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The Use of Stochastic Value Models to Create Technology Roadmaps

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***Abstract*— Since technology is rapidly advancing, systems engineers must now design for adaptability, such that the system can be updated with new components as they become available. Designing for adaptability typically requires analyzing and evaluating technologies at various stages of maturity to determine if they should be incorporated into the design. As such, technology roadmaps are a useful tool to identifying the change in a technology with time. Though traditional technology roadmaps are based on raw performance data, a technology roadmap based on value modeling would be more appropriate for system design. Value modeling is a technique used for evaluating different design decisions while focusing on the needs of the stakeholder. A qualitative model is built to determine what value measures are of concern to the stakeholder; a quantitative model is then built to convert raw performance data into a value score for evaluation. This process can be expanded to show the change in value score based on new technologies through the inclusion of uncertainty and the time domain. The SIPMath® Tool is Microsoft Excel provided a useful tool for building this model. A case study for different unmanned aerial vehicle batteries is presented to display this process.**

Keywords—Technology Roadmap, Adaptability, Value Modeling

I. Introduction

Technology is rapidly and unpredictably advancing, resulting in many systems to use obsolete components by the time that they are fielded. Therefore, modern system design requires that a system be designed for adaptability, such that the system can be updated with new components as they become available [1]. Designing for adaptability requires that the system designers be able to predict the future development of different technologies. This process is typically done through market research and discussions with subject matter experts. These technologies must then be evaluated to determine which ones are relevant as design considerations. Stochastic value modeling offers a method for performing these evaluation processes.

Value modeling is a technique to evaluate different design decisions while focusing on the needs of the stakeholder [2]. The technique involves determining the criteria that is valued by the user, or value measures, and using these measures to derive scores for different design alternatives allowing for easy comparison. This approach can be applied to comparing different technologies at different stages of maturity. However, due to the lack of performance data available for immature technologies, the value model will need to be stochastic. By calculating the projected range of values for each of the future design alternatives and projecting the availability date, a timeframe-value diagram can be built. This chart can be used to inform design decisions as well as investment opportunities.

This paper discusses the use of stochastic value modeling to create a timeframe-value diagram, which identifies the increase in a given technology's value as a function of time. A case-study is presented for rechargeable battery technologies for an unmanned aircraft system (UAS).

II. Overview of Traditional Value Modeling

The value model development process is discussed in detail in [2]. At its most basic level, a value model assigns a score between 0 and 100 to different design alternatives to allow for comparison. The value modelling process ensures that these scores represent the stakeholders' needs. The model consists of qualitative and quantitative components, which translate raw performance data into value scores for each design alternative, as shown in Figure 1. These models translate raw performance data into value scores for different design alternatives. These value scores can then be compared in a cost-value analysis.

A. Qualitative Value Model

Systems engineers must perform a functional decomposition of their system early in the design process, where they decompose the main system objectives into a set of functions [3]. This decomposition typically takes the form of a functional hierarchy. The qualitative value model is built on

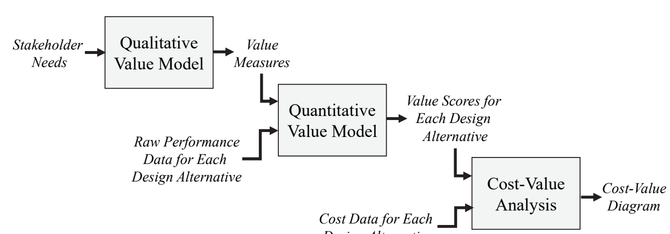

Fig. 1. Steps for a traditional value model. Traditional value modeling involves developing a qualitative and quantitative value model to develop value scores that can be used in a cost-value analysis.

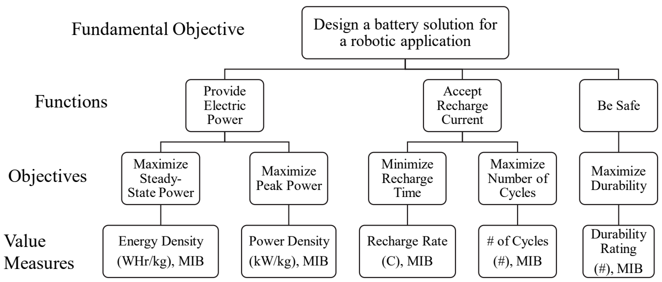

Fig. 2. Value Hierarchy for a battery solution for a UAS application. The value hierarchy has four levels: the fundamental objectives, functions, objectives, and value measures. The value measures become the metrics that are used for analysis in the value model.

this functional hierarchy; each function is assigned objectives with a supporting value measure, creating a value hierarchy.

The value hierarchy for the case study presented in Section IV is depicted in Figure 2. The value hierarchy consists of four levels: the fundamental objective, the critical functions that the system must be able to produce, the objectives of each specific function, and the associated value measure. A value measure is a direct or proxy measure that quantifies achievement of the supporting objective. Simply put, the value measures are the critical design parameters that will drive the selection of a design alternative.

B. Quantitative Value Model

The quantitative value model takes each value measure and places them onto a swing weight matrix. The swing weight matrix, as shown in Figure 3, evaluates each value measure in regards to importance and technology gap. The technology gap identifies how far current solutions are from meeting the stakeholder needs. Each value measure is given a swing weight between 0 and 100 based on its location on the matrix [4]. These weights are then summed for all the value measures and normalized to get a global weight between 0 and 1.

A value function is then built for each value measure. The value function takes the raw performance data as an input and outputs a score between 0 and 100, where 0 is the minimum acceptable value and 100 is the ideal value. The value function translates the raw performance data into a common measure which is necessary because value measures typically have different units. Value functions can be either continuous or discrete; examples of both types are shown in Figure 4.

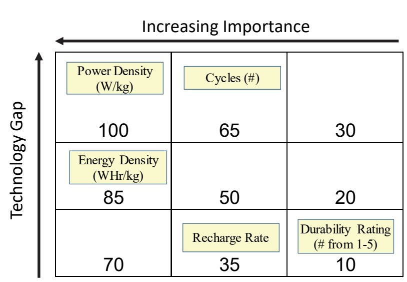

Fig. 3. Swing Weight Matrix consisting of five value measures for a battery solution for a UAS. The position of a value measure in the matrix determines the weight assigned to that value measure in the value model.

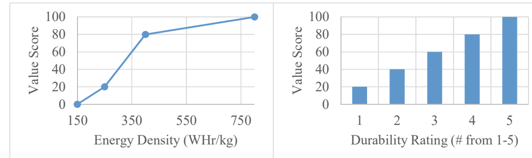

Fig. 4. Examples of continuous and discrete value functions. These two value functions convert raw performance data for a technology into a score between 0 and 100.

C. Cost-Value Diagram

The value model combines raw performance data with value functions and a swing weight matrix to calculate a value score for each alternative as shown in (1).

$$v(x) = \sum_{i=1}^{n} w_i v_i(x_i) \quad (1)$$

In (1), v(x) is the total value of a design alternative, i=1 to n for the number of value measures, x_i is the raw performance score of the design alternative on the ith value measure, v_i (x_i) is the converted raw performance score value for the ith value measure, and w_i is the global weight assigned to the ith value measure. The value score reflects the degree to which a design alternative satisfies stakeholder value. [2].

The resulting value score can be plotted against the associated lifecycle cost in a cost-value diagram. This diagram allows for a trade-off analysis between cost and value between the different design alternatives. Additionally, this diagram displays when a design alternative should not be considered because it is dominated, where another solution has a higher value at a lower cost.

III. Modifications to Traditional Value Modelling for Informing Technology Roadmap

The value modeling process can readily be used to support technology roadmapping efforts. Several studies have addressed the need for a value-focused approach for the roadmapping of complex systems [5-7]. Though each study uses different processes to capture the value of a design alternative, these processes align with the traditional value modeling process outlined in the previous section.

While traditional value modeling works well with existing technologies, modifications must be made to the process to account for technologies at varying stages of maturity. The first change involves accounting for the uncertainty in the raw performance data. The second change requires that the model accounts for the projected date that a technology will be cost-feasible. These changes allow for the building of a technology roadmap which can show the increase in value of a technology with time. This modified process is shown in Figure 5.

A. Adding Uncertainty into Value Models

Traditional value models require accurate performance data to feed into the value functions. Immature technologies may not have accurate performance data available; however, a range of possible values can be estimated. The size of this range will depend on a number of parameters including

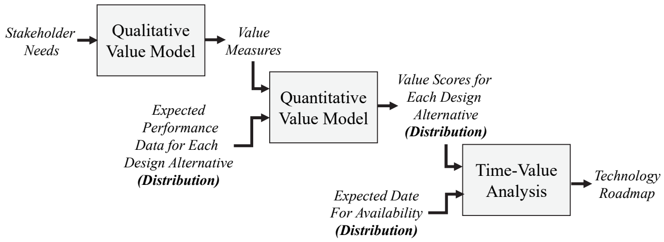

Fig. 5. Modified flowchart of value model used to create a technology roadmap. The qualitative and quantitative value models remain the same; however, the model must now account for uncertainty in the raw performance data and the projected dates for availability.

technological maturity, data availability, stakeholder needs, and environmental scenarios [8].

Since the qualitative and quantitative value models are based on stakeholder needs, the models themselves do not change. However, the solution scoring is based on the specifications of each design alternative; as such these steps will change to incorporate uncertainty. The distribution of raw values will propagates through the value model to create a distribution of value scores, as shown in Figure 5 [9].

Both discrete and continuous distributions can be used for capturing the raw data, as shown in Figure 6. The most common distribution is a triangular distribution, which is defined by a minimum, most likely, and maximum point. The minimum point is often based on the current state of the technology. The most likely point is the projected raw data value with the anticipated development. The maximum point is the raw data value with an increased development effort. Other distributions can also be applied including normal or uniform.

Unless all of the raw data distributions are discrete, the overall value for a design alternative will have a continuous distribution. This distribution will not likely have a standard form; however, it is often approximated as being of a triangular form based on the median value, the 5th percentile value, and the 95th percentile value [10].

B. *Adding the Time Domain*

Though traditional value modeling focuses on how much a solution costs, a technology roadmap focuses more on when technology will not be cost prohibitive. Typically, this time frame is associated with the projected dates for commercial availability. These projections are determined through market research and discussions with subject matter experts.

Similar to the performance data, there is uncertainty associated with the availability date. Therefore, the availability date needs to be modeled as a distribution as well. The

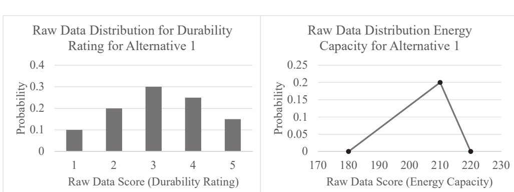

Fig. 6. Discrete (left) and continuous (right) raw data distributions based on expected performance related for a given design alternative.

distribution can treated as a uniform distribution based on the Technology Readiness Level (TRL). For example, a TRL-6 technology can readily be available in 4-6 years; meanwhile a TRL-2 technology could potentially require 7-15 years [11].

C. *Use of SIP Math Tool for Analysis*

Microsoft Excel is a powerful tool for building value models; simple value models are typically built in Microsoft Excel [2]. Excel is useful for collecting and cataloging data, building functions, and performing the calculations discussed in Section 2. Additionally, Excel has plotting capabilities, allowing for graphical outputs, such as a cost-value diagram.

The Stochastic Information Packet Math (SIP-Math) add-on into Excel allows for the inclusion of uncertainty into the value-model [12]. The SIP-Math tool allows a user to define a distribution of values in a single cell in Excel. That cell can then be used as an input to equations, allowing the distribution of values to propagate through a set of calculations. The SIP-Math tool then runs a Monte-Carlo simulation, selecting a value from each distribution and executing all calculations; this process is repeated numerous times to create a distribution of output values. Note that there are other software packages that can perform Monte Carlo simulations; the authors selected the SIPMath Excel add-on for its ability to support model development without having to rerun new simulations when changing parameters.

D. *Value vs. Availability Date Analysis*

By combining traditional value modeling with uncertainty and the time domain, a timeframe-value diagram can be produced. A timeframe-value diagram shows the impact of new technology developments on the value score for a system. A higher value score indicates that a solution is more in-line with the user's needs.

A sample timeframe-value diagram is shown in Figure 7. The technology roadmap shows that the current technology has a value score of approximately 20. Though there is some uncertainty in the current technology value, it does not change by more than 2 points. A value score of 20 indicates that the solution barely meets the minimum requirements for the user.

A next generation technology appears to become available between 2020 and 2023; this technology has a value score of approximately 40, which is substantially higher than the current technology. Since this technology is not fully matured, there is uncertainty in both its value and the date of availability. These uncertainty ranges are expected to decrease as the technology matures.

Two competing technologies become available between 2024 and 2028. These two long-term technologies have substantial overlap between their value scores and availability dates. As such, a systems engineer would continue to monitor both solutions in parallel. If possible, they will try to ensure that their system is designed to accept either technology as they become available. If that is not feasible, they can accept risk by selecting the component with the higher projected value. Alternatively, they can also wait until the technologies

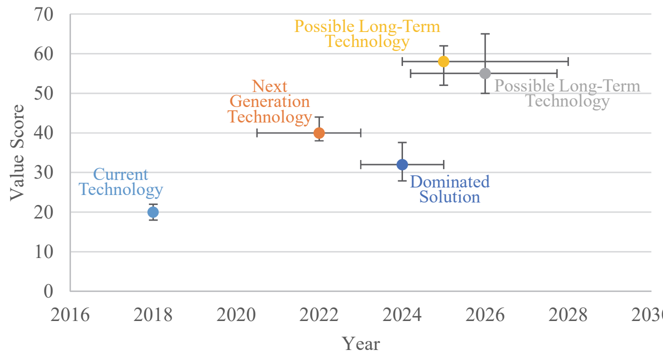

Fig. 7. Value scores and availability years for 5 notional technologies. This roadmap shows a current technology, a next generation technology, two possible long-term technologies, and a dominated technology.

matures to make a decision. In this case, the uncertainty ranges will decrease, allowing for less risk to be assumed.

A dominated solution appears in 2024. The next generation technology is available by this time frame and is more suitable for incorporation into the design based on its higher value scores. Note that there is no overlap between the value scores or availability dates, making that solution completely dominated. If such overlap did exist, the design alternative could be partially dominated, and the systems engineer would have to decide how much risk they are willing to accept by eliminating the design alternative from consideration.

The timeframe-value diagram created through stochastic value modeling allows the systems engineer to evaluate different design alternatives at various stages of maturity. This analysis allows the systems engineer to decide on which technology solutions to include on a technology roadmap and incorporate into the system design.

IV. CASE STUDY –BATTERY TECHNOLOGIES FOR AN UNMANNED AERIAL SYSTEM

A case study is presented to demonstrate the use of stochastic value modelling to create a technology roadmap that can be used to assess different technologies at various stages of maturity. The case study applies this methodology to rechargeable battery solutions for a military-grade unmanned aerial system (UAS).

A. Overview of Requirements

A military-grade UAS has numerous operational requirements related to its power system. The power system must support the mission for the UAS, providing enough power for take-off and landing, maintain an energy capacity large enough for the duration of the flight, and be able to survive landing. After the mission, the power source must be reset, allowing for the next mission. The preference for a UAS power source is a battery, especially for small and mid-size variants. Batteries can typically meet the requirements for a UAS while maintaining a compact, simple system [13].

These operational requirements turn into technical requirements for the battery component. First, the battery shall have a high power density, allowing it to provide enough power for take-off while remaining lightweight. Similarly, it shall have a high energy density to allow it to maximize the mission duration. The power system shall also be durable, rapidly recharged, and last for numerous cycles.

Since requirements must be achievable, the threshold values for these requirements can be set to the state of current technology. Therefore, the threshold values for the power density is 400 W/kg, energy density is 250 WHr/kg, number of cycles is 200, and recharge rate is C/2 [14]. Additionally, the battery should be as durable as commercial batteries.

B. Value Model

The value hierarchy for the rechargeable battery solution is shown in Figure 2. The value hierarchy breaks the fundamental objective of the power system into the following three primary functions: provide electric power, accept recharge current, and be safe. Five value measures are derived from these functions that align with the technical requirements.

Each value measure was put onto a swing weight matrix, as shown in Figure 3. The more heavily weighted value measures are power density, energy density, and number of cycles. The lower weighted value measures include durability and recharge rate. Based on the position in the swing weight matrix, the global weight (w_i) was determined for each value measure.

A value function was created for each value measure; two of these value functions are shown in Figure 4. A simple strategy was used for defining these value measures. The minimal acceptable value for each value measure equates to a score of 0. The threshold value earns a score of 30. The objective value earns a score of 80. And the ideal value earns a score of 100; the ideal value is typically set to a value at which any further improvement in that value measure would result in a minimal improvement for the UAS.

C. Different Technology Candidates

Lithium-ion (Li-ion) batteries dominate the commercial rechargeable battery market. They are ubiquitous, being used in devices ranging from cellphones to laptops to electric vehicles. Li-ion batteries are built such that lithium ions move from the cathode through an electrolyte to the anode during discharge and back when charging; this movement of ions generates a current that can power devices.

Li-ion batteries have been showing a steady increase in energy and power density over the past decade due to better manufacturing processes, wider and longer cell designs, and new battery cooling systems. However, these increases have started to plateau; as such, engineers have started looking towards alternative technologies to achieve improved batteries.

A near term improvement in battery technology comes from changing the cathode. Scientists are developing materials that can compactly store a large amount of lithium ions. A promising chemistry is Lithium Nickel Cobalt Aluminum Oxide ($LiNiCoAlO_2$), which has improved energy densities over traditional Li-ion batteries. However, it has a slightly lower power density and recharge rate than traditional Li-ion batteries. Additionally, the cycle life and durability rating are on-par with traditional Li-ion batteries [15].

Another advancement in battery technology comes from developing better anodes. Currently, Li-ion batteries use graphite at the anode to store the lithium ions. However, advancements in material science will allow for silicon anodes. Lithium-silicon anode (Li-Si anode) batteries have substantially higher energy densities, power densities, and recharge rates. However, the material properties in the anode result in a less durable battery with a shorter cycle life [15].

A longer term improvement in battery technology can come from changing the electrolyte solution from liquid to solid. Solid-state Li-ion batteries can achieve substantially higher energy densities. Additionally, the solid electrolyte makes the battery more durable with an increased cycle life. However, the ions move significantly slower through a solid material than a liquid electrolyte. As such, the solid-state batteries have a limited power density and charge rate [16].

Longer term, two battery chemistries are showing substantial promise as possible replacements to traditional Li-ion. The first, Lithium-air, use porous carbon that captures oxygen at the anode; the lithium ions move across the electrolyte into the porous carbon to bond with the oxygen. This technology has been shown to work as non-rechargeable batteries, achieving a 10x increase in the energy density. A large effort is underway to develop a rechargeable variant, which has had limited success due to a low cycle life. When that issue is resolved, Li-air chemistry will provide a very energy dense batteries with a moderate power density [17].

The second promising novel battery chemistry is Lithium-sulfur (Li-S). These batteries use a sulfur/carbon cathode with a lithium anode, and are expected to be lighter, cheaper, and more powerful than traditional Li-ion batteries. However, they have mechanical issues related to volume expansion. New materials, such as graphene are being integrated into these batteries to attempt to handle these issues [18].

D. Timeframe-Value Diagram

Data was collected for each battery chemistry in regards to each value measures. A stochastic value model was built in Excel with the SIP-Math® Tool to convert the projected performance data into value scores. These raw score were plotted against the anticipated year of availability to create a technology roadmap as shown in Figure 8.

Traditional Li-ion batteries have a value score between 30 and 35. This follows from the value functions being designed such that the current performance specifications equate to a value score of 30. Since multiple sources were used, a range of performance specifications resulted in a range of value scores.

The $LiNiCoAlO_2$ battery will be available in the next few years. Though this battery chemistry has a higher energy density than traditional Li-ion, it has a lower power density and recharge rate. Since the value measure for power density is weighted more heavily than the energy density, this results in a reduced projected value score.

The next battery chemistry that is available is Li-Si Anode. This battery chemistry has a range of values between 43 and 62. The increased energy density, power density, and recharge rates of Li-Si Anode offset the lower durability and cycle life. The battery technology is projected to be available between 2020 and 2025. This large range is due to the substantial research still required to handle the swelling of the silicon matrix during charging.

Rechargeable Li-S batteries are expected to be available between 2024 and 2026. The main benefit of Li-S technology is the reduced cost, as opposed to increased performance. As such, the range of value scores for Li-S overlaps significantly with Li-Si Anode, with the expected value being slightly less.

The battery technology with the highest expected value scores is Solid-state Li-ion batteries. These batteries are expected to have both high energy densities with high cycle life and durability. The power densities and recharge rates are high, though lower than Li-Si anode. As such, though the average value score is higher, the range of values overlaps significantly with Li-Si anode and Li-S.

Li-air batteries are projected to be available between 2026 and 2031. Li-air batteries are expected to have a very high energy density, but a low power density and recharge rate. The low performance in these value measures makes it marginally better than traditional Li-ion, but substantially less than other battery technologies that will be available in that timeframe.

E. Analysis of Timeframe-Value Diagram

Figure 8 shows that each solution can be grouped into one of the following categories: near-term, mid-term, long-term. Near-term solutions are currently available, mid-term solutions are available in the next five years, and long-term solutions are available in the next ten years.

The near-term solution is the traditional Li-ion battery. The technology is well established and commercial cells can be packaged to meet the specific needs of the UAS. Though this battery technology meets the threshold requirements, there is substantial room for improvement.

In the mid-term range are $LiNiCoAlO_2$ and Li-Si Anode batteries. The $LiNiCoAlO_2$ chemistry is dominated by the traditional Li-ion chemistry. As such, the new chemistry will likely not be useful for the UAS application. The traditional Li-ion batteries can be used for the UAS application until the next battery chemistry is developed, which is likely the Li-Si anode batteries that will be available between 2020 and 2024.

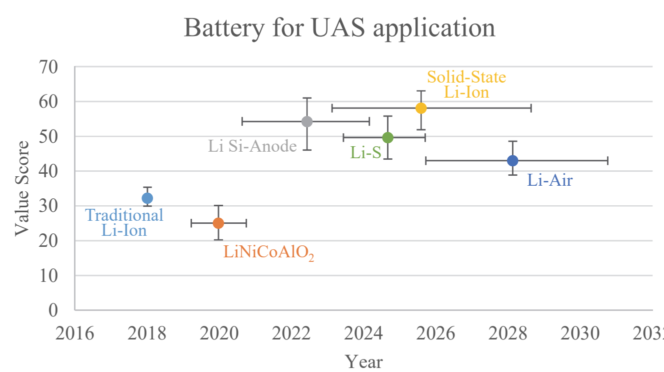

Fig. 8. Value score plotted against the year that the technology is available. This plot allows an engineer to determine which current and future battery solutions would be appropriate for incorporating into the design of a UAS.

Longer term, four different batteries have increased value over traditional Li-ion. One of the solutions, Li-air, is dominated by the other three solutions; as such, it is not a contender to serve as the power source for the UAS. The other three chemistries, Li-Si Anode, Li-S, and Solid-state Li-ion, are all non-dominated, and hence cannot be discounted. As these technologies mature, the uncertainty ranges will decrease, allowing the systems engineer to select the appropriate battery chemistry.

It is projected that the Li-Si anode battery will be the first battery available. As the battery chemistry is further developed, the uncertainty in the value and date available will decrease. Therefore, the battery development should be monitored in the 2020 timeframe to determine more accurate numbers for the value score and availability date. If the performance fails to meet expectations or the availability date is pushed back, Li-S would be an attractive alternative, especially if it is over-performing and ahead of schedule. Similarly, Solid-state Li-ion could potentially have the highest value and be available first if the development effort goes substantially ahead of schedule.

The results from this analysis allows for the system engineer to make design decisions on what technologies to incorporate into the technology roadmap. Since the only battery technology currently available is the Li-ion battery, the system needs to be designed for this chemistry. However, the power system should be designed to account for the advances in battery technology. If possible, the systems engineer would design the system to accept Li-Si Anode, Li-S, and Solid-state Li-ion batteries as they become available. If it is not possible to incorporate all of these technology, they can either accept risk by selecting the technology with the highest projected value or wait until the technologies are more developed.

V. Conclusions

Systems engineers must often design systems in technical fields that are rapidly evolving. They can account for these advances by ensuring that their system be designed with the capacity to accept new technologies as they become available. To design for adaptability, they must be able to project and assess current and future performance for design alternatives.

A technique to assess new technologies through value modeling is presented. Value modeling is a technique used for evaluating different design decisions while focusing on the needs of the stakeholder. Traditional value modeling includes a qualitative and quantitative model. The qualitative model stems from the functional decomposition of the system and determines what value measures are of concern to the stakeholder. A quantitative model is then built to convert raw performance data into a value score for evaluation.

Traditional value modeling can be adapted to create a timeframe-value diagram, which displays the value score of different technology solutions with time. In addition to incorporating the time domain, the model must also include uncertainty, since performance data is not fully defined for immature solutions. The SIPMath® Tool is Microsoft Excel provided a useful tool for building this model.

A stochastic value model was built do demonstrate this process as it relates to a battery solution for an unmanned aerial system. The associated technology roadmap shows that current Lithium-ion battery solutions earn a score of approximately 30. However, with the projected advances in battery technology, three different chemistries—Lithium-silicon anode, Lithium-sulfur, and Solid-state Lithium-ion—will increase that score to approximately 60 within the next 10 years. The timeframe-value diagram can be used to project design decisions for a technology roadmap.

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