot composition	2.542	7
5	Top composition	0.122	17
	Bot composition	1.323	7
6	Top composition	0.145	42
	Bot composition	4.722	8
7	Top composition	0.141	54
	Bot composition	3.958	8

It can be realized that the dynamic PCR models substantially improve the estimation accuracy over the static PCR especially the third order, fourth order and fifth order models. All these three models has been compared and discussed. The difference between these three models is not significant. Thus the fifth order dynamic PCR model is used. Fig. 6 and Fig. 7 show, respectively, the predictions of the static PCR model and the 5th order dynamic PCR model. In these figures, the solid lines represent the actual measured compositions response while the dashed lines represent the corresponding model estimations predictions. Fig. 8 shows the estimation errors. It can be realized that the 5th order dynamic PCR model gives better performance and more accurate predictions or estimation than the static model.

It can be seen from Table 2 that the dynamic PCR models quite significantly enhance the estimation accuracy over the static PCR model, especially the fourth order and fifth order models. The fifth order dynamic PCR model is given in the appendix.

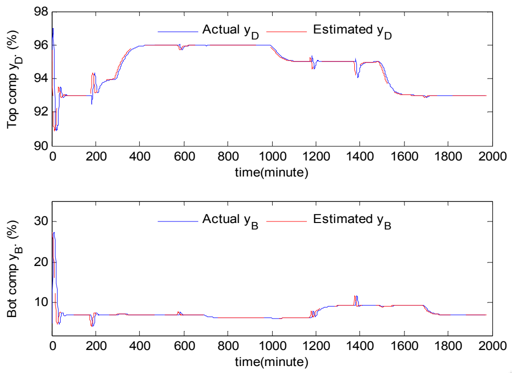

Figure 6: Model predictions of the static PCR model.

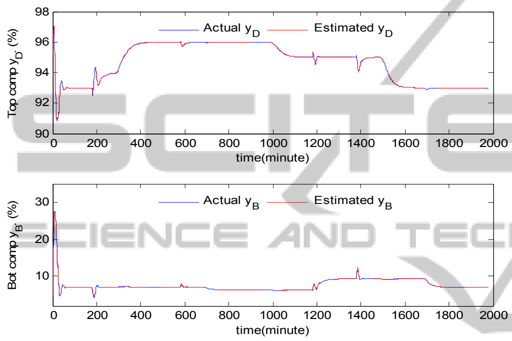

Figure 7: Model predictions the 5th order dynamic PCR model.

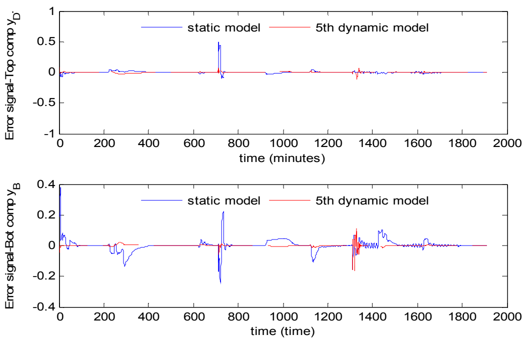

Figure 8: Error signal between the actual and estimated signal.

4 INFERENTIAL ADRC OF DISTILLATION COMPOSITION BASED ON PCR MODELS

The ADRC scheme and inferential control are integrated together to control the top and bottom compositions in the distillation column. The integrated inferential ADRC is shown in Fig. 9.

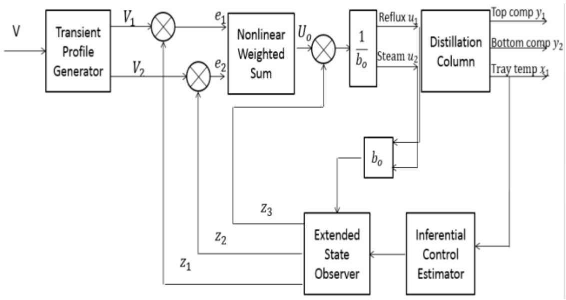

Figure 9: ADRC integrated with the inferential control.

Eight inferential feedback control schemes with eight different software sensors (static and the first to the seventh order dynamic PCR models) were designed and developed.

To investigate the performance of both static and dynamic order models, the following disturbance were added to the simulated distillation column. The feed rate was increased by 15% at the 200th minutes and the 1200th minutes, the feed composition was increased by 15% at the 1400th minutes. Furthermore, series setpoints changes are applied to both top and bottom product compositions. Table 3 shows the SSE (the difference between actual and estimated) of different schemes under the disturbances. It can be seen that the dynamic PCR schemes gives better performance than static PCR model especially the 3rd and 5th order dynamic PCR model based schemes.

Fig. 10 and Fig. 11 demonstrate respectively the responses of static inferential ADRC scheme and dynamic inferential ADRC across a wide range of setpoint changes, feed composition and feed flow rate disturbances. The setpoint signal was smoothed by TPG. It can be seen that both compositions are well controlled and dynamic inferential ADRC gives better performance than the static inferential ADRC despite of large static control errors exist for the bottom product composition. This static control error generated due to the PCR model errors, which can be large when operating condition changes such as setpoint changes and/or disturbance changes.

Table 3: SSE of different control schemes.

Control schemes	SSE in Top comp	SSE in Bottom comp
Static PCR module	1.6889	1.8309
1st order dynamic PCR model	0.2152	4.7203
2nd order dynamic PCR model	0.8406	11.0903
3rd order dynamic PCR model	0.2118	0.7080
4th order dynamic PCR model	2.6854	1.5137
5th order dynamic PCR model	0.1856	0.1551
6th order dynamic PCR model	1.2277	1.3307
7th order dynamic PCR model	0.4868	0.2600

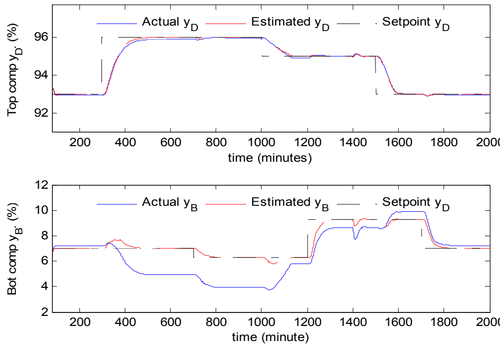

Figure 10: Responses of actual and estimated product compositions of static inferential ADRC (without mean updating).

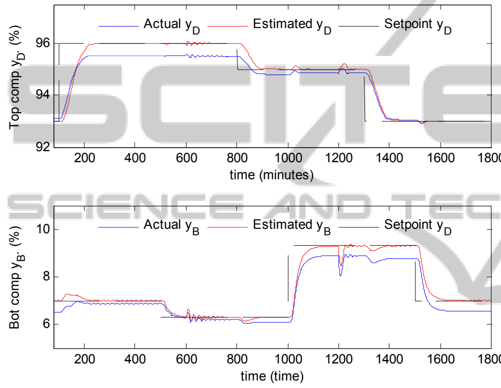

Figure 11: Responses of actual and estimated product compositions of 5th dynamic inferential ADRC (without mean updating).

To overcome the static control off-sets issues due to the continuous changes in process operating conditions, mean updating strategy proposed by Zhang (2006) is implemented here to eliminate control off-set and static estimation. The main idea of mean updating strategy is that when a new steady state is detected, the process variable means are updated. Hence model predictions will be updated. It should be noted here that only occasional product composition measurements are required. Fig. 12 and Fig. 13 indicate the control performance with mean updating technique. It can be shown from these figures that, by using the mean updating technique, the static control offsets are eliminated.

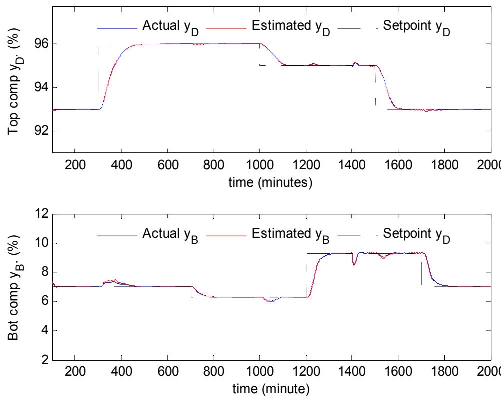

Figure 12: Responses of actual and estimated product compositions of static inferential ADRC (with mean updating).

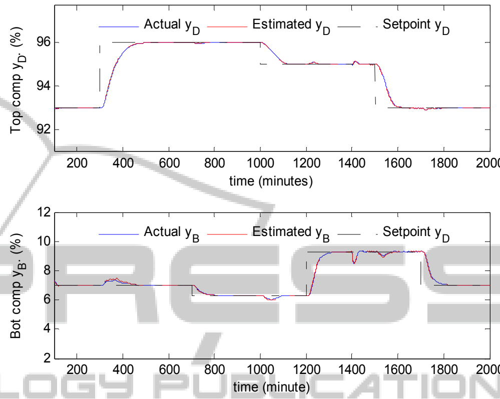

Figure 13: Responses of actual and estimated product compositions of 5th dynamic inferential ADRC (with mean updating).

Table 4: SSE of different control schemes.

Control schemes		Top Comp	Bottom Comp
Static PCR model	Without mean updating	54542	6946.9
	With mean updating	1.6889	1.8309
5th order dynamic PCR model	Without mean updating	165.52	219.59
	With mean updating	0.1856	0.1551

It can be seen from above figures that the resulting control off-sets and steady state model estimation bias have been eliminated through the mean updating technique. Moreover, it can be noticed from Table 4 that the dynamic PCR model has much smaller estimation off-sets than the static PCR model when the operating condition changed. This leads to a result that the dynamic PCR model is more robust than the static PCR model to process operating condition variations.

5 CONCLUSIONS

Static and dynamic inferential ADRC control schemes are proposed for product composition control in distillation columns. Inferential estimation models for product compositions are developed from process operational data using PCR. The estimated product compositions are used as the controlled variables in the ADRC controller. Mean updating technique is used to eliminate the steady state model estimation bias and the resulting control off-sets. The proposed control method is applied to a simulated methanol-water separation column. Simulation results indicate the effectiveness and success of the proposed dynamic inferential ADRC control method over the static inferential ADRC control method.

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APPENDIX

Model parameters of the 5th order dynamic model

Table 5: Top composition parameters.

	t	t-1	t-2	t-3	t-4	t-5
T_1	-0.037	0.006	0.077	0.0914	0.0385	-0.151
T_2	0.0121	-0.039	-0.030	-0.061	0.031	-0.001
T_3	0.115	0.059	0.031	-0.021	-0.002	-0.030
T_4	0.0513	0.014	-0.003	-0.035	-0.009	-0.020
T_5	0.0464	-0.022	-0.021	-0.044	-0.052	-0.016
T_6	-0.083	-0.045	0.056	0.068	0.065	0.016
T_7	-0.138	-0.069	0.020	0.044	0.071	0.055
T_8	-0.171	-0.110	-0.042	-0.023	0.004	0.007
T_9	-0.175	-0.103	-0.015	0.013	0.068	0.100
T_{10}	-0.219	-0.146	-0.088	-0.071	-0.047	-0.017

Table 6: Bottom composition parameters.

	t	t-1	t-2	t-3	t-4	t-5
T_1	-0.569	-0.453	-0.307	-0.140	0.032	0.191
T_2	-0.122	-0.084	-0.037	0.0419	0.154	0.261
T_3	0.0559	0.052	0.0471	0.0596	0.0997	0.142
T_4	0.0191	-0.004	-0.041	-0.076	-0.093	-0.097
T_5	0.083	0.059	0.020	-0.033	-0.084	-0.122
T_6	0.113	0.065	0.016	-0.028	-0.005	-0.062
T_7	0.002	-0.027	-0.047	-0.053	-0.041	-0.015
T_8	0.032	0.014	0.004	0.007	0.026	0.055
T_9	-0.008	-0.033	-0.048	-0.048	-0.027	0.0079
T_{10}	0.017	0.001	-0.004	0.0026	0.028	0.0669