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SHAPING DEPOT MAINTENANCE STRATEGY WITH PREDICTIVE MODELING

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ABSTRACT

Defense fleet managers require maintenance strategies that deliver high readiness, reliable and sustainable combat equipment in the face of operational uncertainty and chaotic tactical environments. Shaping depot maintenance strategy is complex: aircraft, vehicles, and weapons systems operate in unpredictable and dynamic environments while component aging, convoluted maintenance practices, and overlapping sustainment programs all influence requirements. Yet, most predictive analytics efforts are focused on short-term tactics and historical data. As a result, these models cannot deliver the needed long-run precision suitable for depot strategies. Despite new big-data feeds, cloud applications, and innovative visualizations, most underlying predictive models are not suited for the challenge due to a simple reason: The past does not represent the future. Without the appropriate predictive tools, fleet managers lean heavily and cautiously towards doing more maintenance. The underlying assumption is that more maintenance yields more readiness. Four case studies, show successful predictive modeling of depot maintenance complexities. An advanced, approach towards predictive analysis across the lifecycle of defense programs can accurately shape strategies and identify cases where too much maintenance is scheduled.

INTRODUCTION

PEOs, PMs, PdMs and PSMs don't strive to reproduce the past—their goal is to employ lifecycle management strategies that deliver affordable, high readiness across asset lifecycles. Their objectives include delivering reliable and sustainable combat equipment in the face of operational uncertainty and chaotic tactical environments. Fleet managers prepare for events they cannot control by evaluating the effects of these challenges and developing mitigation plans. They demand a good understanding of the effects that today's and tomorrow's decisions will have on future outcomes. They must identify and bound risks and uncertainties.

Shaping depot maintenance strategy is complex: aircraft, vehicles and weapons systems operate in unpredictable and dynamic environments while component aging, convoluted maintenance practices, and overlapping sustainment programs all influence requirements. Accurately developing sound maintenance strategies requires advanced predictive modeling with the ability to deliver precise insights over decades of future operations. This requirement is fundamentally different from that of more simple cases which benefit from a quick, near-term prediction. Yet, most predictive analytics efforts apply underlying models that rely heavily on historical observations. Despite new big data-feeds, cloud applications, and innovative visualizations, the underlying models are inaccurate for a simple reason: The past does not represent the future.

If depot maintenance plans are developed on past years of historical data, these flawed, rear-facing strategies fall short of meeting the sustainment objectives. At best, these predictions—powered by the past—lock programs into that historical view for quarters or years. The aftermath may be unrecoverable. Rear-facing strategies cannot support innovative operations and cannot accurately shape the vision required to get ahead of the effects of aging equipment, fluctuating optempo, and evolving operating environments. Many elements and uncertainties about the future are not represented in historical data. These details are then omitted in rear-facing strategies.

Using rear-facing models that run on historical data yields decision support that is reactive in nature. Even in the case of sophisticated machine learning or elegant Bayesian models, looking back at history, including near-real-time data, produces reactive decision making. Tactics often benefit from a reactionary approach. However, strategy requires anticipation of events and conditions that have not yet emerged in the volumes of history. Depot maintenance requires a balanced strategy to deliver readiness improvements while considering lifecycle costs.

Without the appropriate predictive tools, fleet managers lean heavily and cautiously towards doing more maintenance. The underlying assumption is that more maintenance yields more readiness. Using case studies, examples of successful predictive analysis are detailed with a focus on the complexities of depot maintenance. An advanced, approach towards predictive analysis across the lifecycle of defense programs can accurately portray future outcomes to shape strategies and identify cases where too much maintenance is scheduled.

To successfully depict the interrelated factors across all elements of the asset lifecycle, a predictive analytics solution must model each asset and its parts in detail, reliability of components must be represented, maintenance tasks, supply inventory, logistics, and asset sustainment most all be captured in detail. The interactions between these elements must also be represented. To support depot maintenance strategy, the results from the predictive modeling must span a broad range solutions. Four case studies are examined to illustrate examples:

- Time-based results depicting cost and effects of depot maintenance across a full lifecycle
    - Case Study 1
- Predictive modeling of depot maintenance through asset end-of-life and divestment
    - Case Study 2
- Depot maintenance in support of complex, global, multi-year operations
    - Case Study 3
- Modeling of detailed maintenance tasks and varied depot schedules
    - Case Study 4

Capital intensive defense programs can improve performance while reducing operations and support (O&S) costs by applying progressive strategies to achieve future sustainment objectives while staying ahead of upcoming adversities. Depot maintenance strategies benefit from this approach. With accurate predictive analysis, maintenance can be shaped to a precise scope required to balance the improvement of equipment health while controlling the investment in maintenance resources and limiting asset down time. Depot maintenance plans are shaped years in advance, yet they support dynamic operations across varied tempos and environments. How can these plans leverage advances in predictive modeling and analysis?

Integrated predictive solutions capture volumes of inputs and translate them into accurate, detailed views of future equipment performance, maintenance requirements and costs over time. By employing rigorous predictive modeling solutions, defense programs shape a visionary strategy prepared for future obstacles and focused on long-term sustainment objectives. These case studies illustrate results from this approach.

PREDICTIVE MODELING WITH HIGH RESOULTION DISCRETE EVENT SIMULATION

Using high-resolution, discrete-event, predictive simulation can deliver the accuracy that defense fleet managers require to develop lifecycle management strategies that include life-extension programs through depot maintenance. With simulation-driven analysis analysts generate unique volumes of output from simulated future operations to derive precise predictive results and improve asset lifecycle management. This technical approach uncovers unforeseen lifecycle management challenges and identify root causes. The result is optimized maintenance strategies with controlled cost and risk.

This advanced predictive modeling applies the latest, evolving advances in design of experiments (DOE) to map the many possible future outcomes, across various response metrics, driven by input factors with inherent uncertainty such as component reliability, maintenance task times, operational tempo, and supply chain performance. From volumes of high-resolution simulation output, quantitative relationships between input factors and resulting outcomes are developed to identify the best choices for the long-term management and sustainment of capital-intensive assets.

The modeling beings by representing the details of a multi-indentured bill of materiel (BOM). Each individual serialized platform (aircraft, vehicle, weapon system) is modeled along with the serialized components in the BOM. This detail is depicted in Figure 1 below.

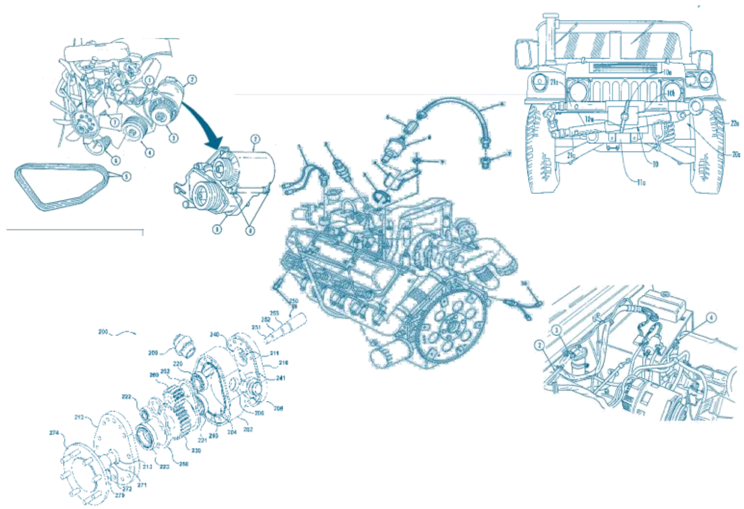

Figure 1: High Resolution Asset Modeling Represents Multi-Indentured BOMs

The predictive model must represent interacting, complex elements of lifecycle management: part-tracking along with a holistic representation of global supply chains, multi-echelon maintenance, complex operations, logistics, component aging, engineering changes, life-extension programs, and inventory management. Effective predictive analytics must be capable of managing high-velocity, high variability, and high-volume data to deliver a holistic view of future fleet management that rear-facing analysis overlooks. The predictive model must:

- Capture the effects and relationships between multiple simultaneous, interdependent physical phenomena.
- Include details from many lifecycle management perspectives: platform configuration; equipment and weapons system performance; fleet size and composition; reliability; maintainability; supply processes and capacity; logistics constraints; and maintenance task times.
- Represent on-going programmatic issues including upgrades, reset, retirements, battle loss, service life extension programs, operations tempo, aging, and degradation.
- Run on attainable, realistic input data requirements.

The simulation must employ comprehensive maintenance models spanning asset populations with serialized equipment and indentured BOM components. Figure 2 below depicts the major modeling areas: System Design, Operations, Maintenance, Logistics, and Repair Parts Inventory. Representative input data is listed within the circle, and output metrics are depicted outside of the circle. The holistic model should realistically depict the layers of uncertainty in the environment while bounding the complexity of asset lifecycles to produce detailed and accurate results.

High-resolution asset models include parts and components throughout several indenture levels in the bill of materials. Component aging is detailed over time. Maintenance is represented as a series of related events starting with equipment inspection, component removal, tear-down, condemnations, repairs, replacements, component builds and installation into the asset. Movement and shipment of assets and parts is included. Sustainment plans, such as depot maintenance, are examined within the full context of world-wide operations and day-to-day maintenance at organizational and intermediate levels.

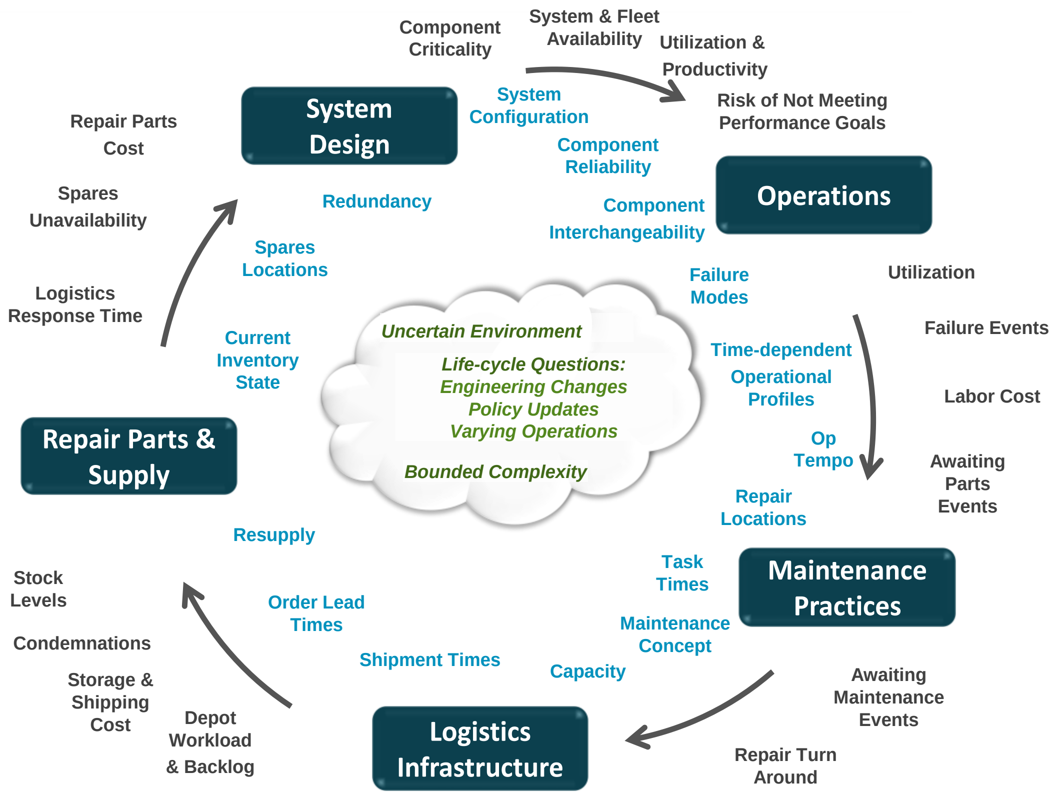

Figure 2: Holistic Lifecycle Model

This predictive analysis effort must be capable of taking on the most challenging data sets—those with large gaps and many errors. Data conditioning techniques must be employed to overcome these data limitations. Advanced DOE methods can help overcome lack of data and poor data quality. Detailed analysis of the result space that maps output metrics and decision outcomes to input factors is achieved by combining high-resolution discrete event simulation with advanced design of experiments techniques such as Nearly Orthogonal Latin Hypercubes (NOLH). This technique efficiently examines large, complex sets of input factors and their effects on predictive metrics. The advantages of these designs are discussed the references (Cioppa and Lucas 2007; Sanchez, Sanchez, and Wan 2014).

CASE STUDY 1: DEPOT MAINTENANCE SCOPE FOR NEW GROUND VEHICLE PROGRAM

In the example below, a ground vehicle fleet was developing its depot maintenance strategy in 2010. The default plan, based on historical experience, was to rebuild each vehicle twice in its lifecycle—seven years apart—to improve sustainment. The depot program would include a full rebuild (0 miles / 0 hours). The objective readiness was 80% materiel availability.

By simulating a set of future scenarios that combined several maintenance strategies with varying operational requirements, a set of results were produced to capture the span decision-making options. Figures 3 and 4 below summarize this case study.

Three intervals between visits to the depot were analyzed: five, seven, and ten years. Cost was essentially unchanged regardless of depot rebuild interval. The seven-year scenario results are shown. The default full-rebuild is shown in the green curves (plots with highest cost and readiness). It produces the best readiness at the highest cost. Eliminating plans for the depot rebuild is shown in the red (lowest cost and readiness). Readiness is unacceptable for this option. Applying a strict inspect-and-replace-only-as-necessary (IROAN) strategy also falls short. The IROAN option is shown in orange (curve above the lowest cost and readiness). However, developing an enhanced IROAN strategy balances readiness and cost. With this plan, engines and suspensions are always replaced and other equipment is replaced only when exceeding 85% of its useful life. The result, in blue (curve below the highest cost and readiness), shows that readiness that nearly matches the full re-build option, and yet yields over $93M in cost avoidance: Total cost of $639M and fleet readiness above 80% operational availability (Ao) for the full lifecycle.

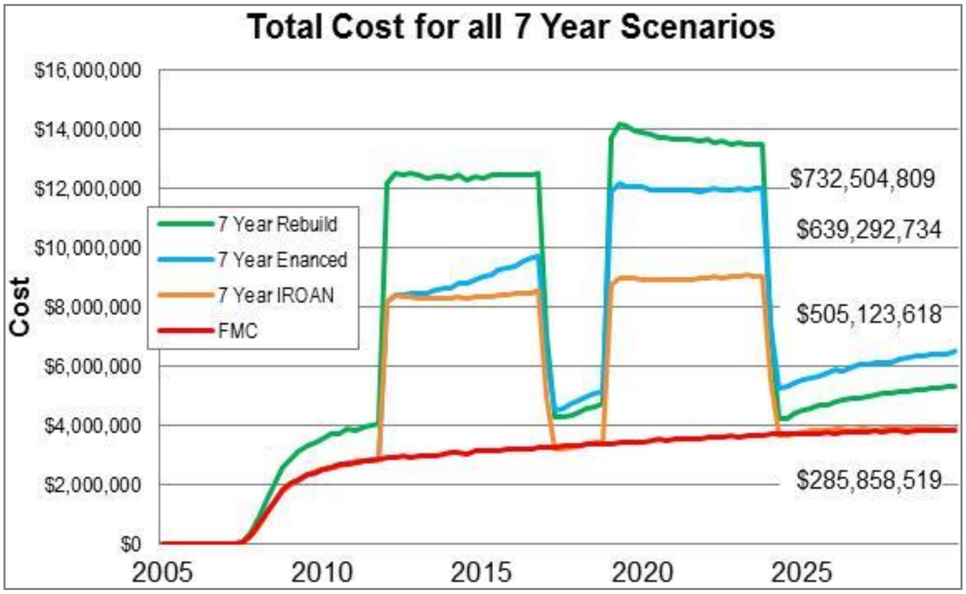

Figure 3: A sample figure

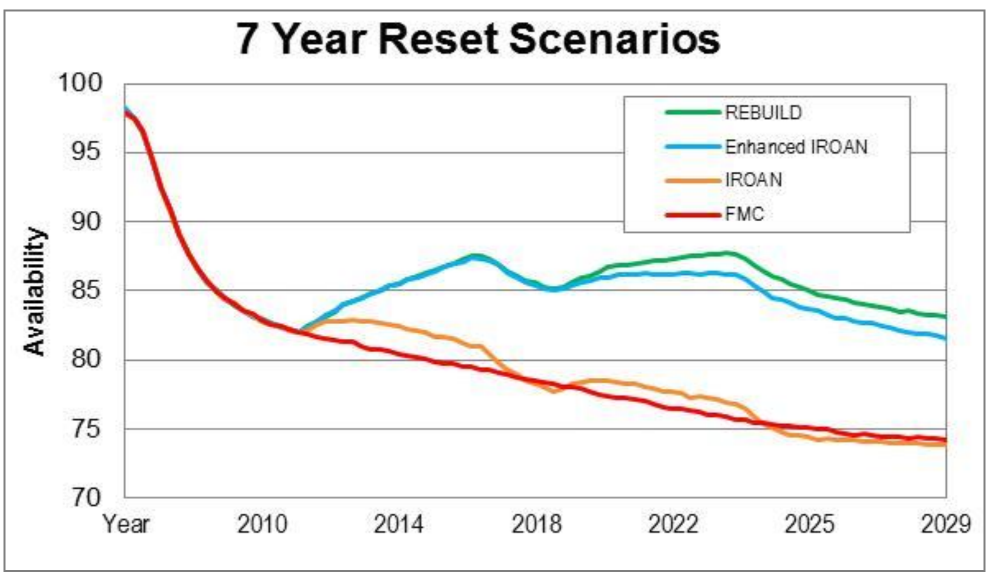

Figure 4: Maintenance Costs over Lifecycle of a Ground Vehicle Fleet

CASE STUDY 2: VEHICLE FLEET END OF LIFE AND DEPOT MAINTENANCE

The second case models an aging ground vehicle fleet that is approaching end of life. To ensure high readiness, a full-rebuild depot maintenance program has been in place for several years. The baseline (blue) plot depicts material availability across the fleet over time. Continuing with the depot program for two more decades results in variability (the plot shades in this area of variability) driven by shipping vehicles to the depot and then realizing the improved reliability after each set of vehicle rebuilds is complete. Overall fleet availability drops as the vehicle population diminishes since the down-time of each vehicle has more influence as retirements continue. To attain these results, each serialized vehicle and all of its parts are modeled in day-to-day operations. Optempo variations by location, inventory buys, shipment delays, maintenance task times, and component reliability are depicted in detail for decades of miles driven.

After evaluating the results, an interesting insight is uncovered: The depot maintenance program is excessive. Maintenance at the operational level alone results in materiel availability above 90%. While depot maintenance improved reliability, the turn-around time at the depot facility needs to be less than a week to make up for the loss of operating hours for each vehicle pulled out of fleet operations during depot maintenance. After exploring more scenarios and varying model inputs to ensure the results hold up to all extremes across possible futures, the recommendation to reduce or stop the depot program emerges as the optimal solution. The yellow line in Figure 6 shows the optimized results: terminating the depot maintenance program. The mean of the resulting materiel availability (yellow line) remains above the midpoint of the area (traced by the blue line) that depicts the baseline case.

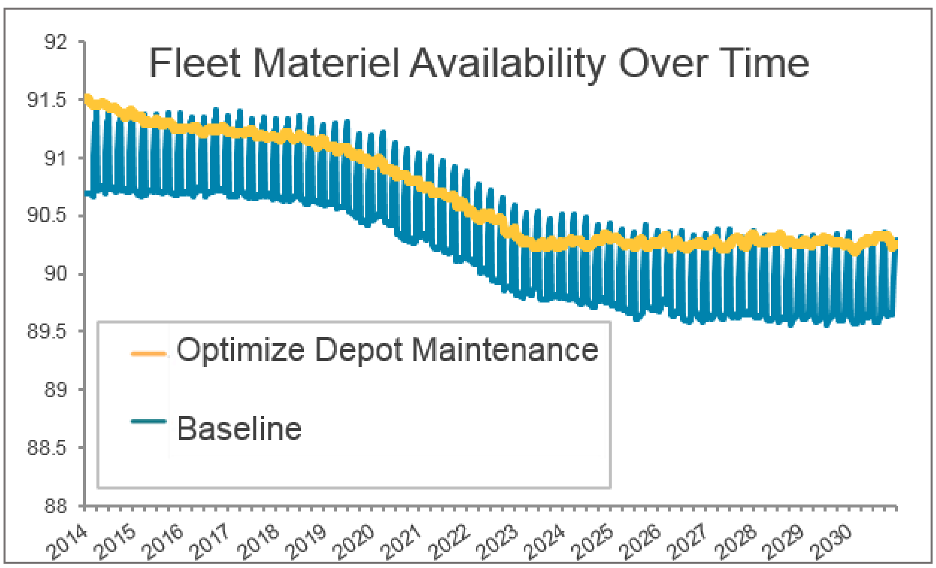

Figure 6: Optimizing Depot Maintenance through End of Life

CASE STUDY 3: RETROGRADE & RESET DEPOT MAINTENANCE

Predictive modeling for depot maintenance strategies must be capable of depicting complex operations and evaluating the effects of a changing environment. This case study includes modeling of retrograde and reset after combat operations. Before the retrograde, in-theater triage maintenance is completed to ensure the most critical repairs are addressed. Upon arrival in

CONUS, vehicles are shipped to either the Barstow depot or the Albany depot. Reset maintenance and component upgrades are accomplished at each depot. Vehicles are returned to the operating units. Vehicles already in CONUS (not part of the retrograde operation) can also be shipped for depot resets. After in-theater triage, but before retrograding, some vehicles are diverted for temporary surge operations in a separate combat theater. Figure 7 below depicts these retrograde and reset operations.

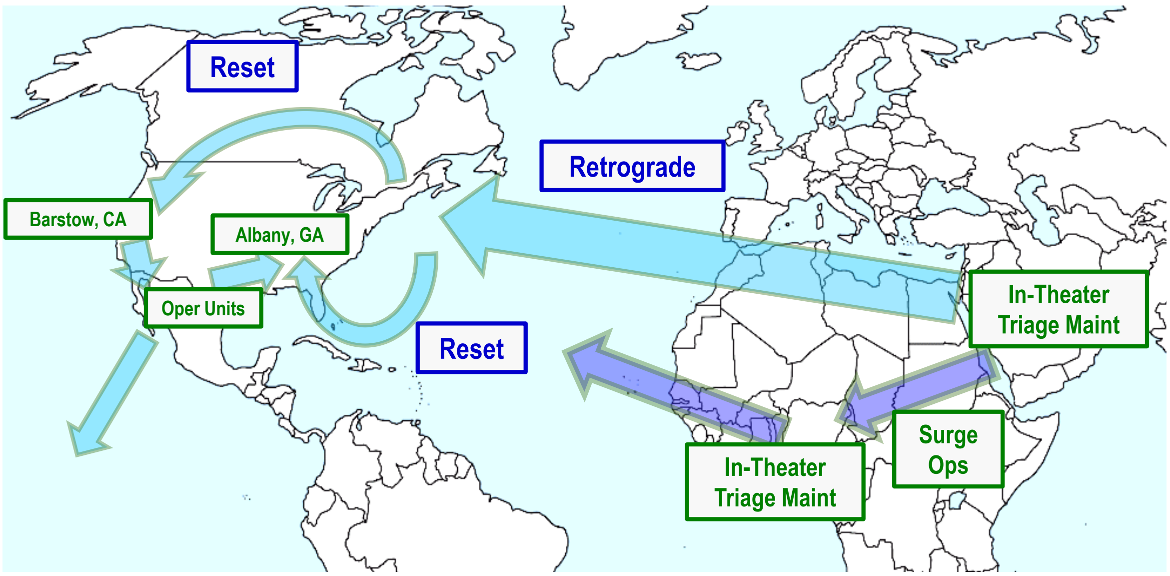

Figure 7: Retrograde & Reset Operations

Advanced DOE with an NOLH design is applied to measure the effects of varying inputs on and complex operations on the depot reset strategy. Variable input factors include:

- Optempo of CONUS operations
- Optempo of combat theater operations
- The duration of surge operations in the second combat theater
- The intensity of surge operations in the second combat theater
- Variability of mean time between failure (MTBF)
- Duration of maintenance task times
- Duration of depot reset maintenance
- Capacity at the Albany depot
- Capacity at the Barstow depot
- Shipping time from theater to each depot

As inputs are each varied across a wide range of values, according to the NOLH design, key measures are tracked in the simulation output: Ao (both in CONUS and in theater), total maintenance cost, logistics response time, and number of vehicles waiting at each depot. Figure 8 summarizes the results of the DOE main effects screening. The input factor-output metric combinations shaded in green depict a measurable statistical significance indicating that the metric is dependent on the input factor. A mathematical relationship is derived to quantify each sensitivity. The slope of each plot depicts the nature of each relationship. Each plotted line represents the mean and is bounded by a curve on either side that depicts the variation of each output as the input factors are adjusted. These results provide a more complete understanding of the possible future outcomes as uncertainties evolve.

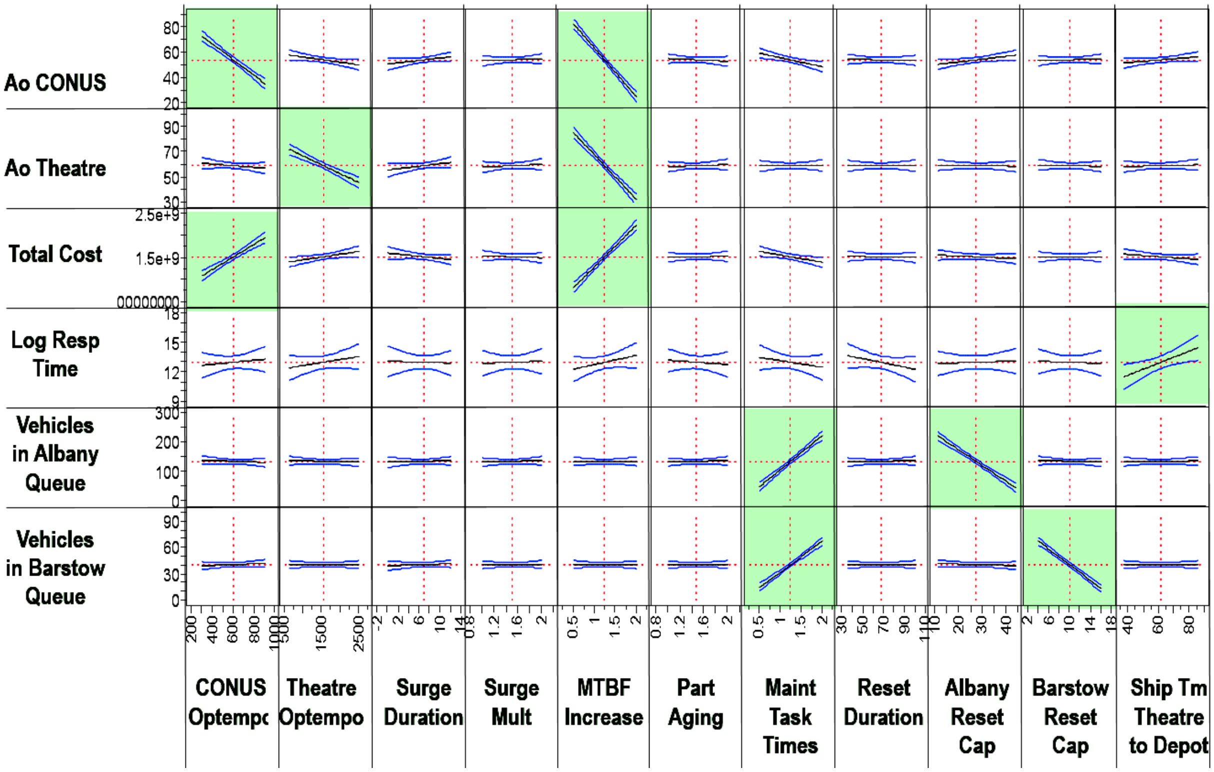

Figure 8: Depot Strategy Main Effects Screening

The DOE analysis enables a thorough evaluation of the effect that multiple factors have on key metrics. In Figure 9 below, the duration of maintenance tasks (horizontal axis) and the capacity of the Albany depot (vertical axis) are mapped to their effect on the resulting number of vehicles awaiting maintenance at the Albany depot. The darker blue shading indicates more vehicles waiting than the lighter shades. The depot capacity is measured in number of vehicles undergoing maintenance simultaneously. The maintenance task duration is shown as a multiplier. The value 1.0 represents historical depot maintenance task times. However, the speed of this work is variable and may slow down (maintenance task time multiplier 2.0) or it may become faster (maintenance task time multiplier 0.5).

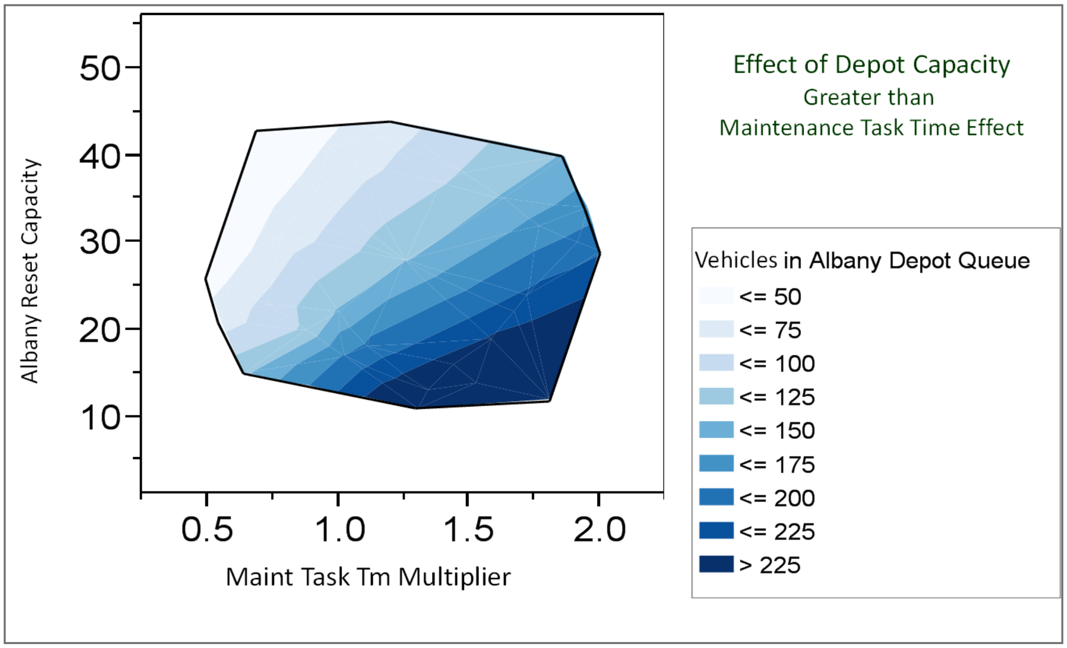

Figure 9: Effects of Depot Capacity and Maintenance Task Time on Depot Throughput

The number of vehicles waiting in the Albany depot queue is affected by both input factors and is driven more by depot capacity than speed of maintenance. So, to improve the throughput at the depot, adding more maintenance bays, maintainers, and tools is more important than accelerating maintenance tasks with current resources. The resulting number of vehicles awaiting maintenance is predicted for each combination of maintenance task time and depot capacity. While only a very limited number of input factor combinations were explicitly run through the simulation, the NOLH design intelligently selects these combinations to map the full result space including combinations of inputs that may have not been simulated. This technique provides a broad understanding of the future, and relationships between strategy inputs and outputs while focusing the predictive analysis.

CASE STUDY 4: DEPOT MAINTENANCE SCHEDULING & READINESS

To support depot maintenance strategy, predictive modeling must detail the effects of depot maintenance schedules as well as the intensity of the sustainment effort represented in the depot scope of work (SOW). This case study depicts an evaluation of three possible future depot schedules: rebuilding twelve, twenty-four or forty vehicles per year. For each schedule, thirteen various combinations of maintenance tasks make up SOW options. Each SOW option details a unique combination of maintenance tasks to be carried out during a depot life-extension program. A total of thirty-nine scenarios are evaluated across a thirty-year period. Each scenario includes detailed representation of each vehicle, across the asset BOM by modeling serialized parts. Repair part inventories, logistics, supply, maintenance, and operations are all detailed along with the variations that may emerge across three decades.

Figure 10 shows the results for the baseline scenario, which includes a full vehicle rebuild as the SOW, across the three schedules. The cost of the rebuilds is high, especially with the aggressive forty-vehicle schedule (up to $2.6B). Yet, the payoff, in terms of readiness, is low. Less than 2% availability is gained by moving from no rebuild program to the twelve-vehicle per year schedule with a full rebuild depot maintenance scope.

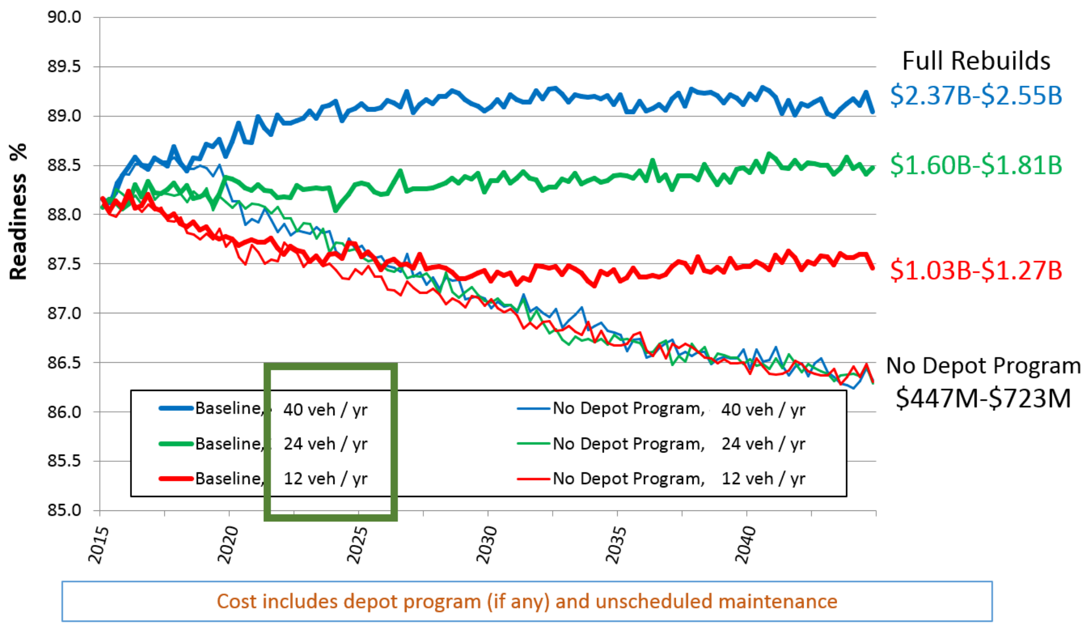

Figure 10: Results from Three Depot Maintenance Schedules

For the most aggressive schedule, forty vehicles per year, Figure 11 shows the effect of various levels of depot maintenance SOW. Thirteen options are depicted. To capture the effect of skillsets for the depot maintainers (artisans) compared to maintenance at the operational units, the No-Depot-Rebuild option is simulated across two scenarios: with the more highly-skilled capabilities of a depot maintainer and with the basic skillsets at the operational units.

The black line showing the highest readiness is the baseline model result with a full rebuild SOW. The remaining alternative SOW options produce results that are grouped together, in the middle of the chart, without significant difference. This group of plots rise to 88.5% Ao and drop to just below 88% over time. These SOW options include: IROAN, replace all 310 depot-level parts, replace the top 20 high-cost parts, replace all parts that cost more than $5,000, replace depot-level high-failure parts, replace all high-failure parts, replace depot-level parts at various cost thresholds, or replace the top 20 cost-drivers.

Regardless of SOW, the results are essentially equal. Thus a depot program adding readiness that translates to 2% fleet availability. The full rebuild SOW, shown by the baseline plot, adds 3% readiness for about $1.7B. The value of that small increase in readiness can now be carefully weighed against its cost over time. A strategy that keeps this program in place will likely be driven by an objective other than readiness improvement. The predictive modeling results are next reproduced under varying conditions that span future uncertainty to ensure that the insights and observations remain consistent.

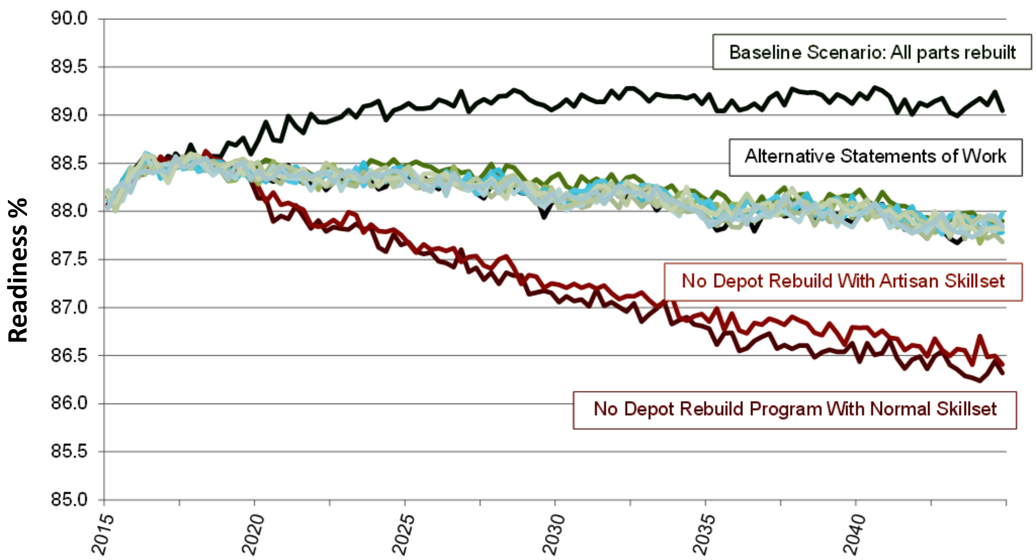

Figure 11: Thirteen Varying Depot Maintenance Scope of Work Plans for 40 veh/yr schedule

SUMMARY

Across all four case studies, high-resolution simulation delivers powerful predictive answers to asset operations and sustainment challenges driven by accurate representation of future performance and a structured approach that generates insights about the future. This advanced predictive analysis approach helps innovative decision makers identify and solve problems months and years before these challenges impact performance and O&S cost. The results far surpass the limitations of rear-facing models running on historical data.

Results generated by these high-resolution predictions are unshackled from past observations. Historical data is *only* used to establish the starting position: Today's conditions. From this point forward the simulation generates accurate future observations that span the many possibilities ahead. Output metrics define in-depth solutions that easily outpace rear-facing analysis ranging from machine learning and big data business intelligence to traditional forecasting.

High-resolution simulation generates data to describe the details of future operations—volumes of future data. The results capture the details needed to portray the effects of aging equipment, changing environments, and transforming processes. Advanced simulation experiment design defines the scenarios to replicate and maps the multi-dimensional result space for future operations. The probability distributions that represent future uncertainty and risk evolve over time. This predictive approach captures the wide breadth of possible future outcomes.

This comprehensive technique explores the unexpected turns forced by dynamic environments along with the effects of aging equipment, changing component reliability, new maintenance programs, changing operations, and the myriad of adjustments that intricate global operations generate every day. The rigorous predictive modeling employed by the case studies successfully evaluates the complexities in developing depot maintenance strategies that span decades into the future in the face of uncertainty.

Applying high-resolution, discrete-event simulation to predictive analysis delivers a visionary maintenance strategies designed to deal with future obstacles and focused on long-term business objectives. The next generation of predictive analysis is being employed now to improve decision-making for fleet managers seeking to develop progressive strategies that maximize readiness while controlling cost.

REFERENCES

1] T.M. Cioppa and T.W. Lucas "Efficient Nearly Orthogonal and Space Filling Latin Hypercubes", Technomertrics 49(1):45-55, 2007.

[2]A Dubi "Predictive Modeling and Simulation for Maximizing System Performance", JMO Publishing, London, Ontario, 2006.

[3]P.J. Sanchez, S.M. Sanchez, and H. Wan, "Simulation Experiments: Better Insights by Design", Winter Simulation Conference, Savannah, GA, 2014.