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Robust Control with Disturbance Estimation Using Echo State Networks for the Twin Rotor Aero-Dynamical System Application ⋆

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Abstract: This paper deals with the application of Echo State Network (ESN) model to robust control of the Twin Rotor Aero-Dynamical System (TRAS) through estimation and cancellation of disturbances. The work describes the modelling process of the plant and control scenarios in which the system is under influence of the unknown disturbances. In such control scenarios the ESN model is used to estimate the disturbances and calculate the input correction in such way to improve the control quality. All data used in experiments are collected from the TRAS through the Matlab/Simulink environment.

Keywords: Echo State Network, Neural Network, Disturbance Estimation, Twin Rotor Aero-Dynamical Control, Robustness

1. INTRODUCTION

Nowadays, it is observed a very rapid and significant development of the automation industry. The increasing requirements for high levels of system performance and reliability in the presence of unexpected changes of system environment cause that the robust control system has received the increasing attention in the last years (e.g. Wang et al. (2013); Yetendje et al. (2012)). Typically the plant runs outside the laboratory environment and can be the subject of the different unknown disturbances. Such situations cannot be predicted but have to be considered during the control system design. To guarantee the needed performance a wide range of disturbances need to be taken into account. Also it is very important to keep simple the methodology of dealing in such cases, especially when handling with the very dynamic systems like servomotors or aero-dynamical systems. Because of the very fast response from that kind of system the methods need to be very efficient and no computational burdening during the work. The very promising solution of such formulated problem are the Artificial Neural Networks (ANN). ANN are well known from its generalizing abilities which are crucial in case of considering a wide range of disturbances. The calculation of the output of the neural network model is also practically instant and requirement of memory resources currently is also non-significant even in case of large structures thanks to much more capable automation equipment than in the past. Only the training of the ANN cannot be carried out in real time but in most situation off-line training is sufficient. Thanks to that properties the ANN are very often used with success in recent researches in the area of automation like fault diagnosis or fault tolerant control (Luzar et al. (2012); Sobhani-Tehrani et al. (2014); Czajkowski et al. (2012); Nørgaard et al. (2000); Noura et al. (2009); Pedro et al. (2013)).

The paper is organized as follows. The general description of the Echo State Network and observer version of the network is described in Section 2. Section 3 presents a robust control strategy and the proposed algorithm of noise estimation and calculation of the control correction. Section 4 describes laboratory installation used in experiments, while experimental results of modelling and control scenarios are included in Section 5.

2. ECHO STATE NETWORK

The Echo State Network are relatively new approach idea to architecture and supervised learning principle of the recurrent neural networks (RNNs). The idea of creating a random and large but fixed recurrent neural network and combining the nonlinear responses of the reservoir (sparsely connected neurons inside the hidden layer of the RNN) through trainable, linear combination for the desired output was presented by Jaeger (2001).
The discrete-time Echo State Network with N reservoir units, K inputs and L outputs is governed by the following state update equation:

$$\begin{aligned}\bar{\mathbf{x}}(n+1) &= f(\mathbf{W}\bar{\mathbf{x}}(n) + \mathbf{W}^{in}\mathbf{u}_c(n) + \mathbf{W}^{fb}\bar{\mathbf{y}}(n)) \\ \bar{\mathbf{y}}(n) &= g(\mathbf{W}^{out}\bar{\mathbf{z}}(n)) \ ,\end{aligned} \tag{1}$$

where $\bar{\mathbf{x}}(n)$ is the N-dimensional reservoir state, f is a sigmoid function (usually the logistic sigmoid or the tanh function), $\mathbf{W}$ is the $N \times N$ reservoir weight matrix, $\mathbf{W}^{in}$ is the $N \times K$ input weight matrix, $\mathbf{W}^{fb}$ is the $N \times L$ output feedback matrix, $\bar{\mathbf{y}}(n)$ is L-dimensional model output

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signal, g is an output activation function typically identity or sigmoid, $\bar{\mathbf{z}}(n) = [\bar{\mathbf{x}}(n); \mathbf{u}_c(n)]$ is the extended system state vector and it is a concatenation of the reservoir and input states.
What is very important especially in the control theory is the possibility to feedback the real output of the system during the work of the plant to obtain system observer. In situation when the system states cannot be measured, those states can be approximated with with ESN in such very easy manner. The equation describing such nonlinear observer are formulated as follows:

$$\begin{aligned}\hat{\mathbf{x}}(n+1) =& f(\mathbf{W}\hat{\mathbf{x}}(n) + \mathbf{W}^{in}\mathbf{u}_c(n) + \mathbf{W}^{fb}\mathbf{y}(n)) \\ \hat{\mathbf{y}}(n) =& g(\mathbf{W}^{out}\hat{\mathbf{z}}(n)) \ ,\end{aligned} \tag{2}$$

where $\mathbf{y}(n))$ is the past measured system output.
To design a proper model using Echo State Networks, the most important task is to tune the global parameters in such way to match the dynamics of the modelled system. Typically the following parameters need to be adjusted to minimize the error between output of the model and modelled system:

- The spectral radius of the reservoir weight matrix.
- The input scaling.
- The output feedback scaling.
- The connectivity of the reservoir weight matrix.
- The reservoir size N.

All these kinds of parameters have to be optimized jointly. The current standard practice to do this is through manual experimentation. The ESN also allows for a very fast and efficient way of designing RNNs-based models. The ESN can be called a very convenient framework for using RNNs in a practical engineering applications (e.g. Plöger et al. (2004); Sheng et al. (2012)).

3. ROBUST CONTROL – DISTURBANCES ESTIMATION

The main idea behind this approach to robust control is very simple and is possible with the use of the representation of the output of the Echo State Model. Typically the disturbances are presented with the use of the output equation as follows:

$$\mathbf{y}(n) = \mathbf{C}\mathbf{x}(n) + \boldsymbol{v}(n) \ , \tag{3}$$

But disturbances can be also understood as the additional unknown input of the system. It is obvious that such disturbance input cannot be manipulated. In such approach the control signal can be defined as the sum of the controller input and unknown disturbance input which influence the work of the system:

$$\mathbf{u}(n) = \mathbf{u}_c(n) + \mathbf{u}_d(n) \tag{4}$$

Now, let the nonlinear discrete system be described as:

$$\begin{aligned}\mathbf{x}(n+1) =& f(\mathbf{x}(n), \mathbf{u}(n)) \\ \mathbf{y}(n) =& \mathbf{C}\mathbf{x}(n) \ ,\end{aligned} \tag{5}$$

In case when disturbances are not taken into consideration (i.e. during the plant modelling) the model state should be very close to system state (not equal due to modelling uncertainty) and can be used as estimate of such unknown system state:

$$\mathbf{x}(n) \approx \bar{\mathbf{x}}(n) \tag{6}$$

Such estimation can be done with the ESN model (1).
In case of the disturbances taken into account the system state can be estimated with the system observer. Using (4) the ESN observer output equation (2) can be reformulated as follows:

$$\hat{\mathbf{y}}(n) = g(\mathbf{W}^{out}[\hat{\mathbf{x}}(n); \mathbf{u}_c(n) + \mathbf{u}_d(n)] \ , \tag{7}$$

because the g is the identity function and in this case is only used for the implementation purpose it can be neglected. The matrix $\mathbf{W}^{out}$ can be divide into two matrices for separate handling of the state and input values:

$$\mathbf{W}^{out} = \begin{bmatrix} \mathbf{W}^{xout} & 0 \\ 0 & \mathbf{W}^{uout} \end{bmatrix} \tag{8}$$

so finally the observer output can be presented as follows:

$$\hat{\mathbf{y}}(n) = \mathbf{W}^{xout}\hat{\mathbf{x}}(n) + \mathbf{W}^{uout}(\mathbf{u}_c(n) + \mathbf{u}_d(n)) \tag{9}$$

using equivalence rule it can be presented with the use of the measured system output:

$$\mathbf{y}(n) = \mathbf{W}^{xout}\hat{\mathbf{x}}(n) + \mathbf{W}^{uout}(\mathbf{u}_c(n) + \mathbf{u}_d(n)) \tag{10}$$

and now it can be very easy used to estimate the unknown disturbance input:

$$\hat{\mathbf{u}}_d(n) = (\mathbf{W}^{uout})^{-}(\mathbf{y}(n) - \mathbf{W}^{xout}\hat{\mathbf{x}}(n)) - \mathbf{u}_c(n) \tag{11}$$

where $(\mathbf{W}^{uout})^{-}$ is the pseudo inverse of the matrix $\mathbf{W}^{uout}$ in the Moore-Penrose sense. The existence of such inversion need to to be assured during the modelling process. Finally, substituting the estimated input disturbances from controller input signal should compensate the unknown disturbances in the process:

$$\mathbf{u}(n) = \mathbf{u}_c(n) + \mathbf{u}_d(n) - \hat{\mathbf{u}}_d(n) \tag{12}$$

and in the effect the control robust to unknown input disturbances should be achieved. The scheme of the proposed control strategy is presented in Fig. 1. In the scheme the reference signal is noted as $\boldsymbol{y}_r(k)$.

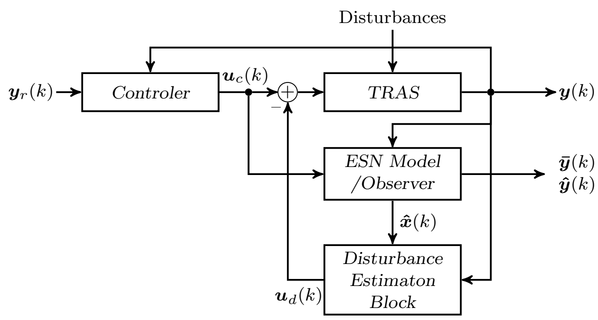

Fig. 1. The scheme of the proposed control approach

4. TWO ROTOR AERO-DYNAMICAL SYSTEM

The Two Rotor Aero-dynamical System (TRAS) is a laboratory set-up designed for control experiments. In certain aspects its behaviour resembles that of a helicopter. From the control point of view it exemplifies a high order nonlinear system with significant cross-couplings. The system is controlled from a PC. Therefore it is delivered with hardware and software which can be easily mounted and installed in a laboratory. The laboratory setup consists of the mechanical unit with power supply and interface to a PC and the dedicated RTDAC/USB2 I/O board configured in the Xilinx technology. The software operates in real time under MS Windows XP/7 32-bit using MATLAB R2009/10,11, Simulink and RTW toolboxes. Real-time is supported by the RT-CON toolbox from INTECO. Control experiments are programmed and executed in real-time in the MATLAB/Simulink environment. The real-life installation is presented in Fig.2, and the scheme of the system is presented on Fig.3.

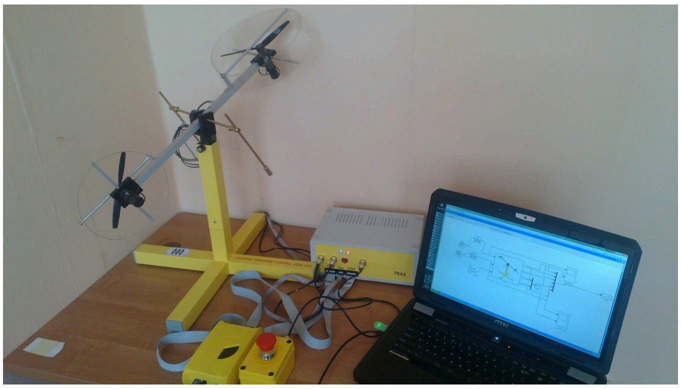

Fig. 2. Two Rotor Aero-dynamical System - laboratory setup.

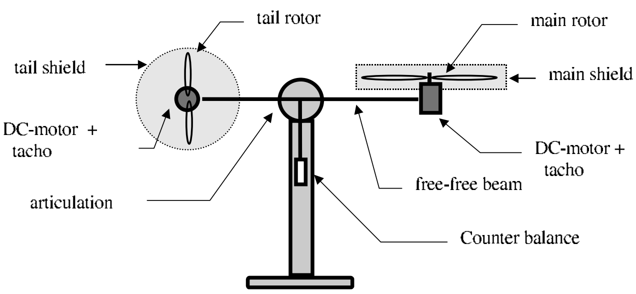

Fig. 3. Two Rotor Aero-dynamical System - parts scheme.

According to the TRAS instruction manual the equations describing the motion of the system can be written as follows:

$$\begin{aligned}\frac{d\Omega_v}{dt} =& \frac{l_m F_v(\omega_m) - \Omega_v k_v + U_h k_{hv} - a_1 \Omega_v abs(\omega_v)}{J_v} \dots \\ &+ \frac{g((A-B)cos\alpha_v - Csin\alpha_v)}{J_v} \dots \\ &- \frac{\frac{1}{2}\Omega_h^2 (A+B+C) sin2\alpha_v U_h k_{hv}}{J_v}\end{aligned} \tag{13}$$

$$\frac{d\alpha_v}{dt} = \Omega_v \tag{14}$$

$$\begin{aligned}\frac{dK_h}{dt} = \frac{M_h}{J_h} =& \frac{l_t F_h(\omega_t) cos\alpha_v - \Omega_h k_h + U_v k_{vh}}{Dsin^2\alpha_v + Ecos^2\alpha_v + F} \dots \\ &- \frac{a_2 \Omega_h abs(\omega_h)}{Dsin^2\alpha_v + Ecos^2\alpha_v + F}\end{aligned} \tag{15}$$

$$\frac{d\alpha_h}{dt} = \Omega_h, \quad \Omega_h = \frac{K_h}{J_h(\alpha_v)}, \tag{16}$$

and two equations describing the motion of rotors:

$$I_h \frac{d\omega_h}{dt} = U_h - H_h^{-1}(\omega_h) \tag{17}$$

and

$$I_v \frac{d\omega_v}{dt} = U_v - H_v^{-1}(\omega_v) \tag{18}$$

where:
Ω_v - angular velocity (pitch velocity) of TRAS beam [rad/s];
Ω_h - angular velocity (azimuth velocity) of TRAS beam [rad/s];
ω_v - rotational speed of main rotor [rad/s];
ω_h - rotational speed of tail rotor [rad/s]
K_h - horizontal angular momentum [N m s];
M_h - horizontal turning torque [Nm];
I_h - moment of inertia of the main rotor.
I_v - moment of inertia of the tail rotor
The descriptions of the other symbols can be found in INTECO (2012).

5. EXPERIMENTS

5.1 Modelling

To apply a model of the system to any control task, the modelling phase of research is a very crucial one. Incorrect model can lead to many problems, including weak performance or lack of the system stability. To build a proper model, the training data describing the process under normal operating conditions is required. The input signal should be as much informative as possible. In this paper the model is trained with the training data which was obtain during the spectral analysis of the TRAS (described in detail in Czajkowski and Patan (2013a)). In this work the system is under an input signal in the form of the chirp signal and given responses are analysed with Discrete Fourier Transform to obtain frequencies for which the system is most responsive. Such approach to system modelling was with success applied to the Model Predictive Control of the TRAS in previous work of the author (Czajkowski and Patan (2013b)). Using those frequencies the training data in the form of a 3 seconds long, random steps were chosen. The data collected was 1000 seconds long. The sampling of 0.01s gave 100000 samples of data. Such high sampling is not needed so the data was resampled to 0.05s which gave 20000 samples. The collected data then was divided into 4000 samples of training data and 16000 samples of validating data.
With correct training data it is possible to carry out the design of the model. The type of the ESN used in this paper to create model is the so-called Leaky ESN (Jaeger et al. (2007)). In case of such ESN the task can be described as adjusting the global network parameters described in Section 2. In many cases the adjusting process is carried out manually which often is a slow and ungrateful process. In this paper the approach based on the Genetic Algorithm is proposed to automate that process. The main task in such case is to define the cost function and optimisation variables. The cost function in this paper it was decide as the Mean Squared Errors (MSE).
Obtained set of the variables gave the performance of 0.017 for training data and 0.032 for testing data. The values of global parameters were as follows:

- The spectral radius = 0.5612.
- The input scaling = 0.3298.

- The output feedback scaling = 0.0306.
- The reservoir size $N = 87$.

Results of the training are presented in following figures. The response of the system for the training is presented in Fig. 4 and squared error in Fig. 5. Next, are presented results obtained with validating data: the response of the system in Fig. 6 and squared error in Fig. 7.

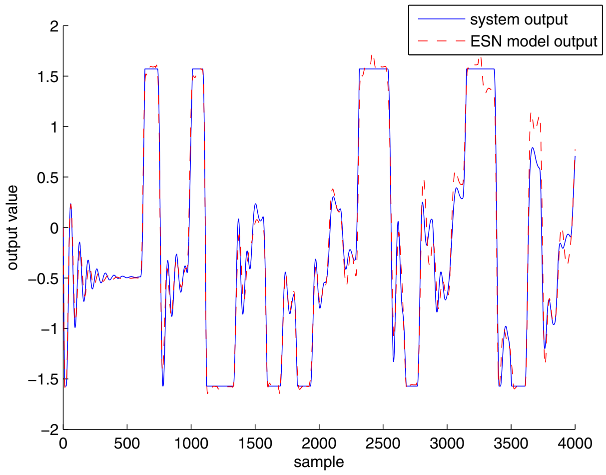

Fig. 4. Modelling results training set: process (blue line), model (red line).

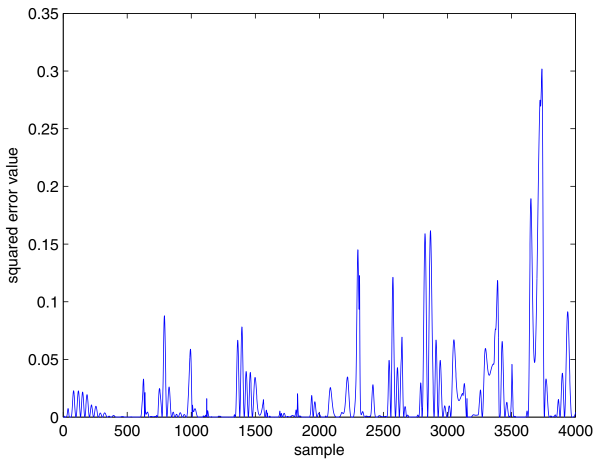

Fig. 5. Modelling results training set: squared errors

5.2 Disturbance Estimation

The main part of the experiments concerned the application control based on methodology described in Section 3. To simplify the experiments the PID controller was used. Two scenarios were carried out. In both the control task was to keep the fixed level of the pitch angle. During the experiments the tail rotor was not used and the azimuth movement was blocked (the only task by the tail rotor is to compensate the azimuth movement, using cross-coupled controller will be the subject of the future researches). In first scenario the disturbances in the form of the random steps were introduced. The range of

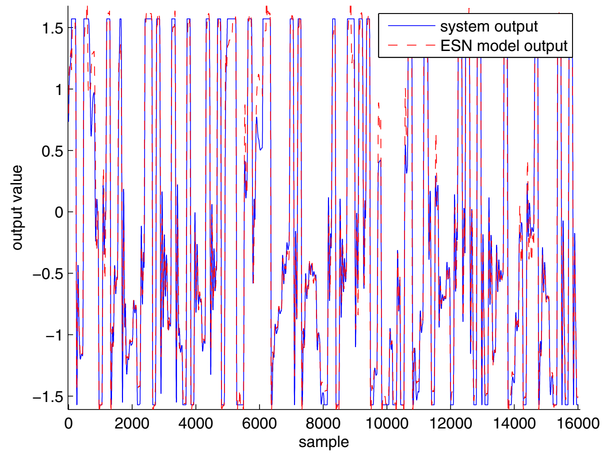

Fig. 6. Modelling results testing set: process (blue line), model (red line).

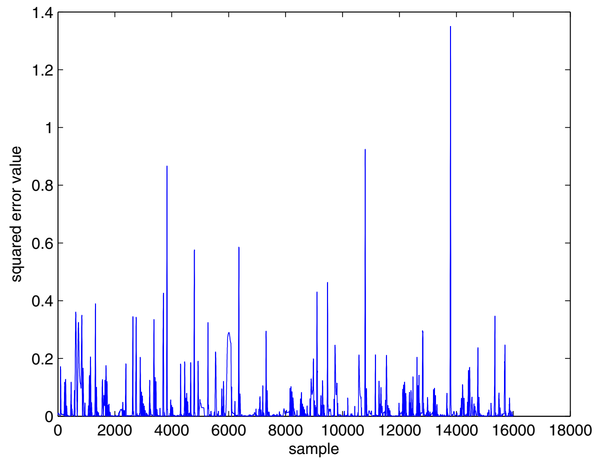

Fig. 7. Modelling results testing set: squared errors

disturbances was assumed as 10% of nominal input signal. The step changing time was fixed at 1 second. The control performance results are presented in Fig. 8. As it is seen the proposed control is much more efficient in such case in comparison to typical application in industry. In Fig. 9 estimation of the disturbances is presented and as it can be observed the estimation is very close to the original unknown disturbances. The control error is presented in Fig. 10

In second scenario the disturbances in form of the three summed up sinusoid were introduced. In this situation also the results are very satisfactory and proposed approach improved the control performance. Similarly the results are presented in Figs. 11-13.

6. CONCLUSION

This work is the first research carried out with the Echo State Network. As it was shown this specific RNNs framework can be used very easily and successfully in application of control system. The great modelling properties of RNNs are well known and thanks to ESN can be applied very easily. Also the Genetic Algorithm can be very important

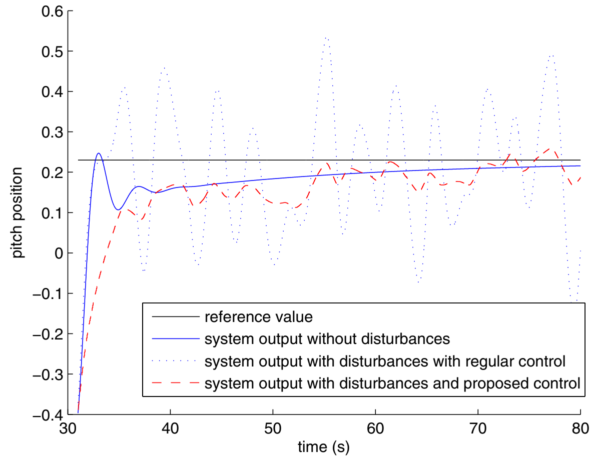

Fig. 8. Comparison of the control performance in the test scenario 1.

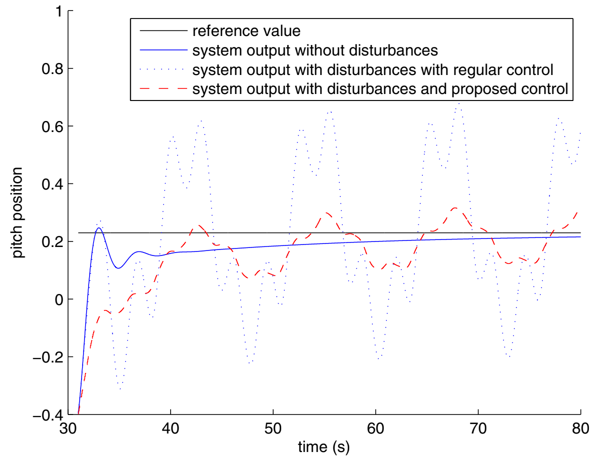

Fig. 11. Comparison of the control performance in the test scenario 2.

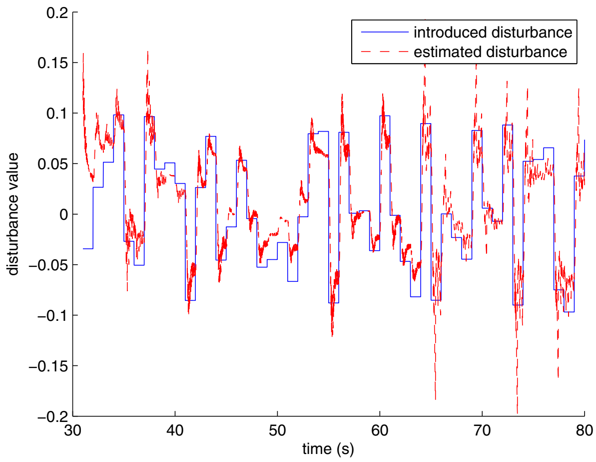

Fig. 9. Estimation of the disturbances affecting the system work in the test scenario 1.

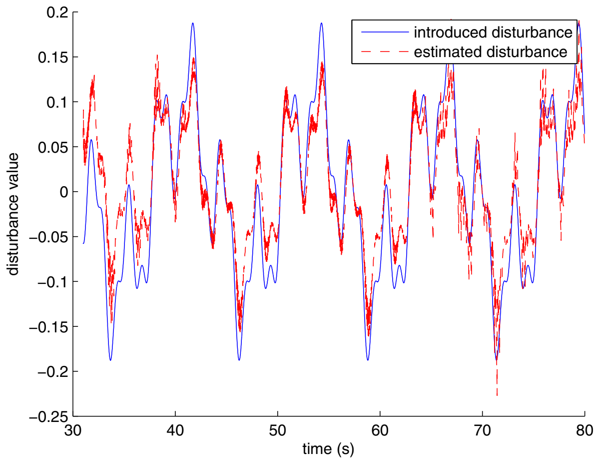

Fig. 12. Estimation of the disturbances affecting the system work in the test scenario 2.

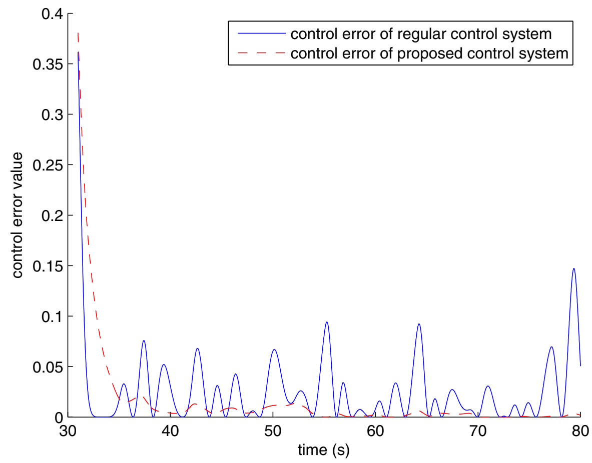

Fig. 10. Comparison of the control error in the test scenario 1: proposed control strategy - red line, regular control strategy - blue line.

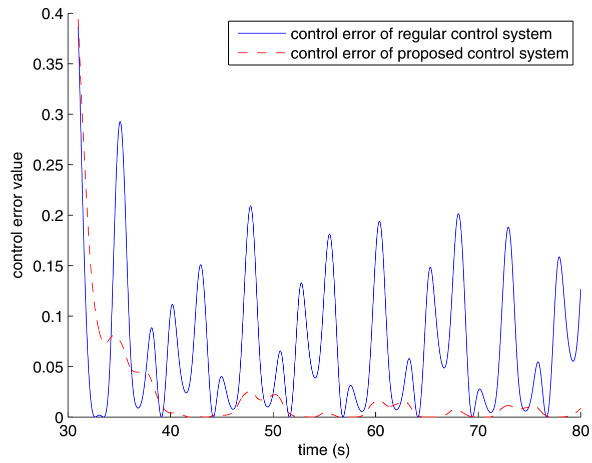

Fig. 13. Comparison of the control error in the test scenario 2: proposed control strategy - red line, regular control strategy - blue line.

tool in case of obtaining the ESN global parameters. The proposed control strategy seems very promising and need to be tested outside the laboratory. Our future work will be focused on using such approach in case of both rotors of the TRAS and substituting the regular PID controller to MPC and adapt such control system in a way to achieve fault tolerance and to try simulate more realistic control situation.

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