Lower Order Transfer Function Identification of Nonlinear MIMO System-Alstom Gasifier

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Abstract

Control problems in process industries are dominated by nonlinear, time varying behaviour, different characteristics of various sensors; multiples control loops and interactions among the control loops. Conventional controllers can control a process to a specific performance, if it is tuned properly and if the sensors and associated measurement circuits are of high quality and moreover, only if the process is linear. Now a days we use model based controller. The first step in model based control design is modelling the plant to be controlled. The System identification deals with the building mathematical model of the dynamic process using input-output data. A simple second order transfer function would be useful in designing the controller. In this paper a linear reduced order model of Alstom gasifier has been identified using Prediction error algorithm. The 100% load condition was identified among three operating conditions 0%, 50% and 100%.

1. Introduction

These days the major source of electricity in India is produced from thermal power i.e., from coal. The vast resources of coal we have are not of high carbon content. The type of coal primarily mined in India is lignite which has less carbon content. We are not being able to maximize the output from the power plants using these coals only because of the inferior quality of coal. As a result there occurs much wastage of these valuable resources. Integrated gasification combined cycle (IGCC) provides a suitable solution to this problem. In this process coal is converted into fuel gas which in turn is used for generating electricity. The efficiency by this process is much higher than the conventional process. Gasification is a thermo-chemical process, that convert any carbonaceous material (Solid Fuel-coal) in to combustible gas known as "producer gas or syngas" by partial oxidation process.

During gasification, the coal is blown through with oxygen and steam while also being heated. Oxygen and water molecules oxidize the coal and produce a gaseous mixture of carbon dioxide (CO_2), carbon monoxide (CO), water vapour (H_2O), and molecular hydrogen (H_2) along with some by-products like tar, phenols, etc. are also possible end products. This process has been conducted in-situ within natural coal and in coal refineries. The desired end product is usually syngas (i.e., a combination of H2 + CO), but the produced coal gas may also be further refined to produce additional quantities of H_2:

3C (i.e., coal) + O_2 + $H_2O \rightarrow H_2$ + 3CO ----------(1)

Coal can be gasified in different ways by properly controlling the mix of coal, oxygen, and steam within the gasifier. There are also numerous options for controlling the flow of coal in the gasification section. Most gasification processes use oxygen as the oxidizing medium. Integrated gasification combined cycle (IGCC), produces power using the combination of gas turbine and steam turbine which yields 40% to 42% efficiency. The fuel gas leaving the gasifier must be cleaned of sulfur compounds and particulates. Cleanup occurs after the gas has been cooled, which reduces overall plant efficiency and increases capital costs. However, hot-gas cleanup technologies are in the early demonstration stage. World gasification capacity is projected to grow by more than 70% by 2015, most of which will occur in Asia, with China expected to achieve the most rapid growth. Our objective of this paper is to enhance the efficiency of gasification process by identifying the lower order model of the system, which can be used for designing model based control strategies.

2. The Alstom Gasifier Model

The coal gasifier model was developed by engineers at the Technology Centre(Alstom). Originally it was written in the Advanced Continuous Simulation Language (ACSL), before being transferred to MATLAB/SIMULINK to facilitate the design and evaluation of control laws. All the significant physical effects are included in the model (e.g., drying processes, desulphurisation process, pyrolysis process, gasification process, mass and heat balances) and it has been validated against measured time histories taken from the British Coal CTDD experimental test facility. The benchmark challenge was issued in two stages. The linear models representing three operating conditions of gasifier at

0%, 50% and 100% was issued in 1977. Roger Dixon ,et.al [1,2] had issued the detailed specification of first challenge. Second round challenge which included load change test and coal disturbance test was issued in 2002. More details concerning the second challengeand a review of gasifier modelling can be found in [3,4]. The described model is a state space model with model order of 25. It is relatively difficult to implement control laws on such a nonlinear process model which has an order of 25.

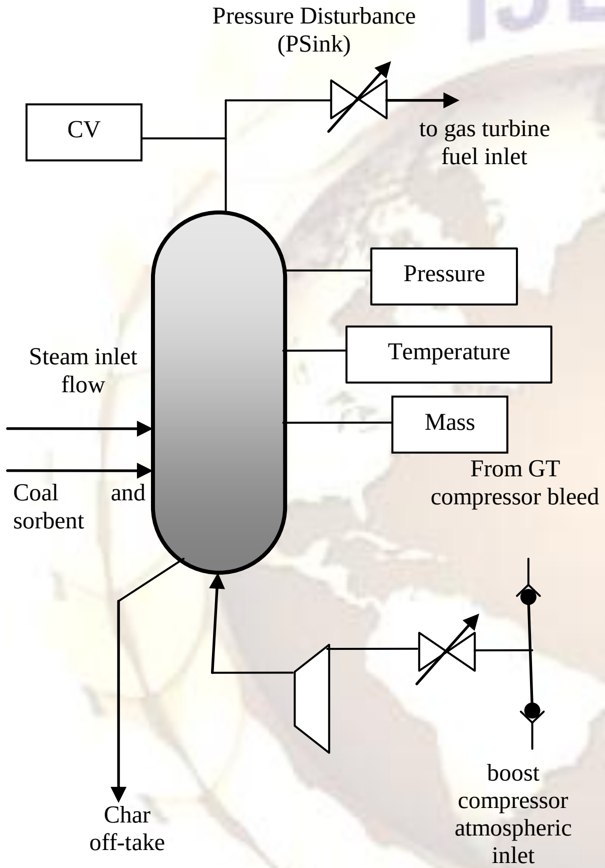

Figure 1.A schematic of Gasifier

A schematic of the plant is shown in Figure 1. The coal gasifier is a highly non-linear, multivariable process, having five controllable inputs and four outputs with a high degree of cross coupling between them. Other non-control inputs for this process model include boundary conditions, adisturbance input (PSINK) which represents pressure disturbances induced as the gas turbine fuel inlet valve is either opened or closed, and a coal quality input.

In the gasification process, pulverised coal and limestone are conveyed by pressurised air into the gasifier. The air and injected steam fluidise the solids in the gasifier and reacts with the carbon and volatiles. The remaining char is removed as bed material from the base of the gasifier or carried out of the top of the gasifier as elutriated fines with the product gas. The quality of the produced gases depends on the calorific value and many other factors such as the pressure of the air and steam to the bed mass and thus making the gasifier a highly coupled system.

2.1 Inputs and Outputs of Gasifier

The controllable inputs are:

1. Char extraction flow- WCHR (kg/s)
2. Air mass flow - WAIR (kg/s)
3. Coal flow - WCOL (kg/s)
4. Steam mass flow - WSTM (kg/s)
5. Limestone mass flow - WLS (kg/s)

The disturbance input is:

6. Sink pressure - PSINK (N/m^2)

The controlled outputs are:

1.fuelgas calorific value-CVGAS (J/kg)
2. bed mass - MASS (kg)
3. fuel gas pressure - PGAS (N/m^2)
4. fuel gas temperature - TGAS (K)

3. System identification

System identification deals with the mathematical modelling of dynamic system using measured input-output data. Unlike modelling from first principles, which requires an in-depth knowledge of the system under consideration, system identification methods can handle a wide range of system dynamics without knowledge of the actual system physics. Choosing a suitable model structure is prerequisite before its estimation. The choice of model structure is based upon understanding of the physical systems. Three types of models are common in system identification: the black-box model, grey-box model, and user-defined model. The black-box model assumes that systems are unknown and all model parameters are adjustable without considering the physical background. The grey-box model assumes that part of the information about the underlying dynamics or some of the physical parameters are known and the model parameters might have some constraints. The user-define model assumes that commonly used parametric models cannot represent the model you want to estimate.

4. Model structure selection

Seyabet.al [5] identified a linearized state space model for 0% load condition for implementing model predictive control strategy and MoreeaTaha [8] presented a different method for modelling. Low order transfer function models are suitable for control tuning studies. In this direction, low order transfer function models for a complete thermal power plant have been obtained by Ponnuswamyet all [6] from a highly nonlinear mathematical model using system identification techniques. Further Rao and Sivakumar identified MIMO system transfer function models using Walsh function technique[7]. In this paper a MIMO linear transfer function model is identified from the simulated process operation data at 100% load conditions using the linearized state space model is available for the ALSTOM benchmark process,. The complete transfer function expected to be in the form:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} & G_{13} & G_{14} & G_{15} \\ G_{21} & G_{22} & G_{23} & G_{24} & G_{25} \\ G_{31} & G_{32} & G_{33} & G_{34} & G_{35} \\ G_{41} & G_{42} & G_{43} & G_{44} & G_{45} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix} + \begin{bmatrix} G_{d1} \\ G_{d2} \\ G_{d3} \\ G_{d4} \end{bmatrix} \times d \quad \text{---------------- (2)}$$

Where,

y_1= fuel gas caloric value (J/kg)
y_2=bed mass (kg)
y_3=fuel gas pressure (N/m^2)
y_4=fuel gas temperature (K)
u_1 =char extraction flow (kg/s)
u_2=air mass flow (kg/s)
u_3=coal flow (kg/s)
u_4=steam mass flow (kg/s)
u_5=limestone mass flow (kg/s)
d =sink pressure (N/m^2)

5. Selection of test input signal and experiment execution

Experimental data is generated either from a single open-loop MIMO experiment (all input channels excited simultaneously) or from open-loop SIMO experiments (one input channel excited at a time). Rudy Agustriyanto, Jie Zhang [9] suggested a method, in which a step change in input at times 500s and 2000s were used and the input-output data constitutes the estimation and validation data (one input channel triggered at a time). Output error method is used to identify a lower order transfer function of the Alstom gasifier. L.Sivakumar,AnithaMary.X[10] identified a reduced order transfer function models for gasifier with minimum IAE and ISE error criterion using Genetic Algorithm. In this present work the five inputs of the plant were simultaneously perturbed with Pseudo Random Binary Signal (PRBS) which were independent of inputs of the plant. The input perturbations amplitude were set to be ±10% about the full load operating point and 10000 input-output signals were recorded.

Figure 2 and figure 3 shows the input-output data. First 7000input-output data pairs were used to identify and the rest 3000 input-output data pairs were used to estimate parameters of five, single output (MISO) models. These models then combined to give five-input, four output model. The input signals combined with the training output data were sampled at 1 second and were used to estimate the system matrices. The proposed algorithm was implemented to fit the estimated. model to the given data.

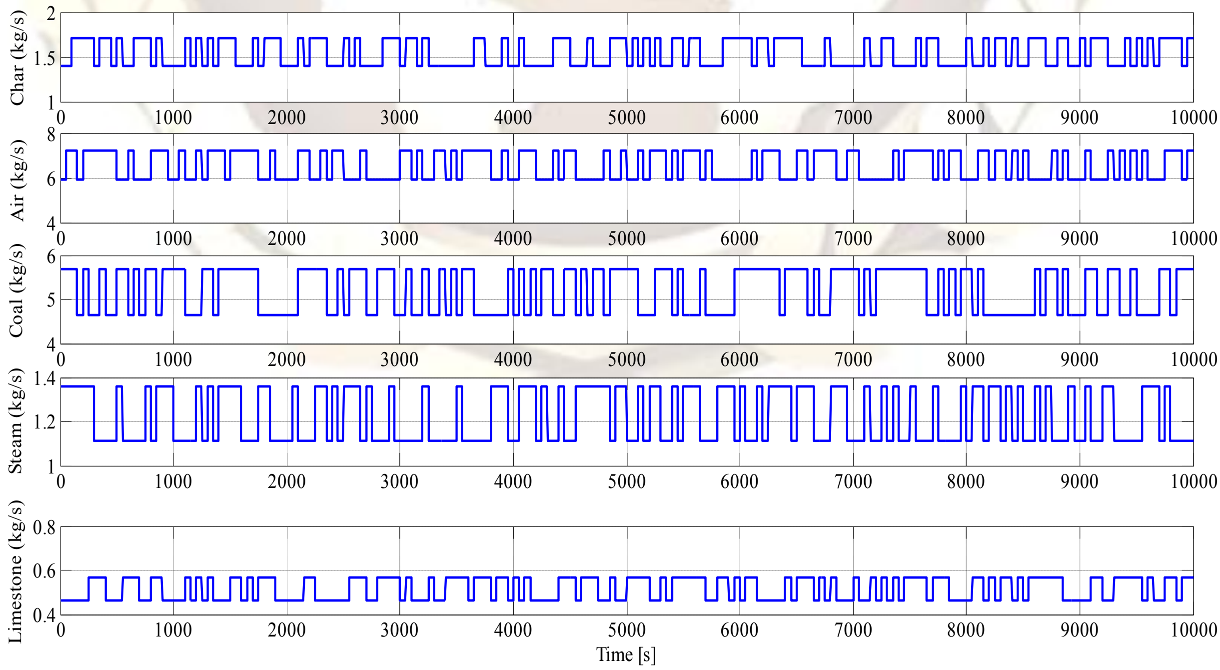

Figure 2.Input Signal to the Gasifier

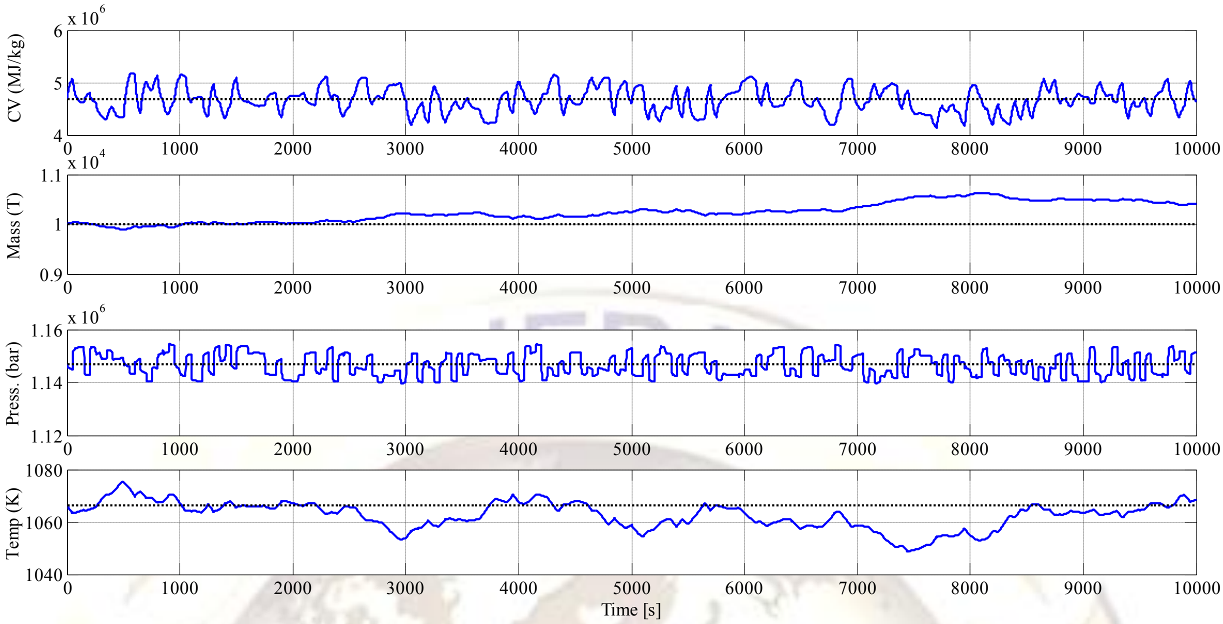

Figure 3.Output Signal of the Gasifier

6. Prediction error algorithm

The search method used for iterative parameter estimation is nonlinear least square estimation. It solves nonlinear least-squares problems, including nonlinear data-fitting problems. Rather than compute the value (the sum of squares), lsqnonlin requires the user-defined function to compute the *vector*-valued function

An important special case for *f(x)* is the nonlinear least squares problem

$$f(x) = \frac{1}{2}\sum_i f i^2(x) = \frac{1}{2}\|F(X)\|_2^2 \text{ ------------(3)}$$

where F(X) is a vector-valued function with component *i* of equal to $f_i(x)$. The basic method used to solve this problem is "Trust Region Methods for Nonlinear Minimization". However, the structure of the nonlinear least squares problem is exploited to enhance efficiency. In particular, an approximate Gauss-Newton direction, i.e., a solution *s*to

$$\min\|Js + F\|_2^2 \text{ ----------------------------(4)}$$

(where*J*is the Jacobian of F(X)) is used to help define the two-dimensional subspace S. Second derivatives of the component function $f_i(x)$ are not used. In each iteration the method of preconditioned conjugate gradients is used to approximately solve the normal equations, i.e.,

$$J^T J S = - J^T F \text{ ---(5)}$$

although the normal equations are not explicitly formed.

In the unconstrained minimization problem, minimize $f(x)$, where, the function takes vector arguments and returns scalars. Suppose we are at a point *x* in *n*-space and we want to improve, i.e., move to a point with a lower function value. The basic idea is to approximate *f* with a simpler function q, which reasonably reflects the behaviour of function f in a neighbourhood N around the point *x*. This neighbourhood is the trust region. A trial step is computed by minimizing (or approximately minimizing) over *N*. This is the trust region sub problem,

$$\min_s\{q(s) \quad s \in N\} \text{ ----------------------------(6)}$$

The current point is updated to be X+s if f(X+s) < $f(x)$ otherwise, the current point remains unchanged and *N*, the region of trust, is shrunk and the trial step computation is repeated.

7. Results and discussion

A varity of model structures are available to assist in modelling asystem. The choice of the model structure is based upon the understanding of the system identificaiton method and insight and understanding into the the systen undergoing identification. Eventhen it is often beneficial to test a number of structures to determine the best one. Different model structures were defined for all the input-output pairs. The system was estimated by using first 7000 input-output samples and the remaining

3000 input-output samples were used for validation. The lower order transfer function nonlinear Alstom gasifier was identified.

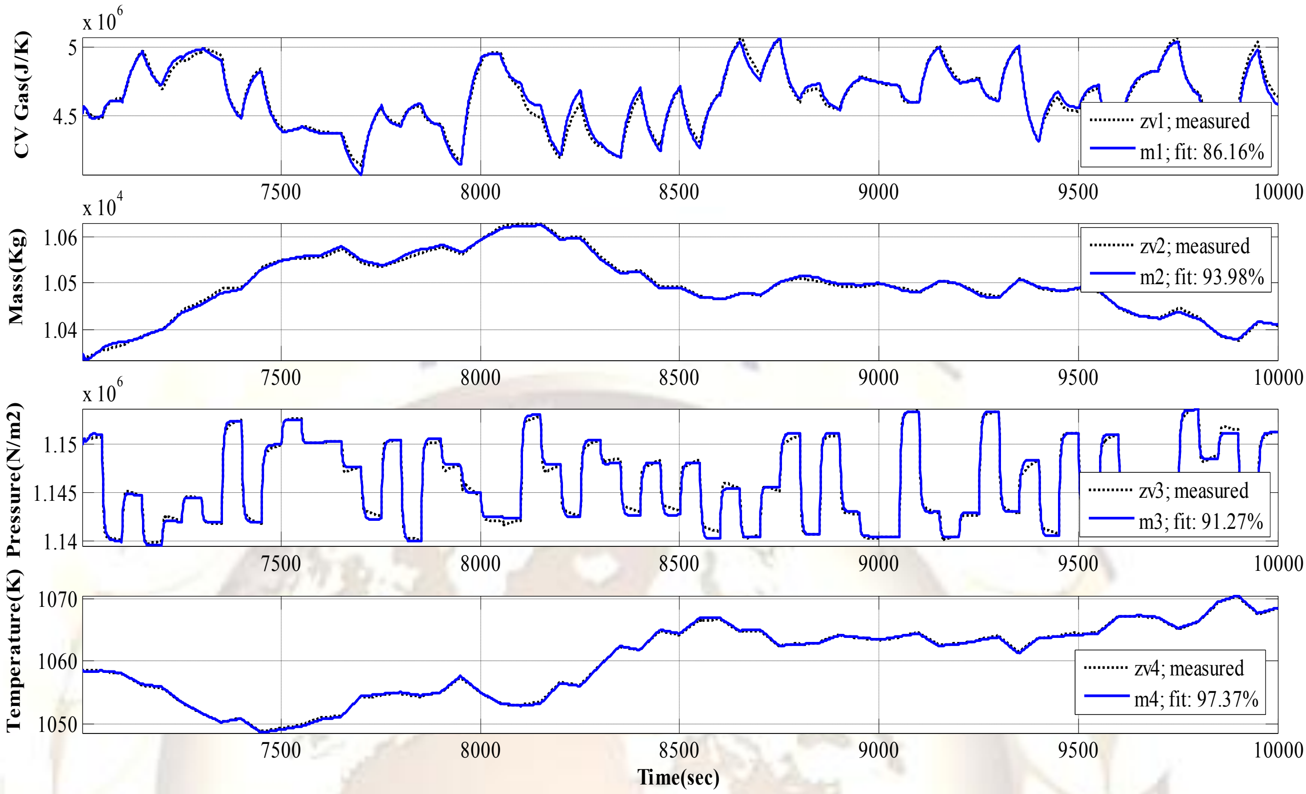

Figure 4.Validation output

The identified transfer function of the Alstom gasifier after carefully selecting the model structures were found to be:

$$G_{11}(s) = \frac{6.8139e6(1+2116.5s)}{(1+105.57s)(1+14907s)} \quad \text{---------------(7)}$$

$$G_{12}(s) = \frac{-1.4419e5}{(1+17.133s)} \quad \text{------------------------------(8)}$$

$$G_{13}(s) = \frac{1.4476e5}{(1+22.908s)} \quad \text{---------------------------(9)}$$

$$G_{14}(s) = \frac{1.8612e5}{(1+28.359s)} \quad \text{--------------------------(10)}$$

$$G_{15}(s) = \frac{-3.2795e5}{(1+858.55s)} \quad \text{----------------------------(11)}$$

$$G_{21}(s) = \frac{-768.33}{(1+760.99s)(1+11.242s)} \quad \text{--------------(12)}$$

$$G_{22}(s) = \frac{-356.37}{(1+851.78s)(1+5.5738s)} \quad \text{--------------(13)}$$

$$G_{23}(s) = \frac{15912}{(1+26492s)(1+5.6257s)} \quad \text{----------(14)}$$

$$G_{24}(s) = \frac{-316.79}{(1+407.89s)(1+6.2036s)} \quad \text{---------(15)}$$

$$G_{25}(s) = \frac{78.335}{(1+520.29s)(1+0.0021819s)} \quad \text{------(16)}$$

$$G_{31}(s) = \frac{2.2933e7}{(1+3.3016e5s)} \quad \text{-----------------------(17)}$$

$$G_{32}(s) = \frac{11725(1+93.303s)}{(1+112.54s)(1+5.1163s)} \quad \text{-------------(18)}$$

$$G_{34}(s) = \frac{15871}{(1+3.1221s)} \quad \text{----------------(19)}$$

$$G_{35}(s) = \frac{-53210}{(1+394.78s)(1+423.65s)} \quad \text{--------(20)}$$

$$G_{41}(s) = \frac{15777}{(1+2.8312e5s)} \quad \text{-------------------------(21)}$$

$$G_{42}(s) = \frac{45.994}{(1+992.17s)} \quad \text{---------------------------(22)}$$

$$G_{43}(s) = \frac{-5304.3}{(1+97539s)} \quad \text{---------------------------(23)}$$

$$G_{44}(s) = \frac{-540.13}{(1+59853s)} \quad \text{--------------------------(24)}$$

$$G_{45}(s) = \frac{-36.738}{(1+952.71s)} \quad \text{---------------------------(25)}$$

$$G_{d1}(s) = \frac{2.9456}{(1+1263.9s)} \quad \text{---------------------------(26)}$$

$$G_{d2}(s) = \frac{-0.070376}{(1+0.0049202s)(1+72.526s)} \quad \text{------(27)}$$

$$G_{d3}(s) = \frac{-11.03}{(1+0.0030731s)(1+0.0022361s)} \quad \text{------(28)}$$

$$G_{d4}(s) = \frac{-0.94306}{(1+11791s)} \quad \text{---------------------------(29)}$$

8. Conclusion

In this paper we have examined the identification of multivariable linear models to be used for controller design which could be used for adaptive control schemes. The identificaiton results shows that the mass, temperture and pressure have better approximation than CV, which means that CV is highly nonlinear than other outputs. A lower order transfer function of highly coupled nonlinear process was identified. An identified model with 85% appriximation is sufficient for adaptive control schemes. This model holds good for adaptive control schemes since its accuracy is above 85%. The models obtained are control-relevant, meaning they retain information that is most important for control purposes.

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