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Analysis and Optimization of Aircraft Electrical Systems using Partial Modeling Techniques

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***Abstract*—In Model-Based Systems Engineering (MBSE), certain model information is needed for early stage analysis such as system architecture analysis. However, often such information is not available, especially when the organization's transformation to MBSE is ongoing, which is typically a long process for many large companies. There is a need for being able to perform some analysis or receive other partial benefit from MBSE, at early stages, without having to fully implement all models with high-fidelity. This paper proposes a novel partial modeling approach to support early stage analysis such as system architecture optimization. The approach includes proper dispositioning of different kinds of models and tools, uncertainty quantification using polynomial chaos expansion, and adaptable system design methods. We demonstrate it on an aircraft electrical power system to support early stage analyses that include load and terminal voltage analyses, and a sustainable electrical architecture optimization.**

Keywords*—*Model-Based Systems Engineering, Electrical Power System, Aircraft, System Adaptability, Polynomial Chaos Expansion

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1. INTRODUCTION

In Model-Based Systems Engineering (MBSE), high-fidelity models are often desirable for some important analyses. On the other hand, large MBSE programs (for example [1]) cannot be completed within a short time frame and often require specific strategy and methodology to execute correctly and efficiently. In a bigger context, transformation to MBSE is a long process for many large companies. All these imply that models with enough details are often limited in early stages of a product development cycle, or early phases of a company's MBSE transformation.

However, sufficient information is still needed to allow early stage analyses to be performed or to be completed in a meaningful way. Thus, there is a need for getting partial benefit from MBSE, at early stages, without having to fully implement all models with high-fidelity.

In this paper, we propose an approach a partial modeling approach to support early stage analysis such as system architecture optimization. The approach includes proper dispositioning of different kinds of models and tools, uncertainty quantification using polynomial chaos expansion, and adaptable architecture optimization.

To demonstrate this approach, we use aircraft electrical system as an example use case. In this example, we have two parts of models. Part 1 is a set of a large number of models that are built for systems throughout the airplane. They describe the airplane with less fidelity and include requirements, and we called them "High Tier Models" here. Part 2 is a set of higher fidelity models of certain parts (called "Detailed Models") that can provide information for needed analyses, however were built with an *in-house tool* rather than off-the-shelf modeling tools being used by high tier models, which we call "High Tier Tool" here. The goal is to leverage two parts of models as much as possible and use minimal modeling effort to complete the needed analyses and to perform architecture optimization. Thus, we can receive some extent of MBSE benefits without needing to wait for whole modeling efforts to be completed to high fidelity which can take years of efforts. The needed analyses include load and terminal voltage analyses, which will be used for architecture design.

2. PAPER ORGANIZATION

Our paper is organized as following: In Section 3, we provide our approach to tackle the problem. Section 4 provides detailed workflow for such an approach. Section 5 provides

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Not subject to U.S. Export Administration Regulations (EAR) (15 C.F.R. Parts 730-774) or U.S. International Traffic in Arms Regulations (ITAR), (22 C.F.R. Parts 120-130 the results on modeling, analyses and architecture design, and Section 6 concludes our study.

3. APPROACH

This section describes our solution. First, the situations we are facing are: High tier models are capable of capturing generically different kinds of requirements and behaviors with a broad set of components, however the corresponding tool is slow in simulations and does not provide specialized electrical analysis tools. On the other hand, these models cover the whole airplane, and allow simulations and analyses with scenarios from the model presence of the other parts of the airplane. Detailed models in this example model a subset of the components of high tier models. They have details that are enough to support the basic steady state analyses for load and voltages that cover only limited ranges. Both high tier and detailed models do not contain battery models.

In addition to support the analyses and architecture design task mentioned earlier, we also leverage this chance to break the capability limitation to support a wider data range and a wider range of systems, to achieve more accurate analytical results with a fast speed when embracing uncertainties. Analyses are known to be slow in the presence of a large amount of uncertainties [2]. Fast and accurate methods enable a wider range of analyses especially those that might be used in a digital twin environment with a large amount of systems. In addition, speed and accuracy are always useful regardless what tools are being used for building and running detailed models.

The solution we explore here is: continue to develop the high tier models to form physical architecture. Abstracting needed information from detailed models into physical architecture and perform needed analyses and architecture optimization there. Note that the same analyses and optimization can also be implemented in the in-house tool or any native tools that support that level of design. When the analyses are fast enough, implementing them in physical architecture allows leveraging other models in the airplane directly and the results being in physical architecture which is needed to synchronized back if the implementation is in the lower level models. It also provides an early analysis capability as well.

To accelerate the simulation and analysis speed, we approximate and abstract the detailed models with Polynomial Chaos Expansion. It has been proven that the approach can scale to simulations with 1000 buses [2] for reasonable accuracy, thus is a fast method.

For the models in high tier models that are not in detailed models, we need to have more details to support our analyses. We refine these models with Polynomial Chaos Expansion (PCE) to only a limited number of degrees, which we call the approach as Partial Modeling. It has been proven recently that limited degree of expansion can provide enough details when missing information about the models [3]. This may result in a higher order inaccuracy, but [2] indicates that is generally not an issue for electrical power systems.

With the analytical results, we can easily perform sustainable architecture optimization using the classical methods described in [4] [5], in early stages in physical architecture level.

4. WORKFLOW

This section provides an example of the modeling and major results.

The major nonlinear expensive computations come from AC power balance due to active and reactive power injections to each bus, which can be modeled as a system of quadratic equations [6] [7],. The variation of load causes stochastic behavior of the whole system, which can be decomposed using Galerkin Method [8] resulting in a PCE as given by the equation below.

$$Y = \sum_{i \in N} c_i \Psi(\boldsymbol{X})$$

Eq.(1)

Where $\boldsymbol{X}$ is a set of orthogonal basis random functions, which we choose Hermite polynomials due to usage pattern generally may lean towards Gaussian. In the future, this can be calibrated with real data.

Per [2] we use 2 degrees for detailed models to obtain enough fidelity. For high tier models that do not have corresponding detailed models, degree 1 is used to limit efforts to partial modeling.

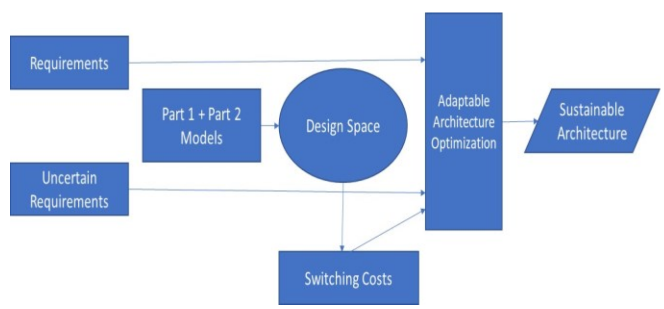

Figure 1-Modeling, Analysis and Optimization

Figure 1 shows the complete process flow, where Part 1 refers to high tier models and Part 2 refers to detailed models. Upon completion of modeling (both parts) in high tier tool which is implemented with needed electrical analysis tool that supports PCE, analytical results on load and voltage drops can be estimated based on stochastic behavior models of loads and proper power sources including batteries. These results are produced for a number of electrical architectures that are enumerated in the "Design Space", to allow the best design to be selected. Switching costs among all different architectures are calculated based on the models. Finally, requirements in high tier models are also linked in and become the constraints of architecture optimization whose process is performed using the adaptable system design methods in [4] [5].

5. Experimental Results

In this section, we illustrate two results: electrical analyses and architecture optimization using adaptable system design methods.

A. Electrical analysis

Aircraft electrical system is safety-critical, therefore it is important to analyze it thoroughly. Many variables may exhibit random behaviors and cannot be simplistically characterized as one or a few constant values. A better solution is to characterize them with stochastic processes, or at least random variables.

As described in the early sections, PCE with Galerkin method is used for intrusive characterization of detailed models, which allows better characterizations of variables involved. The method allows flexible control through expansion length to govern accuracy and computational expenses, results in simpler models that are analyzable with numerical methods. Stochastic variations can be characterized and desirable outputs' (such as voltages) distributions are obtained.

One of the examples we tested is demonstrated in Figure **2**. In this particular experiment, Q1, electrical component 1's reactive power is being varied, in order to test system's responses in other locations to different loads. This kind of analyses are very useful in analyzing and optimizing electrical architecture designs: we can experiment different load situation to test various architectures' requirement satisfactions and performance. Similar methods can be used to test different power sources as well. By varying sources, loads and wiring, etc., different architectures can be examined. This will be used in the next section to support our electrical power system architecture optimization.

In Figure **2**, our result shows V2, voltage magnitude on electrical component 2 changes with Q1 mean value. As Q1 is random, the voltage shows randomness as a distribution, where V2 values falling into 95% confidence intervals are being drawn in this figure.

Although the numbers being shown here are synthetic (non-proprietary), the result demonstrates the usefulness for architecture design. Our experiment also showed, by running with Python algorithm, the result is calculated analytically and much faster (over 10x) than full simulations to achieve similar results.

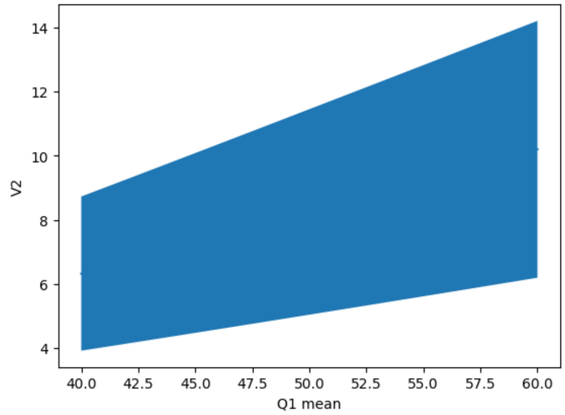

Figure 2-Voltage Characterization

The main problem with simulation is that it is not guarantee to be exhaustive, until you run enough experiments. Simulation time was shown rapidly go up quickly with the size of the power system and use cases involved. When connecting multiple systems together, simulation gets much slower. An airplane is a huge and complex system with many components. Any speed improvement in end-to-end simulations is valuable.

With such a capability, it is now feasible to perform an enumeration of different architectures and search for the optimal design.

B. Architecture Optimization

Architecture optimization, in general, considers many factors, such as requirements including functional and performance wise, etc. and is generally multidisciplinary. In recent years, sustainable architecture optimization (also called adaptable system design) become more and more important, especially for aerospace industry where late changes or fixes are always expensive. These changes almost always happen in this industry, because of long development cycle and long service time during which many situations change. These changes also happen frequently in software product development as well, due to different kinds of uncertainties. They include organizational uncertainty, relational uncertainty, market uncertainty, resource uncertainty, socio-human uncertainty, environmental uncertainty and project uncertainty [9]. Software is more and more used in manufacturing industry today due to complex functional needs from these products.

To perform optimization to obtain a sustainable architecture, three factors must be considered [10] [4] [11]:

1.Mission and requirement evaluations

2.Design space exploration

3.Switching cost estimation

First step of adaptable design is to formally capture the whole airplane requirements. This information is already in the high tier models. For ensuring sustainability, the uncertain requirements must be captured too. Both parts form a complete Mission and Requirement Evaluation Space (MRES). For the uncertain requirement part, in this use case, we use the method in [12]. Airplane missions and requirements heavily impact the capacity required. Regulatory requirements such as ETOP (Extended-range Twin-engine Operations Performance Standard) must be supported in airplane missions, to allow the airplane to fly to nearby airplane when one engine fails. All these form the constraints for the optimization. In high level, mission capabilities can be expressed in models [12], for example, as shown in Figure **3**.

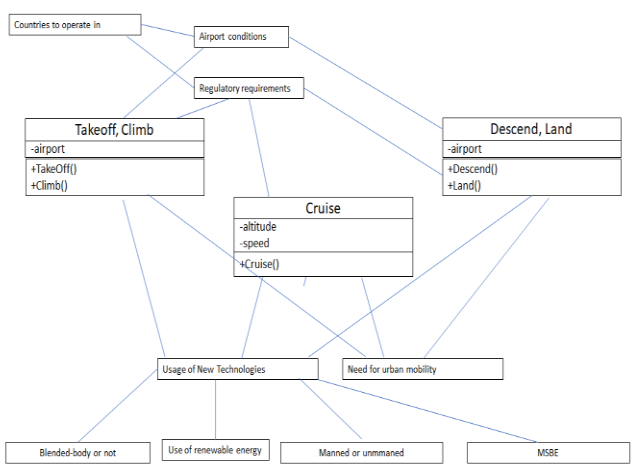

Figure 3-Mission Capability Uncertainties

Next, the design space is produced by enumerating different possible architecture choices and varying parameters produce additional choices. All candidate architectures form the design space each is attached with its capability in supporting all the missions and requirements including the potential future ones in the MRES. As MRES already include potential changes, an architecture's better support to MRES indicate this architecture is more capable of continuing to work without changes should these potential requirement changes happen. Of course, such an architecture may also be more expensive. As the design space attempts to enumerate as many as possible designs in this level of abstraction, if not all, the trade-off study among these designs, when taking into account of their degree of fulfilling the MRES, automatically factors in the needs for design margins. This enables optimization to avoid huge costs in later changes which almost always happen in aerospace industry as mentioned, thus enables sustainability in architecture design.

This can be seen more obviously with the following example on calculating switching costs. Switching cost is the cost of changing one design to another. Once all the candidate architectures are enumerated and form the design space, the switching costs between every pair of architectures are estimated bidirectionally. Typically, a design rarely starts from scratch and often originates from a prior design. The switching costs from prior architecture to each of the candidate architectures are also estimated. Switching cost estimation is available in some commercial tools (such as SEER [13] where the term "reuse cost" is used for switching cost). As an illustrative example, in Figure **4**, suppose Architecture 1 and 2 are both able to meet current missions and requirements, but have very limited supports to some other potential missions and requirements that may be needed in the future. We also assume in terms of other trade off study criteria, these two architectures are pretty similar. Suppose Architecture 3 is able to support these potential changes too, in addition to current required missions and requirements. In Figure **4**, SWCost(a, b) stands for switching cost for changing Architecture a to Architecture b. Suppose Architecture 1 and 2 have similar costs, but Architecture 3 is much more expensive. We will select between Architecture 1 or 2, but then the question is which one? Using adaptable design methods [10] [11], if SWCost(1,3) is much smaller than SWCost(2,3), we will pick Architecture 1, which will minimize cost in the future should these potential changes happen. This is how design margin is automatically factored in in a quantitative manner rather than blindly defining a unfounded number, say, 10% margin, which sometimes can be already very expensive.

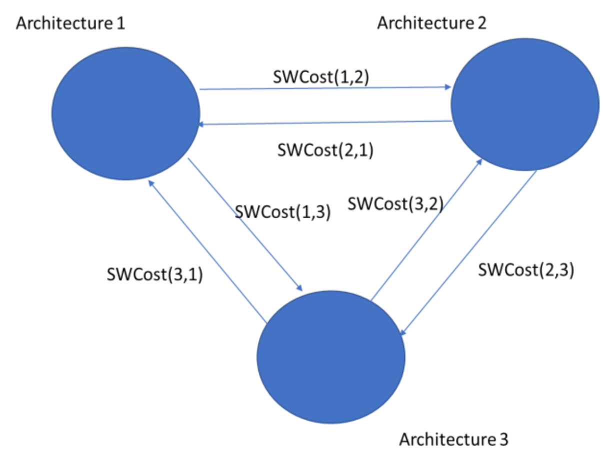

Figure 4-Switching Costs in Design Space

With all such information, the architecture optimization can be performed in the physical architecture level, to support early stage analysis. This completes the workflow described in the last section, and proves the approach provides benefits from MBSE without waiting for the completion of all models in high-fidelity.

Due to the simulation and analysis acceleration obtained from PCE, this can be used in digital twins where a lot of other models in the whole airplane are being executed. Due to the generality of PCE, models of other airplane systems can be constructed the same way. Computational performance is critically important in digital twin, and this provides a possible path to scale to the airplane level.

6. Conclusion

In Model-Based Systems Engineering (MBSE), certain model information is needed for early stage analysis such as system architecture analysis. However, often such information is not available, especially when the organization's transformation to MBSE is ongoing, which is typically a long process for many large companies. There is a need for being able to perform some analysis or receive other partial benefit from MBSE, at early stages, without having to fully implement all models with high-fidelity. This paper proposed a novel partial modeling approach to support early stage analysis such as system architecture optimization. The approach included proper dispositioning of different kinds of models and tools, uncertainty quantification using polynomial chaos expansion, and adaptable system design methods. We demonstrated it on an aircraft electrical power system to support early stage analyses that include load and terminal voltage analyses, and a sustainable electrical architecture optimization. We proved the feasibility of such an approach and indicated this approach is also feasible for digital twins.

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References

[1] H. Zhu and A. McDermott, "Optimal Architecting Strategy for Partially Developed Products: Challenges and Solutions." 2023 IEEE International Systems Conference (SysCon). IEEE, 2023.".

[2] D. Métivier, M. Vuffray and S. Misra , "Efficient polynomial chaos expansion for uncertainty quantification in power systems," *Electric Power Systems Research,* 2020.

[3] S. Oladyshkin and W. Nowak, "Incomplete statistical information limits the utility of high-order polynomial chaos expansions," *Reliability Engineering & System Safety,* 2018.

[4] Zhu, Haifeng, et al. , "Adaptability Metric Analysis for Multi-Mission Design of Manufactured Products and Systems," in *INCOSE International Symposium*, 2016.

[5] R. J. (. i. C. Cloutier, N. J. Hoboken and The Trustees of the Stevens Inst. of Technology, "System Adaptability," in *The Guide to the Systems Engineering Body of Knowledge (SEBoK), v2.8*, 2023.

[6] J. Grainger and W. Stevenson, Power System Analysis, New York : McGraw–Hill, 1994.

[7] K. Moffat, "Introduction to Electric Power Systems lecture notes," [Online]. Available: https://www.keithmoffat.com/intrepslecturenotes.

[8] B. Galerkin, "Rods and Plates, Series Occurring in Various Questions Concerning the Elastic Equilibrium of Rods and Plates," *Vestnik Inzhenerov i Tekhnikov, (Engineers and Technologists Bulletin), Vol. 19, 897-908 (in Russian),(English Translation,* 1915.

[9] M. Haleem, M. F. Farooqui and M. Faisal, "Tackling Requirements Uncertainty in Software Projects: A Cognitive Approach," *International Journal of Cognitive Computing in Engineering,* 2021.

[10] H. Zhu, "Designing systems with adaptability in mind," in *The Sixth International Conference on Complex Systems Design & Management (CSD&M)*, Paris, 2015.

[11] Systems Engineering Body of Knowledge (SEBoK), "System Adaptability," 2023. [Online]. Available: https://sebokwiki.org/wiki/System_Adaptability.

[12] H. Zhu, "A Development Procedure for Discovering Uncertain Requirements," in *IEEE International Systems Conference (SysCon)*, 2023.

[13] Galorath, Inc., "SEER Cost Estimation Tool".