# The Inventory Decision Support Process for Aircraft Inventory Management


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## *ABSTRACT*

*Systems Planning and Analysis, Inc. (SPA) supports enterprise stakeholders of multiple aviation platforms with state-of-the-art decision support through the Inventory Decision Support Process (IDSP). The IDSP is a powerful capability based on Modelling and Simulation that enables stakeholders to align budgets, schedules, and other stove-piped planning activities. This alignment results in an authoritative baseline picture that provides stakeholders with ground truth for decision-making across their enterprise. At the core of IDSP is a simulation engine that forecasts the future state of each asset in the inventory and allows for "what if" explorations with maximum flexibility. This predictive engine relies on our established data processing pipelines and customized data visualizations to generate meaningful results that drive decisions and provide a platform for further analysis. Furthermore, IDSP's prescriptive analytics can determine optimal maintenance, modification, and custody schedules and present them in a single view of long-term future readiness.*

*In this paper the SPA team describes IDSP and a recent application that paired IDSP with a constrained integer optimization solver to efficiently identify a globally best solution, with multiple planning variables and constraints that adhered to the customer's business rules.*


## 1.0 IDSP OVERVIEW

SPA developed and refined the IDSP over a long period supporting the U.S. Department of Defense aviation customers. IDSP derives from an earlier process known as the Naval Synchronization Toolset (NST) Process, which serves Naval aviation clients. As work expanded beyond the original Naval aviation customer, to include the US Air Force for example, SPA developed "IDSP" to reflect a more general application of the process (follow these links for additional examples of IDSP for E-2 and F-16). IDSP is an asset planning process. It is a software-supported decision process that models and forecasts asset availability. SPA developed the Augur modelling and simulation software to facilitate IDSP. The process has three components:

1) Augur software program, i.e., the computational simulation engine.
2) The pre- and post-simulation data science processes for input data analyses and preparation, and data output interpretation and visualization.
3) The operations processes and stakeholder roles in the use of Augur.

IDSP is SPA's man-in-the-loop decision process that helps stakeholders decide the future disposition of assets to organizational units. After the client creates operational schedules, skilled operators use the IDSP software, Augur, to generate authoritative plans in support of strategic decision-making. The fact that this data is considered authoritative (i.e., officially recognized data sets that are certified and provided by the respective owner of the authoritative source) is a key concept in understanding IDSP's power and use.

Using this authoritative data, IDSP forecasts the utilization and future status of each asset and the resultant resourcing level of each user unit. The forecast (also called projection data) is a function of enterprise utilization demands and operational schedules, resource management decisions, maintenance depot requirements, asset capability modifications, and service-life limits.

Operators also employ IDSP for excursion analysis to support strategic decision-making outside of the formal authoritative planning process. The key discriminator between authoritative and excursion work is that the former results in an update of the official inventory planning data, while the latter does not.

## 2.0 CONCEPT OF OPERATIONS (CONOPS)

As part of IDSP, SPA builds CONOPS documents for the effective use of IDSP for each customer. After the customer specifies high-level operational schedules and constraints, SPA incorporates these into the IDSP software to generate authoritative data and support strategic decision-making for all assets in the inventory.

IDSP relies on key stakeholders throughout the process to ensure the data is authoritative. Stakeholders are designated based on their subject-matter expertise and authority. They direct active IDSP operators and provide budgetary and policy guidance to ensure the asset inventory is meeting operational and training requirements. Examples of key stakeholders includes asset custodian planners, operators and operational commanders, and depot and other maintenance teams.

### 2.1 IDSP Workflow

The actual process for executing IDSP has multiple steps that are coordinated to ensure that the results are accurate and reliable. The process begins with collecting all data, plans, and assumptions from the key stakeholders listed above, as well as additional inventory planning activities (budgeting activities, engineering assessments, modification and sustainment plans, etc.). These data often come from different organizations and are not internally consistent. SPA employs a team of data scientists who identify any discrepancies and work with the stakeholders to resolve the differences and prioritize the information from each data source. SPA then prepares or updates the input files for an IDSP run using this adjudicated data. The IDSP team updates the model's business logic using the latest assumptions, policies, and guidelines provided by the stakeholders and then execute Augur, the IDSP modelling and simulation software, to generate acceptable, if not optimal, asset custody and modification plans. Augur exports the simulation results using an Application Programming Interface (API) that the data scientists use to produce reports and visualizations for the customer. These reports include asset-, unit-, and fleet-level analysis on configuration, availability, utilization, and maintenance facility work. An overview of a typical workflow using IDSP is show in Figure 1.

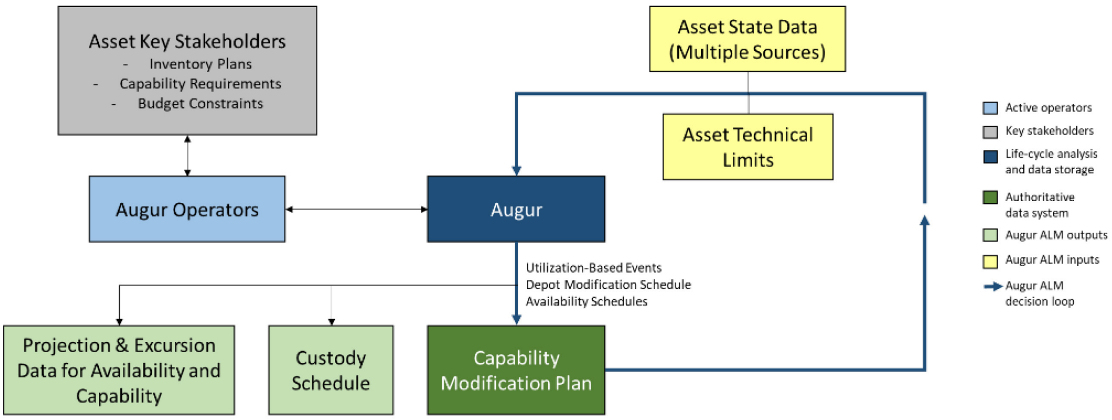


**Figure 1: IDSP workflow process.**

## 2.2 Guiding Principles for Authoritative Data Generation

The fundamental principles for generating authoritative data using IDSP are as follows:

- All data inputs are authoritative and are provided by qualified Subject Matter Experts (SMEs) from the organizational owner of those data elements. If different data sources conflict, cognizant stakeholders are engaged to adjudicate the discrepancies.
- All asset plans and schedules are developed under the direction of cognizant stakeholders.
- Distribution of projection data beyond the stakeholders is not permitted before projections are socialized among stakeholders.
- At the end of each authoritative production cycle, the IDSP model and associated databases are archived so that authoritative plans and data can be reconstructed and analysed later.

# 3.0 PRESCRIPTIVE ANALYTICS

IDSP synchronizes and forecasts inventory management and, in that sense, makes predictions. But “predictive analytics” is not IDSP’s chief strength because that type of analysis is limited in scope. Predictive analysis describes what happened in the past (e.g., looking backwards using regression analysis) and from there predicts expectations for the short-term future. As a forecasting technique, this can be useful but not very powerful.

IDSP bases its answers in prescriptive analytics. Prescriptive analytics focuses on actionable insights gained by projecting into the long-term future. The technique iterates copious amounts of historical data (the authoritative past) with enough planning, budget, and policy information (looking forward) to create deep insight for optimal decision-making. Given that expensive assets, such as fighter jets, ships, and submarines, are meant to last for 50 or more years, the appeal and utility of prescriptive analytics cannot be overstated.

The Augur analytic engine is at the core of IDSP’s prescriptive capabilities. The figure below depicts a simple view of the IDSP and Augur’s place within it. An operator enters data (e.g., operational and maintenance schedules), which Augur computes into optimized utilization and status forecasts. An evaluator (man-in-the-middle) examines the forecast for its suitability, injecting a critical eye into the process. For example, if the evaluator spots an anomaly pertaining to a specific asset, the operator modifies the inputs and Augur re-computes the results until optimal results are achieved. These results create the authoritative baseline from which informed decision making occurs.

The full prescriptive power of the IDSP lies in what comes next. Because decision makers can now depend on the clarity that the baseline provides, they are confidently able to seek further analyses in the form of excursions from the baseline. They are able to ask “what-if” questions that explore useful courses of action that they could not have foreseen without IDSP’s results, thereby benefiting from the process’s prescriptive capabilities.

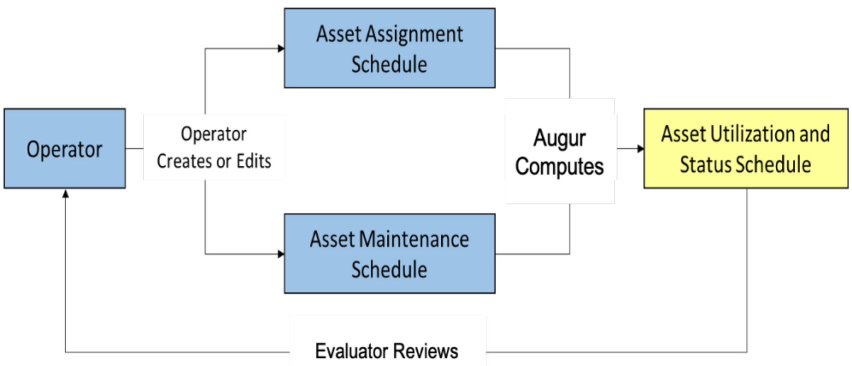


**Figure 2: Prescriptive analytics workflow.**

# 4.0 OPTIMIZATION

The process shown in Figure 2 works well for iterating with stakeholders to build optimized assignment and maintenance schedules for short-term needs. However, when the decision space is large, e.g., large fleets or numerous maintenance induction opportunities, or plans need to be generated to ensure enterprise feasibility, but the timelines involved are beyond a stakeholder's planning horizon, it is helpful to develop algorithms or other automated tools to build optimized schedules. In order to tailor the decision support process for different customers, Augur contains the ability to inject custom logic using "hooks" or plugins that allow SPA to customize the business logic for each customer. SPA utilizes these hooks to create automated scheduling algorithms that can generate optimized long-term schedules based on current leadership priorities. Using analytical solvers, SPA can dramatically reduce the number of iterations an evaluator must review the IDSP generated forecast to identify an optimal solution.

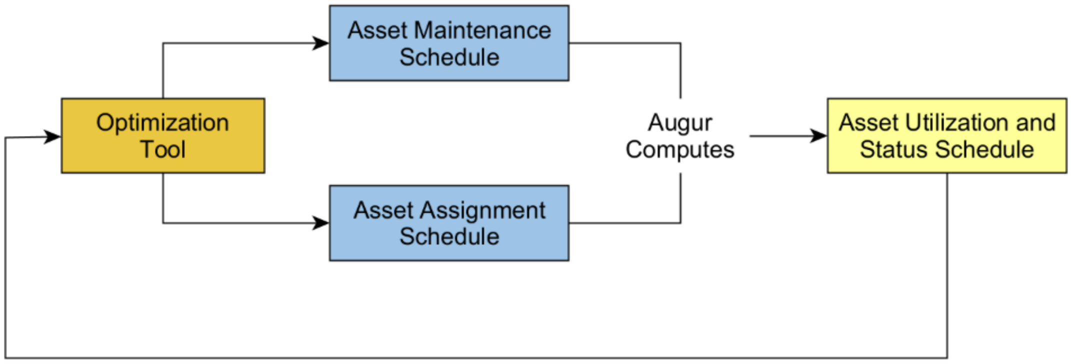


**Figure 3: Optimization workflow.**

As an example application, SPA recently created an automated scheduler algorithm to select candidate aircraft to induct to a limited-capacity, limited-opportunity modification line. Because of the large number of available aircraft candidates, SPA employed automated optimization to maximize capabilities at specific locations, while minimizing wait times between maintenance events. IDSP enables other applications of schedule optimization as well, to include generating long-term modification plans to align capabilities with operational commitments, and minimizing variability in workforce demands at maintenance facilities.

## 4.1 Global Optimization Using Integer-Constraint Programming

The example scheduling algorithm discussed above iterates through each induction date in a sequential manner and finds the optimal candidate for that specific induction slot, thereby finding the locally optimal solution for each induction slot, based on the current set of valid aircraft. A drawback to this approach is that finding the current locally optimal solution may not lead to a globally optimal solution.

Constraint programming solvers resolve the issues that arise from finding local optima—specifically, solvers that use satisfiability methods to find a set of globally optimal solutions. Constraint programming produces a set of feasible solutions from a much larger set of possible solutions. It does this by imposing constraints on the problem, i.e., by introducing new constraints, the set of feasible solutions is reduced. Examples of possible constraints in IDSP are: (1) no overlapping maintenance events, (2) a maximum or minimum total number of maintenance events that can occur at any one time, or (3) modification prerequisites. Integer constraint programming allows for variables that are by definition Boolean (one or zero) or other integer values (inductions can only start on integer number of days, for example).

A simplified example of how this works is provided below. Assume there are five aircraft (A, B, C, D, and E) and three induction slots (1, 2, and 3). The gaps between adjacent, pre-existing events on the aircraft's operational schedule for each possible induction are shown in Table 1. For this example, the enterprise wants to ensure there are no missed inductions nor delays to operational events, so an optimal solution is one that maximizes the time between induction and operational events. Note that N/A indicates when the aircraft already has another event scheduled that would overlap with this induction. The left image of Figure 4 shows all possible induction combinations. The right image shows the optimized inductions that maximize the sum of the squared gaps between adjacent induction dates.

Using constraints alone will produce a set of feasible solutions, but it does not specify which among the set of solutions would be the "best" one. An appropriate objective function provides a quantifiable metric to find the optimal solution among the set of feasible solutions. It is often challenging to find an objective function that all stakeholders within an enterprise agree to; however, an objective function that captures the critical variables of any given stakeholder is often achievable, and an "optimal" solution for that stakeholder can be quantitatively found. A more complete description of constraint programming, optimization, and satisfiability methods are beyond the scope of this document, but the reader can learn more in references 1 and 2.

For the globally optimal solver used with IDSP, SPA uses the CP-SAT solver in Google's OR-Tools (ref. 3). The CP-SAT solver has built-in variables (e.g., intervals and optional intervals) and constraints helper functions (e.g., no overlapping intervals and linear sums) that simplify the tasks of creating and editing the rules. The specific steps that SPA followed for the example above were:

1) Create intervals for all existing tasks (note that overlapping tasks are consolidated to avoid infeasible solutions from overlapping intervals).
2) For each set of inductions, add optional intervals to each aircraft with the induction start and end dates.
3) Add a non-overlapping interval constraint per aircraft.
4) Add a constraint that each induction can only be assigned to one aircraft.
5) Add a constraint that each aircraft can at most receive one induction set (note that induction sets can include multiple inductions per aircraft).
6) Calculate the gap between each induction and the closest other existing tasks. Set the gap to zero if the optional interval is not picked.
7) Create an objective function that maximizes the sum of the squared errors of the gaps.
8) Solve for the case that maximizes the objective function (shown in Table 2).

**Table 1: Days between adjacent events in aircraft's operational schedule.**

| Aircraft | Induction 1 | Induction 2 | Induction 3 |
|---|---|---|---|
| A | 100 | 60 | N/A |
| B | 60 | N/A | 70 |
| C | N/A | 50 | 60 |
| D | 120 | N/A | 80 |
| E | 130 | 110 | 30 |

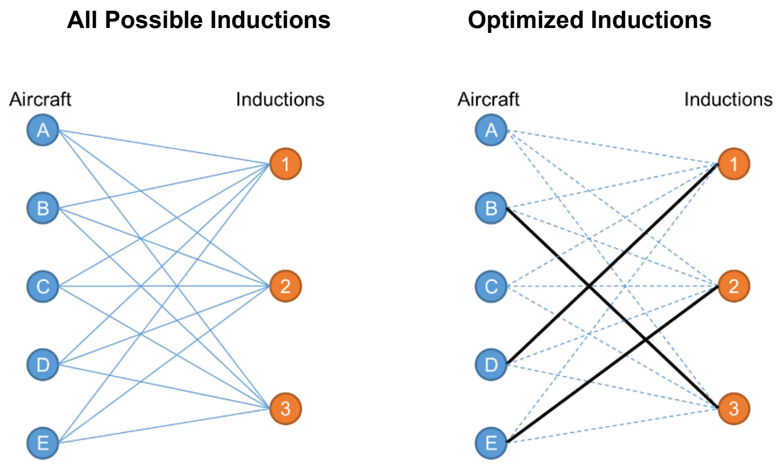


**Figure 4: All possible induction opportunities are shown in the image on the left. The optimized inductions are shown as solid black lines in the figure on the right.**

**Table 2: Optimal pairing of aircraft and induction opportunities.**

| Aircraft | Induction 1 | Induction 2 | Induction 3 |
|---|---|---|---|
| A | 100 | 60 | N/A |
| B | 60 | N/A | 70 |
| C | N/A | 50 | 60 |
| D | 120 | N/A | 80 |
| E | 130 | 110 | 30 |

It is worth highlighting some considerations for achieving automated "optimal" solutions using these IDSP algorithms. As shown in Table 2, where Aircraft D is the globally optimal solution for Induction Slot 1, even though Aircraft E had a longer gap to adjacent events, the globally optimal solution may not be the best choice given immediate information (i.e., it may not align with the locally optimal solution). Globally optimal solutions are achievable if the definition of optimal remains stable. If leadership priorities shift over time and change the objective function defining "optimal," global optimization may not be achievable and local optimization may be preferred.

## 5.0 CONCLUSION

This paper describes the Inventory Decision Support Process and accompanying simulation tool developed by SPA to support U.S. Department of Defense customers. SPA developed this process to provide decision support services to customers responsible for making custody assignments and maintenance plans. By utilizing authoritative data, and resolving discrepancies when they arise, IDSP is able to generate a unified picture for all stakeholders in the organization. With this unified picture, these stakeholders can focus on solving enterprise challenges instead of focusing on the differences in assumptions and analyses from different teams.

In order to accelerate some planning activities, SPA has created automated scheduling algorithms based on subject-matter experts' rules. Algorithms using mixed integer optimization incorporate an objective function to globally optimize the generated schedule.

## 6.0 REFERENCES

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