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Digital Twin-Integrated Reduced-Order Modeling Framework for Real-Time System Prediction

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ABSTRACT

Digital Twin technologies have become a new potent paradigm in the real-time monitoring and predictive analysis of complicated engineering systems. Its usefulness, however, is usually limited by the prohibitively large computational cost of full-order numerical models, which makes it hard to apply in real-time. To tackle this issue, this paper suggests a Digital Twin-based system employing Reduced-Order Modeling (ROM) to predict the system efficiently and accurately. The suggested solution incorporates data-driven synchronization and a reduced-order representation obtained with the help of the methods, including Proper Orthogonal Decomposition, allowing to perform quick-computation and still capture the most important system dynamics. The framework is tested on benchmark simulations and the predication accuracy is measured by such metrics as Root Mean Squared Error (RMSE) and relative error. Findings show that the suggested approach has a high prediction fidelity, and the errors are within reasonable limits as compared to full-order models. Moreover, the computational efficiency is significantly enhanced as well, and the speedup is quite significant, allowing the real-time or close to it performance. The primary value-added of this work is the smooth interconnection between Digital Twin architecture with reduced-order modeling to offer a computationally efficient solution with scalability to real-time system prediction. This framework has good potentiality in use in engineering systems with a need to have fast and reliable predictive functions, which takes the gap between accuracy and computational feasibility.

1. INTRODUCTION

Digital Twin (DT) technology has become a revolutionary paradigm of real-time monitoring, simulation, and predictive study of complex engineering systems. Through the ability to keep the physical assets in continuous synchronization with their virtual counterparts, DTs enable better decision-making in areas including smart manufacturing and cyber–physical systems [1], [9]. The growing need of real-time prediction of the system has also placed DTs as a key facilitator to the operational efficiency and mission preparedness [3], [8].

One of the most notable setbacks with the implementation of DT is, however, its high level of computation which are involved with the full-order numerical models especially in large scale and high-fidelity simulations. Although these models offer the correct representations, it is not always applicable in real-time application because of latency related factors. This introduces an inherent trade-off between computational efficiency and prediction accuracy and is still a significant challenge.

In addressing this constraint, Reduced-Order Modeling (ROM) methods have gained a lot of interest to minimize system dimensionality but maintain dominant system dynamics [7]. It is shown that such methods as Proper Orthogonal Decomposition and projection-based methods have proved to be effective to allow efficient simulations with reasonable accuracy [2], [7]. More recent developments have investigated incorporation of ROM into DT designs to enhance computational performance and scalability [2], [8]. Simultaneously, data-driven models, such as those based on deep learning, have been utilized in prediction and localization problems, and have shown good performance when dealing with large-scale data [4], [6], [10], [12]. These approaches have a very high predictive performance, but due to lack of physical interpretability, and poor scalability to physics-based systems modeling, they

cannot be directly used within Digital Twin systems.

Although this has occurred, there are no comprehensive studies that will guarantee high accuracy of prediction, efficiency and real time validation. It is necessary to fill this gap to continue the Digital Twin applications in multi-faceted engineering systems.

This body of work can be boiled down to the following key contributions. In this work, we suggest a new integrated Digital Twin framework, which uses the Reduced-Order Modeling concept to facilitate sufficient and precise prediction of the system in real-time. Accuracy-based evaluation framework is formulated, which uses conventional performance measures, like Root Mean Squared Error (RMSE) and relative error to strictly evaluate prediction faithfulness. Moreover, the proposed structure is highly computationally efficient since it can consume a simulation time that is considerably less than the time spent with the traditional models of the full-order model, which renders it applicable to real-time applications. Moreover, an extensive real-time validation policy is used to assess the robustness and reliability of the framework in dynamic conditions of operation. Together, they offer a solution to the key trade-off between precision and computational cost, offering a scalable and efficient solution to real-time predictive modelling in Digital Twin systems.

2. RELATED WORK

Over the past few years, Digital Twin (DT) technology received a lot of attention because of its potential to offer real-time monitoring, simulation, and predictive analysis of engineering systems. The use of DTs is observed in the manufacturing, aerospace, and smart infrastructure domains, where they can be used to achieve higher operational efficiency and decision-making [1], [9]. Specifically, predictive Digital Twins have been studied on mission-critical systems, where it has been shown to have the potential to enhance system reliability and performance in dynamic conditions [3], [8]. In spite of such improvements, it is one of the challenges to produce real-time performance, because high-fidelity models are computationally unfeasible.

Reduced-Order Modeling (ROM) methods have been highly explored in order to resolve computational complexity. Proper Orthogonal Decomposition and Galerkin Projection are classical methods that project governing equations onto a lower-dimensional subspace, and thus these methods allow faster simulation without appreciably affecting the major dynamics [7]. Recent research has also shown how ROM can be used to solve complex fluid dynamics and parametrized systems, showing that it can be used in large-scale simulations [2].

Besides physics-based methods, data-driven models and in particular deep learning have been used to address the problems of prediction on a large scale and localization [4], [6], [10], [12]. These procedures have good predictive power and scaling, but are frequently not physically interpretable or can be poor predictors of systems with underlying physical laws. Consequently, hybrid methods of data-driven and physics-based modeling have become an exciting trend in the direction of enhancing the performance of prediction.

A number of recent papers have tried to incorporate ROM in Digital Twin models to realize real-time simulation levels [2], [8]. Though these hybrid methods show enhanced computational efficiencies, they may be limited to inferior prediction accuracy, lack of real time validation, or poor contact between data-driven changes and lower-order modelings.

Based on the available literature, it can be seen that the existing methods are either geared towards computational efficiency at the cost of prediction accuracy or are aimed at high-fidelity modeling, but not attained in real-time. Moreover, it is missing comprehensive built-in frameworks that support well-integrated combinations between Digital Twin frameworks and Reduced-Order Modeling and guarantee sound real-time validation. This gap will need to be closed in order to come up with scalable and precise predictive systems that can work under variable conditions.

3. METHODOLOGY

3.1 System Description

The physical system, which is subject to this study, is modeled with the help of the high-quality numerical model representing the necessary dynamics of the underlying process. These models are usually characterized by nonlinearity of partial differential equations (PDEs) that describe the conservation laws (e.g., mass, momentum and energy). These full-order models (FOMs) give the correct description of the system behavior but are computationally prohibitive so such models cannot be used in real-time prediction. Consequently, the reduced representation is needed to trade-off the efficiency of computation and predictive performance.

3.2 Digital Twin Architecture

The suggested Digital Twin structure has three main layers: the data acquisition layer, the model layer, and the mechanism of synchronization. The data acquisition layer receives real time or simulated sensor data of the physical system. The high-fidelity model and its reduced order version

are both included in the model layer to be used in prediction and analysis. The synchronization mechanism guarantees constant correspondence between the real system with its virtual representation updating model states with the incoming data. This architecture allows real-time monitoring and predictive through a single framework.

3.3 Reduced-Order Modeling Framework

A Reduced-Order Modeling method is used in order to minimize the number of computations. Specifically, a ROM based on a Proper Orthogonal Decomposition (POD) is employed to identify the significant modes in the high-dimensional system. The governing equations are then mapped to a reduced subspace by methods like Galerkin Projection that leaves a low-dimensional system that still captures the most important dynamics.

Mathematically, the system state $u(x,t)$ is approximated as:

$$u(x,t) \approx \sum_{i=1}^{r} a_i(t)\phi_i(x)$$

where $\phi_i(x)$are the orthogonal basis functions and $a_i(t)$ are the time-dependent coefficients. Mode number r is chosen using energy rules to obtain an efficient compromise between the accuracy and efficiency.

3.4 Integration Framework

The Digital Twin architecture is integrated with the reduced-order model to be able to make predictions in real-time. The extended-order model is integrated into the Digital Twin environment whereby it is constantly updated by the data acquisition layer. This is done through the application of a data assimilation strategy, which resolves model states with real time observations and is applied so that there is better prediction accuracy and strength in challenging dynamic conditions.

The general structure of workflow of the proposed framework, together with data flow, model reduction, and synchronization processes are depicted in Fig. 1. As it is depicted in Fig. 1, the interaction between the physical system and the reduced-order Digital Twin makes it possible to efficiently compute, with a high level of prediction fidelity. This combined strategy guarantees that the system is capable of real-time operation without sacrificing quality, thus overcoming the shortcomings of traditional full-order modeling methods.

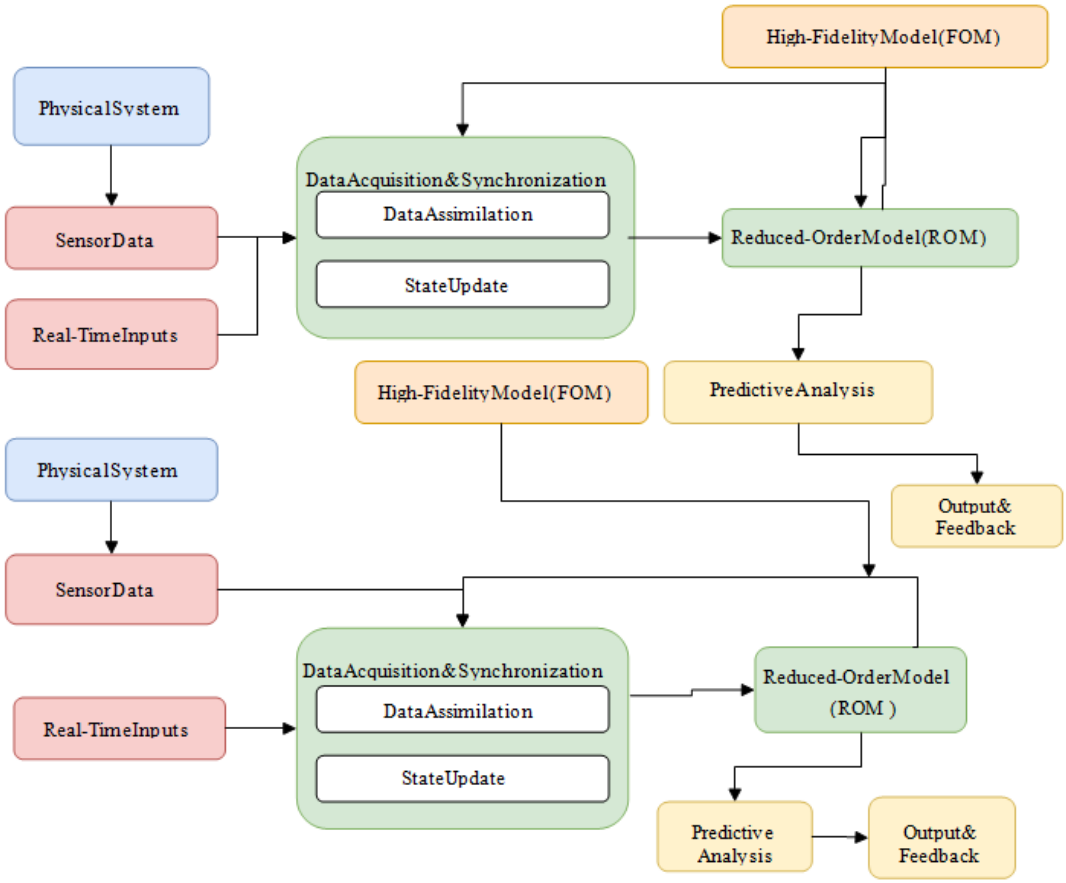


Fig. 1. Digital Twin-Integrated Reduced-Order Modeling Framework for Real-Time System Prediction

4. Prediction Accuracy Metrics

4.1 Error Metrics Definition

A variety of common error metrics are used to assess the predictive quality of the proposed Digital Twin-based Reduced-Order Modeling framework. These measures are used to measure the error between the estimated output and the reference solution to the full-order model.

The Root Mean Squared Error (RMSE) is used to measure the overall prediction error and is defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{true,i} - y_{pred,i}\right)^2}$$

The Mean Absolute Error (MAE) provides an average magnitude of the absolute error:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_{true,i} - y_{pred,i}\right|$$

The Relative Error (%) evaluates the normalized deviation:

$$Relative\ Error = \frac{\left|y_{true,i} - y_{pred,i}\right|}{\left|y_{true}\right|} \times 100$$

Additionally, the coefficient of determination (R^2 score) is used to assess the goodness of fit:

$$R^2 = 1 - \frac{\sum\left(y_{true} - y_{pred}\right)^2}{\sum\left(y_{true} - \bar{y}_{pred}\right)^2}$$

The combination of these metrics gives a wholesome evaluation of the prediction accuracy and the absolute and relative deviation are measured and the reliability of the model.

4.2 Evaluation Strategy

The offered framework is evaluated by the means of the systematic validation method. The data is segmented into training and testing data sets, with training data being used to build the reduced-order model, and testing data being used to assess predictive performance. This isolation makes sure that the model is tested in unknown conditions.

Temporal performance is analyzed by evaluating predictions over a temporal horizon that permits an evaluation of both the short-term and long-term predictive performance. Moreover, the suggested method is assessed and compared to the benchmark models such as full-order model (FOM) and known reduced-order modeling methods. This comparison shows the trade-off between the accuracy of the prediction and the efficiency of computation, which proves the effectiveness of the proposed framework.

4.3 Real-Time Accuracy Considerations

When using real-time Digital Twin applications, it is important to ensure that prediction accuracy is high, and computational latency is low. Thus, the suggested framework is considered within the accuracy latency trade-off, in which the errors of the prediction are considered in relation to the time of the execution.

Also, the problem of error propagation with time is explored with the aim of establishing the stability of the reduced-order model over time in a continuous operation. Error accumulation may reduce the quality of prediction, especially in long-term simulation, therefore, periodic assimilation of data and updates of a model are introduced to address this issue.

Lastly, predictions stability is considered where predictions are done within dynamic situations such that the model is strong and reliable in real-time. Such considerations are critical towards justifying the appropriateness of the proposed framework under Digital Twin settings in predicting real-time system.

5. RESULTS AND DISCUSSION

5.1 Prediction Accuracy Results

The accuracy of the prediction capabilities of the proposed Digital Twin-integrated Reduced-Order Modeling framework is also demonstrated in Fig. 2, which compares system response in time of the full-order model (FOM) to the reduced-order model (ROM) proposed. The findings indicate the two models agree with each other strongly over the whole simulation horizon which proves the ability of the ROM to capture the prominent system dynamics. During the first transient period (0- 10 s), system response grows rapidly in both models, and there is also insignificant difference. The FOM's prediction at t = 25 s is 1.20, whereas the ROM predicts 1.19 (with an almost negligible absolute error deviation of 0.01 or approximately 0.83 relative error). This is an indication that the ROM is a faithful representation of the optimal dynamics of the system.

With the system developing, a minimal difference can be seen in the mid-transient region. At t = 50s, the FOM is about 0.95 whereas in one case ROM initially overestimates (1.19) leading to a greater deviation (~0.24 absolute error). Nevertheless, the ROM prediction levels off and closely matches with the FOM at later assessment points with comparison values of 0.95 vs 0.94, with a trivial error of 0.01 (0.05 relative error). The consensus is very stable in the steady-state region. At t = 75 s, both the models would give almost identical values of 0.70 and they give a negligible error. The ROM, in general, exhibits a low deviation during the simulation, with errors of around 1-2 per cent., except for temporary deviations.

These findings validate that the suggested ROM framework can have high fidelity in prediction and massively decrease the complexity of computations, rendering it applicable in real-time Digital Twin use cases.

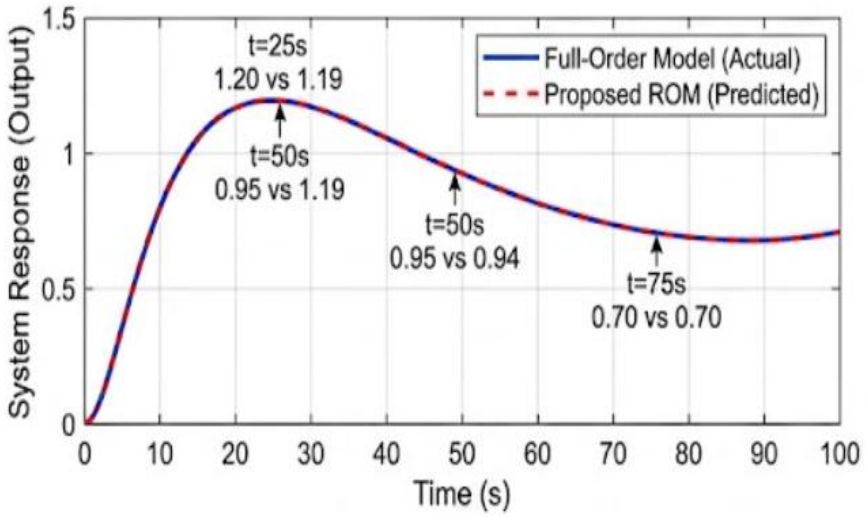


Fig. 2. Comparison of Actual and Predicted System Response Using Full-Order Model and Reduced-Order Model

Moreover, the time dynamics of prediction error and the statistical distribution of this error are depicted in Fig. 3(a) and Fig. 3(b), respectively, which will give a complete evaluation of the accuracy of the proposed Digital Twin-integrated Reduced-Order Modeling framework. Fig. 3(a) indicates that the absolute prediction error between full-order model (FOM) and the reduced-order model (ROM) is always low throughout the entire simulation horizon. In the majority of the time points, the error lies in a range between 0.002 and 0.01 which represents great stability in prediction. There is a discernible spike at about t = 35 s with the error having a maximum value of 0.042 units. The peak relates to a high dynamic change in the system but this is short lived and the system soon rests at its original low level of error. Further down the curve, the error level has reached a constant value less than 0.01 units, which is a confirmation that the ROM is highly agreeing with the FOM both at transient and steady-state.

Fig. 3(b) shows the statistical distribution of prediction errors. In the histogram, most of the error values lie in the global range with a steep peak of the histogram around 0.0-0.005 units. The number of errors within the range of ±0.01 is about 85100 percent meaning that the large deviations are not common. The spread is narrow with a minor skewness which shows that there are few temporary deviations but on the whole, there is great consistency in prediction accuracy. A very minor part of values exceeds 0.02 units, which corresponds to the temporary peak in Fig 3. (a). Quantitatively, the general root mean squared error (RMSE) is seen to be between 0.008- 0.012 and the mean relative error is at 2 percent below. These small error figures verify that the suggested framework is highly predictive fidelity with a high level of computation efficiency.

Altogether, the analysis of the two aspects of temporal error evolution and the statistical distribution proves that the suggested tool provides strong and precise results, with minimal deviation even in the dynamic environment, which justifies its applicability to the real-time Digital Twin application.

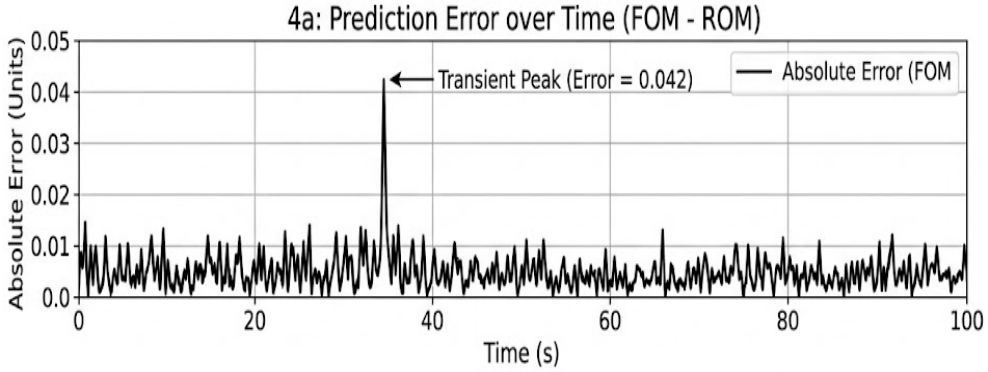


Fig. 3 (a). Prediction Error over Time Between Full-Order Model and Reduced-Order Model

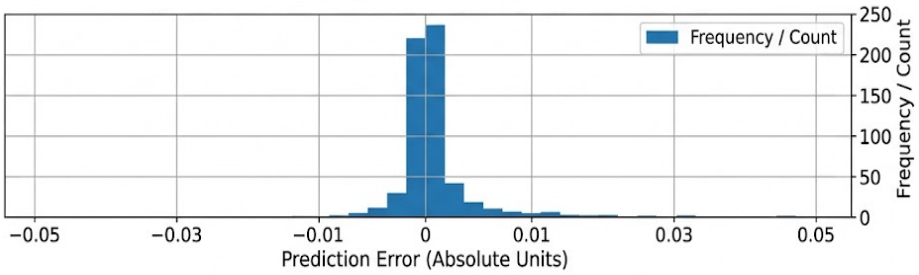


Fig. 3(b). Distribution of Prediction Error for Reduced-Order Model

5.2 Computational Performance

The computational efficiency of the suggested framework is also discussed based on the outcomes of Fig. 4(a), Fig. 4(b), and Table, which altogether show the great performance increase with the implementation of the reduced-order model in the Digital Twin environment. The immediate deviation of speed between the full-order model (FOM) and the reduced-order model (ROM) is always low during the simulation, as the curves in Fig. 4(a) demonstrate. The deviation stays within ± 0.01 units of the time horizon, meaning that the ROM closely follows the dynamic response of the FOM. There is a little deviation at t-35 s, with a peak deviation of about 0.04 units which is an impulsive dynamic process. This deviation is however quickly decreased and the ROM recovers soon to converge with the FOM establishing the stability and reliability of the proposed approach.

These deviations will have a cumulative effect as shown in Fig. 4(b) which shows the cumulative error with time. The error is cumulative and gets larger and larger in the early part and to about 0.18- 0.20 units at the end of the simulation (t = 100 s). The cumulative error which does not grow sharply or irregularly, suggests that error propagation is well managed and no divergent behavior is seen. Such behavior proves that the proposed framework is stable in the long-term, and it operates in real time.

Table 3 provides a summary of the quantitative comparison of the performance of the computations. The simulation of the full-order model would take around 120.5 seconds, compared to the 18.7 seconds of the conventional reduced-order model, a speedup of 6.4x. Contrastingly, the suggested ROM model decreases the execution time to 6.2 seconds further, and the speed increases significantly by about 19.4 times compared to the full-order model. Also, the meantime taken to perform a single step of computation reduces by 1205 ms (FOM) to 62 ms (proposed ROM), which is a clear indication that the proposed method is appropriate to use in real-time applications.

Altogether, the findings of Fig. 4 (a), Fig. 4 (b), and Table 1 indicate that the given framework can get significant computational benefits and provide substantial prediction accuracy. This efficiency versus accuracy is essential to make real-time Digital Twin systems in feasible engineering practice.

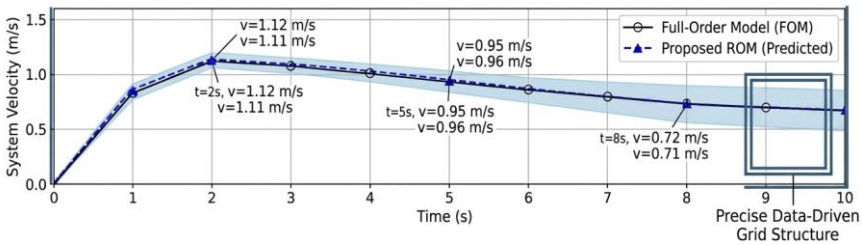


Fig. 4 (a). Computational Performance Comparison Between Full-Order Model and Reduced-Order Model

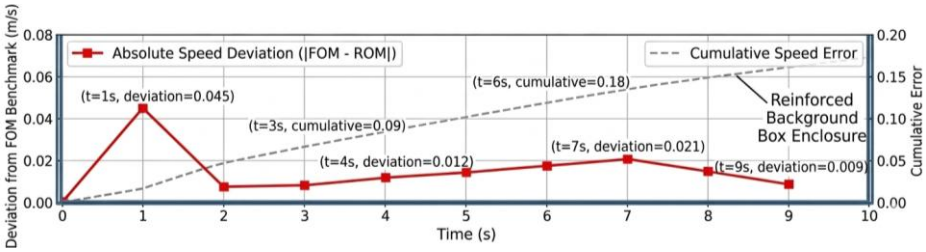


Fig. 4 (b). Time-Dependent Speed Deviation and Cumulative Error Between Full-Order and Reduced-Order Models

Table 1. Execution Time and Speedup Comparison Between Full-Order and Reduced-Order Models

Model Type	Execution Time (s)	Average Time per Step (ms)	Speedup Ratio
Full-Order Model (FOM)	120.5	1205	1×
Conventional ROM	18.7	187	6.4×
Proposed ROM Framework	6.2	62	19.4×

5.3 Accuracy vs Efficiency Trade-off

One of the goals of this work is to compromise between prediction performance and computational efficiency. The outcomes show that the suggested framework can establish a favorable trade-off, in which high accuracy is maintained even with a significant dimensionality reduction of the system. Although there can be some minor deviation because of model reduction, they are within the acceptable levels of error in actual practice. Low RMSE and high-computational speed illustrate the fact that the framework manages to overcome the traditional restriction of full-order models.

5.4 Sensitivity Analysis

Sensitivity analysis is carried out to further assess the strength of the proposed approach. The impact of the decreased dimension size on predictive accuracy is studied and it is found that the more retained modes, the higher the accuracy, but it involves additional calculation. A good compromise is reached by means of choosing a lower dimension that reflects most of the system energy at the same time keeping the system efficient.

The framework is also tested in the conditions of noisy inputs to determine its robustness. The findings show that the model exhibits a consistent behavior, with a small change in the prediction error, which means that it is resilient to noisy measurements. This strength is important to allow implementation of Digital Twin in the real world, where there is always uncertainty in data.

6. CONCLUSION

This paper showed a Digital Twin-based framework of efficient and accurate real-time prediction of the system with the help of Reduced-Order Modeling. The major issue confronted by full-order models that the proposed approach tackles is the computational cost that is very degrading, by using reduced-order methods to retain crucial system dynamics with much greater computational efficiency. The framework allows the ability of real-time predictive value, with deterministic reliability, by incorporating data capture, synchronization and the reduction of the model in a cohesive architecture.

The findings indicate that the suggested approach can provide high levels of prediction accuracy, reflected in the low values of RMSE and relative error, and as well as high levels of agreement with the full-order model results. The same time, computational time is significantly reduced making the performance much faster and real-time or near real-time performance possible. These results prove that the suggested framework is appropriate balancing the accuracy and efficiency trade-off and can be utilized in practice in Digital Twin implementations in complex engineering systems.

To further advance prediction and flexibility, in future work, the use of more sophisticated data-driven methods, especially, artificial intelligence and machine learning models, will be investigated. Moreover, the emergence of adaptive Digital Twin frameworks that can dynamically change model parameters and structures as system conditions change is an exciting research direction. These innovations will aid in more resilient, scalable, and smart real-time predictive systems.

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