# Beartooth: Nuclear Material Processing with MBSE and Digital Twin – 22143

Kaleb Houck *, Troy Burnett ** Chris Ritter ***,
* Idaho National Laboratory

## ABSTRACT

Digital engineering offers a unique opportunity to fundamentally change how the design, construction, and operation of complex projects are performed. These projects consistently demonstrate challenges to project managers to meeting cost, schedule, and performance requirements. Currently, engineering teams operate in siloed tools and disparate teams. Data connections across design, procurement, construction, and operations systems are translated manually or over performed over brittle point-to-point integrations. Uncoordinated and disjointed data exchange across these siloes increases the risk of silent errors. These silent errors cascade across the effort and lead to uncontrollable risk during project execution, resulting in significant delays and cost overruns.

Furthermore, these projects, when completed, are not designed for the rapid digitization that allows for advanced analytics, such as artificial intelligence (AI), machine learning (ML), or digital twinning. These digital advancements provide great opportunities to reduce cost and schedule. The path to these opportunities is embracing digital engineering. Digital engineering can break down these siloes and ensure a project is ready to be part of the digital future from its onset. The wide variety of tools, vendors, and processes creates the need for a standard toolset to normalize and integrate these datasets. To that end, Idaho National Laboratory (INL) has developed DeepLynx as a key tool in solving this problem. DeepLynx brings those siloed efforts into an integrated platform that operates over the course of a projects lifecycle and integrates to widely used enterprise scale software.

Beartooth is a cutting-edge research and development testbed for processing novel special nuclear material (SNM) feedstocks. In addition to its processing capabilities, the testbed will incorporate digital engineering concepts, such as AI/ML and digital twins, to bring new insights into material processing that will assist in alleviating problems that have plagued the nuclear industry. This testbed is physically reconfigurable and can be used for novel chemical processes, which creates a challenge to ensure that sensor systems are adequately configured to enable a digital twin. Additionally, the digital twin and its data system will need to be equally adaptable and configurable.

This paper will go into the benefits, challenges, and lessons learned in using digital engineering on a complex system utilizing model-based systems engineering (MBSE) and digital twin as core components of the engineering effort. The paper will breakdown how MBSE was used in discovering early issues with the configuration as initially laid out using a legacy document-based process. The paper will also discuss the opportunities brought on by using a digital thread and twin to create interactive collaboration in design and the future possibilities for these technologies during operation of the fuel cycle testbed. Finally, this paper will go over the use and planned use of mixed reality and metaverse technologies for use in design, training, and operation.

## INTRODUCTION

Idaho National Laboratory is the Department of Energy's nuclear engineering laboratory and the home of the Digital Innovation Center of Excellence (DICE). Beartooth is a cutting-edge research and development testbed for processing novel SNM feedstocks that will integrate INL's latest efforts in AI, ML, and digital twin. New nuclear energy designs in the form of small modular reactors and microreactors has also prompted the design of new nuclear fuels. These new fuels bring interest and concern around issues such as waste management and nonproliferation [1]. It is critical that understanding around these concerns is delivered in a timely manner to ensure the United States government's ability to enable these new technologies and continue to be able to monitor their impact abroad. Digital twins and mixed reality will provide novel insights at an unprecedented pace by providing and analyzing data in real time using sensors integrated into the testbed.

## DISCUSSION

### Digital Engineering at Idaho National Laboratory

Digital Engineering is a radical departure for how the nuclear energy industry runs their complex plants today. Traditional nuclear power plant operators are moving to a more sustainable business model. They aim to achieve it by upgrading software systems and implementing new systems to automate operations that were traditionally manual. In doing so, these operators aim to lower cost and reduce maintenance by identifying potential issues before they occur. However, simply acquiring more software does not make the digital picture any clearer and if not done well can make it harder to see. Without digital engineering being involved in creating the digital picture, organizations will be trapped in digital siloes and prevented from truly utilizing data in an optimal way.

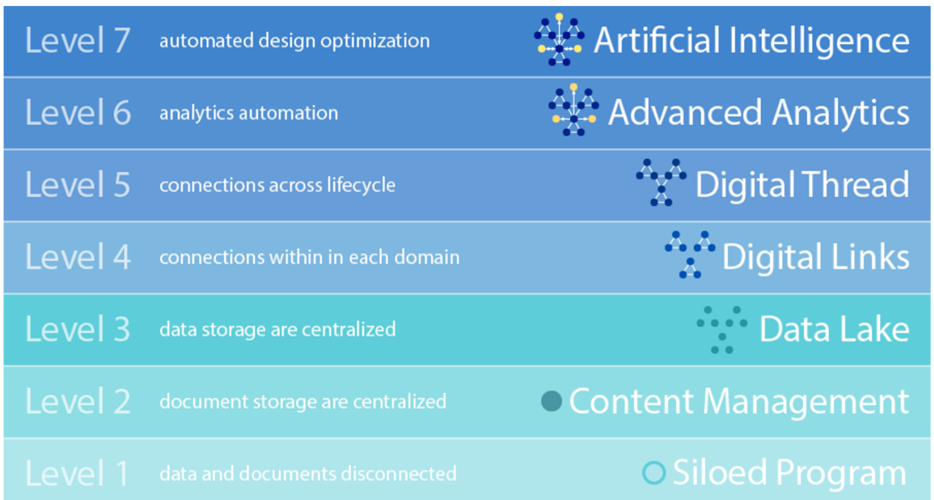


Fig. 1. Digital Maturity Model.

INL's digital engineering approach starts with MBSE. It is critical to map out the systems and their data pictures to establish a digital thread. Products like IBM's Jazz and Innoslate are being used as an alternative to traditional document-based approaches. The digital thread design created from this effort allows for the team to tie data siloes from across the lifecycle of a system together. This approach also provides a platform to prevent domain siloes from forming [2]. Mapping out the data picture brings visibility into all the systems that need to integrate into the digital thread, as well as the data that will need to be mapped into a central model called an ontology. Finally, it provides an opportunity to work with various system owners to understand the business needs. Figure 1 demonstrates what the vision is for the maturity path for these efforts. The final product of this digital engineering effort is enabling AI/ML and data fusion, ultimately satisfying those business needs in ways that operators were unable to achieve previously.

One of the biggest impediments to a digital thread is the need to integrate from various systems into a centralized and understandable data warehouse. The challenge is that there are many vendors, each providing their own solution to each business need. This produces at each operator a unique to them system of point-to-point integrations. This type of integration scheme produces a brittle business systems environment and makes a digital thread difficult to attain. Additionally, it creates a situation where the problem is solved by each member of that domain alone. Many of these integrations are also done in a batch-wise fashion and do not provide real-time integrations between systems. INL's solution to this issue is creating open-source solutions such as the DeepLynx data warehouse. Figure 2 demonstrates how DeepLynx aims to provide a data infrastructure that can provide normalization of data regarding a domain, such as nuclear, and provide a wide range of integrations to common systems used in that domain out of the box.

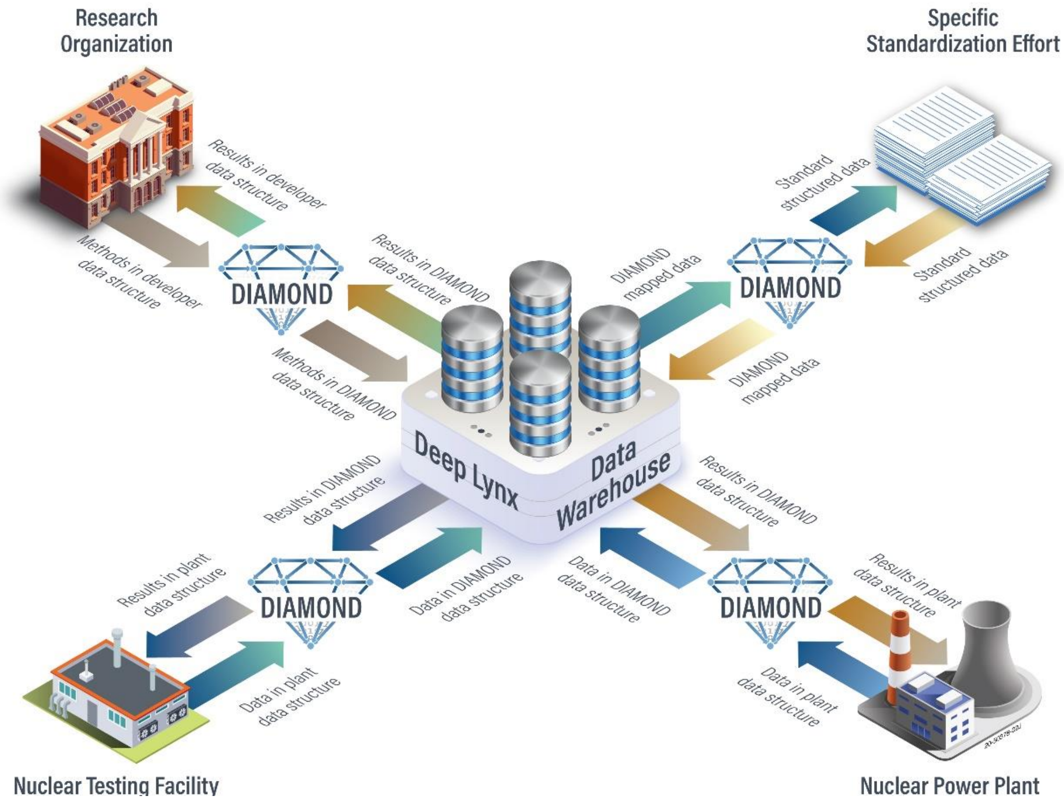


Fig. 2. DeepLynx Ecosystem.

To that end, the DeepLynx platform provides integration to systems engineering tools, asset management platforms, operations systems, AI/ML platforms such as Jupyter Notebook, and other integrations. The ease of integrating with the platform is enabling partners, such as TerraPower, to utilize the power of a digital engineering platform without tailoring their existing solutions to another system. Additionally, the data warehouse uses an ontology-based storage scheme that enables data normalization around domains with a wide variety of tools. Ultimately, the digital thread that is formed by the combination of the real-time data acquisitions and centralized location of information produce the backbone of a digital twin.

A key part of the approach is providing a standardized way of storing data from a variety of systems across an entire domain. An ontology is simply a formal naming convention where formalized language is used to define data and its relationships [3]. The purpose for doing this is to enable domain experts to communicate the structure of their data in a way that is more natural to them. The benefit of building an ontology is that the domain can be described in "natural language" using relationships, such as "A User has a Work Order, a Work Order is related to a piece of equipment," and translated into a data structure. Without an ontology, software engineers would be forced to interview business owners and derive the data and its relationships themselves. As the data structures are defined application by application, they remain disparate and isolated, unable to communicate and establish the digital thread. This is the process used today by enterprise system designers in creating a traditional schema used by relational databases.

Due to a lack of options that were either open or widely used, the team opted to create an ontology to represent the data used by the nuclear power domain. The DIAMOND ontology uses standardized toplevel ontologies to provide interoperability with other ontologies. This effort was initially created with a partnership with a commercial partner, Curtiss-Wright, and continues to be developed working with companies such as TerraPower and GE. Having this ontology operating as an open-source collaboration with many partners ensures a complete representation of the solution space and enables rapid adoption of digital engineering solutions. A complete ontology for a domain enables AI/ML across multiple sites and implementations and is critical to wide adoption of digital twins.

## Beartooth's Purpose and Roadmap

Beartooth is being built at INL's Material and Fuels Complex and will be a novel nuclear fuel cycle testbed. New nuclear technology creates a need for the United States to be able to analyze and understand the chemistry, nuclear, waste, and nonproliferation aspects of new fuels. The unique challenge of having one testbed test a variety of fuel cycles is due to the wide variety of chemicals and processes that would need to be tested. To accomplish this large range of goals, this testbed will be reconfigurable, posing as a complicated system to derive and trace requirements. This testbed, beyond pushing the envelope for nuclear capabilities, will also be a pioneering effort for digital engineering. Beartooth, visualized in in Figure 3, has utilized digital engineering products like virtual reality (VR) from the start of the project. A full digital twin of not just process sensors but novel chemical sensors will be developed. It will explore what a reconfigurable system means for a digital thread and be an early operational user of the DeepLynx/DIAMOND platforms. Beartooth will provide future nonproliferation experts an area to train on the wide variety of technologies that will be deployed in the future with both physical and digital capabilities. Furthermore, a successful deployment of the digital twin will provide a look at the future capabilities possible to enable International Atomic Energy Agency (IAEA) remote compliance validation.

Fig. 3. Beartooth VR Conceptual Mockup.

The goal of the testbed is to provide enlightening information on these novel fuel cycles in a timeframe that is impactful, and a digital twin will be essential to this end. The idea of a digital twin is something that is poorly defined and often mixed up with marketing language [4]. To better define a digital twin to the interdisciplinary team, a metaphor was developed to explain the concept. Imagine buying a car. Over time the user becomes familiar with that car and can tell when something is not quite right due to various bumps, vibrations, and noises. This is simply a heuristic developed with human senses. With these heuristics users are able determine issues with a system before they cause a problem and fix them before there is a consequence. The composition of a digital twin is a real-time digital product that operates right along with the physical system using various sensors. This “twin” feels the bumps and noises at a greater fidelity than human senses are able and provides those senses to the user real time as the asset is operated. Now, for systems that are complex it is difficult for humans to generate meaningful heuristics. This could be due to their size, in the case of currently deployed light water reactors, or potentially due to senses that humans simply do not possess, such as being able to see infrared or ultraviolet waves. The challenge that the digital engineering effort will be solving is providing the digital thread platform and producing heuristics or model-training with machine learning for these complex systems. The heuristics could predict maintenance needs or aid in nonproliferation detection. The team is working to find the best processes to bring these digital twins to these complex systems.

There are a few core processes that the testbed will perform to process SNM. These processes can change dramatically between testing different fuel cycles. It is a difficult system engineering task to manage the ever-shifting interfaces and requirements of each process. This is especially true given that the system reconfiguration is not just a physical change, a chemical change, but also a digital system change. Modeling Beartooth early using an MBSE methodology early in a set of diagrams and terms that all parties could understand was essential to identifying potential future pain points.

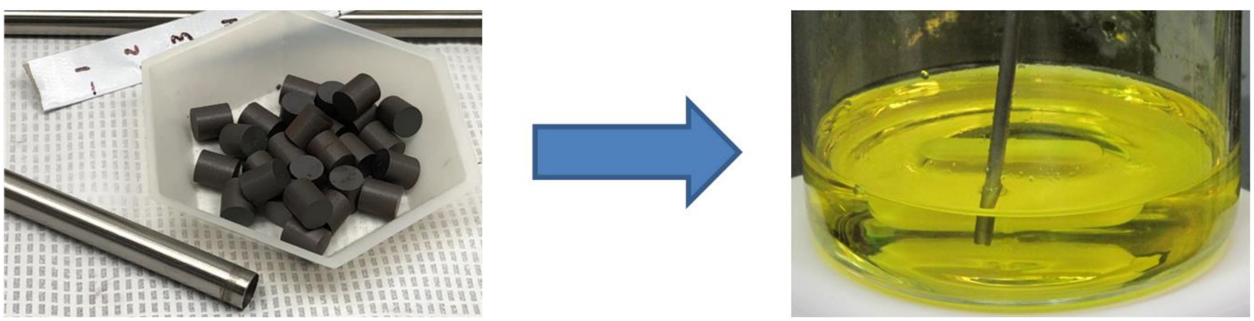

Fig. 4. Metal Dissolution.

Digital twins are often deployed for systems for long lifetimes with predictable processes. What makes Beartooth unique is the need to develop a twin and follow-on AI/ML effort to present useful signals on a reconfigurable system with processes that are “messy” and complex. SNM dissolution is one of the operations needed in a nuclear fuel cycle. Figure 4 demonstrates a common dissolution of a uranium feedstock. Dissolution is where you use various chemicals and heat to turn a metal into a solution. The digital engineering team has outstanding questions regarding this process: First, what are the data points useful in a process like this? Second, what sensors are needed to capture those data points? Finally, how can those sensors and data acquisition be integrated without hampering the primary mission of this testbed?

In the design of the actual glovebox/centrifugal contactor system, there is high certainty in the success of the design. INL has been focused on quality nuclear engineering for decades. What is new to this world-class team is incorporating sensors into whole new areas of the system design. Digital twins have never been incorporated into a system such as this. The digital engineering team has been focusing primarily on these physical/digital integrations because it is the area most likely for a mistake to be made in these early phases. It has been essential to have a digital system proponent involved in every stage of system design.

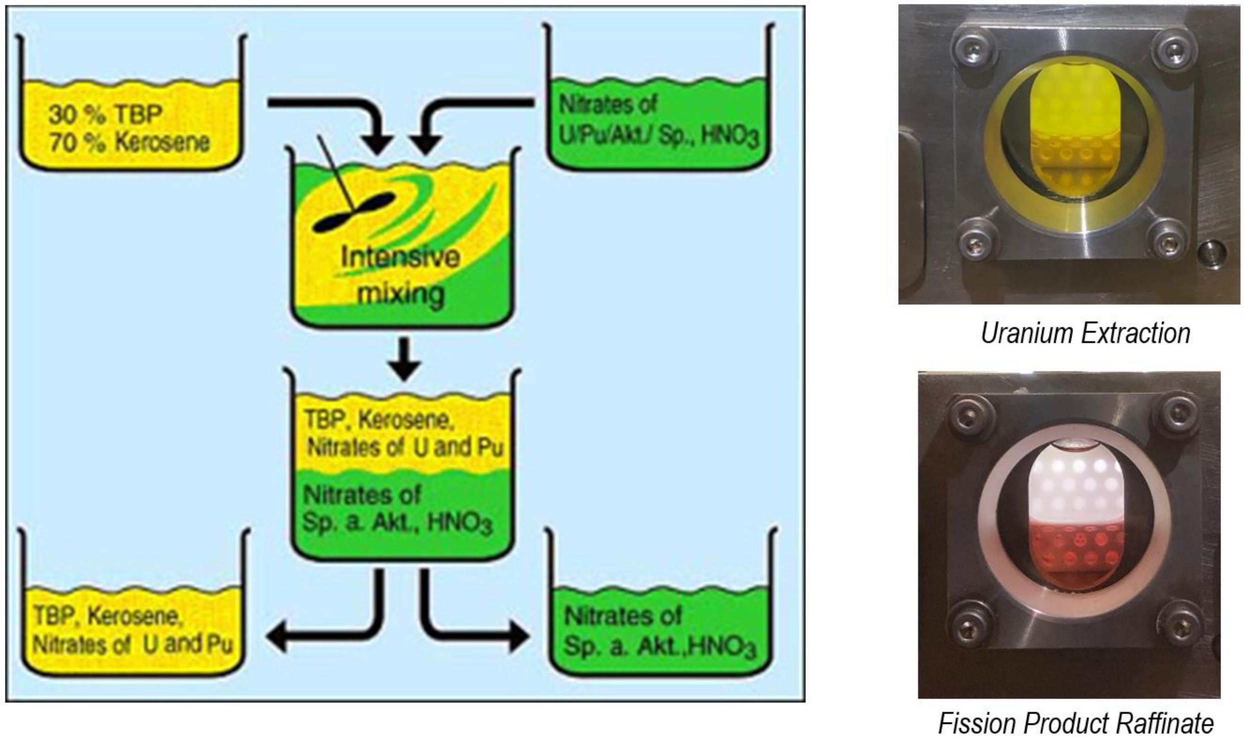


Fig. 5. Separations.

The heart and soul of this system is the centrifugal contactor system. Figure 5 represents what the separation processes look like. These systems spin liquid material, may enter their own material into the stream, and then push the material to next contactor, tank, or a kiln. Solvent extraction removes what was used to dissolve the feedstock material. An additional output of this process is the raffinate products. The raffinate process produces liquid remnants that are a useful area of study for both waste management and nonproliferation. Developing novel and useful signals for such a messy process is difficult. Turbulence is introduced into the system due to the “violent” action of the mechanics and air introduced into the flow. This presents a unique problem with using chemical sensors on in transit material. This is an active area of discussion on the system-of-systems team. Chemical sensors take a long time to take measurements of value. The process moves fast and produces noisy signals. The question is how to design a system capable of capturing useful signals without slowing down the process?

The final output of the system is refined and purified fuel products. Conversion is the process where purified liquid streams are converted into solid products. The mass can be hard to track because air introduced into the system introduces mass that is not present in the parent material, and the hold-up is left in various system components. These challenges make nuclear material accountability rather difficult. A key challenge is measuring compliance with nonproliferation. The goal is to use digital twin to help figure out how to address nuclear material accountability and nonproliferation in these complex environments. The right heuristics may enable assurance of compliance in scaled-up implementations of these fuel cycles.

There have been a series of challenges to implementing a digital twin with Beartooth. The largest of the issues is coordinating multidisciplinary efforts so that the challenges do not create information siloes. This team has been using MBSE models as a method to facilitate communication across disciplines and using that as the medium for finalizing decisions. Integrating a digital system is foreign to most of those involved and its required pushing stakeholders to think how their piece of the effort will factor into it. Another challenge is that the physical design is maturing faster than the digital design. The conceptual design of the piping and instrumentation diagram (P&ID) was completed before basic questions on the twin were addressed.

### Models-based Systems Engineering

The first step to addressing these big challenges is producing a single source of truth for the team. Often project documentation is shared between small parts of an effort and these parts represent reality that is not shared with the greater team. The team's MBSE tool, Innoslate, is the source of truth on requirements. The team decided to use Lifecycle Modeling Language (LML) to describe the systems functions. One of the core goals of LML is simplifying the representation such that more stakeholders could better understand and collaborate in the MBSE process [5]. The effort primarily uses two diagrams out of the LML standard: Asset Diagram and the Action Diagram.

The Action Diagram is where the project's systems engineer would complete the functional breakdown of the system. These functional diagrams are also functional simulation of the system as well. These diagrams are a powerful tool; however, this functional analysis was hard for the stakeholders to fully grasp at first. The Asset Diagram was far more understandable by the various stakeholders. To facilitate communication and understanding around the MBSE process, the P&ID, an artifact all the engineers were quite familiar with, was translated into an Asset Diagram.

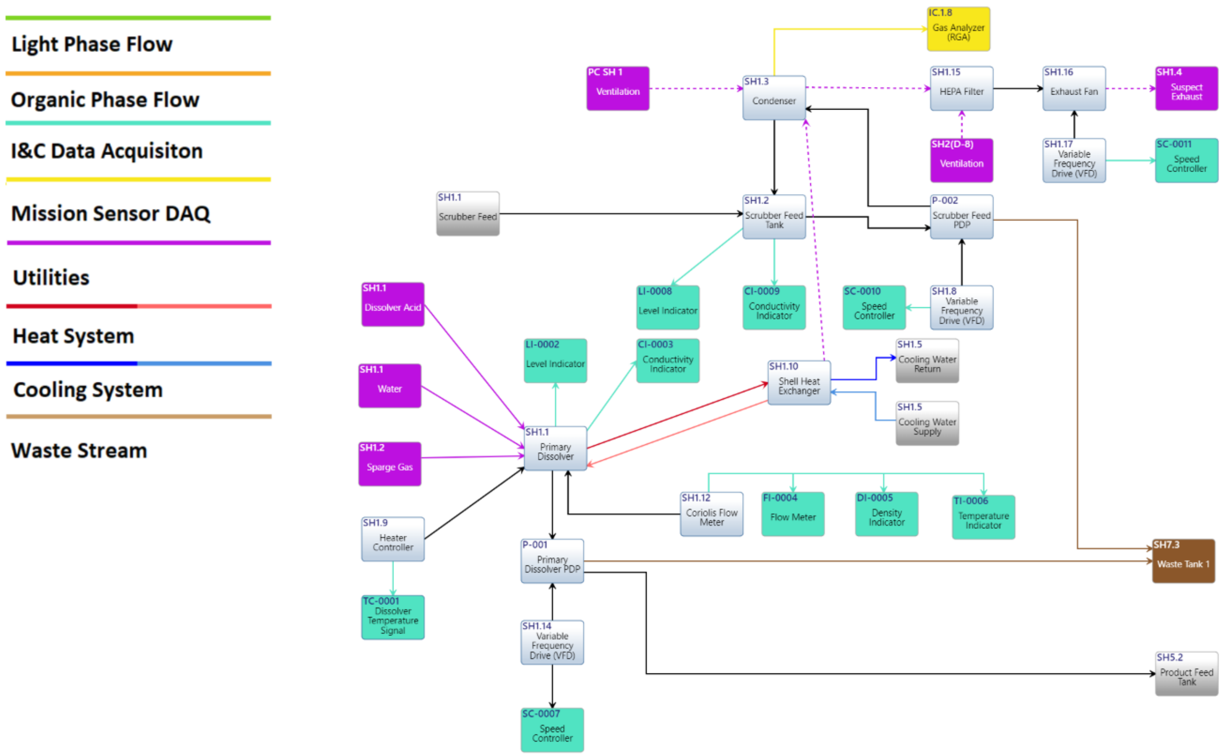


Fig. 6. View of Dissolver System and its Subsystems.

This LML view of the P&ID introduced the team to the idea of functional relationships between systems rather than a physical relationship. This was especially important as one of the early acquisitions to complete was for sensors. Using functional diagrams and functional language, the subject matter experts were able to narrow down the acquisitions for sensors they knew would be needed. Some of the sensors identified to be procured initially may have physical constraints preventing use with the current design.

Identifying these constraints early meant the diagrams had a substantial effect on cost savings. MBSE has shown in other efforts that "…applying Model-Based Development can realize average cost savings of between 25 to 30 percent and time savings of 35 to 40 percent." [6].

The various functional systems and the systems that would be used for digital acquisition were identified largely using the MBSE process. The identified subsystems enabled stakeholders to better be able to ask questions by focusing on each "color." Furthermore, the functional processes are what the digital twin needs to be able to visualize and provide insight. Some requirements were derived through pointed questions on these visualized systems. The project saved time on the digital engineering components by handling these questions early.

Additionally, the teams would be able to easily see and understand which components had data acquisition (DAQ) systems and question which components should have the DAQ systems. In MBSE software, a database provides an integrated set of data and set of relationships for each component. In Figure 6, a user could trace to the packages in the DeepLynx software where the DAQ, processing, and other functions are performed for each item.

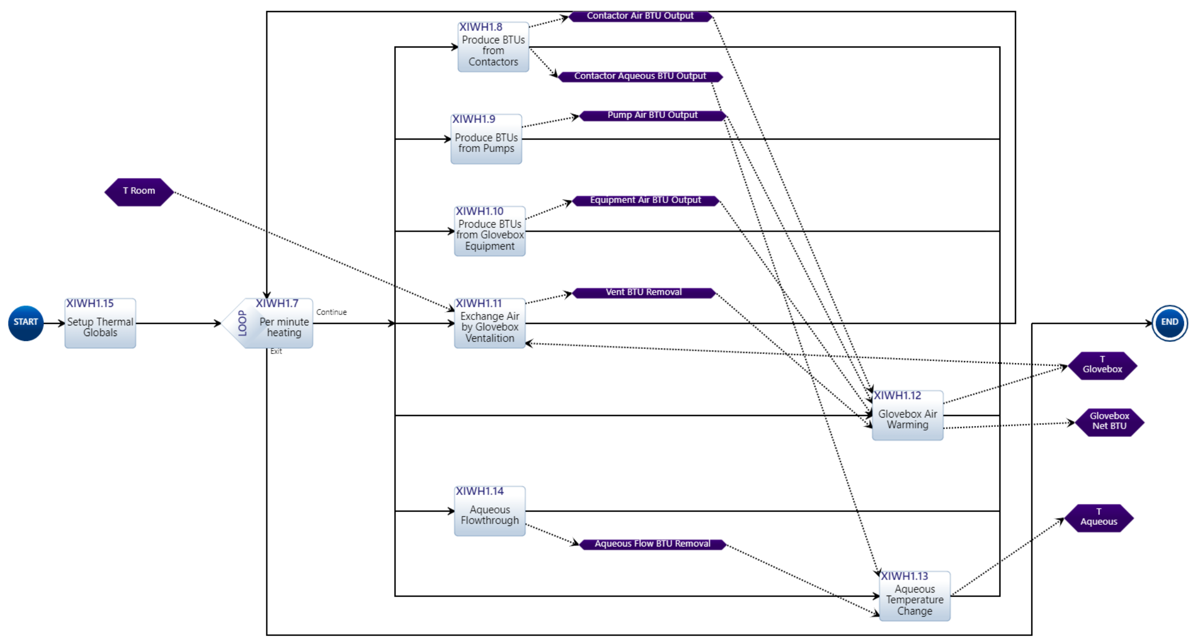


Fig. 7. Heat Flow Action Diagram.

The MBSE team reviewed the design document's first draft and ended up finding an opportunity to show how modeling could be used to verify the functional design of a system. In Figure 7, an LML action diagram shows the various functions that generate and dissipate heat in the glovebox system. It is a simple system and one that enabled demonstration of what a functional break down of a design would look like in a model validation simulation. Each of the gray boxes represent a system function and the purple boxes are resources representing various levels of heat in this situation. Requirements around heat management are tied directly to the test cases and their results. After running one of the discrete simulators on the diagram identified, it was discovered that the math did not add up.

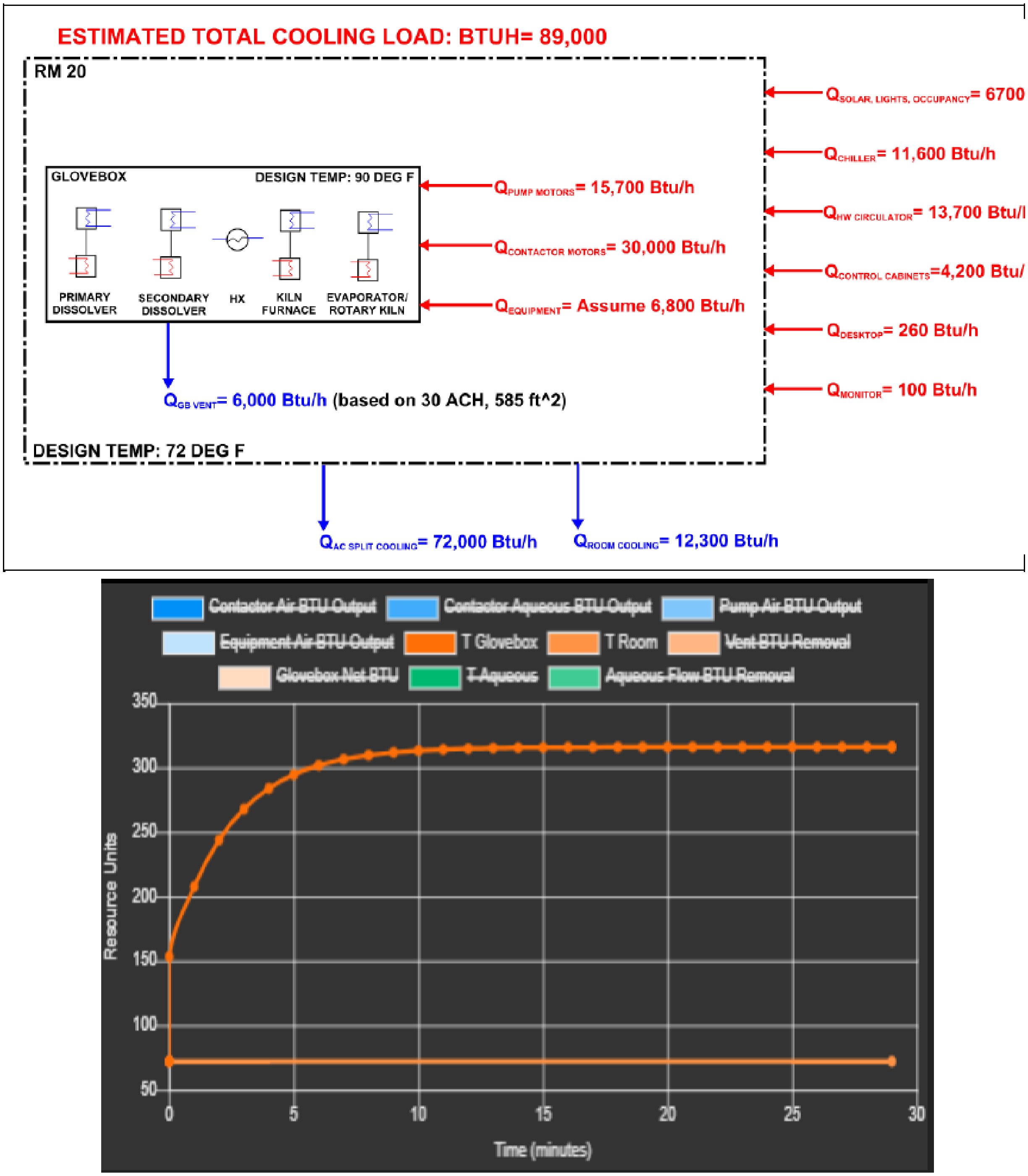

Fig. 8. Heat Dissipation Simulation.

Assumptions were made using some basic thermodynamics, and the MBSE team was unable to use the model to show the design operating at desired temperatures. This meant at the very least, the documentation was incomplete regarding some parameters such as how much heat the fluid was taking away from the contactors. It also became obvious that parameters, such as run time (how long would kilns be on consecutively), were not discussed in the design at all and play a large role in heat management and the operational requirements. Using the diagram/simulation in Figure 7, the database linked requirements were validated to this functional model in Figure 8. Presenting these findings to the contractor in a group meeting and after a quick evaluation of what was done, everyone agreed something was missing from the design document. Verifying the correctness of the documentation and its assumptions saved cost and schedule for rework that would have occurred after preliminary design.

**Digital Thread, Digital Twin, and Mixed Reality for Design and Operations**

This testbed design presents unique challenges for a novel technology. The first challenge is the reconfigurability of the system. Twins have been targeted largely for systems that have stable designs. A power plant, as an example, offers an opportunity for deciding exactly what data points you want, finding a data acquisition method, and then using that data for the lifetime of the system with little concern to any of those processes changing. The testbed challenges that common paradigm. The core issue is ensuring that the testbed's digital twin can satisfy all current and future needs.

Reconfigurability comes in many forms for this system. The piping between the contactors can change without anything else changing. How does the system figure out which configuration is active? Will the team have to manually adjust the twin or is there an automated path to doing so? Where do sensors need to be within the system? Does the cramped space both in the room and in the system allow for moving sensors around the system? Furthermore, for some of the data, there was no existing ontological structure for storing the data. How is this data hierarchically structured?

Finally, digital twins are aimed at "living" for the lifetime of a system. What does that mean for a reconfigurable system? The most common digital twin application is predictive maintenance. If there is a need to totally reset and archive data between experiments, will the AI/ML algorithms employed for that purpose work properly? What if there are experiments that are sensitive and do not want that level of data acquisition at all? This can be likened to lending your car out for a few months and then jumping back into the driving seat. The car might feel different, but does that mean something is wrong? Is it a difference of configurations or did your algorithms get too fine tuned to a previous configuration? These are questions that will need to be addressed to produce a meaningful digital twin for this system.

With the design modeled and data points laid out, the digital twin team started looking at what could be prototyped. Twins are supposed to live alongside a physical asset, and in this case, there is no fabricated asset in place yet. However, there is an existing digital thread platform, several sensors, and an extended reality (XR) environment. The XR environment will allow for users to have an earlier view of operational data to start envisioning areas for potential data fusion. Also, with the MBSE models having already laid out the physical boundaries, as well as the digital boundaries, the team has started creating a virtual twin to set up expected data to begin creating AI/ML on. Early use of augmented reality (AR) allowed for quick understanding of scale and components using common consumer devices like cell phones and tablets. This AR view of the testbed is unfortunately hampered by a small field of view (FOV) that phones and tablets offer and do not provide a good sense of depth perception.

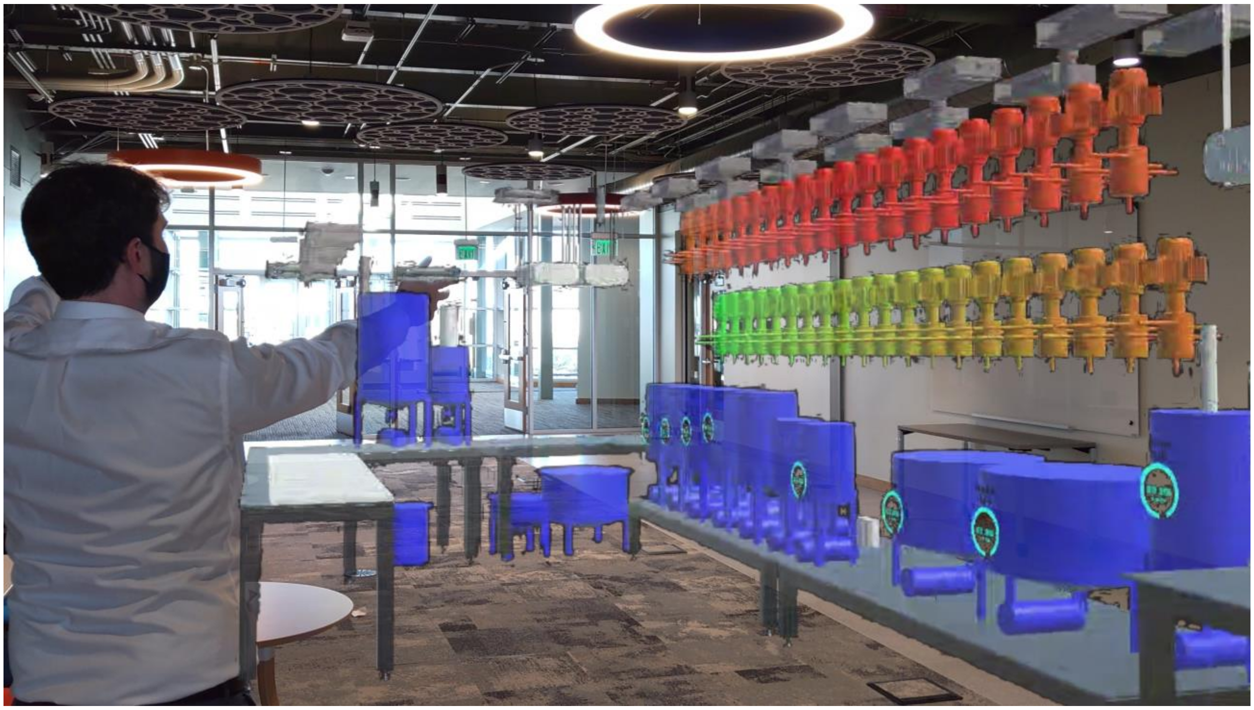

Fig. 9. Mixed Reality Demonstration of Prototype Digital Twin.

The team has created a prototype twin in mixed reality (MR) using Microsoft’s HoloLens 2. MR is different than VR in that it does not replace your view of the actual world, and augmented reality in that it interacts and persists its virtual layer with the real world. This allowed a full-size demonstration of the system design in an appropriately sized space, as seen in Figure 9. Mixed reality provides a view that provides good understanding of depth perception and scale as it allows the user to see a true three-dimensional view of the testbed in one’s physical environment. This presented an opportunity to the team to better understand the dimensions of the design intuitively, and better interact with the human factors aspect of the system. This presents unique opportunities to catch issues in preliminary design when revisions are cheap to correct. Not shown in Figure 9 is the actual glovebox that holds these elements. The red-yellow-green mapped items are demonstrating heat-flows using a simulation tied to the cloud-based digital thread in real time. The tanks in blue are gray when empty but turn blue as they fill. The dials on the tanks show extrapolated fill rates that a normal fill indicator would not show an operator.

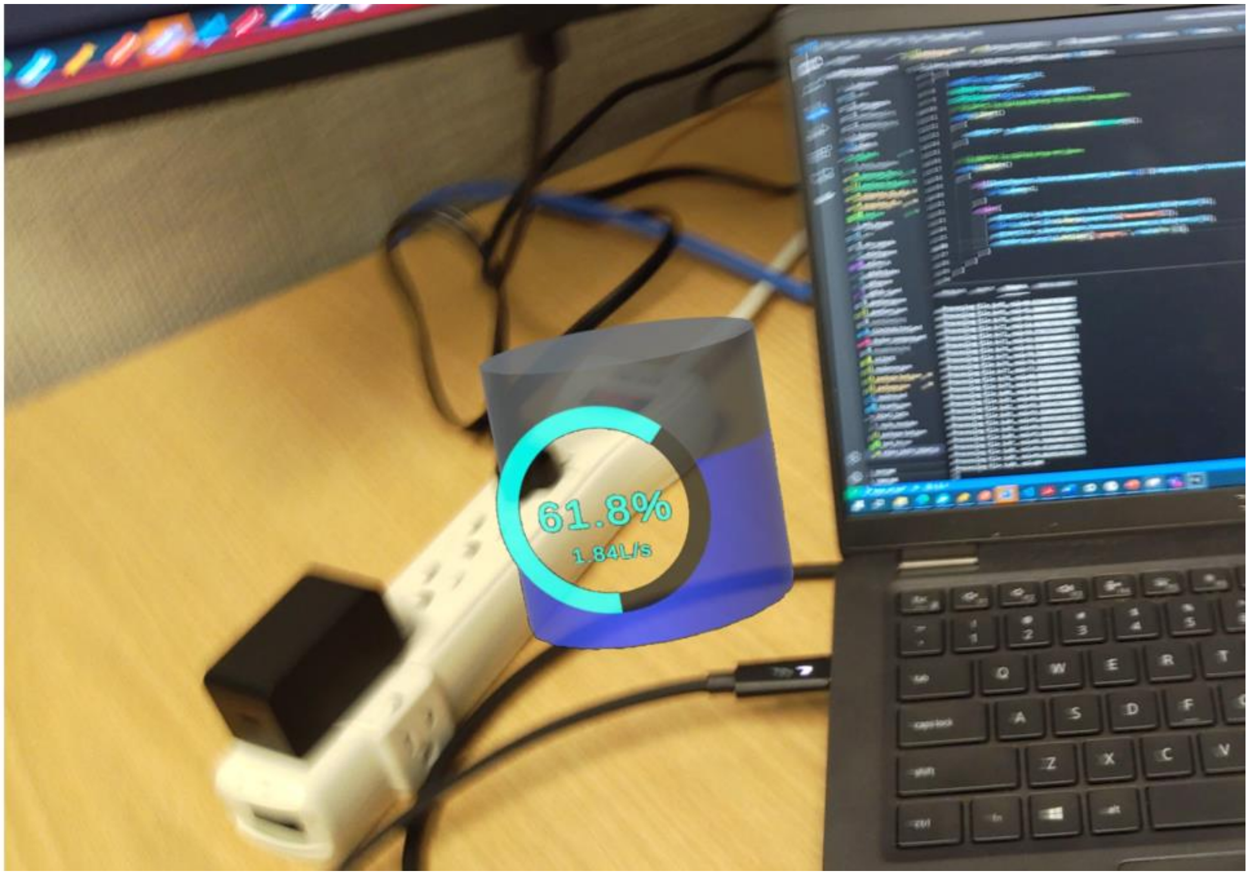

Fig. 10. Operational MR Prototype.

Beyond the design value of MR and digital twin, the team is incorporating operational use cases into both technologies. Dashboards are already a common tool of businesses but require a device to be in the hands of a user and require that user to move their focus away from the task at hand. Figure 10 demonstrates a real-time representation of a tank, its fill level, and its calculated fill rate hovering near a workstation. This mixed reality representation brings benefit to both experimental users and system maintainers to be able to see the status of system components in real time without having to carry around a tablet, phone, or laptop. The team has demonstrated already the ability to have persistent system elements report status as the user moves around a room or works on other efforts.

## CONCLUSIONS

In conclusion, when implementing digital engineering, there are many areas for challenges and successes. Starting an effort using MBSE can be a cornerstone of the effort encouraging interdisciplinary teams to engage with one another early. Establishing clear terms and understanding of complex concepts early is essential. Creating metaphors to make digital engineering products like digital twins relatable was essential to working with groups in different domains. This allowed them to understand how they fit into the digital process and how their processes would need to change to work in this new paradigm.

Along with those metaphors it was essential to distinguish a digital twin from traditional modeling and simulation. Ensuring the ability to capture real-time data from various domains was no small task. Most of these experts are familiar with performing their operations as batch-wise samples rather than as a continuous effort. Most stakeholders assumed they could feed the twin after the fact. Real time can mean something different depending on what the actual process requires. Some of the chemical processes and sensors operate on the scales of minutes rather than microseconds. In this situation a minute resolution was "real time." Success requires the digital team to be involved with all the system groups and understand their needs, their digital toolsets (or lack of), and interfaces both physical and digital. This is critical to properly identifying data points and potential signals. A twin can only see what it has been enabled to through the combination of hardware, software, and policy. Complex projects will increasingly move to a cyber-physical paradigm and digital engineering will be essential to project success.

## REFERENCES

[1] C. L. | News, Energy, and P. | July 28th 2021, "Non-proliferation experts send letter of concern over New Brunswick nuclear project," *Canada's National Observer*, Jul. 28, 2021. http://www.nationalobserver.com/2021/07/28/news/non-proliferation-experts-send-letter-concern-over-new-brunswick-nuclear-project (accessed Jan. 18, 2022).

[2] "Digital Thread | DICE," *dice.inl.gov*. https://dice.inl.gov/digital-thread/ (accessed Jan. 18, 2022).

[3] "What is an Ontology?," www-ksl.stanford.edu. http://www-ksl.stanford.edu/kst/what-is-an-ontology.html.

[4]E. Simon, "Beyond buzzwords: digital twin maturity spectrum," SNC LAVALIN. https://www.snclavalin.com/en/beyond-engineering/beyond-buzzwords-digital-twin-maturity-spectrum (accessed Jan. 18, 2022).

[5]" Lifecycle Modeling Language," Lifecycle Modeling Language. https://lifecyclemodeling.org/ (accessed Jan. 19, 2022).

[6]P. Els, "Model-based systems save development time and money," Automotive IQ, Apr. 03, 2019. https://www.automotive-iq.com/autonomous-drive/columns/model-based-systems-save-development-time-and-money (accessed Jan. 19, 2022).