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# Decentralized Co-Optimization of Water and Energy Distribution Systems

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# Overview

- Chapter 1: Introduction
- Chapter 2: Micro Water-Energy Nexus (MWEN)
- Chapter 3: Centralized Network Operation of MWEN
- Chapter 4: Decentralized Networked Microgrid Energy Management
- Chapter 5: Decentralized Water-Energy Co-Optimization
- Chapter 6: Distribution-Level Water-Energy Nexus
- Chapter 7: Conclusions and Future Work

# Chapter 1

# Introduction

# Motivation

- Both water and electricity are crucial resources
  - Scarcity of one resource can greatly impact the other
    - A severe drought affected more than a third of the United States in 2012, limiting water availability that constrained the operation of some power plants and other energy production infrastructure [1]
    - Winter storm Uri in 2021 caused a loss in water pressure that impacted the power grid and back-up generators, affecting primarily groundwater systems and wastewater treatment units [2]
- Water and energy management co-optimization can yield greater efficiency, reliability, and security [3]
  - Local power and water production and distribution
  - Independent operation from both main grid and water systems

[1] E. Moniz "Ensuring the Resiliency of Our Future Water and Energy Systems." *Energy.gov*, June 2014, https://www.energy.gov/articles/ensuring-resiliency-our-future-water-and-energy-systems.
[2] C. E. Haddock, "Winter Storm Uri Impacts to City of Houston Water and Wastewater Systems," Mar. 2021, https://www.houstontx.gov/govtrelations/2021lege/3.10.2021-Haddock-Uri-HUA-Statement.pdf.
[3] F. Moazeni, J. Khazaei, J. P. Pera Mendes, "Maximizing energy efficiency of islanded micro water-energy nexus using co-optimization of water demand and energy consumption," *Applied Energy*, vol. 266, 2020.

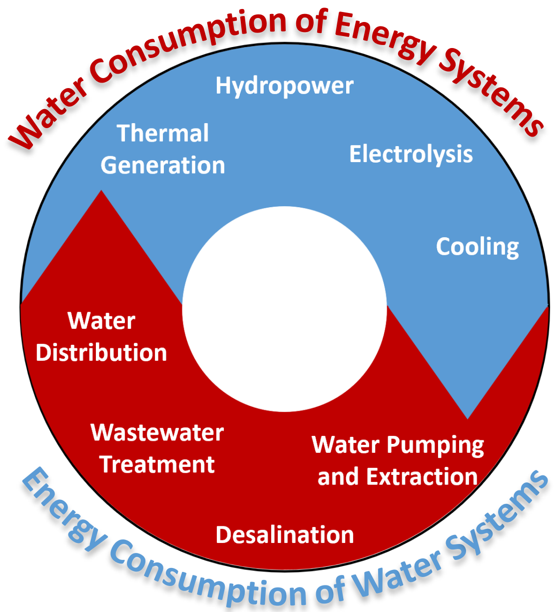
# Energy and Water Management Similarities

| Energy Management [1] | Water Management [2] |
|---|---|
| **Various Distributed Resources:** Controllable generators (e.g., diesel and natural gas gens.), renewable energy sources (e.g., solar and wind power), energy storage systems (e.g., BES and HES) | **Various Distributed Resources:** Water treatment (e.g., wastewater, reservoir water, ground water, etc.), water desalination, rainwater, water storage tanks |
| **Energy Demand:** Residential, commercial, industrial loads | **Water Demand:** Residential, agricultural, industrial, ecological uses |
| **Unit Commitment:** Scheduling of generators and energy storage units | **Unit Commitment:** Scheduling of water treatment plants and water pumps |
| **Economic Dispatch:** Controlling generating resources to achieve supply-demand balance. Minimize system operation costs | **Economic Dispatch:** Treating and dispatching sufficient water to match demand. Minimize water treatment and distribution costs. |

[1] C. A. Marino, M. Marufuzzaman, "A microgrid energy management system based on chance-constrained stochastic optimization and big data analytics," *Computers & Industrial Engineering*, vol. 143, 2020.
[2] K. Gnawali, K. H. Han, Z. W. Geem, K. S. Jun, and K. T. Yum, "Economic Dispatch Optimization of Multi-Water Resources: A Case Study of an Island in South Korea," *Sustainability*, vol. 11, no. 21, Oct. 2019.

# Water-Energy Nexus

- Relationship and interdependencies of water and energy distribution [1]
  - Water used for electrical energy generation
    - Thermoelectric generators
    - Hydroelectric plants
    - Hydrogen Energy Storage (Electrolysis)
  - Electricity used for clean water production
    - Water treatment
      - Wastewater treatment, freshwater treatment, water desalination, etc.
    - Pumps/water distribution equipment




- Optimization of water and energy distribution
  - Interdependent simultaneous supply of potable water and electrical power [2]
    - Considers electrical power used for water related purposes
    - Considers water used for power related purposes

[1] G. Pereira, A. González and R. Ríos, "Systematic Literature Review of Water-Energy Nexus: An Overview of the field and analysis of the top 50 influential papers," *2020 IEEE Congreso Bienal de Argentina (ARGENCON)*, Resistencia, Argentina, pp. 1-8, 2020.
[2] A. Panagopoulo, "Water-energy nexus: desalination technologies and renewable energy sources," *Environmental Science Pollution Research,* vol. 28, 2021.

# Research Gaps

- **Limited cross-utility integration**
  - Water and energy treated as loosely coupled
    - Often neglecting system interdependencies and detailed dynamics
  - Full integration of different interdependencies between utilities
    - Water consumption of energy systems
    - Energy consumption of water systems
- **Operational complexities**
  - Comprehensive co-optimization modeling
    - Consider complex nonlinear and mixed-integer formulations for accurate system representations
  - Advanced modeling and computation techniques needed
- **Ownership and governance**
  - Institutional separation of water and energy utilities
    - Consider systems independence and privacy requirements
  - Need to achieve distributed optimization to accommodate separate management and ownership

# Research Roadmap

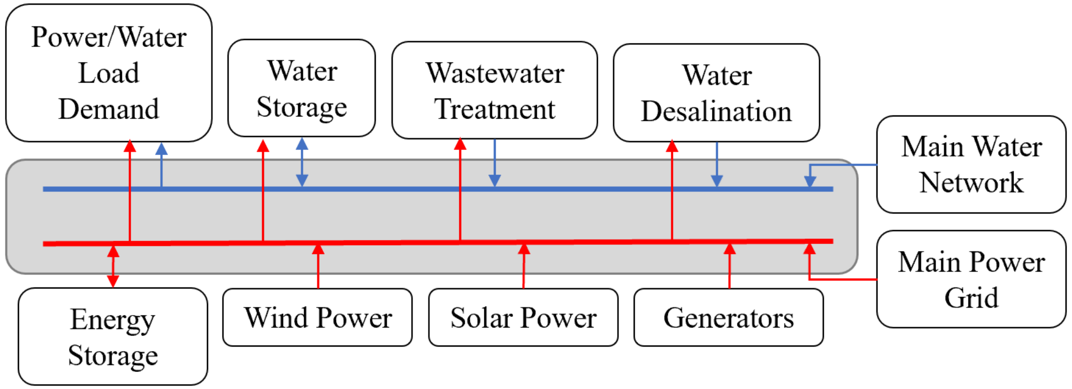
| Micro Water-Energy Nexus | Centralized Water-Energy Networks | Decentralized Network of Microgrids | Decentralized Water-Energy Co-Optimization | Distribution Level Water-Energy Nexus | Conclusions & Future Work |
|---|---|---|---|---|---|
| • MWEN model formulation<br>• MWEN operation and system implementation examples<br>• Cost-Benefit Analysis | • Central node centralized networks of MGs<br>• Network of MWEN systems<br>• Proportional exchange algorithm<br>• Network operation benefit analysis | • ADMM for distributed optimization<br>• Objective-based approach to ADMM<br>• Decentralized optimization performance results | • Decentralization of Water-Energy Nexus<br>• Distributed optimization of MWEN via ADMM<br>• Computational benefits results | • Water and electricity distribution modeling<br>• Physical characteristics of power lines and water pipes<br>• Distribution-Level WEN model convexification<br>• Decentralized algorithm performance | |

# Chapter 2

# Micro Water-Energy Nexus

# MWEN Problem Description

- Small-scale water-energy management and distribution co-optimization
- Goal: To improve and provide combined cost reductions for small-scale water and energy distribution
- Model involves:
  - Energy and water resource management
    - Local generators and water treatment units
  - Renewable generation
  - Coupling with main grid and main water distribution system (WDS)
  - Battery energy storage and water storage tanks
  - Residential and commercial water and energy demand




MWEN resource management system diagram

# MWEN Optimization Model

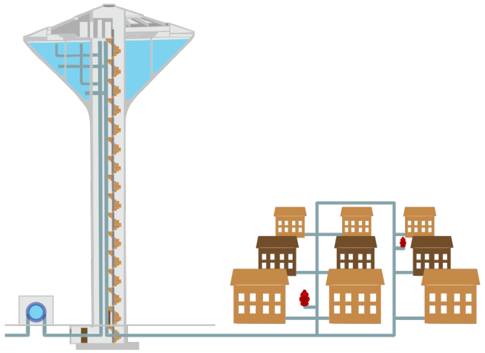
- Day-ahead optimization
  - Mixed integer nonlinear programming (MINLP)
- Objective: Minimize total operation costs
  - Objective Function: $minimize\ f_{cost} = f_E + f_W$
    - Power Distribution Cost: $f_E = \Delta t \cdot \sum_{t \in T} \left\{ \sum_{g \in G} \left( C_g^{NL_G} u_{g,t}^G + C_g^{Op_G} P_{g,t}^G \right) + C_t^{grid+} P_t^{grid+} \right\}$
      - Energy costs and cost associated with running generators per hour
    - Water Distribution Cost: $f_W = \Delta t \cdot \sum_{t \in T} \{ C^{Op_{WW}} W_t^{WW} + C^{Op_{WT}} W_t^{WT} + C_t^{main+} W_t^{main+} \}$
      - Water import cost and costs of running treatment plants per volume of water
        - Including operational expenses such as labor, chemicals, and maintenance costs [1], [2]
  - System constraints involve microgrid energy management (MEM) elements, and micro water management (MWM) elements

[1] A. W. Sekandari, "Cost Comparison Analysis of Wastewater Treatment Plants," *IJSTE – International Journal of Science, Technology and Engineering*, vol. 6, 2019.
[2] Advisan, "The Cost of Desalination," [Online]. Available: https://prod-cm.advisian.com/en/global-perspectives/the-cost-of-desalination.

# System Constraints

- MEM system constraints include:
  - Generator output limits
  - Main grid import limits
  - Energy storage limits
    - Charging/discharging
    - Charge level
  - Power Balance
    - All power input set to balance out combination of power demand and renewable generation

- MWM system constraints include:
  - Water treatment output flow rate limits
    - Wastewater and desalination units
      - Wastewater also features untreated wastewater reservoir capacity limits
  - Water treatment power consumption
    - Power consumed per output flow rate produced
  - Water storage system limits
    - Water fill up and release
    - Water storage level
  - “Water Balance”
    - Balance of water demand and combined flow rate produced by water resources

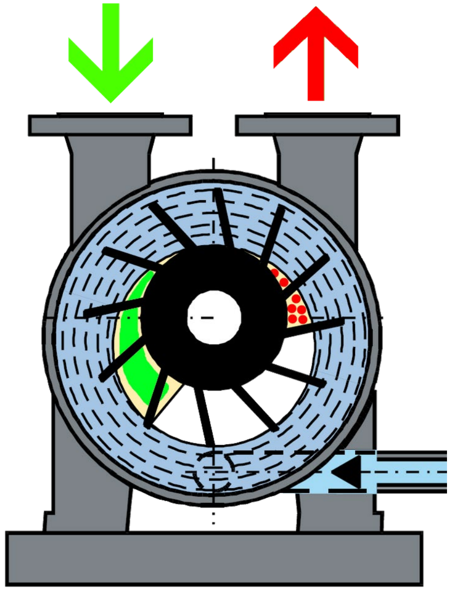


# Water-Energy Interdependence

- Power balance involves power consumption of MWM system
  - Power balance constraint: $\sum_{g \in G} P_{g,t}^{G} + \sum_{e \in S_E} \left[ P_{e,t}^{ESd} - P_{e,t}^{ESc} \right] + P_t^{grid+} = P_t^{net}, (\forall t \in T)$
    - Net load: $P_t^{net} = P_t^{L} - P_t^{WP} - P_t^{SP} + P_t^{MWM}, (\forall t \in T)$
    - MWM power consumption: $P_t^{MWM} = \underbrace{P_t^{WW} + P_t^{WT}}_{\text{Power consumption of treatment units}} + \underbrace{P_{pump,t}^{WW} + P_{pump,t}^{WT} + \sum_{s \in S_W} P_{pump,s,t}^{ST}}_{\text{Power consumption of output pumps of each water resource}}, (\forall t \in T)$
    - Wastewater: $W_t^{WW} = \gamma^{WW} P_t^{WW} \ , \ (t \in T)$
    - Water Desalination: $W_t^{WT} = \gamma^{WT} P_t^{WT} \ , \ (t \in T)$
      - $\gamma$ represents rate of amount of water treated per unit of energy consumed (e.g., $m^3$/kWh)

# Water Pumps Power Consumption

- Electric power consumption of water pumps can be represented with a quadratic relation as a function of water flow rate output
  - $P_{pump} = a_{pump} W^2 + b_{pump} W + c_{pump}$
    - $a$, $b$, and $c$ coefficients are obtained based on properties of the water pumps
    - Relationship is known as "pump curve" and data points are provided by manufacturer's datasheets [1]
- For every water source
  - $P_{pump,t}^{WW} = a_{pump}^{WW} \left(W_t^{WW}\right)^2 + b_{pump}^{WW} \left(W_t^{WW}\right) + c_{pump}^{WW} u_t^{WW}, \ (\forall t \in T)$
  - $P_{pump,t}^{WT} = a_{pump}^{WT} \left(W_t^{WT}\right)^2 + b_{pump}^{WT} \left(W_t^{WT}\right) + c_{pump}^{WD} u_t^{WT} \ , \ (\forall t \in T)$
  - $P_{pump,s,t}^{ST} = a_{pump}^{ST} \left(W_{s,t}^{STc}\right)^2 + b_{pump}^{ST} \left(W_{s,t}^{STc}\right) + c_{pump}^{ST} u_{s,t}^{STc} \ , \ (\forall s \in S_W, t \in T)$
    - Water storage uses a pump to fill up tanks, and a simple valve to release stored water
    - Release occurs with normal pressure due to water weight and gravitational force

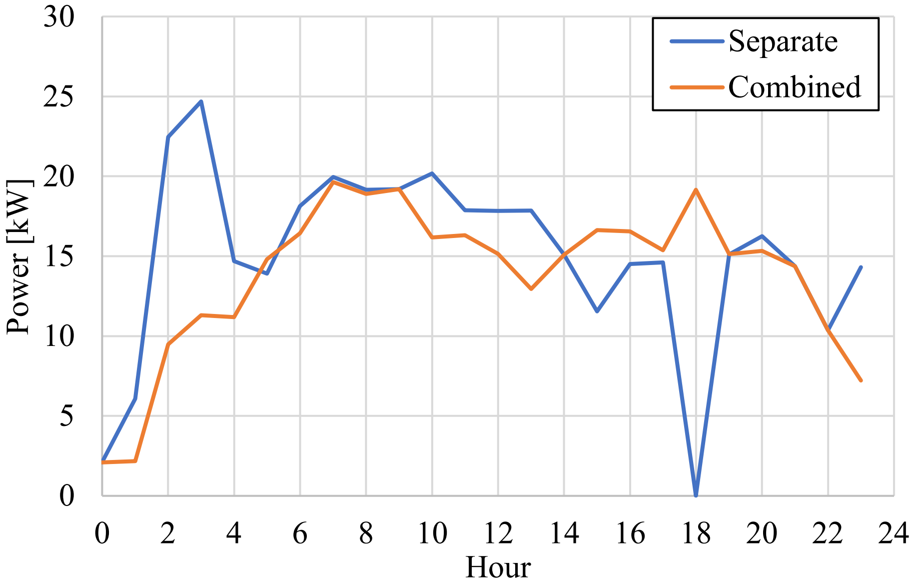


[1] B. Ulanicki, J. Kahler, and B. Coulbeck, "Modeling the efficiency and power characteristics of a pump group," *Journal of Water Resources Planning and Management*, vol. 134, no. 1, pp. 88-93, 2008.

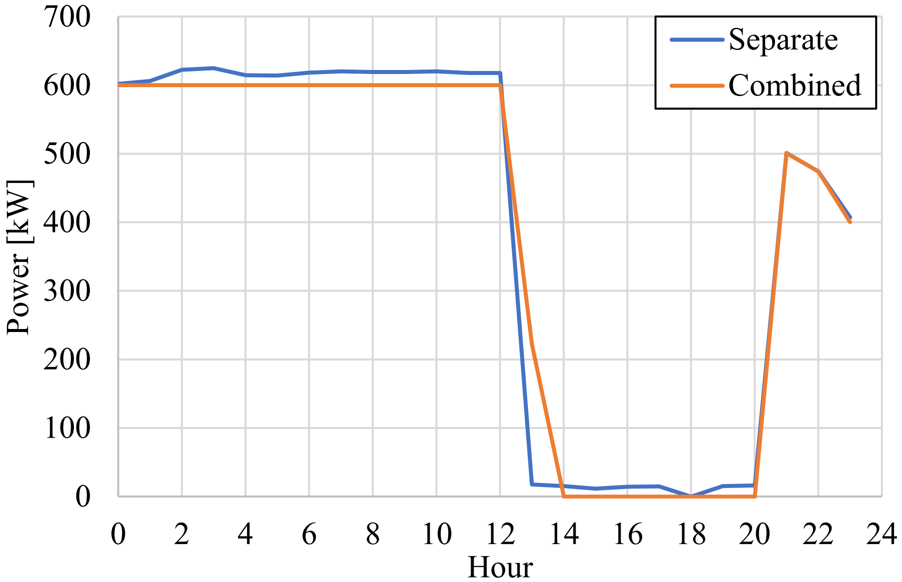
# Separate and Combined Operations Comparison

- Benchmark case: separate operation of microgrid energy management (MEM) and micro water management (MWM) systems
  - MWM meets its water demand using power from main grid
    - MWM operation cost function: $f_W = \Delta t \cdot \sum_{t\in T}\left\{C^{Op_{WW}} W_t^{WW} + C^{Op_{WD}} W_t^{WD} + C_t^{main+} W_t^{main+} + C_t^{grid+}\left(\underbrace{P_t^{WW} + P_t^{WT} + P_{pump,t}^{WW} + P_{pump,t}^{WT} + \sum_{s\in S_W} P_{pump,s,t}^{ST}}_{\text{Water treatment and pumps power consumption}}\right)\right\}$
    - Variable price is known by MWM operator
  - MEM meets only residential and commercial power demand
    - MEM Power Balance: $\sum_{g\in G} P_{g,t}^{G} + \sum_{e\in S_E}\left[P_{e,t}^{ESd} - P_{e,t}^{ESc}\right] + P_t^{grid+} = P_t^{L} - P_t^{WP} - P_t^{SP}\ ,\ (\forall t \in T)$
    - Excluding MWM power consumption
- Water-Energy Co-Optimization case: implements MWEN system
  - Energy costs of MWM power consumption incur by MEM operator
- Comparison will show combined operation cost reductions

# Resource Operation Analysis




MWM system power consumption




Main grid power import

- Access to local variety of energy resources in the microgrid allows for a more strategic economic dispatch
  - Water management power consumption profile changes for a more strategic use of energy sources
  - Main grid import during peak hours is reduced

# Cost Benefit Analysis

Operation costs for separate MEM and MWM operations, as well as combined MWEN operation

| | Separate Operation | Combined MWEN Operation | Difference |
|---|---|---|---|
| **MEM Op. Cost** | \$298.13 | \$312.16 | \$14.03 (4.60%) |
| **MWM Op. Cost** | \$181.86 | \$160.08 | \$21.78 (12.74%) |
| **TOTAL** | \$479.99 | \$472.24 | \$7.75 (1.63%) |

- Overall combined operation cost reduction of 1.6%
  - Microgrid energy management (MEM) operation costs went up by 4.6%, but micro water management (MWM) operation costs went down by 12.7%
    - MWM power consumption cost in separate case:
      - $\Delta t \cdot \sum_{t \in T} C_t^{grid+} P_t^{MWM} = \$19.98$
    - MEM cost increase represents the new energy costs of MWM power consumption in combined case
      - I.e., MWM Power consumption cost: \$19.98 → \$14.03
    - Energy costs of MWM power consumption reduced by **29.8%**

# Chapter 2: Summary

- The proposed Micro Water-Energy Nexus (MWEN) operation provides important economic benefits
  - Water distribution costs related to energy consumption are reduced by 30%
- **Research Contribution:**
  - Expanded <u>cross-utility integration</u> of a variety of water-energy interdependencies
    - Energy intensity of different treatment processes
      - Wastewater
      - Desalination
    - Power consumption of water pumps

**Publications:**

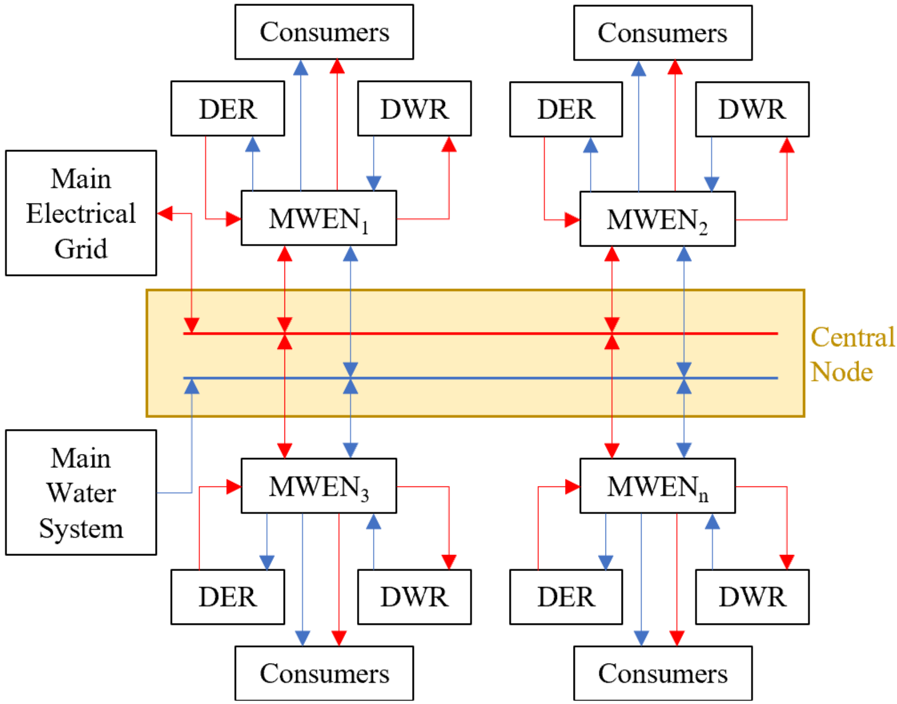
- J. Silva-Rodriguez and X. Li, "Water-Energy Co-Optimization for Community-Scale Microgrids," *2021 North American Power Symposium (NAPS)*, College Station, TX, USA, 2021, pp. 1-6, doi: 10.1109/NAPS52732.2021.9654518.

# Chapter 3

## Centralized Network Operation of Micro Water-Energy Nexus

# Network of MWEN Systems

- Networked Micro Water-Energy Nexus (Net-MWEN)
  - Multiple individual nearby systems interconnected
  - Strategic water and energy distribution
  - Collaborative resource exchange to collectively minimize operation costs
- Centralized Operation
  - All resources are scheduled by central management system for optimal sharing among network participants
    - Information from all participants communicated through central system
  - Central Node Topology



# Net-MWEN Co-Optimization

- Water-Energy Co-Optimization across multiple networked MWEN systems
  - $minimize\ \sum_{m \in M} f_{cost,m} = \sum_{m \in M} \left[ f_{E,m} + f_{W,m} \right]$
- Both water and energy distribution follow a central node topology
  - All power and water flows through a central bus and junction, respectively
- System assumptions/considerations:
  - Trading with main grid and main WDS is less beneficial than trading within the network [1]
    - Energy pricing: $C_t^{grid-} \leq C_t^{Np} \leq C_t^{grid+}$
    - Water pricing: $C_t^{Nw} \leq C_t^{main+}$
      - No water export due to constant water price

[1] W. Zhang and Y. Xu, "Distributed Optimal Control for Multiple Microgrids in a Distribution Network," *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 3765-3779, July 2019, DOI: 10.1109/TSG.2018.2834921.

# Proportional Exchange

- Network optimization is executed as a single entity system
  - Minimizing combined cost of all local MWEN systems as a whole
    - Individual MWEN exchange cost becomes irrelevant
      - **May result in solutions that do not benefit all MWEN equally**
  - Proportional adjustment of power and water exchanges among MWEN is needed
    - Fair economic benefits to all participants must be achieved
    - Overall Net-MWEN minimum cost solution must be preserved
- Proportional Exchange Algorithm (PEA)
  - Post-optimization processing balancing power and water exchanges based on individual supply and demand needs

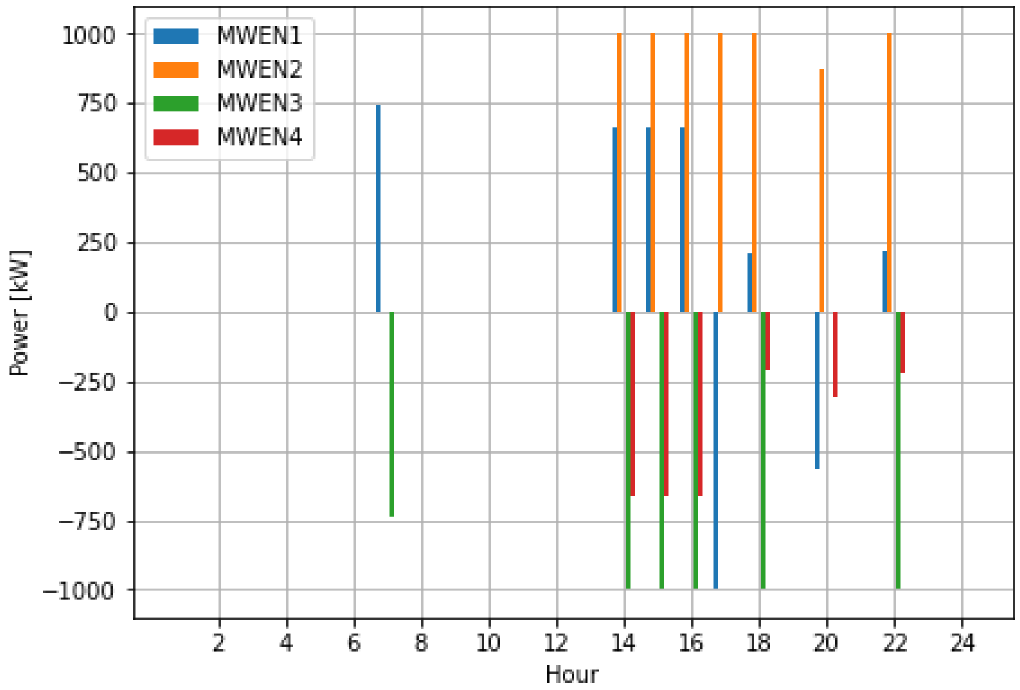
Algorithm 1: PEA for power exchange in networks of MWENs.

1. Solve MWEN optimization and obtain power exchanges $P_{m,n,t}^{N+}$ and $P_{m,n,t}^{N-}$, and the net exchanges of each microgrid $P_{m,t}^{E}$.
2. Allocate space for new variables $P_{m,t}^{E+}$ and $P_{m,t}^{E-}$
3. **For** $t$ in $T$
4.   **For** $m$ in $M$
5.     **If** $p_{m,t}^{N+} = 1$
6.       Set $P_{m,t}^{E+} = \left|P_{m,t}^{E}\right|$ and $P_{m,t}^{E-} = 0$
7.     **Else**
8.       Set $P_{m,t}^{E+} = 0$ and $P_{m,t}^{E-} = \left|P_{m,t}^{E}\right|$
9.   **end For**
10.   **For** $m$ in $M$
11.     **If** $p_{m,t}^{N+} = 1$
12.       **If** $\sum_{m \in M} P_{m,t}^{E+} > \sum_{m \in M} P_{m,t}^{E-}$
13.         **For** $n$ in $M$ $(m \neq n)$
14.           $P_{m,n,t}^{N+} = \frac{P_{m,t}^{E+}}{\sum_{m \in M} P_{m,t}^{E+}} \cdot P_{n,t}^{E-}$
15.         **end For**
16.       **Else**
17.         **For** $n$ in $M$ $(m \neq n)$
18.           $P_{m,n,t}^{N+} = \frac{P_{m,t}^{E+}}{\sum_{m \in M} P_{m,t}^{E-}} \cdot P_{n,t}^{E-}$
19.         **end For**
20.       Set $P_{m,t}^{grid+} = P_{m,t}^{E+} - \sum_{n \in M, n \neq m} P_{m,n,t}^{N+}$ and $P_{m,t}^{grid-} = 0$
21.     **Else**
22.       **If** $\sum_{m \in M} P_{m,t}^{E+} < \sum_{m \in M} P_{m,t}^{E-}$
23.         **For** $n$ in $M$ $(m \neq n)$
24.           $P_{m,n,t}^{N-} = \frac{P_{m,t}^{E-}}{\sum_{m \in M} P_{m,t}^{E-}} \cdot P_{n,t}^{E+}$
25.         **end For**
26.       **Else**
27.         **For** $n$ in $M$ $(m \neq n)$
28.           $P_{m,n,t}^{N-} = \frac{P_{m,t}^{E-}}{\sum_{m \in M} P_{m,t}^{E+}} \cdot P_{n,t}^{E+}$
29.         **end For**
30.       Set $P_{m,t}^{grid-} = P_{m,t}^{E-} - \sum_{n \in M, n \neq m} P_{m,n,t}^{N-}$ and $P_{m,t}^{grid+} = 0$
31.   **end For**
32. **end For**

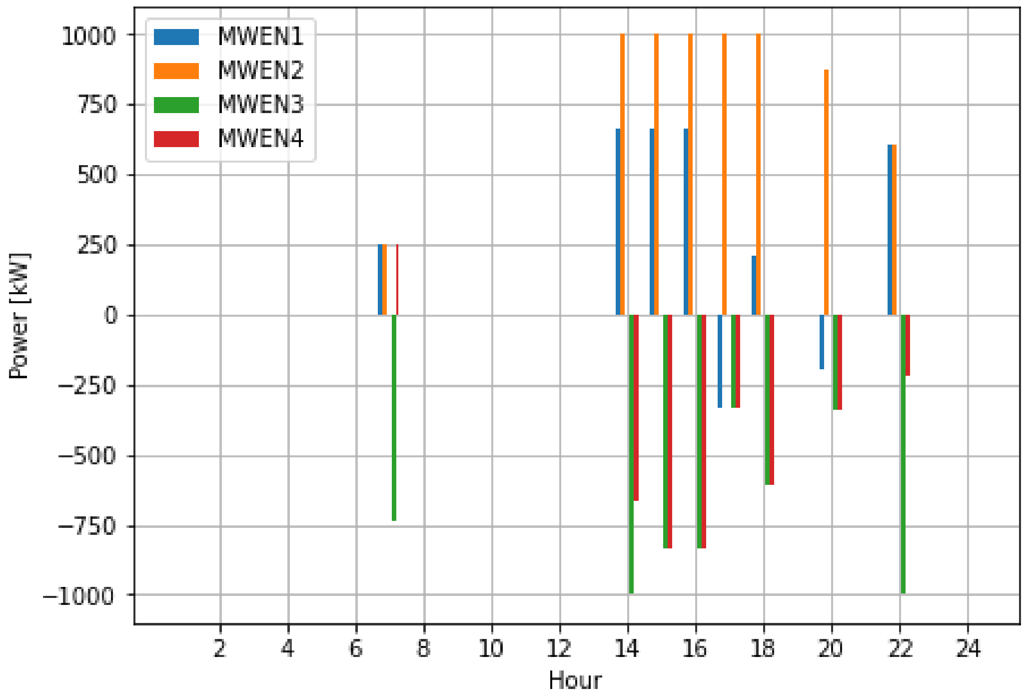
*Similar for water exchange

# PEA Analysis Results

- Exchanges of electric power among MWEN systems are more balanced when the proposed proportional exchange algorithm (PEA) is introduced



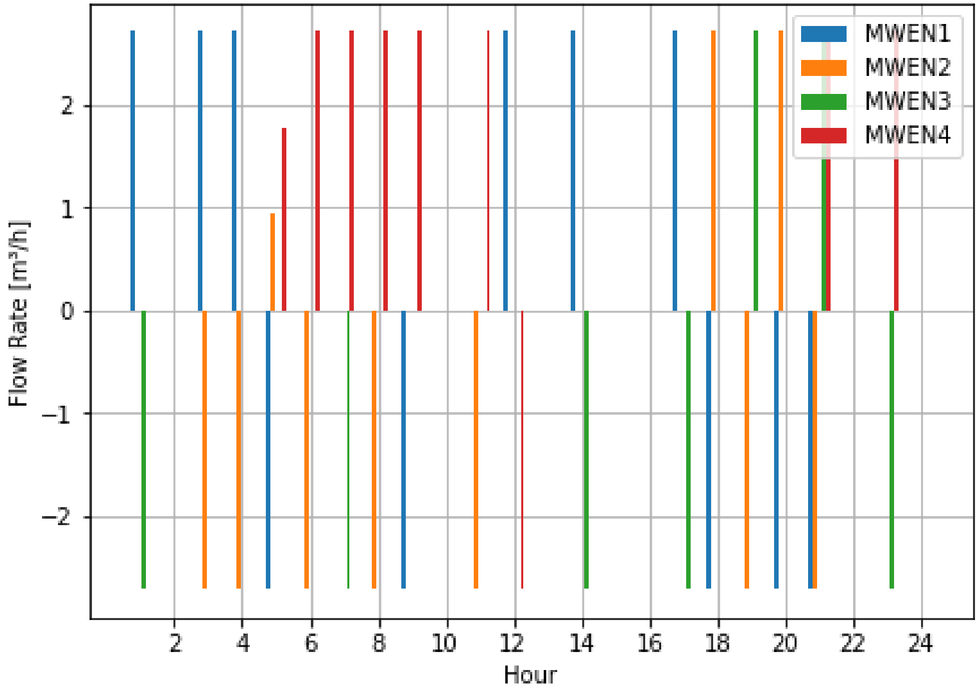

Network Power Exchanges Without PEA



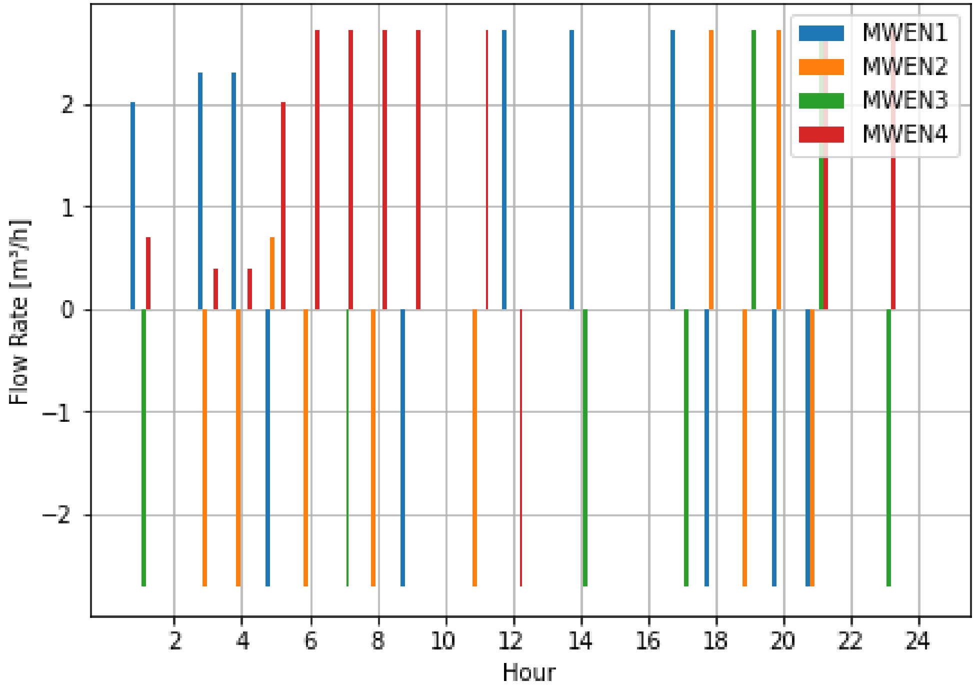

Network Power Exchanges With PEA

# PEA Analysis Results

- Similar results for water exchange among MWEN systems
  - More balanced exchange among participants



Network Water Exchanges Without PEA



Network Water Exchanges With PEA

# Economic Benefits Results

- There is substantial operation costs reductions for each MWEN system
  - An overall combined reduction of 5.4% is achieved

| MWEN | Separate MWEN Cost | Combined NetMWEN Cost | % Difference |
|---|---|---|---|
| 1 | $406.43 | $396.34 | 2.48% |
| 2 | $1371.85 | $1318.83 | 3.86% |
| 3 | $155.55 | $120.03 | 22.84% |
| 4 | $-78.44 | $-80.02 | 2.01% |
| TOTAL | $1855.40 | $1755.18 | 5.40% |

# Chapter 3: Summary

- A combined operation cost reduction is achieved among all participants compared to their separate operation
- The implemented proportional exchange algorithm (PEA) ensures a fair economic benefit balance based on individual system import/export needs when main grid and water network are a present
- **Research Contributions:**
  - Cross-utility integration across multiple localities
  - Network-level operational complexity considering individual economic benefits

**Publications:**

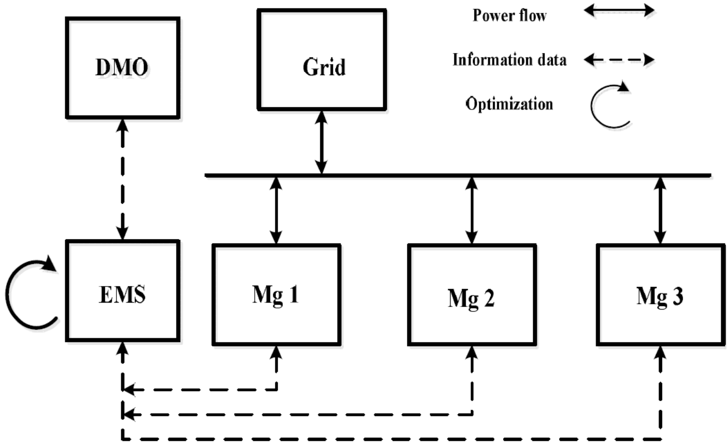
- J. Silva-Rodriguez and X. Li, "Centralized Networked Micro Water-Energy Nexus with Proportional Exchange Among Participants," *2022 North American Power Symposium (NAPS)*, Salt Lake City, UT, USA, 2022, pp. 1-6, doi: 10.1109/NAPS56150.2022.10012160.

# Chapter 4

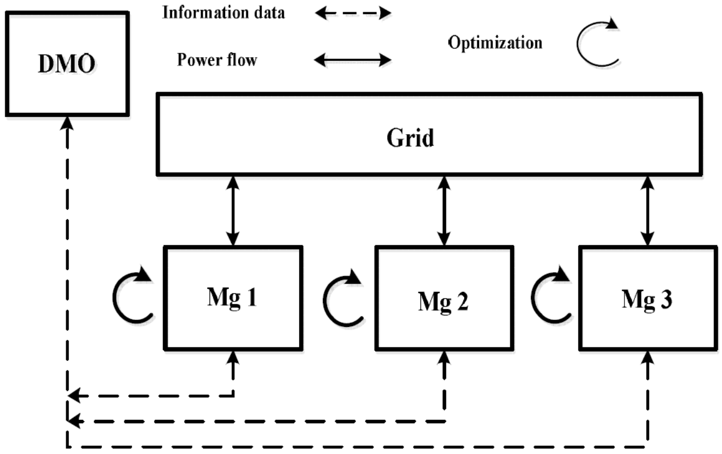
# Decentralized Networked Microgrid Energy Management

# Centralized vs. Decentralized Network Operation

- Centralized energy management
  - All relevant information of each microgrid at the disposal of a single energy management system [1]
  - Significant investment to implement control center [2]
  - Privacy concerns for network participants [2]
- Decentralized energy management
  - Each MG schedules itself separately with minimal information sharing with other MGs [1]
  - Robustness against communication failures [2]
  - Privacy protection of local MG information [2]
- Fully distributed optimization method needed
  - **Alternating Direction Method of Multipliers (ADMM)**




Centralized energy management




Decentralized energy management

[1] F. Khavari, A. Badri, A. Zangeneh and M. Shafiekhani, “A comparison of centralized and decentralized energy-management models of multi-microgrid systems,” *2017 Smart Grid Conference (SGC)*, Tehran, Iran, 2017, pp. 1-6.
[2] C. Feng, F. Wen, et al., “Decentralized Energy Management of Networked Microgrid Based on Alternating-Direction Multiplier Method,” *Energies*, vol. 11, 2018.

# Alternating Direction Method of Multipliers (ADMM)

- ADMM is often applied to solve problems where the function optimization can be carried out locally, and then coordinated globally via constraints
  - For example: interconnection of microgrids into a distribution network to solve a decentralized energy-management model
- Network decomposition for ADMM implementation is possible for problems of the form [1]:
  - $minimize\ f(x) = \sum_{i \in N} f_i(x_i)$ Sum of local objective functions
    $subject\ to\ \sum_{i \in N} A_i x_i = b$ Global constraint
- Then the problem is relaxed with an augmented Lagrangian [1]:
  - $L(x, y) = \sum_{i \in N} f_i(x) + \sum_{i \in N} \underline{\lambda}^T A_i x_i - \underline{\lambda}^T b + \frac{\rho}{2} \left\| \sum_{i \in N} A_i x_i - b \right\|_2^2$

Penalty Parameter

Lagrange Multiplier

[1] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Found. Trends Mach. Learn.*, vol. 3, no. 1, pp. 10–12, 2011.

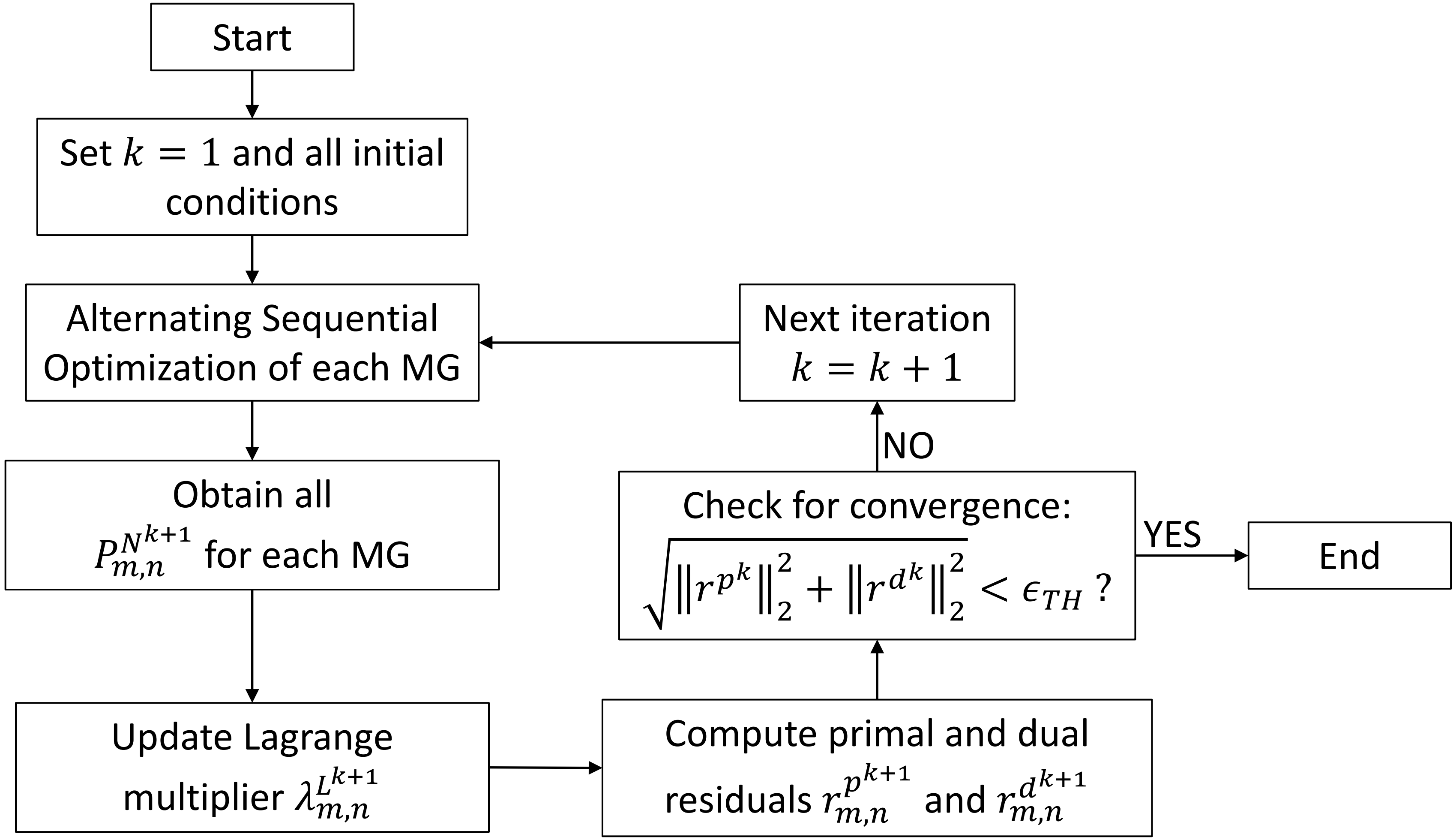
# Network of Microgrids Optimization Model

- Optimization model for centralized operation
- Objective function: $minimize\ \sum_{m\in M} f_{cost,m}$ → Sum of local objective functions
  - $f_{cost,m} = \sum_{t\in T} \Delta t \left\{ \sum_{g\in G} \left[ \left( C_{m,t}^{NL_G} u_{m,t}^{G} + C_{m}^{Op_G} P_{m,t}^{G} \right) \right] + C_t^{grid+} P_{m,t}^{grid+} - C_t^{grid-} P_{m,t}^{grid-} + C_t^{Np} \underline{P_{m,n,t}^{N}} \right\}$

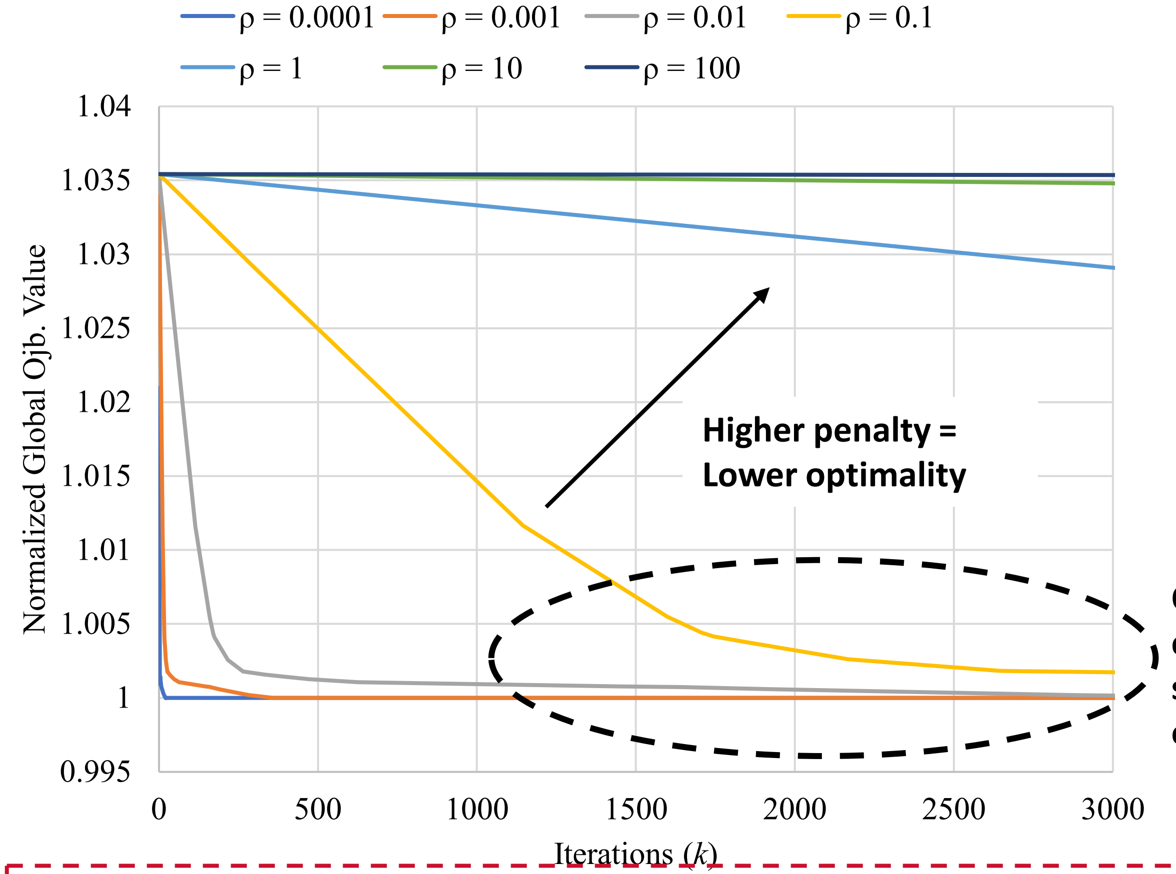
Power Exchanges between microgrid *m* and microgrid *n*.
Positive quantity: power import.
Negative quantity: power export.

- Global Constraint: network power exchanges
  - $P_{m,n,t}^{N} + P_{n,m,t}^{N} = 0,\ (\forall m, n \in M, n \neq m, t \in T)$
    - The import of microgrid *m* coming from *n* must be equal in magnitude to the export of *n* going to *m*
- Augmented Lagrangian
  - $L_\rho = \sum_{m\in M} f_{cost,m} + \sum_{m\in M} \sum_{t\in T} \sum_{n\in N, n\neq m} \left[ \lambda_{m,n,t}^{L} \left( \boldsymbol{P_{m,n,t}^{N}} + \boldsymbol{P_{n,m,t}^{N}} \right) + \frac{\rho}{2} \left( \boldsymbol{P_{m,n,t}^{N}} + \boldsymbol{P_{n,m,t}^{N}} \right)^2 \right]$

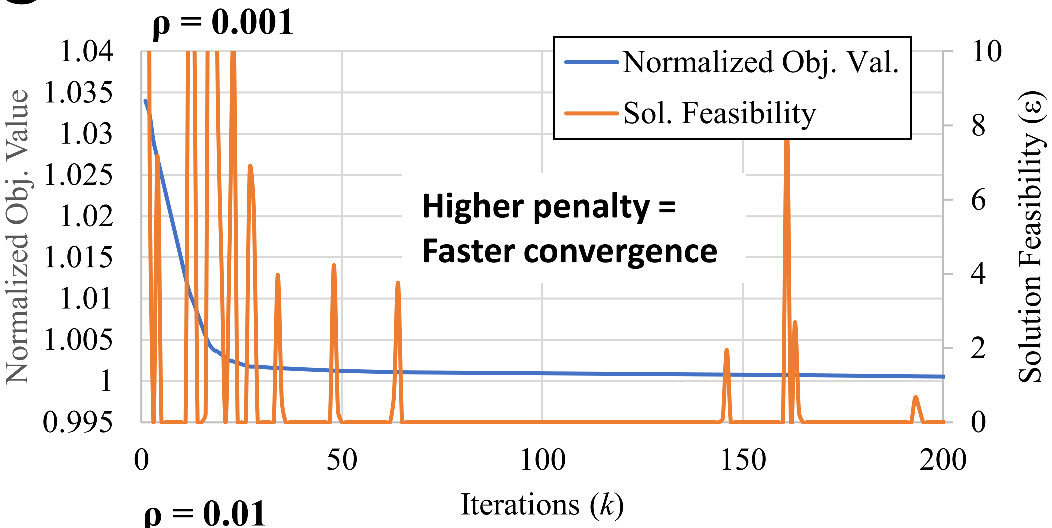
# ADMM Algorithm for Network of Microgrids

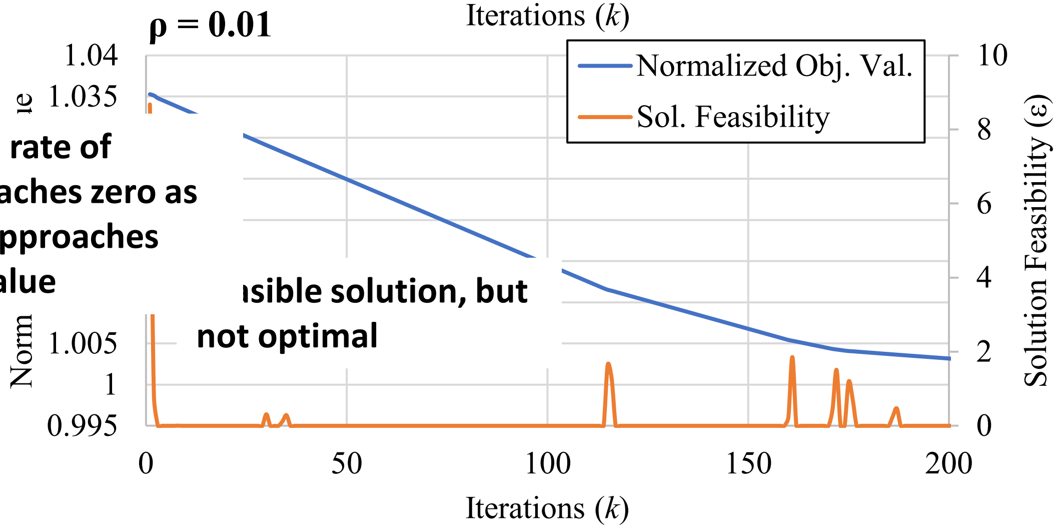


# ADMM Convergence Analysis



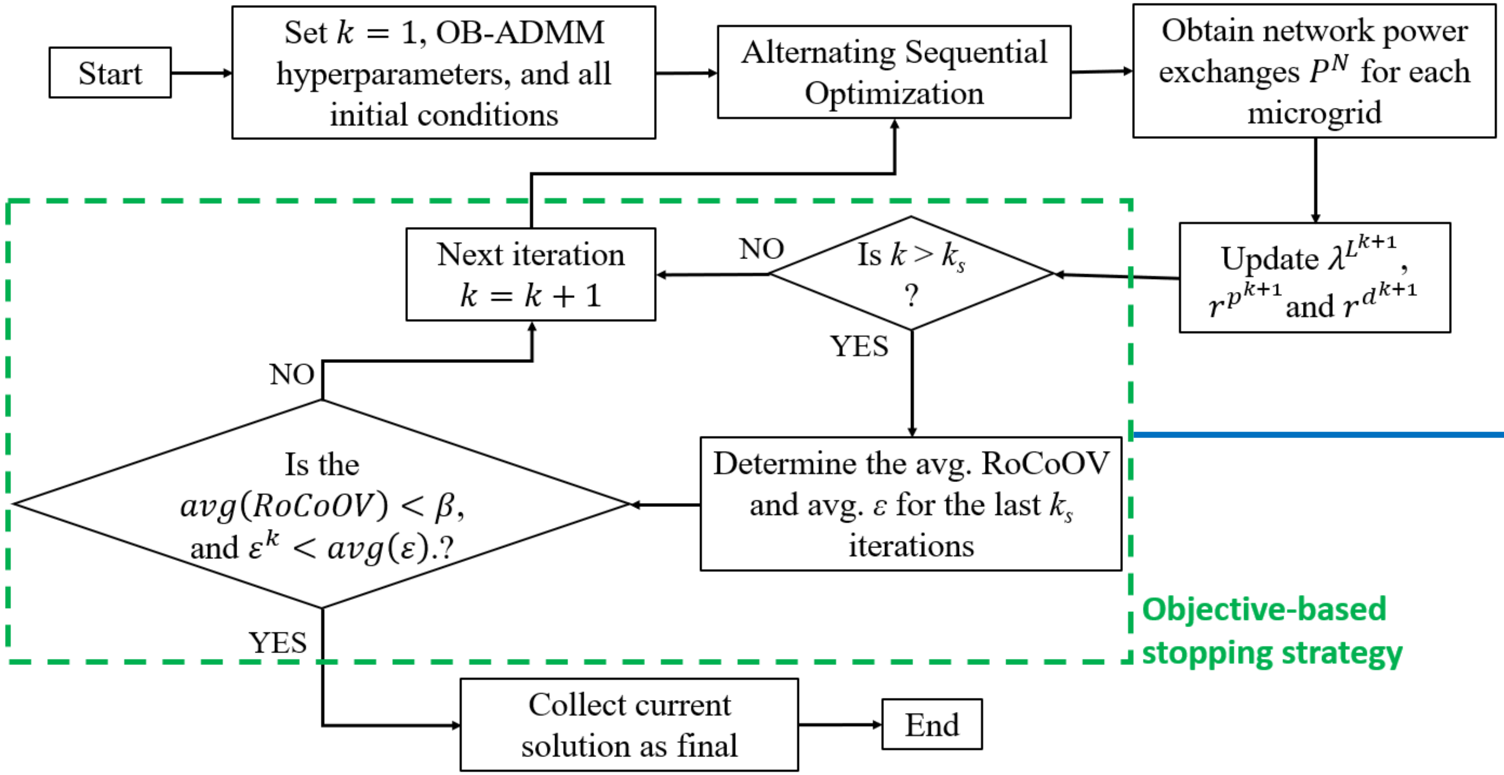

Obj. value rate of change reaches zero as solution approaches optimal value




*A combination of solution feasibility and global objective value must be considered to determine convergence

# Objective-Based Approach




In addition to:

$$\sqrt{\|r^{L^k}\|_2^2 + \|s^{L^k}\|_2^2} < \epsilon_{TH}$$

| | |
|---|---|
| $\beta$: | Average rate of change of the objective value (RoCoOV) threshold. |
| $\varepsilon_{th}$: | Feasibility metric threshold for single-node microgrid ADMM formulation. |

# Standard ADMM vs. OB-ADMM

- Objective-based ADMM (OB-ADMM) introduces two new hyperparameters
  - $k_s$: Iteration offset
    - Number of iterations through which avg. solution feasibility and obj. value rate of change is analyzed
  - $\beta$: Obj. value rate of change threshold
    - Minimum rate of change of objective value in the last $k_s$ iterations
  - Optimality increases with higher $k_s$ and lower $\beta$, at the expense of taking more iterations
    - Higher guarantee of optimality than standard ADMM

Results for a penalty $\rho = 0.001$ and $\varepsilon_{th} = 0.01$

Standard ADMM results

| Iterations (k) | % Difference from Optimal Obj. Value |
|---|---|
| 6 | 2.290 % |

OB-ADMM results

| Iteration Offset ($k_s$) | Avg. Obj. Value Change Threshold (β) | Iterations (k) | % Difference from Optimal Obj. Value |
|---|---|---|---|
| 50 | 0.001 | 407 | 0.000 % |
| 50 | 0.01 | 374 | 0.148 % |
| 50 | 0.1 | 74 | 0.103 % |
| 25 | 0.001 | 385 | 0.000 % |
| 25 | 0.01 | 305 | 0.014 % |
| 25 | 0.1 | 52 | 0.121 % |

# Importance of Initial Values for ADMM

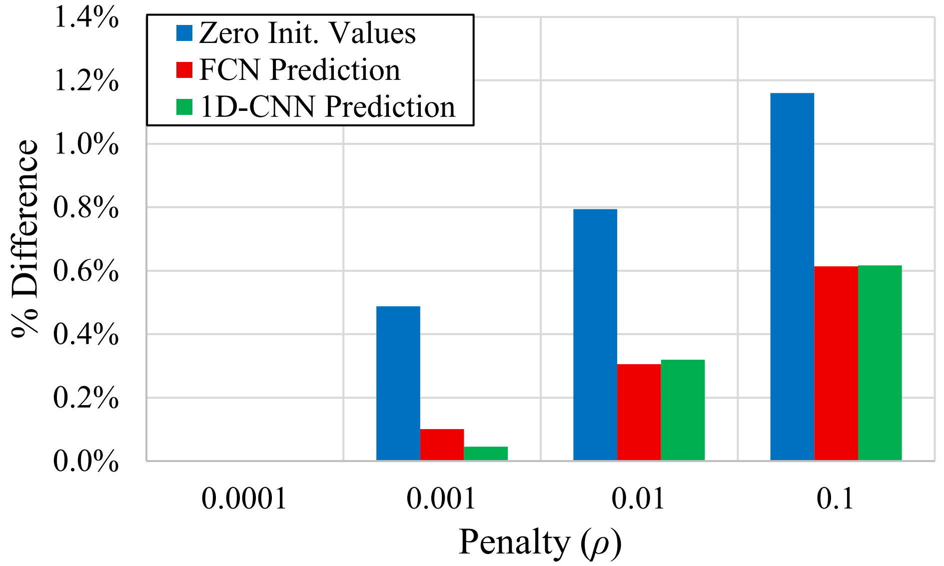
- Premise: Closer initial values are to the actual solution may yield higher optimality
  - However, in a real situation, the global optimal solution for the network is not known
  - Power exchange must be estimated as close as possible and used as initial values for the ADMM algorithm

| Penalty (ρ) | Offset percentage (%) | Standard ADMM | | OB-ADMM | |
|---|---|---|---|---|---|
| | | Iterations (k) | Obj Val % Difference | Iterations (k) | Obj Val % Difference |
| 0.001 | Zero init. values | 25 | 1.2417 | 283 | 0.4876 |
| | 30 | 19 | 0.0999 | 79 | 0.0036 |
| | 20 | 18 | 0.0133 | 45 | 0.0026 |
| | 10 | 27 | 0.0019 | 46 | 0.0004 |
| 0.01 | Zero init. values | 4 | 29.878 | 619 | 0.8110 |
| | 30 | 6 | 5.0553 | 98 | 0.1198 |
| | 20 | 17 | 0.6957 | 73 | 0.0792 |
| | 10 | 20 | 0.0603 | 49 | 0.0371 |
| 0.1 | Zero init. values | 13 | 32.196 | 2601 | 1.1709 |
| | 30 | 3 | 7.0544 | 651 | 0.1367 |
| | 20 | 3 | 4.3536 | 435 | 0.0934 |
| | 10 | 5 | 2.0364 | 220 | 0.0485 |

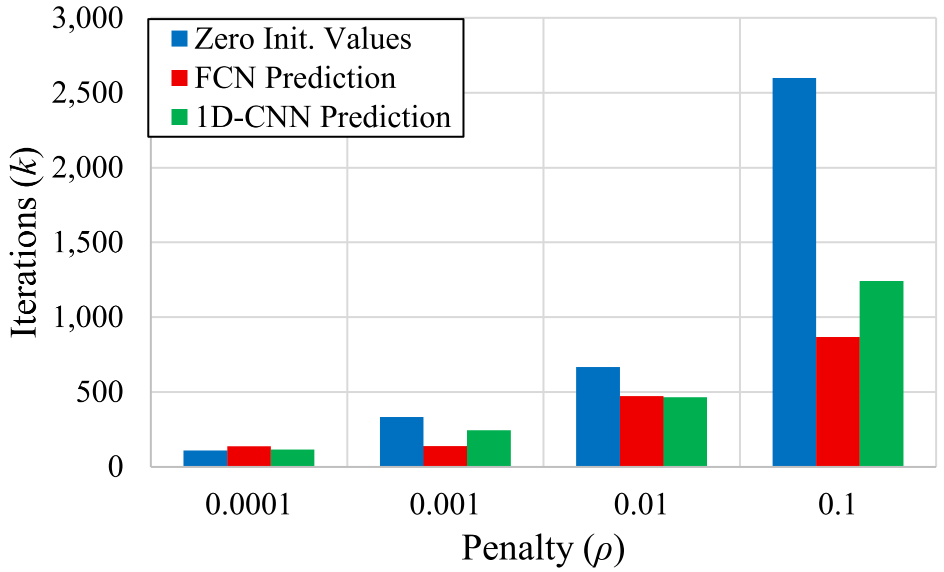
- Improved optimality
- Lower number of iteration when using OB-ADMM

# ADMM ML-Assisted Model Evaluation

- Using a fully connected network (FCN) and a convolutional neural network (CNN)
  - Models trained with 4,000 sample cases of different MG net load and grid prices
    - 10% of cases for testing and 10% for validation
  - 50 additional evaluation cases
- Model Performance




Final optimality as % difference from centralized benchmark



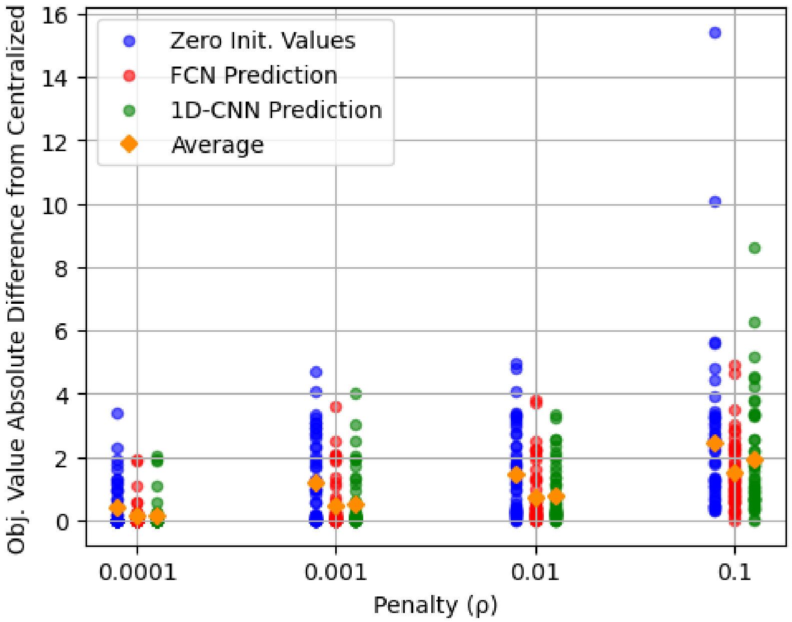

Number of iterations taken to achieve solution.

# ML-Assisted Method Robustness Analysis

Average % improvement of obj. value and iterations for each ML model using OB-ADMM

| Penalty (ρ) | FCN | | 1D-CNN | |
|---|---|---|---|---|
| | Obj. Value | Iterations | Obj. Value | Iterations |
| 0.0001 | 66.748% | 14.230% | 58.469% | -2.145% |
| 0.001 | 59.420% | 7.977% | 55.566% | 9.784% |
| 0.01 | 49.340% | -0.906% | 45.523% | 0.814% |
| 0.1 | 39.546% | 36.953% | 21.617% | 54.449% |

- Substantial optimality improvement compared to simply using zero initial values
- Number of iterations improves as well for most penalty selections
- OB-ADMM + ML initial value predictions increases final optimality and robustness towards penalty value selection




Absolute obj. value difference from centralized benchmark for the 50 additional test cases

# Chapter 4: Summary

- Decentralized approach achieves privacy preservation for MG network participants
  - Only communicate power exchange within the network
- Objective-based ADMM provides higher guarantee of global optimal solution
  - Coupled with initial value predictions via machine learning (ML), final solution optimality as well as algorithm robustness can be further improved
- **Research Contributions:**
  - Decentralized approach preserves autonomy and privacy needed for separate <u>ownership and governance</u> of each utility
  - <u>Operational complexity</u> is advanced by enhancing ADMM with objective-based and ML approaches

**Publications:**

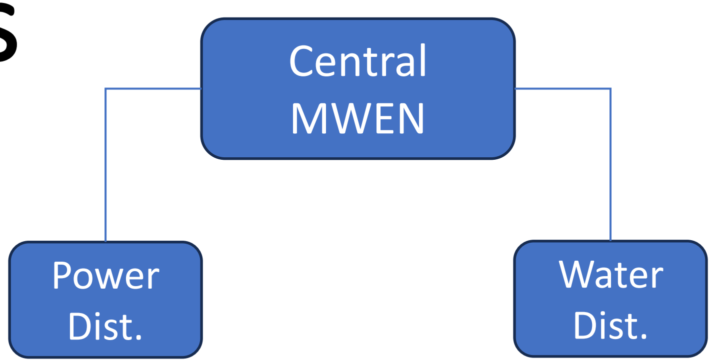
- Jesus Silva-Rodriguez, Xingpeng Li, Gino Lim, "Privacy-Preserving Networked Microgrid Energy Management via Objective-Based ADMM," *Electric Power Systems Research (PSSC Special Issue)*, 2026, [Under Review].
- Jesus Silva-Rodriguez and Xingpeng Li, "Decentralized Operations of Multi-Microgrid Systems: ML-Enhanced ADMM for Improved Optimality," *Applied Energy*, 2026, [Under Review].

# Chapter 5

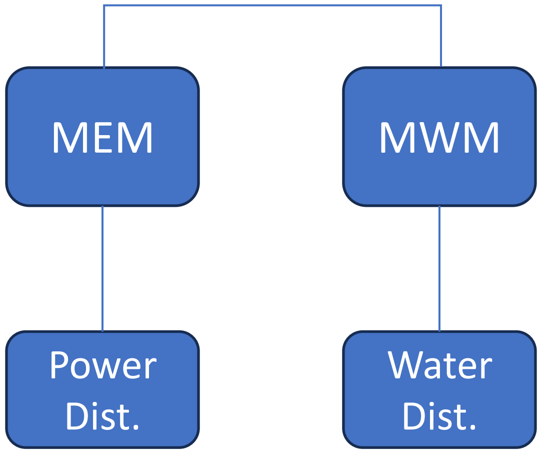
# Decentralized Water-Energy Co-Optimization

# Decentralized Water-Energy Operations

- Current water and electrical systems do not share control and operations
  - Water and electrical utilities are owned and operated separately
  - A centralized operation would require both systems to be under a single management system
- A decentralized micro water-energy nexus (MWEN) would be a more realistic application
  - Both systems may retain their autonomy
    - Microgrid energy management (MEM)
    - Micro water management (MWM)




Centralized Management




Decentralized Management

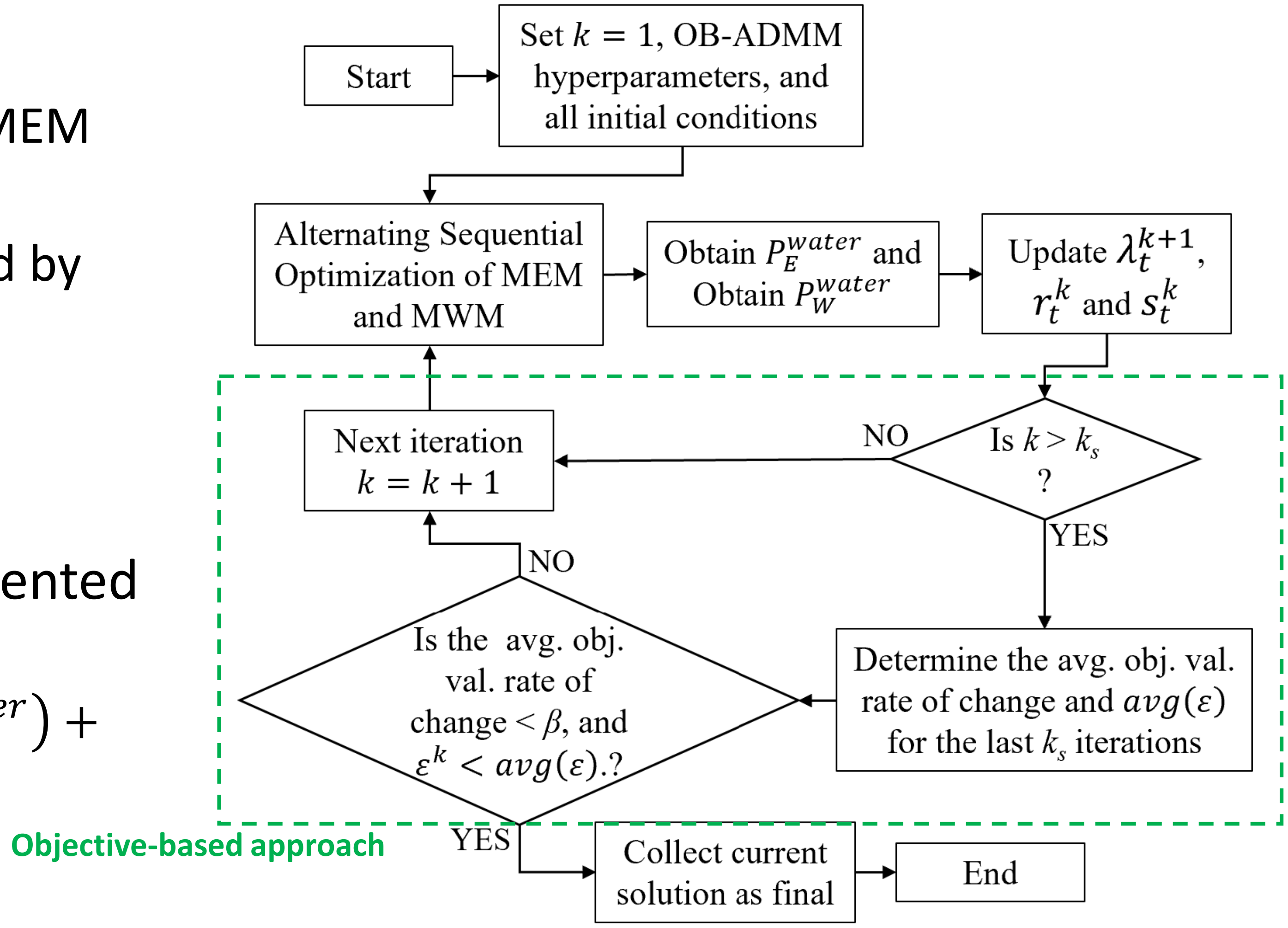
# ADMM for Decentralized MWEN

- Network decomposition for ADMM is possible in problems of the form:
  - $minimize\ f(x) = \sum_{i \in N} f_i(x_i)$
    $subject\ to\ \sum_{i \in N} A_i x_i = b$
  - Two systems (MEM and MWM): $N = 2$
    - $f_1 = f_E$ and $f_2 = f_W$
      - $f_E = \Delta t \cdot \sum_{t \in T} \left\{ \sum_{g \in G} \left( C_g^{NLG} u_{g,t}^G + C_g^{OpG} P_{g,t}^G \right) + C_t^{grid+} P_t^{grid+} \right\}$
      - $f_W = \Delta t \cdot \sum_{t \in T} \left\{ C^{OpWW} W_t^{WW} + C^{OpWT} W_t^{WT} + C_t^{main+} W_t^{main+} \right\}$
    - Power balance constraint: $\sum_{g \in G} P_{g,t}^G + \sum_{e \in S_E} \left[ P_{e,t}^{ESd} - P_{e,t}^{ESc} \right] + P_t^{grid+} = P_t^L - P_t^{WP} - P_t^{SP} + \boldsymbol{P_t^{MWM}}, (\forall t \in T)$
    - MWM power consumption: $\boldsymbol{P_t^{MWM}} = P_t^{WW} + P_t^{WT} + P_{pump,t}^{WW} + P_{pump,t}^{WT} + \sum_{s \in S_W} P_{pump,s,t}^{ST}, (\forall t \in T)$

**Global variable**

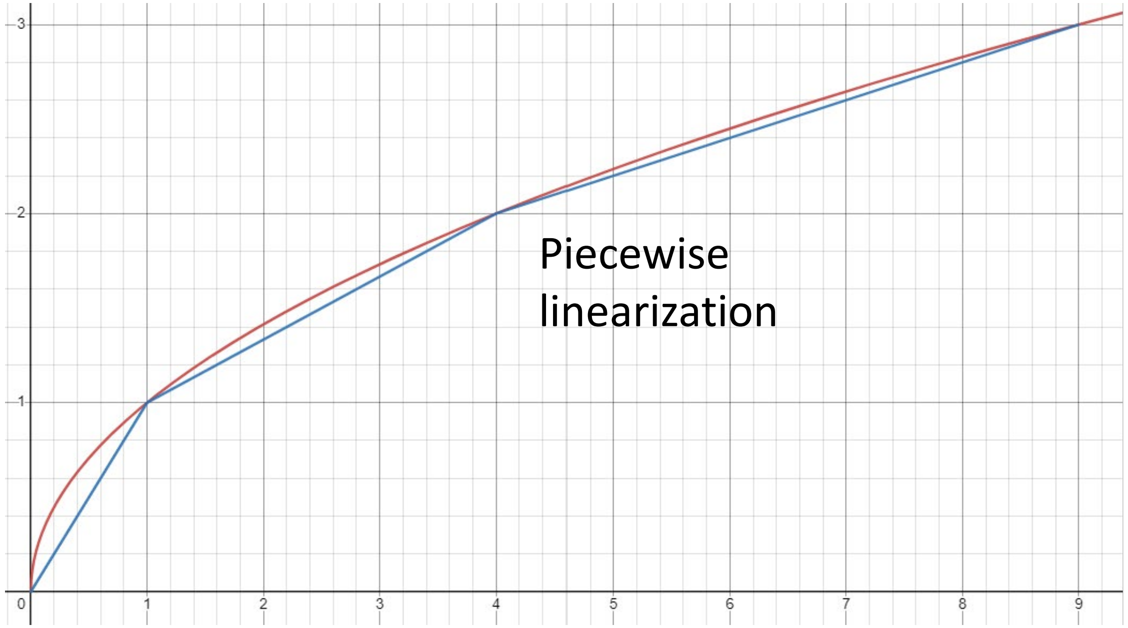
# ADMM for Decentralized MWEN

- Variable Duplication
  - MWM power consumption assumed by MEM operator: $P_{E,t}^{MWM}$
  - MWM power consumption as determined by MWM operator itself: $P_{W,t}^{MWM}$
- Global Constraint (i.e., $\sum_{i \in N} A_i x_i = b$)
  - $P_{E,t}^{MWM} - P_{W,t}^{MWM} = 0$
  - Relaxing constraint and forming augmented Lagrangian for ADMM algorithm:
    - $L_\rho = f_E + f_W + \sum_{t \in T} \lambda_t \left(P_{E,t}^{water} - P_{W,t}^{water}\right) + \frac{\rho}{2} \sum_{t \in T} \left(P_{E,t}^{water} - P_{W,t}^{water}\right)^2$



# Pump Power Constraints Linearization

- ADMM is a simple but powerful algorithm well suited for distributed convex optimization [1]
- MWEN Co-Optimization model is not convex
  - Water pump's power consumption equality constraints are non-affine functions [2]
    - $P_{pump} = aW^2 + bW + c$
    - Equation must be convexified
- Piecewise Linearization
  - Linearization via heuristics least-squares method [3]
    - Fitting multiple linear functions to input data, creating a piecewise linear fit
    - $P_{pump} \in F = \{aW + b\}^{\hat{v}}$
      - $\hat{v}$: number of linear functions of the piecewise set $F$



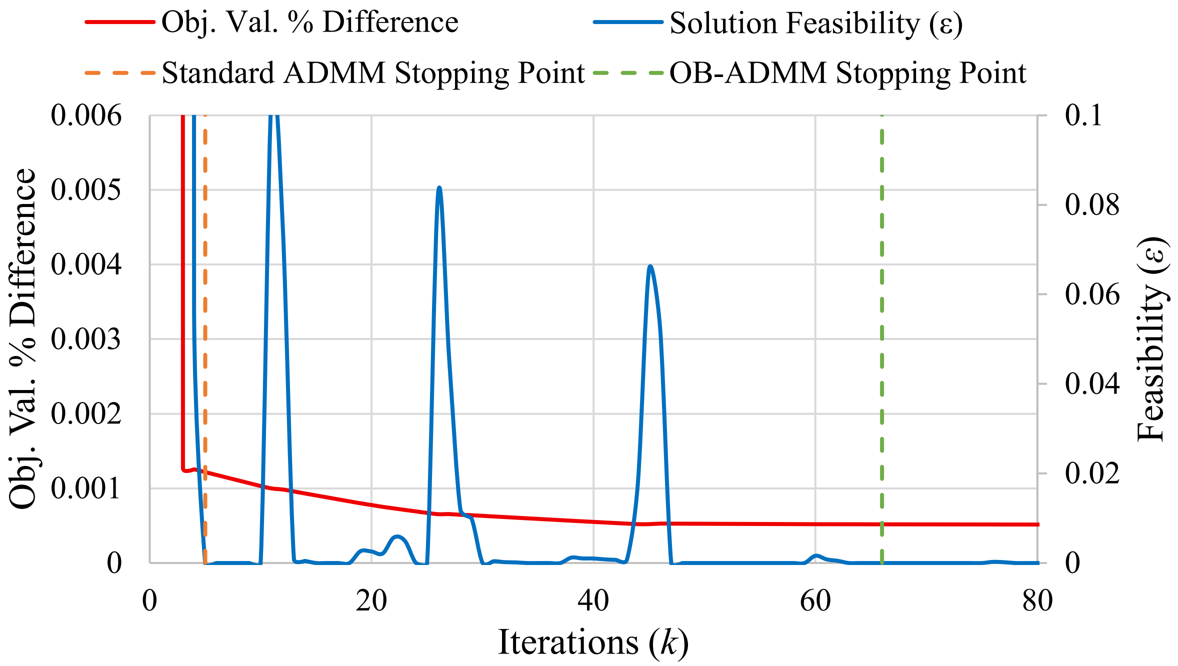

[1] S. Boyd, N. Parikh, E. Chu, B. Peleato, J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Found. Trends Mach. Learn.*, vol. 3, no. 1, pp. 1–24, Jan. 2011.

[2] S. Boyd, L. Vandenberghe, "Convex Optimization," *Cambridge University Press*, 7th Edition, pp. 136-138, 2009.

[3] A. Magnani and S. P. Boyd, "Convex piecewise-linear fitting," *Optimize Eng.*, vol. 10, no. 1, pp. 1–17, 2009.

# Standard ADMM vs. OB-ADMM Approach

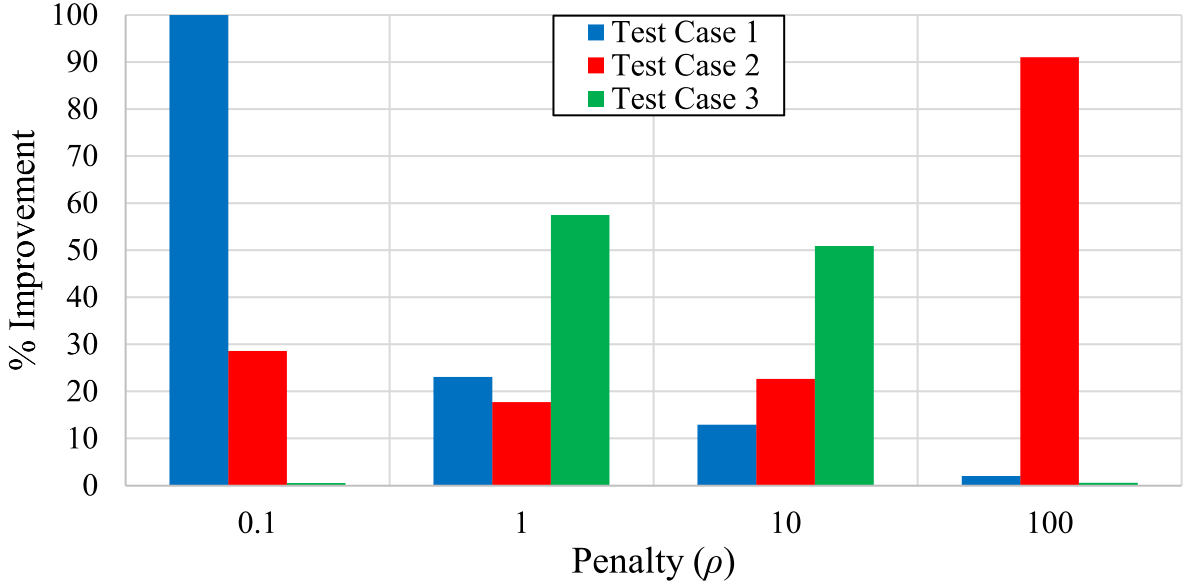
- $\varepsilon_{th} = 0.001, \beta = 0.001, k_s = 25$




Solution optimality and feasibility for MWEN via standard ADMM and OB-ADMM with $\rho$ = 1.

Results for MWEN standard and objective-based ADMM

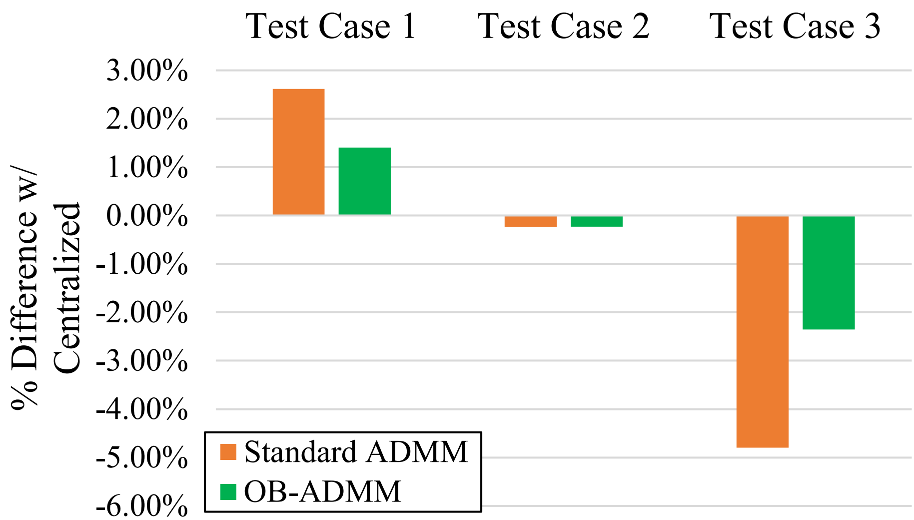
| Penalty $\rho$ | Standard ADMM | | OB-ADMM | |
|---|---|---|---|---|
| | % Difference w/ Centralized | Iterations ($k$) | % Difference w/ Centralized | Iterations ($k$) |
| 0.1 | 0.05% | 5 | 0.05% | 66 |
| 1 | 0.12% | 5 | 0.05% | 66 |
| 10 | 0.14% | 5 | 0.07% | 253 |
| 100 | 0.14% | 5 | 0.14% | 28 |



# Test Cases Results

- OB-ADMM is used to solve three different test cases
  - Test Case 1: 70 residential units and 3 commercial units, grid-connected
  - Test Case 2: 100 residential units and 4 commercial units, grid-connected
  - Test Case 3: 60 residential units and 2 commercial units, isolated


Objective value deviation from centralized model result for each ADMM approach.




Micro water management net energy consumption deviation from centralized model result for each ADMM approach.

# Chapter 5: Summary

- The proposed decentralized model is able to obtain a global optimal solution
  - Both operation cost and MWM energy consumption converge to the same quantities obtained by the centralized model
- Implementing OB-ADMM yielded optimality and convergence robustness compared to standard ADMM for MWEN problem
- **Research Contributions:**
  - Micro Water-Energy Nexus formulated for full system privacy and independent operation to maintain separate ownership and governance between water and energy systems
  - Piecewise linearization of pumps power consumption addresses operational complexities of non-convex formulation

**Publications:**

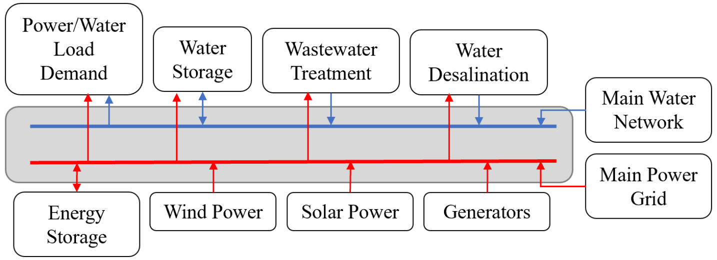
- J. Silva-Rodriguez and X. Li, “Decentralized micro water-energy co-optimization for small communities,” *Electric Power Systems Research*, vol. 234, 2024, doi: 10.1016/j.epsr.2024.110611.

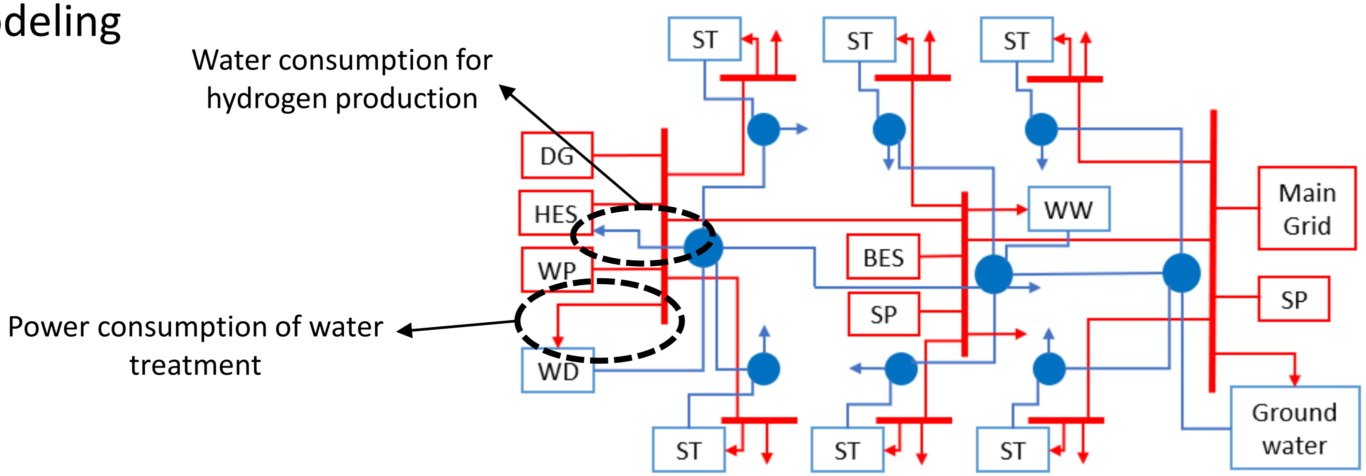
# Chapter 6

## Distribution-Level Water-Energy Nexus

# Micro Water-Energy Co-Optimization

- Water-Energy Nexus Distribution Network Modeling
  - Community-Scale: single-node models with small-scale distributed resources
  - Distribution-Level: multi-node interconnected system
    - Requires physical network modeling
      - Power lines
        - Power flow
        - Thermal limits
        - Voltage limits
      - Water pipes
        - Water pipe flow
        - Water flow limits
        - Pressure limits
    - Modeling of additional interdependencies between distribution systems
      - Water demand of electricity resources
      - Power demand of water resources



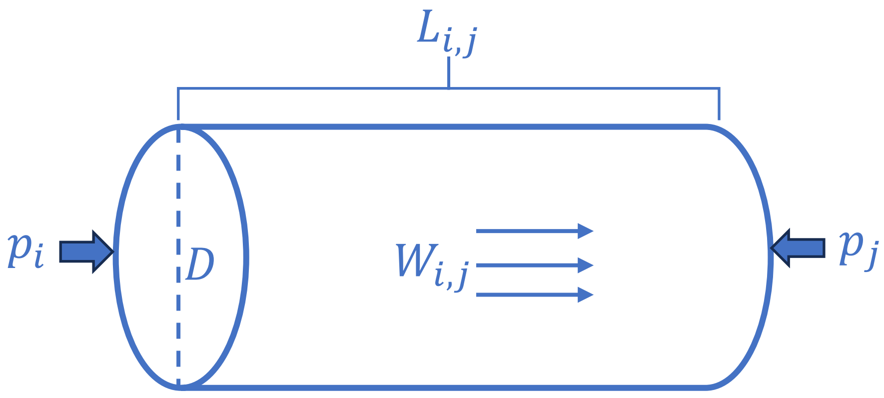
# Distribution System Power Flow (DistFlow) [1]

- Power flow for radial distribution networks [1]
- Second-order cone relaxation (SOCR) [2]
  - $\sum_{i\in N_u(j)}\left[P^l_{ij,t} - (I_{ij,t})^2 R_{ij}\right] = \sum_{i\in N_d(j)}\left[P^l_{ji}\right] + P_j^{load} - P_j^{gen}$ , $\forall j \in N, t \in T$
  - $\sum_{i\in N_u(j)}\left[Q^l_{ij,t} - (I_{ij,t})^2 X_{ij}\right] = \sum_{i\in N_d(j)}\left[Q^l_{ji}\right] + Q_j^{load} - Q_j^{gen}$ , $\forall j \in N, t \in T$
  - $(\overline{V}_{j,t})^2 = (\overline{V}_{i,t})^2 - 2\left(R_{ij}P^l_{ij,t} + X_{ij}Q^l_{ij,t}\right) + \left[(R_{ij})^2 + (X_{ij})^2\right](I_{ij,t})^2$ , $\forall i,j \in N, t \in T$
  - $\left(P^l_{ij,t}\right)^2 + \left(Q^l_{ij,t}\right)^2 \overset{\leq}{=} (I_{ij,t})^2(\overline{V}_{i,t})^2$ , $\forall i,j \in N, t \in T$
    - Making this an inequality creates a convex solution space rather than a tight nonconvex space.
    - However, this is a <u>relaxation</u>
      - Expanded solution space involves new points not feasible in original model
    - Inequality must be as close to equality as possible to reflect a real and possible solution

[1] M. Baran and F. F. Wu, Optimal sizing of capacitors placed on a radial distribution system," *IEEE Transactions on Power Delivery*, vol. 4, no. 1, pp. 735-743, Jan. 1989.
[2] A. Alizadeh, M. A. Allam, B. Cao, I. Kamwa, M. Xu, "On the application of the branch DistFlow using second-order conic programming in microgrids," *Electric Power Systems Research*, vol. 245, 2025.

# Water Pipe Flow Constraints

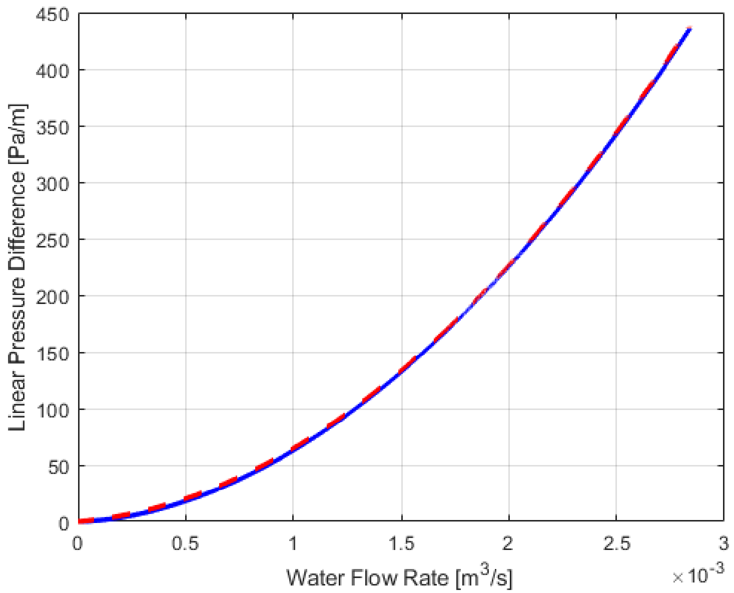
- Nodal pressure difference as a function of water flow rate [1]
  - $p_{i,t} - p_{j,t} = r_{i,j}^{l}\left(W_{i,j,t}^{l}\right)^{2}$ , $\forall\, i,j = 1,2,\dots,J, t \in T$
    - Darcy-Weisbach equation for incompressible fluids
  - Resistance factor $r^l$ is also a function of water flow rate
    - $r = f_D \frac{8\rho_w L}{\pi^2 D^5}$
      - Where $f_D = \frac{1.325}{\left[ln\left(\frac{\varepsilon}{3.7D}+\frac{5.74}{Re^{0.9}}\right)\right]^2}$
    - Reynolds number *Re* depends on water flow rate within the pipe
      - $Re = \frac{4W^{l}\rho_w}{\pi D \mu}$
  - Thus, we have
    - $p_{i,t} - p_{j,t} = \left(\frac{10.6\rho_w L_{i,j}}{\pi^2 D^5\left[ln\left(\frac{\varepsilon}{3.7D}+\frac{5.74}{\left(\frac{4W_{ij}^{l}\rho_w}{\pi D \mu}\right)^{0.9}}\right)\right]^2}\right)\cdot {W_{ij}^{l}}^{2}$




[1] P. R. Simpson, & S. Elhay, "Formulating the water distribution system equations in terms of heads and velocity," *10th Annual Symposium on Water Distribution Systems Analysis*, 2008.

# Darcy-Weisbach Quadratic Approximation

- Water pipe flow can be approximated as a quadratic expression
  - $\frac{p_{i,t}-p_{j,t}}{L_{ij}} = f(W)$
- Assuming commercial steel pipes of 2-in diameters with a maximum flow rate of 10.23 m³/h [1], [2]
  - $f(W) = (4.8570 \times 10^7)W^2 + (1.6210 \times 10^4)W \left[\frac{N}{m^3}\right]$
    - For 10,000 points plotted of original expression, an $R^2$ of 0.9998 is reached
  - This approximation requires absolute value of flow rate *W*
    - No direction is captured
  - Quadratic equality constraint:
    - $\frac{p_{i,t}-p_{j,t}}{L_{i,j}} = A_{i,j,t}\left[(4.8570 \times 10^7)\left(W_{i,j,t}^l\right)^2 + (1.6210 \times 10^4)W_{i,j,t}^l\right] \ , \ \forall i,j = 1,\dots,J, t \in T$
      - $A_{i,j,t} \in \{-1,1\}$: integer variable to represent flow direction




*$W^l$ must be in m³/s (SI units) for this expression to be dimensionally correct

# Water Pipe Flows SOCR

- Leveraging the same second order cone relaxation (SOCR) approach for DistFlow
- Derived quadratic constraint can be relaxed as an inequality
  - $p_{i,t} - p_{j,t} \geq L_{i,j}\left[(4.8570 \times 10^7)\left(W^l_{i,j,t}\right)^2 + (1.6210 \times 10^4)W^l_{i,j,t}\right] - (1 - y_{i,j,t})M \;,\; \forall i,j \in J, i < j, t \in T$
  - $p_{j,t} - p_{i,t} \geq L_{i,j}\left[(4.8570 \times 10^7)\left(W^l_{i,j,t}\right)^2 + (1.6210 \times 10^4)W^l_{i,j,t}\right] - y_{i,j,t}M \;,\; \forall i,j \in, J, i < j, t \in T$
  - $A_{i,j,t} = 1 - 2y_{i,j,t} \;,\; \forall i,j \in, J, i < j, t \in T$
    - $y_{i,j,t}$: Binary auxiliary variable to help define flow direction $A_{i,j,t}$
      - "BigM" method is used to establish constraints to ensure flow direction
      - Note that $W^l_{i,j,t} \geq 0$
  - Water balance must be updated to correctly account for water flow into and out of each junction node *i*
    - $W^{WW}_{i,t} + W^{WT}_{i,t} - \sum_{j \in J, i<j}\left[A_{i,j,t}W^l_{i,j,t}\right] + \sum_{j \in J, j<i}\left[A_{j,i,t}W^l_{j,i,t}\right] + W^{STd}_{i,t} - W^{STc}_{i,t} = W^L_{i,t} \;,\; \forall i \in J, t \in T$

# Centralized Benchmark Solution

- Objective function
  - $f_{cost} = f_E + f_W = \sum_{t\in T} \Delta t \cdot \Big\{ \sum_{i\in N} \Big[ \Big( C_i^{GOp} P_{i,t}^G + C_i^{GNL} u_{i,t}^G \Big) + C_t^{grid+} P_{i,t}^{grid+} + \Omega^l \sum_{j\in N, j\neq i} I_{i,j,t}^S R_{i,j} \Big] + \sum_{i\in J} \Big[ C_i^{OpWW} W_{i,t}^{WW} + C_i^{OpWT} W_{i,t}^{WT} \Big] + \Omega^p \sum_{i,j\in J, i<j} [2w_{i,j,t} - (p_{i,t} - p_{j,t})] \Big\}$
- Optimal SOCR penalization weight parameters
  - Using Optuna [1], a Python-based open source hyperparameter optimization framework, a combination of $\Omega^l$ and $\Omega^p$ is obtained for optimal objective value, SOCR error, and computation time
  - Optimal weight parameters:
    - $\Omega^l = 15$
    - $\Omega^p = 0.1$

DistWEN centralized benchmark solution with and without SOCR penalizations

| Weight Parameters | Objective Value | Optimal Cost [$] | Line Current SOCR RMSE [$A^2$] | Nodal Linear Pressure Difference SOCR RMSE [MPa] | Computation Time [s] |
|---|---|---|---|---|---|
| Zero | 1403.17 | 1403.17 | 16.975 | 1.1867 | 32.315 |
| Optimal | 1405.89 | 1403.16 | 1.1234E-5 | 1.4057E-6 | 46.764 |

[1] T. Akiba, S. Sano, T. Yanase, T. Ohta, M. Koyama, "Optuna: A Next-generation Hyperparameter Optimization Framework," *Proceedings of the 25th ACM DIGKDD International Conference on Knowledge Discovery and Data Mining*, Association for Computing Machinery, New York, NY, 2019.

# DistWEN Model Decentralization

- Model Interdependencies (i.e., global constraints):
  - Active power demand at every node:
    - $P_{i,t}^{net} = P_{i,t}^{L} - P_{i,t}^{WP} - P_{i,t}^{SP} - P_{i,t}^{G} - P_{i,t}^{ESd} + P_{i,t}^{ESc} + P_{i,t}^{WW} + P_{i,t}^{WT} + P_{pump,i,t}^{WW} + P_{pump,i,t}^{WT} + P_{pump,i,t}^{ST}, \forall i \in N, t \in T$
  - Reactive power demand at every node:
    - $Q_{i,t}^{net} = Q_{t}^{L} - Q_{t}^{WP} - Q_{t}^{SP} - Q_{i,t}^{G} - Q_{i,t}^{ESd} + Q_{i,t}^{ESc} + Q_{i,t}^{WW} + Q_{i,t}^{WT} + Q_{pump,i,t}^{WW} + Q_{pump,i,t}^{WT} + Q_{pump,i,t}^{ST}, \forall i \in N, t \in T$
  - Water balance:
    - $W_{i,t}^{WW} + W_{i,t}^{WT} - \sum_{j \in J, i<j}[F_{i,j,t}] + \sum_{j \in J, j<i}[F_{j,i,t}] + W_{i,t}^{STd} - W_{i,t}^{STc} = W_{i,t}^{L} + W_{i,t}^{ES}, \forall i \in J, t \in T$
      - $F_{i,j,t} = A_{i,j,t} W_{i,j,t}^{l}, \forall i, j \in J, i < j, t \in T$

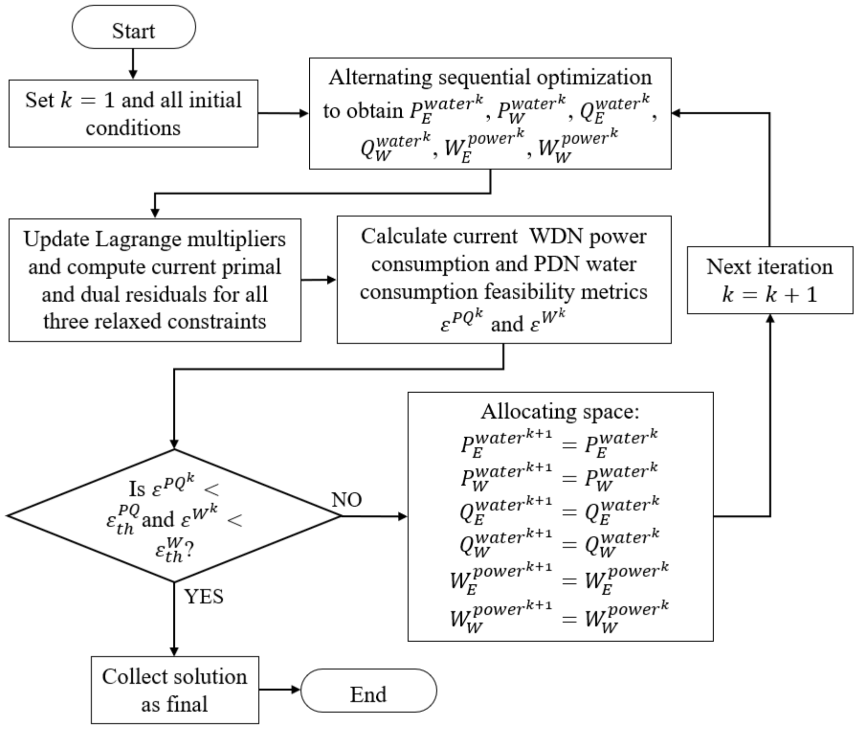
# Global Variable Definitions

- Additional auxiliary variables defined to facilitate decentralization
  - Active power consumption of WDN:
    - $P_{i,t}^{water} = P_{i,t}^{WW} + P_{i,t}^{WT} + P_{pump,i,t}^{WW} + P_{pump,i,t}^{WT} + P_{pump,i,t}^{ST}, \forall i \in N, t \in T$
  - Reactive power consumption of WDN:
    - $Q_{i,t}^{water} = Q_{i,t}^{WW} + Q_{i,t}^{WT} + Q_{pump,i,t}^{WW} + Q_{pump,i,t}^{WT} + Q_{pump,i,t}^{ST}, \forall i \in N, t \in T$
  - Water consumption of PDN:
    - $W_{i,t}^{power} = W_{i,t}^{ES}, \forall i \in J, t \in T$
- Variable duplication
  - Global variables are duplicated, with each duplicate declared by each system
    - $P_{E,i,t}^{water} = P_{W,i,t}^{water}, \forall i \in N, t \in T$
    - $Q_{E,i,t}^{water} = Q_{W,i,t}^{water}, \forall i \in N, t \in T$
    - $W_{E,i,t}^{power} = W_{W,i,t}^{power}, \forall i \in J, t \in T$

Global constraints to be relaxed for ADMM implementation

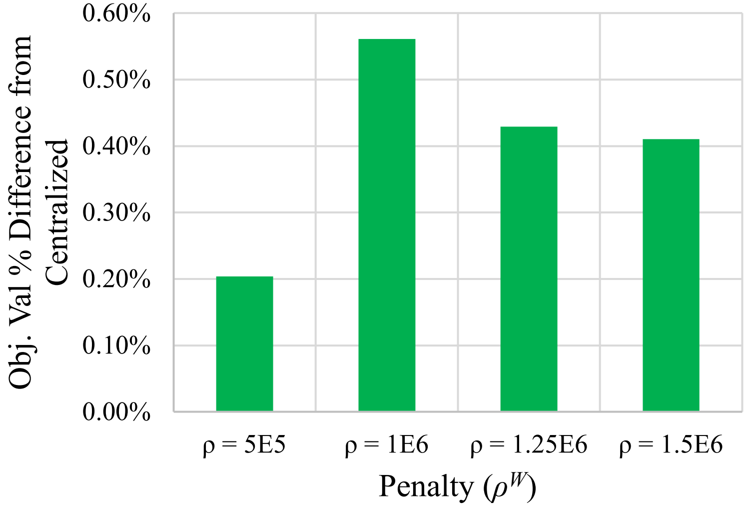
# DistWEN ADMM Convergence Criteria

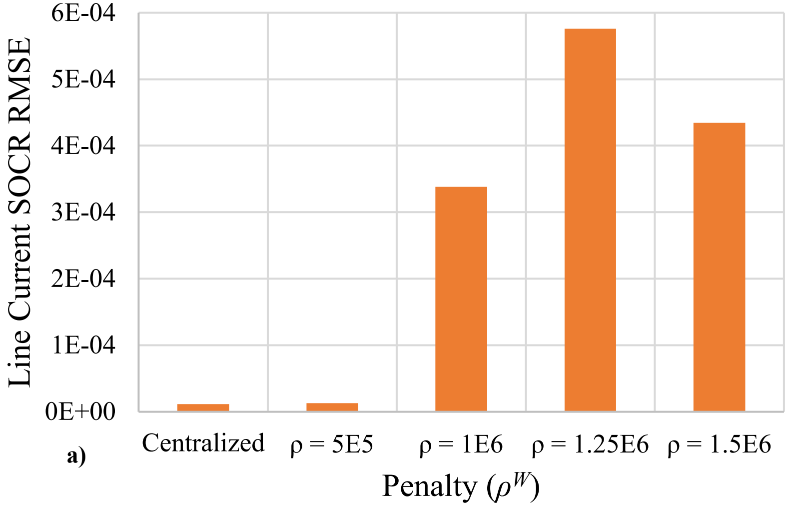
- Primal and Dual residuals are defined as usual
  - For a problem with a global constraint of the form:
    - $x_i = z_i$
  - Primal Residual:
    - $r^{p^{k+1}} = \sum_{i \in N} \left( x_i^{k+1} - z_i^{k+1} \right)$
  - Dual Residual:
    - $r^{d^{k+1}} = \sum_{i \in N} \left( x_i^{k+1} - z_i^{k+1} + z_i^k - x_i^k \right)$
- Two feasibility metrics are used to check for convergence
  - WDN Power consumption feasibility:
    - $\varepsilon^{PQ^k} = \sqrt{\left\| r^{p_P^k}, r^{p_Q^k} \right\|_2^2 + \left\| r^{d_P^k}, r^{d_Q^k} \right\|_2^2}$
  - PDN Water consumption feasibility:
    - $\varepsilon^{W^k} = \sqrt{\left\| r^{pw^k} \right\|_2^2 + \left\| r^{dw^k} \right\|_2^2}$



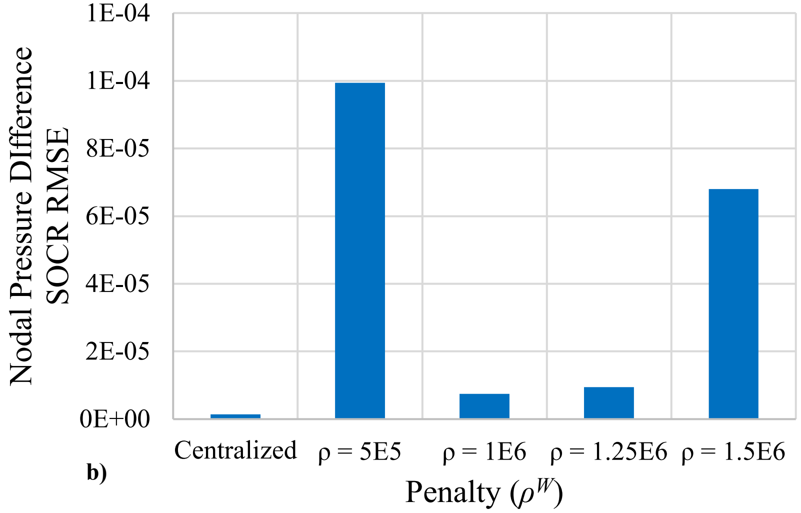
ADMM algorithm for Decentralized DistWEN Model

# Optimality and Error Minimization




a)

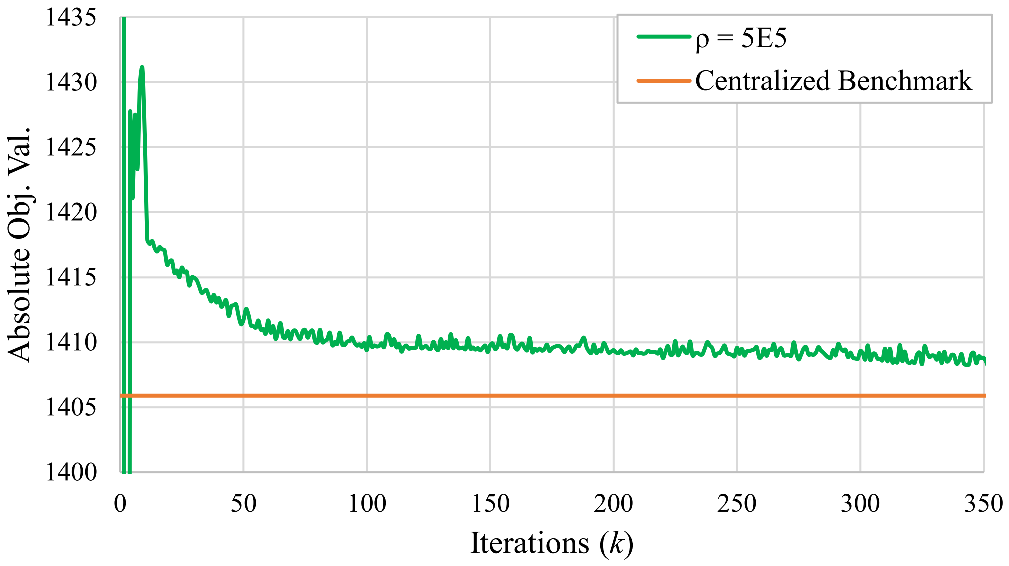


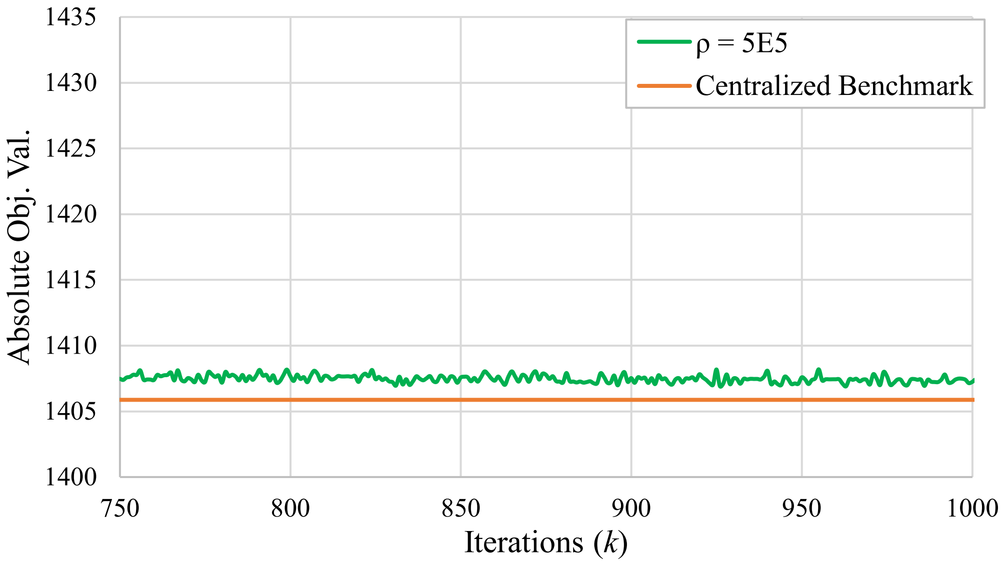

b)

- Near-optimal results achieve, with < 0.6% deviation from centralized benchmark solution
- Best optimality obtained with $\rho^W = 5 \times 10^5$, yielding lowest line current SOCR error, but highest nodal pressure difference SOCR error
- Hence, effective decentralization of DistWEN co-optimization is achieved
  - However, further refinement may be beneficial to reduce SOCR errors, as well as increased optimality

# Convergence Behavior

- Objective value converges in an oscillatory manner
  - Consequence of using an optimality gap of 0.1%
    - Necessary to keep computation time reasonable for every ADMM iteration
  - This hinders the possibility of properly tracking the rate of change of the obj. value (RoCoOV)
    - That is, objective-based ADMM cannot be applied as currently defined
  - Nonetheless, obj. value is converging towards optimum
    - Standard ADMM still effective
      - OB-ADMM would require further research for implementation



# Chapter 6: Summary

- **Research Contributions:**
  - Effectively convexified distribution-level water-energy nexus (DistWEN) co-optimization model, addressing operational complexities of the original model
    - Now compatible with decentralized algorithms
  - Decentralized DistWEN model enabled coordinated operation of a power distribution network (PDN) and a water distribution network (WDN) without full system integration and data sharing, preserving their separate ownership and governance
    - Decentralized operation closely matched that of the centralized model with at most 0.6% deviation
  - Full cross-utility integration implemented by coupling systems via power consumption of the WDN and water consumption of the PDN

# Conclusions and Future Work

# Contributions

1. Developed micro water-energy nexus (MWEN) co-optimization model, reducing total costs with combined operation vs. separate operation
2. Extended MWEN concept to networked operations of MWEN systems and introduced a proportional exchange algorithm for fair economic benefit allocation
3. Proposed and formulated an objective-based ADMM (OB-ADMM) for decentralized microgrid energy management with improved optimality results
4. Applied OB-ADMM to enable privacy-preserving decentralized MWEN co-optimization
5. Formulated a convex distribution-level water-energy nexus (DistWEN) co-optimization model integrating water and power distribution network operations
6. Implemented a decentralized DistWEN model via ADMM, achieving results with low deviation from optimal results of centralized model

# Future Work

- Immediate Next Steps:
  - Improve decentralized DistWEN formulation to reduce SOCR feasibility errors, improve final optimality, and enhance convergence checks
    - Potentially consider dynamic optimality gap, integer relaxations, and/or machine-learning initial value predictions/binary states predictions
  - Explore adaptive or automated penalty update strategies to improve ADMM performance
    - Including dynamic adjustment of SOCR penalization weight parameters
- Long-Term Next Steps:
  - Incorporate uncertainty modeling (e.g., stochastic programming or robust optimization) into the co-optimization framework
    - For prediction of demands, renewable generation, and water availability
  - Extend decentralized DistWEN concept to multi-utility/multi-resource co-ordination with broader scalability and infrastructure interconnection
    - Incorporate natural gas, hydrogen, or even transportation
  - Investigate market mechanisms and pricing schemes for interconnected multi-resource systems

# Additional Projects

- **Lunar Surface Power System Project | Oct. 2022 – Oct. 2023**
  - *Support from: NASA, EPRI, CenterPoint Energy*
  - Design analyses for ARTEMIS south polar lunar surface power system
- **Energy Flexibility Technology Survey Study | Nov. 2023 – Nov. 2024**
  - *Support from*: Shell International
  - Comprehensive review of energy flexible technologies across generators, loads, and energy storage systems
- **Cable Degradation and Remaining Useful Life Prediction for Proactive Cable Replacement | Mar. 2024 – May 2025**
  - *Support from*: DOE, CenterPoint Energy
  - Data-driven framework for EV load projection and resulting thermal cable degradation for proactive cable replacement planning

# List of Publications


1) J. Silva-Rodriguez and X. Li, "Water-Energy Co-Optimization for Community-Scale Microgrids," *2021 North American Power Symposium (NAPS)*, College Station, TX, USA, 2021.
2) J. Silva-Rodriguez and X. Li, "Centralized Networked Micro Water-Energy Nexus with Proportional Exchange Among Participants," *2022 North American Power Symposium (NAPS)*, Salt Lake City, UT, USA, 2022.
3) C. Zhao, J. Silva-Rodriguez and X. Li, "Resilient Operational Planning for Microgrids Against Extreme Events", *Hawaii International Conference on System Sciences*, Maui, Hawaii, USA, 2023.
4) J. Silva-Rodriguez, J. Lu and X. Li, "Cost-Benefit Analysis and Comparisons for Different Offshore Wind Energy Transmission Systems", *Offshore Technology Conference*, Houston, TX, USA, 2023.
5) J. Silva-Rodriguez, X. Li, "Decentralized micro water-energy co-optimization for small communities," *Electric Power Systems Research*, vol. 234, 2024.
6) J. Silva-Rodriguez, E. Raffoul and X. Li, "LSTM-Based Net Load Forecasting for Wind and Solar Power-Equipped Microgrids," *2024 56th North American Power Symposium (NAPS)*, El Paso, TX, USA, 2024.
7) J. Silva-Rodriguez, T. Zhao, R. Mo, E. Endler, X. Li, "Grid-Edge Energy Flexible Technologies: A Comparative Analysis Across Generators, Loads, and Energy Storage," *Renewable and Sustainable Energy Reviews*, 2026, [Under Review].
8) J. Silva-Rodriguez and X. Li, "Decentralized Operations of Multi-Microgrid Systems: ML-Enhanced ADMM for Improved Optimality," *Applied Energy*, 2026, [Under Review].
9) J. Silva-Rodriguez, X. Li, G. Lim, "Privacy-Preserving Networked Microgrid Energy Management via Objective-Based ADMM," *Power Systems Computational Conference*, Limassol, Cyprus, 2026, [Under Review].
10) J. Silva-Rodriguez and X. Li, "ADMM Penalty Parameter Evaluation for Networked Microgrid Energy Management," *IEEE PES General Meeting*, Montreal, Quebec, Canada, 2026, [Under Review].
11) L. Fang, J. Silva-Rodriguez, X. Li, "Data-Driven EV Charging Load Profile Estimation and Typical EV Daily Load Dataset Generation," *IEEE PES General Meeting*, Montreal, Quebec, Canada, 2026, [Under Review].
12) J. Silva-Rodriguez, E. Raffoul, L. Fang, J. D. Wright, R. Fatima, G. J. Boyle, K. Mohamed, J. Di Girolamo, E. Easton, X. Li, "Cable Degradation Estimation and Remaining Useful Life Prediction for Distribution Networks with High EV Penetration," *IEEE Transactions on Power Delivery*, 2026, [Under Review].
13) J. Silva-Rodriguez, R. Raj, H. Krishnamoorthy, X. Li, "Lunar Surface Power System Architecture: Optimal Design and Components Analysis," [In Preparation].

# Thank You!

¿? **QUESTIONS?** ¿?