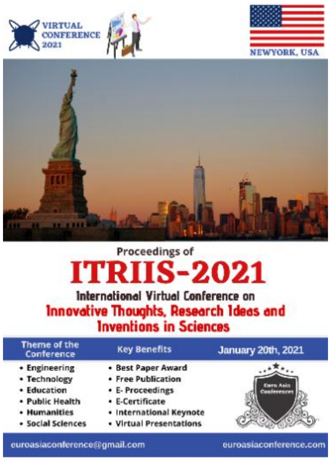

EXAMINATION OF NONLINEAR SYSTEM IDENTIFICATION PARAMETERS OF MODEL SMOKESTACK USING HAMMERSTEIN–WIENER MODEL

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Abstract

System identification is simply the estimation of the mathematical model of the building from the input and output vibration data obtained through the structures. Thanks to the predicted mathematical model, the reactions of the building to dynamic effects can be predicted. The use of system identification method in civil engineering area has been increasing and developing in recent years. The reason for this is undoubtedly the high success rate of the system identification method in estimating the mathematical model. It allows civil engineers to make safer designs with the correct estimation of the mathematical model. The aim of this study is to reveal the mathematical model of the model smokestack with the system identification method. There are linear and nonlinear approaches in system identification method. In this study, the method of system identification with nonlinear approach was used. The mathematical models employed in identification are used to the equations of motion, and a nonlinear system identification of model smokestack using Hammerstein–Wiener Model. The most important point in the results obtained from the analysis is the accuracy rate of the mathematical model. Finally, nonlinear system identification of the model smokestack results demonstrated that fit to estimation data was nearly 100 % and it can be concluded that Hammerstein–Wiener system identification method is efficient and accurate in identifying mathematical model of the model smokestack.

Introduction

Natural gas-fired heaters significantly reduce deposits due to natural gas burning and work much cleaner and more efficient than conventional solid fuels. In most cases, there is no need to clean the gas flue annually. Freestanding or loose smokestack luminaires due to corrosion over time may pose serious hazards due to the leakage of carbon monoxide into the structures. For this reason, it is recommended that the smokestacks are inspected annually and cleaned regularly to avoid these problems.

A characteristic problem of smokestacks is the formation of deposits on the walls of the smokestack structure when using solid fuel. These deposits can interfere with the flow of air and, more importantly, are flammable and can cause dangerous smokestack fires if debris in the smokestacks ignites. These kinds of effects affect the dynamic properties of the smokestacks (frequency, mode shapes, damping ratios) very little.

The most important factors affecting the dynamic behavior of the smokestacks are the environmental ones. These environmental factors can be counted as wind (direction, speed and pressure), temperature (humidity, temperature change). The change of environmental parameters is particularly effective in tall smokestacks. With the effect of wind, vortex can occur and this may cause resonance. To prevent this, additional plates can be placed along the smokestack to reduce vortex effects. Changes in temperature-related parameters can cause serious corrosion effects in the smokestacks and dangerous structural situations may arise as a result of changes in dynamic parameters. In smokestacks with high temperature, it can also pose serious structural problems in changes in air temperature and humidity. In order to prevent the effects of all these environmental factors on the dynamic behavior of the smokestacks, it is appropriate to evaluate long-term meteorological data and make projects according to these data. Today, there are many smokestacks built without considering these environmental factors. It will be useful to evaluate these smokestacks by making dynamic analysis again according to the long-term meteorological data. The most important results for a smokestack project are to observe the development (season change), as well as the structure and structure-induced change of conditions (period, seasons, etc.) to produce the best results. For all these reasons, this sample study has been carried out for the correct determination of the dynamic parameters on the smokestack.

System identification (SI) is a modeling process for an unknown system based on a set of input outputs and is used in various engineering fields [5], [6], [7], [15], [16], [17], [18]. This more detailed system topology can improve the performance of the model by defining a true nonlinear system, both actuator nonlinear and sensor nonlinear [25]. Some studies have also shown that the H-W system can approach almost all higher order nonlinear systems relatively well [26], [27]. The block structured class allows the separation of the linear dynamic part and the nonlinear static part into different subsystems (Hammerstein, Wiener, Hammerstein - Wiener, etc.) that can be interconnected in a different order. The more general model of this class is the Hammerstein-Wiener (HW) model, which consists of three subsystems in which a linear block is embedded between two non-linear subsystems [33], [34].

Hammerstein-Wiener Model

Hammerstein-Wiener models describe dynamic systems using one or two static nonlinear blocks in series with a linear block. The linear block is a discrete transfer function that represents the dynamic component of the model.
This block diagram represents the structure of Hammerstein-Wiener model in figure 1:

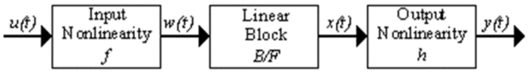

Figure 1: Block diagram of Hammerstein-Wiener model

Where, *f* is a nonlinear function that transforms input data $u(t)$ as $w(t)=f(u(t))$. $w(t)$, an internal variable, is the output of the Input Nonlinearity block and has the same dimension as $u(t)$.

B/F is a linear transfer function that transforms $w(t)$ as $x(t)= B/F w(t)$.

$x(t)$, an internal variable, is the output of the Linear block and has the same dimension as $y(t)$. *B* and *F* are similar to polynomials in a linear Output-Error model

For *ny* outputs and nu inputs, the linear block is a transfer function matrix containing entries:

$$\frac{B_{j,i}(q)}{F_{j,i}(q)}$$

where $j = 1,2,...,ny$ and $i = 1,2,...,nu$.

h is a nonlinear function that maps the output of the linear block $x(t)$ to the system output $y(t)$ as $y(t) = h(x(t))$.

Because *f* acts on the input port of the linear block, this function is called the input nonlinearity. Similarly, because facts on the output port of the linear block, this function is called the output nonlinearity. If your system contains several inputs and outputs, you must define the functions *f* and *h* for each input and output signal. You do not have to include both the input and the output nonlinearity in the model structure. When a model contains only the input nonlinearity *f*, it is called a Hammerstein model. Similarly, when the model contains only the output nonlinearity *h*, it is called a Wiener model. The software computes the Hammerstein-Wiener model output y in three stages:

1.Compute $w(t) = f(u(t))$ from the input data.

$w(t)$ is an input to the linear transfer function *B/F*.

The input nonlinearity is a static (memory less) function, where the value of the output a given time *t* depends only on the input value at time *t*.

You can configure the input nonlinearity as a sigmoid network, wavelet network, saturation, dead zone, piecewise linear function, one-dimensional polynomial, or a custom network. You can also remove the input nonlinearity.

2. Compute the output of the linear block using $w(t)$ and initial conditions:

$x(t) = (B/F) w(t)$.

You can configure the linear block by specifying the orders of numerator *B* and denominator *F*.

3. Compute the model output by transforming the output of the linear block $x(t)$ using the nonlinear function *h* as

$y(t)= h(x(t))$.

Similar to the input nonlinearity, the output nonlinearity is a static function. You can configure the output nonlinearity in the same way as the input nonlinearity. You can also remove the output nonlinearity, such that $y(t) = x(t)$.

Description of Model Smokestack

The model smokestack is made of concrete. The concrete class used is C20. (in Turkish Standards Institution- TSE). The height of the model smokestack is designed as 80 cm. The model smokestack has a diameter of 25 cm. It was produced by determining the wall thickness as 2.5 cm. The foundation on which the model smokestack sits is 30 * 30 * 5 cm. One triaxial accelerometer is placed on the model smokestack to get output data. Input data were obtained through a seismometer. The measurements were carried out in the Ondokuz Mayis University Civil Engineering Laboratory. The model smokestack and accelerometer given in figure 2.

Figure 2: The model smokestack

Obtaining Data Results

The data obtained from the model smokestack in the Ondokuz Mayis University Civil Engineering Laboratory environment was processed with Matlab package program. System Identification Toolbox is used in the study. System Identification Toolbox™ provides MATLAB® functions, Simulink® blocks, and an app for constructing mathematical models of dynamic systems from measured input-output data. It lets you create and use models of dynamic systems not easily modeled from first principles or specifications. You can use time-domain and frequency-domain input-output data to identify continuous-time and discrete-time transfer functions, process models, and state-space models. The toolbox also provides algorithms for embedded online parameter estimation [9], [33], [34].

sys =n4sid (data,nx) estimates a discrete-time state-space model sys of order nx using data, which can be time-domain or frequency-domain data. sys is a model of the following form:

A, B, C, D, and K are state-space matrices. u(t) is the input, y(t) is the output, e(t) is the disturbance, and x(t) is the vector of nx states.

All entries of A, B, C, and K are free estimable parameters by default. For dynamic systems, D is fixed to zero by default, meaning that the system has no feed through. For static systems (nx = 0), D is an estimable parameter by default [9], [33], [34].

Figures, e.g., a diagram, must be entered as a pure 'image' using the Word 'Insert special' option in the 'Editing' menu. The image should be fixed in relation to the text body by using the 'Image' option in the 'Format' menu. From the 'Image' option one selects the 'Layout' entry, followed by the 'In-line-with-text' option and carriage return.

Discrete-time identified state-space model:

$x(t+Ts) = A\ x(t) + B\ u(t) + K\ e(t)$

$y(t) = C\ x(t) + D\ u(t) + e(t)$

A, B, C, D and K Matrices obtained with MATLAB as a result of the analysis of the model smokestack;

A=

$$\begin{matrix} 0.414 & -1.467 & -1.778 & 1.377 \\ -0.017 & 0.211 & 0.981 & -1.640 \\ 0.488 & 0.218 & -1.288 & 1.476 \\ 0.089 & 0.248 & -0.506 & 0.975 \end{matrix}$$

B=

$$\begin{matrix} -2.481e-05 \\ 2.288e-05 \\ 1.719e-05 \\ 1.994e-05 \end{matrix}$$

C=

$$1.728e-14\ 1.429e-14\ -8.975e-15\ 3.309e-14$$

D=

$$1.15$$

K=

$$\begin{matrix} 3549781926207.93 \\ 2127726869570.10 \\ -3084794481476.18 \\ 4572206917117.64 \end{matrix}$$

After analyzing the data in MATLAB using N4SID the following results are summaries in Figures (3- 10).

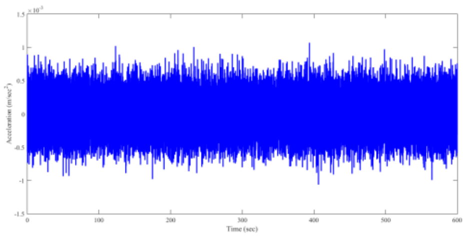

Figure 3: İnput signals

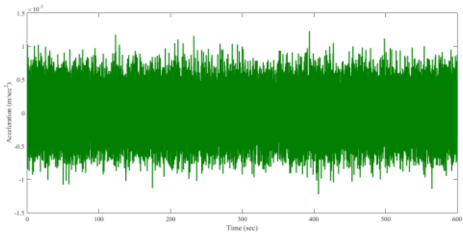

Figure 4: Output signals

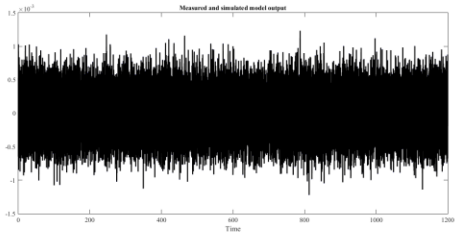

Figure 5: Model Output (Fit to estimation data 100 %)

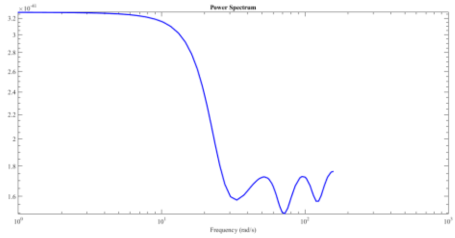

Figure 6: Power spectrum graphics

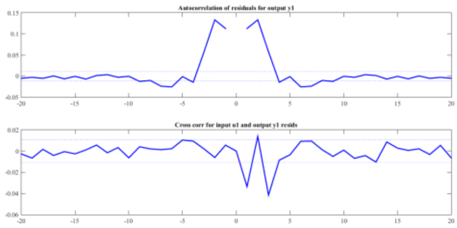

Figure 7: Autocorrelation of residuals for output graphics

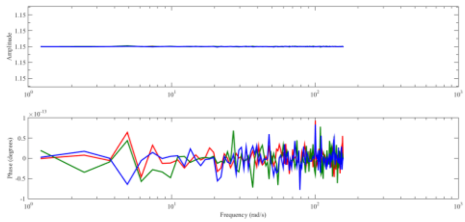

Figure 8: Frequency function graphics

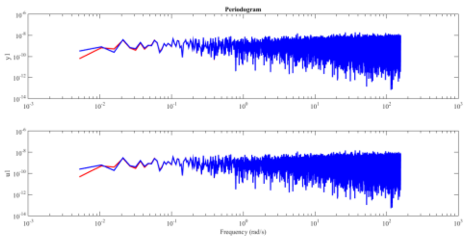

Figure 9: Periodogram

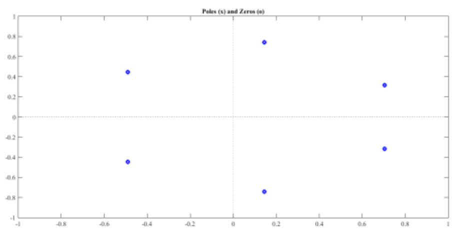

Figure 10: Poles and zeros graphics

Conclusions

To validate the performance of nonlinear system identification, a series of experiments are conducted on a model smokestack to environmental seismic ground motions; structural response data was used off-line to estimate black-box state-space model. Ground motions and structural response measurements were used by the subspace system identification method to derive a complete input–output state-space model of the model smokestack. The mathematical model of the structure is extracted from the estimated input–output state-space model. With the use of only structural response data, output-only state-space models of the system are also estimated by subspace system identification. Also, a new method of Hammerstein–Wiener Models is used with Nonlinear system identification of model smokestack identification tool is proposed to identify the modal properties of structures. A, B, C, D and K matrices of the model smokestack were obtained. Finally, nonlinear system identification of the model smokestack results demonstrated that fit to estimation data was nearly 100 % and it can be concluded that Hammerstein–Wiener system identification method is efficient and accurate in identifying mathematical model of smokestack. Thus, the current dynamic parameters of the smokestacks, which are under many negative dynamic factors such as heat-temperature change, humidity, vortex and wind, can be determined successfully.

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