System identification matlab example pdf

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Trial Software Test Software Updates Product Updates Creating linear and non-linear dynamic system models from the measured input data of the toolbox identification system™ provides MATLAB® features, Simulink® blocks, and an application to build mathematical models of dynamic systems from measured output data. This allows you to create and use models of dynamic systems that are not easy to model according to the first principles or specifications. Time and frequency domain I/O data can be used to determine the functions of continuous time and discrete time, process models, and government space models. The toolkit also includes algorithms for built-in online settings. The toolkit provides identification methods such as maximum probability, minimizing prediction errors (PEM) and identifying a subspace system. To represent the dynamics of the nonlinear system, you can evaluate Hammerstein-Weiner models and non-linear ARX models with wave network, tree division, and sigmoid network non-linears. The toolkit identifies the system's gray box to assess the parameters of the user-defined model. The identified model can be used to predict the reaction of the system and plant modeling in Simulink. The toolkit also supports simulation of time-series data and time series prediction. System identification is a methodology for constructing mathematical models of dynamic systems using measurements of the system's input and output signals. The system identification process requires you to:Measure input and output signals from your system in time or frequency domain. Choose the model structure. Apply the evaluation method to evaluate values for adjustable parameters in the candidate model structure. Evaluate the model to see if the model is adequate to your application needs. In a dynamic system, output values depend on both the instantaneous values of inputs and the system's past behavior. For example, a car seat is a dynamic system - the shape of the seat (position) depends both on the current weight of the passenger (instant value) and on how long the passenger has been driving in the car (past behavior). A model is a mathematical relationship between input and output variables of the system. Dynamic system models are usually described by differential or discernible equations, transmission functions, state and space equations, and zero profit models. You can present dynamic models in both continuous and discrete form. An common example of a dynamic model is the dynamic motion equation of the damper spring mass. As can be seen from the figures below, the mass in response to the force F (t) applied on the basis to which the mass is attached. The entry and exit of this system are force F (t) and moving y (t), respectively. You can represent the same physical system as a few Model. For example, you can imagine the mass-spring damper system in continuous time as a second-order differential equation: here m is mass, k is a constant of spring stiffness, and c is the damping factor. The solution of this differential equation allows to define the shift of mass y(t) as a function of external force F (t) at any time t for known values of permanent M, C, and k.Consider displacement y(t) and speed v(t)'dy(t)dt as variable states:You can express the previous motion equation as a model of state-space system:Matrix A, B and C associated with constants , c, and k as follows: You can also get a model of the function of the transfer system of the spring mass-damper system by taking the conversion of Laplace differential equation:Here, s is the Laplace variable. Suppose you can only observe the input and output variables F (t) and y(t) of the mass-spring-damper system at discrete moments and NTs, where Ts is a fixed time interval and Nos 0, 1, 2,.... Variables are said to be tested using Ts sampling time. Model parameters are associated with the constants of the m, c and k system, and the time of the Ts.This difference shows the dynamic nature of the model. The value of moving at instant t depends not only on the F force in the previous point in time, but also on the displacement values in the previous two moments of time y (t-1) and y (t-2). This equation can be used to calculate bias at a specific time. The move is presented as a weighted sum of past input and output values: This equation shows an iterative way to generate y(t output values), starting with the baseline y(0) and y(1) and F (t) input measurements. This calculation is called a simulation. In addition, the output at a given time t can be calculated using the measured output values at the previous two points in time and input at the previous point in time. This calculation is called prediction. For more information about modeling and forecasting using the model, see the topics on the Modeling and Forecasting page. You can also present a discrete motion equation in the forms of public space and function transfer, performing transformations similar to those described in the continuous dynamic example model.System identification uses input and output signals that you measure from the system to estimate the values of adjustable parameters in a given model structure. Models can be created using time domain I/O signals, frequency reaction data, time-series signals, and time-row. To get it A good model of your system, you have to measure data that reflect the dynamic behavior of the system. The accuracy of the model depends on the quality of the measurement data, which in turn depends on your experimental design. Time domain data consists of input and output variables that you record with a single sampling interval over a period of time. For example, if you measure the input pressure of F(t) and the mass displacement of the y(t) spring-mass-damper system illustrated in dynamic systems and models with a uniform sample frequency of 10 Hz, you get the following vectors of measured values: here are Ts 0.1 seconds and NTs the time of the last measurement. If you want to build a discrete time model from this data, umeas and ymeas data vectors and Ts sampling time provide enough information to create such a model. If you want to build a continuous time model, you should also know the inter-family input behavior during the experiment. For example, the entry may be permanent (zero-order) or linear (first-order retention) between samples. Frequency domain data is a measurement of system input and output variables that you record or store in a frequency domain. Fourier's frequency signals convert the corresponding time-domain signals. Domain frequency data can also represent the system's frequency response represented by a set of complex response values in a given frequency range. Frequency response describes exits to sinusoidal inputs. If the input wave is a sinus wave with frequency, the output is also a sinus wave of the same frequency, the amplitude of which A (I) times exceeds the amplitude of the input signal and the phase shift of the Φ (I) in relation to the input signal. Frequency reaction A (I)e (iΦ(I)). In the case of the mass-spring-damper system, you can obtain frequency response data using sineidal input force and measuring the corresponding amplation amplitude and phase shift response within a number of input frequencies. Frequency domain data can be used to build both discrete and continuous models of the system. System identification requires that your data capture the important dynamics of your system. A good experimental design ensures that you measure the correct variables with enough precision and duration to capture the dynamics you want to model. In general, your experiment should: Use input that properly excites the dynamics of the system. For example, one step is rarely enough excitement. Measure the data long enough to capture important time constants. Set up a data collection system that has a good signal-to-noise ratio. Measure data at appropriate sampling intervals or frequency resolution. You can analyze the quality before creating the model using the features and methods described in Analyze Data. For The For you can analyze the input spectrums to determine whether input signals have sufficient power over the bandwidth of the system. Use tips to analyze and process your specific data. You can also analyze your data to determine peak frequencies, input delays, important time constants, and non-linear data using non-parametric analysis tools in this toolkit. This information can be used to customize model structures to build models on data. For more information, see: Model structure is a mathematical link between input and output variables that contains unknown parameters. Examples of model structures are transmission functions with adjustable poles and zeros, state and space equations with unknown system matrixes, and non-linear parametrical functions. The following equation of difference is a simple pattern structure: Here, a and b are adjustable parameters. The system identification process requires selecting the model structure and using evaluation methods to determine the numerical values of the model parameters. You can use one of the following approaches to choose the structure of the model: You want a model that is able to reproduce measured data and as easy as possible. You can try the different mathematical structures available in the toolkit. This approach to modeling is called black box modeling. You need a specific structure for a model that can be derived from the first principles, but don't know the numerical values of its parameters. The structure of the model can be presented as a set of equations or as a system of public space in MATLAB® and evaluate the values of its parameters based on data. This approach is known as modeling a gray box. System Identification Toolbox software ™ model parameters, minimizing the error between the model's output and the measured response. The output ymodel linear model is given byymodel (t) - Gu (t)Here G is a function of transmission. To determine G, the toolkit minimizes the difference between the ymodel (t) and the measured output of ymeas (t). The minimization criterion is a weighted error rate, v(t), wherev (t) - ymeas (t) - ymodel (t.ymodel (t) is one of the following: Modeled response (Gu(t) model for this input u(t)Predicted model response for this input u't and past ,... The output measurement (t-1), ymeas (t-2) is therefore called a simulation error or forecasting error. frequency range, for example, pay more attention to lower frequencies and consider higher-frequency noise noise You can also set a criterion for the target application need for a model, such as modeling or forecasting. Identify options for optimizing iterative evaluation algorithms. Most of the evaluation algorithms in this toolkit are iterative. You can set up an iterative evaluation algorithm by specifying parameters such as optimization method and maximum iterations. For more information about setting up an evaluation algorithm, see Black Box Modeling useful when your main interest is to install the data regardless of the specific mathematical structure of the model. The toolkit provides several linear and non-linear structures of the black box model, which have traditionally been useful for presenting dynamic systems. These model structures vary in complexity depending on the flexibility required to account for the dynamics and noise in the system. You can select one of these structures and calculate its parameters to match the measured response data. Modeling black boxes is usually a trial and error process where you evaluate the parameters of different structures and compare the results. Typically, you start with a simple linear model structure and progress towards more complex structures. You can also choose the model structure because you are more familiar with this structure or because you have specific application needs. The simplest linear structures of the black box require several customization options: Evaluating some of these structures also uses non-quotative evaluation algorithms, which further reduces complexity. You can customize the model structure by ordering the model. Determining the order of the model varies depending on the type of model you choose. For example, if you choose to represent a transmission function, the order of the model is related to the number of poles and zeros. To represent the state of the space, the order of the model corresponds to the number of states. In some cases, such as linear ARX and government model structures, you can rate the order of the model based on data. If simple model structures do not produce good models, you can choose more complex model structures by defining a higher model order for the same linear model structure. The higher order of the model increases the flexibility of the model to capture complex phenomena. However, an unreasonably high order can make the model less reliable. Explicit noise modeling by incorporating the Term He (t), as shown in the following equation.y (t) - Gu (t) - He (t)Here H simulates additive violation, considering the violation as the output of a linear system controlled by a white source of noise e(t). Using a model structure that clearly simulates additive impairment can help improve the accuracy of the measured G component. when your main interest is to use the model to predict future response values. Using a different linear structure of the model. Use the model's linear structure. Non-linear models have more flexibility in capturing complex phenomena than linear models of similar orders. Ultimately, you choose the simplest model structure that best fits your measured data. For more information, see Line Model Assessment using a quick start. For example, you can separate measured dynamics (G) from noise dynamics (H) to get a simpler model that only represents the relationship between you and you. You can also linearly linear nonlineous model of the operating point. The linear model is often sufficient to accurately describe the dynamics of the system, and in most cases the best practice is to first attempt to match linear models. If the output of the linear model does not reproduce the measured output enough, you may need to use a non-linear model. You can assess the need to use a nonlineary model structure by planning the system's response to input. If you notice that the answers vary depending on the level of input or sign, try using a non-linear model. For example, if the output response to a step input is faster than a step-down response, you may need a non-linear model. Before you build a non-linear model of a system that you know is non-linear, try to convert input and output variables so that the link between the converted variables is linear. For example, consider a system that has current and voltage, like the inputs to the dive heater, and the temperature of the heated liquid as an outlet. The output depends on the inputs through the power of the heater, which is equal to the current and voltage product. Instead of building a non-linear model for this two input and one output system, you can create a new input variable by taking the current and voltage product and building a linear model, describing the relationship between power and temperature. If you can't identify conversion variables that give a linear link between input and output variables, you can use nonlinear structures such as nonlinear MODELS ARX or Hammerstein-Wiener. For a list of supported non-linear model structures and when to use them, see, in most cases, you select the model structure and evaluate the model parameters with a single command. Consider the mass-spring damper system described in dynamic systems and models. If you don't know the equations of motion of this system, you can use the black modeling approach to create a creation For example, you can evaluate the transmission functions or model of the public space by specifying orders for these model structures. The transfer function is the ratio of polynomies: for a mass-spring damper, this transfer function is a zero-and-two-pole system. At discrete time, the mass-spring-damper transmission function can be where the model orders correspond to the number of numerator and denominator ratios (nb No. 1 and nf No. 2), and the I/O delay is the lowest z-1 in the numerical rate (nk No. 1). In continuous times, you can build a linear model of the transmission function with the tfest command. Here, data is measured I/O data presented as an iddata object, and the order of the model is a set of poles (2) and number zeros (0). Similarly, you can build a discrete model of output output with the oe command. The model's order is nb nf nk (1 2 1). Normally, you don't know the order model in advance. Try a few model order values until you find orders that produce an acceptable model. You can also select the state space structure to represent the mass-spring damper system and evaluate the model parameters using a ssest or n4sid command. Here, the second argument 2 represents the order or number of states in the model. In modeling black boxes do not need a motion equation for the system - only the assumption about the order of the model. For more information on building models, see Steps to use the system identification application and evaluate the model Commands.In in some situations, you can deduce the structure of the model from the physical principles. For example, the mathematical relationship between input force and mass movement in the spring-mass damper system illustrated in dynamic systems and models is well known. In the form of state space, the model is given to the extent that x(t) - y/t);v (t) is the vector of the state. Odds A, B and C are model parameters: A 0 1; -k/m -c/m'B - 0; 1/m'C - 1 0, you fully know the structure of the model, but do not know the value of its parameters - m, c and k.In the approach of the gray box, you use the data to estimate the values of unknown parameters of your model. You specify the structure of the model by a set of differential or difference equations in MATLAB and provide some initial guess for these unknown parameters. Typically, you build models of gray boxes, creating a pattern structure. Set up model settings with original values and limitations (if any). Applying the evaluation method to the model structure and calculating the values of the model parameters. The following table summarizes the ways in which you can specify the structure of the grey box model. Grey-Box Structure RepresentationLearn MoreRepresent the structure of the model of public space as You can calculate the values of parameters such as m, C and K from the space matrix of state A and B. For example, m 1/B(2) and -A (2,1)m. Representation of the structure of the state space model as an idgrey model object. You can directly estimate the values of the parameters m, c and k.Grey-Box Model EstimationAfter you evaluate the model, you can evaluate the quality of the model by: Ultimately, you have to evaluate the quality of your model based on whether the model adequately meets the needs of your application. For information on other available model analysis methods, see if these changes do not improve results, you may need to review experimental design and data collection procedures. Typically, you evaluate the quality of the model by comparing the model's response to the measured output for the same input. Suppose we use a approach to modeling black boxes to create dynamic models of the spring mass damper system. You try different structures and order models such as:model1 and arx (data, No2 1 1); Model2 No n4sid (data, 3) You can model these models with a specific input and compare their responses with the measured offset values for the same input applied to the real system. The next figure compares simulated and measured responses to enter a step. The figure indicates that model2 is better than model1 because model2 is better than the data (65% vs. 83%). For more information, see the topics on the Compare Output page with measured data. that are accurate in the trust region. The size of this region is determined by the uncertainties of the parameters calculated during the assessment. The scale of uncertainty ensures that the model is secure. Significant uncertainty of parameters may be the result of unreasonably high patterns, inadequate levels of input arousal, and poor signal-to-noise ratios in measured data. You can calculate and visualize the impact of parameters uncertainty on the model in time and frequency domains using maps with a zero pole, sections of Bode's response and response phases. For example, in the next Bode graph of the appraisal model, shaded areas represent the uncertainty of the amplitude and the frequency reaction phase of a model calculated using uncertainty of parameters. The plot shows that the uncertainty is low only in the frequency range from 5 to 50 rad/s, which indicates that the model is reliable only in this frequency range. For more information, see More Resources to learn more about specific aspects of system identification theory and applications. The following book describes methods of system identification and physical modeling: Lung, Lennart and Torkel Glad. 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