Using fmdtools Models as Low-fidelity Digital Twins for Operations Support and In-time Decision Making

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Let us consider the following wildland firefighting scenario. During a rapidly growing wildland fire, a safety issue in a surveillance aircraft requires all aircraft of that type to be grounded. The decision-makers find an surveillance Unmanned Aerial Vehicle (UAV) fleet that can increase firefighting capacity as an alternative for the grounded fleet. Theoretically, the UAV can increase the firefighting capacity significantly when compared other remaining options. However, given that this is a safety-critical, complex operation that involves coordination between a variety of assets, the decision-makers want to weigh the benefits versus the risk of grounding the surveillance aircraft and operating the new UAV fleet. One way to study this is to analyze the performance and resilience of the system in a variety of potential nominal and hazardous operational scenarios. The decision-makers have a run-time monitoring model and a high fidelity simulation model of the system which they plan to use to perform the above studies. But, there are numerous challenges to using such simulation models.

- Complex systems and Systems-of-Systems like the wildland firefighting scenario are subject to high levels of uncertainty (because of both the inherent variability of the underlying dynamics and because of incomplete information) and thus cannot be meaningfully characterized at high-fidelity.
- Because of this underlying uncertainty, as well as the difficulty of verifying model results in new, unforeseen scenarios, the more relevant consideration is not providing a single precise, high-fidelity prediction, but a distribution of possible outcomes that can readily generalize to new situations.
- Quantifying this uncertainty often requires running an underlying simulation many different times. Using a high-fidelity model to make decisions in this situation will likely be impractical within any reasonable time-frame due to the computational expense.
- The UAV fleet will interact with humans throughout the system (e.g., incident commander, aerial commander, ground crew, etc.) and affect how the humans interact with the system. Also, decision-makers need to understand how the new asset will share the system's environment with the human stakeholders and interact with them. Also, the humans will need certain level of awareness and training about the new asset. They have no way of determining this through the simulation, and have no time to perform detailed human factors studies and provide comprehensive training on the UAV.

While these challenges are complicated, solving them requires a simpler solution. An easy-to-use, computationally cheap, simple model that represents the system with reasonable accuracy can help the decision makers quickly adapt the new changes to the system (the retiring of the surveillance aircraft fleet and introduction of the UAV fleet in the wildland firefighting case above) and simulate a wide range of scenarios to study the resilience and performance. One problem with such simple models is that they lack fidelity, resulting in high uncertainties. So, using them alone will not allow decision-makers to develop a complete understanding of the situation at hand. However, the simpler models can be used to complement the more detailed studies by narrowing the search space (in detailed simulations, resulting in reduced computational cost) and allowing for contingency planning while the more detailed studies are performed. Early design stage resilience simulation tools have the ability to fulfill this role given that they have the following abilities. First, they need to be able to analyze the resilience and performance of all aspects (hardware, software, and human) of the system, including their interactions (human-hardware, human-software, etc.). Second, they need to be continuously updated while the system is in operation to make sure that the simulation models are in sync with the current state of the system.

The fmdtools toolkit is an early design stage resilience analysis toolkit that can dynamically simulate both nominal and hazardous operational scenarios with a relatively simple model setup and low computational cost [1]. It includes features to model human-machine interaction along with performance shaping factor modeling [2, 3]. It can also model performance degradation over long periods of time [4]. While this tool is promising in terms of being able to

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complement the more detailed simulations that might be needed in situations like the ones above, it is still a design-time tool, which means that it has to be adapted to be used during run-time. The fmdtools models can be converted into a digital twin to support its run-time application. The continuous information exchange between the physical twin and the fmdtools-based digital twin can help keep the fmdtools model in sync with the current state of the system. The degradation models and the fault prediction capabilities can benefit from the current data, resulting in more accurate predictions, which in turn can enhance the fmdtools-based digital twin's ability to help with decision-making and support high-fidelity simulation.

While there are numerous definitions for the Digital Twin (DT), they can be summed as a DT is a virtual representation of a physical system that is interconnected with the physical system through the exchange of data [5]. A majority of literature characterizes the DT as should be at the highest possible fidelity (or an "ultra realistic representation" of the physical system) [5–8]. With the expectation of high-fidelity models, the interconnection between the physical and virtual twins is also expected to be real-time with the internet of things sensors, web services, and so on [5–8]. However, some researchers have noted that these expectations of high-fidelity models with real-time, continuous interconnections are not realistic [5, 6]. Achieving high fidelity is not achievable because of a lack of data, uncertainties, computational cost, and network speeds [5, 6]. In fact, past literature reviews found that none of the available literature on DT has actual high-fidelity twins [5, 6]. Expectation of a real-time sync is not practical due to the varying nature of data collection [5]. Data can be collected at varying frequencies through a variety of data collection means [5]. Hence, the updates may only be performed when data becomes available. In a human-in-the-loop system, the actions the human performs on the physical system based on information from the virtual system may not be in real-time [6].

In addition to what is cited in past research, we believe that the expectation for high-fidelity twins with real-time data synchronization can limit the usage of DTs in several applications as follows:

- In complex systems of systems, like the firefighting scenario described above, maintaining high fidelity DTs for individual assets will be costly both computationally and monetarily, and require significant resources for real-time synchronization. Past research has proposed DT networks [9] to handle such situations, but these networks will also suffer from the same practical limitations above.
- In systems with limited information or stochastic dynamics, it may not be possible to provide a twin that accurately represents the current state of the system. In these cases, it is more important for simulations to characterize the underlying uncertainty in the system state, which may be computationally costly (and unneccesary) to perform at high fidelity.
- When creating DTs for systems with human interactions, it will not be possible to represent the humans in the digital twins because it is impossible to create high-fidelity digital human twins. While there is some research in representing the human in digital twins [10], none of them represent the human's in high fidelity. An alternative will be to omit the human digital twin and create a human-in-the-loop DT. However, the systems boundaries between the virtual and physical twins will be difference in this case, raising the question if having different systems boundaries will qualify them as twins?

To overcome these limitations, researchers have proposed that lower fidelity DTs should be explored as long as they fulfill the intended purpose of the DT [5, 6]. Additionally, it is also recommended that non-real-time data synchronization should be considered to allow for manual inspection and updates in human-in-the-loop DTs [5, 6]. To this effect, in this research, we will explore a framework to convert fmdtools models to low-fidelity DTs that can be used during run-time as decision support and minimize complexity in more detailed simulations when running high fidelity studies are not feasible. The fmdtools-based DT will be different from existing human DTs in its capabilities to represent the human DT. Instead of representing specific parts of the human body [11, 12] or physical actions [13, 14], the human element in the fmdtools-based DT will be able to represent both physical and cognitive actions and human performance through action sequence graphs and performance-shaping factors. An airport taxiway model will be used to demonstrate how this fmdtools-based DT will help decision makers make decisions during its run-time use.

I. Simulation of Resilience in fmdtools

The fmdtools library is an open-source python package * that was developed for simulating the resilience of complex engineered systems in the early stages of design [1]. Models developed in fmdtools are structured using a high-level functional representation of the system, where function classes define high-level tasks performed by the system and their nominal/faulty behaviors and flows define the flow of material, energy, and information between these functions. Simulating these models thus involves iteratively propagating behaviors between functions over time until defined

*https://github.com/nasa/fmdtools

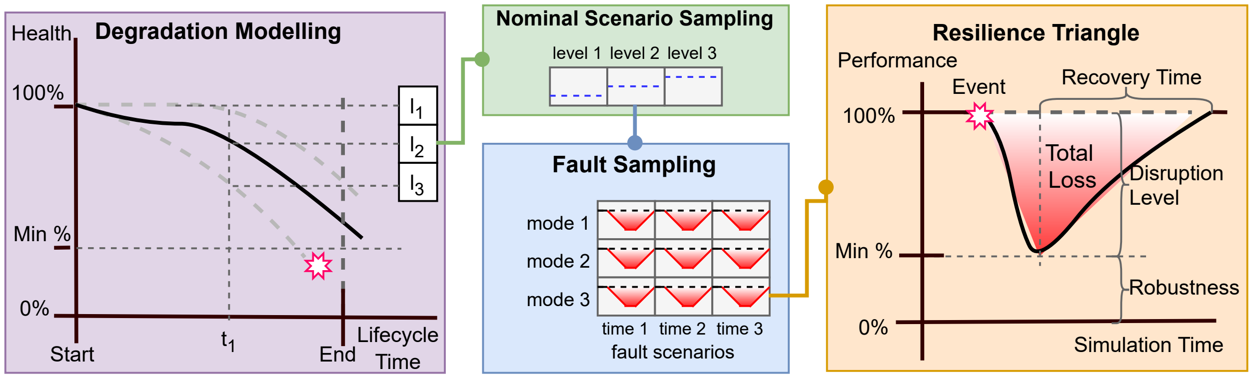

Fig. 1 Overall fmdtools degradation-based resilience analysis approach.

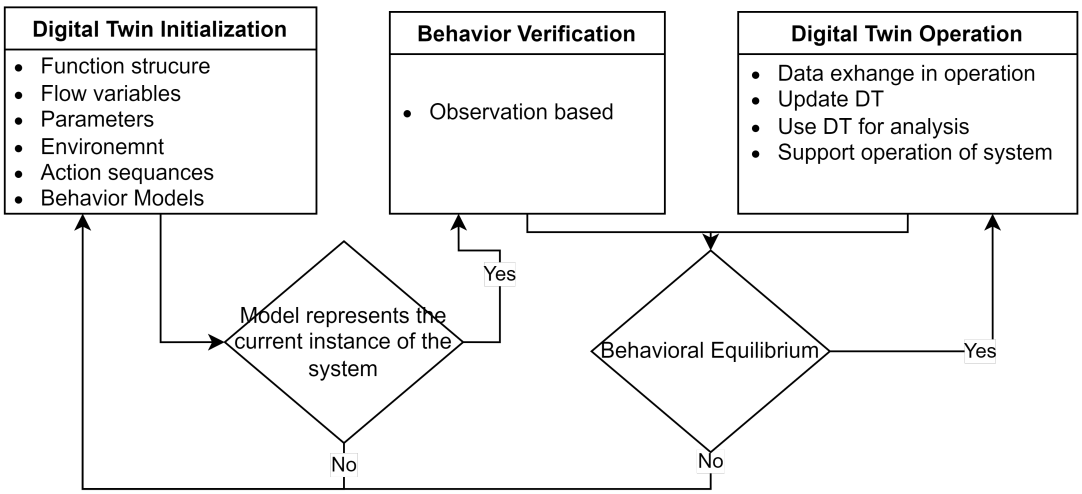

Fig. 2 A high level approach to convert fmdtools-based models to Digital Twins

simulation end-conditions are met. To assess resilience, faults can be injected at defined phases and times during the simulation [15], and the results classified according to metrics defined by the analyst (e.g., expected cost, losses, etc).

While the fmdtools library was originally developed to augment and enable traditional functional hazard analysis (i.e., analysis of single systems with limited external interactions), its capabilities have since been extended to better represent and analyze more complex systems-of-systems with human interactions, motivated by the goal of simulating aerial firefighting [16, 17]. The following capabilities have been developed specifically to enable this:

1) Parameter sampling approaches that enable the simulation of a wide variety of operational configurations, both in nominal and faulty scenarios,
2) Ability to represent stochastic behavior via internal random states representing uncertain (e.g., human or external) behaviors,
3) Ability to represent human and autonomous control actions within functions using action sequence graphs [2],
4) Ability to represent degradation of human and component-related performance over the operational life of the system using degradation models (see Fig: 1), and their effect resilience via performance shaping factors [4].

While fmdtools feature development is ongoing, these capabilities enable the simulation of systems-of-systems with interactions between humans and autonomous systems [3], as exemplified by the smart-stereo firefighting model [16, 17].

II. Methodology

The fmdtools toolkit is a simulation toolkit, where the models are developed to support resilience studies. The difference between a DT and a simulation model is that the DT represents a single instance of a system with some interconnection (in the form of data exchange) between the physical and virtual twins [5, 6]. To this effect, to create a fmdtools model-based DT, the fmdtools model need to be converted to represent a specific instance of the system with some interconnection with the physical twin in the form of data exchange at predetermined frequencies. This conversion of fmdtools models into DTs can be achieved by following the approach presented in Fig. 2, which include three main phases (DT initialization, behavior verification, and DT Operation).

The DT initialization phase may happen during the design of the system (when DT is created for the first time) or during the operation of the system (when an update to the existing system model is needed). In this phase, the fmdtools model will be converted to represent a specific instance of the system, and the data-sharing structure between the physical and virtual twins will be defined. To represent a specific instance of the system, the fmdtools model function structure, flow variables, parameters, and operating environment-related constructs must be updated. For example, in an airport taxiway model, the taxiway map, number of assets, number of runways, gates, and so on should be modified to represent the specific airport the model will be used on. Next, a decision on what data will be needed to keep the model continuously updated needs to be made. This may include behavior-, parameter-, and degradation-related data. Finally, the data exchange frequency needs to be determined based on the specific needs and scope of the twin. For example, the human performance shaping factor experience-related parameters should only be updated when there is a change in personnel.

The behavior verification phase happens when the system is in operation. After the DT has been initialized, it is important to verify and validate that the behaviors of the fmdtools-based DT match with the behaviors of the physical twin. In this phase, when a behavior mismatch is identified, the users may revert to the DT initialization phase to update the model behavior based on the available data and observations. This process will have to be iterated until there is a “behavioral equilibrium" (at least in the operational context that the system has encountered so far) between the virtual and physical twin. In the context of this research, we define “Behavioral equilibrium" as the ability of the virtual and physical twins to match each other's behaviors within an acceptable margin of error for the operational scenarios that physical twin has experienced so far in its life cycle. Once the “behavioral equilibrium" is reached, the DT operation phase is initiated. In this phase, the data exchange is initiated and operated as planned in the DT initialization phase. The incoming data should be used to update the DT. The DT may be used to perform studies and simulations. The physical system may be controlled and updated based on the simulation. However, whenever the “behavioral equilibrium" is disturbed, the users need to revert to the behavior verification phase. The DT operations phase is when users can use the fmdtools models to help decision making.

III. Case Study and Expected Results

We will use an airport taxiway case study to demonstrate the use of fmdtools-based DTs as decision support during the run-time of complex systems. The taxiway operations will include assets taxing to gates, takeoff, and landing, while ground vehicles share some of the taxiways to service assets. The asset types will include both manually operated and autonomous aircraft and helicopters. The ground vehicles will be operated manually by an operator. The Air Traffic Control (ATC) will assign gates and taxiways and provide clearance for landing and takeoff while resolving any conflicts in sharing the taxiway. Note that the process of creating fmdtools models and analyzing them is well documented in past research (Refs. [1–4, 15–17]). Hence, we will not go into detail on how to construct the model or update it to maintain it as a DT. Instead, the focus will be on how to use the model to inform decision-making during the run-time of a complex system. Specifically, we will study some what-if scenarios (e.g., what happens if a new asset is introduced into the system or an asset type is grounded) to understand how the resulting situations can be used to inform decision-making. Then, we will also explore the utility of a low-fidelity human DT being built into the DT for such decision support.

IV. Conclusion

To conclude, this research will explore the use of fmdtools toolkit-based models as low-fidelity DTs when using more high-fidelity models is not feasible for decision support during the run-time of systems. To this effect, we will present a systematic approach to using fmdtools models as DTs to ensure that the fmdtools models have the characteristics of DTs. The fmdtools-based DT models can then be used to support decision-making to maintain system resiliency during the run-time of systems. There are a few benefits to using such low-fidelity simulations. First, fmdtools models are relatively easy to construct. So, when a change to system architecture is required, the fmdtools-based DT can be adapted quickly to facilitate early studies while the more detailed models are modified. Secondly, the fmdtools-based DT studies can be used to narrow the search space for high-fidelity simulation, reducing the time and computational costs for performing high-fidelity simulations. Thirdly, the fmdtools-based DT will have the human built-in, which means that it can be used to identify conditions that promote ideal human performance and safety before more detailed human factors studies are performed. Finally, high-level fmdtools models can be simulated over stochastic variables quickly to quantify the distribution of possible outcomes, which makes it more appropriate for running in-time when the underlying system behavior is uncertain. In summary, the fmdtools-based DT that results from this research can be used to perform quick-and-dirty what-if scenarios-based simulations to help guide decision making to complement the more detailed studies.

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