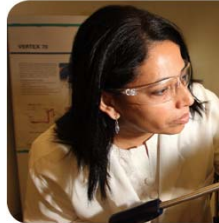
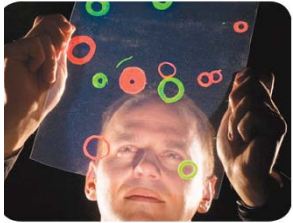


Unclassified Unlimited Release (UUR)

Constellation Scheduling Under Uncertainty: Models and Benefits



GSAW 2017

Securing the Future

March 14th, 2017

Christopher G. Valicka*
Jean-Paul Watson



*Exceptional
service
in the
national
interest*



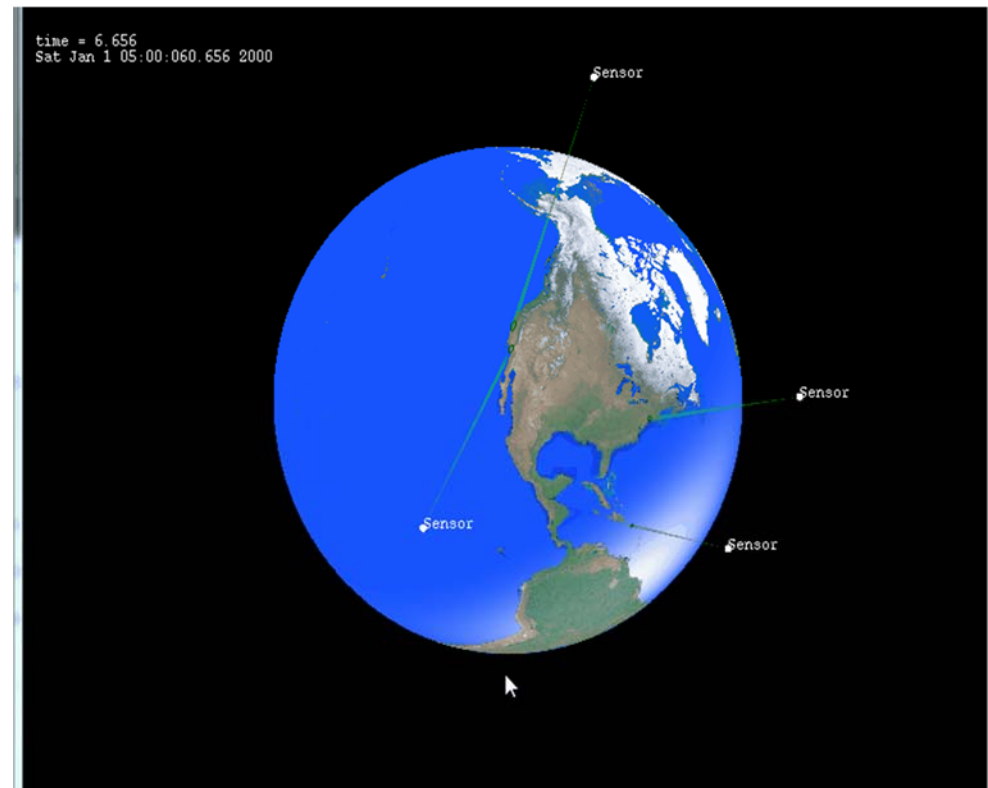
*Correspondence: cgvalic@sandia.gov

Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000. SAND NO. 2015-4322 C

© 2017 by Sandia National Laboratories. Published by The Aerospace Corporation with permission.

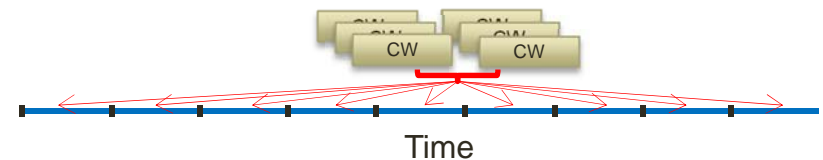
Overview

- A remote sensing constellation scheduling problem
- A Mixed-Integer Program (MIP) for constellation scheduling
 - Results
- Stochastic scheduling models
- Computational results
- Ongoing and future research



The Constellation Scheduling Problem

- Problem:
 - Manage a collection of satellites scheduled to monitor physical locations in space and time
- Challenge:
 - Sensors have **highly flexible capabilities**, not captured in current scheduling models and technologies
 - Schedules underutilize expensive sensors
 - Missed collection opportunities can impact national security
 - Evolving events and uncertainties necessitate:
 - Efficient consideration of alternative schedules
 - Timely schedule generation
- Assumption:
 - The performance of the constellation will be evaluated w.r.t a fixed set of *collection windows*



How is a Collection Window Defined?

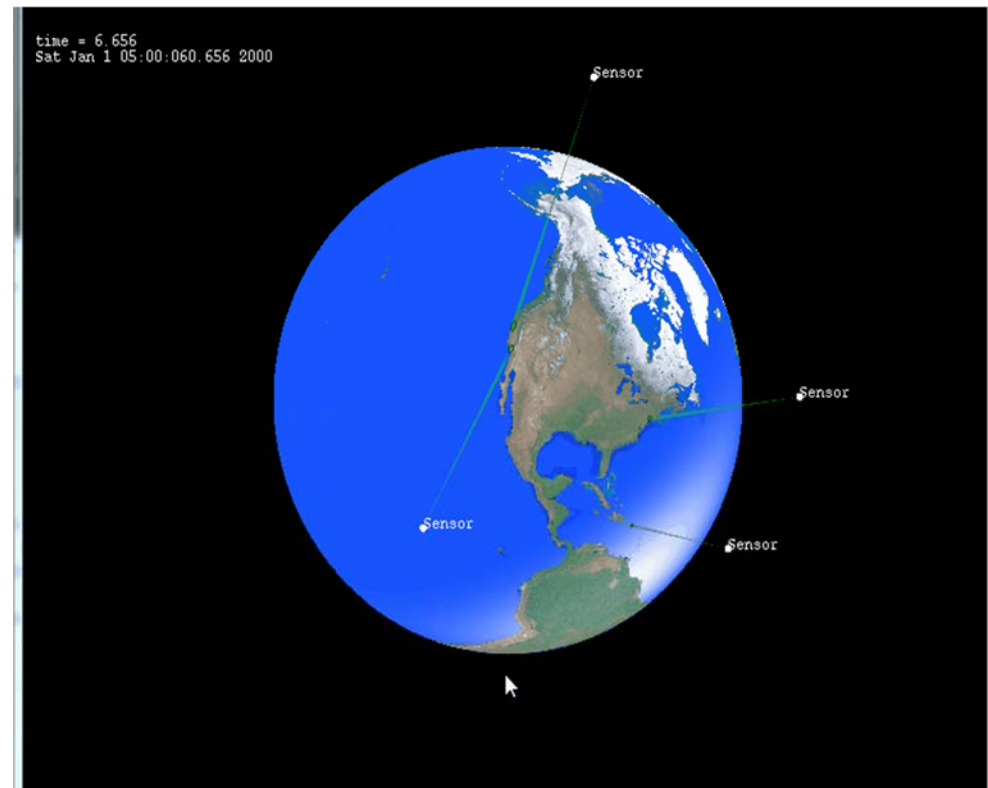
- **Start time**
 - Time window: list of potential collection start times
 - Duration: fixed and known before building schedule
- **Configuration:** sensor configuration needed for collection
 - **Physical location:**
 - The location that needs to be observed; precise requirements depend on the sensing technology
- **Performance:** predicted observation quality. Impacted by sensor, sun, target geometry, weather, physical location scene, etc.
- **Priority:** importance relative to other collection windows
- **Category:** hierarchical importance (required, essential, desired)

Collection Window Categories

- **Category 1 (required):** Unique to a given sensor. Sensor's schedule must include all corresponding category 1 collection windows
 - Example: collection windows scheduled for the safety and proper operation of a specific sensor; other collections a planner can *force* onto the sensor schedule
- **Category 2 (essential):** In general, of high priority. In some cases, preempted by higher priority Category 3 collection windows
 - Example: periodic sensor calibration activities
- **Category 3 (desired):** The vast majority of collection windows to be scheduled. Most often lower priority than Category 2 collection windows
 - Example: weather collections, reconnaissance, scientific measurement (vegetation cover, sea currents), etc.

Overview

- A remote sensing constellation scheduling problem
- **A Mixed-Integer Program (MIP) for constellation scheduling**
 - **Results**
- Stochastic scheduling models
- Computational results
- Ongoing and future research



Our Approach

- Scheduling problems can be notoriously **hard** to solve (NP-Hard).
- We are using **Operations Research based heuristics**:
 - Apply a MIP solver using an optimality tolerance (e.g. 1%)
 - Final solution **guaranteed** to be near-optimal or optimal
 - Small tolerances can significantly reduce time to solution
- MIPs facilitate **rapid exploration of alternate formulations and solution methods** and disambiguate the solver from the model
 - Quickly assess different formulations
 - Objective functions, constraint equations
 - Readily extensible to incorporate uncertainty
- Sensitivity analysis
 - Determine active/limiting constraints
 - Rigorously determine the effects of changing objectives, adding/removing constraints and decision variables

Related Work

- Satellite scheduling algorithms favor custom rule-based techniques
 - Feasible schedules produced quickly, but without rigorous solution confidence

- Academic research is divided into two camps
 - Heuristics and metaheuristics
 - Comparisons of satellite scheduling (Globus et. al 2004)
 - Genetic algorithms (Lining et. Al 2009)
 - Simulated annealing (Peng et. al 2011)
 - Greedy local (Dungan et. al 2011)
 - Ant colony optimization (Wang et. al 2009)

 - Exact methods (less research)
 - Integer programming (Liao, 2007) - small model size



Artist's rendering of GOES-R
Credits: NASA



Artist's rendering of Sentinel-1A
Credits: ESA

Constellation Scheduling Mixed-Integer Program

$$\max \sum \frac{\alpha \delta_{i,k,t} p_k d_k q_{k,t}}{\sum_{k \in K} p_k d_k q_k}, i \in I, k \in K, t \in T$$

$$w_k = \sum_{i \in I, t \in T} \delta_{i,k,t}, \forall k \in K$$

$$s.t. \quad w_k = 1, \forall k \in K_1$$

$$w_k \leq 1, \forall k \in K \setminus K_1$$

$$\sum_{k \in K} \delta_{i,k,t} \leq 1 - \sum_{k \in K, \bar{t} \in C(k,t)} \delta_{i,k,\bar{t}}, \forall i \in I, t \in T$$

$$\delta_{i,k,t} \in \{0,1\} i \in I, k \in K, t \in T$$

- Objective: schedule as many activities as possible with rewards for high priority, high quality, high duration collections
- Convenience variable denoting whether or not a collection window was scheduled
- Category one collection windows must be scheduled
- Other collections can be scheduled at most once
- Collections can not be scheduled concurrently on a single sensor


Where:

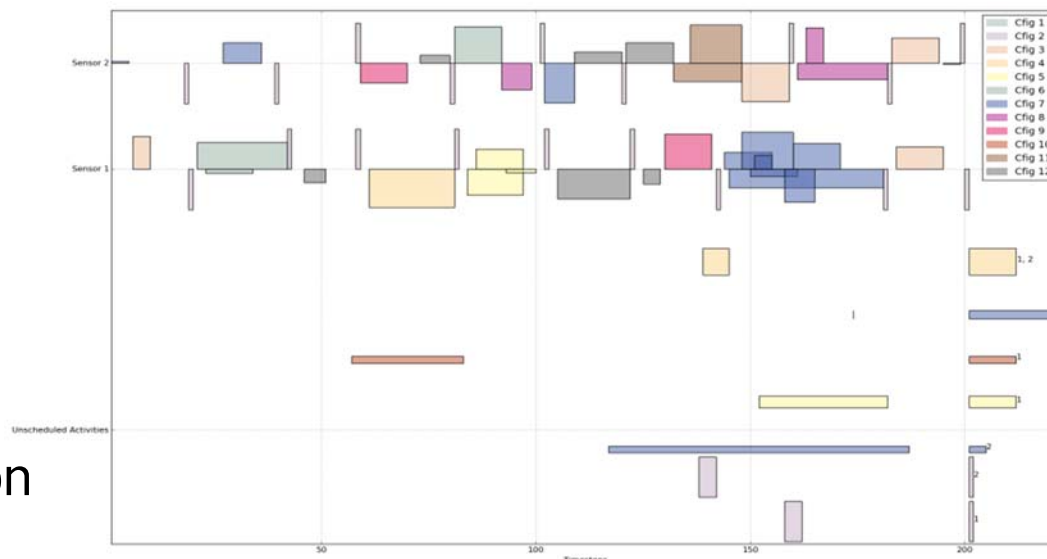
- $\delta_{i,k,t}$: whether collection window k starts at time t on sensor i
- $q_{i,k,t}$: quality of starting collection window k at time t on sensor i
- d_k, p_k : duration and priority of collection window k
- $C(k,t)$: set of feasible start times for collection window k before time t
- α : scaling constant (e.g. 100)

Predicted Observation Quality: $q_{i,k,t}$

- Using a medium- or high-fidelity physics based simulation, build a performance score normalized between 0 and 1, composed of the following metrics:
 - Geometric access
 - Coverage
 - Probability of detection (PD)
 - Closely Spaced Objects (CSO)
- These scores depend on:
 - Weather, collection window scene background, sensor optics, etc.
- Predicted observation quality is calculated off-line, in advance of scheduling for all sensor, collection window, and start time combinations

Results - Constellation Scheduling MIP

- Solutions within **99%+** of optimal in minutes using untuned *Gurobi* solver
 - Solving to provably optimal usually occurs within one hour
 - Linux machine with:
 - 64 cores, 1 TB RAM
- Models implemented using Sandia's Pyomo optimization software library
 - www.pyomo.org 
- Typical problem scale:
 - Two sensors
 - 1440 timesteps
 - 450 collection windows



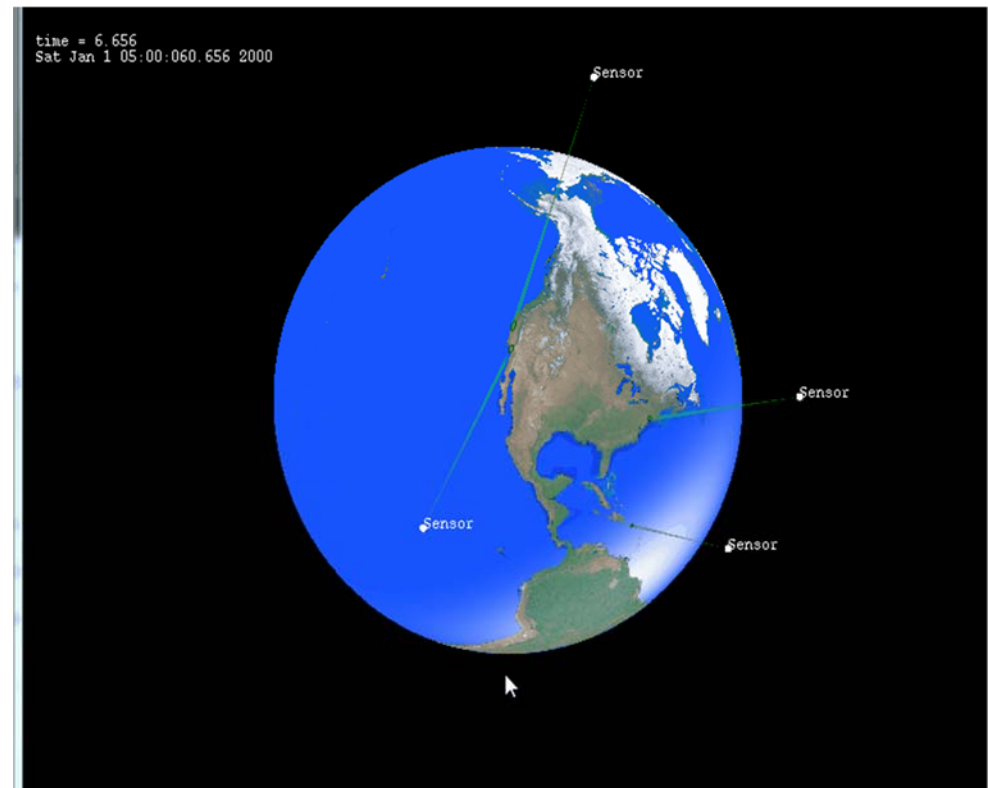
Example schedule with model modified to allow collection windows sharing configurations to run concurrently.

Notes on Constellation Scheduling MIP

- Established a set of benchmark problem instances
 - Differing numbers of satellites [1,10]
 - Large time-windows (w/ majority spanning the entire planning time horizon)
 - Competing priorities
 - Time-varying predicted observation quality
- Benchmark instances aim to be applicable for model extensions
 - All collection windows include a set of feasible configurations
- The model assumes prescience. In reality, after planning:
 - Collection windows are added to the queue
 - Predicted weather is or is not realized
 - Collection fails to reveal desired information

Overview

- A remote sensing constellation scheduling problem
- A Mixed-Integer Program (MIP) for constellation scheduling
 - Results
- **Stochastic scheduling models**
- Computational results
- Ongoing and future research

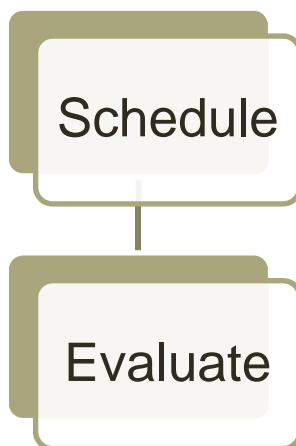


Stochastic Scheduling Models

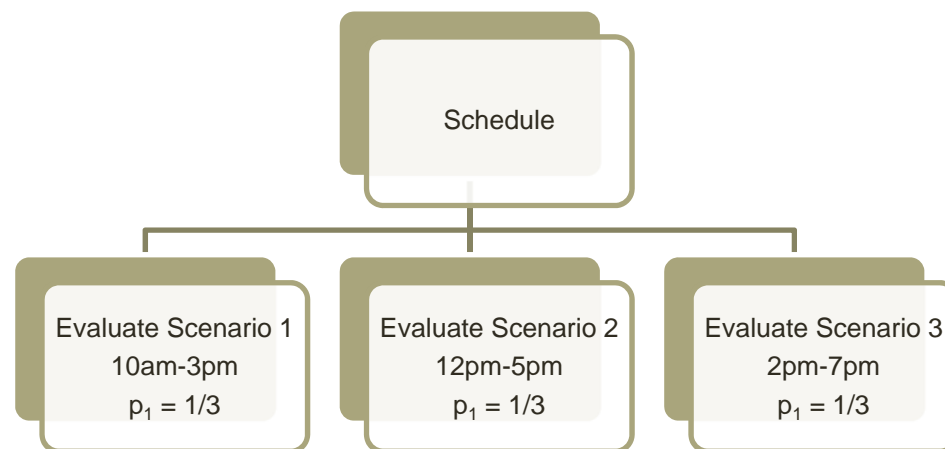
- Developed distinct scenario-based stochastic MIP models to address the following areas of sensor scheduling uncertainty:
 - *Ad hoc* collection windows
 - Described by scenarios modeling collection windows with uncertain start times and durations
 - *Ad hoc* collection windows assume **highest** priority
 - Produced schedules will be resilient to disruptions and include a plan for “getting back on schedule”
 - Weather
 - Uncertain performance of scheduled collection windows based on weather (cloud-cover) scenarios
 - Produced schedules will be resilient to performance effects caused by weather

MIP vs. Stochastic MIP Comparison

MIP
 $Max f(x)$

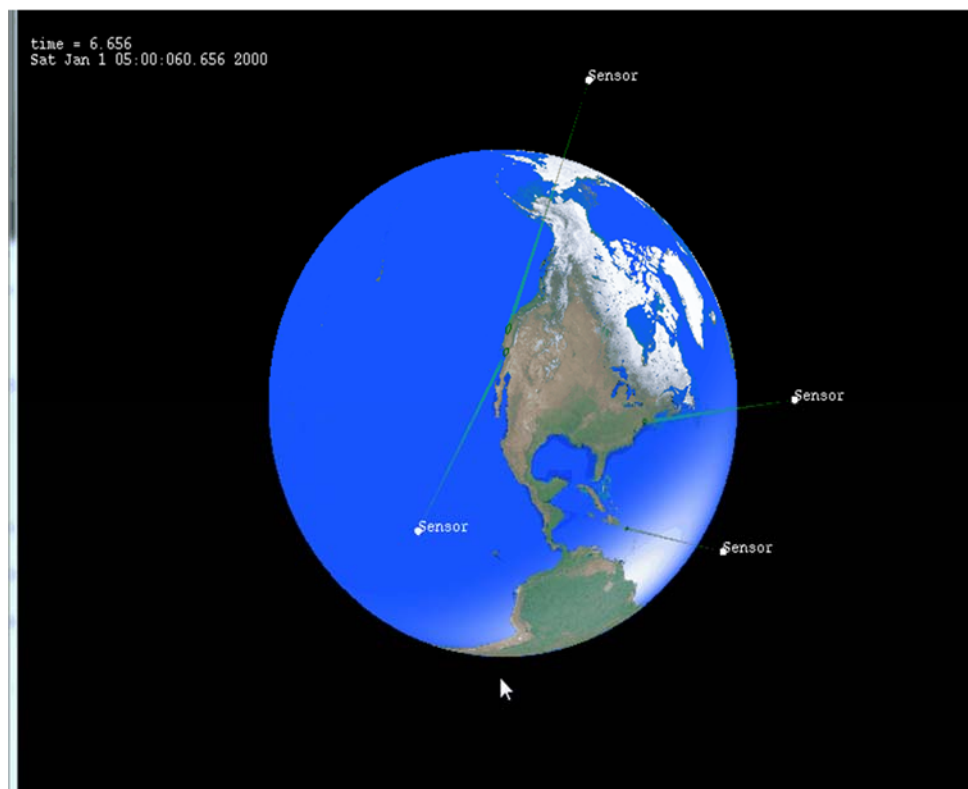


Stochastic
 $Max \mathbb{E}[f(x)]$



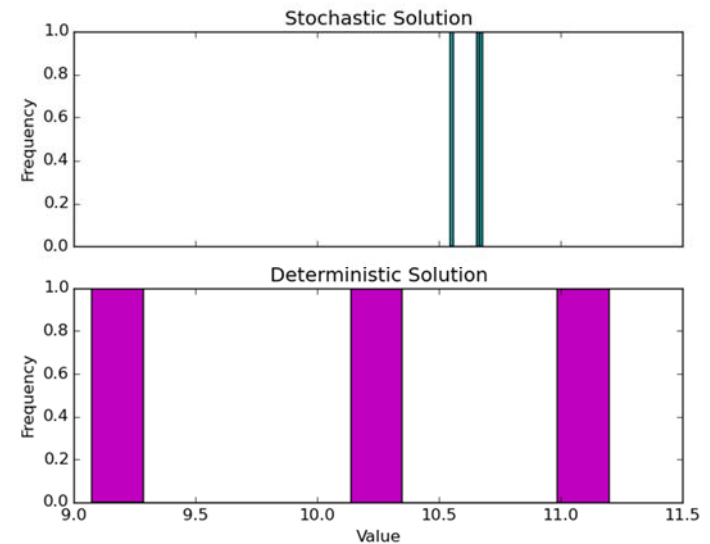
Overview

- A remote sensing constellation scheduling problem
- A Mixed-Integer Program (MIP) for constellation scheduling
 - Results
- Stochastic scheduling models
- **Computational results**
- Ongoing and future research



Results - Stochastic MIPs

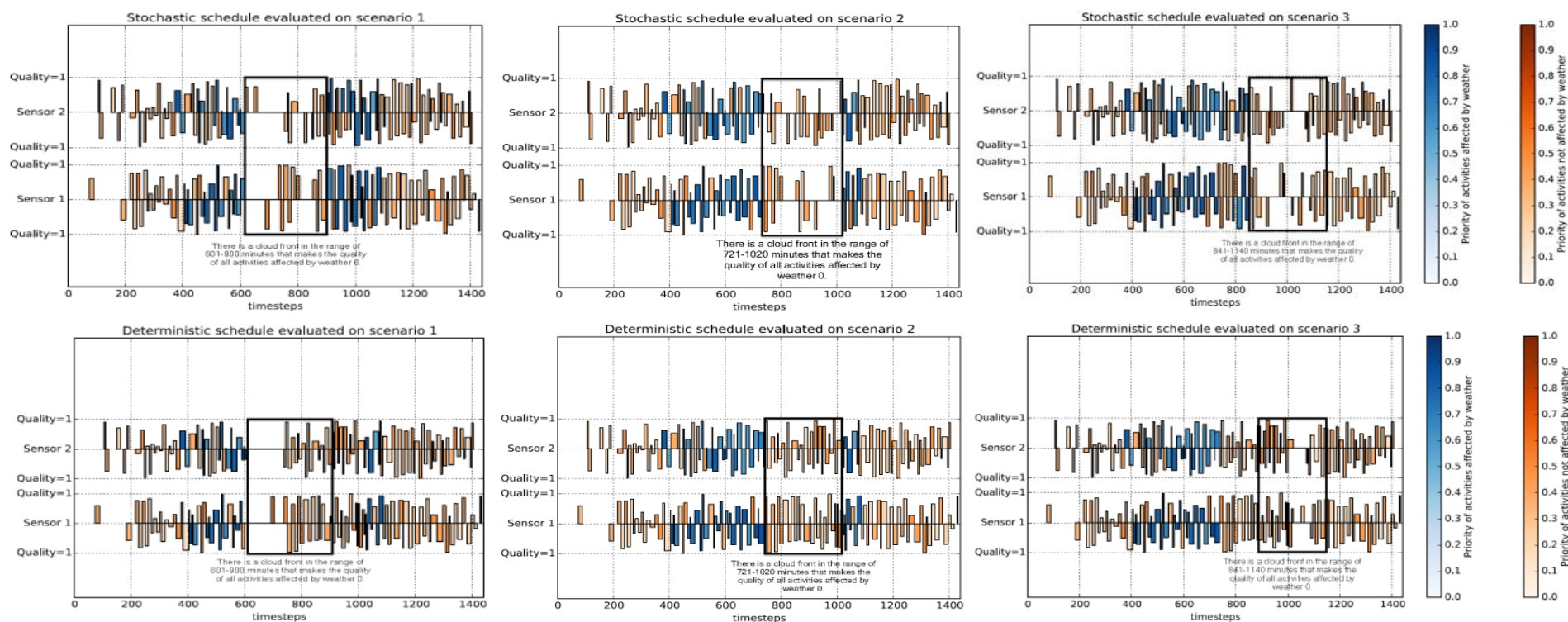
- Exploring the value of stochastic solution
 - Current models are giving a ~5% Value of Stochastic Solution (VSS)
- We are solving the extensive form (EF)
 - Generate a larger MIP with decision variables for each scenario
 - Modify original MIP objective function
- Typically solves to optimal within one hour
- We can use Pyomo's PySP Progressive Hedging (PH) metaheuristic to solve problems with many scenarios



Objective function values for schedules produced with stochastic and deterministic models (three weather scenarios)

Results - Stochastic MIPs (cont.)

- Collection windows are either **affected** or **unaffected** by clouds:
- Three scenarios, each with a different time of cloud arrival
 - Weather front in black rectangles (no value for collections affected by weather)

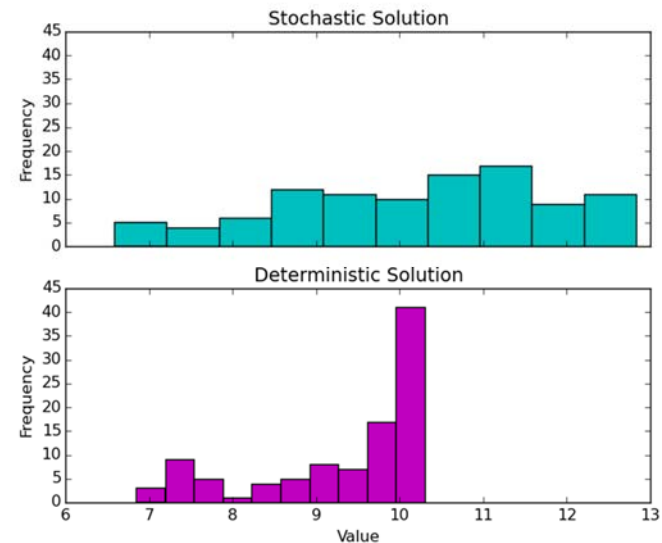


Results - Stochastic MIPs (cont.)

- Model prevents collection windows below defined quality threshold (q^0) from being considered for scheduling
 - Under different scenarios, collection windows can be above or below q^0 depending on scheduled time and sensor

- By updating the model to allow these collections to be scheduled, we are seeing upwards of an 8% Value of Stochastic Solution (VSS)

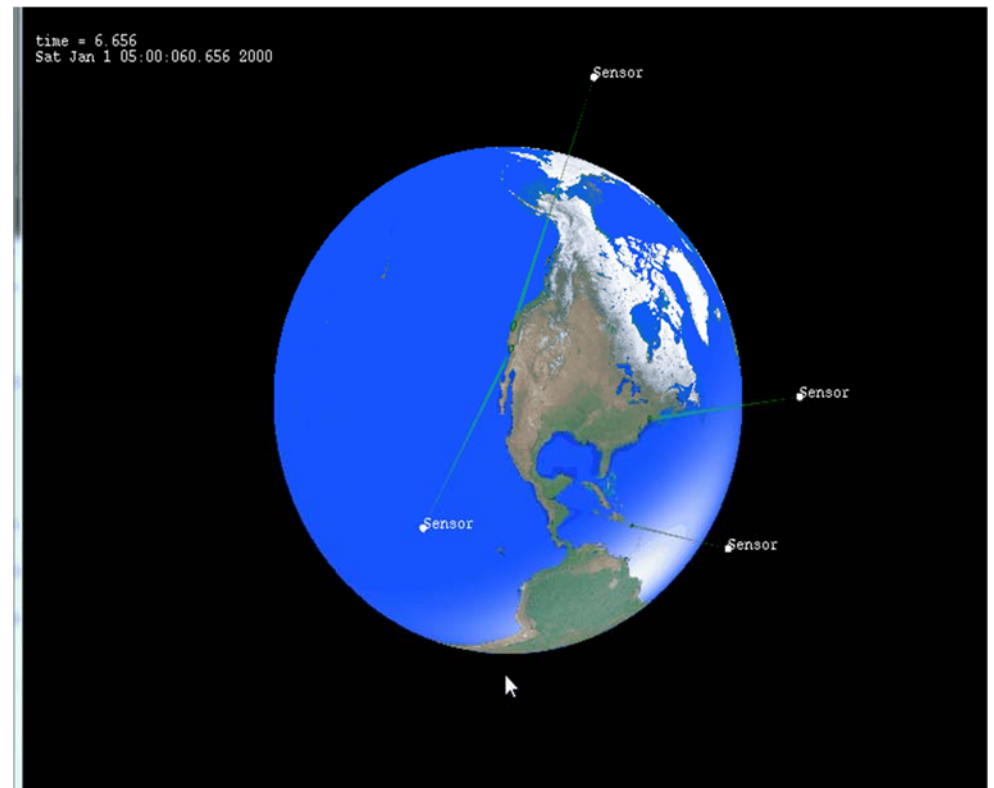
- We are solving the extensive form (EF) with 100 weather scenarios to optimal on the order of a few hours



Objective function values for schedules produced with updated stochastic and deterministic models (100 weather scenarios)

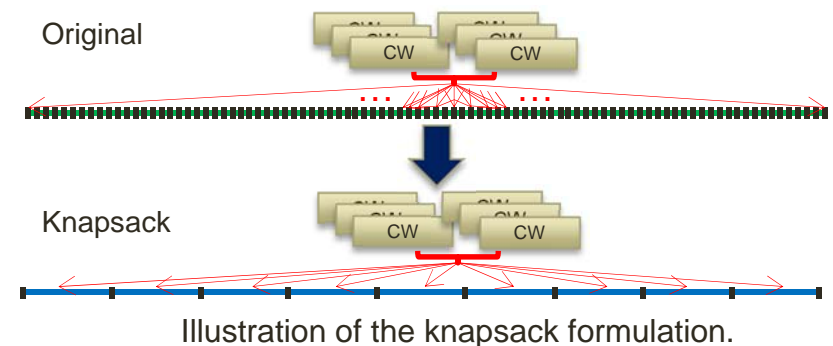
Overview

- A remote sensing constellation scheduling problem
- A Mixed-Integer Program (MIP) for constellation scheduling
 - Results
- Stochastic scheduling models
- Computational results
- **Ongoing and future research**



Ongoing Research and Future Work

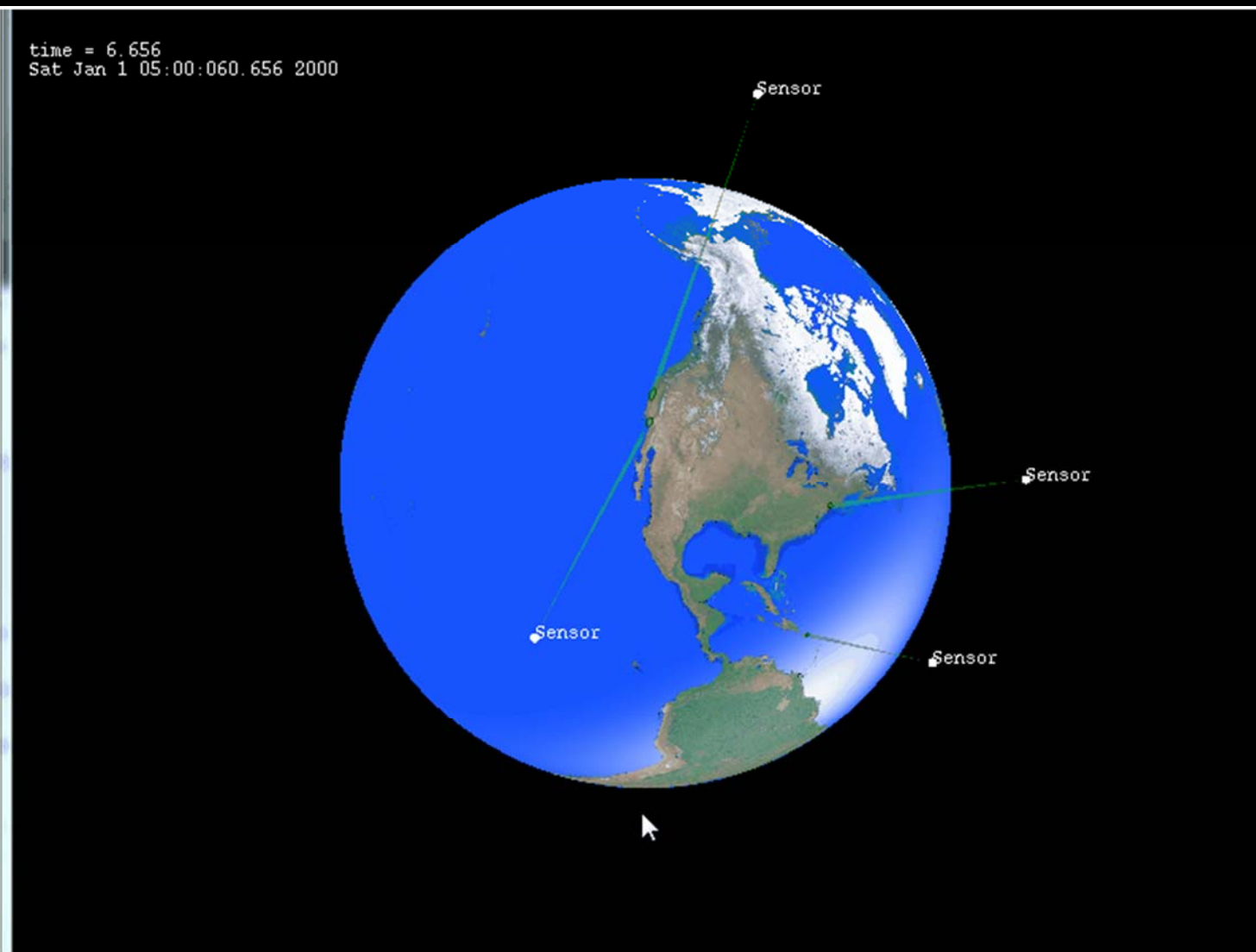
- Exploring several alternative formulations
 - Allow concurrent activities subject to constraints
 - Exploiting periodic calibration activities (“knapsack”)
- With Texas A&M, investigating models where collections can choose from multiple configurations
- Soliciting sensor operator expertise to meaningfully define q_{ikt}
- Exploring interrelated coverage optimization problems:
 - Sensor footprint mosaics without gaps, guaranteed properties
 - Sub-footprint placement according to BW constraints



Ongoing Research and Future Work (cont.)

- Interested to partner with satellite planners/operators to create representative *ad hoc* and weather scenarios
- Additional model constraints, objective functions
 - Scheduling of collection windows requiring multiple satellites
 - Exploring the effects of removing duration from the objective
 - Use coarser model over longer timeframe (multiple days) in conjunction with existing model (**time-value of information**)
- Solver tuning
 - Extending OR-based heuristic implementations developed by Texas A&M to stochastic models
 - To date, models produce many similar schedules
 - Produce definitions for “dissimilar” schedules

Questions?



Stochastic MIP- *ad hoc* Collection Windows

$$\text{Max } f(x) + \mathbb{E}[g(x, \tilde{\xi})]$$

$$\text{s.t. } Ax \leq b$$

$$x \in X,$$

where

$$g(\delta, \xi) = \text{Max } h(\gamma(\xi), \Gamma(\xi))$$

$$\begin{aligned} \text{s.t. } & \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \Delta_{ikt}^{\xi} - \Omega_k^{\xi} = 0 && \forall k \in \mathcal{K}_4, \\ & \sum_{k \in \mathcal{K}_4} \Delta_{ik\bar{t}}^{\xi} \leq 1 - \sum_{k \in \mathcal{K}_4} \sum_{t \in \mathcal{C}(k, \bar{t})} \Delta_{ik\bar{t}}^{\xi} && \forall \bar{t} \in \mathcal{T}, i \in \mathcal{I} \\ & \Omega_k^{\xi} = 1 && \forall k \in \mathcal{K}_4, \\ & y_{ikk_z t}^{\xi} + (1 - \Delta_{ikt}^{\xi}) \geq \delta_{ikk_z t} && \forall i \in \mathcal{I}, k, k_z \in \mathcal{K}_4^p, t \in \mathcal{T}, \\ & (1 - y_{ikk_z t}^{\xi}) + \Delta_{ik_j t_j}^{\xi} \geq 1 && \forall i, k_j, k_z, t_j, t_z \in \mathcal{K}_4^p, \\ & (1 - y_{ik_j t_j k_z t_z}^{\xi}) \geq 1 - \delta_{ik_z t_z} && \forall i, k_j, k_z, t_j, t_z \in \mathcal{K}_4^p, \\ & \gamma_{ikt}^{\xi} + \sum_{k_z \in \mathcal{K}_1} \sum_{t_z \in \mathcal{T}} y_{ikt k_z t_z}^{\xi} \geq 1 && \forall i, k, k_z, t, t_z \in \mathcal{K}_4^p, \\ & (1 - \gamma_{ikt}^{\xi}) + (1 - y_{ikt k_z t_z}^{\xi}) \geq 1 && \forall i, k, t, k_z, t_z \in \mathcal{K}_4^p, \\ & \Gamma_{ik_z t_z}^{\xi} + (1 - y_{ikt k_z t_z}^{\xi}) + (1 - \gamma_{ikt}^{\xi}) \geq 1 && \forall i, k, t, k_z, t_z \in \mathcal{K}_4^p, \\ & (1 - \Gamma_{ik_z t_z}^{\xi}) + \sum_{k \in \mathcal{K}_4} \sum_{t \in \mathcal{T}} y_{ikk_z t}^{\xi} \geq 1 && \forall i, k_z, t_z \in \mathcal{K}_4^p, \\ & (1 - \Gamma_{ik_z t_z}^{\xi}) + \sum_{k \in \mathcal{K}_4} \sum_{t \in \mathcal{T}} \gamma_{ikt}^{\xi} \geq 1 && \forall i, k_z, t_z \in \mathcal{K}_4^p, \\ & \Omega_k^{\xi} \in \{0, 1\} && \forall k \in \mathcal{K}_4 \\ & \Delta_{ikt}^{\xi} \in \{0, 1\} && \forall k \in \mathcal{K}_4, i \in \mathcal{I}, t \in \mathcal{T} \\ & y_{ikk_z t}^{\xi} \in \{0, 1\} && \forall i, k_j, k_z, t_j, t_z \in \mathcal{K}_4^p, \\ & \gamma_{ikt}^{\xi} \in \{0, 1\} && \forall i \in \mathcal{I}, k \in \mathcal{K}_4, t \in \mathcal{T} \\ & \Gamma_{ikt}^{\xi} \in \{0, 1\} && \forall i \in \mathcal{I}, k \in \mathcal{K}, t \in \mathcal{T} \end{aligned}$$