Bridging the Gap between High-Fidelity Multi-Disciplinary Simulation and the Design of Military Systems with Physics-Based Surrogates

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ABSTRACT

During this age of attention on acquisition reform, a method of shortening the timeline, reducing cost, and increasing the fielded vehicle's performance is essential. Achieving the large reduction in timeline desired will require more than process improvements. Although Model-Based Systems Engineering will help, it is in improving the model and making it available earlier that a revolutionary change can occur. This paper describes a method of incorporating physics-based computational science and engineering much earlier in the design cycle through surrogates, as well as the potential payoff of doing so.

1.0 BACKGROUND

Over the last several decades the US government, industry, and academia have created a rich foundation of physics-based analytics (PBA), including computational science and engineering (CSE) tools for fluid dynamics and propulsion (CFD), structural mechanics (CSM), structural dynamics (CSD), and electromagnetics (CEM), to name just a few. These tools have made great progress becoming applicable to the entire envelope of operation of targeted vehicles. However, over the last few decades of development the focus of these CSE tools has been on individual improvements to each of them, rather than multi-disciplinary integration of the tools into a system-level view of the vehicle. Further, while these PBA tools have become accurate and robust, they still require computational times many orders-of-magnitude larger than real-time, making them difficult-to-impossible to incorporate into a design setting, or for decision making at the speed of relevance.

For example, a Computational Fluid Dynamics (CFD) code that is extremely accurate, but requires a day or more of wall-clock time to compute a single point in the sky is not very useful to the Stability and Control (S&C) engineer that needs an entire envelope of solutions to populate the "plant" of the automatic flight control system. The S&C engineer also needs to include the effects of other disciplines, such as aeroelasticity and/or thermal elasticity, in the plant to get an accurate response during operational use in many cases. This same reasoning applies to the Loads engineer using the CFD code. It is of critical importance that the focus move from single discipline use of CFD to an integrated multi-disciplinary use at the speed necessary to impact the other disciplines, in other words at the "speed-of-relevance."

One of the driving reasons to make these changes to our focus is the need to reduce the overall timeline of the vehicle development cycle. Due to increased complexity in the system and late detection of defects, among others, the development cycle is growing from years to decades in our major aircraft programs. One sure way to reduce the timeline is to move the use of high-fidelity tools to the left on the timeline to eliminate defects in designs long before the first aircraft is manufactured or even before the first wind tunnel model is tested. The earlier a design decision is "locked-down" the more impact it has on the lifecycle cost of that system. A better understanding of the system response and performance earlier can aid in increased iterations of the design and an optimization of the vehicle can be achieved, ensuring these "locked-down" decisions are the correct ones.

So, the question becomes, "How do I take CSE solutions that require days on thousands of compute cores and incorporate them in a model of the system that is faster than real-time to execute, accurate enough to represent the system, robust enough to work at all flight conditions, and requiring resources that can even reside on-board the aircraft?" Clearly a new approach is required that includes additional software over the physics-based codes themselves. A software stack that can take large amounts of high-fidelity data and even data gathered empirically across the aircraft envelope and represent it as a fast-executing model of the system will be extremely useful to decision makers. The key ingredient in this new software is the ability to create physics-based surrogates that retain the accuracy of the high-fidelity methods, but are very fast to execute.

2.0 DECISION SOFTWARE STACK

This section describes a software infrastructure to support this vision that incorporates Physics-Based Analytics (PBA), Data-Driven Analytics (DDA), Digital Surrogates (DS), and Decision Support Apps (DSA) and some examples of each. Figure 2-1 is a depiction of this software stack that also gives an indication of how each element interacts with the others. The next several sub-sections describe the elements of the Decision Software Pyramid of Figure 2-1.

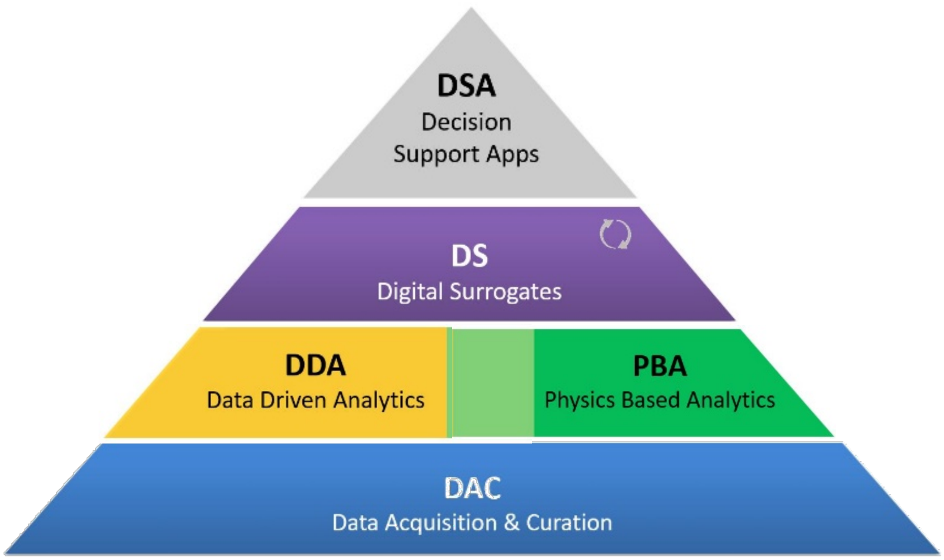

Figure 2-1: Decision Software Pyramid.

2.1 Physics-Based Analytics (PBA)

PBA software are founded on physics first-principals, such as the Navier-Stokes equations for CFD, Maxwell's Equations for CEM, and Newton's 2nd Law for CSM or CSD. The governing equations, boundary conditions, initial conditions, and closure equations are typically solved along with some discretized representation of the geometry to obtain an approximate solution constrained by the physics being represented. Solution of these large systems of equations for complex aircraft can require days to compute using thousands of compute cores, depending on the desired accuracy and geometric complexity.

Example physics codes for CFD in general use today are HPCMP CREATE™ Kestrel[1-3] and Helios[4], NASA’s FUN3D[5], Ansys Fluent[6], Metacomp’s CFD++[7], Siemens STAR-CCM+ [8], to list just a few. These codes are proving quite good at simulating detailed static and dynamic aerodynamics of vehicles for a wide range of conditions. Similarly, CSM, CSD, and CEM have government and commercial software available. All of these high-fidelity codes require computational resources that make them difficult to integrate into a design optimization loop, but they are reliable and accurate to varying degrees.

2.2 Data Acquisition and Curation (DAC)

In addition to the available PBA, there is a wealth of available flight and ground test data, as well as maintenance data from logistics centers and industry partners that could be used for decision making. However, the wealth of data (possibly measured in Tera-bytes to Peta-bytes) is not easily searched, and may not even reside in the same locations or reside in digital form on the same computer systems, making it difficult to use to irrelevant for decision makers. It is essential to have a method of data acquisition and curation (DAC) for Program of Record (POR) systems that make the data available in a usable form. Software must be available to put all of the data in a format that is easily read, and all of the necessary data needs to be accessible through connected hardware across an accessible network. Obviously, the advantage of including this data is tying the resulting surrogate or system model to the reality of the flying aircraft when that data is available.

2.3 Data-Driven Analytics (DDA)

Once the data is available and usable, new tools using Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) for Data-Driven Analytics (DDA) can be applied to allow trends and inferences from the data to affect the developing system throughout its lifecycle.

2.4 Digital Surrogates (DS)

Once PBA and DDA exist for an air, land, or sea vehicle, a method of interrogating the results must be available with response times that are relevant for the desired use. For example, PBA may be desirable for new vehicles under consideration in which little or no test data exists. High-fidelity aerodynamics, propulsion, and structures data are needed to combine into a system-level look at the flight performance of a vehicle (e.g., required fuel and available payload for a particular mission trajectory). However, computing this data using PBA may require days to weeks on tens of thousands of supercomputer processors to compute the required trajectory as a time-accurate simulation. These computational requirements would make the PBA irrelevant to current system planners or new system designers who need faster turnaround. Similarly for DDA, if an aircraft, ship, or ground vehicle has been in service for a period of time and it is important to leave it operational as long as possible, DDA could be used to make a decision on whether the vehicle needs to be taken out of service based on historical maintenance data. However, searching Tera-bytes of data on disparate computer systems to determine its state of health may require more than the required time for the decision. It may also be desirable to augment the DDA with PBA to understand the system's performance in new, untested operational conditions. Clearly PBA or DDA individually, or PBA and DDA together need to be used to create a "surrogate" that can be used to give the required data in the desired timeframe.

A surrogate is an "on-demand" source for technical information for an air, land, or sea vehicle or weapon system. Given design data (geometry, materials, operational envelope) and/or historical data (inspection, maintenance, operational history, test, and sensor data) for a weapon system or vehicle, we want immediate access to performance (aeromechanical, hydromechanical), state (structural, thermal), and signature (electromagnetic, infrared, acoustic) information. A digital surrogate can be synthesized using PBA and DDA described above using these inputs to produce the required performance, state, and signature information. The digital surrogate could encompass the full system operational envelope, run faster than real-time, and execute on modest computer resources - laptop or hand-held devices.

Surrogates can be built in many ways, depending on the desired accuracy and performance. It could be as simple as a very large database of points computed with PBA that are used to interpolate to the desired input conditions. Unfortunately, this becomes untenable for complex systems with non-linearities, due to the number of points required to get the interpolation accuracy desired. A more useful approach is to use the PBA codes to produce data that is used by Artificial Intelligence (AI)/Machine Learning (ML) tools to produce a surrogate from the data with much improved performance for points within the cloud of PBA solutions. For example, a CFD code can be used to compute the resulting coefficients of lift, drag, and pitching moment (C_L, C_D, C_M) for input angle-of-attack, sideslip, and pitch rate (alpha, beta, q) as a function of time that describes a manoeuvre. A set of these manoeuvres at a set of flight conditions (Mach, Altitude) can then be used as the inputs to a neural network (see Figure 2-2) that creates a surrogate. The same approach can be used for distributed loads if a Proper Orthogonal Decomposition (POD) of the surface loads is computed from the CFD results and used as inputs to the neural network. DDA representing wind tunnel and flight test data can be added to the inputs, as well to get a surrogate based on both PBA and DDA. It is important to note that the PBA and DDA resources are still necessary, but they can be pre-computed with an optimal number of required solutions and conditions required at a moment's notice computed with the surrogate instead.

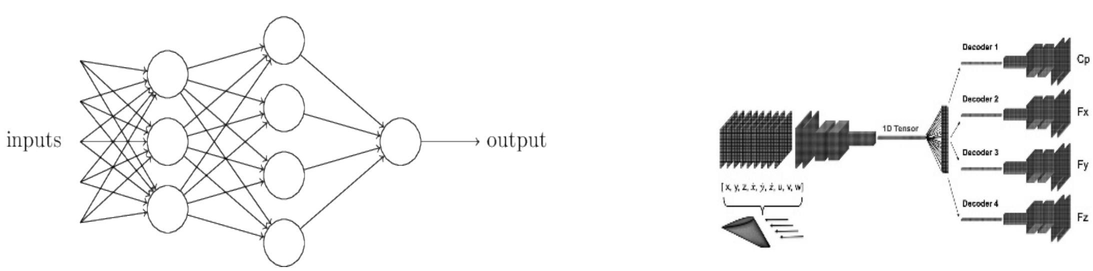

Figure 2-2: Example Neural Networks.

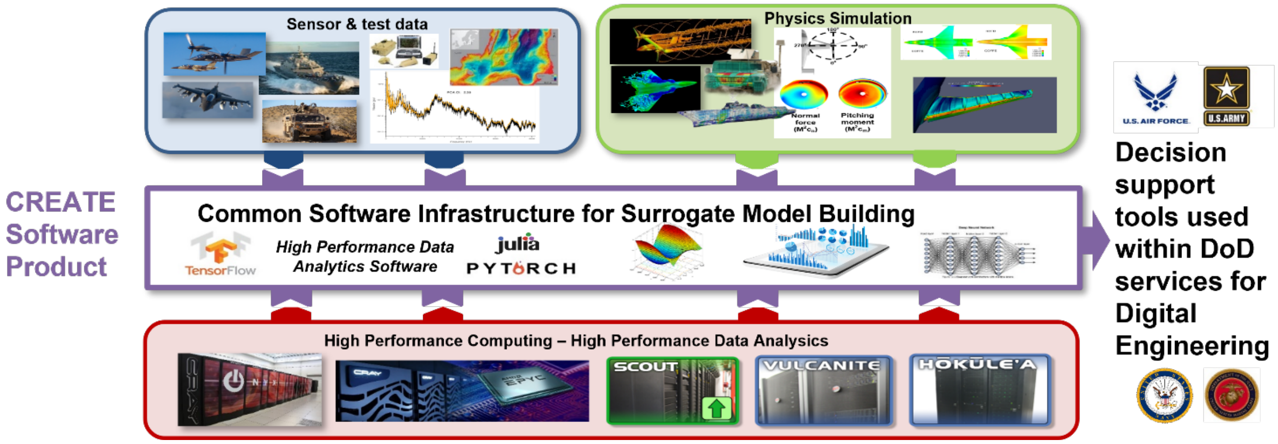

Figure 2-3: Example Surrogate Software Development Library.

The key to this approach is to make the surrogate build process robust and automated for the PBA and DDA codes used in the process. Figure 2-3 above depicts a process the US DoD High Performance Computing Modernization Program (HPCMP) Computational Research and Engineering Acquisition Tools and Environments CREATE™ program is developing to build the surrogates using the CREATE PBA codes, HPCMP supercomputers, and aircraft historical data. As can be seen in the middle section of the figure, the intent is not to develop new codes for AI/ML. Off-the-shelf tools like PYToRCH[9], TensorFlow[10], Julia[11], and Dakota[12] are examples of codes that are being linked as libraries in the process. The power of productionizing and automating this process is that if the design changes (e.g., outer mold line, structural materials, thermal properties) the surrogates can be re-generated immediately maintaining an accurate relevant model through the acquisition cycle.

2.5 Decision Support Apps (DSA)

A Decision Support App (DSA) can be produced specifically for POR systems and their desired uses that take advantage of the digital surrogates, but roll up the data along with other surrogates to perform a decision support function, such as mission analysis or maintenance scheduling. These DSA can be fast, mobile, and available where needed for decision makers in all phases of the acquisition lifecycle. They could be used across a range of applications from research and engineering to test and evaluation, as well as by maintenance and logistics engineers, or even by operational leaders.

Examples of DSA exist today. Two examples of these codes are aircraft design codes that incorporate mission analysis, such as HPCMP CREATE™ ADAPT[13], or war campaign modelling, such as AFSIM[14]. These codes require models with very fast turn-around to produce the vehicle performance, state, and signature, and have traditionally achieved this by using models with limited accuracy or applicability. By replacing the low-fidelity models with physics-based surrogates, the output of codes like ADAPT and AFSIM are greatly improved.

3.0 AIRCRAFT DEVELOPMENT IMPLICATIONS

Having the software stack described in section 2 has the implication that a system-level model of the vehicle can be produced as early as the conceptual or preliminary design phase, and can be improved as more and more details of the vehicle are defined. This is described in Figure 3-1 below. In the early phases of design, the shape of the vehicle is known but the underlying structure, control surfaces, and even the propulsion system are unknown. Having a physics-based surrogate model of the aircraft allows a much more accurate performance estimate to help in sizing of the vehicle, or even down-selecting from 100's of configurations to 10's of configurations. As the design progresses, these additional details can be included in the PBAs to produce a more refined physics-based model. An automated robust process of generating the updated surrogates gives the designers more freedom to iterate through candidate configurations until a much more optimized set of configurations is available to progress through the down-select process. Figure 3-1 represents that improved detail for the aerodynamic, structural, propulsion, control, and even thermal disciplines.

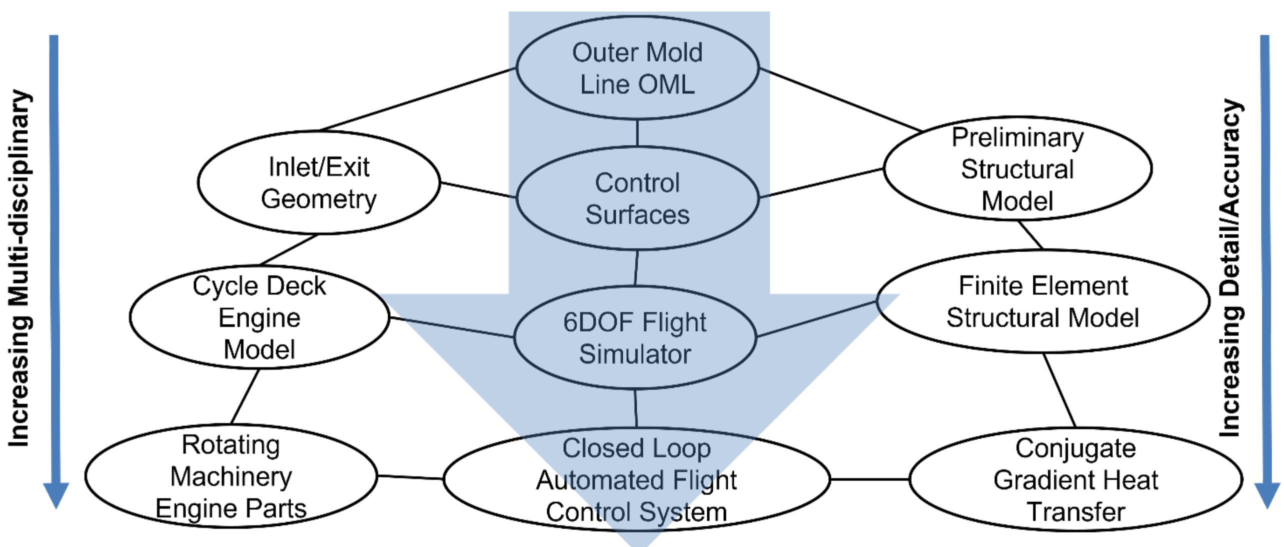

Figure 3-1: Aircraft System View.

It is also important to realize that this process can change the use of the high-fidelity physics codes from its current use today of understanding and fixing known deficiencies in the vehicle, to discovering the issues even before first flight. For example, every US fighter developed in the modern age has had modifications of the control surface sizes. These deficiencies are typically due to an inadequacy in understanding nonlinear aerodynamic effects until flight. Multi-disciplinary effects are also culprits of design deficiencies and by including these additional disciplines in the surrogate an understanding of these integration issues can be detected. By using the physics-based surrogates the design space can be searched efficiently to determine where these deficiencies exist and eliminate them long before flight test. This capability represents a tremendous potential cost savings to the air vehicle program.

4.0 SUMMARY AND CONCLUSIONS

A method of incorporating physics-based analytics (PBA) and historical ground and flight test data (DDA) into the design process earlier has been presented and each of the elements in the software stack has been described. The process of building physics-informed surrogates has also been presented along with the implications of their use. The case has also been made that physics-based surrogates are the key ingredient to a digital transformation of acquisition that can shorten the time to initial operational capability and reduce cost, goals greatly desired by the US DoD.

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