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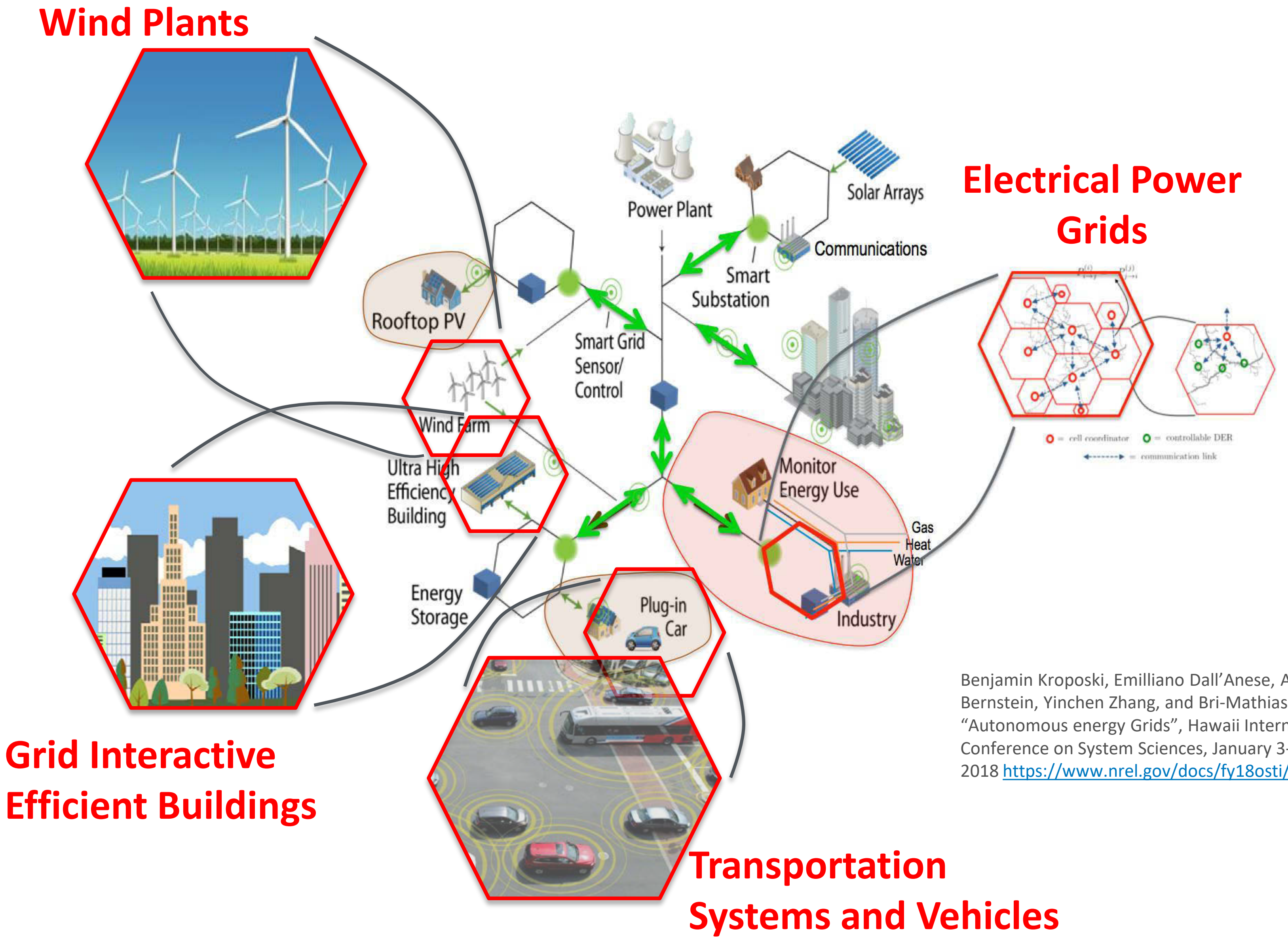
A Framework for Autonomous Wind Farms
Distributed Optimization for Wind

Jennifer King
Christopher Bay, Paul Fleming, Kathryn Johnson, Emiliano Dall-Anese, Lucy Pao, Mingyi Hong

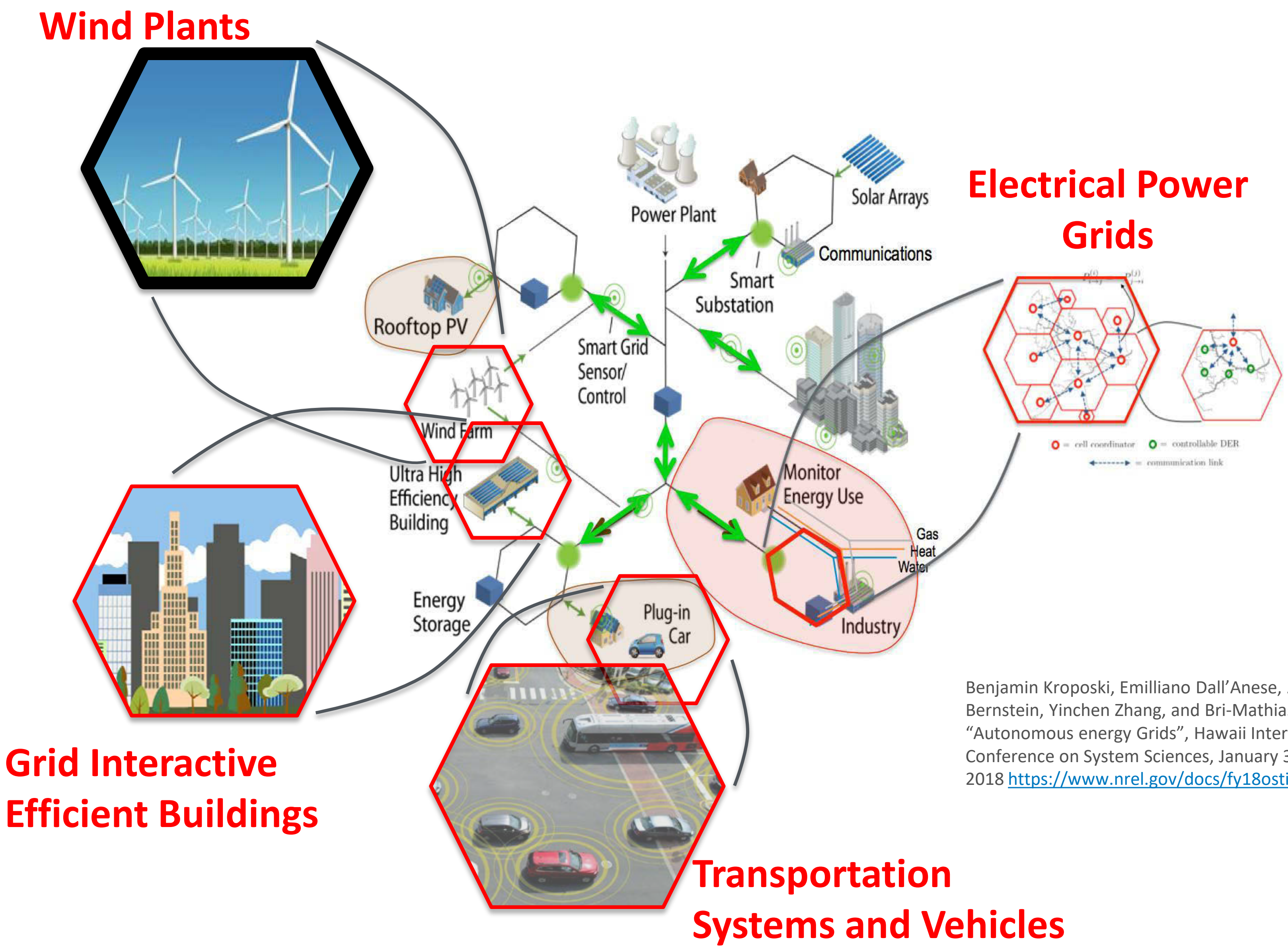
Innovative Optimization and Control Methods for Highly Distributed Autonomous Systems workshop
April 11, 2019
Golden, Colorado

Autonomous Energy Systems



Benjamin Kroposki, Emilliano Dall'Anese, Andrey Bernstein, Yinchen Zhang, and Bri-Mathias Hodge, "Autonomous energy Grids", Hawaii International Conference on System Sciences, January 3-6, 2018, 2018 https://www.nrel.gov/docs/fy18osti/68712.pdf

Autonomous Energy Systems



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Overview

- Exploit the multi-agent structure in wind plants
  - Distributed optimization for real-time control
  - Takes advantage of the **spatial and temporal structure** of the problem to reduce computational costs

Outline

- Wind farm modeling and control
- Distributed optimization framework
- Wind direction example
- Maximizing power example
- Conclusions and future work

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- **Wind farm modeling and control**
- Distributed optimization framework
- Wind direction example
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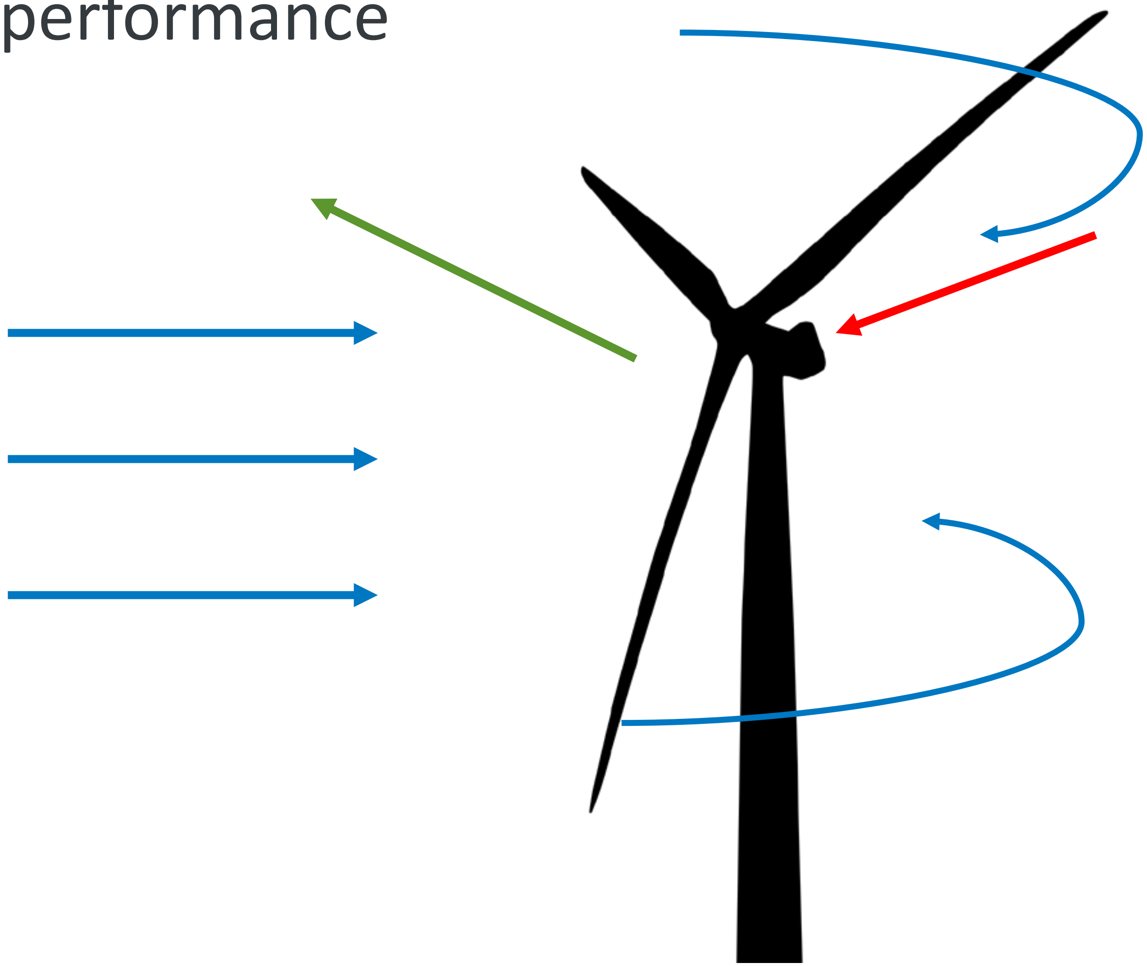
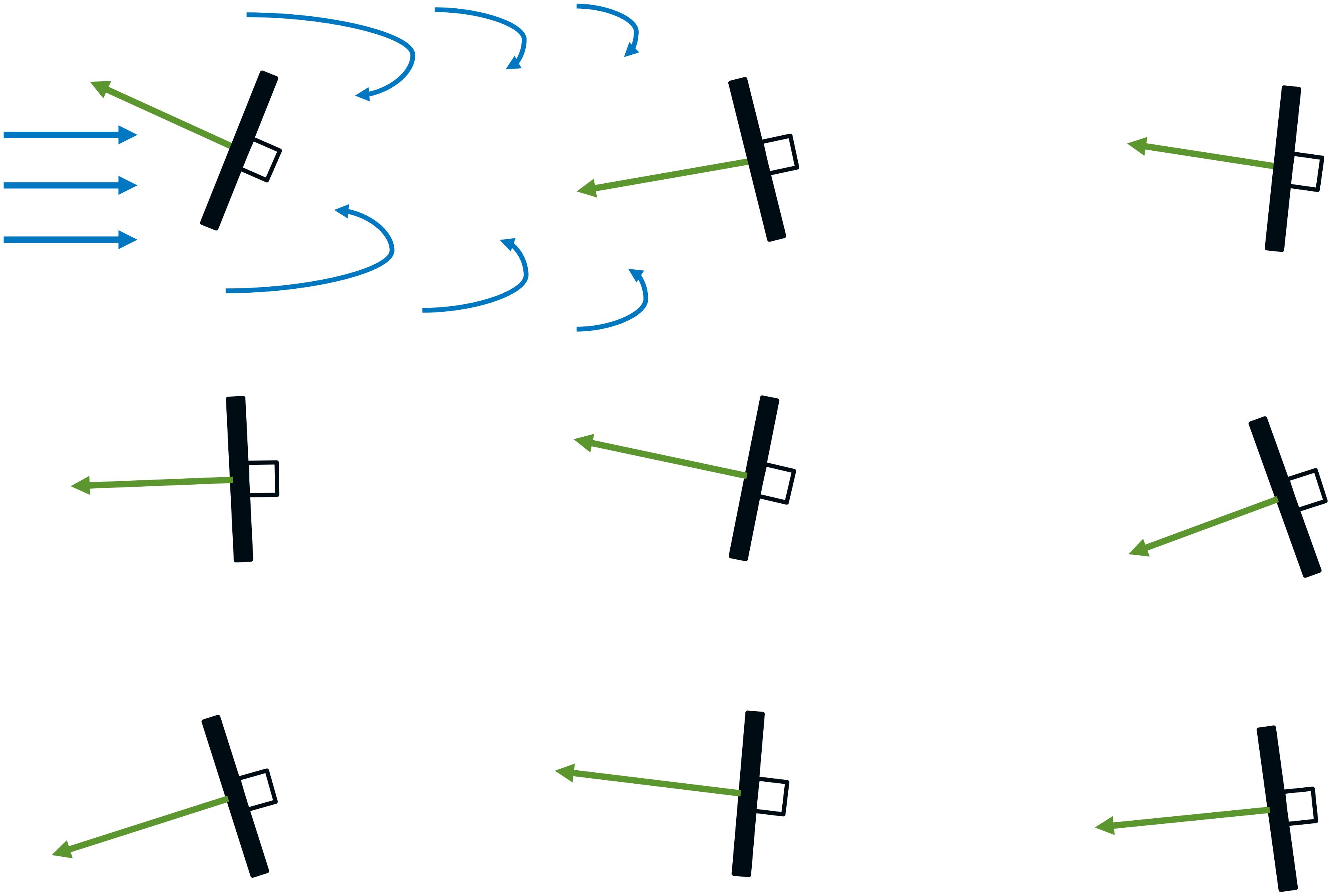
Current Wind Turbine Operation

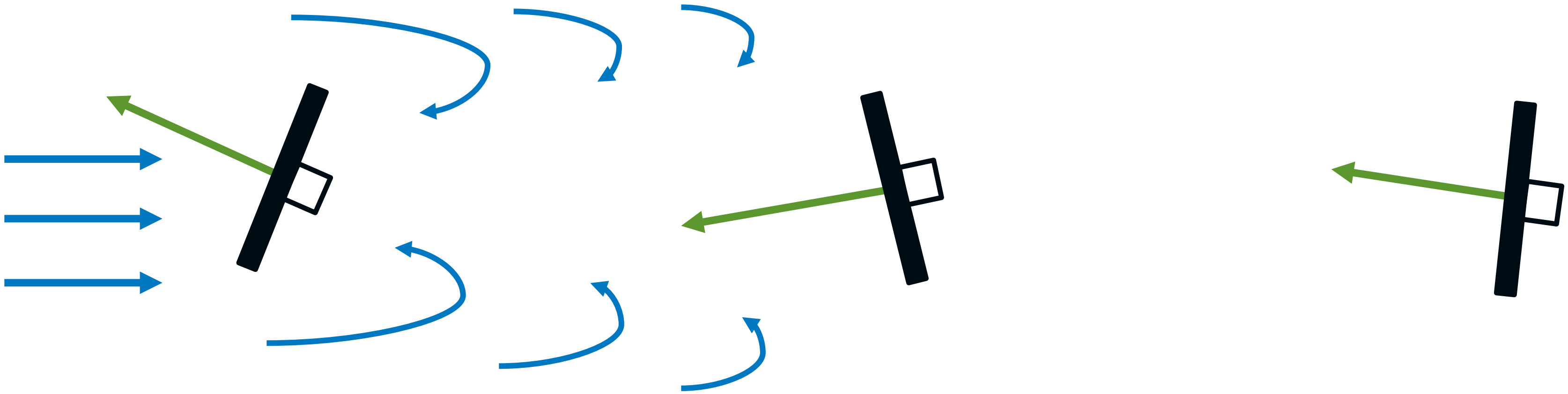
- Turbines operate individually, optimize their own performance

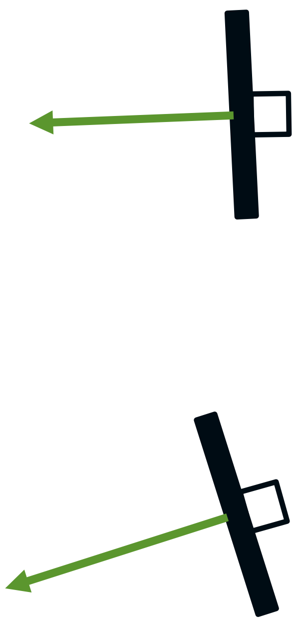


Current Wind Turbine Operation



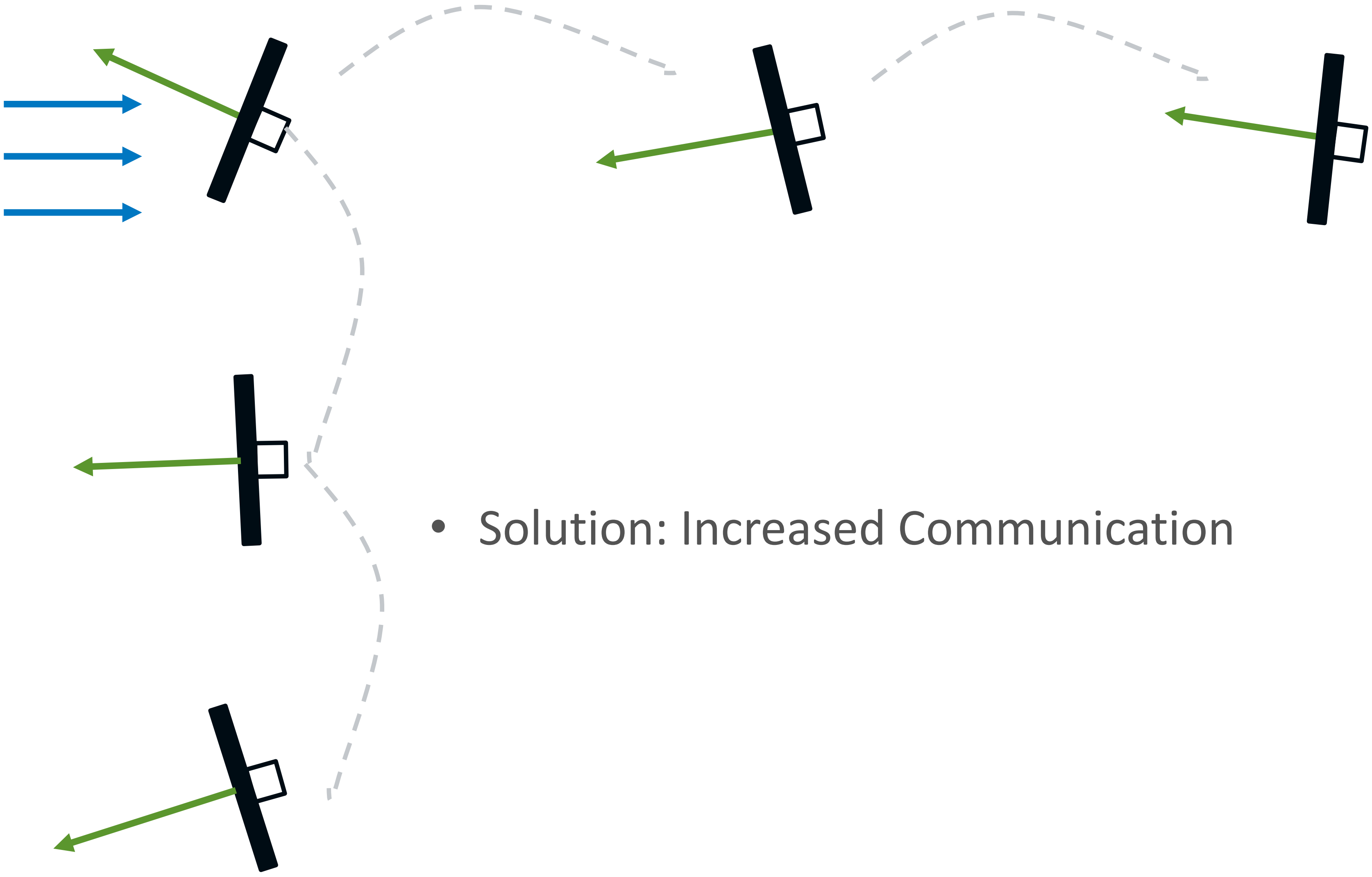
Current Wind Turbine Operation





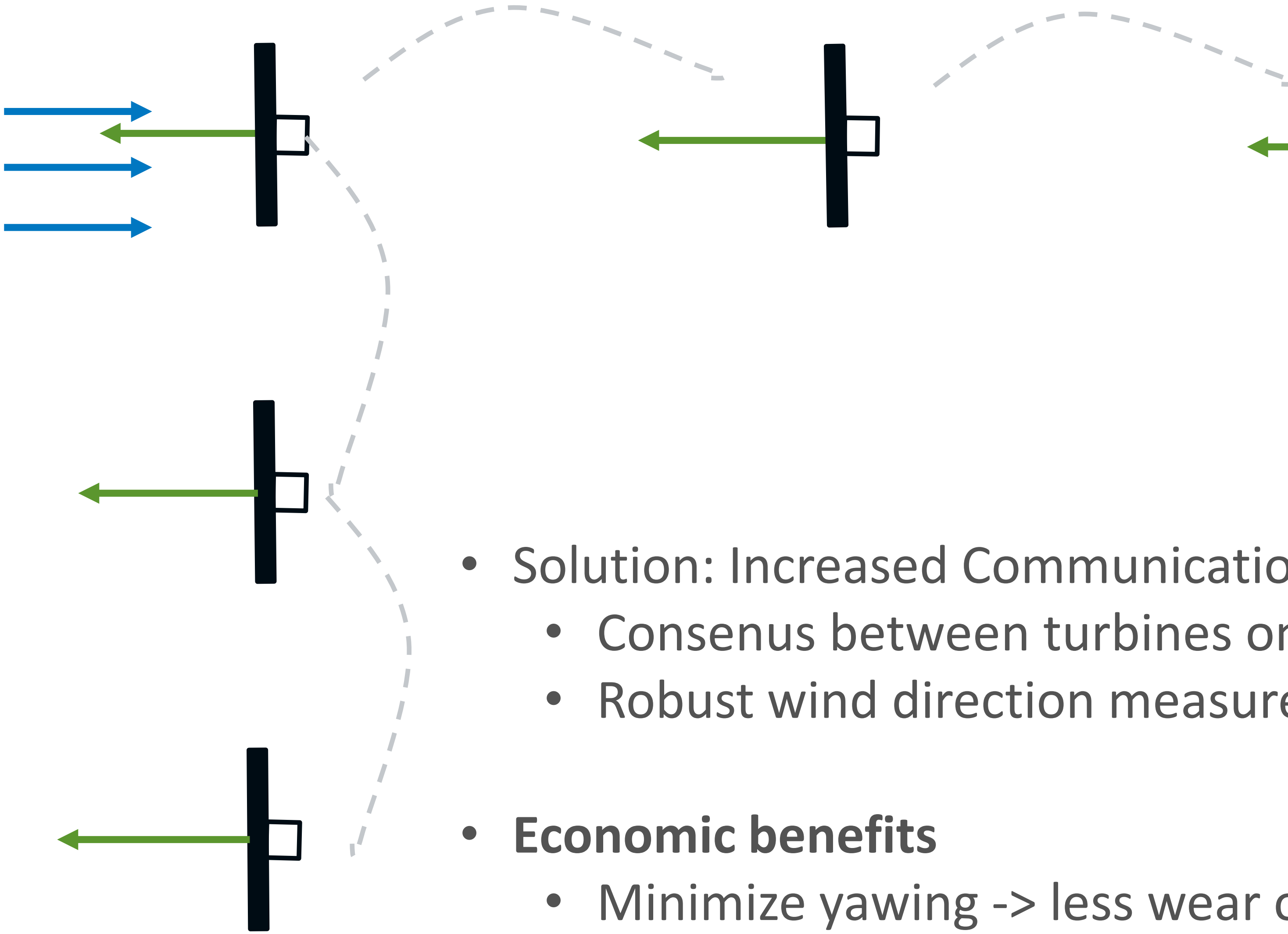
- Issues with this approach
  - Lose power - yaw misalignment
  - Constantly yawing - noisy wind vane signal

Future Wind Turbine Operation



- Solution: Increased Communication

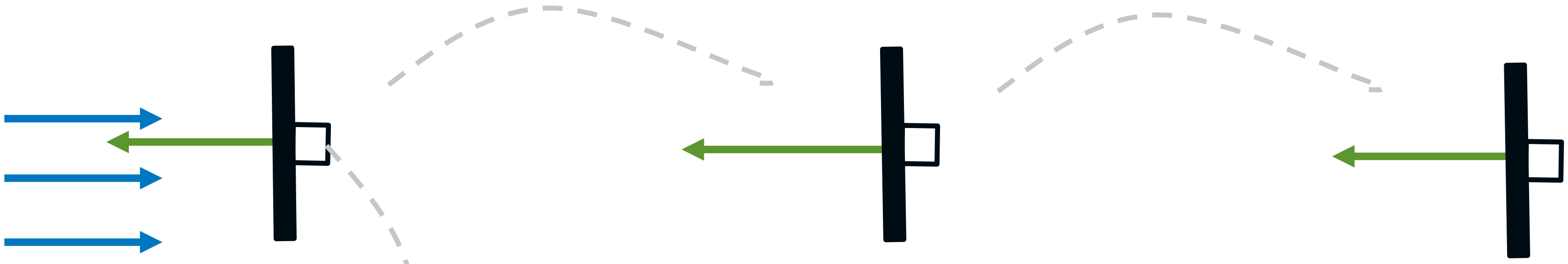
Future Wind Turbine Operation

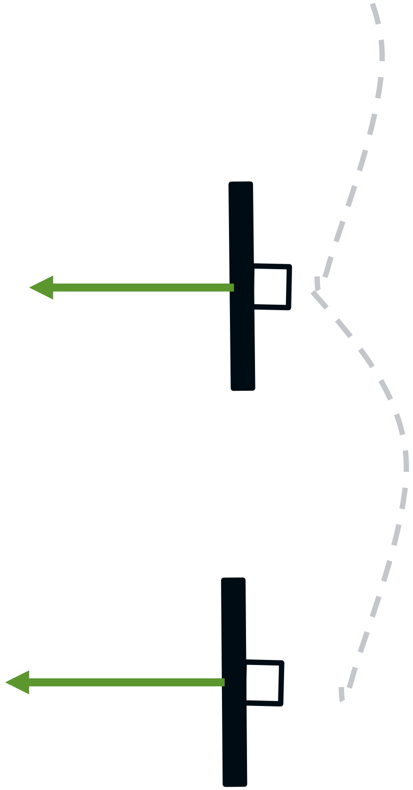


- Solution: Increased Communication
  - Consenus between turbines on direction
  - Robust wind direction measurement

- **Economic benefits**
  - Minimize yawing -> less wear on yaw drive
  - Aligned with wind -> increase power capture

Future Wind Farm Control

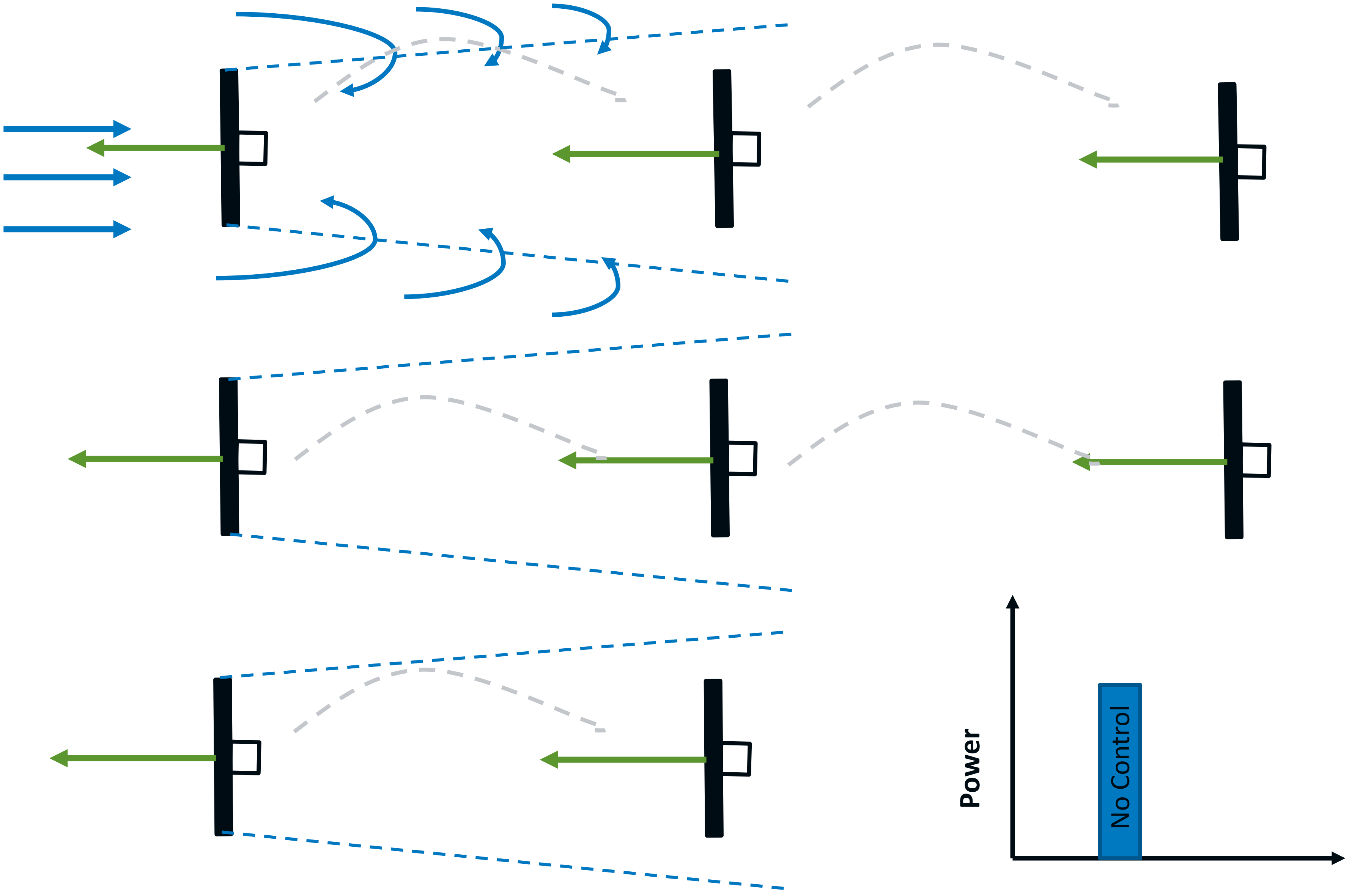




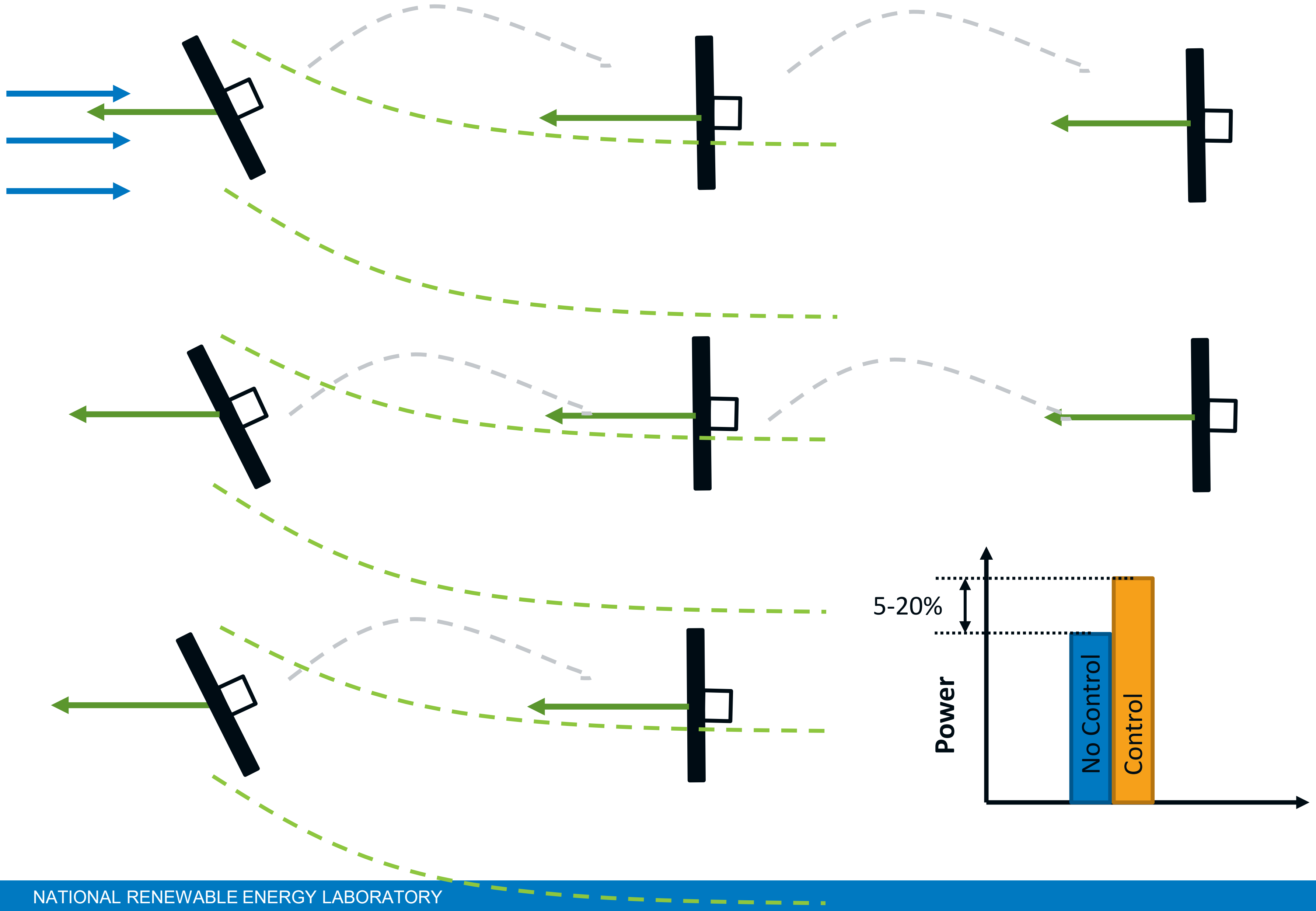
- Increased communication can give wind farms greater
  - Controllability
  - Observability
  - Predictability

  from the perspective of the AES grid

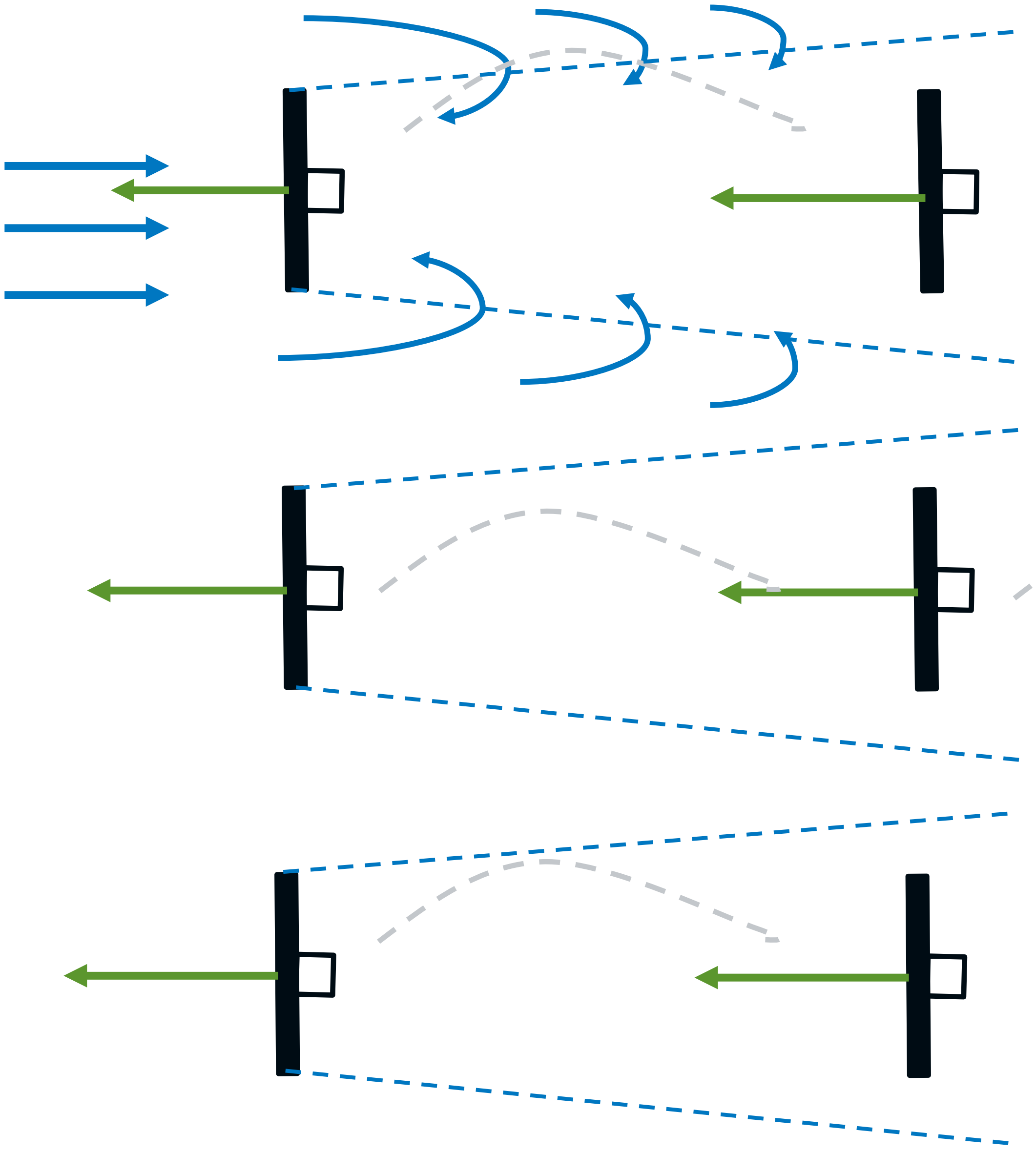
Wind Farm Control Objectives

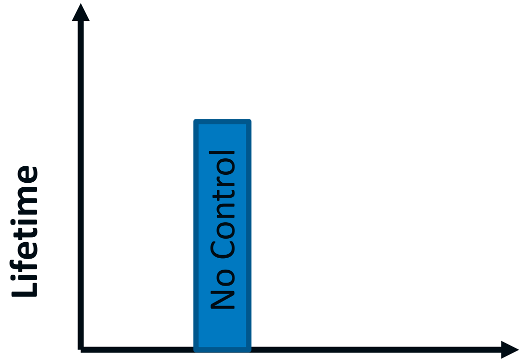


Wind Farm Control Objectives – Maximize Power

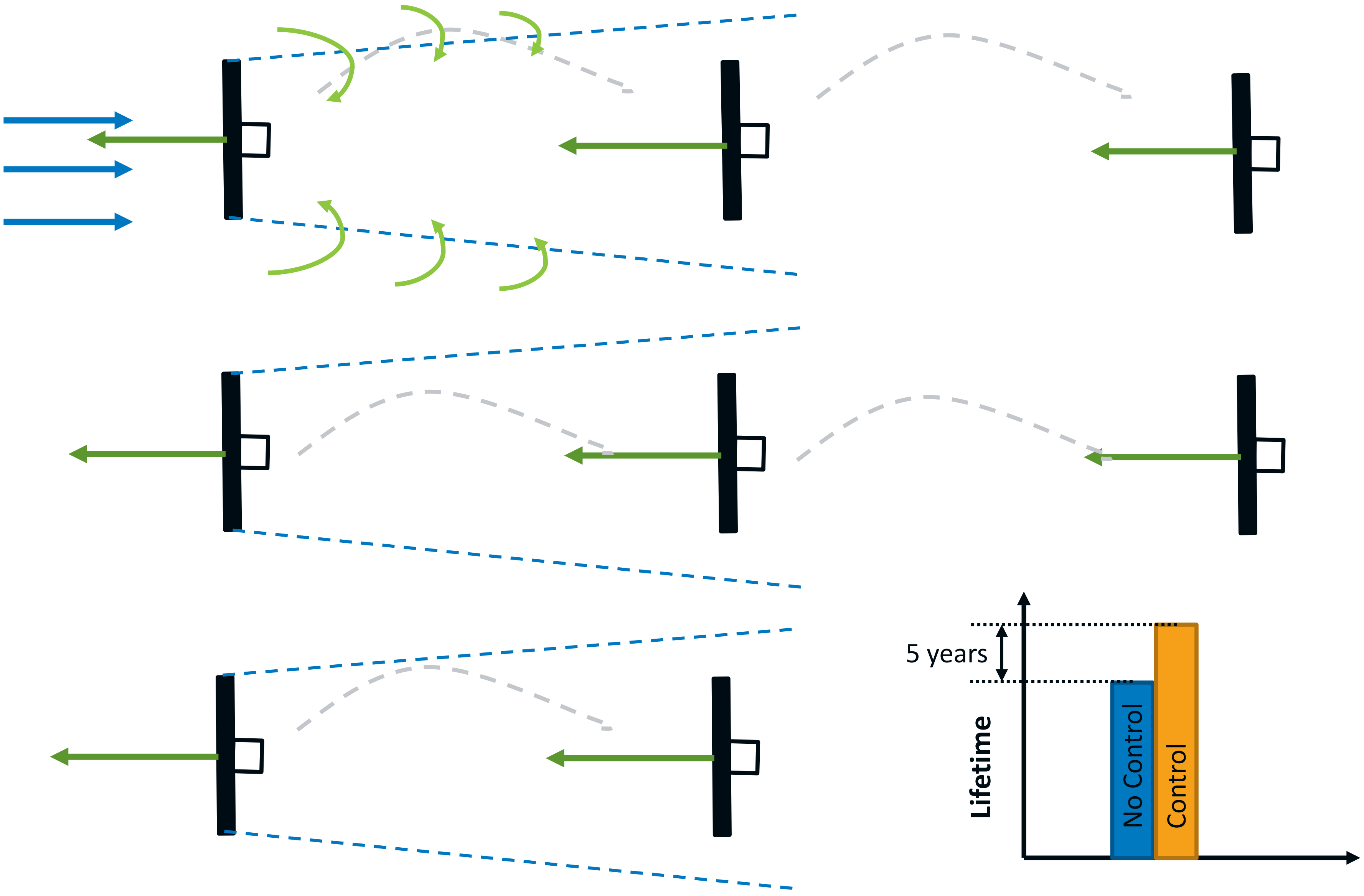


Wind Farm Control Objectives – Minimize Loads

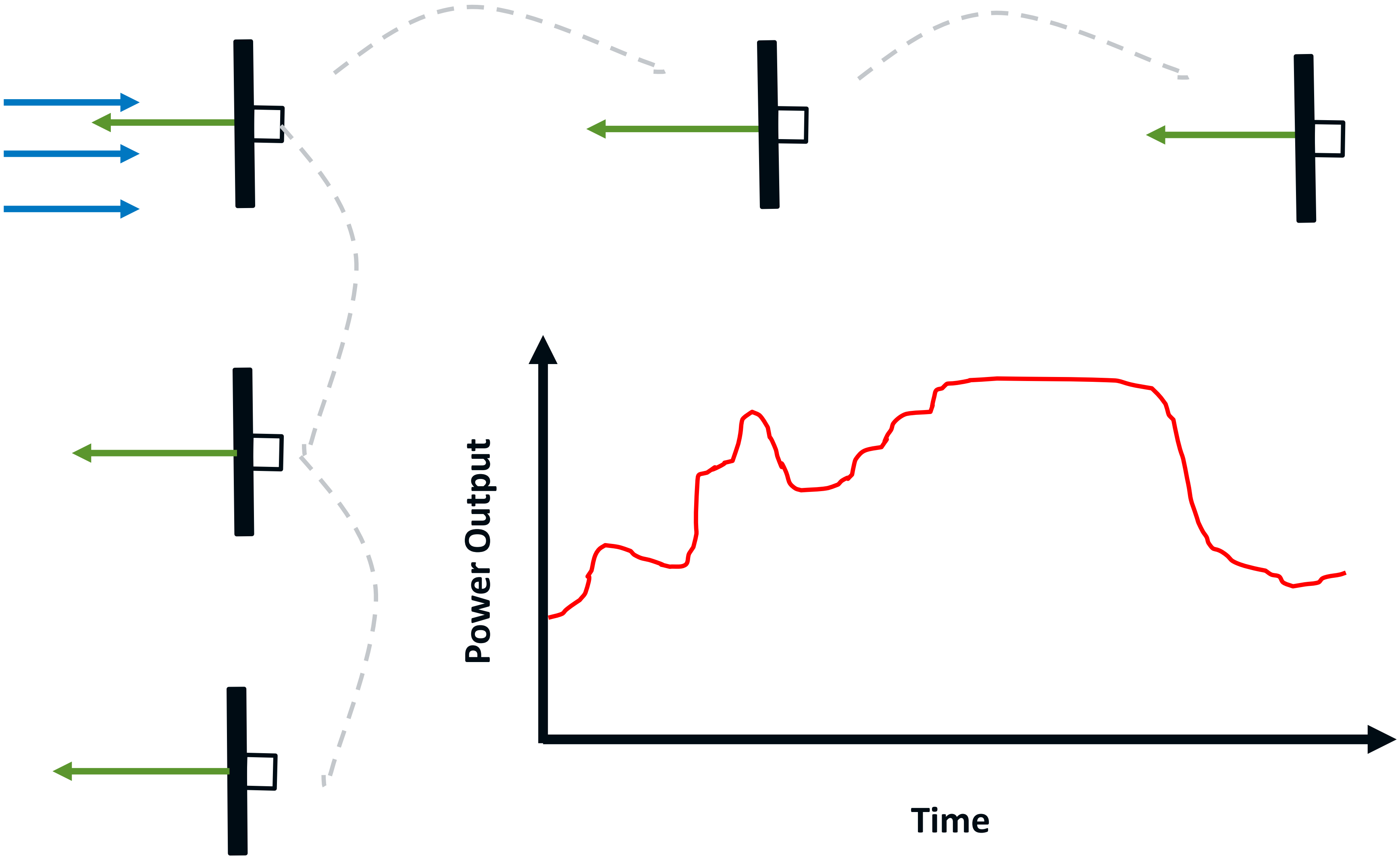




Wind Farm Control Objectives

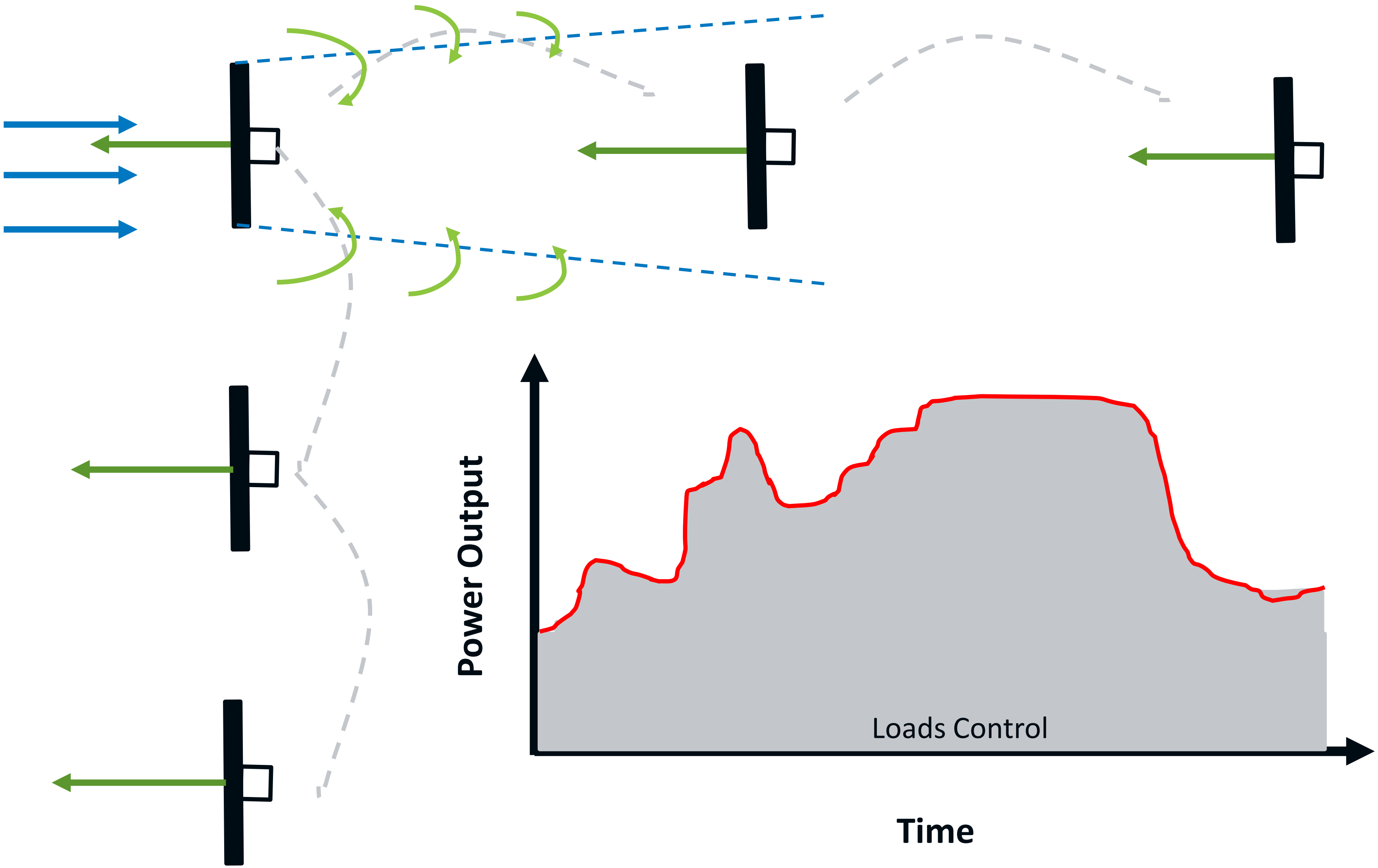


Wind Farm Control Objectives – Grid Interaction



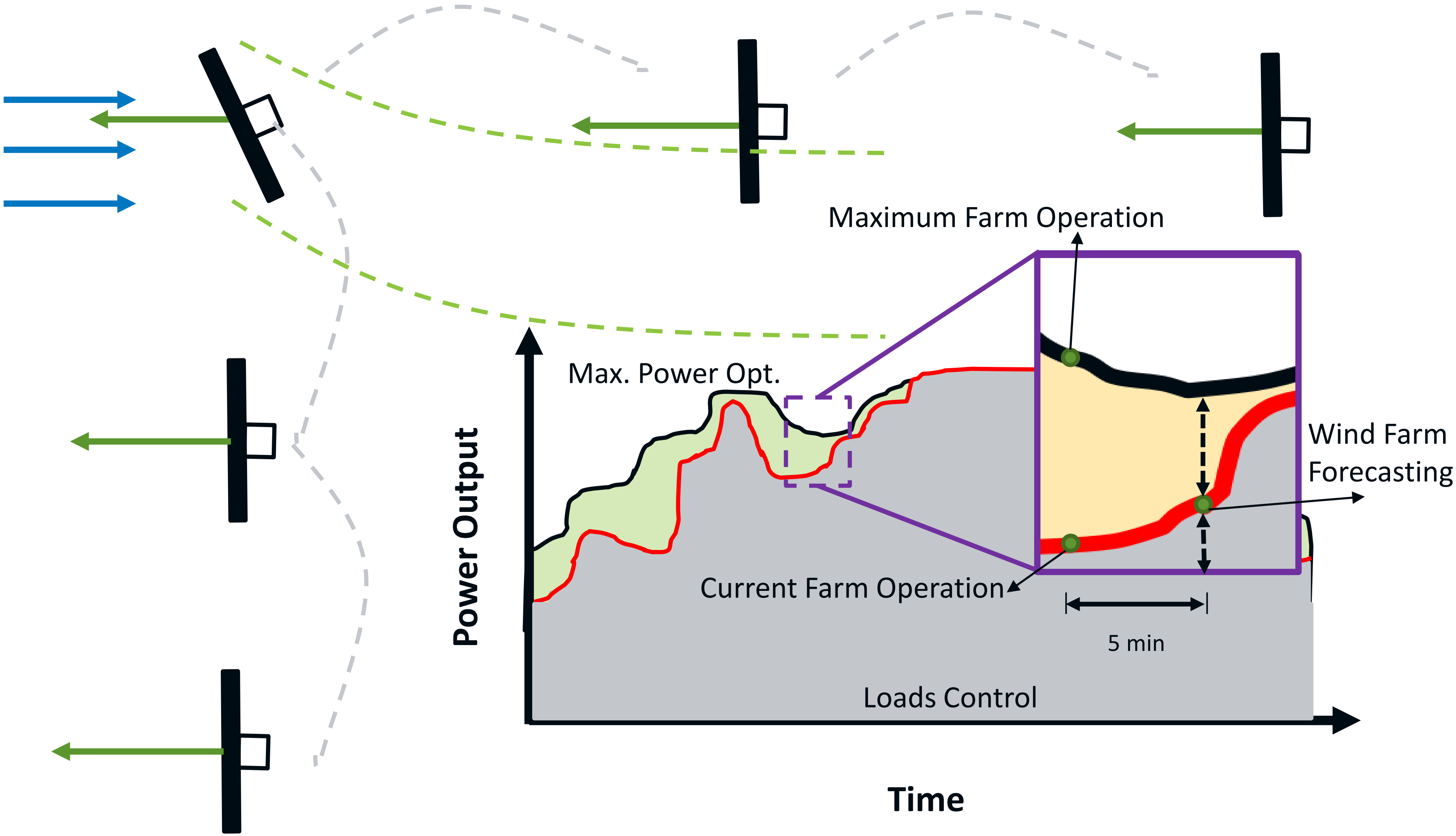
Common industry approach: variable resistor on output of wind farm

Future Wind Farm Operation and Control



Grid operators: Wind farms can decrease power in matter of minutes
Wind farm Owner/Operator: Minimize loads

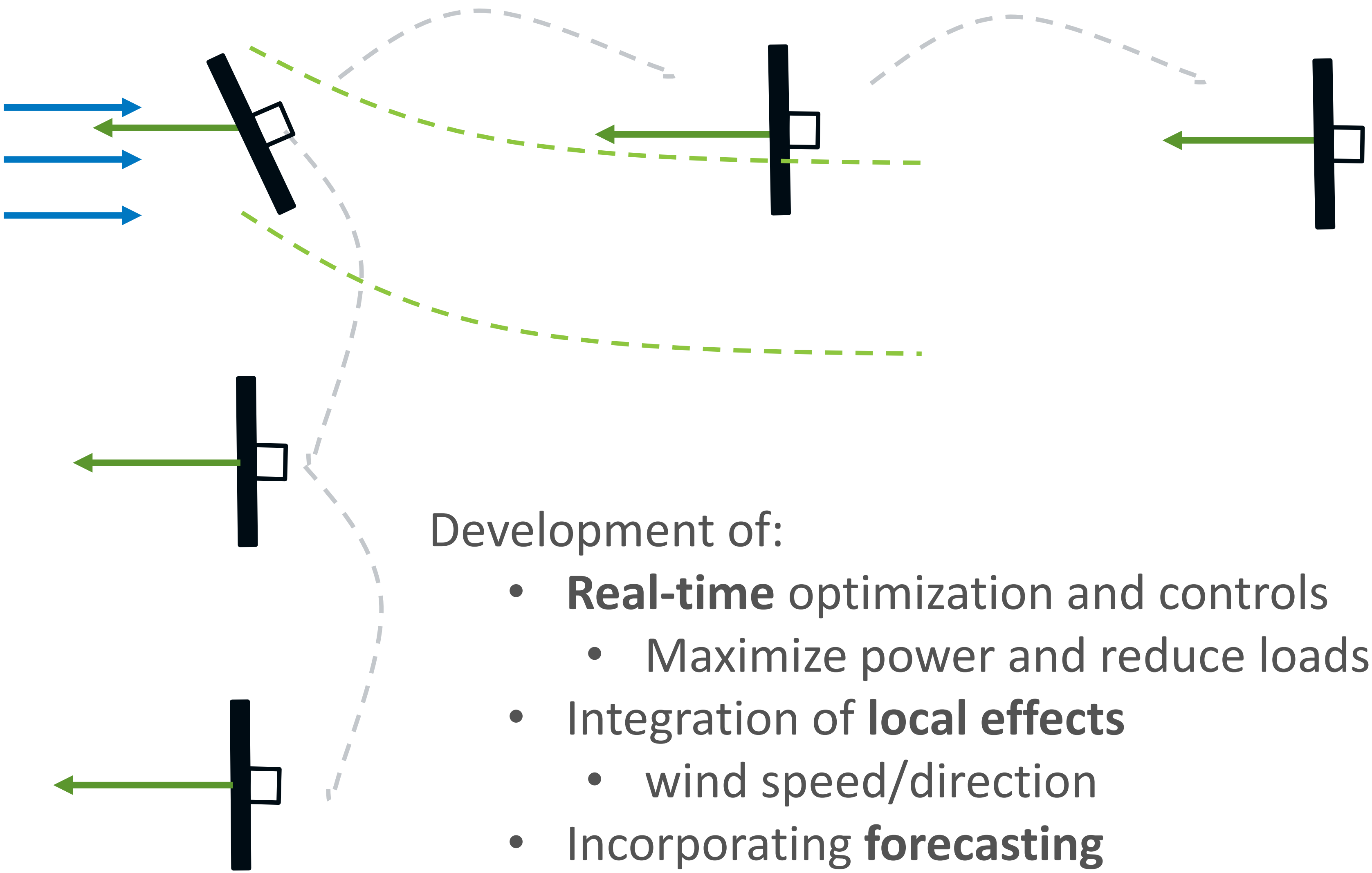
Future Wind Farm Operation and Control



Grid operators: How much can the wind farm go up?

Wind farm owner/operators: maximize power, predict future output

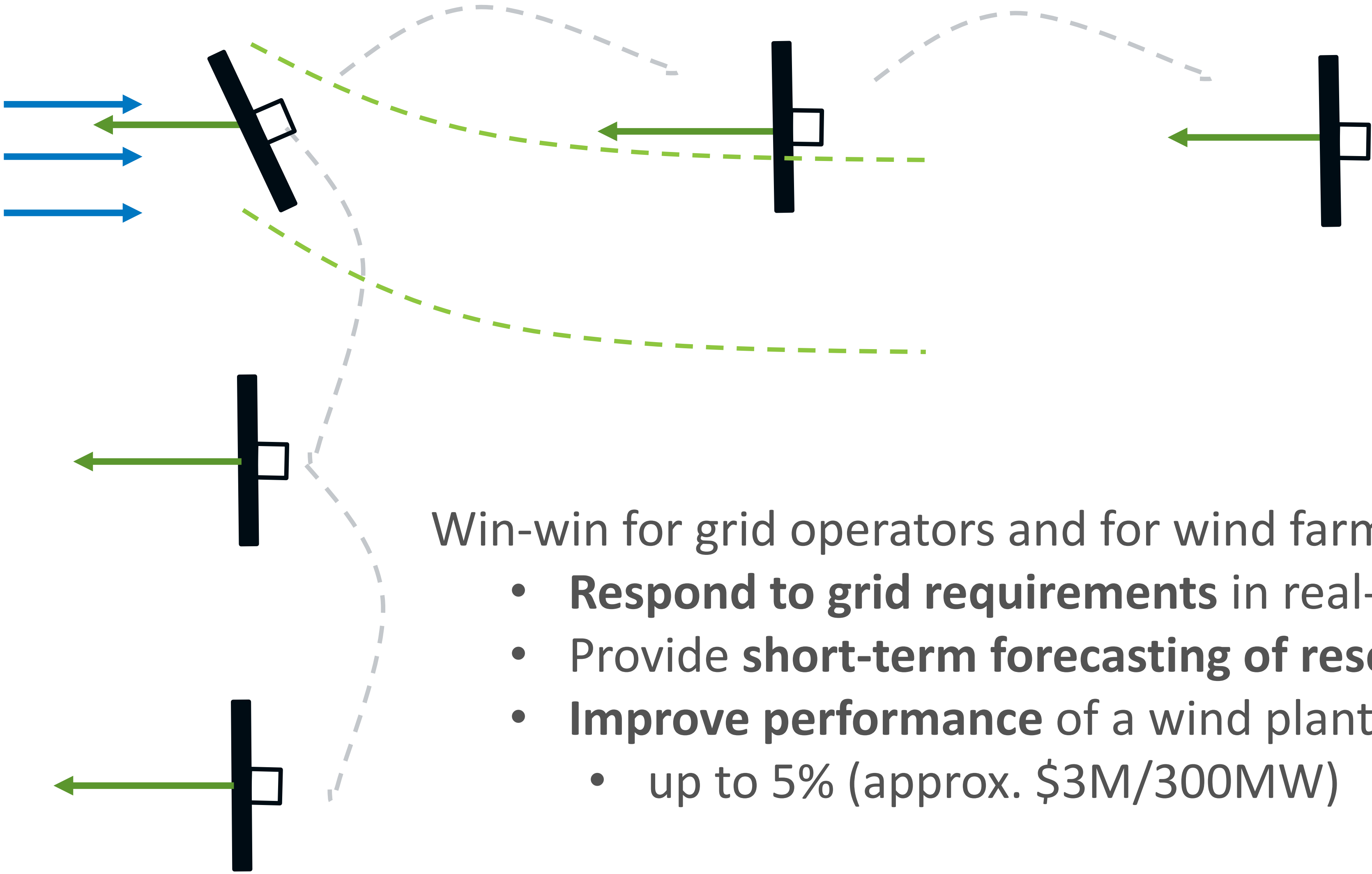
Technical Challenges and Advances in AES



Development of:

- **Real-time** optimization and controls
  - Maximize power and reduce loads
- Integration of **local effects**
  - wind speed/direction
- Incorporating **forecasting**
  - short- and long-term

Outcomes of AES for Wind Energy



Win-win for grid operators and for wind farms

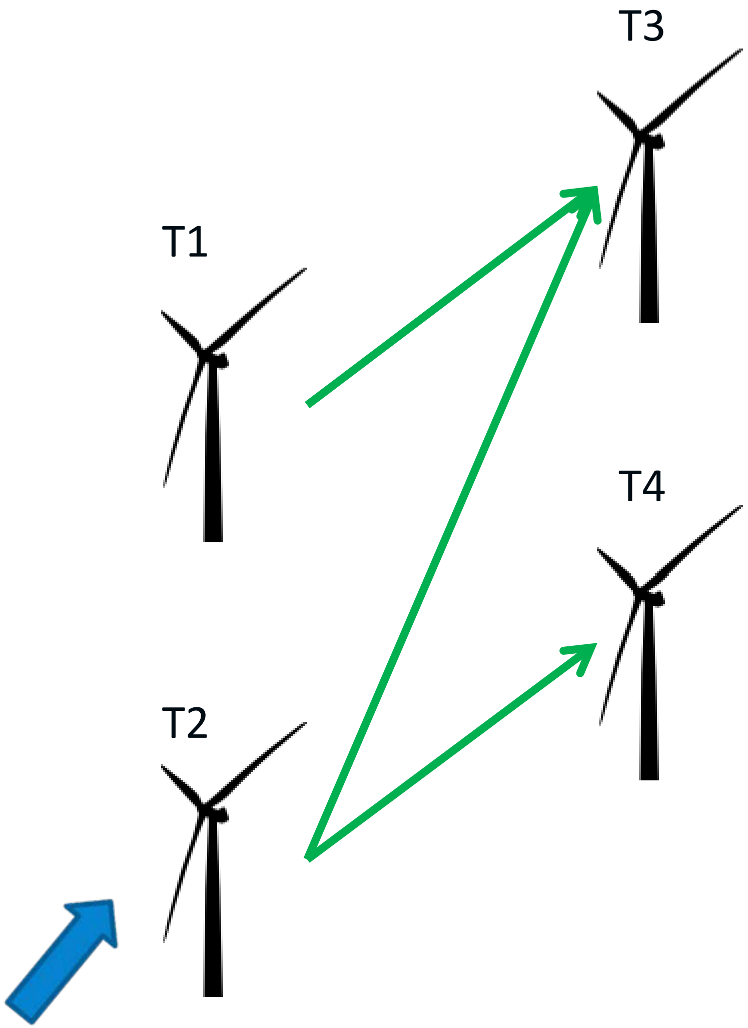
- **Respond to grid requirements** in real-time
- Provide **short-term forecasting of reserves**
- **Improve performance** of a wind plant
  - up to 5% (approx. $3M/300MW)

Outline

- Wind farm modeling and control
- **Distributed optimization framework**
- Wind direction example
- Maximizing power example
- Conclusions and future work

Wind Farm as a Network

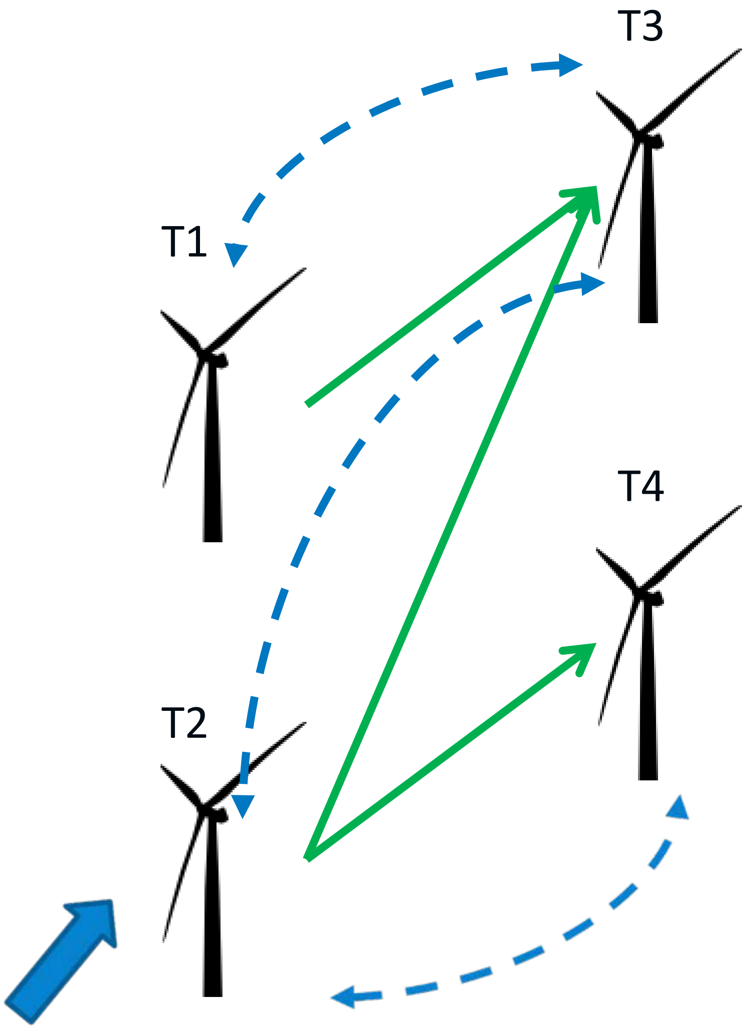
Wind Farm as a Directed Graph



**Information flows downstream

Physical Network, i.e. Wake Interactions

Wind Farm as an Undirected Graph



**Information flows downstream

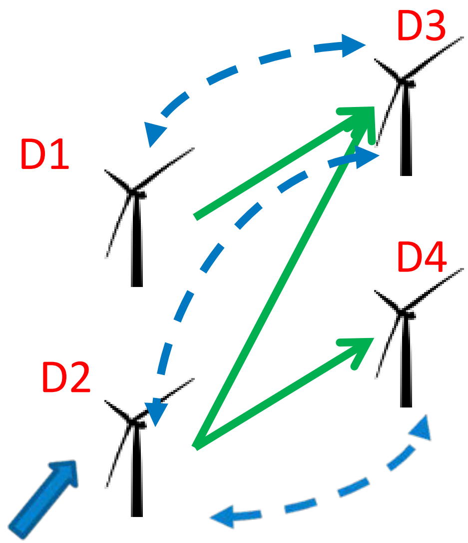
Physical Network, i.e. Wake Interactions

Communication Network, i.e. message passing

**Information about turbine controls is passed between interacting turbines

Distributed Formulation

Wind Farm Problem

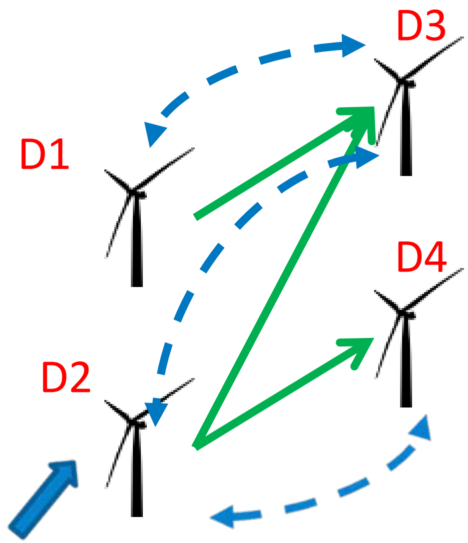


Generalized Form

$$\min_{\{x_i \in X_i\}} \left(\sum_{i=1}^{N} f_i(x_i) \right)$$

Distributed Formulation

Wind Farm Problem



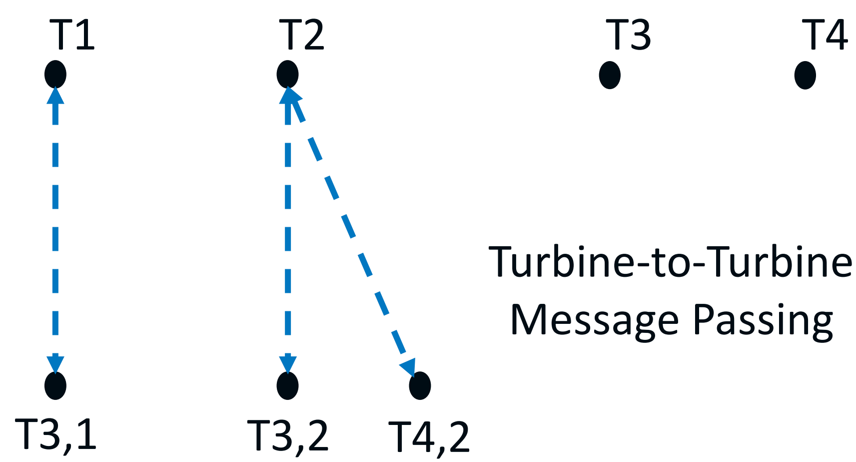
Where:

- $x_1 = [\gamma_1] \rightarrow$ turbine inputs
- $x_2 = [\gamma_2]$
- $x_3 = [\gamma_3, \gamma_{3,1}, \gamma_{3,2}]$
- $x_4 = [\gamma_4, \gamma_{4,2}]$
- $f_i = D_i \rightarrow$ diff. in wind direction

Generalized Form

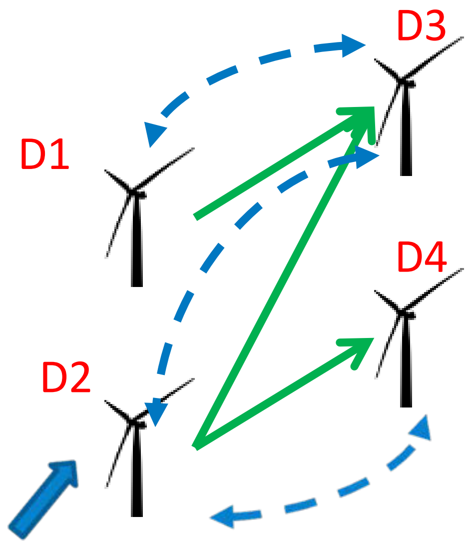
$$\min_{\{x_i \in X_i\}} \left(\sum_{i=1}^{N} \boxed{f_i}\boxed{(x_i)} \right)$$

Network Topology



Distributed Formulation

Wind Farm Problem



Where:

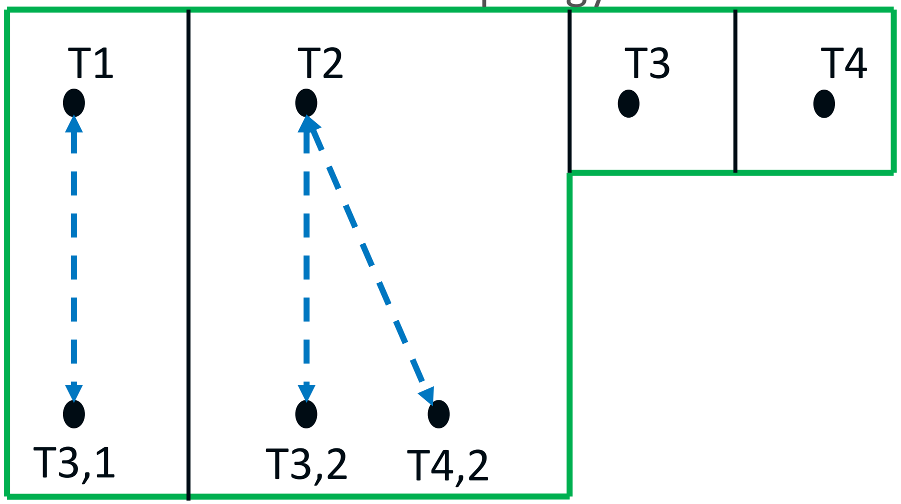
- $x_1 = [\gamma_1]$
- $x_2 = [\gamma_2]$
- $x_3 = [\gamma_3, \gamma_{3,1}, \gamma_{3,2}]$
- $x_4 = [\gamma_4, \gamma_{4,2}]$
- D_i = diff. in wind direction
- A contains structure of graph

Generalized Form

$$\min_{\{x_i \in X_i\}} \left(\sum_{i=1}^{N} \boxed{f_i} \boxed{(x_i)} \right)$$

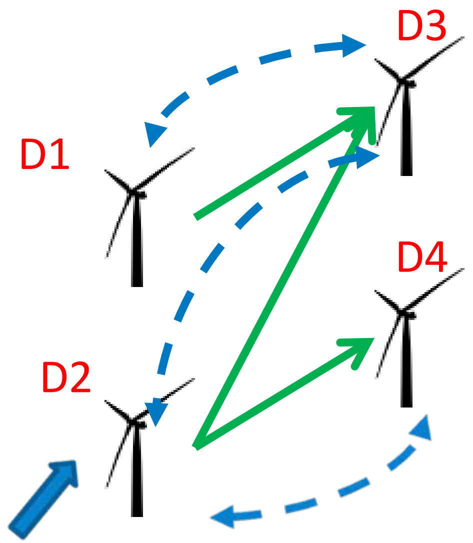
$$subject\ to: Ax = 0$$

Network Topology



Distributed Formulation – Network Term

Wind Farm Problem



Where:

- $x_1 = [\gamma_1]$
- $x_2 = [\gamma_2]$
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- $x_4 = [\gamma_4, \gamma_{4,2}]$
- D_i = diff. in wind direction
- A contains structure of graph

Generalized Form

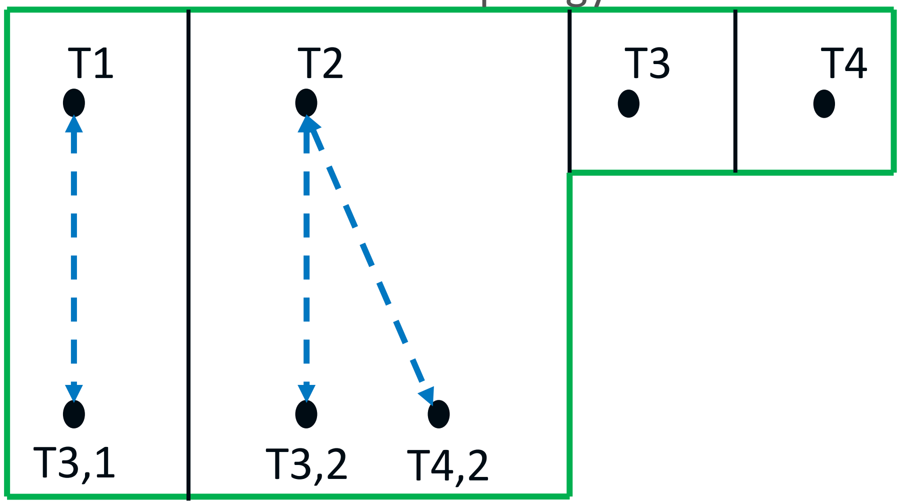
$$\min_{\{x_i \in X_i\}} \boxed{\left(\sum_{i=1}^{N} f_i(x_i) \right)} + \boxed{\sum_{(j,k)\in\mathcal{E}} g_{jk}(x_j, x_k)}$$

$$subject\ to: Ax = 0$$

Node objective Edge objective

Hallac et. al. 2015 – Network Lasso

Network Topology



Outline

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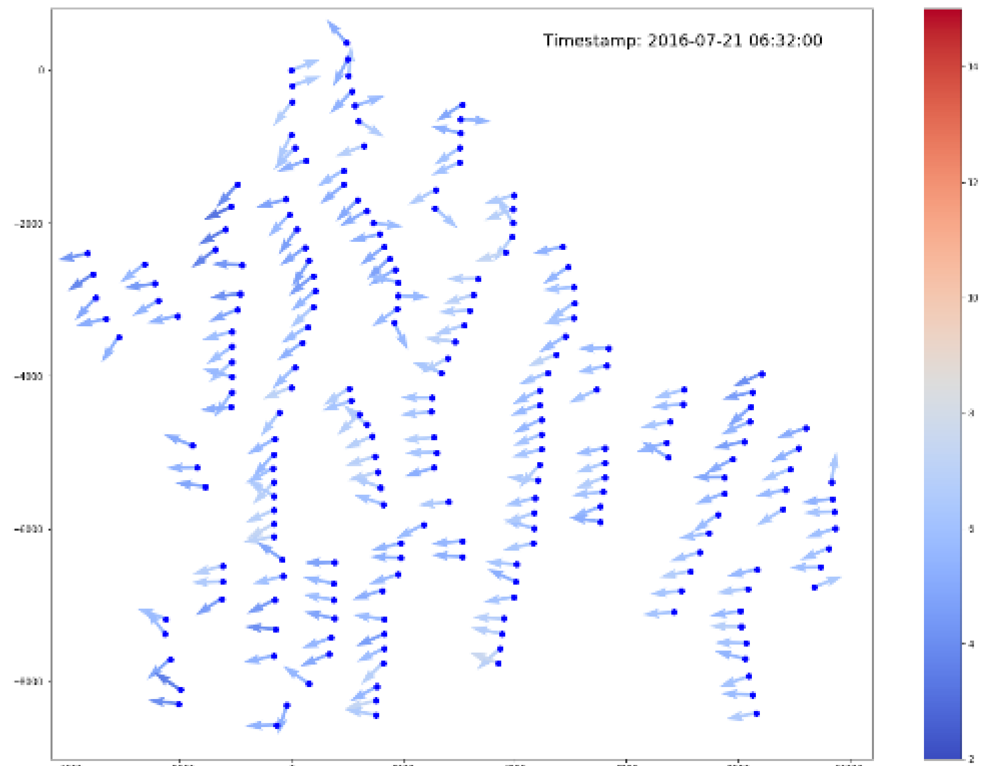
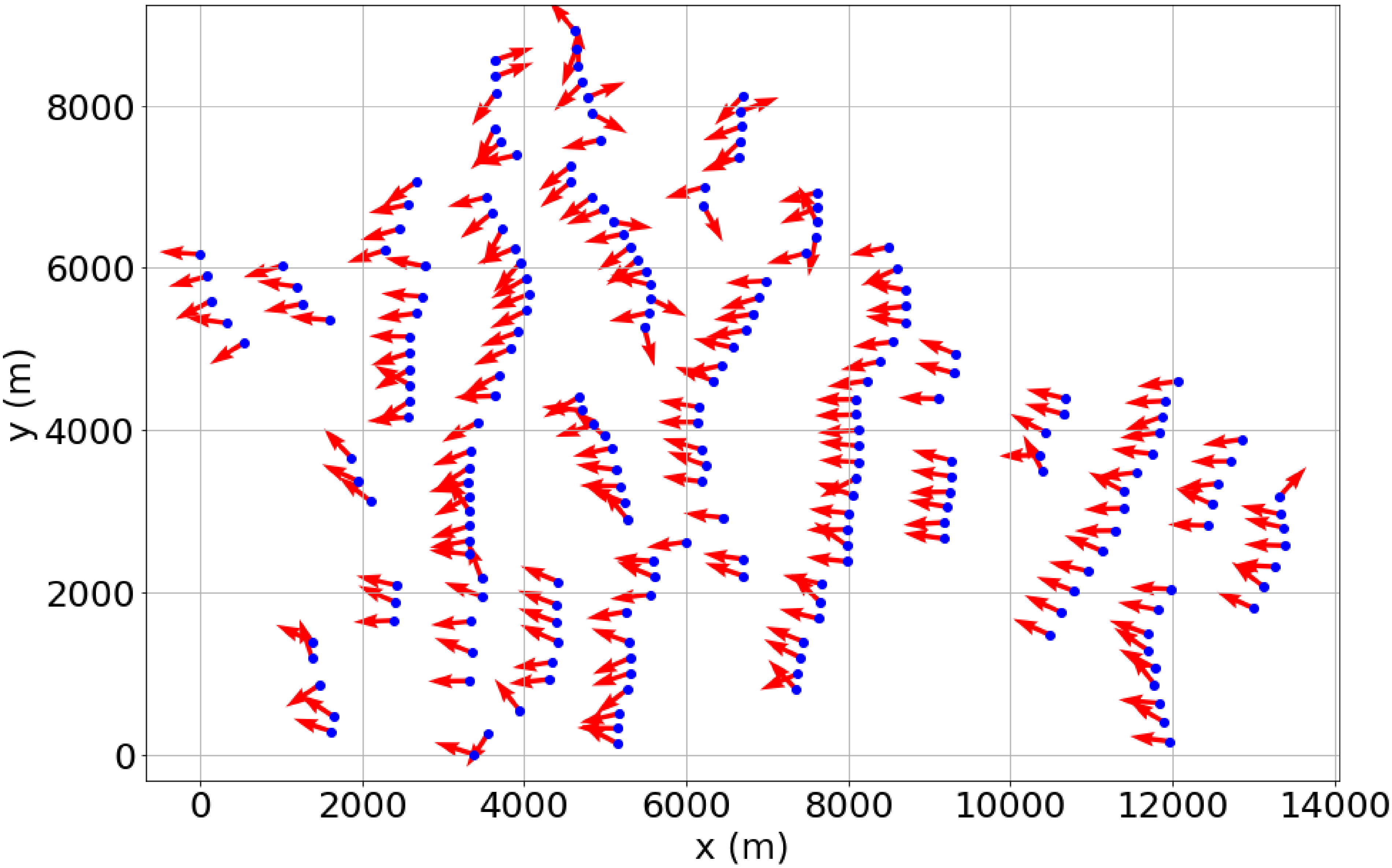
Example: Wind Direction Consensus

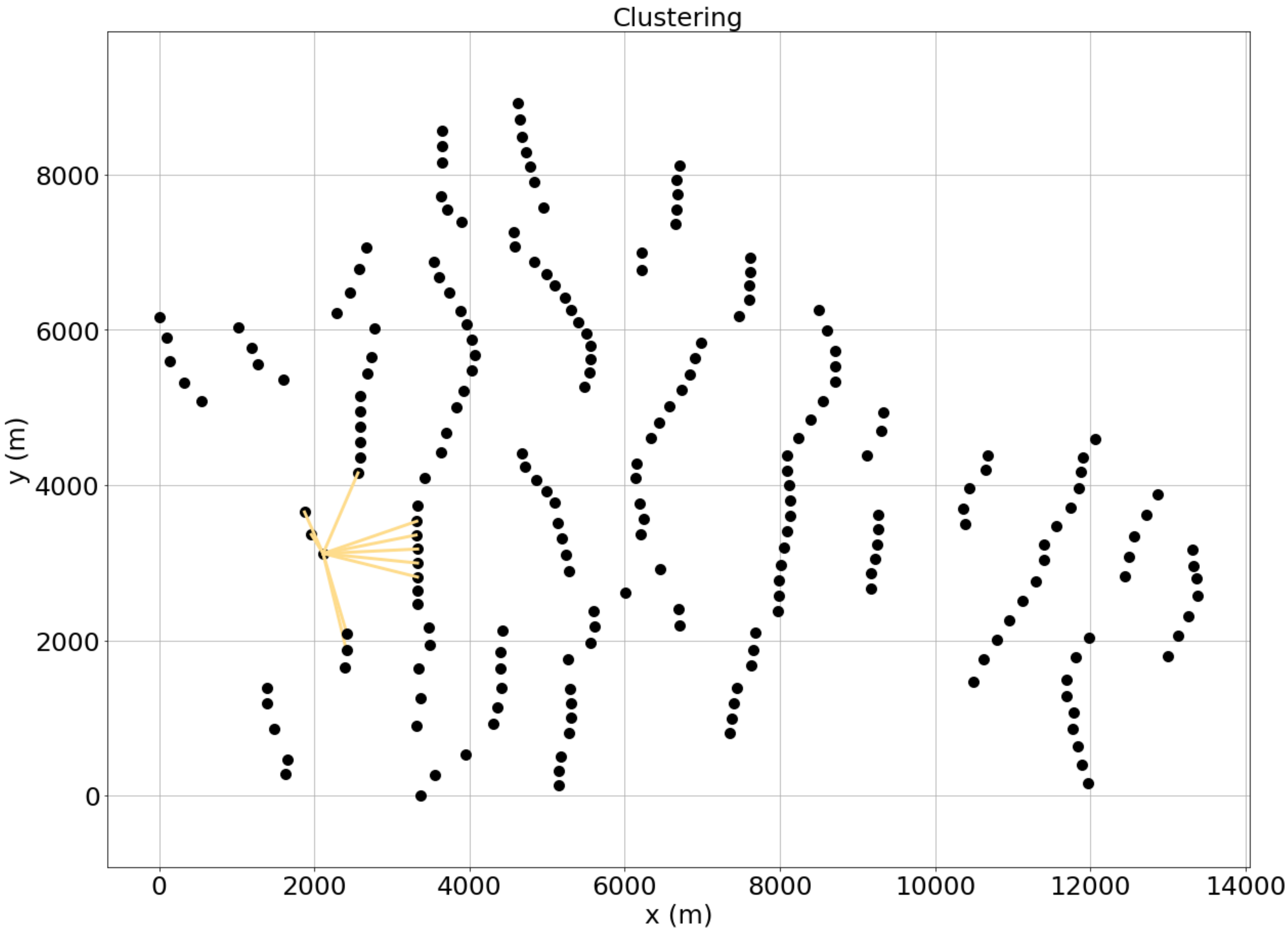
- Incorporate information from nearby turbines
- A better wind direction estimate → improved power



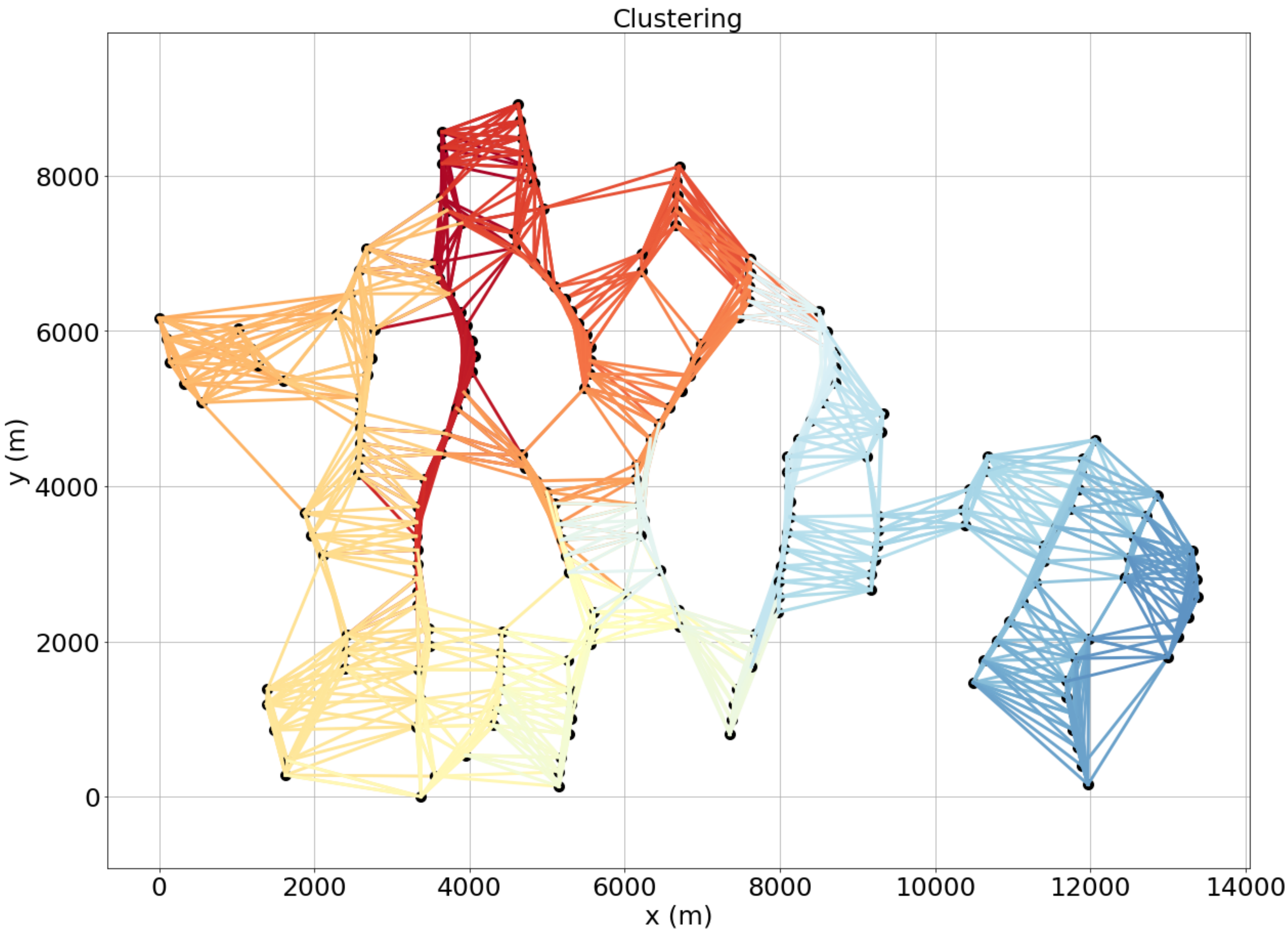
Wind Direction Recorded at Each Turbine



Network Topology – Nearest Neighbor



Network Topology



Objective Function

Node objective

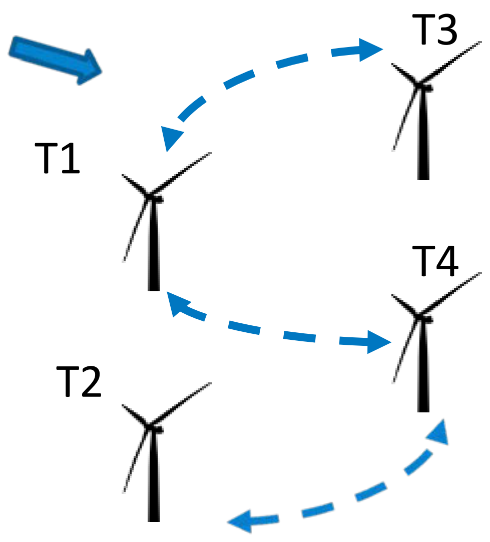
$$\min_{\{x_i \in X_i\}} \boxed{\left(\sum_{i \in V}^{N} f_i\,(x_i)\right)} + \boxed{\left(\lambda \sum_{(j,k) \in \mathcal{E}} g_{jk}(x_j, x_k)\right)}$$

Edge objective

$$subject\ to: Ax = 0$$

Network structure (nearest neighbor)

- **Node objective**: match individual direction measurement
  - $(x_i - x_{measure})^2$



- Edge objective: match nearby turbines
  - $w_{jk}|x_j - x_k|$
  - *j* and *k* are connected nodes
  - Incentive for T1 to match T3 and T4

Example: Wind Direction Consensus

Node objective

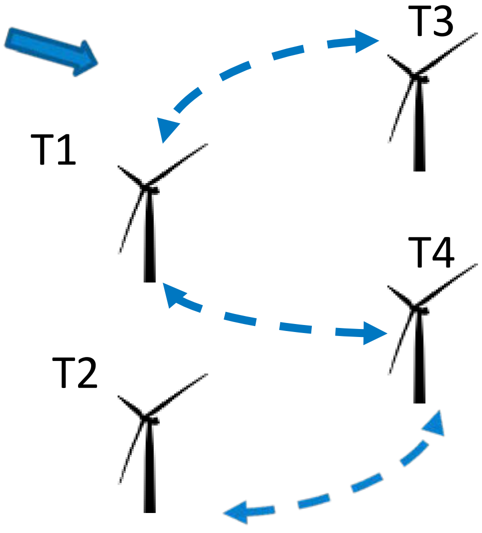
$$\min_{\{x_i \in X_i\}} \boxed{\left(\sum_{i \in V}^{N} (x_i - x_{measure})^2 \right)} + \boxed{\left(\lambda \sum_{(j,k) \in \mathcal{E}} w_{jk} |x_j - x_k| \right)}$$

Edge objective

$$subject\ to: Ax = 0$$

Network structure (nearest neighbor)

- Tune λ – how much should you trust neighbors?
- Objective function can be solved in closed form
  - For "almost consensus” problem
- Solve using an iterative approach
  - Alternating direction method of multipliers
- Solved at every 1 minute
  - Solve time = 0.5s



Example: Wind Direction Consensus

Node objective

$$\min_{\{x,z\}} \boxed{\left(\sum_{i\in V}^{N}(x_i - x_{measure})^2\right)} + \boxed{\left(\lambda \sum_{(j,k)\in\mathcal{E}} w_{jk}|z_{jk} - z_{kj}|\right)}$$

Edge objective

$$subject\ to: x_i = z_{ij}, \qquad i = 1, \ldots, m \quad j \in N(i)$$

- Iterative approach:
  - Solve for *x* – minimize the node objective
  - Solve for *z* – minimize differences across edges
    - *z* is a copy of the node variable at each of the connected nodes
  - Subject to: all the copies should equal the node
  - Note: $x_i \mathrel{!}= z_{ji}$ is not a constraint

Example: Wind Direction Consensus

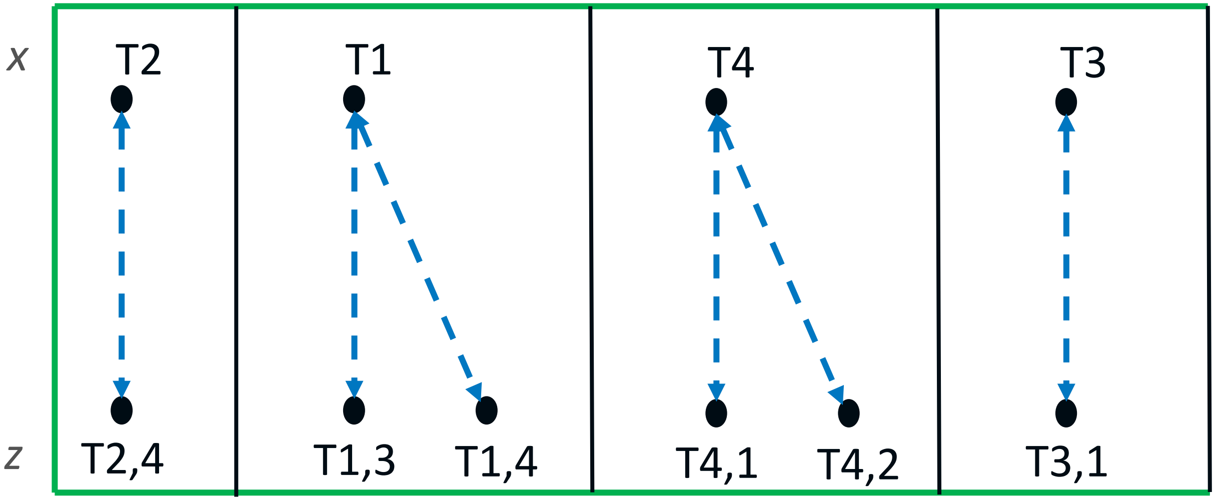
$$\min_{\{x,z\}} \left(\boxed{\sum_{i \in V}^{N} (x_i - x_{measure})^2} \right) + \left(\lambda \sum_{(j,k) \in \mathcal{E}} w_{jk} |z_{jk} - z_{kj}| \right)$$

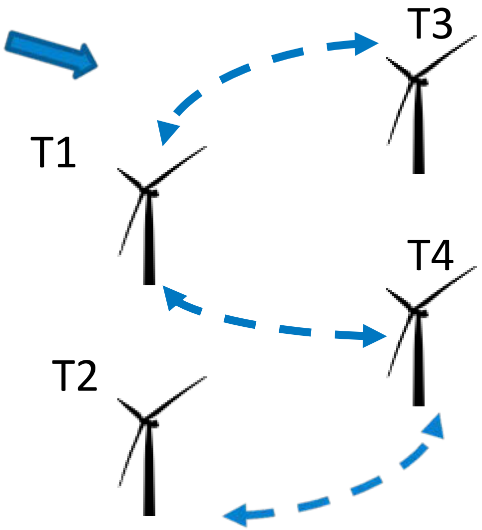
Node objective

Edge objective

$$subject\ to: x_i = z_{ij}, \qquad i = 1, \ldots, m \quad j \in N(i)$$

Constraints: resulting graph structure





Example: Wind Direction Consensus

Node objective $$\min_{\{x,z\}} \left(\boxed{\sum_{i \in V}^{N} (x_i - x_{measure})^2} \right) + \left(\lambda \sum_{(j,k)\in\mathcal{E}} w_{jk} |z_{jk} - z_{kj}| \right)$$ Edge objective

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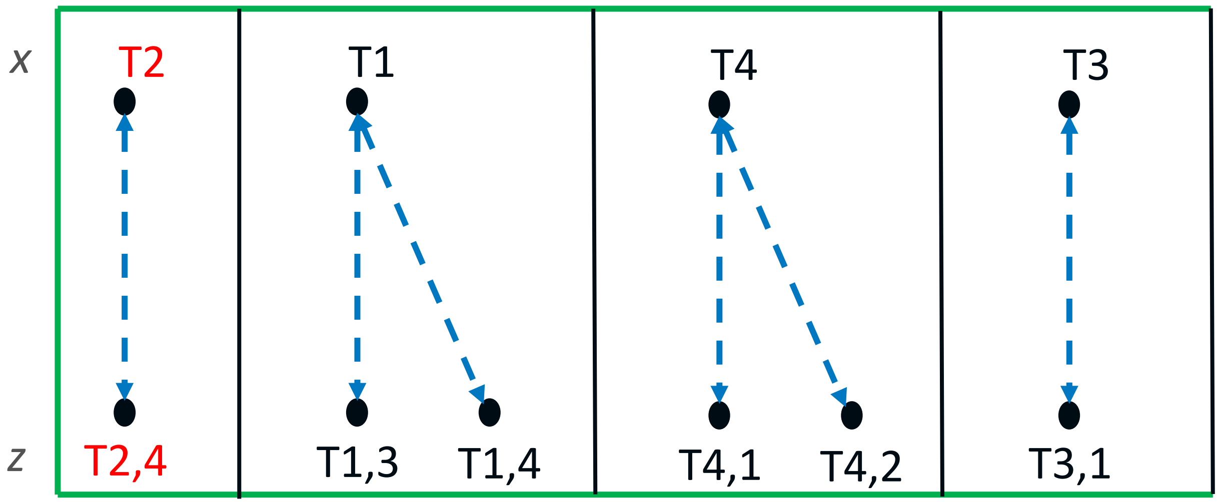

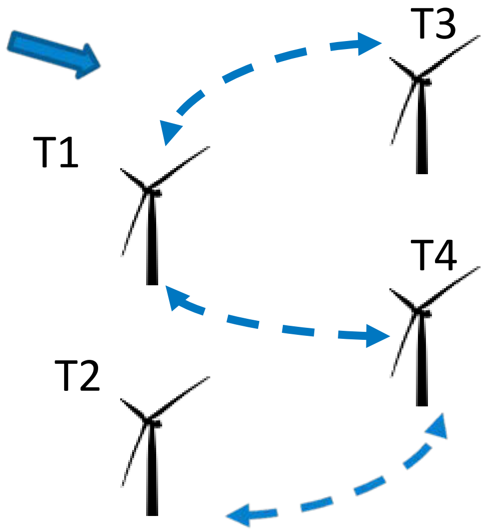

Example: Wind Direction Consensus

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$$\min_{\{x,z\}} \boxed{\left(\sum_{i\in V}^{N} (x_i - x_{measure})^2 \right)} + \boxed{\left(\lambda \sum_{(j,k)\in\mathcal{E}} w_{jk}|z_{jk} - z_{kj}| \right)}$$

Edge objective

$$subject\ to: x_i = z_{ij}, \qquad i = 1, \dots, m \quad j \in N(i)$$

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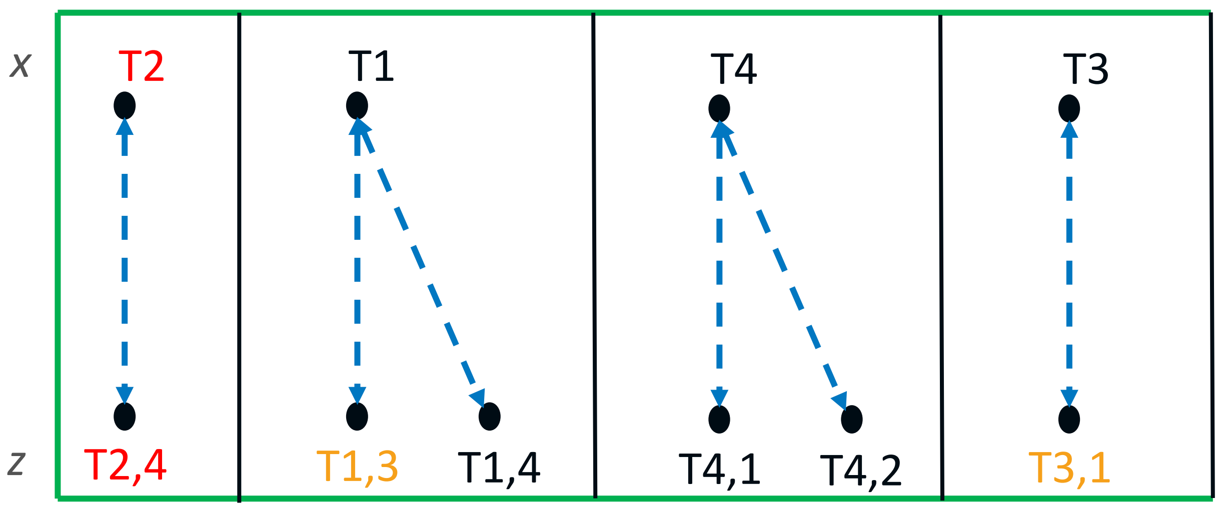
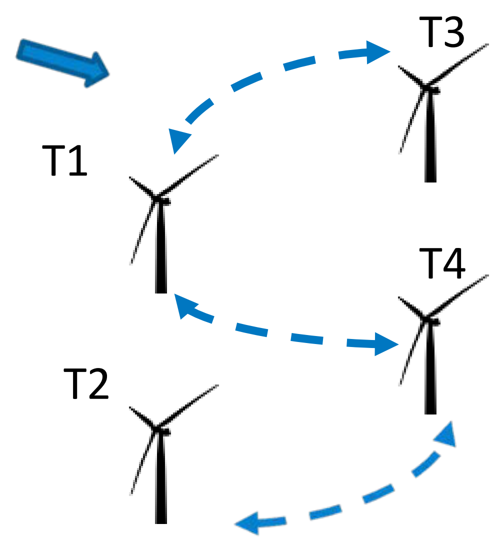




$z_{ij} != z_{ji}$, i.e. T1,3 does not need to match T3,1, but their differences will be heavily penalized

Objective Function –Identify Outliers

Node objective

$$\min_{\{x,b\}} \boxed{\left(\sum_{i\in V}^{N} f_i\,(x_i, b_i) \right)} + \left(\lambda_1 \sum_{(j,k)\in \mathcal{E}} g_{jk}(x_j, x_k) \right) + \lambda_2 \sum_{i\in V}^{N} |b_i|$$

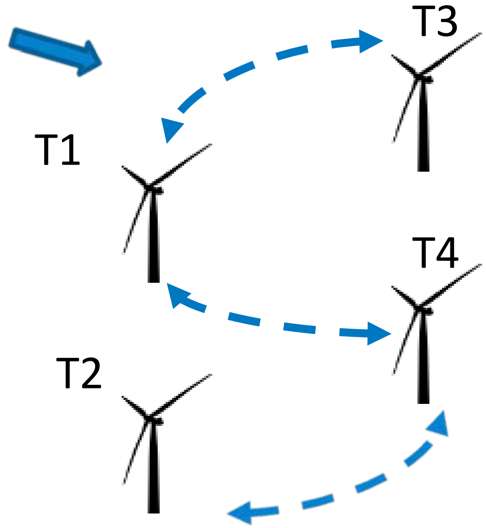
Sparsity in outliers

Edge objective

$$subject\ to: Ax = 0$$

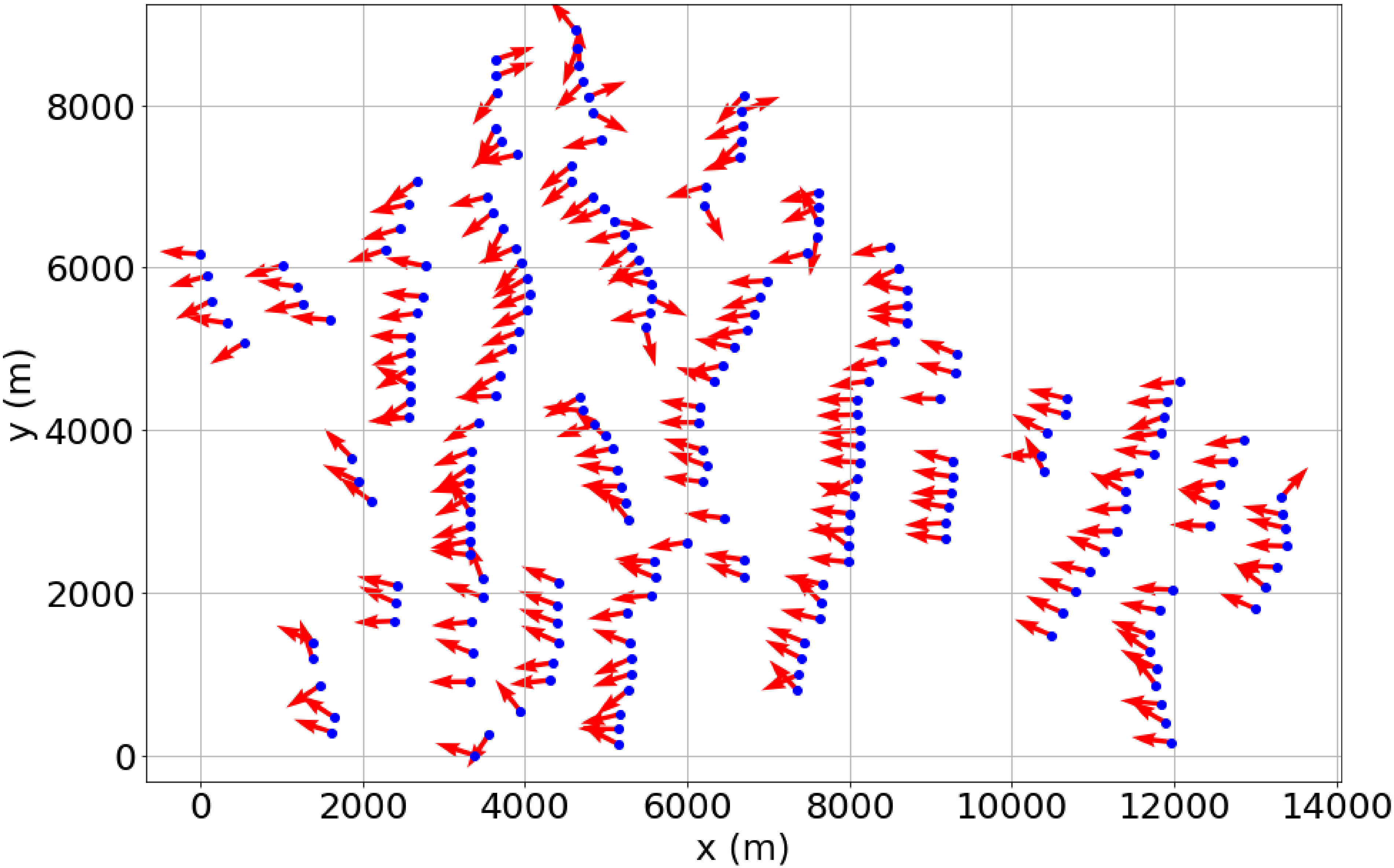
Network structure (nearest neighbor)

- Identifying Outliers
  - $(x_i - x_{measure} - b_i)^2$
  - Helps to identify faults in vane readings

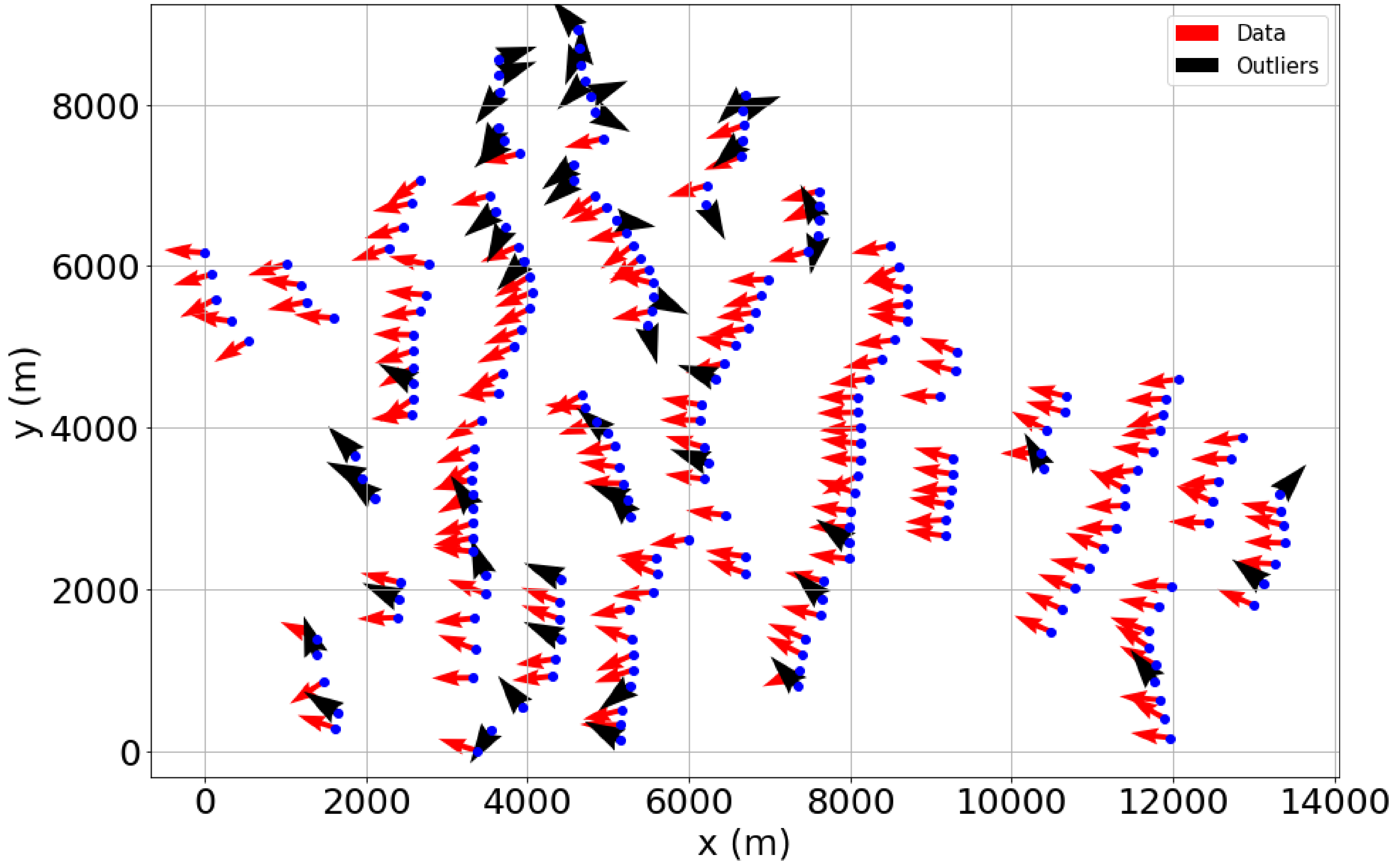


- Edge objective: match nearby turbines
  - $w_{jk}|x_j - x_k|$
  - *j* and *k* are connected nodes
  - Incentive for T1 to match T3 and T4

Identifying Outliers

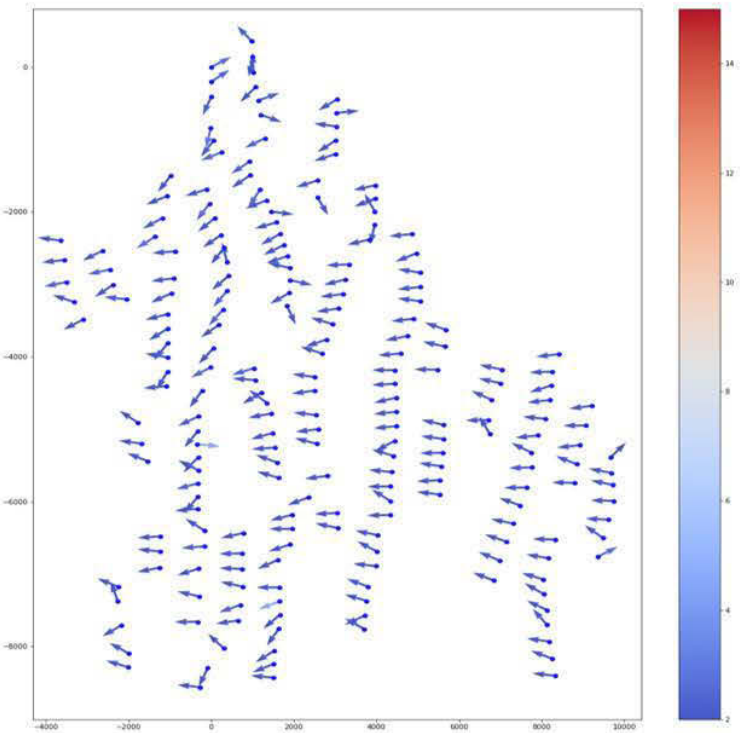


Identifying Outliers

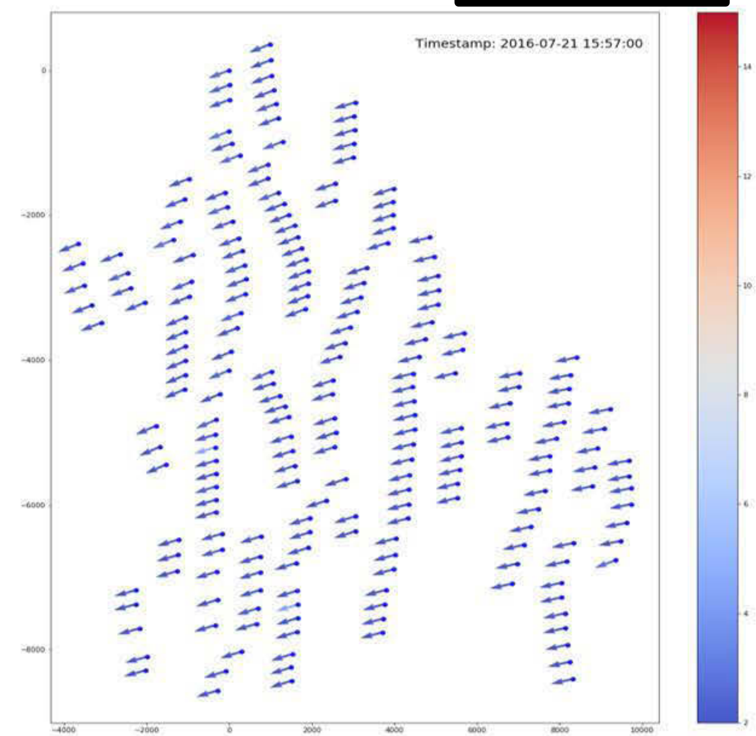


Results

Real Data

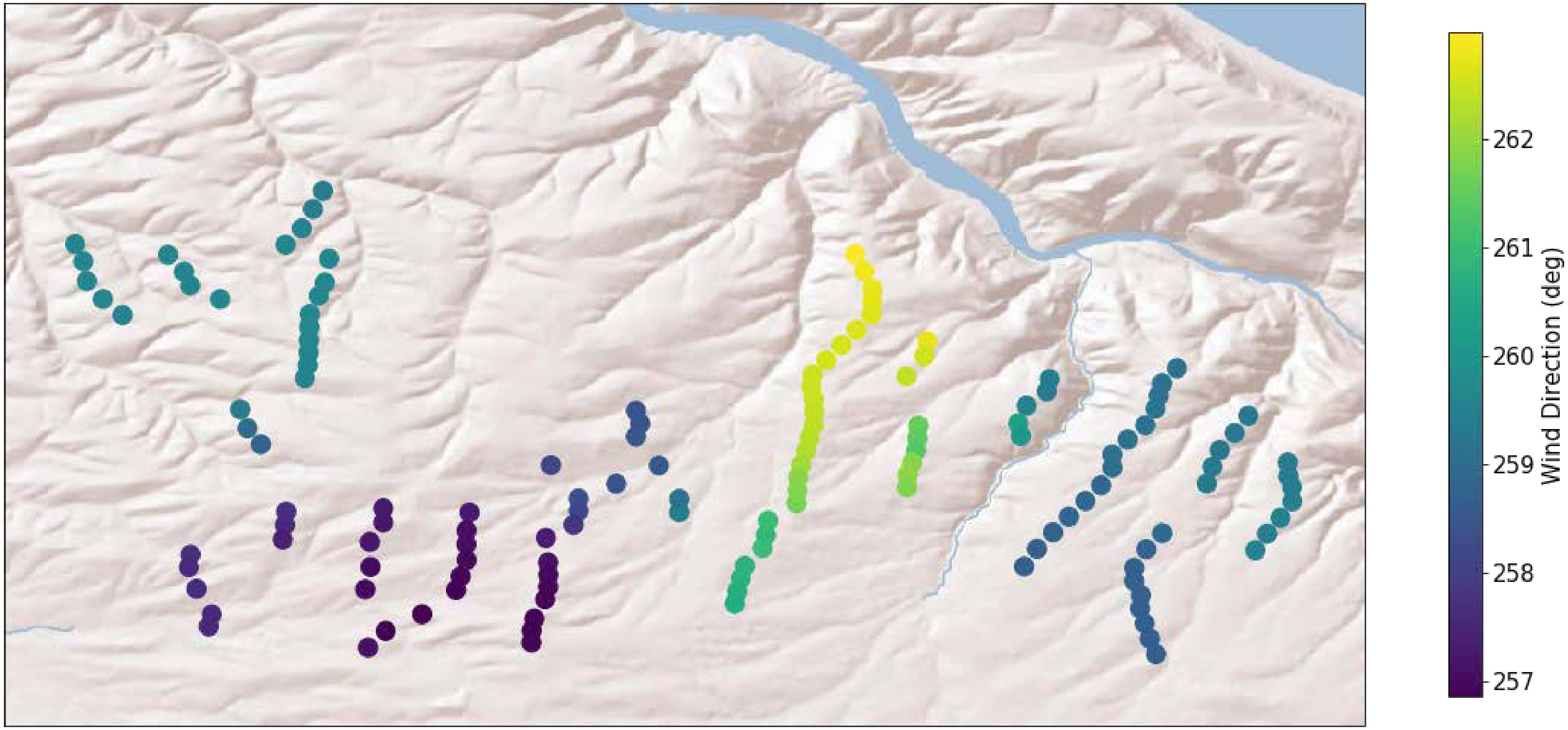


Simulated Impacts

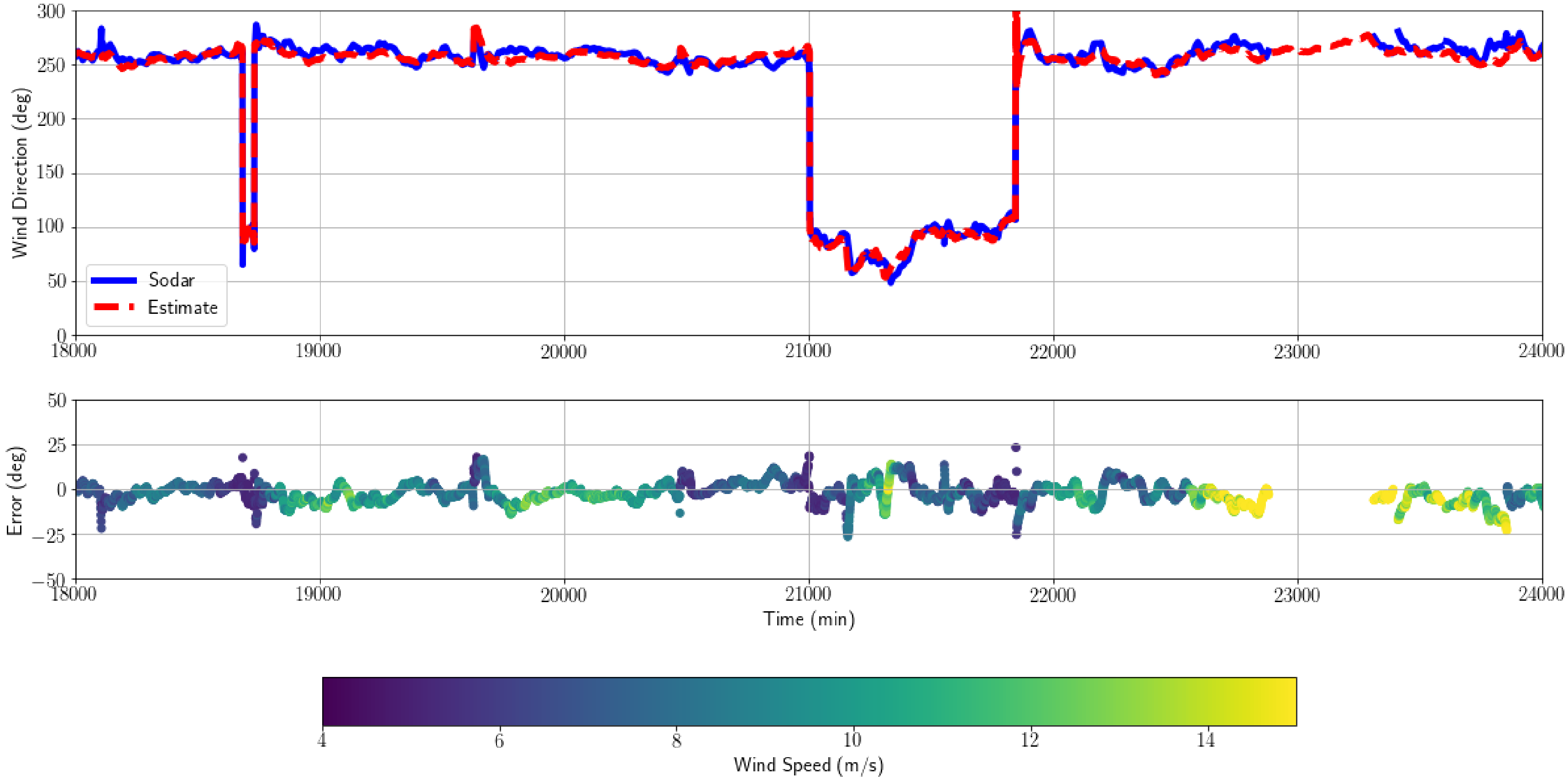


By aggregating individual wind turbine measurements of wind direction, a consensus algorithm can produce a more reliable and predictive estimate of wind direction

Wind Direction Across Complex Terrain



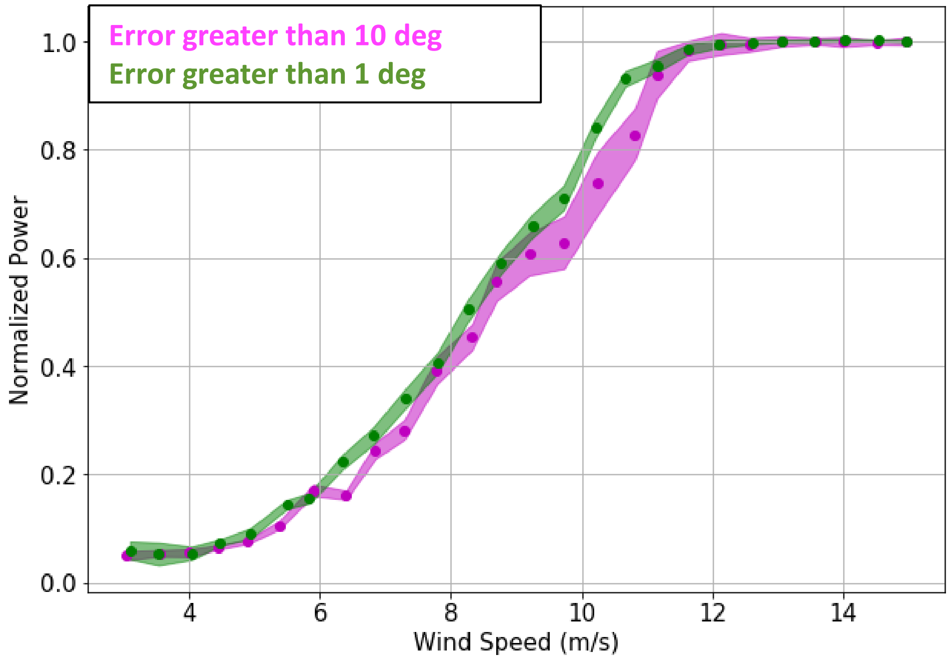
Validation with Sodar



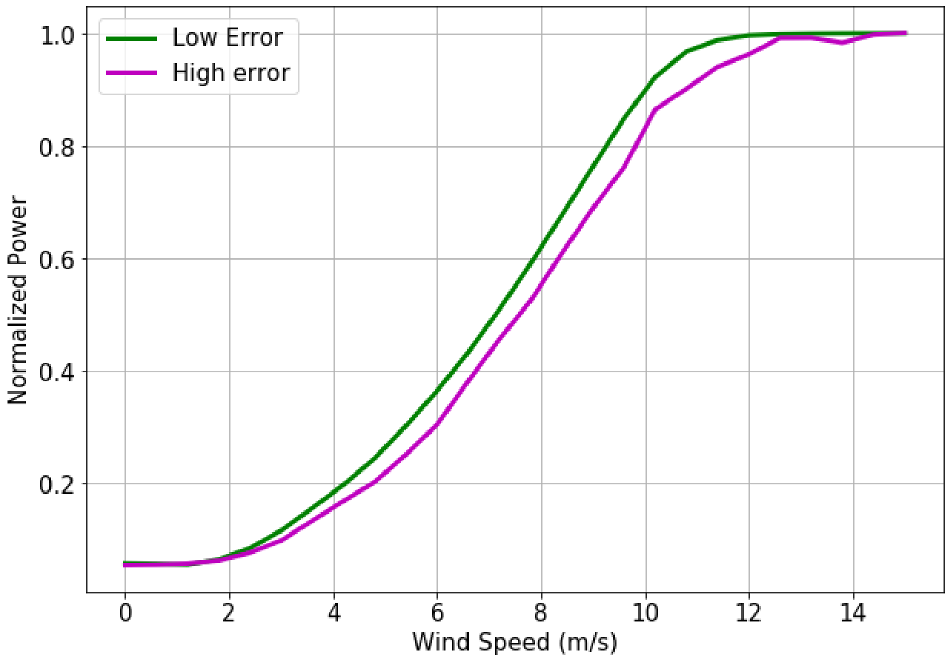
Turbine Power Curves

Error = perceived wind direction – wind direction from consensus

**Turbines aligned with the consensus wind direction produce more power



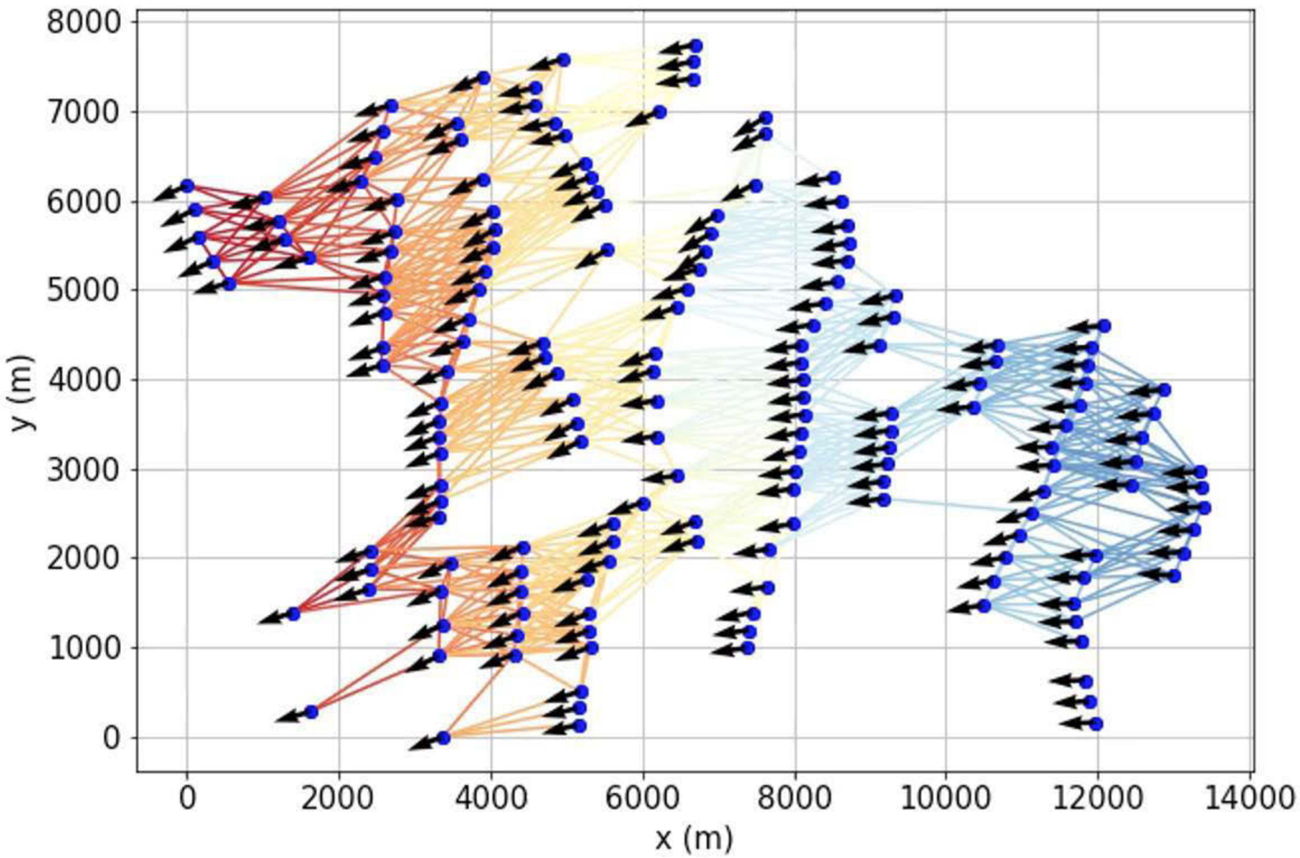
Single Turbine



All Turbines

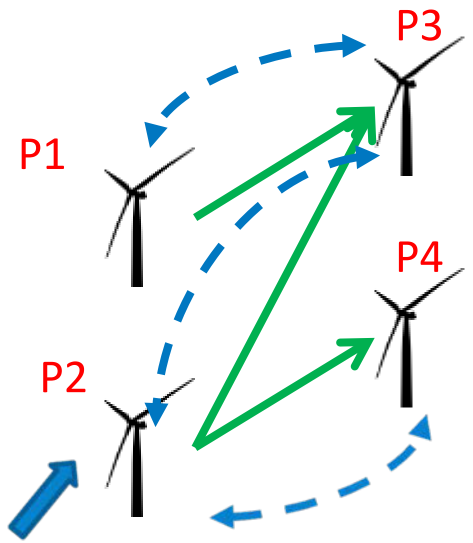
Potential for an additional 1-5% AEP gain

Current Work – Short-Term Forecasting/Max Power



Distributed Formulation – Next Steps

Wind Farm Problem



Where:

- $x_1 = [\gamma_1]$
- $x_2 = [\gamma_2]$
- $x_3 = [\gamma_3, \gamma_{3,1}, \gamma_{3,2}]$
- $x_4 = [\gamma_4, \gamma_{4,2}]$
- P_i = turbine power
- A contains structure of graph

Generalized Form

$$\min_{\{x_i \in X_i\}} \left(\sum_{i=1}^{N} \boxed{f_i} \boxed{(x_i,} t) \right)$$

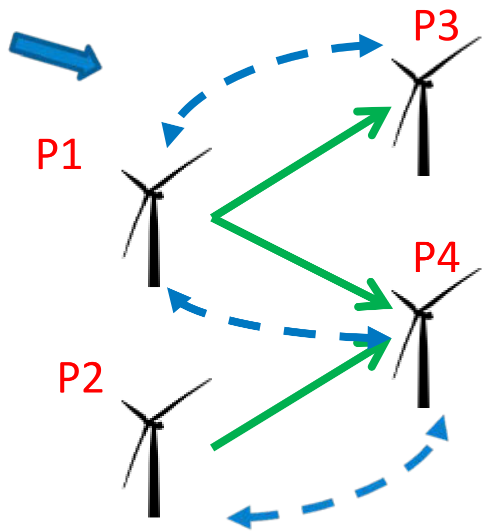
$$subject\ to: A(t)x = 0$$

Challenges

- Determine connections b/w turbines (**A**)
- $f_i(x_i)$ is non-convex
- **A(t)** is time-varying/data-driven

Distributed Formulation – Next Steps

Wind Farm Problem



Where:

- $x_1 = [\gamma_1]$
- $x_2 = [\gamma_2]$
- $x_3 = [\gamma_3, \gamma_{3,1}]$
- $x_4 = [\gamma_4, \gamma_{4,1}, \gamma_{4,2}]$
- P_i = turbine power
- A contains structure of graph

Generalized Form

$$\min_{\{x_i \in X_i\}} \left(\sum_{i=1}^{N} \tilde{f}_i(x_i, t) \right)$$

$$subject\ to: A(t)x = 0$$

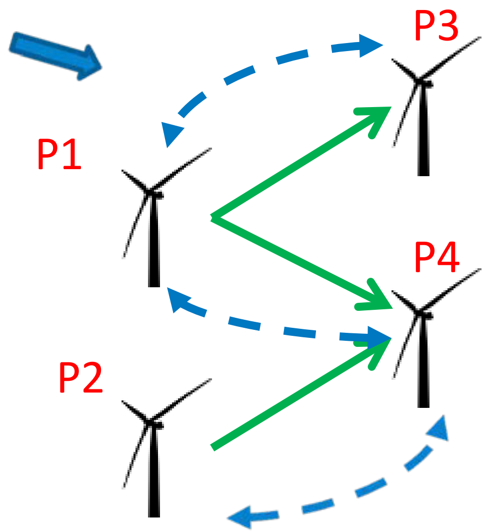
Challenges

- Determine connections b/w turbines (**A**)
- $f_i(x_i)$ is non-convex
- **A(t)** is time-varying/data-driven

- $\tilde{f}_i$ is an approximate functional form
  - Feedback to correct for mismatches
  - Online optimization
  - Dall-Anese – Simonetto '16

Distributed Formulation – Next Steps

Wind Farm Problem



Where:

- $x_1 = [\gamma_1]$
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- $x_3 = [\gamma_3, \gamma_{3,1}]$
- $x_4 = [\gamma_4, \gamma_{4,1}, \gamma_{4,2}]$
- P_i = turbine power
- A contains structure of graph

Generalized Form

$$\min_{\{x_i \in X_i\}} \left(\sum_{i=1}^{N} \boxed{f_i^{true}} \boxed{(x_i,} t) \right)$$

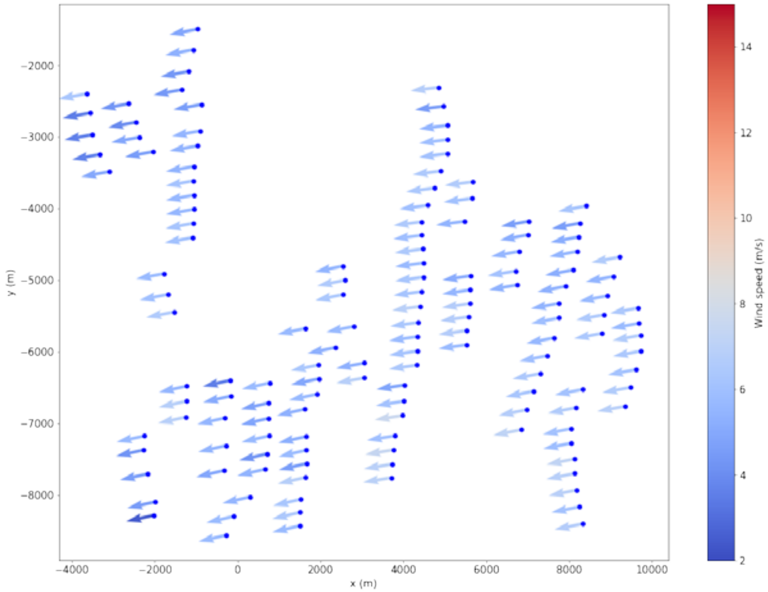
$$subject\ to: A(t)x = 0$$

Challenges

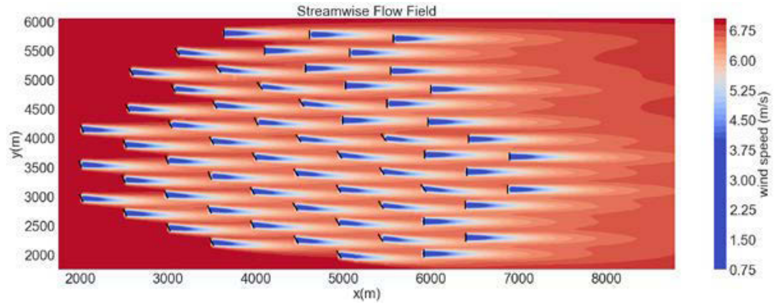
- Determine connections b/w turbines (**A**)
- $f_i(x_i)$ is non-convex
- **A(t)** is time-varying/data-driven
- f_i^{true} is unknown
  - No gradient information
  - Learn gradient from measurements
  - No results for non-convex settings

Conclusions and Future Work

- Distributed optimization framework
  - Wind farm as a network
  - Low-order structure
  - Computationally Efficient



- Future Work
  - Time-varying graphs
  - Nonconvex optimization techniques
    - Proximal primal-dual algorithm



Thank you

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