XGEO PNT Automated Scheduling (XPAS): an Update

Ground System Architectures Workshop (GSAW)

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XPAS is the Controlling Hub of the iPNT XGEO Architecture

Future missions in XGEO space will require cost-effective PNT

The Aerospace Corporation's iPNT concept requires no new spacecraft or ground stations—only XPAS, the ground-based control system that is the subject of this paper

The XGEO PNT Automated Scheduler (XPAS) will

- **Maintain a database of XGEO missions and participating government and commercial ground antennas**
- **Receive PNT requests from XGEO missions (scheduled or on demand)**
- **Identify the best-located antenna to upload the iPNT signal and request support**

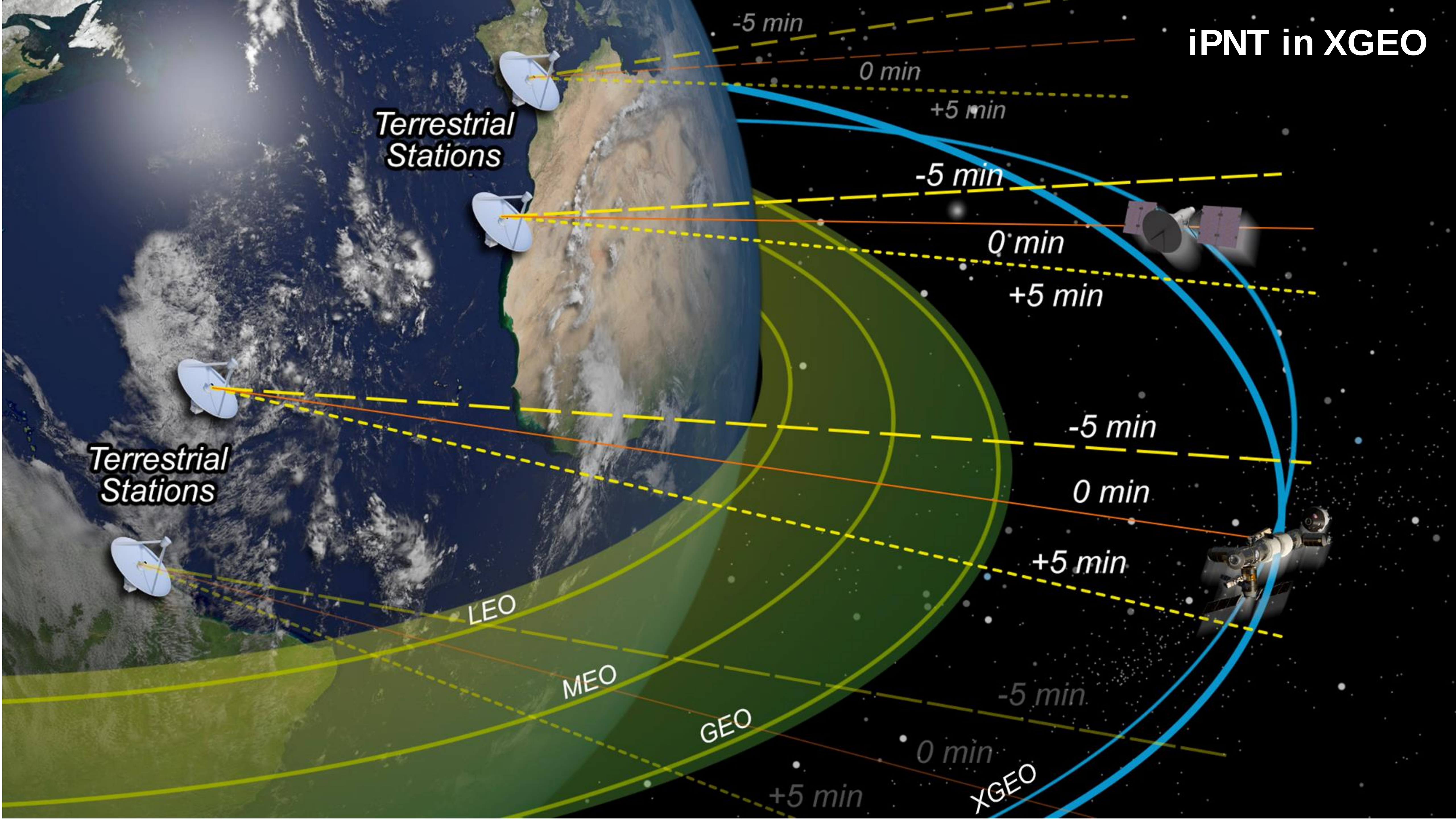
Available ground antennas will execute the uploads and confirm to XPAS

The XPAS architecture will be scalable to XGEO missions and ground antennas for spacecraft with various orbits, missions, security requirements, priorities, accuracy requirements, timeliness, etc.

XPAS will be virtually automatic, with minimal personnel; we intend it to run on a PC or equivalent

This presentation updates our GSAW 2022 presentation by revisiting potential algorithms and focusing on developing and assessing the automated scheduling portion of XPAS

iPNT in XGEO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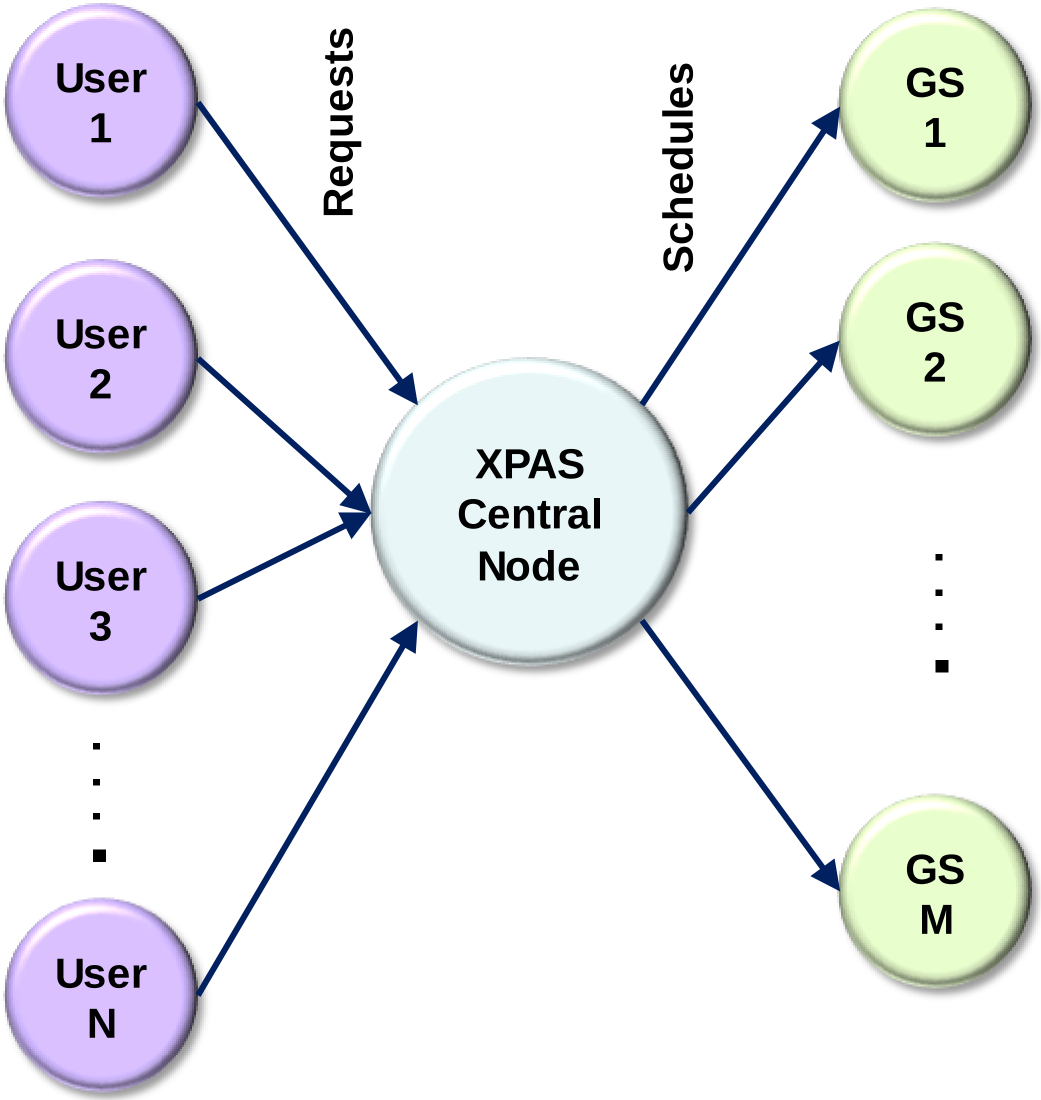
Developing XPAS: a High-level Centralized Architecture

After GSAW 2022, we began investigating architecture considerations



- Users send requests asynchronously
- The central node examines current schedule and finds best time slot across the ground stations (GS) with
  - Suitable communication path with sufficient power to reach user
  - Either an empty time slot or capacity to move an existing scheduled communication to a different GS or time slot to enable a new communication
- When the central node receives an acknowledgement (ACK or NACK) from a user, it relays the ACK/NACK to requesting customer
- The central node stores all messaging and scheduling in one of two ways:
  - Distributed cloud architecture
  - Replicate all user information at each customer site
- Customers and users can access messaging and scheduling that pertains to their requests

Developing XPAS: a High-level Decentralized Architecture

We will use modeling & simulation to select between centralized or decentralized architecture

- Users send requests asynchronously

- The XPAS central node selects an XPAS decentralized node and passes it a user request

- The XPAS decentralized node examines schedule and determines if it can meet a request, along with the request value and the quality
  - *If it can meet request, it reports its ability to meet the request along with PNT value/quality*
  - *If cannot meet request, it declines*

- The XPAS central node compares opportunities from each GS and chooses the best one
  - *If it removes a future scheduled request that is less important than the current request, the central node attempts to reschedule across all GS*

- When the central node receives an acknowledgement (ACK or NACK) from the user, it relays the ACK/NACK to requesting customer

Key Architecture Parameters

For GSAW 2023, we identified key architecture parameters but still need actual values

- Ground stations
  - *Number and location*
  - *Tx/Rx strength, frequencies, bandwidth, etc.*
  - *Slew time parameters (acceleration, velocity, function)*
  - *Duty cycle*
  - *Estimated time/power required to send each signal*
- Users
  - *Rx/Tx strength, frequencies, bandwidth, etc.:*
will this spacecraft receive more than it transmits?
  - *Receiver sensitivity*
  - *Base value of spacecraft (mission importance)*

- Ground station-to-spacecraft Tx/Rx parameters
  - *Distance, timing, etc.*
- Orbit estimation stability/variability – position estimate degradation over time
- Impact on quality and value of collection angles, Tx and Rx parameters, etc.

We intend XPAS to be responsive to such parameters and to be scalable to quantities of customers

We Are Designing XPAS to a Flexible and Evolving CONOPS

We will accommodate a broad range of key parameters and metrics

- Number and location of ground stations

- For each ground station, performance parameters
  - *Signal strength, frequency, bandwidth, etc.*
  - *Duty cycle*
  - *Available computation capacity (usually not a problem if on the ground)*
  - *Quantified model of effect of key parameters that influence satellite receiver PNT signal strength/quality*
  - *Associated estimates of time/power required to send each signal*
  - *Slew time functions*

- Orbit estimation stability/variability – position estimate degradation over time

- Receiver sensitivity of each PNT customer

- Relative importance of each customer

What Do We Need in the CONOPS for Cost-effectiveness?

- Can we improve on the assumption that “customers will have to pay more for higher-tier service”?
  - *An economic model can obviate tiers and provide better optimization*
  - *Adjusting collection value by parameters can simplify and improve performance*

- “On a fixed schedule thereafter or upon request,” the system sends PNT
  - *Fixing the schedule a priori is an easier solution because there is much less schedule disruption*
    - Disruption would be caused by orbital changes that require modifications to pointing or unplanned requests for PNT (such as engine burns to modify trajectories)
  - *Can we presume that, even if a fixed schedule is the ideal, we will still need to make changes to it because of orbit drift?*
    - It will be at least somewhat dynamic
    - At the very least, even with ‘fixed’ scheduling, the scheduler will need repair due to orbit drift

- When tasking cadence is in competition, do we solve by lengthening the time between collects uniformly for all satellites?
  - *E.g., if User A is intended to receive PNT Y times per month, and User B is intended to receive PNT 2Y times per month, do both decrease by the same factor? Or does User B not get cut back while User A is cut back drastically?*

Prioritization and payment models are important drivers for success

Revisiting Algorithms: AI-ML Enabled Automated Scheduling Algorithms

Brief definitions & descriptions updating our GSAW 2022 presentation

	Genetic [1,2]	Deep Reinforcement Learning [3]	Reinforcement Learning for Multi-agent Scheduling [4]
Definition	A machine learning technique that uses an evolution-based heuristic.	AI that combines deep learning & reinforcement learning	An event-driven decision process that sequentially assigns agents the best feasible tasks when they finish the previous task
Description	**Steps for learning using a genetic algorithm [1]:** 1. Create an initial population 2. Perform mating and mutation to improve the population 3. Assign a fitness score to each individual in the population 4. Pass the fittest individuals on to the next population	**Fundamentally represented as a Markov Decision Process** Typically consists of an agent that interacts with an environment by observing rewards for actions that it takes	**Steps for learning the best new task for each agent:** 1. Create an agent-task graph 2. Choose best cooperative task assignment for idle agents in a computationally efficient manner, using a softmax function across the tasks 3. Apply a simple normalized reward between the current policy and baseline policy

Revisiting Algorithms: Non-AI-ML Automated Scheduling Algorithms

Brief definitions & descriptions updating our GSAW 2022 presentation

	Greedy [1]	Mixed-integer Linear Programming [2]	Combinatorial Optimization [3]	AFSCN Manual Scheduling Program (ASP) [4]
Definition	Heuristic optimization approach that makes the locally optimal choice at each stage of the computation with the hope of finding a global optimum	Solves a problem with a linear objective function, bounds, linear but no nonlinear constraints, & some objective function components having integer values	Search process for finding an optimal solution within a finite set of possible solutions: during the search, the algorithm evaluates each solution, returning the solution with the best value at the end of the search	Air Force Satellite Control Network (AFSCN) Scheduling Program (ASP)
Description	**Comprises five components:** 1. Candidate set from which solution is created 2. Selection function chooses best candidate to add to the solution 3. Feasibility function determines if a candidate contributes to a solution 4. Objective function assigns a value to a complete or partial solution 5. Solution function indicates when a complete solution has been discovered	Popular approach in Operations Research applications **The approach is defined by the problems it can solve:** i.e., the objective function must be linear; constraints must be linear; and at least some components of the objective function must have integer values	Popular approach in Operations Research applications **Two components allow "intelligent" decisions:** 1. Objective function, which evaluates quality of a solution 2. The algorithm that combines stepwise choices to build a solutions	**Description:** manual scheduling technique that uses heuristics to simulate the actions of Air Force personnel **Inputs:** satellite orbital elements, ground station lat/lon/alt, antenna locations, antenna visibility constraints, desired outputs **Outputs**: visibility plots, antenna sites, supported/non-supported satellites, statistics

AI-ML Candidate Algorithm Pros & Cons

Last year's presentation only mentioned genetic and deep reinforcement learning

	Genetic [1-3]	Deep Reinforcement Learning [4]	RL for Multi-agent Scheduling [5]
Pros	• Well-established general purpose multi-objective optimizer • Flexible for multi-band multi-mode sensors • Likely to reach a usable solution	• JPL published a 2021 paper recommending this approach for NASA Deep Space Network (DSN) scheduling, which is a problem of comparable scope to XGEO iPNT automated scheduling	• Straightforward algorithm that creates workable solutions quickly • Assigns tasks to agents that are idle
Cons	• Not necessarily the best for automated scheduling • Operation time > greedy • Intense compute resources required • Not interpretable for decision makers • Has been used by Aerospace to develop planned schedule but not actual one adjusted based on request (i.e., a schedule request that perturbs scheduling, requiring a revised schedule)	• Not interpretable for decision makers	• Applies a Markov Decision Process at each event • Sequential decision process that only looks at currently idle agents at each event – looking ahead would increase performance at the cost of increased computation time

Non-AI-ML Candidate Algorithm Pros & Cons

This year, we identified more candidate non-AI-ML algorithms, too, like combinatorial optimization

	Greedy [1,2]	Mixed-integer Linear Programming [1]	Combinatorial Optimization [3]	AFSCN Manual Scheduling Program (ASP) [4]
Pros	• Faster than genetic for non-contentious scheduling problems • More interpretable for decision makers than genetic	• Deterministic • Interpretable • Well-established for severely contentious scheduling problems with tightly packed contacts with very little gap time • Scheduling tiers sequentially “bakes in” priorities	• Aerospace has experience applying this approach in a distributed form for a problem of similar scope and sees a straightforward path forward for extending it to XGEO iPNT automated scheduling • Expected to recover from perturbations more quickly than AI-ML like deep reinforcement learning • Method is interpretable for decision makers	• Deterministic • Interpretable • Well-established
Cons	• Generally does not provide globally optimized solutions • Not interpretable for decision makers • Not recommended for problems with sub-problems that require optimization (e.g., sorting problems)	• Not AI-ML so not adaptive • Can only optimize one objective—e.g., requires scheduling tiers sequentially	• Can get stuck in local rather than global maxima/minima—requires carefully designed heuristics or memory to avoid this pitfall	• Long execution time compared to automated methods • Not easy to scale

What's next? Prepare for and hold an algorithm "Bake-off"…

Implement & compare Deep Reinforcement Learning & Combinatorial Optimization vs Manual

Preparation

- Obtain the detailed CONOPS *or make assumptions* required to evaluate performance
- Obtain or reproduce JPL's deep reinforcement learning algorithm onto a compute platform
- Obtain ore reproduce a combinatorial optimization algorithm onto a compute platform
- Obtain or reproduce a manual scheduling algorithm onto a compute platform

Assumption

- The solution team will use the Aerospace AI/autonomy Solution Architecting process (AASA), which includes the Aerospace Trusted AI (TAI) Framework, to select or develop the best algorithm & assess it
  - *The AASA and the TAI Framework processes support whichever algorithm is shown to work best*
  - *The solution team will assess the prototypes using Aerospace's digital engineering crawl-walk-run testbeds*
    - E.g., to determine whether centralized or distributed automated scheduling is preferable

Evaluation

- Verify expectations using modeling & simulation:
  - ***Combinatorial optimization should recover better*** *from perturbations created by scheduling requests*
  - ***Centralized automated scheduling with a hot back-up*** *capability for redundancy should suffice*
- Verify how the three candidate algorithms perform & ***design the architecture around the best choice***

The Way Forward

We need your engagement and help

- We recommend automated scheduling to support the emerging urgent need for reliable, cost-effective PNT infrastructure to accommodate proliferation in XGEO

- Since presenting last year, we understand the trade space better and have identified the most promising candidate algorithms to prototype and assess

- We also have digital engineering processes & testbeds for developing and assessing our prototypes

- However, we still need your input to flesh out the CONOPS and performance metrics for the XPAS

- We hope that this presentation continues the dialog we opened last year—we want to hear from you:
  - *What have you tried?*
  - *What were your lessons learned?*
  - *What do you recommend?*

Thanks!

Summary

We still need your engagement and help

We recommend automated scheduling to support the emerging urgent need for reliable, cost-effective PNT infrastructure to accommodate proliferation in XGEO.

Since presenting last year, we understand the trade space better and have identified the most promising candidate algorithms to prototype and assess.

We also have digital engineering processes & testbeds for developing and assessing our prototypes.

However, we still need your input to flesh out the CONOPS and performance metrics for the XPAS.

For example, does it make sense to you to assume that each upload takes

5, 10, or 30 minutes with 1, 2, or 5 simultaneous uploads

and 10, 50, or 100 active customers and compare how XPAS performs vs manual scheduling?

We hope that this presentation continues the dialog we opened last year—we want to hear from you.

What have you tried? What were your lessons learned? What do you recommend?

THANKS!

Additional Details

- Additional details for implementing XPAS
- Sample application: Digital Engineering testbeds for confidence-building
- Material from our GSAW 2022 presentation on XPAS

XPAS Algorithm Implementation Considerations

Investigating more algorithms for GSAW 2023 led us to consider how to implement them

- Agents: XPAS node(s) processing the collections

- States: discrete points that mark the path of an agent. Some states will be targets.

- Actions: an agent can either add a target to the schedule or move on to the next state

- Rewards: the rewards for each target would be weighted depending on the user priority, geometry, etc.
  – *Rewards ensure that there is no unintentional duplication of effort (i.e., multiple agents aren't collecting the same targets)*

- Simulations for training agents may be available from a library like OpenAI Gym

Resource Allocation Model & Scenarios

This material updates our GSAW 2022 presentation

Resource Allocation

- Some ground station–satellite signals are better at certain times:
  - *Elevation angle from ground to satellite*
  - *Ground station signal strength*
  - *Target satellite receiver strength*
  - *Etc.*
- These parameters should influence pairing of ground stations to satellites

Upload (min)	# Simultaneous Uploads	Active Customers
5	1	10
10	2	50
30	5	100

Scenarios

1. Single user
   - Verify reliably finding an optimal solution to minimize use of resources to meet the user's request
2. Two users
   - Demonstrate consistent ability to solve the over-constrained problem when scheduling to support User A meets a request from User B that conflicts the existing scheduling
3. Multiple users
   - Demonstrate that the scheduling solution scales up appropriately or identify when/why it breaks down

Additional Assumptions for XPAS

This material updates our GSAW 2023 presentation

XPAS assumes dynamic scheduling

- A fixed schedule created to fill a long pre-specified period (a day or week) is easier to develop and requires less computation
- New requests after the schedule is completed cause disruption, but, for many applications, disruptive requests are common

Transmission quality

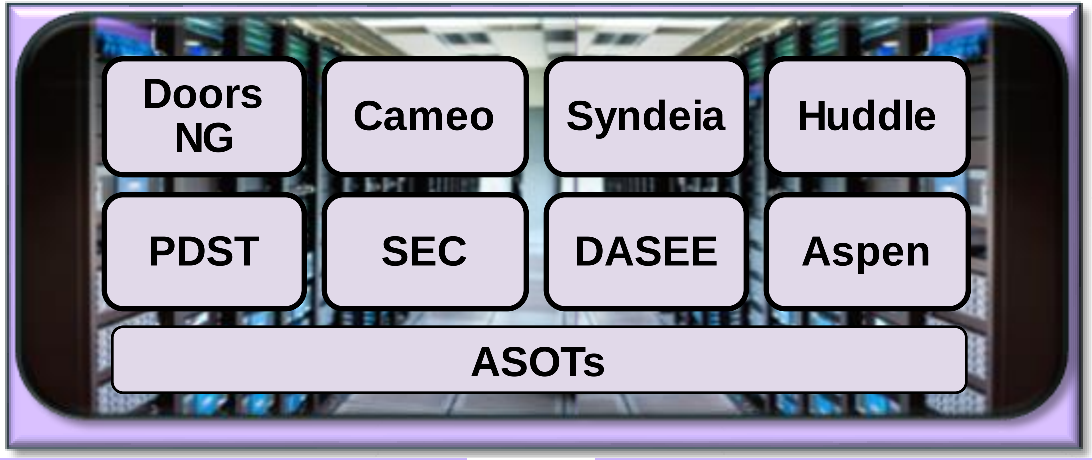
- Transmission quality is a function of the quality of the Tx, Rx, pointing accuracy, and geometry
- Transmission quality is **not** binary (either “good enough” or “not good enough”)

Lab, Field, & In-space Testbeds Work Together in Crawl, Walk, Run for Confidence Building

Aerospace's testbeds coordinate through digital engineering

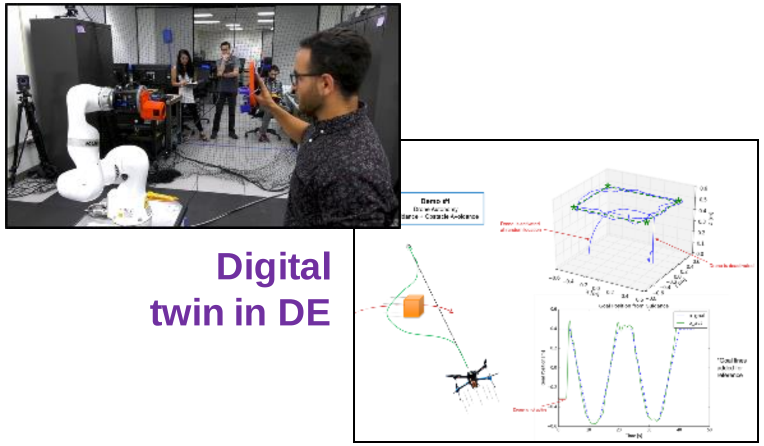
The digital twin developed in software *matures in fidelity* as work proceeds through the testbeds

Environment with M&S, Analysis, SiTL, & HiTL Tools



Digital twin
in digital engineering (DE)

Testbed Demonstrations

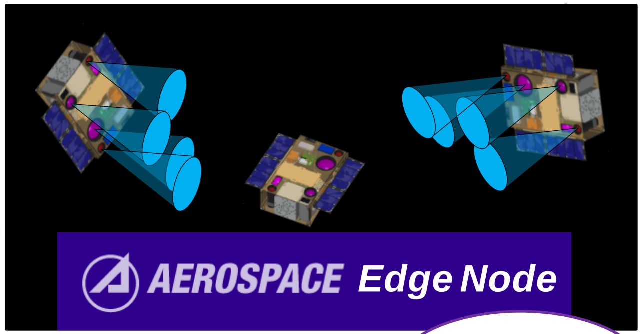


Digital twin in DE

Help!

Digital twin
in DE

Comms are OK; everything is working



Everything is working

Testing in the Instrumented CAVE Lab

Field testing with UAS

In-space AI/autonomy testing with Edge Node

Crawl → **Walk** → **Run**

Aerospace's lab, field, and in-space testbeds work together to support spiral development and test approaches

XGEO PNT Problem & Solution Statements

Problem Statement: Need PNT in XGEO

- Users in XGEO orbits (i.e., operating beyond GEO) need position-navigation-timing (PNT) solutions that are accurate and timely
- Existing PNT systems are not optimized for XGEO
  - *Approaches like iPNT can solve this problem, but, in turn, they can create potential traffic overloads*
- Various users will present with various needs
  - *E.g.,. A military user may need a high-priority solution to perform a maneuver while a commercial user just needs an answer within the next 30 minutes*
- Sometimes, user needs will conflict
  - *In some cases, satisfying one user request will leave one or more other requests unsatisfied*
  - *More users = more conflict*

Solution Statement: iPNT for XGEO

- Our inverted PNT (iPNT) approach can optimize a PNT solution for XGEO
- Existing ground stations would provide PNT solutions based on scheduling user requests
  - *The iPNT system must accept the ground and space elements as they are*
  - *The iPNT system must not add costly requirements*
- Automated scheduling will minimize the degree to which satisfying one requests causes other requests to go unsatisfied

The 2023 presentation updates the 2022 presentation on the automated scheduling portion of the iPNT solution

XGEO iPNT Scheduling Problem & Solution Statements

Problem Statement: Need Scheduling

- Manually-based systems require human operators
- As XGEO users proliferate, more operators will be needed to keep up with demand for PNT solutions
- Time to provide scheduling increases with proliferation of users as complexity rises and conflicts become more frequent
- Scale will rise to the point that hiring more operators becomes untenable
- Retrofitting a manual solution with automation after the fact is much more difficult than building in the needed AI/autonomy from inception
  - *E.g., it is often more challenging to get buy-in from humans using the system to trust it*

Solution Statement: AI-ML Automated Scheduling

- We propose an automated scheduling solution because it can accommodate increasing numbers of users without increasing human workload or response time
  - *No need to hire more and more operators*
- iPNT scheduling is amenable to AI-enabled automated scheduling
  - *The inputs, outputs, and concept of operations can be defined for a growing number of users and for changing conditions*
  - *Of the automated scheduling solutions we're aware of so far, AI-ML seems the most promising because it can adapt to these changes*
  - *Specification of performance and how to monitor and control as well as when, why, and how to retrain or replace the AI-ML would produce an AI-enabled solution that builds in trust*

How do we expect our iPNT system to work?

And what is the XPAS automated scheduler's role?

Before launch, each customer agrees to an Interface Control Document (ICD) with the system that specifies technical configuration, mission needs, and CONOPS

Upon launch, the new mission sends a "launch confirmation" to the system to allow an initial PNT fix

The system sends a PNT upload to the customer's spacecraft, and its control center confirms receipt, closing the loop between the system and the spacecraft

On a fixed schedule thereafter or upon request, the system uploads a PNT solution by aiming antennas at the calculated spacecraft position, and the spacecraft control center confirms receipt

The process continues for the life of the spacecraft mission, with requirements changing as the mission proceeds either in accordance with the ICD or changes to the ICD based on the evolving situation

XGEO PNT Automated Scheduling (XPAS) is responsible for efficiently managing this process without human intervention

Focus on Automated Scheduling for Solution Scalability & Longevity

This work on automated scheduling to support XGEO PNT is just beginning

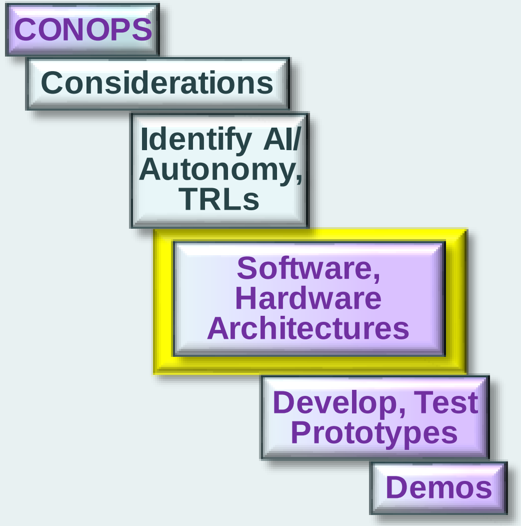
- The XGEO PNT problem has many parts
  - *These include orbital mechanics, user requirements (e.g., solution accuracies, response times for timeliness, update frequencies), safeguarding/firewalling sensitive user information, timely allocation of ground resources, etc.*
  - *Latencies and limited availability of ground resources require an infrastructure for managing solutions, especially when user needs conflict*
- As PNT needs in XGEO proliferate, manual scheduling will be overcome by needs and challenges
  - *Manual scheduling comes with high operation cost due to negotiation and human-in-loop, time required to schedule, system scalability*
  - *Automation can run 24/7, reduce time to produce scheduling solutions while requiring fewer human operators, and scale up without increasing costs; thus,* ***automated scheduling is key to this PNT infrastructure***
- Multi-variable optimization techniques will be required to coordinate across potentially competing variables and user needs
- We intend to identify an appropriate automated scheduling approach, cost function(s), quality of service metric(s), and a concept of operations for the levels of service we propose
  - *We will initially demonstrate single representative use cases and scale up to supporting proliferated constellations*
  - *Fundamental modeling and simulation is part of this effort, starting with selecting candidate algorithms and testing them for one user at a time and scaling up*

We intend to map out the software, process, test cases, and next steps needed for a complete XGEO PNT scheduling solution—not to solve the problem but to show that we can solve it

Working toward an AI-enabled Automated Scheduling Solution

Aerospace has a process for developing trustworthy AI-enabled solutions

Aerospace AI Solution Architecting Process



Software and hardware architectures require iterative co-design to build in tests, monitoring, and control for trust

Perform the model trade analyses

Model architecture requires optimization:

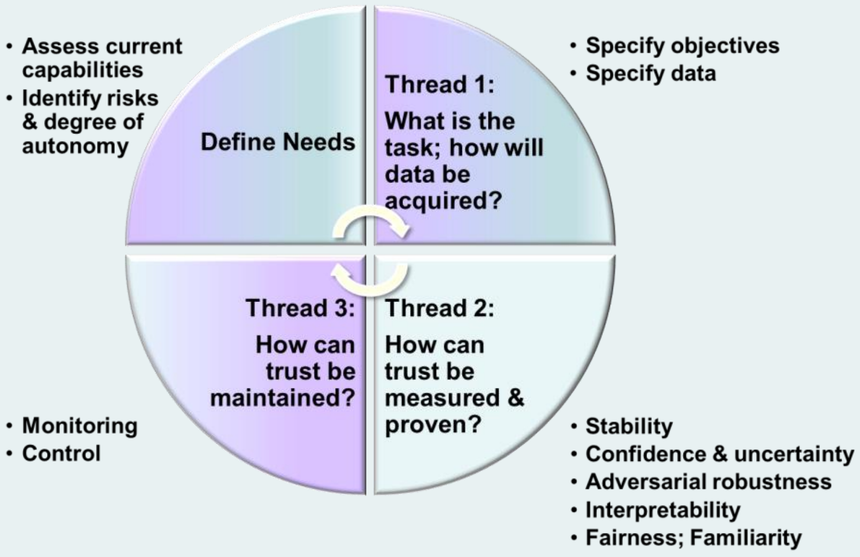
- **Model size, Data sources**
- **Languages, Libraries**
- **Accuracy**
  - More complex model
  - Harder to train
  - More data, compute resources
- **Simplicity**
  - Smaller model
  - Fewer parameters
  - Less data, compute resources
  - Might reduce overfitting
- **Transfer learning vs learning from scratch**

Select or design the model

Use AI Solution Architecture inputs, e.g., trades, to select/design a feasible, appropriately sized model:

- CONOPS
- Considerations
- AI/Autonomy needs
- Model size
- Data needs and availability
  - Data sources, quality, etc. (5Vs)
  - Design of and 5V requirements for simulated data
- Ceiling analysis
- Hardware constraints

Use the Trusted AI Framework to build trust in the model in from inception



Trusted AI is a nascent field requiring explicit definitions into <u>meaningful</u>, <u>generalizable</u>, <u>measurable</u>, and <u>testable</u> attributes. High consequence environments often entail high risk in mission criticality, algorithm complexity to meet mission criticality and complexity, and level of autonomy to meet issues like communications latency. data volume, etc.; technical, cost, and schedule risks must be quantified so they can be mitigated

Complexity of the CONOPS, considerations, & constraints drive the AI design. The following slides give a taste of this analysis to help show that the automated scheduling problem is tractable and amenable to AI-ML.

Considerations

Needs & Scenarios

Needs

- What is needed is a feasible scheduling solution set that avoids saturating XGEO ground stations and resolves request conflicts
- Automate the operation as much as possible (currently, scheduling is done manually)
  - *Automated operation would make our iPNT solution more scalable and affordable*

Scenarios

We will identify candidate automated scheduling algorithms, implement one (possibly more, if a “bake-off” is merited), and see how the algorithm(s) perform in the following scenarios

- *Ensure correct implementation and understand which conditions lead to the algorithm(s) bottle-necking*

1. Single user
   - Verify reliably finding an optimal solution to minimize use of resources to meet the user’s request
2. Two users
   - Demonstrate consistent ability to solve the over-constrained problem when scheduling to support User A meets a request from User B that conflicts the existing scheduling
3. Multiple users
   - Demonstrate that the scheduling solution scales up appropriately or identify when/why it breaks down

Considerations

Constraints & Objectives

Growth

- The system should be “elastic” to grow seamlessly to support hundreds of XGEO spacecraft

Minimize equipment needs

- The system should employ the minimum quantity of ground stations and the time needed from each

Minimize costs

- The system should avoid any “standing Army” (i.e., scaling up should not require increasing numbers of operators)

Mission capable

- The system must meet every “customer’s” needs for timeliness and precision

System efficiency

- The system must allocate resources in real time to avoid resource allocation conflicts

A Few Assumptions

Different users will have different needs; more users will have more needs

We assume a three-tiered service to accommodate a variety of users with a variety of needs

Gold tier

- Users requiring the most urgent solutions, the highest update frequencies, etc.
- Example: military users about to perform maneuvers; commercial customers who need spacecraft PNT to assess whether their launch succeeded

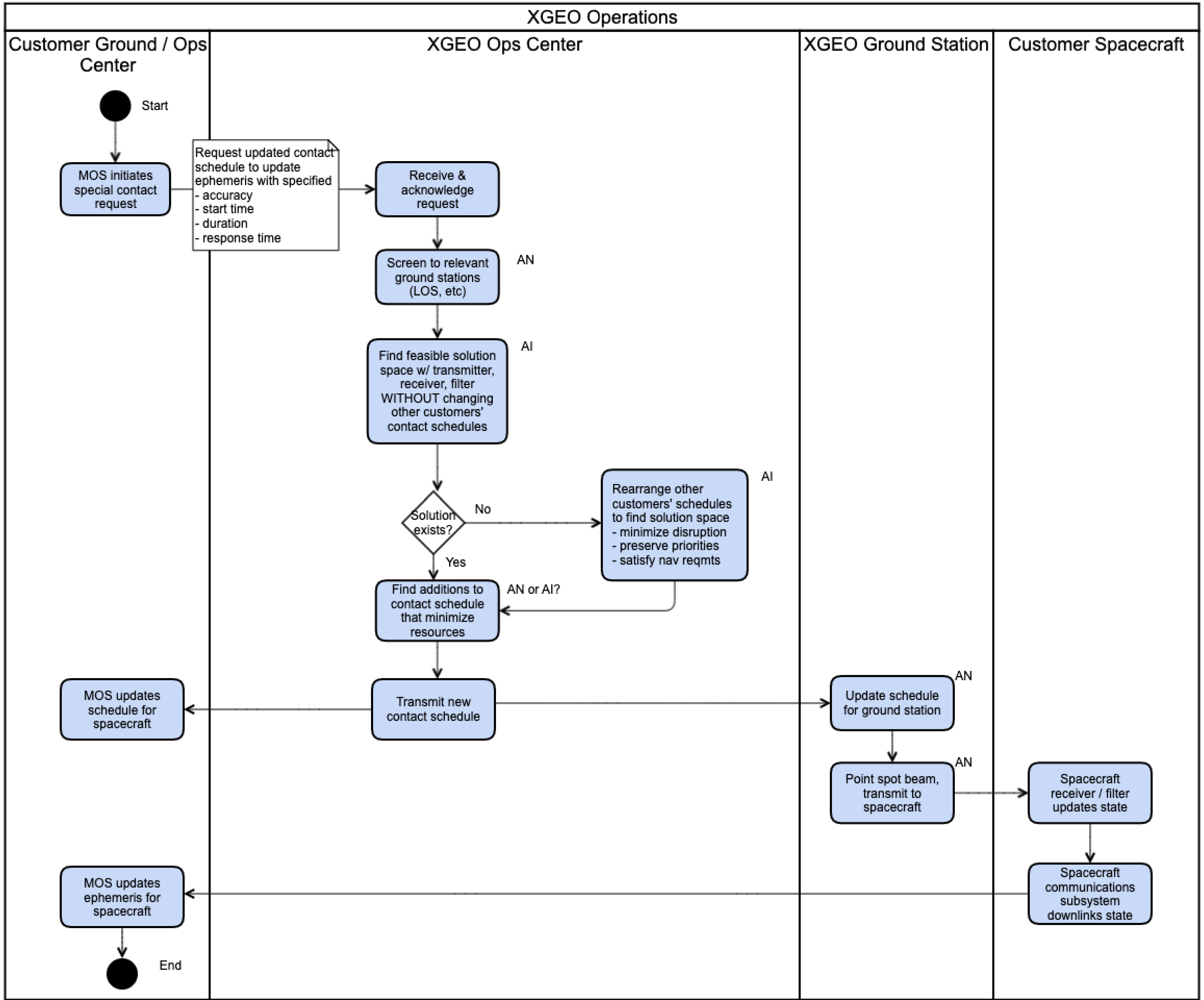
Silver tier

- Users that can tolerate some delay or that require somewhat less frequent updates
- Example: routine but regular military, science, or commercial users

Bronze tier

- Users that can tolerate more scheduling interruptions to accommodate top-priority users or that require even less frequent updates
- Example: routine commercial users

Customers will have to pay more for higher-tier service. Automated scheduling caps those costs because growing numbers of users will not require hiring of greater numbers of operators.



XGEO PNT Automated Scheduler (XPAS) Activity Diagram

- We assume gold, silver, and bronze tiers of PNT service users in XGEO
- As this activity diagram shows, XPAS must schedule PNT solutions by tier priority and satisfy new requests without disrupting servicing of existing requests

Legend

- *Automation (AN): machine takes action where there is no uncertainty*
- *Autonomy (AY): machine makes decisions and takes action to manage uncertainty*
- *Machine Learning (ML): in a learning system, performance improves with experience*
- *Artificial Intelligence (AI): machine does what a human normally would do*
- *Expert System (ES): AI using rules-based reasoning that captures human expert decision processes*

Activity Diagram Details

This use case covers AI/autonomy for the proposed XGEO PNT system

- In general, this is a resource allocation planning and scheduling problem
  - *Very similar to the Deep Space Network (DSN) scheduling problem*
- In this use case, PNT signals are sent ONLY from ground stations to user spacecraft beyond geosynchronous orbit
  - *At a later date, we may examine adding space-based signals.*
- ~20 ground stations form the basis of the XGEO iPNT system
  - *Each ground station has a narrow spot beam that can be quickly re-pointed to different user spacecraft*
  - *This gives ~20 dB advantage over an omni antenna to overcome the $1/R^2$ space loss*
  - *XGEO ground stations will have zero impact on the existing GPS ground stations and satellites*
- The automated scheduling notions presented here help the XGEO iPNT system provide updates to customer spacecraft (aka "users")
  - *The scope of AI/autonomy here is to plan and schedule resource allocation to service user PNT*
  - *This includes minimizing operations staff, optimizing link parameters and filter parameters, accommodating dynamic priority levels for customer service, and navigation requirements that vary over mission phases*
  - *For example, position and velocity accuracy requirements may increase before and after a maneuver*
- Planning and scheduling algorithms must also integrate with simulations that drive system design to create new ground stations and transmitters
  - *Thus, the AI/autonomy should integrate with Model Based System Engineering or digital engineering models*

Activity Diagram Details

Pre-conditions & assumptions for the XGEO iPNT system (i.e., the "system") and customers/users

- At start of use case, the system has an existing solution set for schedule and link parameters for all customer spacecraft ("users")
- The system "knows" user receiver and filter capabilities
- The system can simulate performance of user receiver and Kalman filter
- System can point spot beams
- System has a high-fidelity model of its own capacity envelope
  - *Number of users it can service*
  - *User-required accuracies and ranges*
  - *Includes a digital engineering analysis framework*
- System maintains a sophisticated priority scheme for customers that include timing and mission phase
  - *Some customers may have higher priority in certain mission phases and lower priority in other phases*
- Customers know the system capabilities
  - *Documented in **generic** User's Guide and **customer-specific** Interface Control Document (ICD)*
- ICD defines user communication protocol and more
  - *Maximum range etc. are documented in the ICD.*
  - *System can change contact schedule (with same or worse timing and accuracy for low priority customers) per terms in the ICD with automatic notification to affected users but without negotiation with them*
  - *Customers consent to terms defined in ICD*
- Users maintain Kalman filters onboard
- Customer ephemeris is accurate enough to enable system to point spot beams
- Customer ground/operations send ephemeris updates to system periodically
  - *System always has latest ephemeris for spacecraft*
- Customer maintains own operations team and navigation capabilities

Activity Diagram Details

Outcomes/post-conditions, exceptions/caveats, and AI, ML, and autonomy requirements

Outcomes and post-conditions

- Customer spacecraft receives enough contacts to enable the customer to generate updated ephemeris with required accuracy

Exceptions and caveats

- Interference and threats
- A feasible solution space cannot be found even after rearranging other customers' contact schedules

AI, ML, and autonomy requirements

- The primary need is for automated planning and scheduling to find a feasible solution set that avoids saturating the ground stations with PNT requests.
  - *There are two versions of an AI-enabled solution: one where the algorithm is constrained to not violate other customers' contact schedules and another where the algorithm can change others' contact schedules*
- AI may also play a role in optimizing contact schedules to minimize resource utilization
  - *In this case, resource utilization can mean contact duration, but the objective function may contain additional terms*
  - *For example, the objective function may include operational cost (staff, power transmission, etc.)*
- Other parts of the iPNT system may also require automation

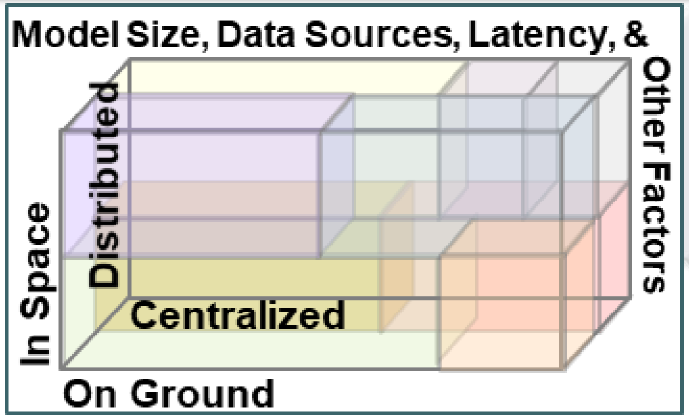
AI-ML/autonomy trade space: what does a solution landscape look like?

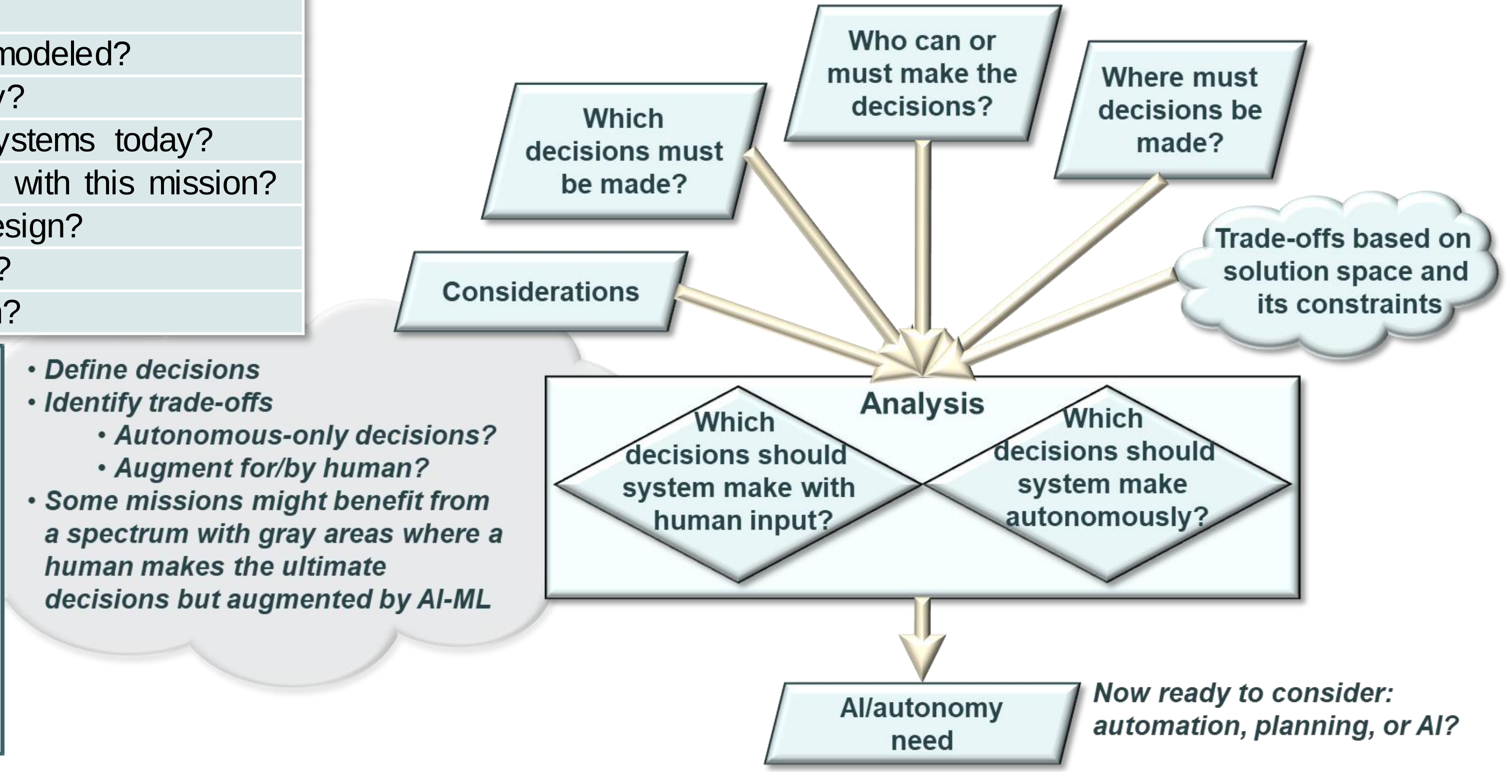
Factors like those illustrated below drive whether, which, and where for using AI/autonomy

Are real time instructions or responses required?	
How hostile or benign is the operating environment?	
Are there more nodes than human operators can control?	
Is there data/model/environment uncertainty? If so, where and how much?	
5Vs of Data: Volume, Velocity, Variety, Veracity Value?	
	Is the data imagery? Telemetry? Other signals?
	What size data? How frequent? Streams or batches?
	What fidelity is required or expected?
Does distance latency preclude real time comms?	
How well can the system, control, and environment be modeled?	
How much can be accomplished using non-AI/autonomy?	
How do human operators make decisions with similar systems today?	
What are the current policies, and how do they intersect with this mission?	
Is the operational team a constraint, or is it subject to design?	
Cost/schedule/risk? Supplier skill sets? Test capabilities?	
If AI/autonomy is required, where, which, and how much?	

What we know:

- Autonomy is required to make our XPAS scheduling solution sustainable as the population of users scales up
  - *We expect to have to interleave among priorities*
- Real-time PNT may not be needed or feasible
- Processing will be centralized on the ground





Candidate algorithms: which are best for automated scheduling?

We are researching which algorithms to implement (e.g., for a bake-off)

AI-ML

- ML
  - Supervised
    - Support Vector Machines
    - Bayesian networks
  - Unsupervised
    - Clustering (e.g., k-means, hierarchical, fuzzy c-means
    - Principal Component Analysis
    - Genetic algorithms
  - Reinforcement
    - Q-learning, W-learning
- AI
  - Neural Networks
    - Configurations include feed-forward, deep, recurrent, etc.
    - Applications include anomaly detection, identification/classification, computer vision, regression for solution optimization, etc.

Non-AI-ML (e.g., statistical, optimal control, etc.)

- Multi-objective optimization (e.g., Pareto, in which improving one factor degrades at least one other)
- Greedy algorithms
- Decision theory
- Mixed-integer linear programming
- Rulebases, including fuzzy

Each technique has benefits and drawbacks

- Approaches that learn and evolve over time are more resilient to changing conditions (e.g., onboard sensor degradation, environmental changes)
  - *However, they pose challenges for trust (e.g., interpretability, maintaining performance over time as conditions change, etc.)*

Two promising approaches we will explore:

- **Genetic algorithms are useful for parallelization and multi-objective optimization—solutions improve over time—and Aerospace is using them for scheduling**
- **JPL developed a deep reinforcement learning neural network for Deep Space Network scheduling**

Next Steps for XPAS

We need your engagement and your help

There is a need for reliable, cost-effective PNT infrastructure to accommodate proliferation in XGEO.

An iPNT solution minimizes cost, schedule, risk. To maximize elasticity, automated scheduling is needed.

We believe the automated scheduling problem is tractable and amenable to AI-ML, hence XPAS.

This work is only beginning, so next steps include, for example, laying out the trade space so that we can select candidate algorithms and perform modeling and simulation to see which to implement.

Part of this includes identifying performance metrics for the XPAS AI-enabled automated scheduler,

Identifying figures of merit for the PNT service, etc. For example, we need measures of effectiveness we can compare against a manual system as a function of system parameters.

For example, we can assume that each upload takes 5, 10, or 30 minutes with 1, 2, or 5 simultaneous uploads and 10, 50, or 100 active customers and compare how XPAS performs vs manual scheduling.

We hope that this presentation opens a dialog so that we can hear from you.

What have you tried? What were your lessons learned? What do you recommend?

THANKS!

Sponsorship

As an FFRDC, Aerospace is a trusted partner for handling sensitive information without entanglements that for-profit contractors could encounter

We can also help commercial and academic interests who might also operate in XGEO

Opening the playing field to commercial users should increase our overall agility for operating in XGEO

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