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Artificial Intelligence Reduced Order Observer Design for Output Feedback Control

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Abstract: In modern control engineering, the rising demand for streamlined state estimation in dynamic systems has made the development of reduced-order observers a critical area of study. This paper explores the integration of neural networks into observer design, utilizing their specialized ability to learn unknown dynamics and approximate complex nonlinear functions. In this paper, we propose the use of neural-network-based reduced-order observer designed which maps the relationship between system inputs, measurable outputs, and hidden state variables. The method uses the physics-in-formed neural networks formulation, which provides a powerful paradigm for solving partial differential equations for large dimensions of dynamical systems. The method facilitates precise estimation even when a comprehensive analytical plant model is unavailable. By utilizing a reduced-order architecture, the framework minimizes computational overhead, making it ideal for real-time practical applications. Furthermore, the approach exhibits high resilience against parameter uncertainties and system nonlinearities. Simulation data confirms that this intelligent observer configuration delivers significant accuracy and strong convergence performance.

Keywords: Reduced order observer, Output feedback control, State-space representation, Artificial intelligence, Neural networks.

Introduction

In modern control systems, output feedback control is widely employed when full state measurement of a dynamic system is not available or practical. Many real-world systems contain internal state variables that cannot be directly measured due to physical limitations, sensor cost, noise sensitivity, or technological constraints (Farkane et al., 2025). In such cases, an observer is designed to estimate the unmeasured states of the system using the available output measurements and knowledge of the system model. The observer functions as a dynamic estimator that reconstructs the internal state vector by comparing the measured system output with the estimated output and correcting the estimation error continuously (Miao & Gatsis, 2022). This estimated state information is then used within the feedback controller to achieve the desired control performance. Observer-based output feedback control is particularly valuable because it allows the implementation of state feedback strategies without requiring direct measurement of every state variable (Padovani et al., 2024). The design objective of the observer is to ensure that the estimation error converges to zero rapidly so that the estimated states closely track the true system states over time. Consequently, the observer becomes an essential component in many practical control applications where complete state measurement is unavailable.

A neural-network-based observer is an advanced estimation technique used to reconstruct the internal states of a dynamic system when an output feedback control is desired and the state variables cannot be directly measured. In conventional control systems, observers such as the Luenberger observer or Kalman filter rely heavily on accurate mathematical models of the plant (Yuan et al., 2020). Neural networks, as an artificial intelligence technique, on the other hand offer an alternative approach when the system is highly nonlinear, uncertain, or difficult to model precisely (Zhang et al., 2014). Neural-network-based observer design has therefore been considered as an important research direction for modeling of dynamic systems. Early work in this area proposed adaptive recurrent neural-network observers in which neural weights are updated online for estimation while maintaining observer stability. Subsequent research improved these methods by relaxing restrictive assumptions and broadening applicability to wider classes (Huang et al., 2005). More recent studies have developed robust adaptive observers using multi-time-scale neural networks, demonstrating that Lyapunov-based learning laws can ensure bounded state, output, and weight-estimation errors while improving convergence and robustness (Fu et al., 2016). Additional neural observer frameworks have been proposed for networked control systems, delayed systems, and uncertain plants, where adaptive estimators learn system nonlinearities online without exact prior knowledge of the plant model (Hua & Guan, 2014).

As a matter of fact, many researchers presented different methodologies in developing improved observer design for output feedback control (Asadi & Moallem, 2025; Ailiang et al., 2020). However, in spite of the many algorithms developed, no method can provide acceptable results for all kinds of networks, as presented by many different methods presented early (Alsmadi et al., 2024; Alsmadi et al., 2020). In this paper, we will present a different artificial neural network technique for a reduced order observer that will permit the design of output feedback control with some advantages as illustrated in this paper. The reduced-order observer focuses only on estimating the dominant dynamics of the system, leading to reducing computational complexity and implementation cost. This makes it especially useful in real-time and embedded control applications, where efficiency is critical (Shin et al., 2025). The order of the new observer is based on how perturbed the system is; that is, the reduction process depends on the system time scale (Alsmadi et al., 2019). This time scale typically separates the system into *slow* and *fast* subsystems, allowing analysts to study each behavior independently through different techniques such as time-scale decomposition and boundary layer analysis. The system in this case reduces to a lower-order “slow” subsystem, while the fast dynamics are assumed to have reached their quasi-steady state.

Reduced Order Observer ANN Design

Artificial Neural Networks technology is a modern technique that excels in dealing with linear and mainly nonlinear problems and effectively handles massive amounts of information. In control systems, ANNs can be extensively and efficiently used in reduced order observer designs due to its robustness and accuracy in system performance. ANNs are characterized by their speed, high responsiveness, and high reliability based on their training (Jamil et al., 2015). The ANN observer is designed by first collecting input-output data from the plant under different operating conditions and then training a neural network to learn the hidden relationship between measurable inputs, outputs, and internal states. The proposed design process is presented as laid in Figure 1 for a full seventh order system with a third order reduced observer. In this section, we will present the main methodology sections as to where and how the ANN has been employed.

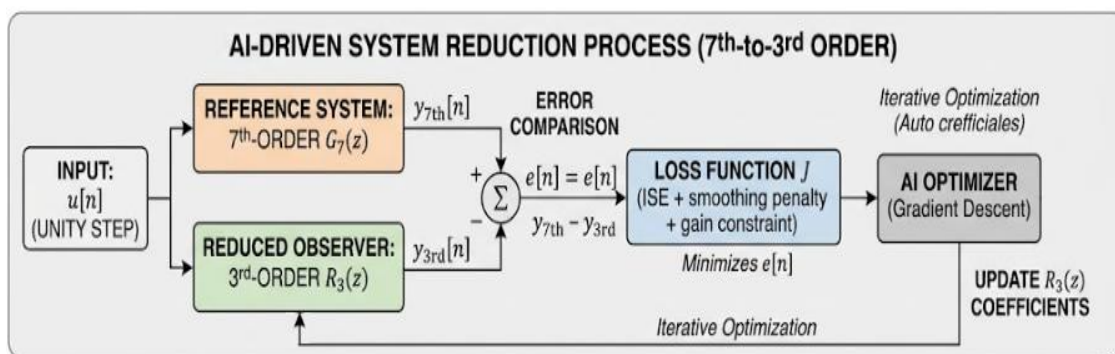


Figure 1. Reduced order observer design.

Here, we utilize a specialized type of Physics-Informed Neural Network (PINN) configured as an iterative optimization loop for system identification (Bai et al., 2026). This architecture does not only predict

coefficients; it also simultaneously predicts the coefficients and simulates the system to calculate the dynamic loss. The customized network for a third order reduced observer, seen in Figure 2, takes the system reference data as input and outputs the optimized coefficients of the minimized reduced-order observer. It consists of two main sections: A fully connected deep network to compress the dynamic features, and a physics-informed loss layer which uses the predicted coefficients (a_i, b_i) to simulate the discrete-time dynamics of the reduced observer.

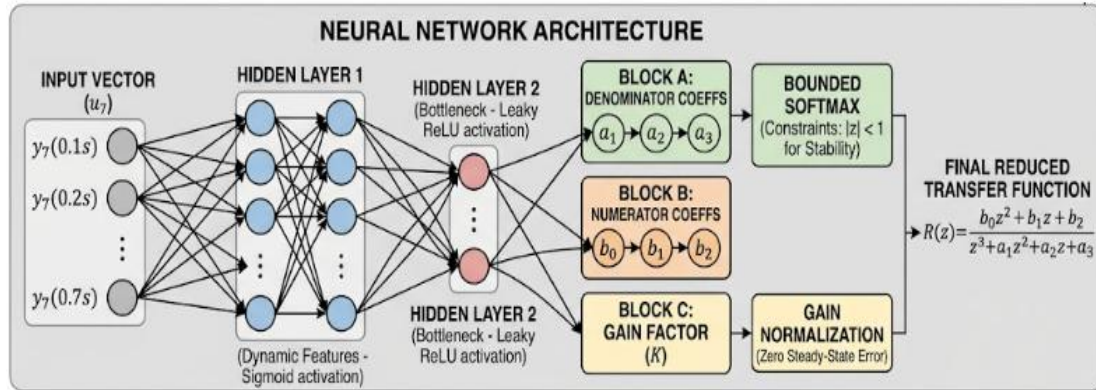


Figure 2. Neural network architecture of a reduced order observer design.

The initial section uses standard deep learning to map the full-order system response into a simplified vector representation. The network receives the vector containing the given samples of the full-order discrete-time response given as:

$$u_{input} = [y_{i_full_order}, i = 1, \dots, \# \text{ of sampled data}] \quad (1)$$

The input vector is then mapped through the first layer as following:

$$L_1 = \alpha_1 [v_1 u_{input} + v_1] \quad (2)$$

where v_1 and v_1 are adjustable weights and biases of the first layer, and α_1 is the non-linear activation function.

The second hidden layer is an important layer as it forces the network to find the dominant poles (modes) while learning to reduce the observer to a minimized vector by applying the following representation:

$$L_{compressed} = \alpha_2 [v_2 L_1 + v_2] \quad (3)$$

The output layer directly generates the coefficients of the reduced order observer,

$$\hat{C}_{coefficients} = [\hat{a}_i, \hat{b}_i]^T \quad (4)$$

while linear scaling and activation being used to ensure that the generated coefficients are maintained within a practical stable range as following:

$$\hat{C}_{coefficients} = \text{softmax}[v_3 L_{compressed} + v_3] \quad (5)$$

The primary equation driving the entire reduction process is the cost function (J), where the AI optimizer focuses on its minimization. The goal of training is to find a set of coefficients $(\hat{a}_i, \hat{b}_i)$ that minimizes the following total cost given by:

$$J(\hat{a}_i, \hat{b}_i) = w_1 \text{MSE} + w_2 \text{Spikiness_Penalty} \quad (6)$$

where w_i are customizable weights that define the optimization priorities, such as smoothness over absolute peak matching. Each term in the cost function represents a specific performance metric of the discrete-time system

response. The term MSE (Mean Squared Error) is used to force the reduced model observer to follow the original full order model through a given number, of samples. That is,

$$MSE = \frac{1}{N} \sum_{k=0}^{N-1} (y_{full_order}[k \Delta t] - y_{reduced_observer}[k \Delta t, \hat{a}, \hat{b}])^2 \quad (7)$$

where N is the total number of samples, and Δ is the sampling interval (0.1s).

The network updates are obtained by computing the partial derivative of the total cost with respect to all of the adjustable weights (v_i, v_i),

$$v_{new} = v_{old} - \eta \frac{\partial j}{\partial v_{old}} \quad (8)$$

In order to capture the important dynamics, especially at the transient period, we introduce the derivative penalty, where this term penalizes rapid changes. This term is given by:

$$Spikiness_Penalti = \frac{1}{N-1} \sum_{k=1}^{N-1} (y_{reduced_observer}[k] - y_{reduced_observer}[k-1])^2 \quad (9)$$

In addition to that, we enforce a constraint that ensures matching at the steady state. This constraint is given by

$$e_{gain} = (G_{full_order}(steady_state) - G_{reduced_observer}(steady_state))^2 \approx 0 \quad (10)$$

where G is the system DC gain.

Results and Discussion

To investigate the proposed reduced order observer model design, the following discrete 7th order system investigated in the literature is considered,

$$G(z)_{full} = \frac{2.0434z^6 - 4.9825z^5 + 6.57z^4 - 5.8189z^3 + 3.636z^2 - 1.4105z + 0.2997}{z^7 - 2.46z^6 + 3.433z^5 - 3.333z^4 + 2.546z^3 - 1.584z^2 + 0.7478z - 0.252}$$

As the system provides a response with different dynamics, especially for the transient response as seen in Figure 1, finding the reduced order observer was started with a very low order (i.e. 2nd order), then increasing finding the order as necessary to capture the dominant dynamics. Using the proposed methodology, the following 3rd order reduced observer was obtained

$$G(z)_{reduced_observer} = \frac{1.3268z^2 - 2.2378z + 1.0955}{z^3 - 2.1814z^2 + 1.8637z - 0.6288}$$

with two zeros and three poles.

To investigate the performance of this observer, the full order system and reduced order observer were simulated to a unity step input with results obtained as seen in Figure 3. As observed, the two responses converge within about 3 seconds, with a relatively acceptable range of error for the transient response. The new approach has also been investigated and compared with the performance of the work of (Telescu et al. 2013) Their reduced order model was obtained with a 5th order given as following:

$$G_r(z) = \frac{2.043z^5 - 3.057z^4 + 2.195z^3 - 1.545z^2 + 0.8617z}{z^5 - 1.518z^4 + 1.270z^3 - 1.032z^2 + 0.7539z - 0.3156}$$

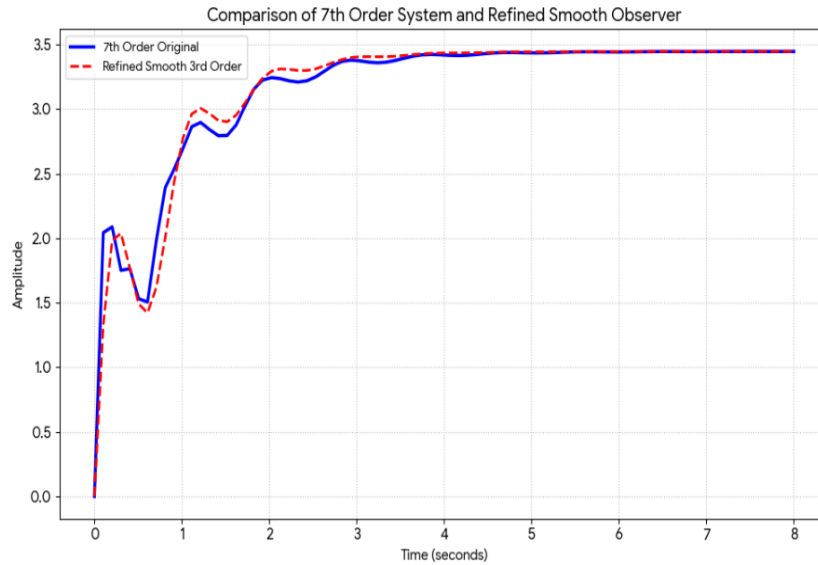


Figure 3. Full 7th order model and reduced 3rd order observer unity step responses.

Here, the model is given with five zeros and five poles (5th order reduced model), while ours is having only two zeros and three poles (3rd order reduced model). In addition to that, simulation results to a unity step inputs are obtained as shown in Figure 4. As observed, in addition to the previous notes, the Telescu's model diverges in less than two seconds.

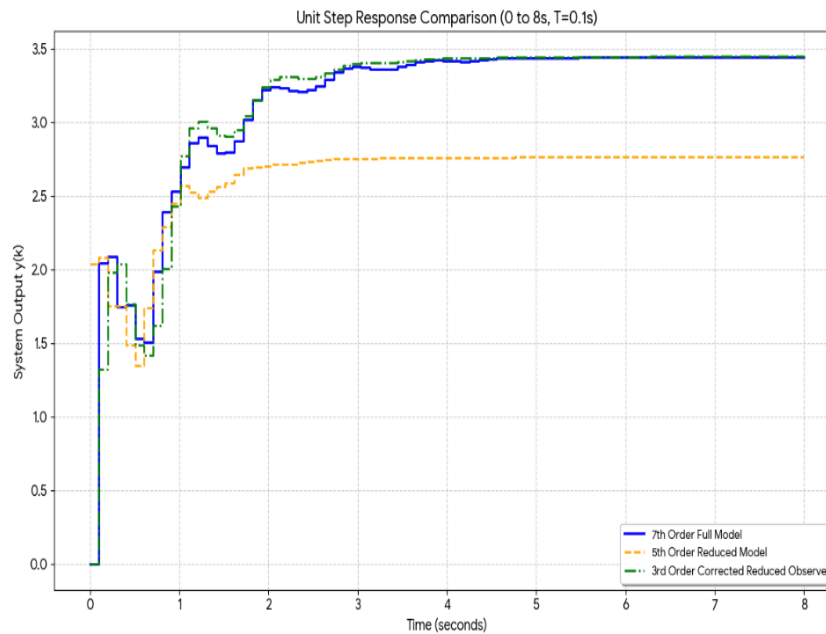


Figure 4. Full 7th order model, 5th and 3rd reduced order observers' unity step responses.

Conclusion

In this research, we have demonstrated that integrating artificial intelligence (AI) performed as (ANNs) into the design of reduced-order observers offers a highly effective and intelligent alternative to conventional estimation techniques derived from full-order systems. Using the learning capabilities of ANNs, the proposed approach successfully captures the essential system dynamics while significantly reducing model complexity for output feedback control. Results indicate that the neural-network-based reduced-order observer achieves superior estimation accuracy, faster convergence, and improved robustness when compared to traditional observer designs. This enhancement can be attributed to the adaptive nature of AI networks, which allows the observer to generalize nonlinear relationships and compensate for modeling inaccuracies that are typically difficult to handle using classical methods. Furthermore, the reduction in system order leads to lower computational

burden, making the approach more suitable for real-time implementation in practical control applications. Overall, the proposed methodology opens new directions for future research, particularly in extending the framework to strongly nonlinear systems where traditional methods may fail to deliver comparable performance.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest.

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