



Multilinear Extensions in Submodular Optimization for Optimal Sensor Scheduling in Nonlinear Networks

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Sensors Node Scheduling (SNS) in Networks

Sensing, Observability, and State Estimation as Foundations for Control



Essential for state-estimate

A first step is to enable accurate state-estimates



Combinatorial in Nature

Cannot handle larger systems



Suboptimal Solutions

Approximate problem formulations rendering it scalable

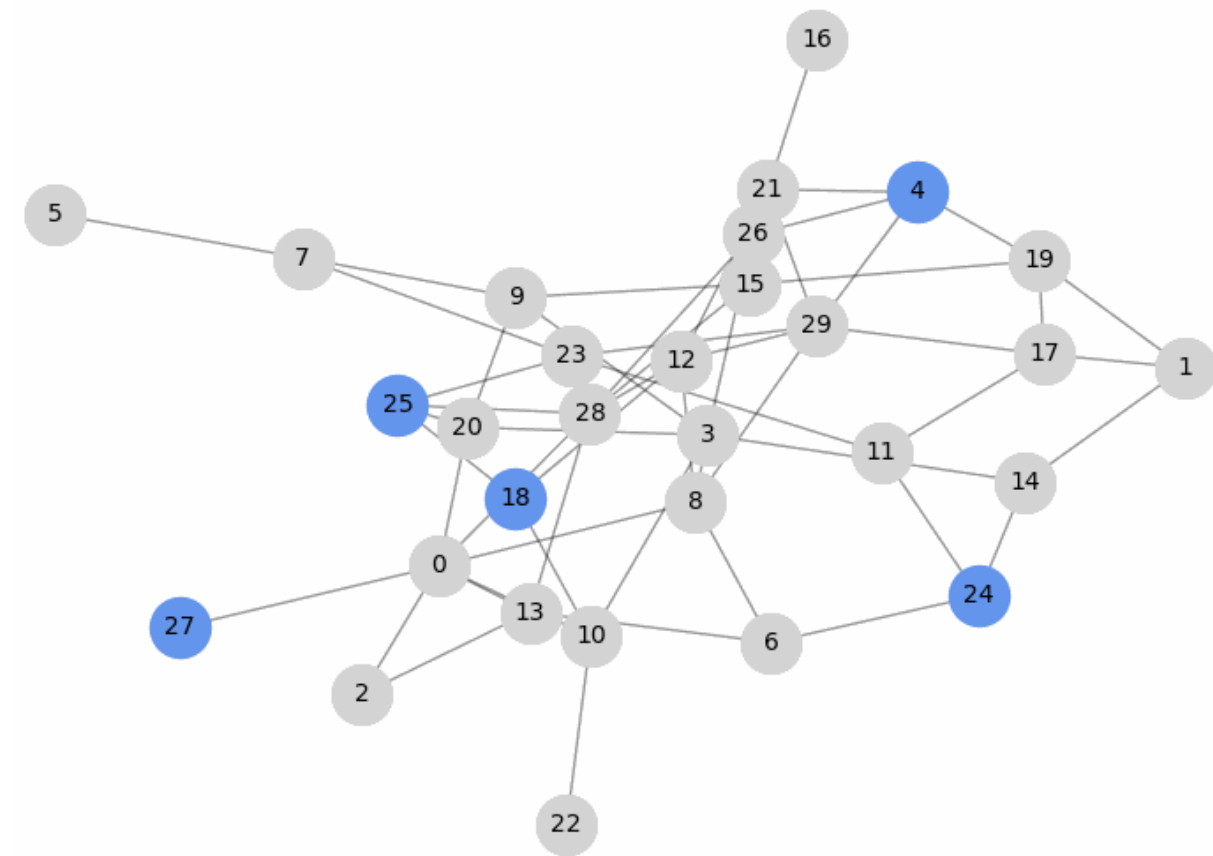
Applications

Power Networks

Transportation

Water Networks

Chemical Networks



The Sensor Scheduling Problem

A Submodular Optimization Approach for Sensor Allocation

1

Submodular
Maximization

$$f^* = \underset{S \subseteq \mathcal{V}, S \in \mathcal{I}}{\text{maximize}} f(S)$$

One definition of
Submodularity

For any, $\mathcal{A} \subseteq \mathcal{B} \subseteq \mathcal{V}$

$$f(\mathcal{A} \cup \{s\}) - f(\mathcal{A}) \geq f(\mathcal{B} \cup \{s\}) - f(\mathcal{B})$$

Kia, 2025



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Submodular Maximization

\mathcal{I}

Matroid Constraint
 $\mathcal{M} = (\mathcal{V}, \mathcal{I})$
(i) $\emptyset \in \mathcal{I}$
(ii) $A \subseteq B \in \mathcal{I} \Rightarrow A \in \mathcal{I}$
(iii) $A, B \in \mathcal{I}, |A| < |B|$
 $\exists s \in B \setminus A, A \cup \{s\} \in \mathcal{I}$

$\mathcal{I} = \mathcal{I}_c$

$\mathcal{I} = \mathcal{I}_p$

Uniform Matroid

$$\mathcal{I}_c = \{S \subseteq \mathcal{V} : |S| = r\}$$

(e.g., selecting r sensors from the entire network)

Partition Matroid

$$\mathcal{V} = \bigcup_{i=1}^{\kappa} \mathcal{S}_i$$

$$\mathcal{I}_p = \{S \subseteq \mathcal{V} : |S \cap \mathcal{S}_i| \leq \kappa_i\}$$

(e.g., selecting sensors with at most κ_i per subsystem)

Kia, 2025



Extensions in Submodular Optimization

Multilinear Extension for Submodular maximization

1

Submodular
Maximization

2

Multilinear
Extension

$$F_S^* = \underset{S \subseteq V, S \in \mathcal{I}_c}{\text{maximize}} \quad F(\mathbf{x})$$

$$F : [0, 1]^n \rightarrow \mathbb{R}_{\geq 0}$$

Inclusion
probability

$$F(\mathbf{x}) = \sum_{S \subseteq V} f(S) \prod_{s \in S} [\mathbf{x}]_s \prod_{s \notin S} (1 - [\mathbf{x}]_s)$$

How to compute?

Exclusion
probability

Calinescu et al., 2009



Extensions in Submodular Optimization

Multi-linear Extension for Submodular maximization

1 Submodular Maximization

2 Multilinear Extension

3 Computing the Extension

$$F(\mathbf{x}) = \sum_{\mathcal{S} \subseteq \mathcal{V}} f(\mathcal{S}) \prod_{s \in \mathcal{S}} [\mathbf{x}]_s \prod_{s \notin \mathcal{S}} (1 - [\mathbf{x}]_s)$$

Method of expectation

$$F(\mathbf{x}) = \mathbb{E} [f(\mathcal{S}_{\mathbf{x}})]$$

Element s inclusion and exclusion in \mathcal{S}

Other methods

- Exact Methods: closed form expressions
- Approx. Method: Taylor series expansion

Iyer et al., 2014



Extensions in Submodular Optimization

Continuous Greedy Algorithm

1 Submodular
Maximization

2 Multilinear
Extension

3 Computing the
Extension

4 Algorithm

Chekuri and Quanrud, 2019



$$\operatorname{argmax}_{S \in \mathcal{I}} \sum_{s \in S} \mathbb{E} [f(S_x \cup \{s\}) - f(S_x \setminus \{s\})]$$

- A path is defined: $\mathbf{x} : [0, 1] \rightarrow \mathcal{S}_x$
- The output is: $\mathbf{x}(1)$
- A discrete solution is then obtained using a pipage rounding algorithm



Observability-based SNS in Nonlinear Systems

Control-theoretic SNS problem

1

Observability-
based SNS

Observability Gramian
with sensor selection

$$\mathbf{W}(\gamma, \mathbf{x}_0)$$

$$f^* = \underset{S \subseteq \mathcal{V}, S \in \mathcal{I}}{\text{maximize}} f(S)$$

$$\begin{aligned} &\text{trace}(\mathbf{W}(\cdot)) \\ &\log \det(\mathbf{W}(\cdot)) \\ &\text{rank}(\mathbf{W}(\cdot)) \end{aligned}$$

S encodes binary nodes selected γ

Modular and
Submodular Properties

Summers et al., 2016



Observability-based SNS in Nonlinear Systems

Gramian Computation for Nonlinear Systems

1

Observability-
based SNS

2

Computing the
Gramian

System
Linearization

This measure of observability is only valid around *operating regions*

A. Rouhani *et al.* 2017

Lie Derivatives

Qualitative observability measures that are high order

S. Lall *et al.* 1999
A. J. Krener and K. Ide, 2009

Empirical
Gramian

Not applicable to large-scale networks

A. Rouhani *et al.* 2017



Observability-based SNS in Nonlinear Systems

From Nonlinear to Variational Dynamics

1 Observability-based SNS

2 Computing the Gramian

3 Variational Dynamics

Discrete Variational System Dynamics

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \tilde{\mathbf{f}}(\mathbf{x}_{k-1})$$

Variational Form

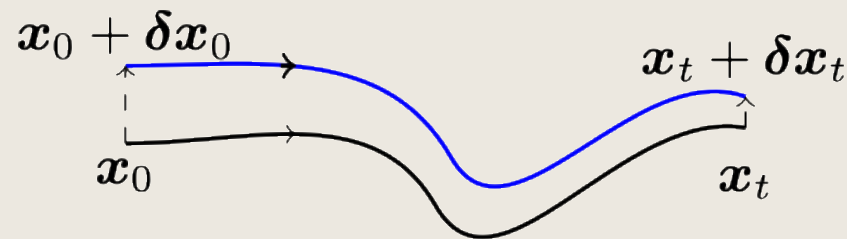
$$\delta \mathbf{x}_k = \Phi_0^k(\mathbf{x}_0) \delta \mathbf{x}_0$$

Variational Mapping Function

$$\Phi_0^k = \Phi_{k-1}^k \Phi_{k-2}^{k-1} \dots \Phi_0^1 \Phi_0^0 = \prod_{i=1}^{i=k} \Phi_{i-1}^i$$

Computed along using chain rule

Simply follows the system trajectory along the tangent space



Kawano and Scherpen, 2019



Observability-based SNS in Nonlinear Systems

Building the Variational Observability Gramian (Var-Gram)

1 Observability-based SNS

2 Computing the Gramian

3 Variational Dynamics

4 Variational Gramian

Kazma and Taha, 2024



Var-Gram

$$V_o(\mathcal{S}) = \sum_{j \in \mathcal{S}} \left(\sum_{i=0}^{N-1} (\varphi_0^i)^\top \tilde{c}_j^\top \tilde{c}_j \varphi_0^i \right)$$

Column vectors of Φ_0^k

Equivalent to LTI Gramian

$$V_o(\mathbf{x}_0) = \mathbf{W}(\mathbf{x}_0)$$

Equivalent to Empirical Gramian

$$V_o(\mathbf{x}_0) = \mathbf{W}_{\text{emp}}(\mathbf{x}_0)$$



Case Studies – Combustion Reaction Network

System Setup and Parameters

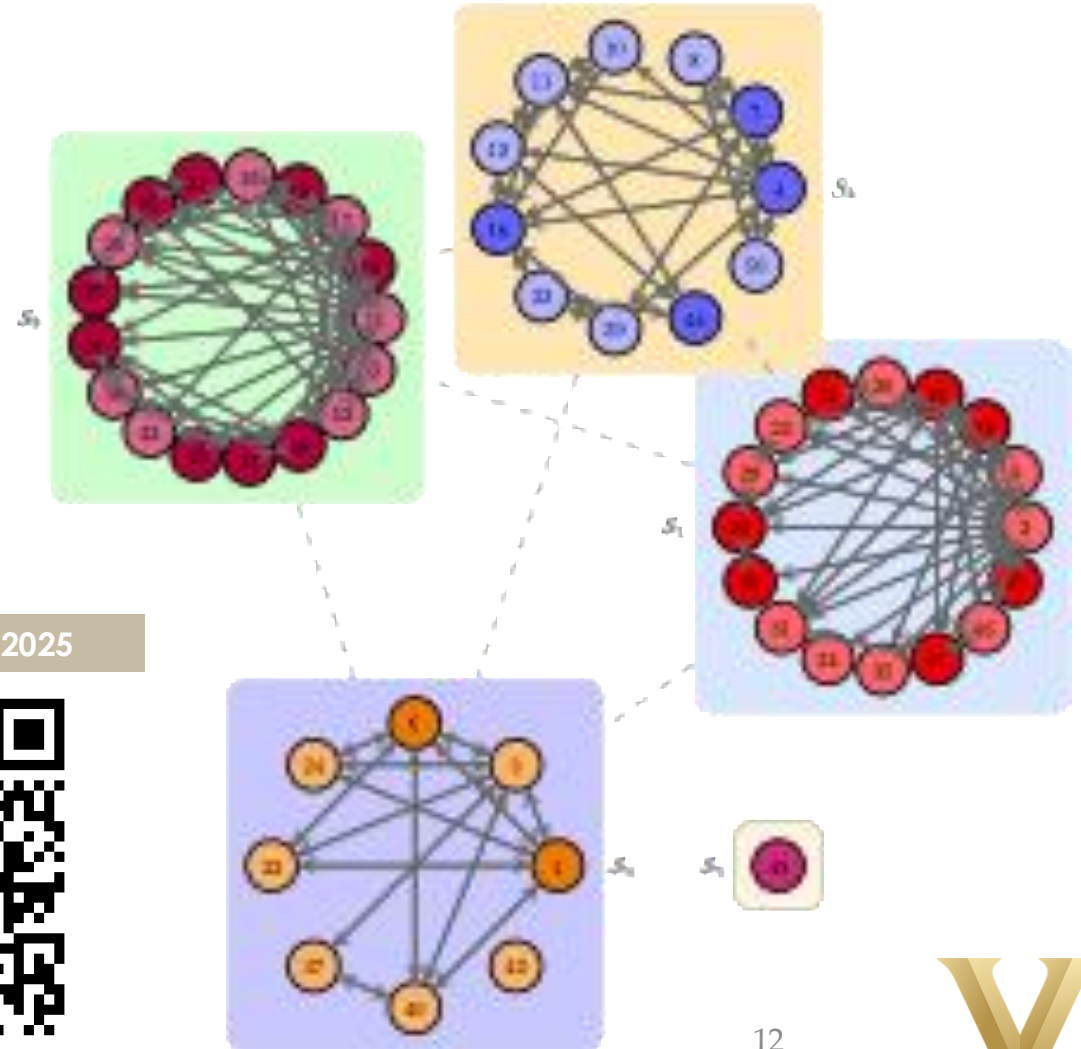
GRI30 - Methane Combustion

- $\dot{\mathbf{x}}(t) = \Theta\psi(\mathbf{x}(t))$
- 325 chemical reactions
- 53 species model

Parameters

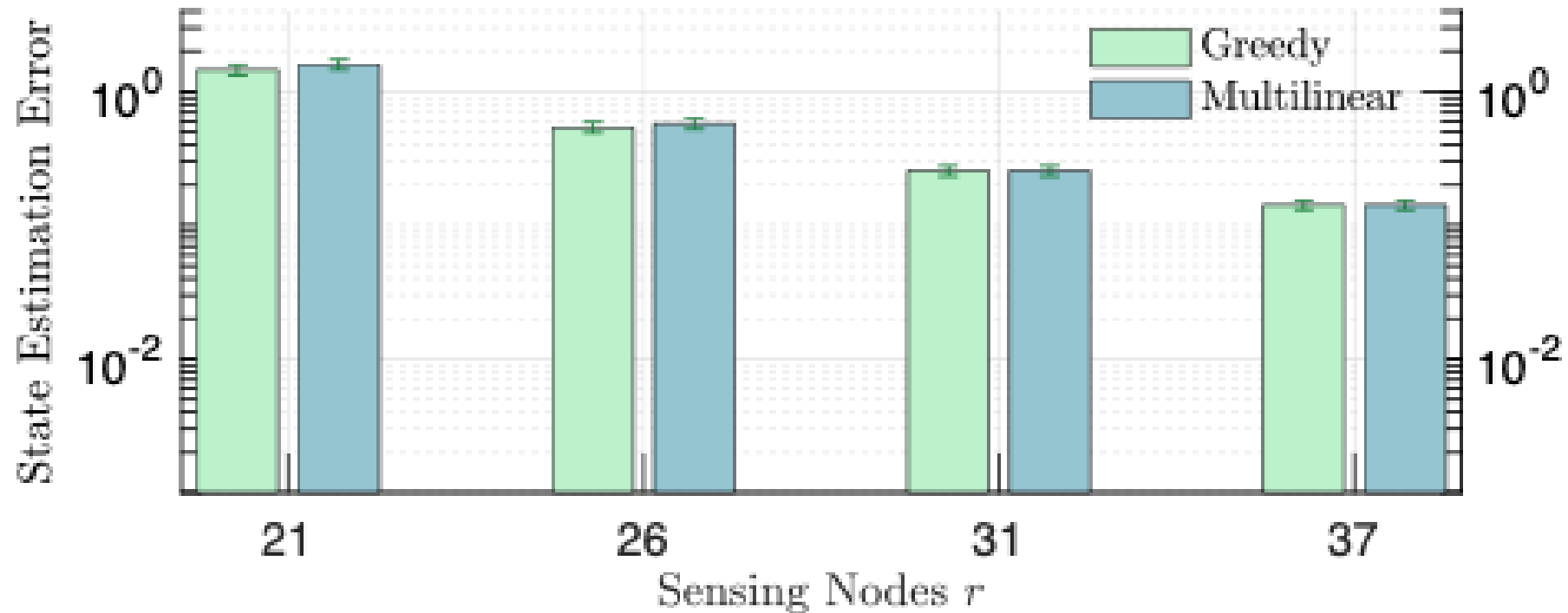
- Observation Horizon
 $N = 1000$
- Initial Concentrations:
 $\mathbf{x}_0 = [0, 0, 0, 2, \dots, 1, \dots, 7.52, \dots, 0]$

$$\sum_{i=1}^{n_x} q_{ji} \mathcal{R}_i \Leftrightarrow \sum_{i=1}^{n_x} w_{ji} \mathcal{R}_i$$



SNS State-estimation Error

The optimality is the same
simple greedy Vs. the multilinear extension



$$\text{Relative Error: } e = \|\mathbf{x}_{\text{true}} - \hat{\mathbf{x}}\|_2 / \|\mathbf{x}_{\text{true}}\|_2$$

On initial states estimates



Concluding Notes and Future Directions



Submodular Approach for SNS in Nonlinear Networks

Variational dynamics for Var-Gram computations



Multilinear Extensions for Observability-based Submodular SNS

Validated the use of such extension within the control-oriented framework



Application of multilinear extensions for distributed

Constraints that allocate sensors across partitioned systems



Application of New Parallel Algorithms

Faster methods that can handle even larger systems



Questions?



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July 9th, 2025

