

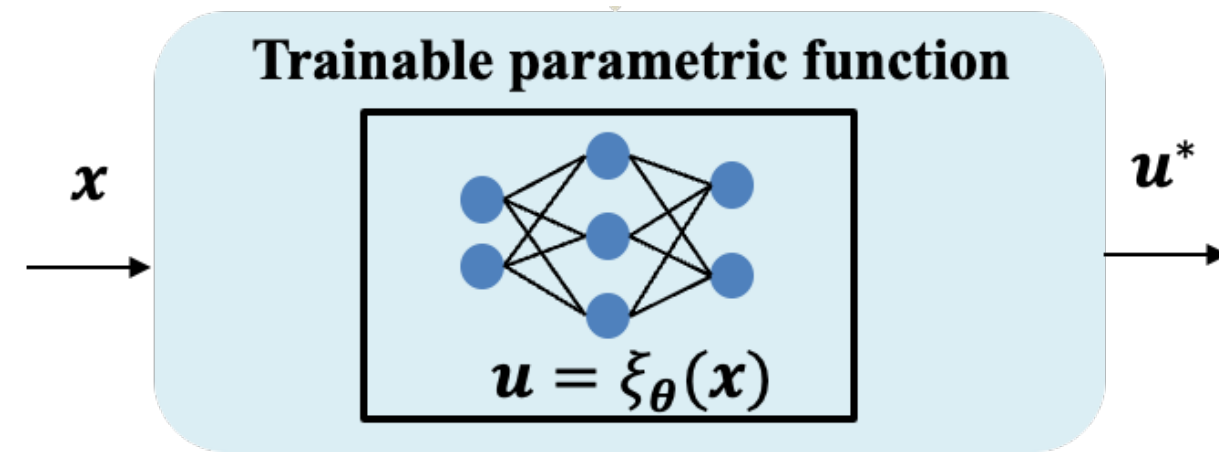
# Towards Reliable AI-based energy system optimizers

## BACKGROUND:

- The information processing of sensor-based systems is complicated by factors such as sensor dropout due to technological failures, transmission delays, and complications arising from the integration of new sensors during system expansion.
- Conventional models, with their fixed input dimensions, often fail to handle unordered, distributed, and asynchronous data collections—common issues in contested and congested environments.

## METHODS:

- Machine learning-assisted solutions to dynamically changing sensor networks



- Our new LOOP – PE (Learning to Optimize the Optimization Process – Permutation Equivariance version) method is designed to optimize operations while handling the complexities of information processing in sensor networks.

## RESULTS:

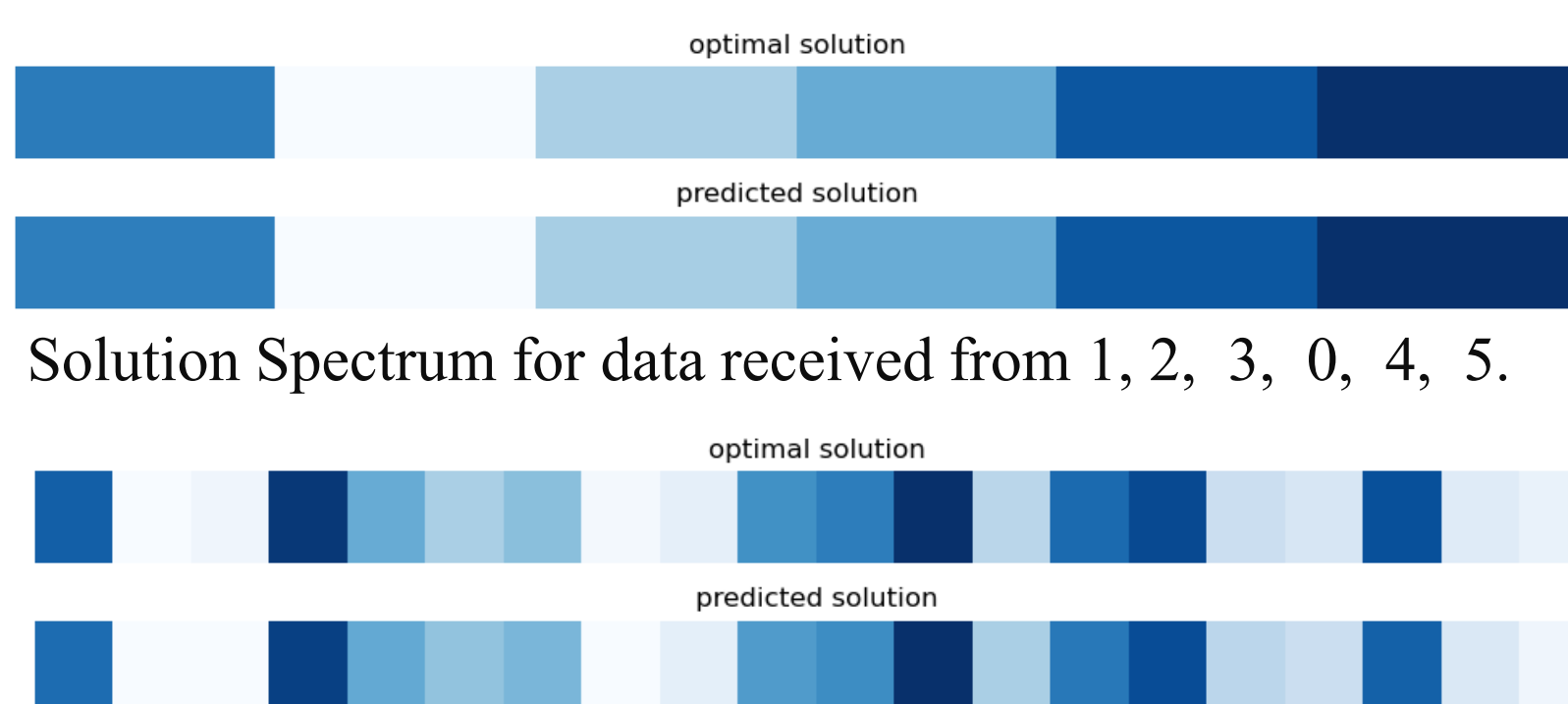
Test system: Managing 20 distributed generator agents. Assume only a random number of sensors received the corresponding agent's input parameters.

Table 1: Computational Time Comparison

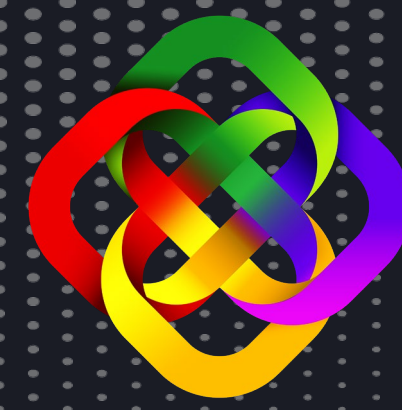
Performance Metric	Gurobi Solver Time (ms)	Proposed Method Time (ms)
Average	6.48	0.33
Minimum	5.02	0.30
Maximum	24.34	0.58

Table 2: Optimality and Feasibility Gaps of Our LOOP – PE Method.

Metric	Optimality Gap			Feasibility gap
	Average	Minimum	Maximum	Minimum
Compared against baseline	0.04	0.00	0.13	0.00

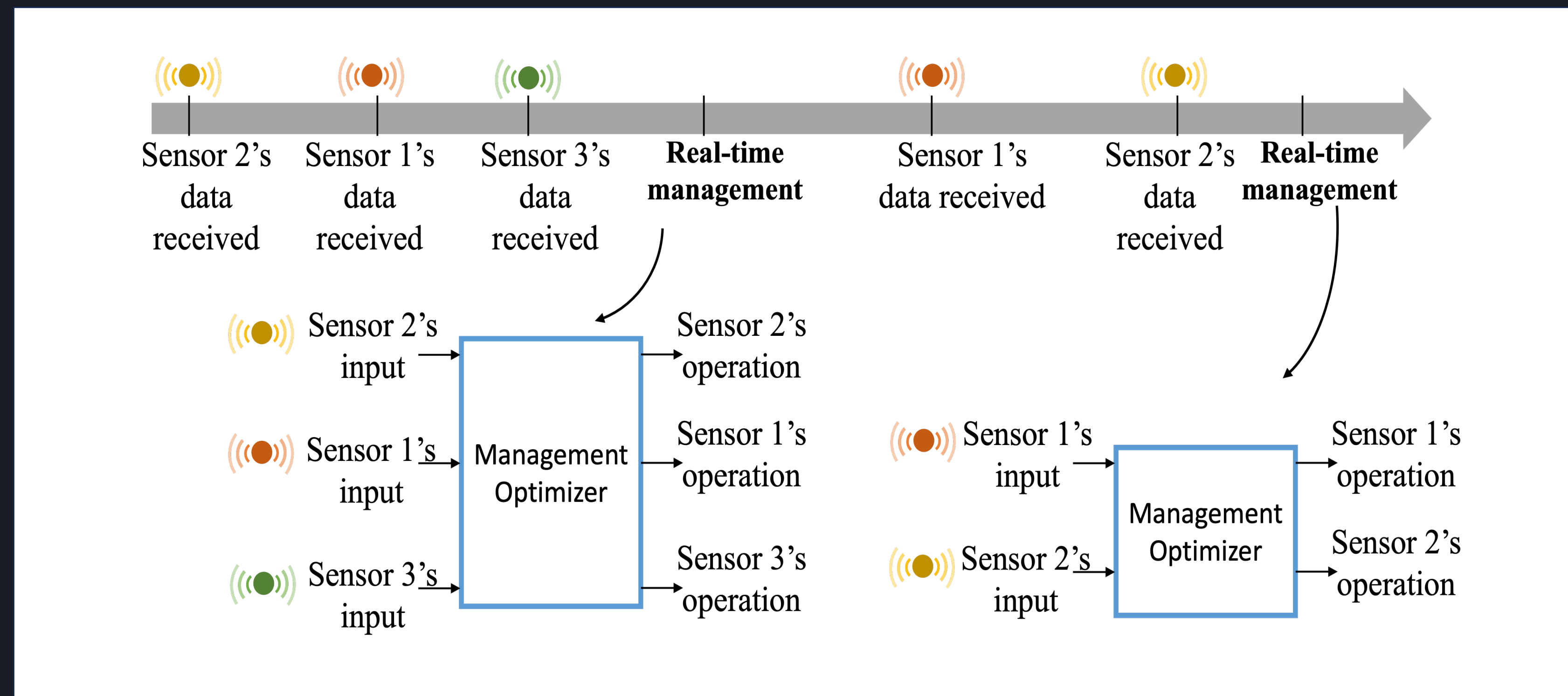


Solution Spectrum for Data Received from Sensors 1, 7, 2, 19, 8, 18, 16, 15, 12, 5, 6, 4, 9, 10, 13, 0, 17, 14, 3, 11.



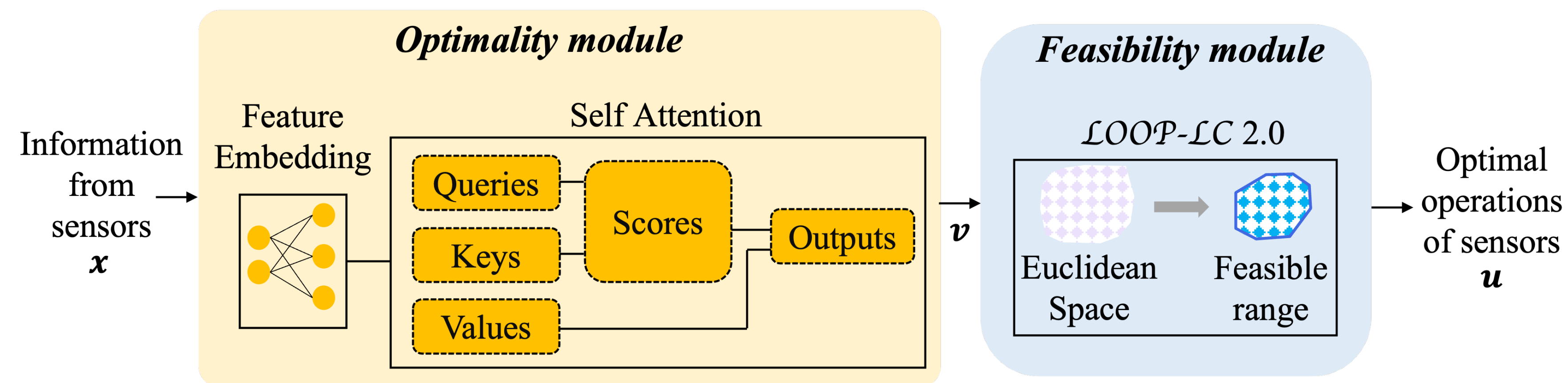
# Our Permutation Equivariance methods enables neural optimizers to deal with information delays in sensor networks.

## Permutation Equivariance Framework



The optimization problem possesses the permutation equivariance property with respect to  $x$  and  $u$ . This property allows the system to treat all sensors as interchangeable, a crucial advantage in dynamic environments where sensor roles and identities may shift.

## Our proposed LOOP – PE method



## Problem Formulation

The primary objective in managing the sensor-based system is to optimize the collective behavior of all sensors while adhering to operational constraints.

$$\min f(\mathbf{u}, \mathbf{x}) = \sum_{i \in \mathcal{N}_A} f^i(\mathbf{u}^i, \mathbf{x}^i)$$

$$\mathbf{u} = [\mathbf{u}^1, \dots, \mathbf{u}^i, \dots, \forall i \in \mathcal{N}_A], \mathbf{x} = [\mathbf{x}^1, \dots, \mathbf{x}^i, \dots, \forall i \in \mathcal{N}_A]$$

$$\text{local constraints: } \begin{cases} \mathbf{A}_{\text{eq}}(\mathbf{x}^i)\mathbf{u}^i + \mathbf{B}_{\text{eq}}(\mathbf{x}^i) = \mathbf{0} \\ \mathbf{A}_{\text{ineq}}(\mathbf{x}^i)\mathbf{u}^i + \mathbf{B}_{\text{ineq}}(\mathbf{x}^i) \leq \mathbf{0} \end{cases}, \forall i \in \mathcal{N}_A$$

$$\text{coupled constraints: } \sum_{i \in \mathcal{N}_A} [\mathbf{A}(\mathbf{x}^i)\mathbf{u}^i + \mathbf{B}(\mathbf{x}^i)] \leq \mathbf{0}$$

## Foundation of our solution

- The Optimality Module achieves permutation equivariance because its feature embedding mechanism processes all features simultaneously, weighing them according to content rather than order. Its self-attention mechanism assesses the relationship between each sensor's features relative to others, independent of their sequence in the input.
- The Feasibility Module uses our LOOP – LC 2.0 model to convert the predictions into practical, constraint-compliant actions, ensuring flexibility and robustness across different sensor setups and dynamics. The denominator term, computing the maximum across permutations, remains invariant to any permutation of input  $v$ .

$$\mathbf{u} = \mathbb{T}(\mathbf{v}) = \mathbf{u}_0(\mathbf{x}) + \frac{1}{\max_r \left\{ \left[ \frac{\sum_{i \in \mathcal{N}_A} \mathbf{H}(\mathbf{x}^i)\mathbf{v}^i}{\sum_{i \in \mathcal{N}_A} \mathbf{h}(\mathbf{x}^i)} \right]^r \right\}} \mathbf{v}$$

Combined, for any permutation  $\sigma$  over the set  $\mathcal{N}_A$ , the optimizer satisfies:

$$[\mathbf{u}^{\sigma(1)}, \dots, \mathbf{u}^{\sigma(i)}, \dots, \forall i \in \mathcal{N}_A] = \xi([\mathbf{x}^{\sigma(1)}, \dots, \mathbf{x}^{\sigma(i)}, \dots, \forall i \in \mathcal{N}_A])$$



Javad Mohammadi, Assistant Professor, UT Austin

Collaborators : ERIKA ARDILES-CRUZ (AFRL), DAVID FERRIS (AFRL), ALEX AVED (AFRL)

