

# *Model **P**redictive **C**ontrol Architecture for Optimizing **E**arth **S**cience Data Collection (PCAES)*

ESTF2015

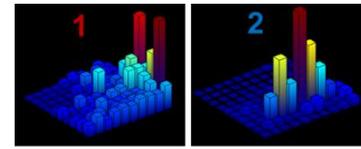
23rd -25th June 2015

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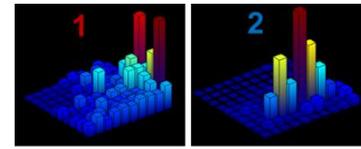
# PCAES Summary



- **ESTO/ AIST funded with start on May 1 2015 and completion on April 30 2017.**
- **TRL start at 2 end at TRL 4.**
- **Demonstrate new SW architecture borrowed from control theory to optimize ESFL remote sensing data collection.**
- **Main output product is ability to generate optimized\* power map and demonstrate this capability through simulation and lab HW implementation.**
  - \*Optimized with respect to science data value.
- **Year 1**
  - Requirements flowdown for end-to-end modeling
  - Generation of multi-layer scenes for testing of the MPC-based architecture.
  - Evaluate optimization algorithms, in particular quadratic programming and gradient-based algorithms which can both handles constraints.
  - Conduct sensitivity tests to understand how weighting the effects the performance of science extraction and refining the optimization metrics.
  - Study of computation time versus optimization.
- **Year 2**
  - HW implementation in the adaptive lidar lab
  - Model validation and update



# Collecting More High Value Earth Science Data

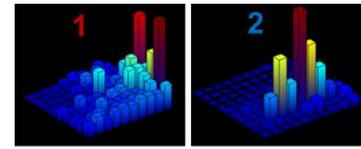


- Challenging budgets demand reconsideration data collection process and data exploitation.
- The remote sensing field benefits from a myriad of sensors and sensor suites of increasing capability and complexity. Meanwhile, on-board systems for real-time control of instruments have been limited in general to a few traditional architectures.
- Focus of this program is to optimize instrument or instruments data collection capability using advanced software architectures.
- Optimized systems many times result in complex systems. Characteristics are:
  - Multiple constraints, nonlinear physics, time-varying systems, interacting, multivariable systems and sometimes sparse data or missing data.
- Multiple Earth Science applications:
  - Trend is for higher capability, scene-directed instruments in the future
  - We focus program on multi-beam lidar systems (for example – electronically steerable flash lidar (ESFL))





# Comparison to Standard Lidar Systems (Calipso base-line)

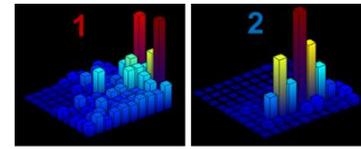


- Standard lidar system has narrow fixed ground track
  - Highly inefficient due to clouds, repeat data, misses more interesting data.

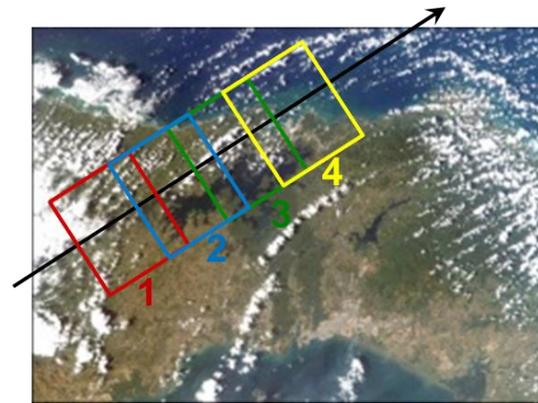
Architectural Component	Current (CALIPSO-type) Mission Paradigm	Model Predictive Controller Paradigm
Transmitted Laser Beam	Single Laser – Single Beam	Single Laser – Multiple Deflected Beams Number, pointing, amplitude set via MPC defined rules/weighting
Beam Pointing	Fixed	Dynamic – Adjustable for each frame
Receiver Pixels	Three, each boresighted to laser	256 x 256 Flash Focal Plane Array – sub-filled to achieve necessary SNR
Ground Sampling	Fixed – Along track only	Adaptive Both Along and Cross track
Data Density	Fixed – Set by laser rep rate and orbit track	Adaptive – set by laser rep rate, beam configuration, and orbit track
Operational Control	Fixed – autonomous Uplinked manual mode control	Multi Process Controller - Autonomous/Adaptive
Data bases	Geoid	Geoid, DEM, Maps to support objectives
Secondary Onboard Sensors	Cloud Context Imager , Infrared Imager, Star tracker, GPS receiver	Same, plus additional as needed e.g. steerable radar for precipitation
Onboard Image Analysis	None	Cloud Discriminators, Lidar Image Analyzers, Passive Camera Scene Analyzers User defined (uploadable) mission driven scene discriminators.
Lidar Optimization Goal	Maximize SNR using weakest signal (stratospheric Rayleigh scattering) – fixed	Maximize SNR for each Controller defined objective for each laser pulse
Lidar Optimization Method	Manual uplinked commands on quarterly schedule Day/night Gains switched twice/day	MPC control sets lidar configuration to achieve SNR required to meet mission objectives, done for each frame



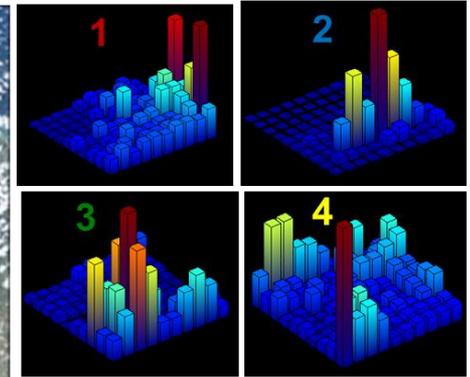
# Example Problem Geometry and Power Maps of Ground Scenes



- The scene on the left of the Panama canal has a satellite ground track with 4 time-separated instantaneous lidar field-of-views.
- Assume sun-synchronous orbit at 700 km.
- If we use a much simplified metric of light (clouds) areas are not of interest (weight=0) and darker areas contain our science (weight=1) we can compute the optimal power maps for our ESFL system for each frame (see right-hand images).
- Note how fast the optimal weighting changes for beam control between 4 images.



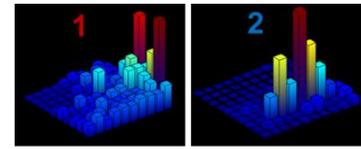
Ground track and moving FOV over Panama canal



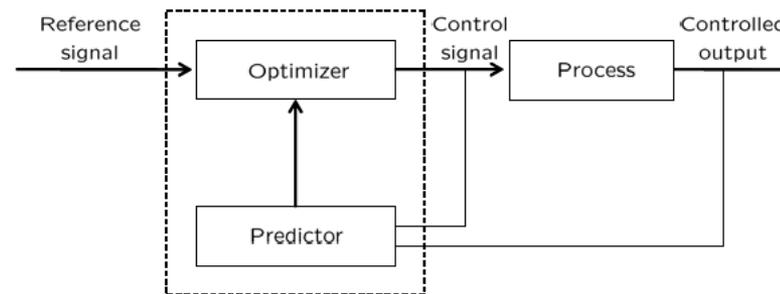
Power map before thresholding



# What is Model Predictive Control (MPC)



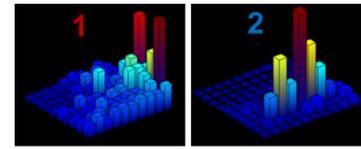
- We have borrowed a control system architecture that has proven to be highly successful optimizing complex non-space systems called model predictive control (MPC).
  - A conceptual analogy of MPC is frequently made to a driver in an automobile. Driving through a city is very complicated and a difficult process to describe due to complex and changing scenes, and the presence of many constraints (velocity, brake stopping rate, other cars, weather, etc.).
  - However, by making a series of continual corrections and taking into account future events and past knowledge, one is able to navigate and get to ones destination.
  - MPC works in a similar fashion, predicting future trajectories from embedded models, past data and sensor updates, optimizing with respect to constraints, weighting, and performance metrics, and then applying a control signal to some type of actuator.



Most basic MPC architecture is very simple



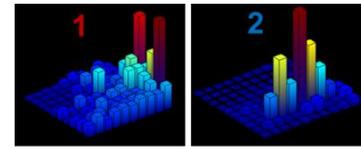
# PCAES Involves Many Intersecting Fields of Study



- MPC has a very general architecture and therefore it needs to be focused for the ESFL problem. To minimize the work load, understanding analogies are important for extracting methods/ algorithms from previous work.
- This will require a broad understanding of MPC and a variety of implementations including use for:
  - Wind power control with lidar
  - Vision guided closed loop control
  - Autonomous robotic systems
- Several other technology areas need to be understood:
  - Sparse data representation and ground data spatial correlation (kriging)
  - Predictive models
  - Subspace system ID and in particular data-driven approaches
  - Hierarchical architectures and include work already done in autonomous control from space (JPL). How is hierarchical architecture and functions partitioned.
  - Optimization approaches since computational speed is important.
  - How DEMs are used and interaction with other data.
  - Planning algorithms

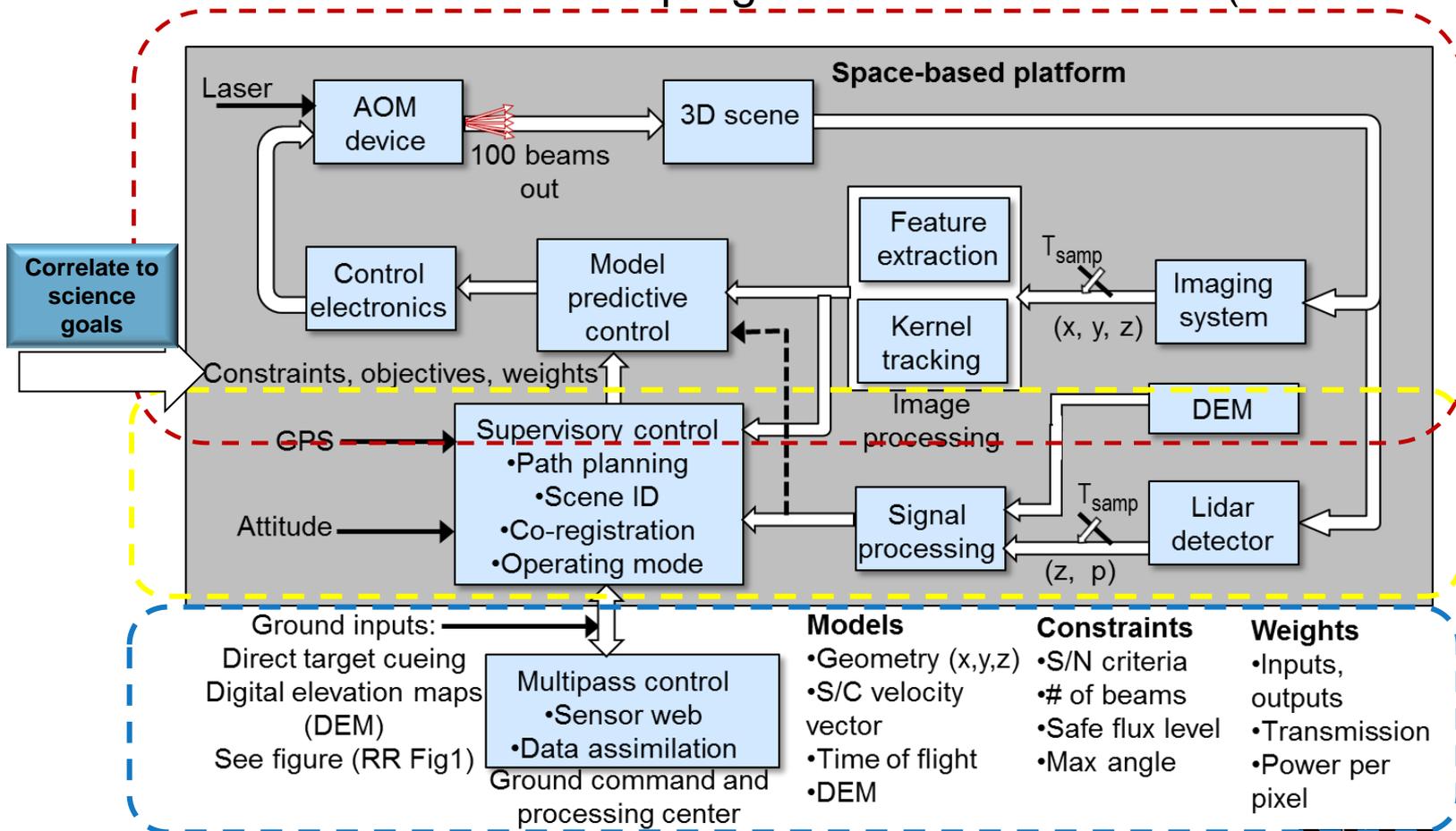


# MPC Supports Development of Hierarchical Systems



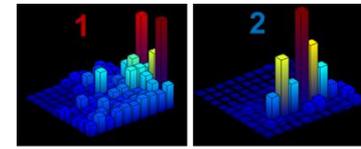
- Challenges: Data can be sparse, process dynamics are time-varying

Focus of PCAES program – fast lower level (sub-second)

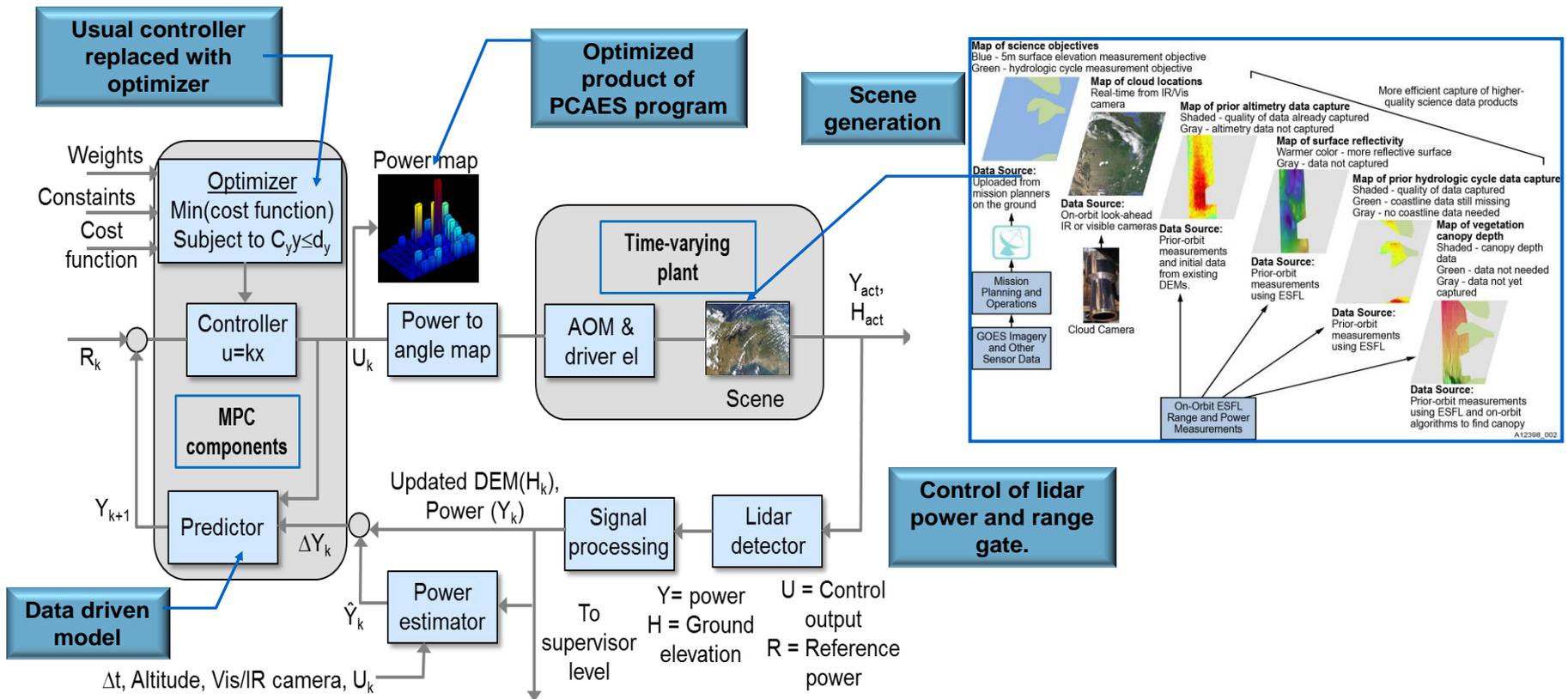




# Lower Level Architecture

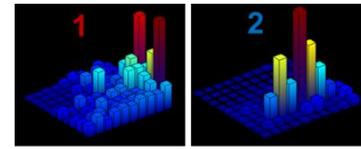


- What we simulate is shown below. What is simulated in the lab is different since there is no lidar return signal.





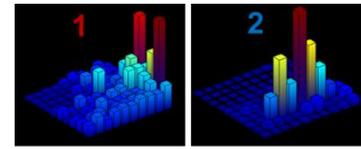
# Unique Aspects of MPC Solution to ESFL Beam Control (1/2)



- The MPC architecture is very general which makes it a powerful tool for solving a wide range of complex problems – however one must selectively tune the details for each unique application to fully take advantage of it's inherent capabilities.
- The MPC problem must be recast into a remote sensing problem and the remote sensing problem recast as a control problem. What is plant? What is impulse response? What are cloud obscurations? What is actuation? Camera (2 D) info versus lidar information (3D) – what is equivalent feedback term?
- Time-varying “plant model” versus dynamic modeled plant. In fact, there is no dynamic model of plant – only I/O data of time-varying system. – we don't want an explicit model.
  - Borrow concepts from data-driven MPC control where only I/O data used.
  - This is not completely correct as a dynamic model of the S/C ACS is needed for retargetting maneuvers.



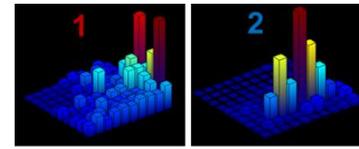
# Unique Aspects of MPC Solution to ESFL Beam Control (2/2)



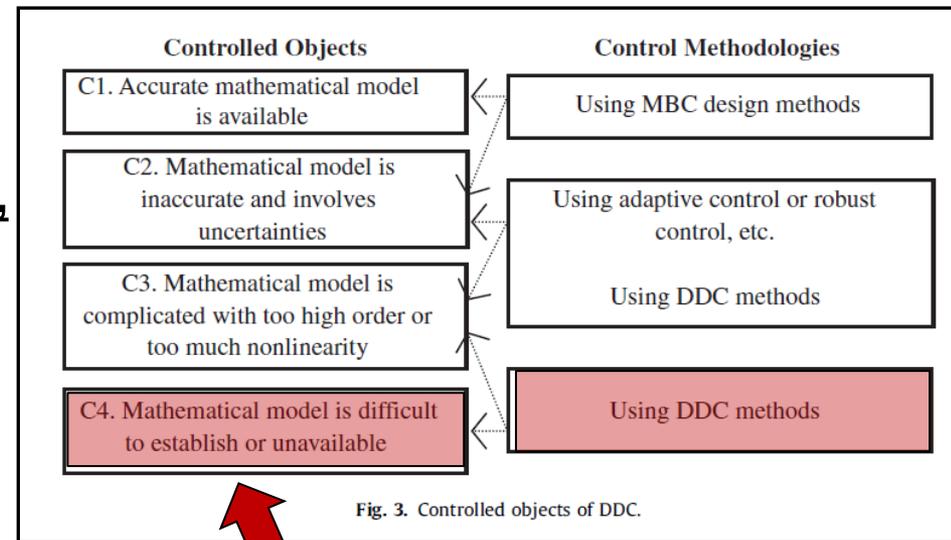
- **What we are controlling (spatial distribution of power, possibly range gate) is not the science (DEM) although contributes to the overall data quality.**
  - Use concepts from luminance control for vision-based MPC. Use concepts from ultrasonic control as equivalent to lidar range gating for 3<sup>rd</sup> dimension
- **Classical MPC involves system ID with impulses or steps to ID model.**
  - ESFL inputs (to the “plant” – scene) are always impulses of varying power and the power out is a time-delayed waveform with varying temporal ( or height) resolution. Unlike impulse response from dynamical systems, the correlation of each discrete time component can be very low at times depending upon the scene (vegetation, ground, etc).
- **Data is sparse due to obscurations (clouds, smoke, etc)**
  - In control terms, part of the scene is unobservable although we may have some a-priori information.
- **Control system is actually described as hybrid due to the discrete nature of the moves. Most MPC based controllers are designed around continuous systems.**
  - A **hybrid system** is a dynamic **system** that exhibits both continuous and discrete dynamic behavior – a **system** that can both flow (described by a differential equation) and jump (described by a difference equation or control graph).



# Data Driven Control (DDC) [Hou2013] Basis for Predictor

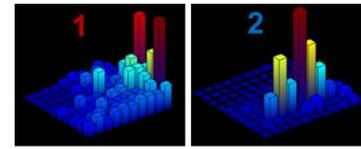


- “Until now, there have been a few DDC methods, but they are characterized by different names, such as data-driven control, data-based control, modeless control, MFAC (model-free adaptive control), IFT (iterative feedback tuning), VRFT (virtual reference feedback tuning), and ILC (iterative learning control). Strictly speaking, there are some differences between the terms data-driven control and data-based control. Data-driven control hints that the process is a closed loop control and its starting point and destination are both data, while data-based control means the process is an open loop control and only the starting point uses data.”





# Summary



- **Very general architecture well-developed from ground and aerospace community should translate well to support future optimized Earth science missions.**
  - Must tailor the architecture to the application but overall approach will transfer to other missions.
- **There are several challenges identified but appear to have solutions.**
  - Ultimately, “optimally” approach will be sub-optimal due to computational limitations and knowledge limitations in predictor.
  - Correlate weights to science desired.