Abstract

The reduced basis finite element analysis (RB-FEA) technology was utilized for performing structural analyses of a semi-submersible drilling rig. The digital twin of the drilling rig based on the RB-FEA technology is about 1000 times faster to analyze than a conventional FEA model, without any compromise in the accuracy of the solution. The global model was established by integrating the individual components of the RB-FEA model with associated material properties, loads, and boundary conditions. The software for mapping of the wave loads (generated by software such as WAMIT/WADAM) onto the hull structure of the drilling rig was developed. Time domain strength and fatigue analyses were then performed for the whole structure that also included the highly refined fatigue sensitive regions of the drilling rig.

The results from the study demonstrated the efficiency and the accuracy of the RB-FEA based technology. The speedup and level of detail achieved through the RB-FEA technology is a key enabler for the digital twin technology since it enables true condition-based modeling of large and critical assets, allowing all relevant structural details to be included in the model, along with sensor and inspection-based condition data such as cracks, corrosion, and damage due to impact or collision. Asset life extension – enabled by the digital twin and condition-based monitoring using sensor systems – is the key to capitalizing on the value of existing facilities that are operating near (or beyond) their original design life.

Introduction

The concept of digital twin has been around for some time in the oil and gas industry. At a basic level a digital twin is a virtual model of a physical asset. In the case of oil and gas operations, it is a model of any production and processing asset, such as a semi-submersible or a drillship. Pairing the virtual and physical worlds via a digital twin allows analysis of data and system monitoring in a way that dramatically improves operations, preventing downtime, reducing maintenance costs, and providing data that can be used to streamline operations throughout the lifecycle of the asset.

Finite Element Analysis (FEA) has been the industry standard technology for structural analysis since the 1970s. It enables detailed calculations of all relevant structural quantities and with appropriate post-processing it allows standards-based calculations of key outputs such as buckling capacity utilization and structural fatigue. However, in practice the key limitation of FEA is that it is computationally intensive and therefore practitioners will limit their model size or detail to be at most 2 or 3 million FEA degrees of freedom. Work-around for these limitations include use of coarse global models with fine sub-models in highly stressed areas to perform the required range of structural analysis tasks. Sub-modeling comes with its own set of drawbacks, for example one must maintain multiple submodels for each asset and ensure they remain consistent each time an update or modification is performed. Additionally, sub-models inherently ignore non-local effects, e.g. the effect of a defect in one sub-model cannot be propagated to other sub-models.
Advances in sensor technology, machine learning and internet of things (IoT) are enablers for the “digital oilfield”. These technologies need to be complemented by analysis tools to achieve a truly digital oilfield. The most important limitation of the FEA workflows is that they are not compatible with the other technologies that form the core of the digital oilfield, e.g. sensors, big data, and machine learning. FEA is too slow to keep up with sensor feeds, and cannot be run enough times to collect statistical data that can be used for big data analysis of machine learning. Also, due to the limitations of the submodeling approach it is only able to provide detailed structural integrity insights on regions that have been designated a priori for detailed sub-modeling.

To overcome these limitations and fully leverage the benefits of coupling physics based simulation with the other key digital technologies, what is needed is a solver that enables both fully detailed global modeling of floating assets, as well as a significant increase in solver speed. This is exactly what is provided by Reduced Basis FEA, or RB-FEA.

**RB-FEA Methodology**

The RB method is a well-established technique for reduced-order modeling of parametrized partial differential equations. It has been applied widely in contexts where many-query analysis (such as optimization, or statistical analysis) or real-time response is required.

To apply the RB method, a parametrized partial difference equation (PDE) must first be defined. This requires a geometric domain (e.g. defined by an FEA mesh with shell or solid elements), a physics type (e.g. equilibrium elasticity), boundary conditions, and a vector of model parameters to be defined. Each entry of the vector of model parameters typically defines a distinct property of the model, e.g.:

- material properties such as Young’s modulus, Poisson ratio, or density on subdomains of the model,
- loads and boundary conditions on surfaces of the model,
- geometry, such as size or shape of sub-regions of the model.

Once the above data is specified we have a parametrized family of models in which any specific choice of the model’s parameter vector within the allowable range corresponds to a different model. With conventional FEA one would have to solve a distinct FEA problem for each distinct choice of parameter vector, which can be computationally intensive. The RB method addresses this via a two-phase Offline/Online approach: First a Reduced Basis approximation is constructed during the Offline phase, and then the Reduced Basis approximation is utilized for fast analysis during the Online phase. We provide a more detailed description of each phase below.

The Offline phase builds up an RB approximation by selection of a sequence of parameter vectors within the model’s parameter range. The parameter vectors are selected by the RB Greedy Algorithm, which uses a residual-based error estimator to identify the parameter vector that is least-well represented with the current RB approximation. A full FEA solve is performed for each newly selected parameter, and the solution for that FEA problem is orthogonalized with respect to the previously selected solutions and added to a set of RB basis functions. A corresponding dataset is also calculated for each FEA solve to enable us to efficiently evaluate the RB approximation itself (discussed below), as well as the residual-based error estimator that is used in Greedy parameter selection. The Greedy Algorithm has been extensively analyzed in the literature, and it has been shown subject to reasonable assumptions to deliver exponential convergence. Thus, this method enables us to build up an accurate RB approximation to the parametrized PDE by solving a sequence of FEA problems.

The Offline stage terminates once the residual based error estimator indicates that a pre-specified error tolerance has been reached by the RB approximation. At this point, we may then proceed with the Online phase, in which the RB approximation can be solved for any parameter vector within the allowable range. The RB approximation consists of a Galerkin projection with the identical form as the original FEA problem, but in which the projection is performed only over the RB approximation space, rather than the FEA approximation space. The RB approximation space usually consists of between 10 and 100 basis functions, and hence offers a very large reduction in model size compared to the FEA approximation which may have dimension greater than $10^3$ or $10^5$. This dimension reduction is the source of the large acceleration provided by RB. Also, the RB method can provide an a posteriori error estimate for the RB approximation, which bounds the error between the RB approximation and the result that would have been obtained had we run the corresponding FEA solve.

We note that theOffline stage can be computationally intensive, since it can involve many FEA solves for many different “Greedyly selected” parameter vectors. However, the Offline stage need only be performed once, and the resulting RB approximation can be reused as many times as it is needed. Based on this framework it is now clear why the RB method is well suited to both the many-query case – in which the upfront cost of the Offline phase is amortized over many Online solves – and the real-time context – in which the cost of the Offline stage is not relevant since all that matters is the speed of the Online solves.
The RB method described above is highly effective for Offline/Online model reduction of parametrized PDEs. However, to apply the methodology to industrial-scale problems it has been found to be very beneficial to combine the RB method with a component-based substructuring approach, which we refer to here as RB-FEA.

The substructuring formulation separates the degrees of freedom in a model into interface degrees of freedom and component interior degrees of freedom. RB-FEA then consists of applying the RB method to component interiors, and a transfer eigenvalue “optimal modes” degree of freedom reduction on component interfaces. The combination of these reduction methods on component interiors and interfaces leads to a highly efficient computational procedure in the Online stage, in which large models can be solved orders of magnitude faster than with conventional FEA, while also permitting the same parametric variations at the component level as described in the previous section for the RB method. In fact, an RB-FEA model can enable a very large number of parameters since a model may consist of 1000 components or more, and if each component has only a few parameters then the overall model can contain well over 1000 parameters. This capability for handling many-parameter problems, which is facilitated by the component-based divide-and-conquer approach, is far beyond the capabilities of most model reduction techniques as the so-called “curse of dimensionality” typically imposes strong limits on the number of parameters that can be considered.

As with the RB method, RB-FEA also consists of both an Offline and Online phase. The Offline phase requires applying the RB training process to component interiors as well as “optimal mode” model reduction on component interfaces. Hence the Offline stage may be quite computationally intensive. However, we note that the Offline phase only ever involves computations based on one or a few components, which means that the training can be applied component-by-component to build up a large set of components, and then large component-based models can be solved while only ever performing FEA solves of a size that is a small fraction of the overall model size.

The RB-FEA Online phase consists of assembly of a reduced system of equations in which the component interior degrees of freedom are obtained via fast RB solves for the component interiors. Once system assembly is complete, we then solve the reduced system and can post-process and visualize results as needed, analogously to standard FEA.

For a detailed Digital Twin of a floating asset, this reduced system for an RB-FEA model may have size of approximately 10,000 to 500,000 degrees of freedom, which would typically correspond to a reduction of about 1000 compared to the number of degrees of freedom (dof) for an FEA model with an equivalent level of detail. The reduction in system size, and the fast matrix/vector assembly due to RB on component interiors is the enabler for RB-FEA’s fast and scalable analysis of large-scale models. We also note that RB-FEA is based on standard FEA meshes, and hence an FEA analysis of an RB-FEA model can be performed easily. Figure 1 shows the steps involved in the RB-FEA and conventional FEA workflows.
An example of the use of RB-FEA approach for the crack analysis within an FPSO is shown in Figure 2. The global model was built by assembling more than 850 components. The number of FEA dof for this model was of the order of 30 million. The global model had highly refined local regions that allowed:

- modelling of localized defects e.g. cracks, corrosion, damage etc.
- evaluation of crack propagation quantities e.g. J-integrals
- fatigue analysis on condition-based models
- capturing cumulative effects of all identified defects.

Figure 2: FPSO structural modelling and crack analysis based on the RB-FEA approach.

Drilling Rig Case Study

The application of the RB-FEA technology for a digital twin is presented here for a drilling semi-submersible. The primary focus of the study was to investigate the hydrodynamic loading on floating structure and fracture mechanics in a global model. Hydrodynamic loading analysis can require thousands of solves. Akselos’ RB-FEA makes this fast and efficient for large, detailed models. The semi-submersible is a relatively coarse model used for validation purposes, with approximately 400,000 FEA degrees of freedom, including beam elements and mass elements to model the top-side. The RB-FEA solve in this case requires 0.4 seconds, compared to 45 seconds for FEA. For each time step, wave pressures (generated by software such as WAMIT/WADAM) are mapped onto the hull (see Figure 3), and the RB-FEA solve is performed in less than one second. This speedup in computational capability makes it possible to carry out time domain fatigue analysis of large offshore structures, which previously was not possible because of the vast amount of time needed to perform the calculations using conventional FEA software programs. Applying the capabilities of the RB-FEA method, actual sensor measurements of platform motions and wave data now can be used to perform detailed fatigue assessments.
The RB-FEA global models, with highly refined local regions, enable evaluation of J-integrals and other fracture mechanics quantities within the context of a global (i.e. full-asset) solution. Parametric models enable crack geometry to be updated in seconds – speeding up analysis and studies. A significant step toward improving maintenance is the capability for inspection results to be imported directly into the global model so crack growth assessments can be performed to optimize inspection intervals.

Conclusions

The digital twin has been proven in other industries such as aerospace as a reliable and versatile tool. Improvement in the computational time achieved using RB-FEA based digital twin along with the integration of sensor and inspection data is a significant step in moving the offshore oil and gas industry towards a real-time condition based risk assessment. History has shown that major accidents result when there is a breach in multiple safeguards or barriers. Experience with complex engineered systems demonstrates the need for recognizing and developing an approach to assessing and managing real-time degradation of barriers in an interactive way during operations which recognize rare but potentially catastrophic failures. Until now, the challenge has been that companies have been grappling with the degradation of critical barriers while at the same time struggling with a large volume of data coming from multiple sources. Without a harmonized process for extracting and managing the appropriate vital data, it was not possible to get value from the influx of information coming from disparate streams in dissimilar formats. The digital twin addresses that problem by delivering a common data platform that enables the timely exchange of information among stakeholders to help prevent these types of accidents in the future.

References

