Sensor Networks for Mapping Environmentally-Distributed Radioactivity

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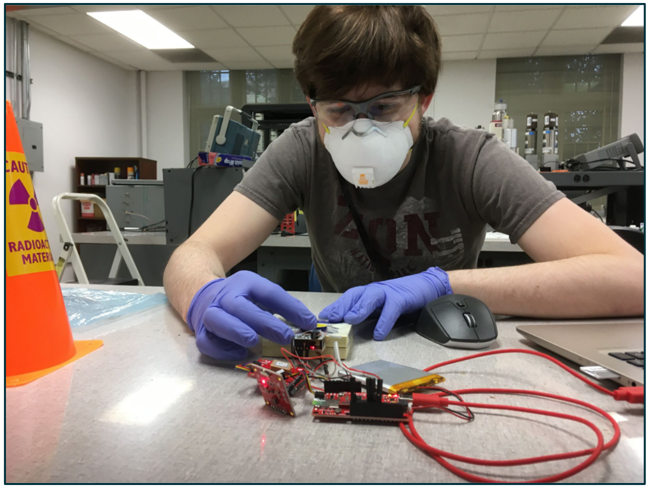
Outline

- **Introduction**
- **Motivations & Objectives**
    - Background
    - Problem spaces

- **Modelling Framework**
    - Source terms
    - Design parameter modeling
    - Network algorithms
    - Evaluations & analysis

- **Current Efforts & Next Steps**
    - Multi-objective optimization
    - Ongoing Work

Introduction



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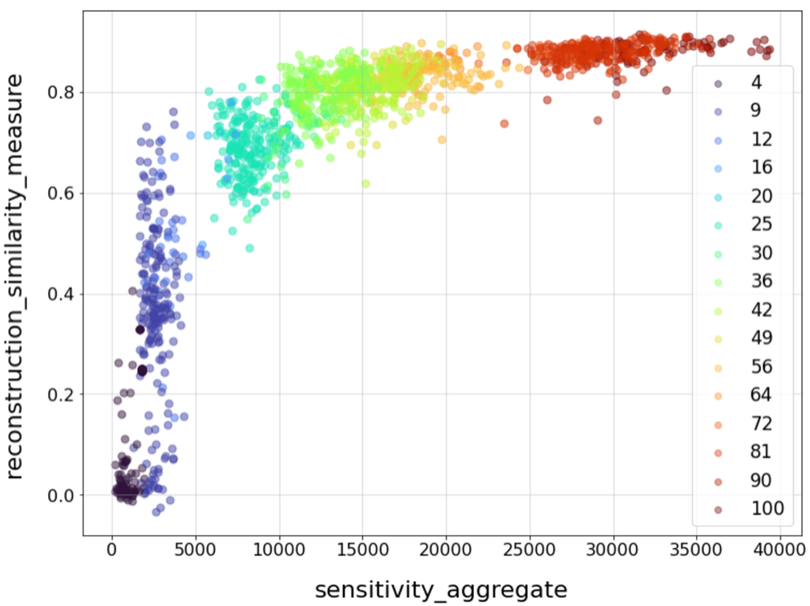
NSSC Research Focus Areas: Radiation Detection, Computing and Optimization in Nuclear Applications
Planned Graduation Date: Spring 2024

Lab Mentor and Partner Laboratory: Ren Cooper, LBNL



Mission Relevance of Research: This research focuses on development of a new system that may be deployed for long periods of time to continuously monitor radioactive contamination of a wide area. Network-wide methods are then used to synthesize individual node data to model the whole spatial field, which may be of interest in accident scenarios as well as for emergency response. Additionally, such a system would drastically improve the capability to collect real-world ground truth data from explosive dispersals of contaminants in testing scenarios.

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Background

- Radioactive dispersal incidents present uniquely challenging scenarios for practical management
  - Possibility of threats to public health
  - Comprehensive spatial measurement usually impossible
  - State-of-the-art systems not equipped for long-term in-situ measurements

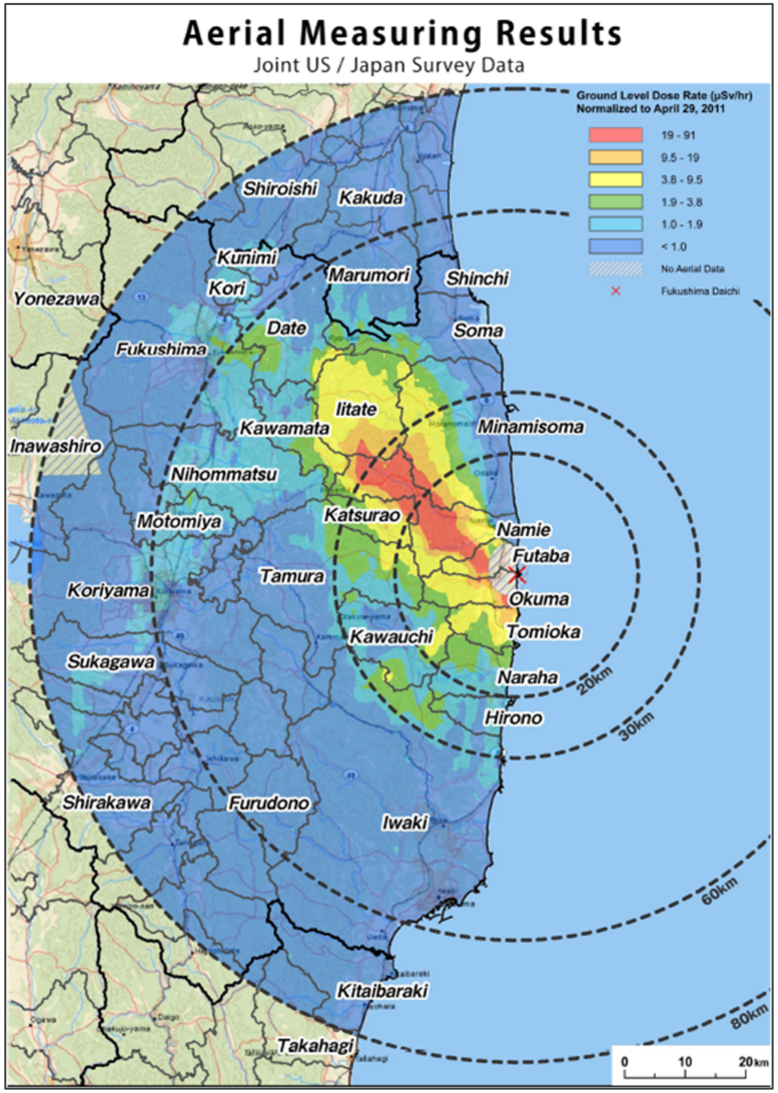

Fig 1: Aerial radioactivity measurements, Fukushima reactor area
image courtesy of US DOE

High-Level Conceptualization

- **Motivating objective:** address gap in long-term/continuous wide area monitoring with deployable network of sensor modules
    - Mesh network of radiation measurement nodes capable of intercommunication
    - Data transmission to central edge-processing fusion center
    - Power management by design; offloading processing allowing sensors to remain in field for extended periods of time
    - System capable of real-world data collection on plumes and deposition profiles in a manner that would cleanly preserve time-domain data

- Thus far, this work has centered upon the modeling and simulation of such a networked sensor array in software

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Framework Diagram

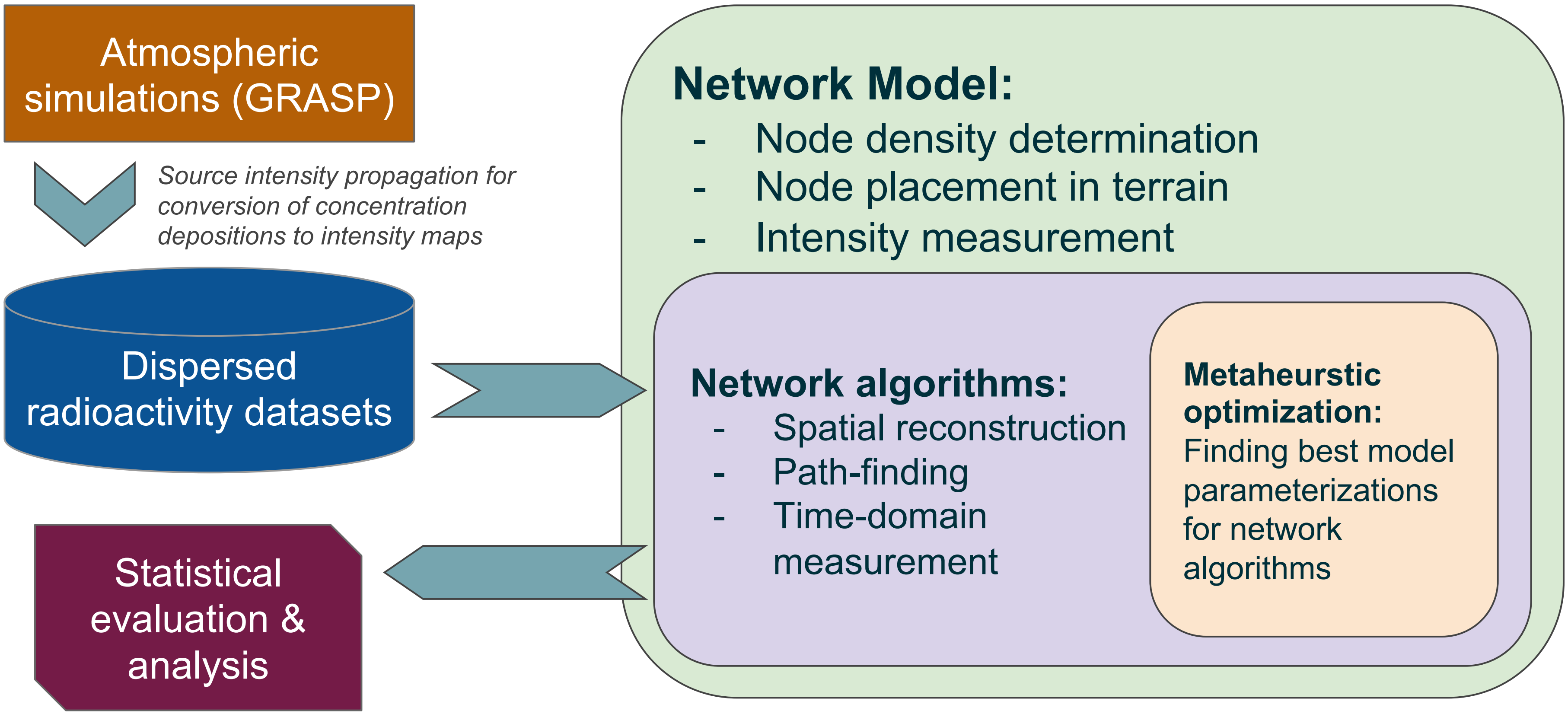


***Fig. 2**: Diagram of sensor network modeling framework operation.*

Realism in Datasets from Simulation

- We employ **GRASP** (GPU Resident Atmospheric Simulation Program) for simulation of atmospheric dispersion of contaminants
- Parameterizations of terrain and wind tuned to real-life geographic areas of interest to approximate plume deposition to generate realistic source scenarios

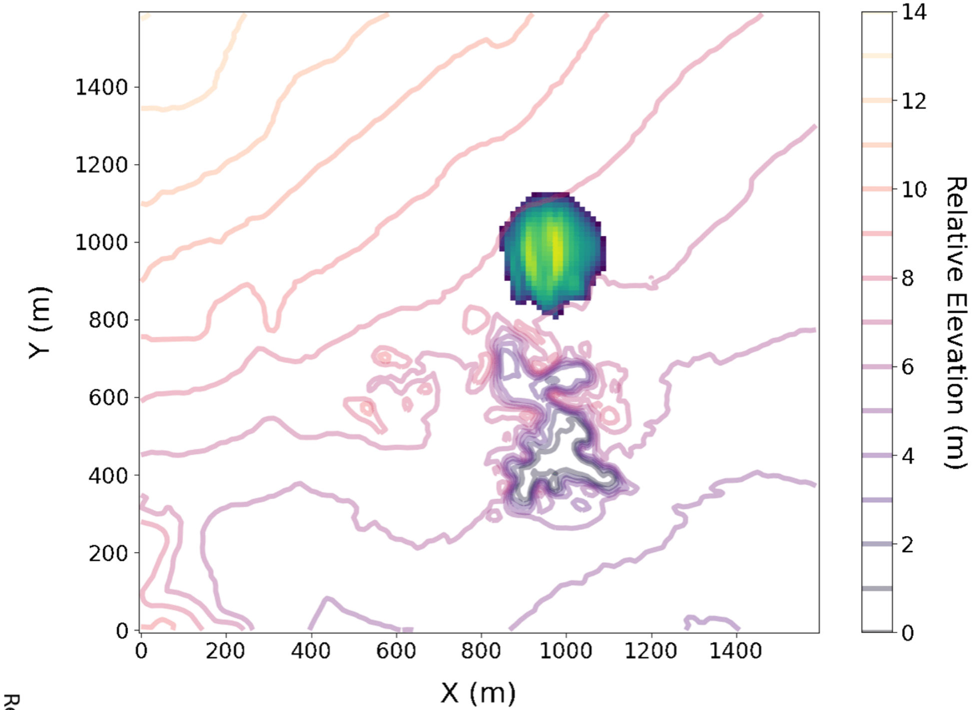


Fig. 3 (above): Top-down view (summed over **Z**) of sample tracer emission in Idaho Falls terrain.

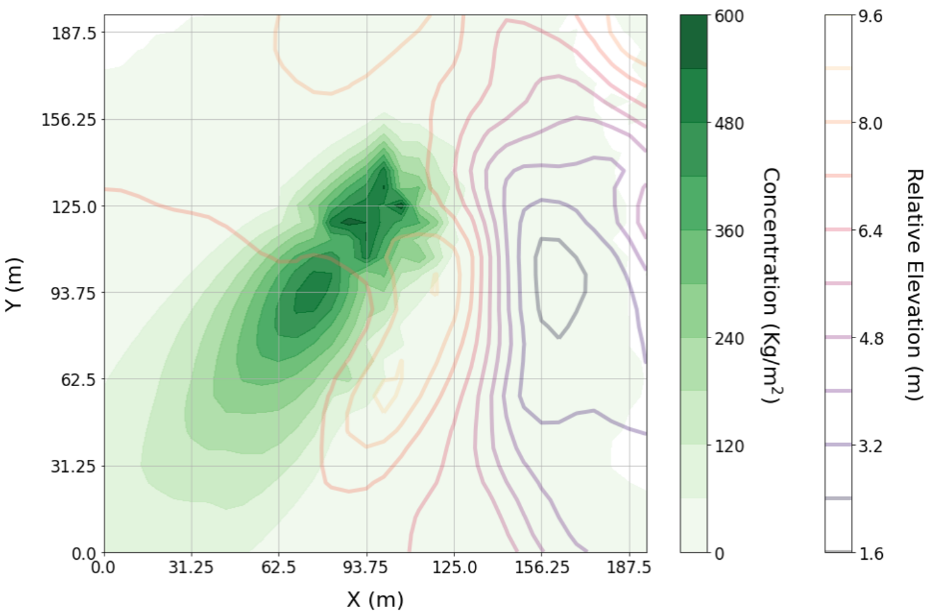


Fig. 4 (left): Simulated deposition sample in Idaho Falls terrain.

Network Design Parameters

- **Network node density:** How many nodes should be placed in a geographical area of given size? What pattern should the placement follow to maximize their sensitivity?
- **Reconstruction algorithm:** What algorithm should be used to reconstruct the intensity map from sparse node measurements?
- **Terrain complexity:** What is the effect of occluding terrain on the performance of such a network, whether directly or indirectly?
- **Temporal behavior:** How should node sensitivities to changes in source term be altered over time? Can we add nodes to the network once deployed? How should malfunctions in nodes be handled?

Network Node Placement

- Reconstruction will improve with greater node density
- However,
  - Nodes may be expensive, practically or otherwise
  - More nodes will increase the power burden on the fusion center

- Therefore, for a number ***N*** nodes, we should aim to place them in such a way as to gain maximum information for the highly underdetermined problem of distribution reconstruction

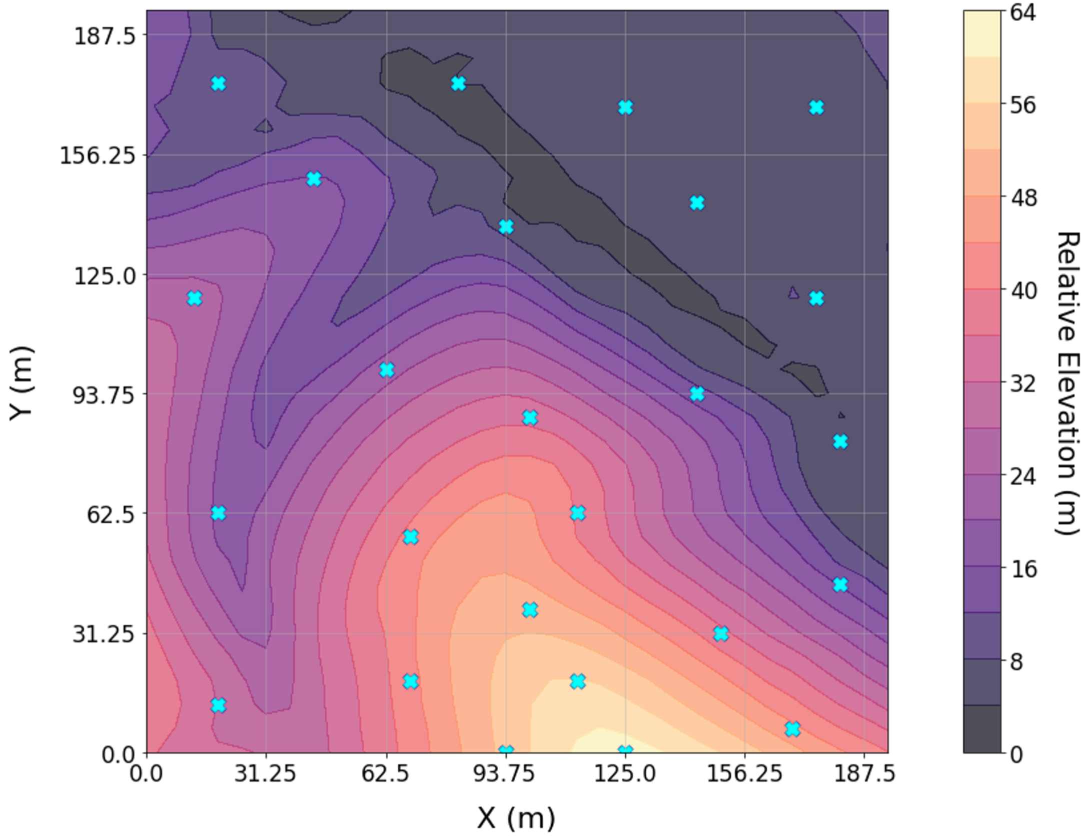


__Fig. 5__: Example placement of 25 nodes in section of Oak Ridge terrain using Lloyd's algorithm for Voronoi centroids, weighted by sensitivity gradients

Spatial Intensity Reconstruction

- Bicubic interpolation and Gaussian process regression primary methods
- We also explore reconstruction via integration of image-to-image translation models as transfer functions

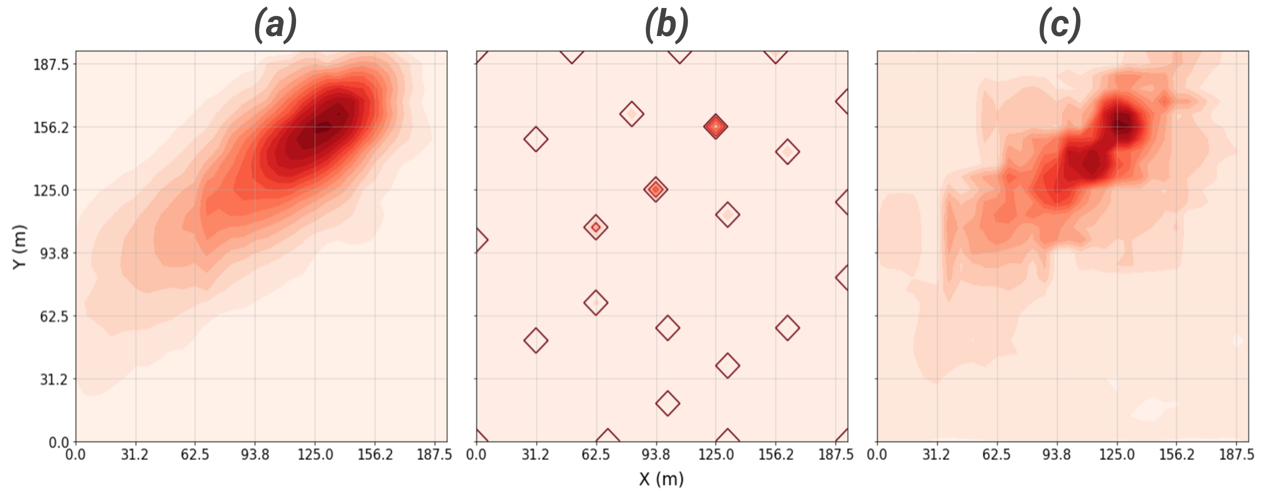
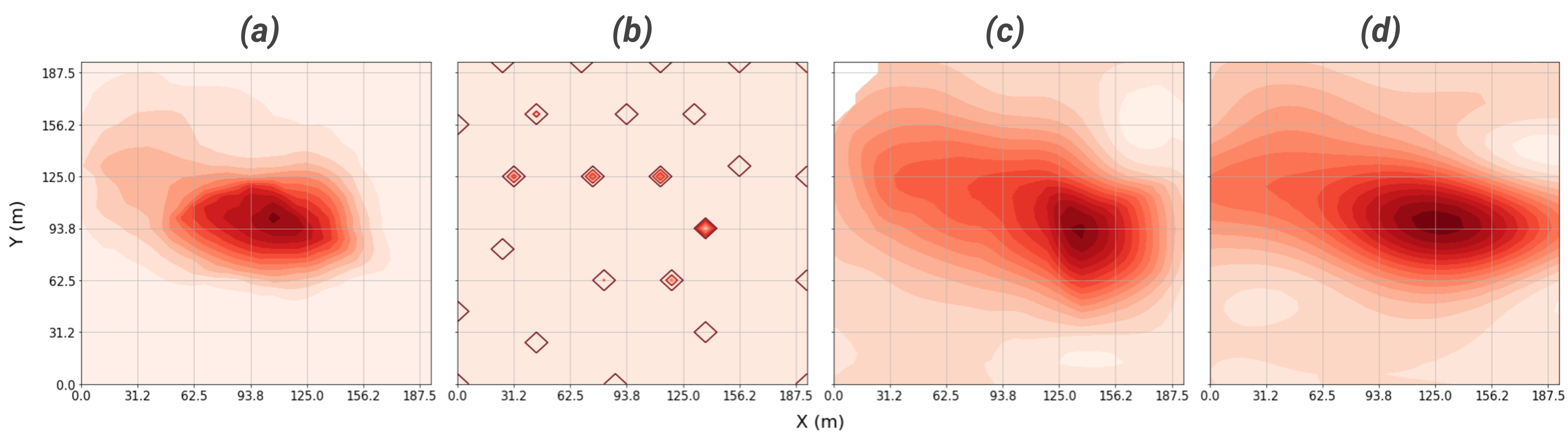
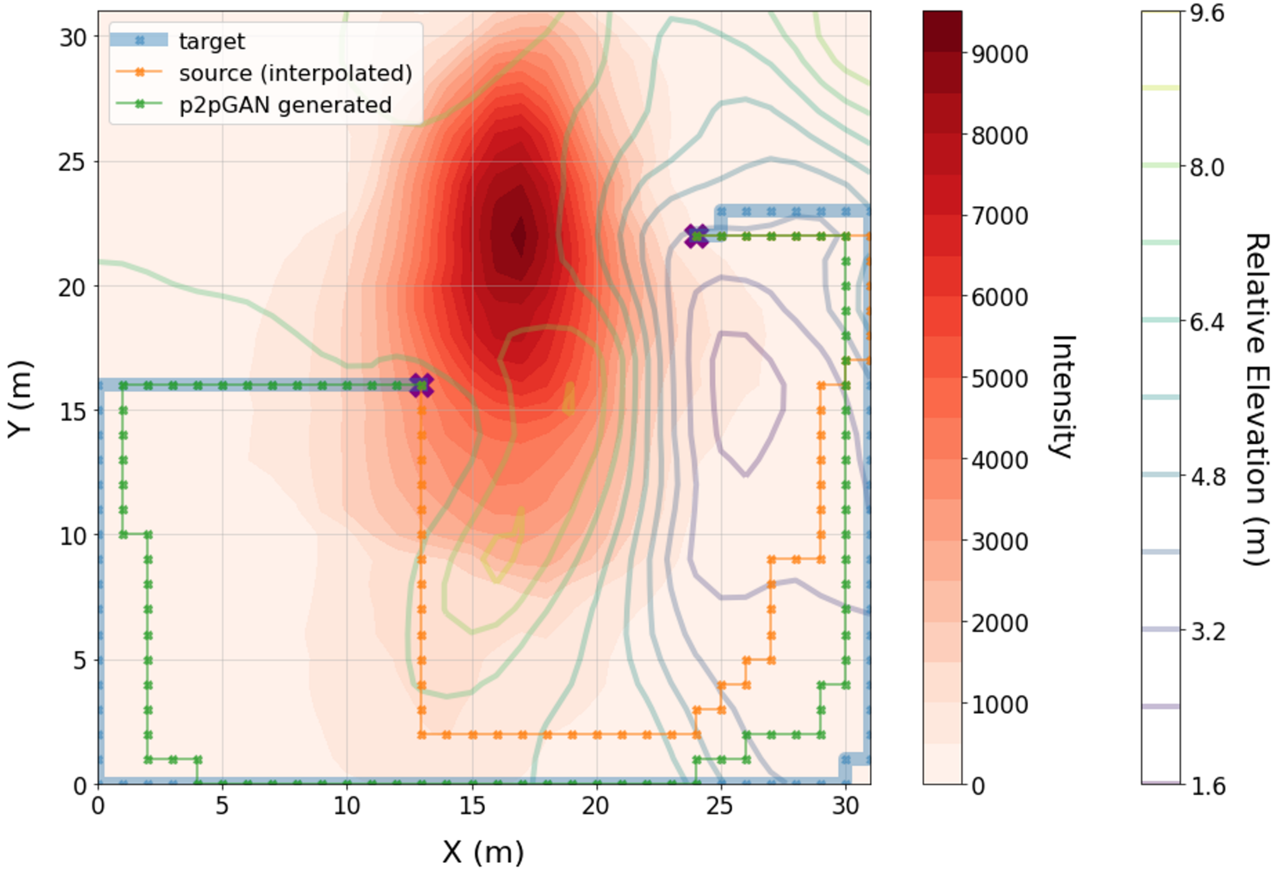


Fig. 6 (above): *Ground truth intensity sample* ***(a)****; sparse input* ***(b)****, reconstruction with p2pGAN* ***(c)****;*

Fig. 7 (below): *sample of deposition intensity* ***(a)*** *with network measurement* ***(b)*** *and interpolated* ***(c)*** *and GPR* ***(d)*** *reconstruction;*



Path Planning



- Composite cost-function of path complexity and dose received utilized in preliminary work to find route through field
- Improving reconstructions consequently affects the results of path-finding algorithms used

Fig. 8: *Sample pathing comparison using composite MO A* algorithm; target (ground truth), interpolated, and p2pGAN-generated spatial intensity maps used in Idaho Falls terrain using 25 nodes;*

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Multi-Objective Optimization

- Many of our problems balance conflicting objectives:
  - Fitness of reconstruction versus node density
  - Path length versus dose received
  - Measurement frequency versus accuracy of time-varying signal
- Difficulty in attempting to land on conclusive results due to inherent trade-offs in the problems and large parameter space

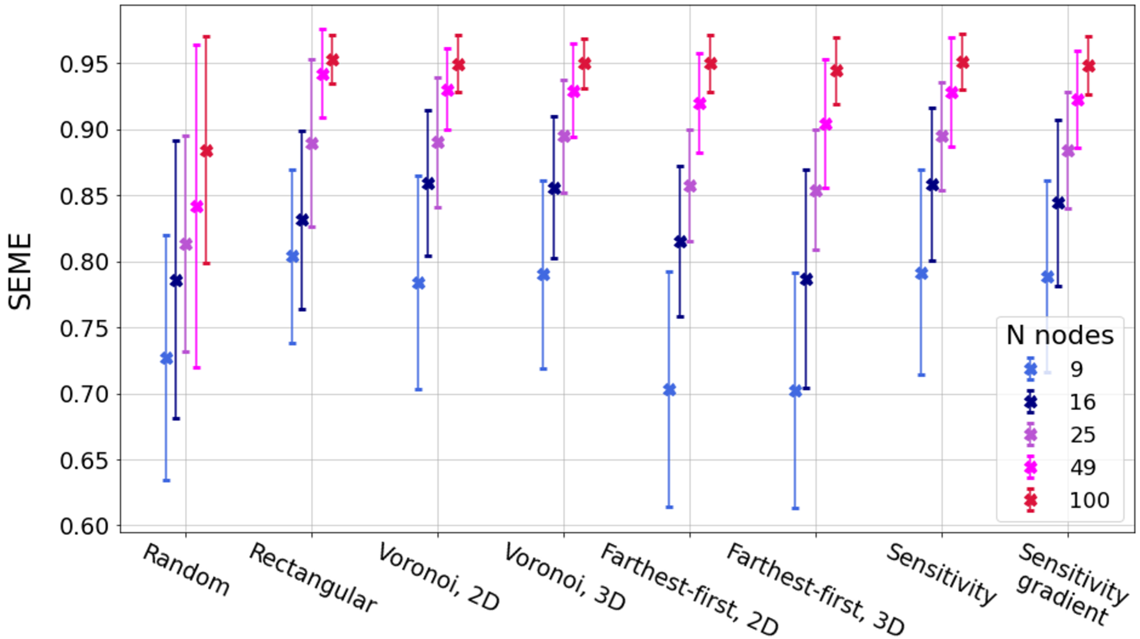


***Fig. 9**: Shallow node density parameter exploration for reconstruction fitness across node placement methods.*

Optimizing the Time-Domain Measurement Problem

- Background: transmitting a new measurement to the edge for processing requires the node to expend power
  - Applying detection of concept drift as basis to determine appropriate update intervals
  - Yet, determining how a drift detection algorithm should be parameterized to handle this data and minimize both objectives is not obvious

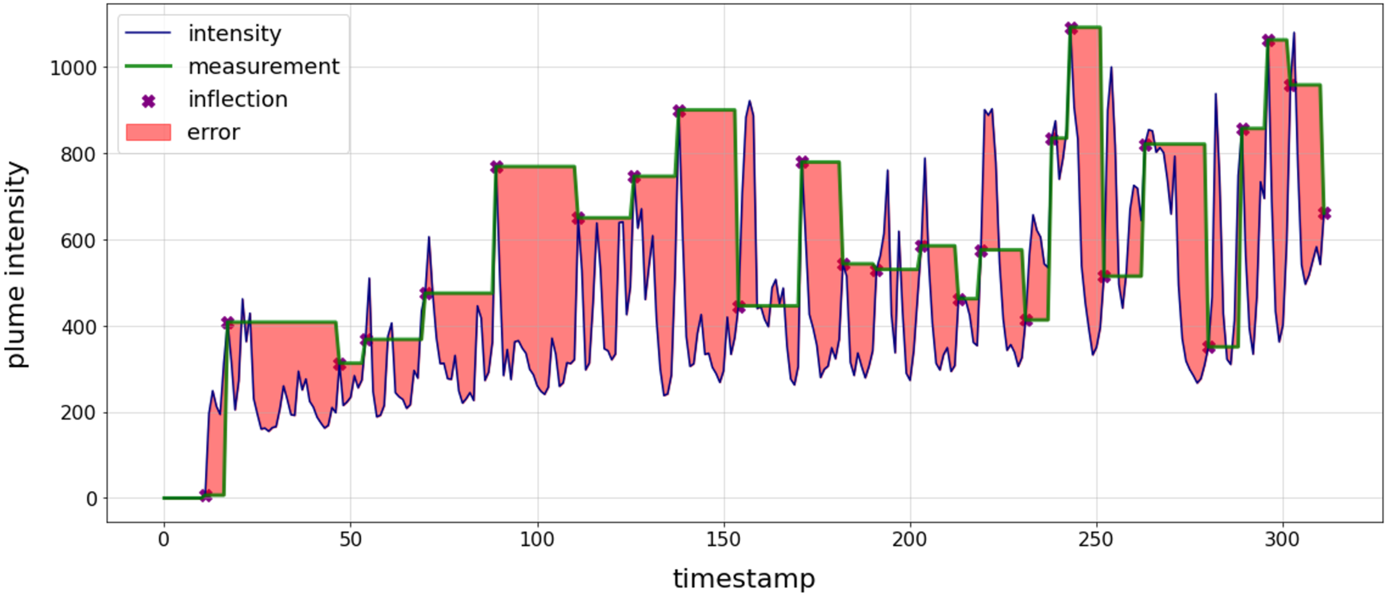


Fig. 10*: Example of tradeoff in time-domain between measurement error and measurement frequency with drift detection algorithm applied; data signal from single node located in Idaho Falls terrain.*

Optimizing the Time-Domain Measurement Problem

- Multi-objective evolutionary algorithm applied to time-domain measurement problem

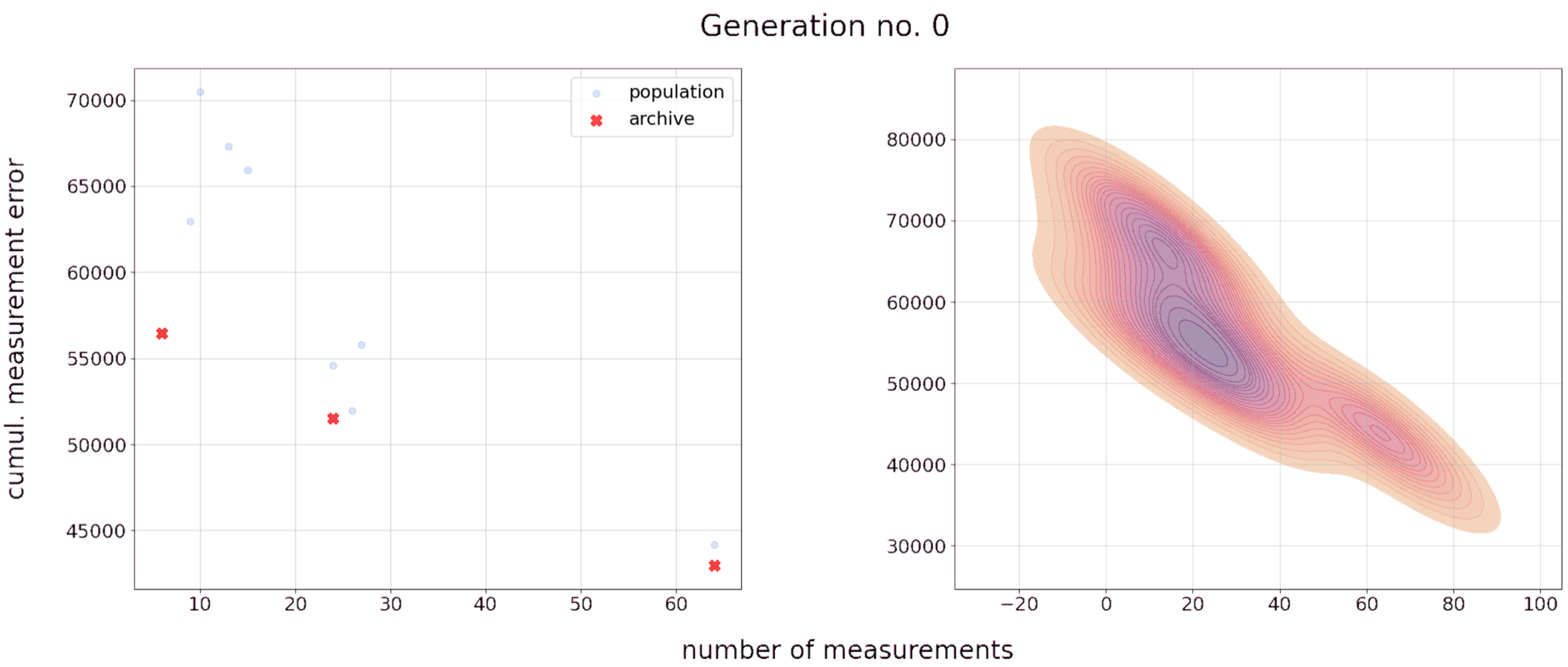


***Fig. 11**: **Left:** Development of Pareto frontier in archive (**red**) over population generations (**blue**). **Right:** KDE plot over generations of population density in objective space.*

Optimizing the Time-Domain Measurement Problem

- Expanding on multi-objective optimization for diverse problems
  - Explaining objective space distribution in terms of algorithm parameters (see **Fig. 12**)
  - Building towards more complete problem characterizations by including additional parameters and constraints

- Improving realism in source terms and using them to build larger and more robust datasets
- Identifying other network algorithms to implement and evaluate

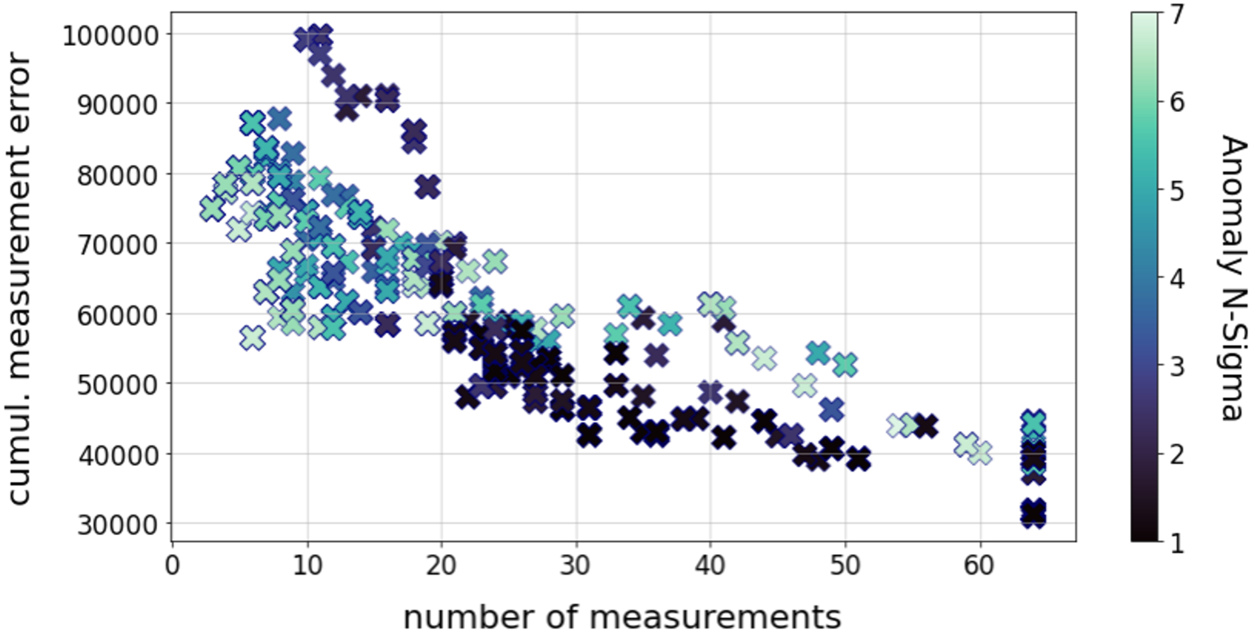


***Fig. 12**: Population individuals evolutionary algorithm results, colored by anomaly n-sigma parameter value of solution.*

Approach to Multi-Objective Pathfinding

- Formulating an MO pathfinding algorithm demands a method to equitably balance measures of fitness for each objective
- However, heuristics of best-case performance are not always obvious

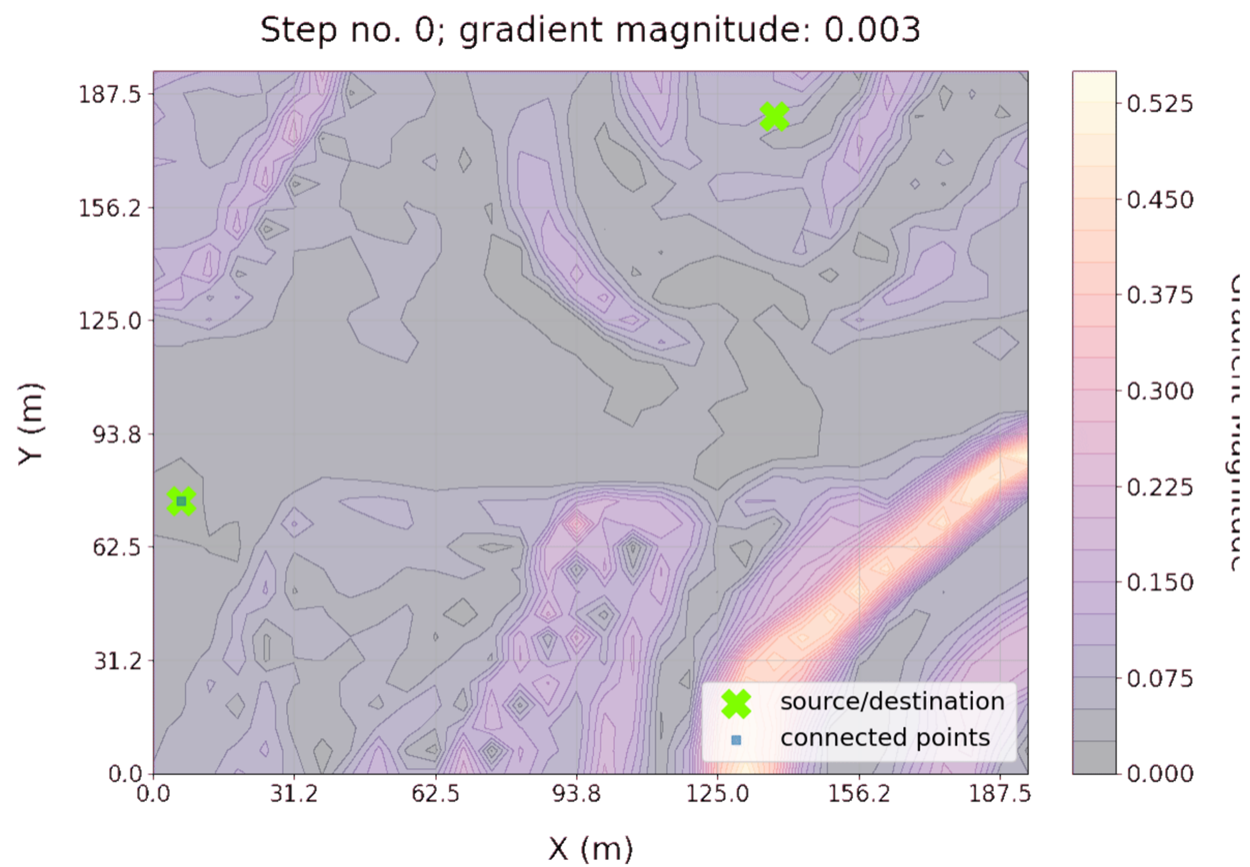


Fig. 13: Heuristic calculation for elevation change objective; the space is "flooded" by progressively raising the allowable gradient until a path is possible between source and destination.

Approach to Multi-Objective Pathfinding (cont'd)

- Whereas distance is usually the only objective, elevation change and dose received must be considered here; therefore, heuristic maps are calculated using novel methods

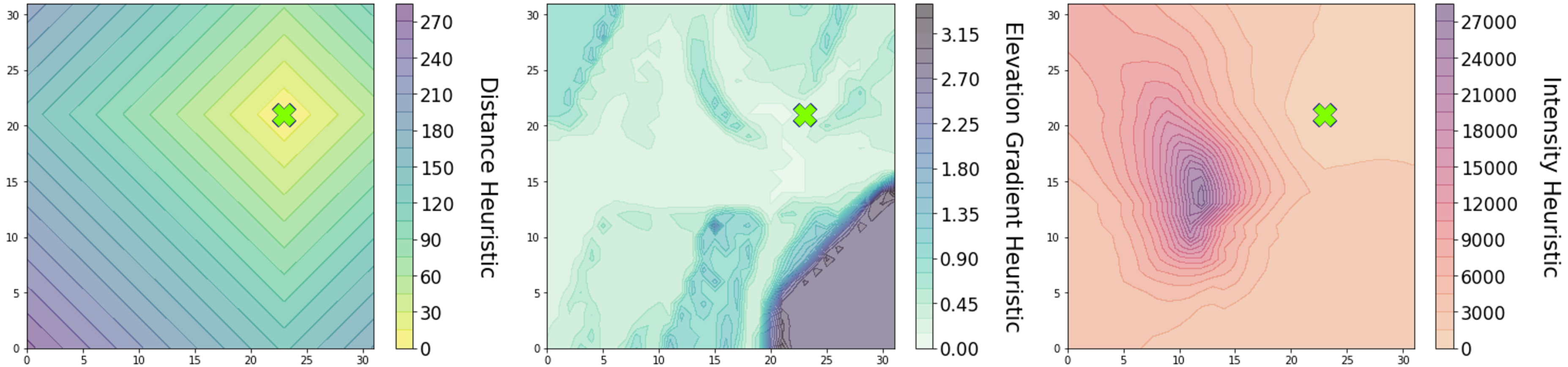


Fig. 14: *Heuristic maps for distance, elevation gradient, & dose received; destination point marked as green* ***X***.

Pareto A* Demonstration

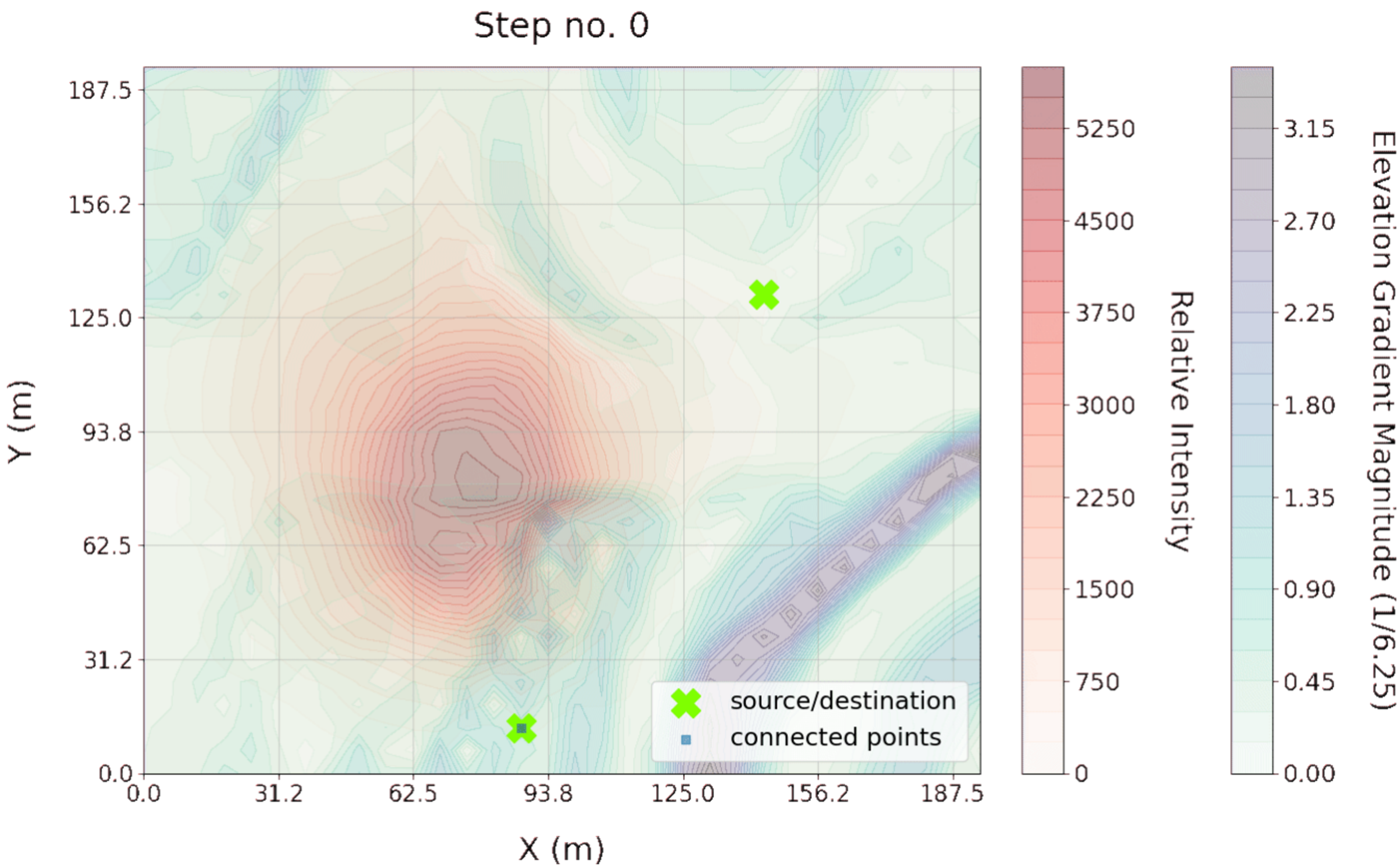


Fig. 15*: Sample results of Pareto A* algorithm, weighted to equally balance distance, elevation gradient and intensity received.*

MOEA on Pareto A*: Sample Results

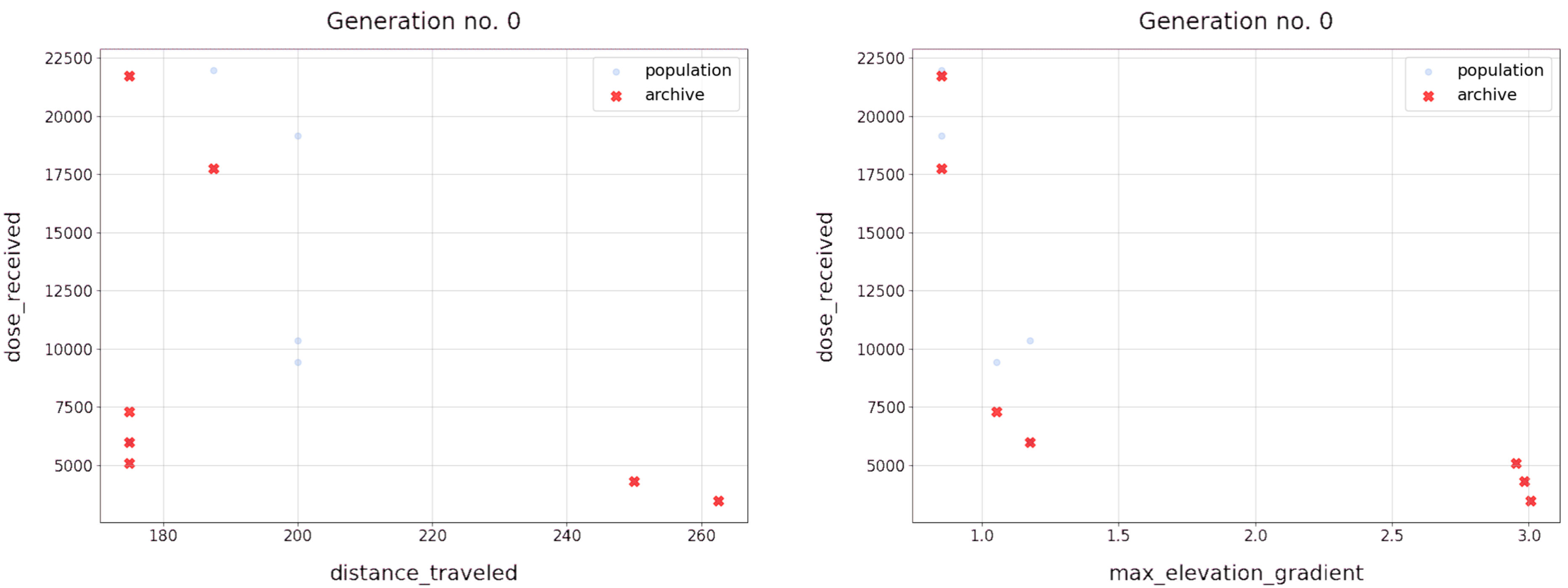


Fig. 16*: Development of Pareto frontier approximation in archive (****red****) over generations of population (****blue****) in two dimensions of the problem's three-dimensional objective space.*

MOEA on Pareto A*: Candidate Solutions

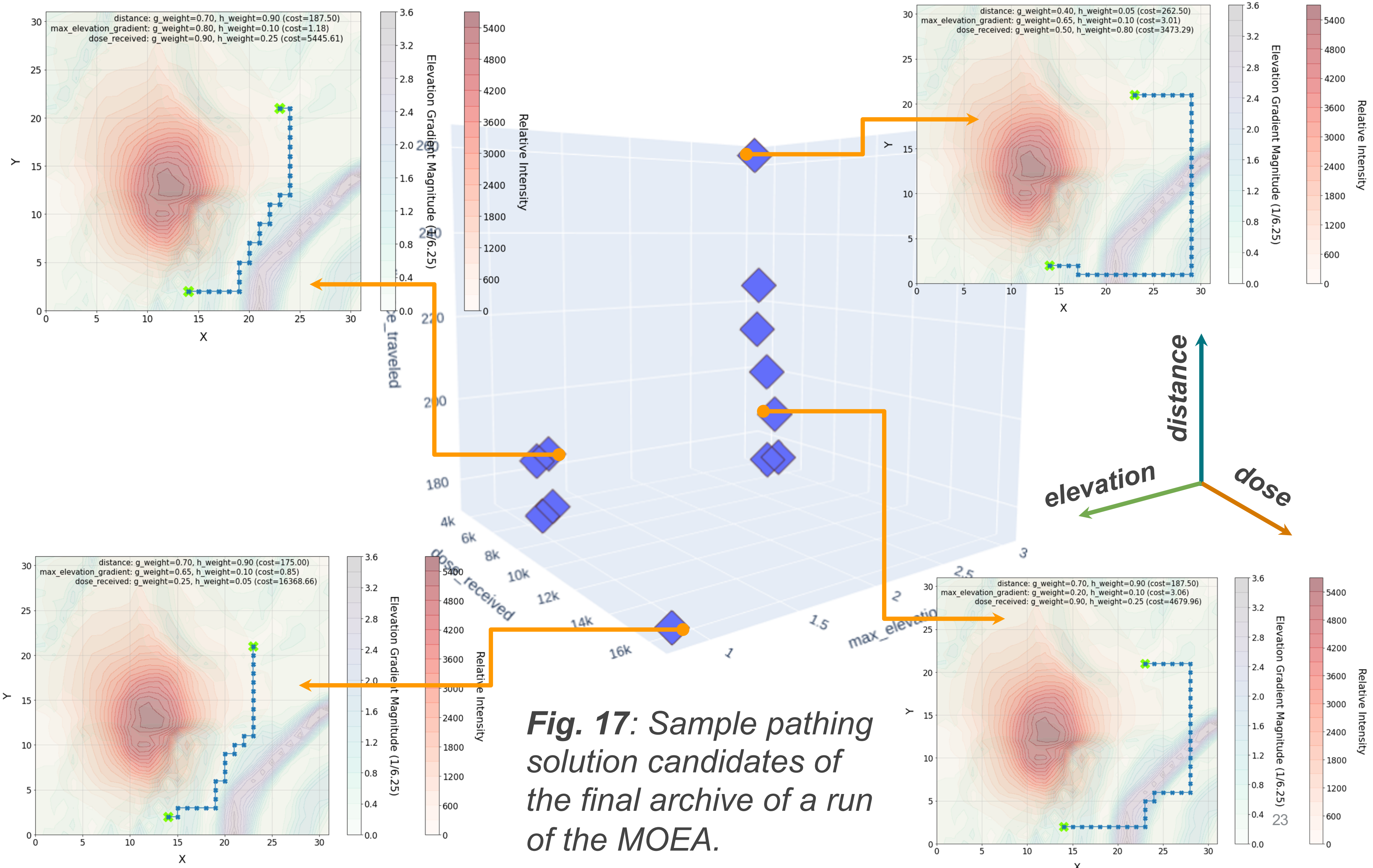
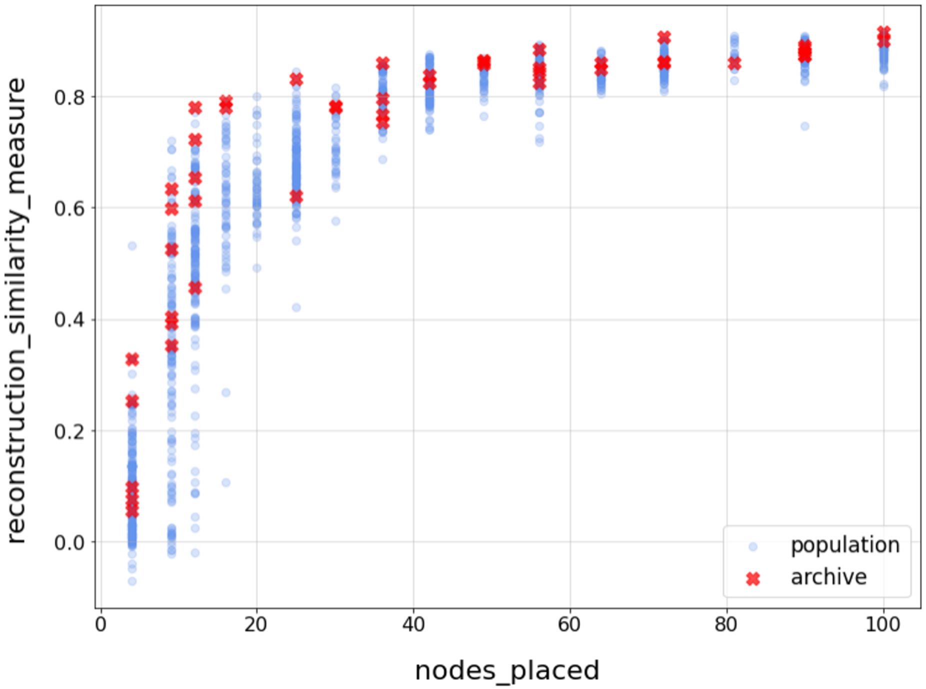


***Fig. 17**: Sample pathing solution candidates of the final archive of a run of the MOEA.*

Multi-Objective Node Placement

- Objectives considered in node placement are quantity of nodes placed, reconstruction similarity, min. internode distance, and overall sensitivity



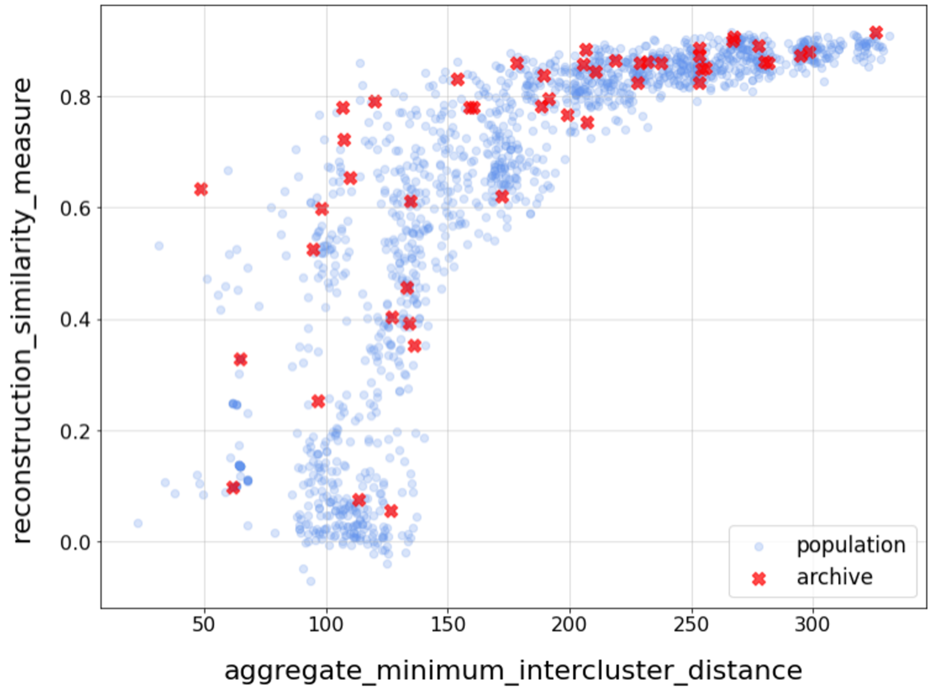
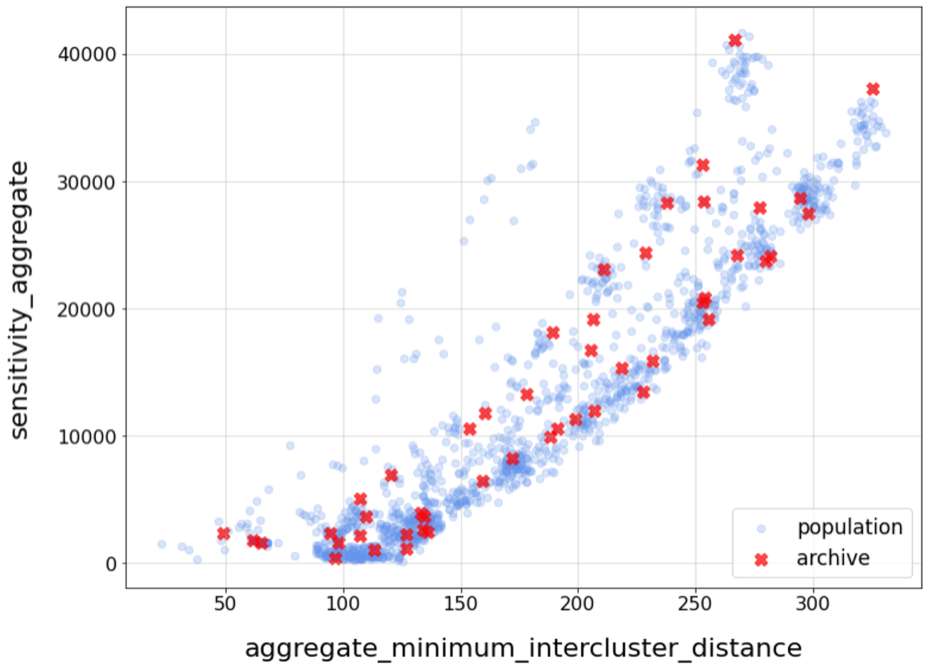


Fig. 18*: Pareto frontier approximation in archive (****red****) over generations of population (****blue****) in two dimensions of the problem's four-dimensional objective space.*

Node Placement - Pareto Front Approx. Coloring

- Visualizing the population in objective space allows for explainability via coloring by parameters



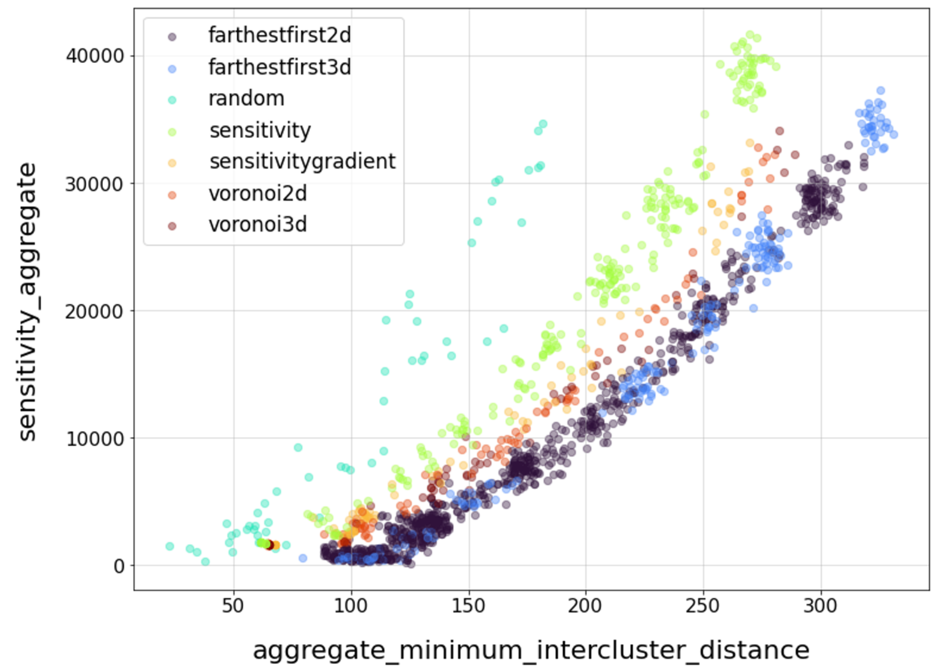


***Fig. 19**: Coloring of individuals in population by placement method parameter in 2D slice of objective space for objectives of minimum internode distance and sensitivity.*

The NSSC Experience

- I have had the privilege to be participate in summer programs, including:
  - George Washington University's 2021 Nuclear Security Policy Boot Camp
  - The 2022 NSSC-LANL Keeping Nonproliferation Science Summer Program

- Support and funding from NSSC has also allowed me to present at conferences:
  - IEEE NSS/MIC 2021: "**A Modeling Framework for Distributed Radioactivity Sensor Networks**" (oral presentation)
  - UPR 2021: "A**pproaches to Wide Area Sensor Networks for Distributed Radioactivity Mapping**" (poster)
  - SORMA West 2021: "**Approaches to Wide Area Sensor Networks for Distributed Radioactivity**" (poster)

- The NSSC has allowed me to further grow my network of connections at national labs with the contacts I have made at LANL via initiating the Keepin program

- Overall, what I value most about the NSSC is that is has provided me the intellectual freedom to explore some of the research topics that interest me most

Acknowledgements

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Thank you! Questions?

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