TAT-C ML: Machine Learning for Enhanced Trade-Space Analysis of Constellations

Daniel Selva (Texas A&M University)

PI: Jacqueline Le Moigne (GSFC)

Co-Is: P. Dabney, M. Holland, S. Hughes (GSFC); S. Nag (BAERI); A. Siddiqi, V. Foreman (MIT); P. Grogan (Stevens)

2018 ESTF workshop

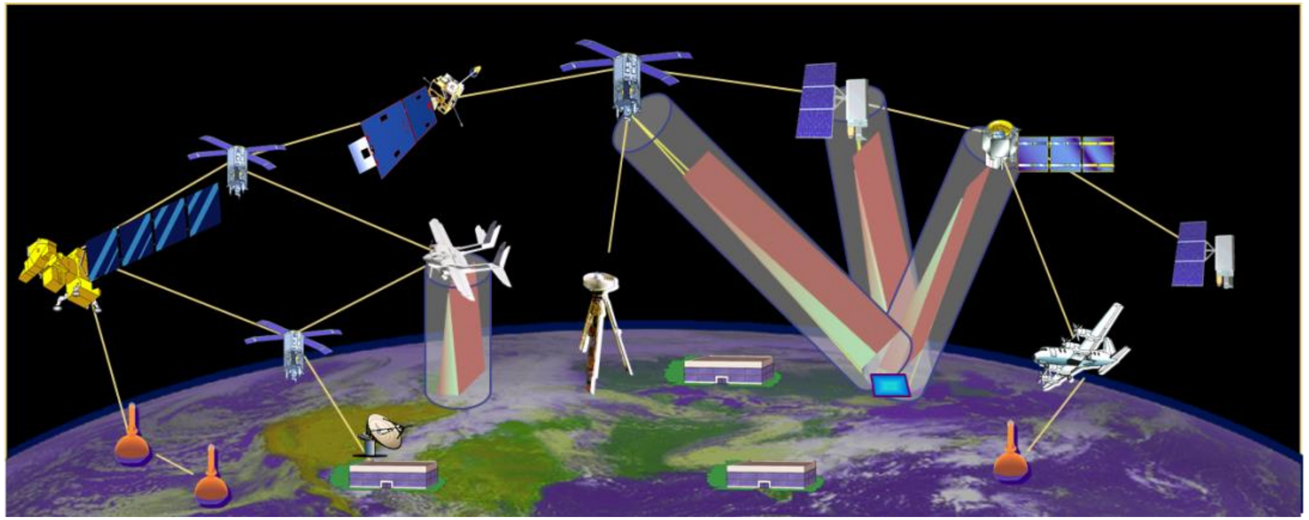
Session B1: Enabling Distributing Missions and Constellations

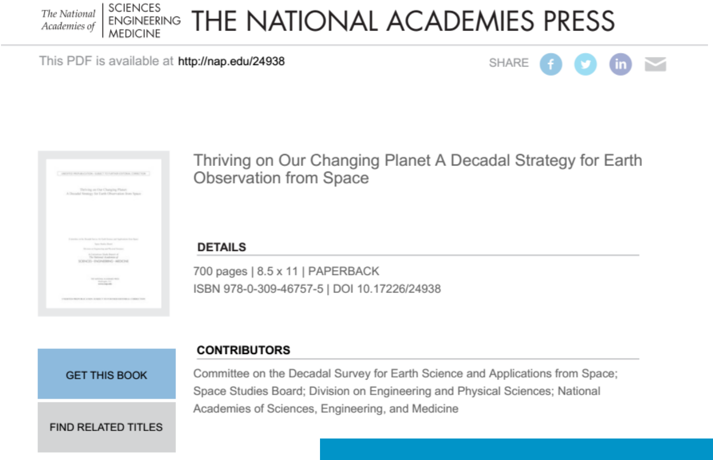
June 12, 2018

Outline

- Motivation for DSM
- Challenges in Pre-Phase A studies for DSM
- TAT-C (AIST14): Overview and limitations
- TAT-C ML (AIST16)
- Enhancing tradespace search with AI and ML
  - Evolutionary algorithm
  - Adaptive operator selection
  - Knowledge-driven operators (offline)
  - Online learning of operators through feature extraction
- Next steps

Distributed Satellite Missions (DSM) will play a role in future Earth Observing Systems





The National Academies of SCIENCES ENGINEERING MEDICINE THE NATIONAL ACADEMIES PRESS

This PDF is available at http://nap.edu/24938 SHARE

Thriving on Our Changing Planet A Decadal Strategy for Earth Observation from Space

DETAILS

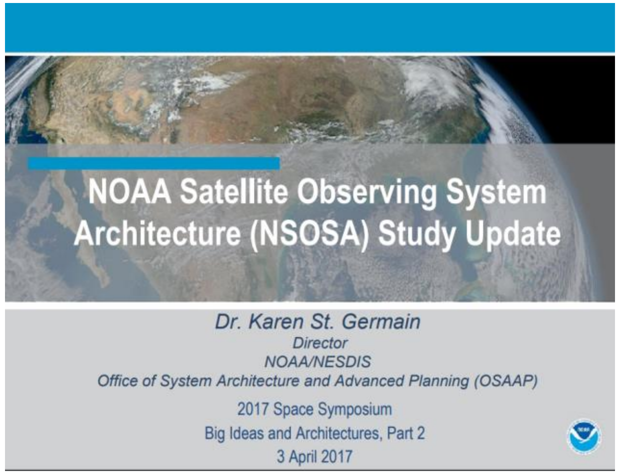
700 pages | 8.5 x 11 | PAPERBACK
ISBN 978-0-309-46757-5 | DOI 10.17226/24938

GET THIS BOOK

FIND RELATED TITLES

CONTRIBUTORS

Committee on the Decadal Survey for Earth Science and Applications from Space; Space Studies Board; Division on Engineering and Physical Sciences; National Academies of Sciences, Engineering, and Medicine

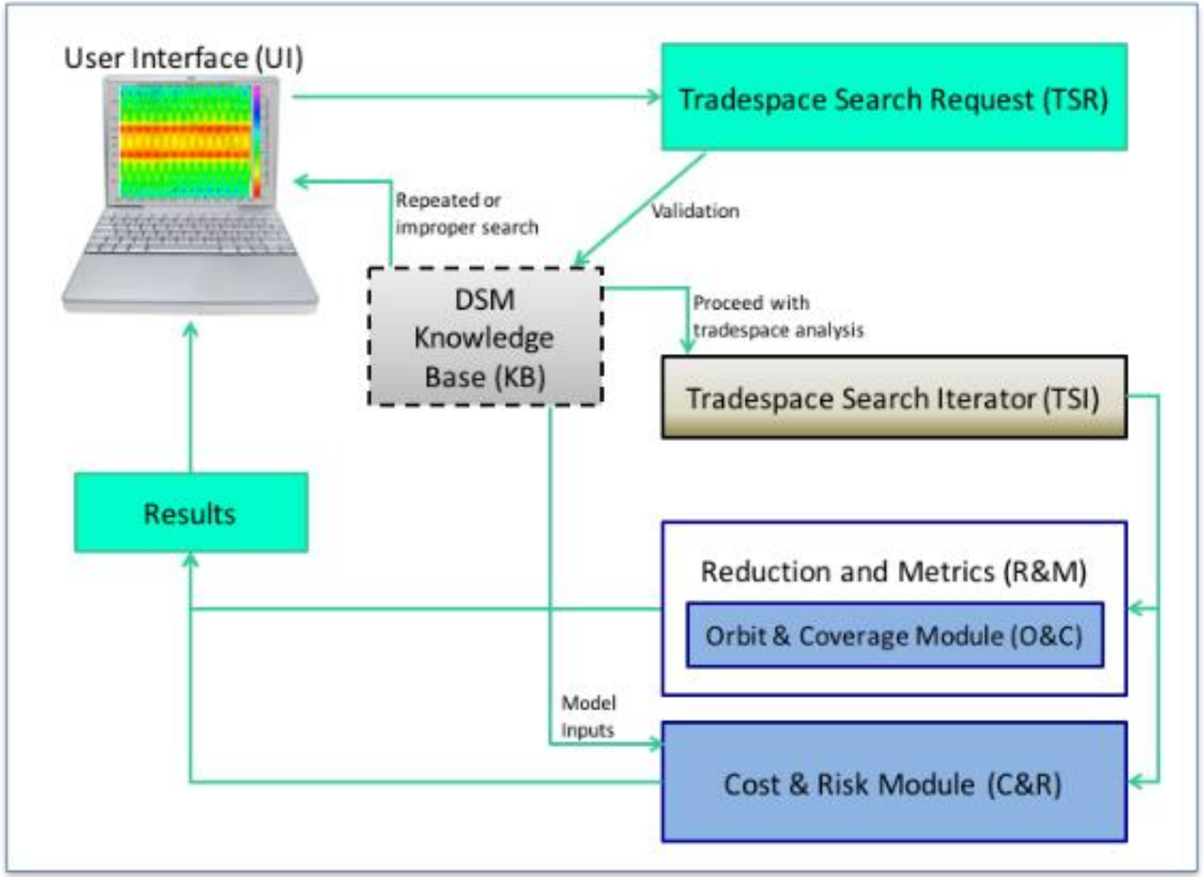


Current Pre-Phase A tools are not well suited for DSM

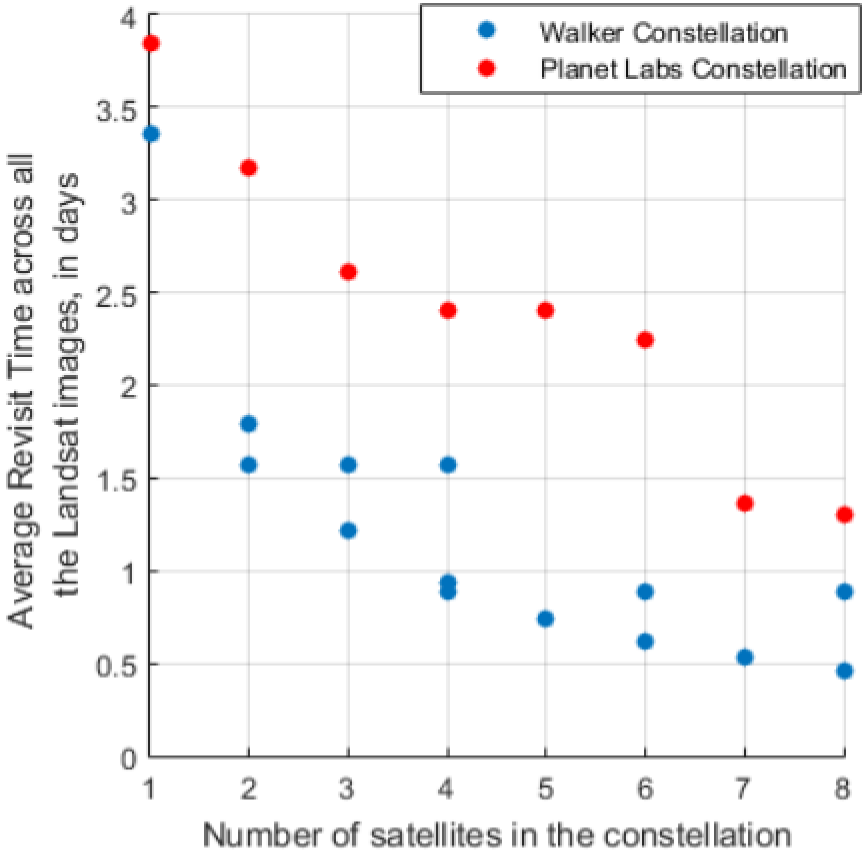
- Needs in Pre-phase A:
  - Check **feasibility** of meeting requirements
  - Evaluate a sufficient number of **alternatives**
  - Conduct **trade studies** and **what-if analyses**
  - Propagate satellite orbits with sufficient accuracy over long periods of time
  - Calculate performance metrics (e.g., mean revisit time) and others (e.g., cost, risk)
- Challenges
  - High number of vehicles to simulate
  - Combinatorial explosion of alternatives
  - Both of these significantly increase computational cost
- TAT-C (AIST14) was developed to address these challenges

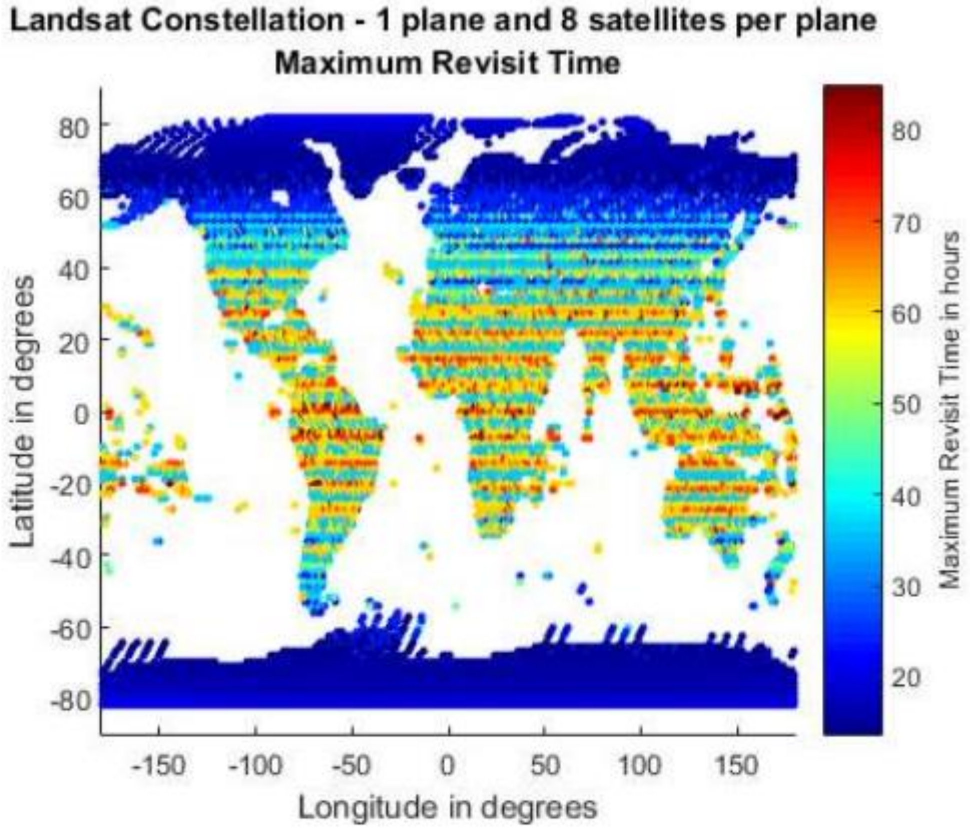
Tradespace Analysis Tool for Constellations (TAT-C, AIST14 project)

- Goal: To Provide a framework to perform pre-Phase A mission analysis of DSM
- Handle multiple spacecraft sharing mission objectives
- Explore tradespace of variables for pre-defined science, cost and risk goals and metrics
- Optimize cost and performance across multiple instruments and platforms instead of one at a time
- Include sets from smallsats through flagships



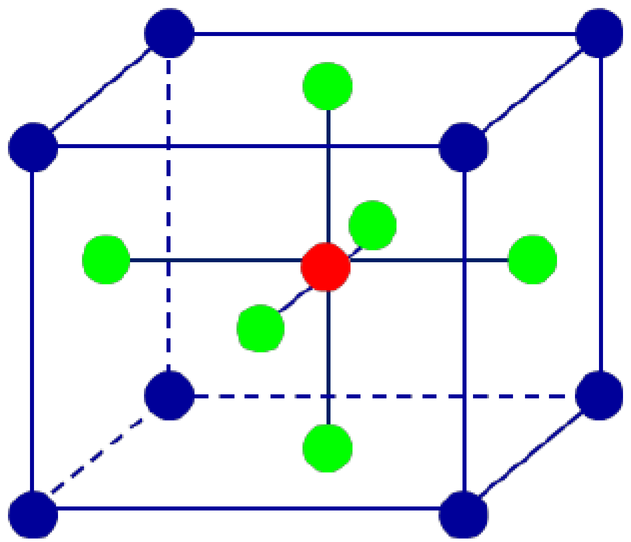
TAT-C Example of results: Sustainable Land Imaging





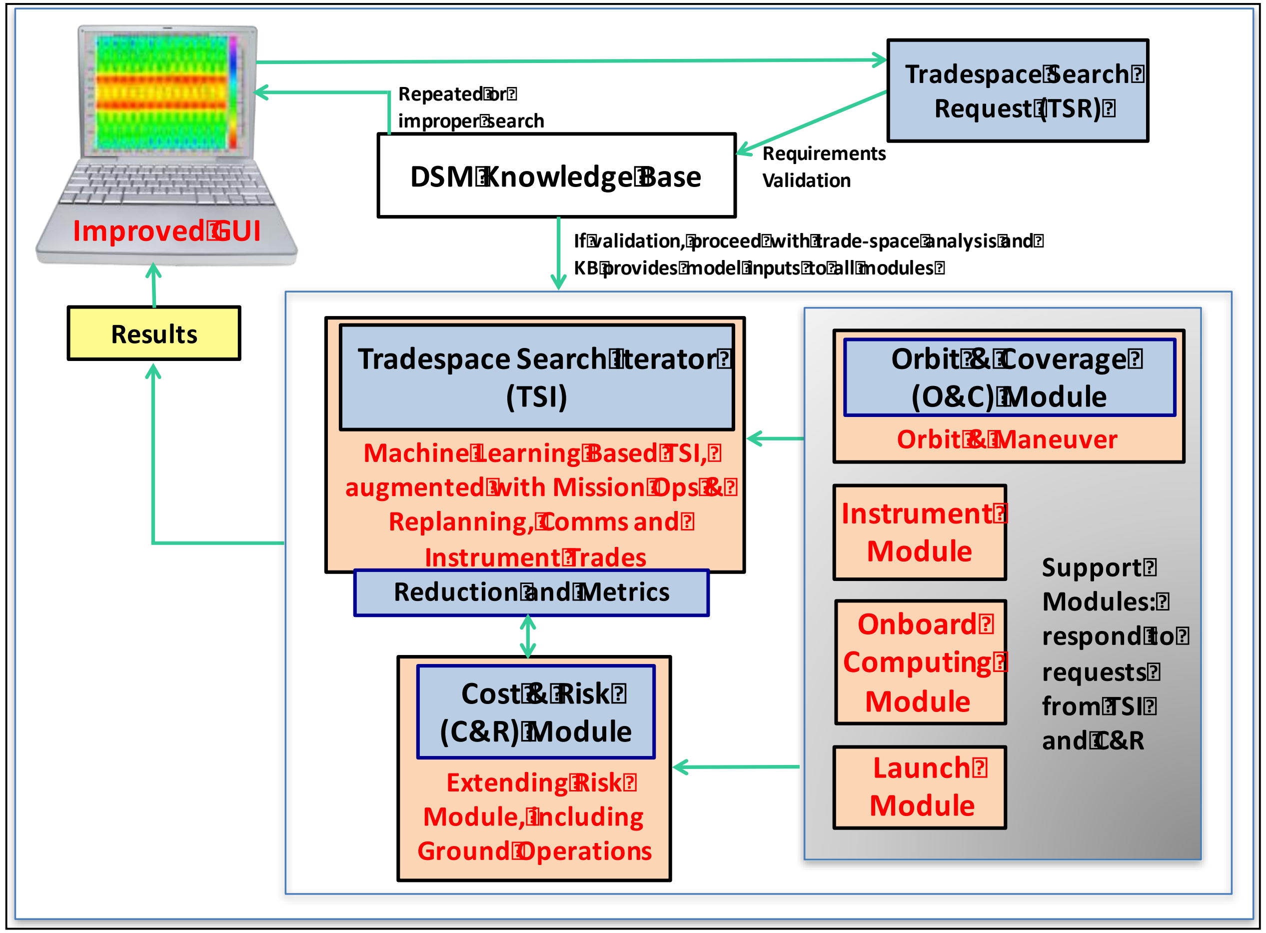
TAT-C's tradespace search capabilities are limited

- Currently, TAT-C uses a brute-force design of experiments approach for searching the tradespace
- No optimization – just screening of the tradespace
- Many unpromising architectures are evaluated
- Cannot start seeing results until all alternatives have been evaluated



TAT-C ML (AIST16 project)

- Increase the dimensionality and modeling depth of TAT-C's trade-space analysis capabilities with:
  - Various trajectories, orbital planes, mission replanning, orbit and Maneuver Modeling, etc.
  - New modules (instrument, launch, onboard computing, etc.)
  - Optimize the Trade-Space Exploration by Utilizing Machine Learning and a Fully Functional Knowledge Base (KB) to Efficiently Traverse a Large Trade-Space

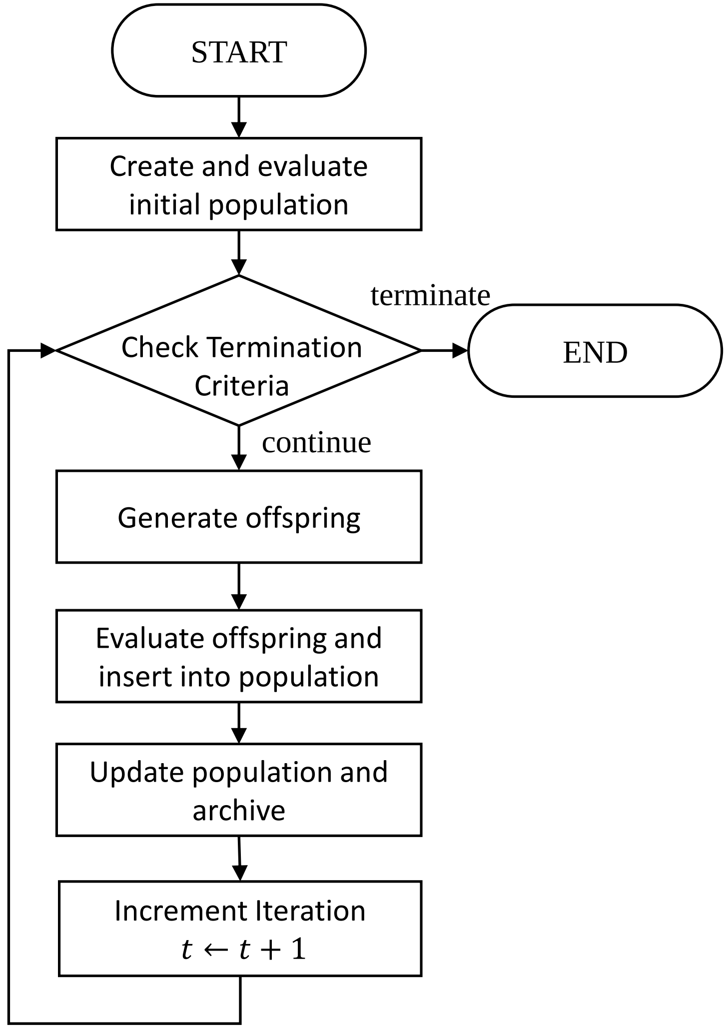


Enhancing tradespace search with AI and ML

- Speed up the search and avoid unnecessary expensive function evaluations
- Baseline search/optimization using a multi-objective evolutionary algorithm (epsilon-MOEA). Example: min avg revisit time and min cost
- Maintain a pool of operators and use ML to figure out which ones work best (~reinforcement learning)
- Pool may contain:
  - Domain-independent operators: different kinds of Crossover, mutation, etc.
  - Or Domain-specific!
- Domain-specific operators may be available before the search or discovered online
  - Use feature extraction techniques (association rule mining, mRMR)

Baseline evolutionary algorithm: ε-MOEA

- Evolutionary algorithms mimic natural evolution
- Main operators:
  - Selection
  - Crossover
  - Mutation
- Many types of crossover/mutation exist, each with parameters to tune
- Epsilon-MOEA
  - Steady-state algorithm
  - Maintains an archive of best solutions found so far



Baseline evolutionary algorithm

Adaptive operator selection (AOS)

- Pool of operators; ML layer to learn which one(s) work best
- Credit assignment: Measure performance of each operator over time
  - $c_{i,t}$ = credit received by o_i at iteration t
  - Example: $c_{i,t} \propto f(\vec{\boldsymbol{x}}^{p}) - f(\vec{\boldsymbol{x}}^{o_i,t})$
- Operator selection: Assign solutions to operators proportionally to their quality ($q_{i,t}$ = quality of operator o_i at iteration t). For example:

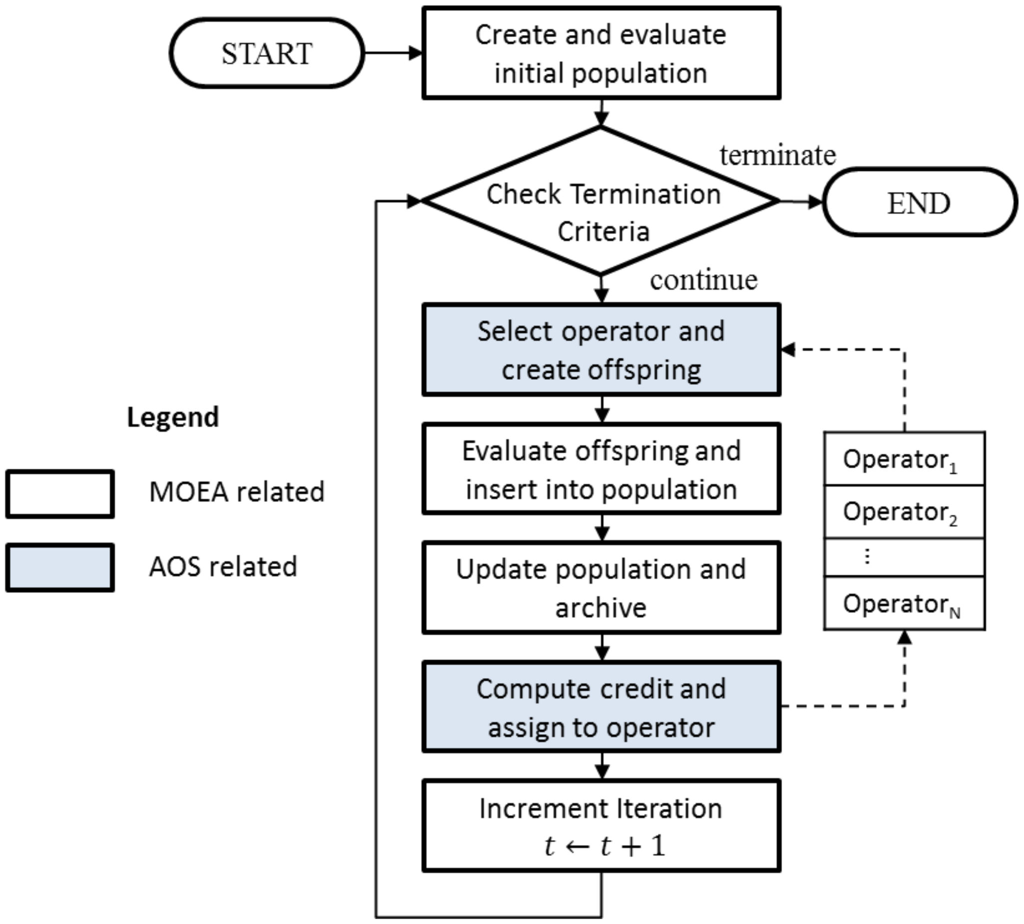
$$q_{i,t+1} = (1-\alpha) \cdot q_{i,t} + \alpha \cdot c_{i,t}$$

$$p_{i,t+1} = p_{min} + (1 - |O| \cdot p_{min}) \cdot \frac{q_{i,t+1}}{\sum_{j=1}^{|O|} q_{j,t+1}}$$

$\alpha \in [0,1]$ = adaptation rate

p_{min} = minimum selection probability

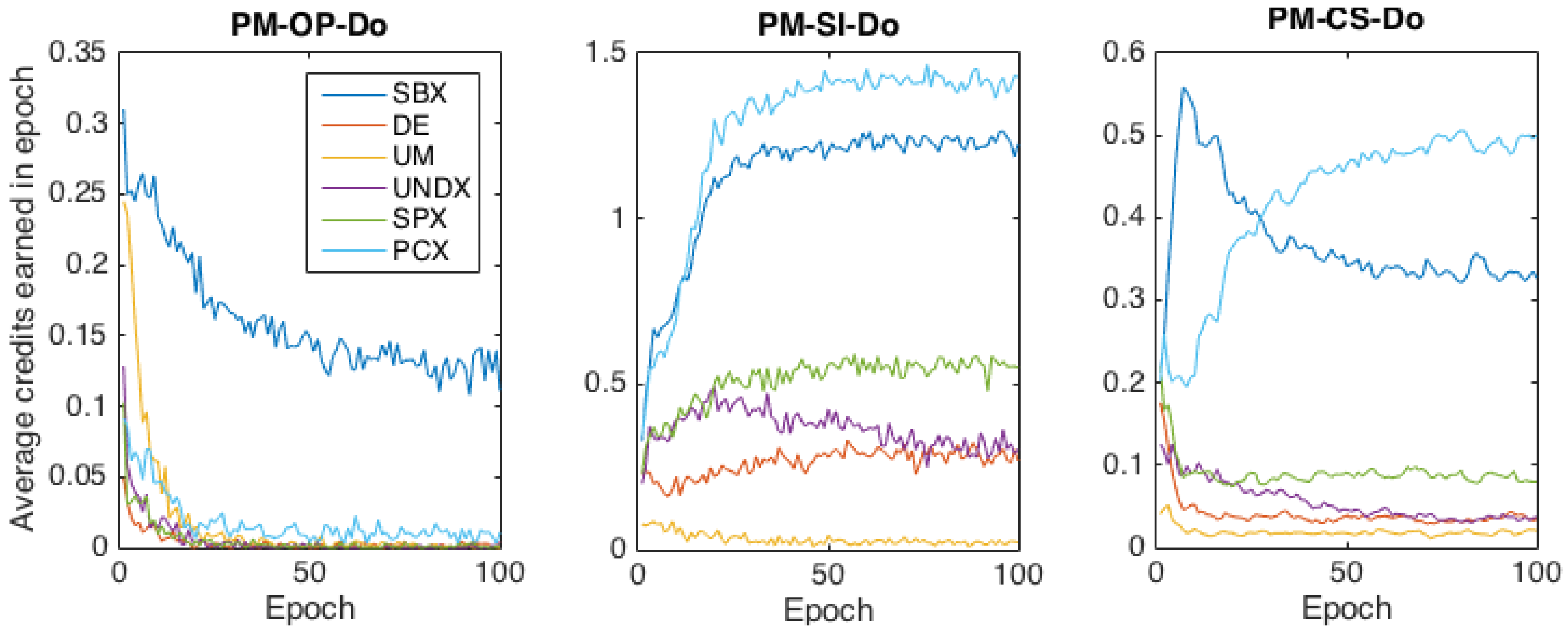
Probability matching operator selection



MOEA+AOS

AOS works with benchmark problems

- We measured performance of 9 different AOS approaches (new and existing) on 26 different benchmarking multi-objective problems (WFG, UF, DTLZ)
- AOS consistently outperform state-of-the-art EA over wide range of problems
- AOS discover the operator(s) that work better for each problem

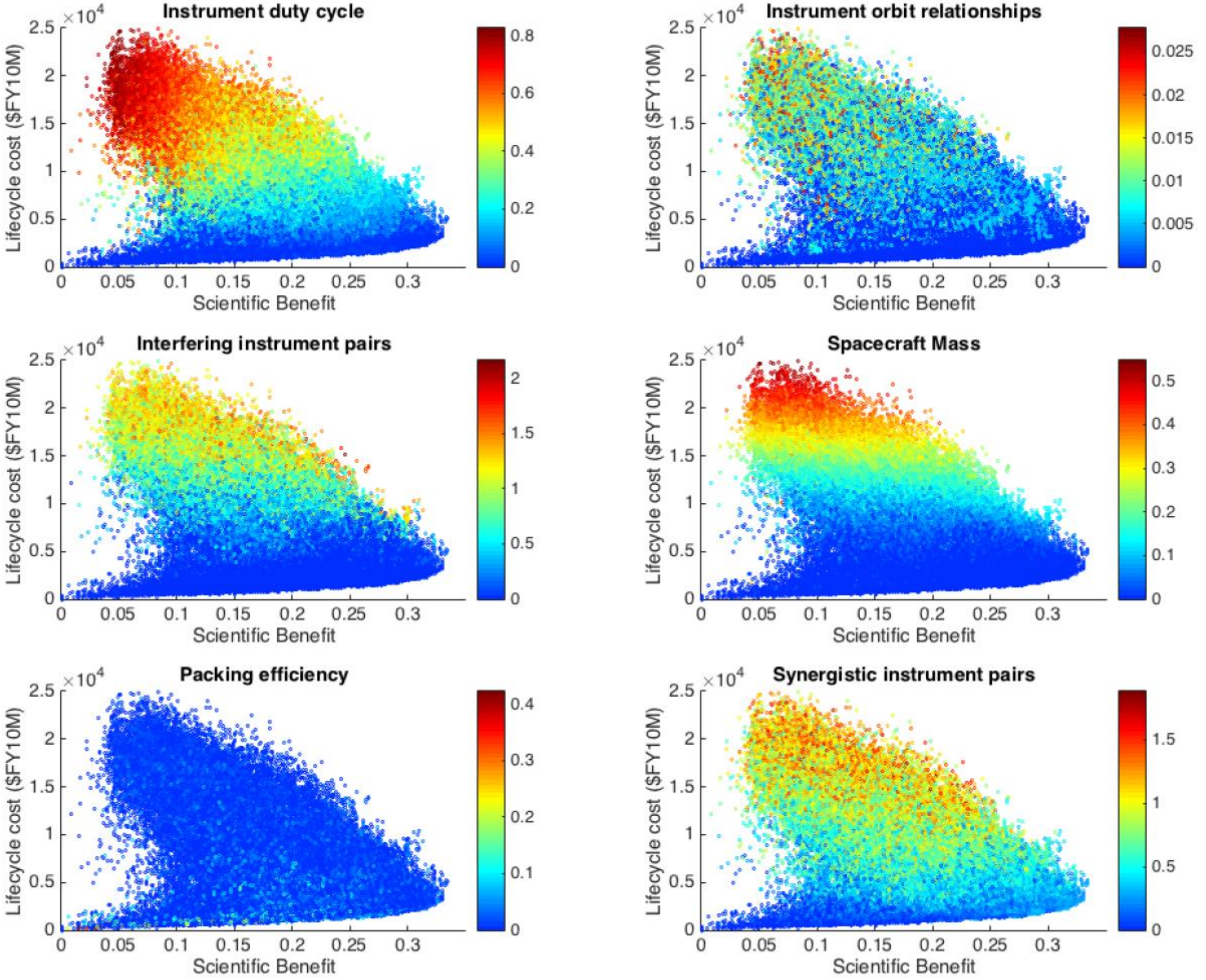


Adding knowledge-driven operators

- Domain- and potentially problem-specific operators
- Expressed in first-order logic format
- Stored in knowledge base; can be reused

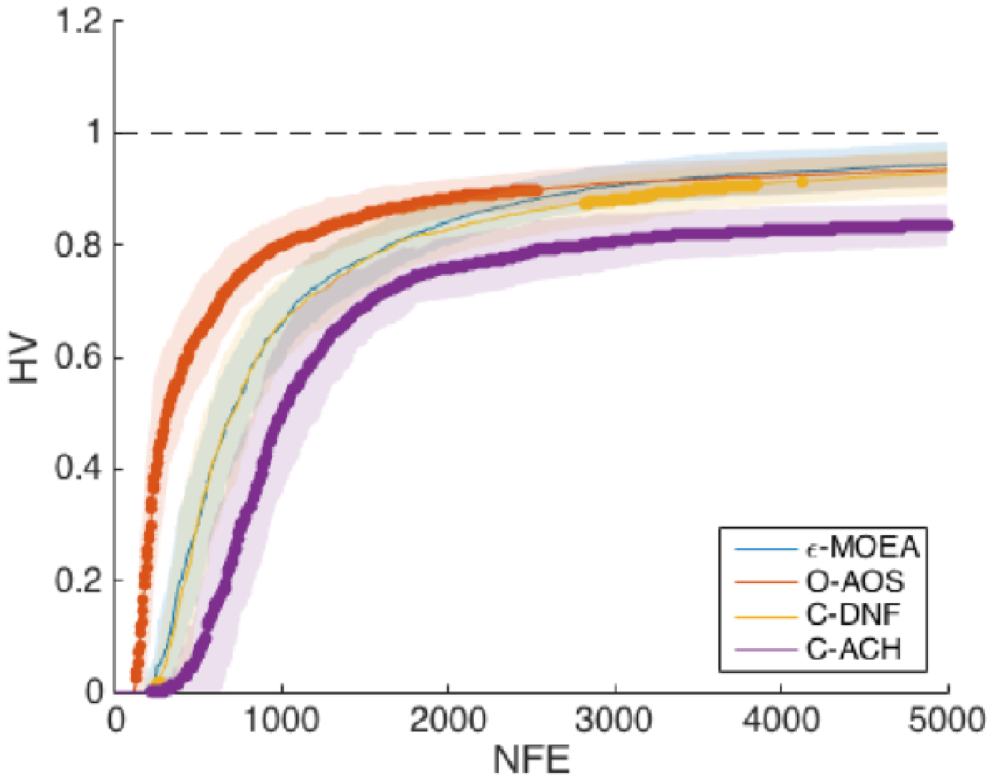
Heuristic	Description
ADD-SYNERGY	Adds instrument to a random orbit so as to capture a currently missed synergy
REMOVE-INTERFERENCE	Removes instrument from random orbit so as to eliminate a current interference
IMPROVE-ORBIT	Moves random instrument to a better orbit
REMOVE SUPERFLUOUS	Removes superfluous instrument from a random orbit
ADD-TO-SMALL-SAT	Adds random instrument to a random small satellite
REMOVE-FROM-BIG-SAT	Removes random instrument from a random big satellite

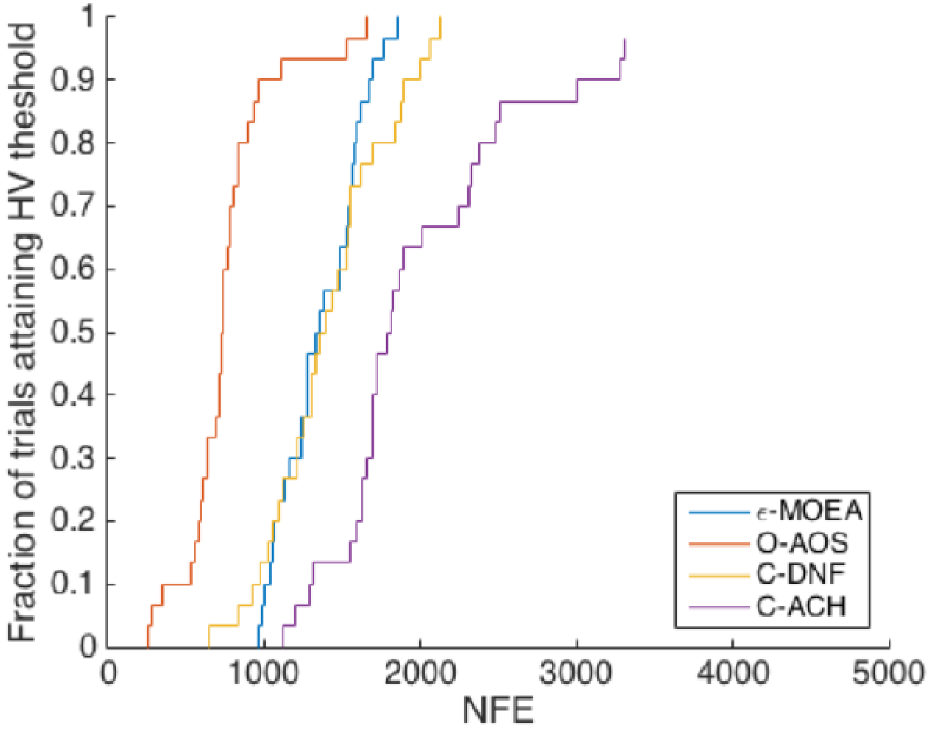
Using knowledge-driven operators is challenging



- Rely on quality of knowledge
- Reasonable expert knowledge may be useless for a particular problem
- Reduction in diversity of solutions
- Premature convergence

AOS enables using existing knowledge (adaptive operators better than constraints)

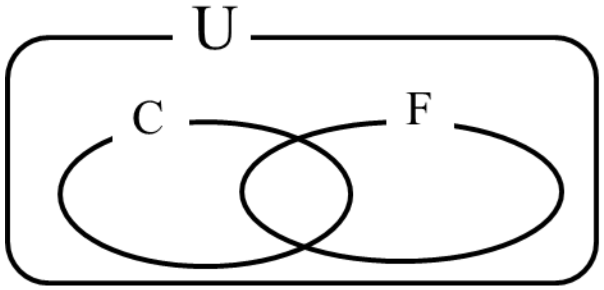




O-AOS: Operators – Adaptive Operator Selection
C-DNF: Constraints – Disjunctive Normal Form
C-ACH: Constraints – Adaptive Constraint Handling
HV: hypervolume (performance metric in MOO, large-is-better)
NFE: Number of function evaluations
Thick lines: Statistically significantly higher median than ε-MOEA (Wilcoxon rank-sum, $n = 30, P < 0.05$)

On-line discovery of new operators

- New operators can be discovered online using feature extraction
- Approach:
  - Use association rule mining (a priori algorithm) to search space of conjunctions of features for target region C (top 25% architectures)
  - Use mRMR to select best 4 features
  - Make operators from best features
  - Add operators to pool
  - Repeat every 1000 iterations



U: All possible designs
C: Designs within target region
F: Designs with the feature

$$supp(F) \equiv \frac{|F|}{|U|}$$

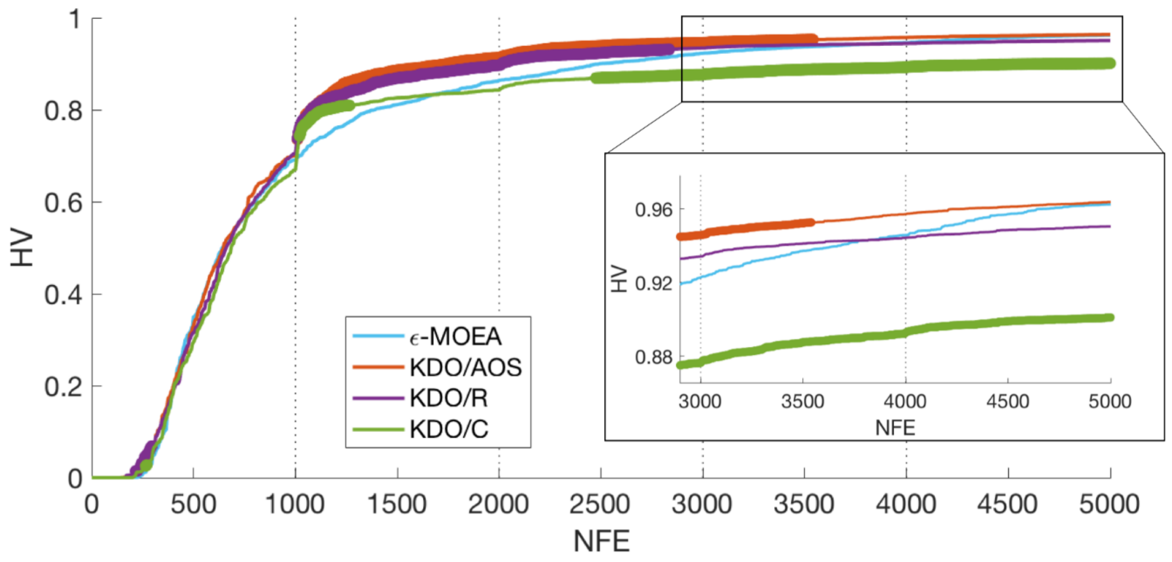
$$conf(F \Rightarrow C) = \frac{supp(F \cap C)}{supp(F)}$$ (consistency, specificity)

$$conf(\mathrm{C} \Rightarrow \mathrm{F}) = \frac{supp(F \cap C)}{supp(\mathrm{C})}$$ (coverage, generality)

mRMR: $$\Phi_i = \Phi_{i-1} \cup \left(\max_{F_i \in \Phi \setminus \Phi_{i-1}} \left[\underbrace{I(F_i, C)}_{\text{relevancy}} - \underbrace{\frac{1}{i-1} \sum_{F_j \in \Phi_{i-1}} I\left(F_i, F_j\right)}_{\text{redundancy}} \right] \right)$$

New operators also improve search efficiency

Feature Name	Arguments	Description
Present	I_i	I_i is present in at least one of the orbits
Absent	I_i	I_i is absent in all orbits
InOrbit	O_i, I_j	I_j is assigned to O_i
NotInOrbit	O_i, I_j	I_j is not assigned to O_i
Together	$I_i, I_j, (I_k)$	$I_i, I_j, (I_k)$ are assigned together in any one of the orbits
TogetherInOrbit	$O_i, I_j, I_k, (I_l)$	$I_j, I_k, (I_l)$ are assigned together in O_i
Separate	$I_i, I_j, (I_k)$	$I_i, I_j, (I_k)$ are not assigned to the same orbit
EmptyOrbit	O_i	No instrument is assigned in O_i
NumOrbitUsed	n	n is the number of orbits with at least one instrument
NumInstruments	$(O_i), n$	n is the number of instruments in any orbit (or in orbit O_i)



- KDO: Knowledge-Driven Optimization
- \AOS: Adaptive Operator Selection
- \R: Random Operator Selection
- \C: Operators as Constraints
- HV: hypervolume (performance metric in MOO, large-is-better)
- NFE: Number of function evaluations
- Thick lines: Statistically significantly higher median than ε-MOEA (Wilcoxon rank-sum, $n = 30, P < 0.05$)

Status and future work

- Finalizing overall architecture of TAT-C ML
- Integrating MOEA-AOS with TAT-C
- Integrating MOEA-AOS with KB
- Demonstration of TAT-C prototype with KB and eps-MOEA by August
- Develop operators for coverage problems
- Integrate an validate AOS capability with offline operators
- Integrate and validate online learning
- Validated tool by August 2019