



# Using Smart Meters to Improve the Management of Water Distribution Systems

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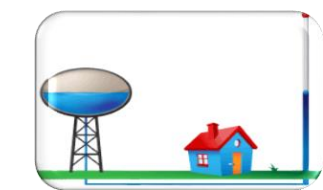
## Water Systems Management

### DMA Design and Implementation

Water distribution systems (WDSs) are dynamic and complex with networks with difficulties in achieving management goals, including:

#### Pressure uniformity across the network

Controlling pressure from the source is difficult, due to the location of demands and changes in elevation, leading to considerable pressure variations and ineffective energy consumption



#### Leakage detection

Isolated metered areas facilitate water balance to check for unaccounted water losses



**Objective** → To partition a water distribution system into isolated and measured sub-sectors called District Meter Areas (DMAs)

## Methodology

### Objective Function:

$$\text{Minimize CVDS} = \frac{1}{N_{\text{DMA}} - 1} \sum_{i=1}^{N_{\text{DMA}}} (D_i - D_{\text{av}})$$

Optimization algorithm: Pattern Search

Where: CVDS: Coefficient of variation of demand between DMAs.

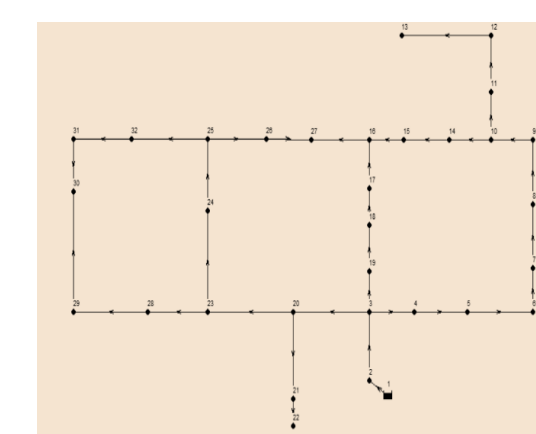
$n_{\text{dmAs}}$ : Number of defined DMAs.

$D_i$ : total demand of each DMA over the extended period of simulation.

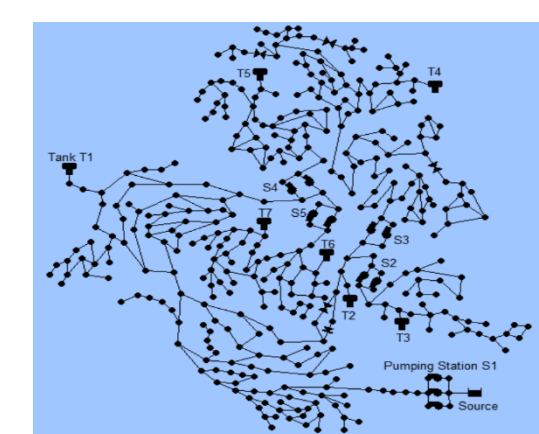
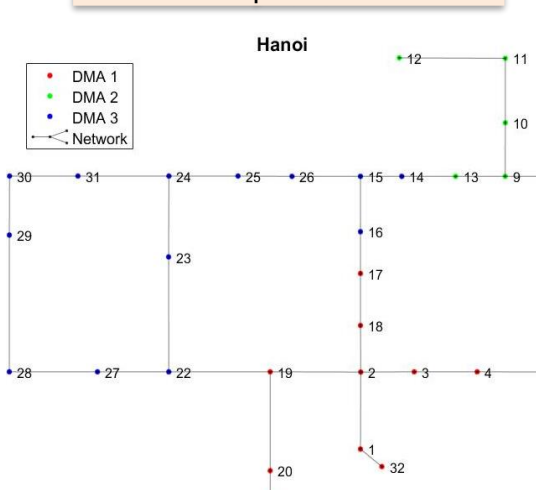
$D_{\text{av}}$ : average of the demands.

- A multi-step simulation-optimization approach is developed to minimize the coefficient of variation of demand similarity (CVDS) between DMAs
- (1) K-means and Johnson's Shortest Path algorithms create a range of possible DMAs by grouping nodes, then, a weighted graph using hydraulic and physical components (diameter, length, and water demand) is optimized by applying Pattern Search Algorithm
- (2) A heuristic approach based on the process of swapping nodes between connected DMAs improves the CVDS among DMAs
- (3) Hydraulic and quality constraints are fulfilled to complement the design.

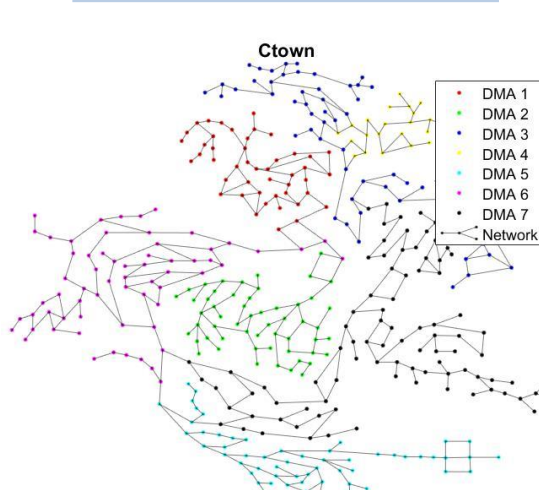
## Application and Results



Hanoi  
Junctions: 31  
Reservoir: 1  
Pipes: 34



C-Town  
Junctions: 388 Reservoir: 1  
Tanks: 7 Pipes: 429  
Pumps: 11 Valves: 4



References:  
 • Pesantez, J. E., Berglund, E. Z., & Mahinthakumar, G. (2019). Multiphase procedure to design district metered areas for water distribution networks. *Journal of Water Resources Planning and Management*, 145(8), 04019031  
 • Pesantez, J. E., Berglund, E. Z., & Mahinthakumar, G. (2020). Geospatial and hydraulic simulation to design district metered areas for large water distribution networks. *Journal of Water Resources Planning and Management*, 146(7), 06020010

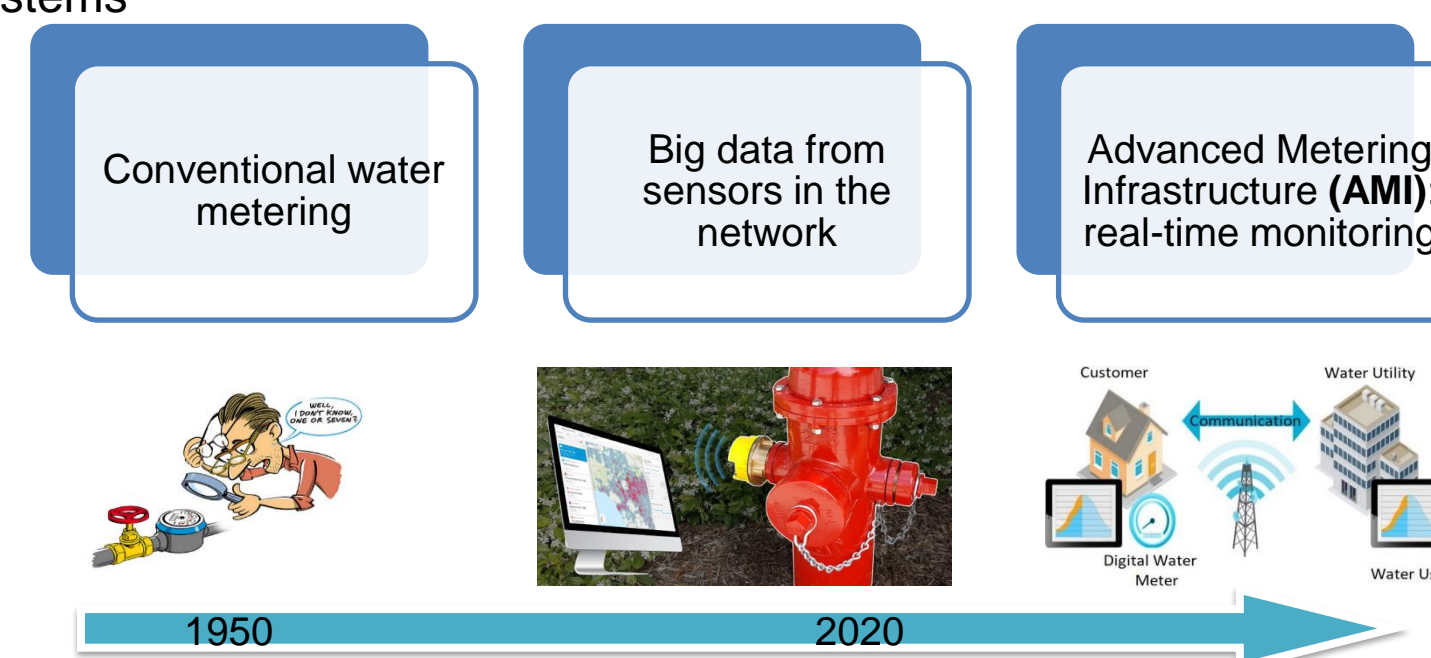
## Demand from Smart Meters

### Forecasting Demand with Advanced Metering Infrastructure (AMI)

Utilities are implementing Advanced Metering Infrastructure (AMI) at the user level

Forecasting models at the user level and with a high temporal resolution:

- Diurnal demand patterns at the user-level
- Tailored feedback about customer's water consumption
- Post-meter leak identification at the user-level
- Real-time operation of water systems



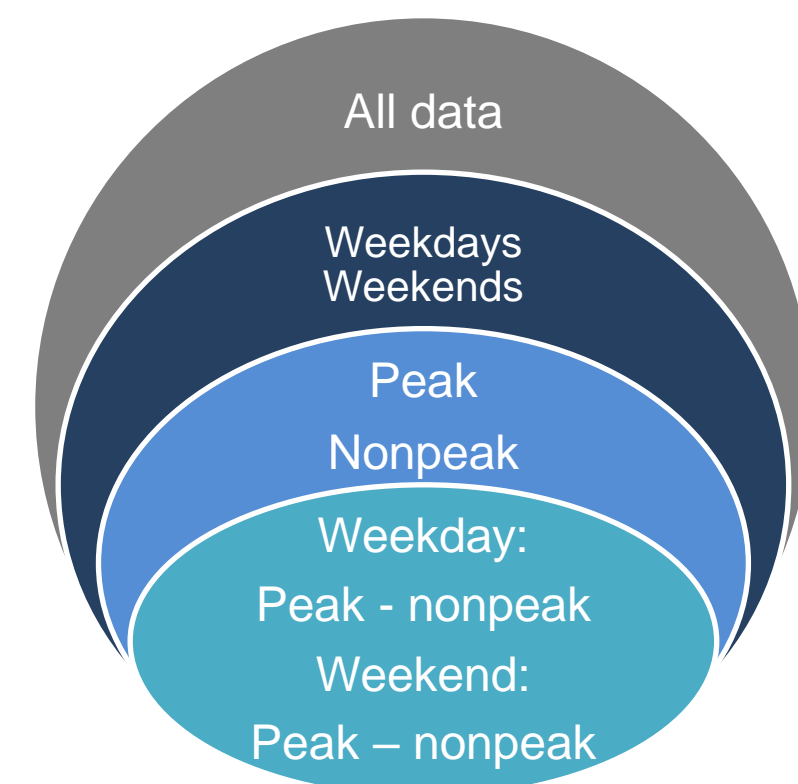
**Objectives** → To explore the use of smart meter data for forecasting hourly water demand at the user level:

To test data analysis settings and methods:

- Clustering
- Types of predictors
- Size of data sets
- Machine learning methods

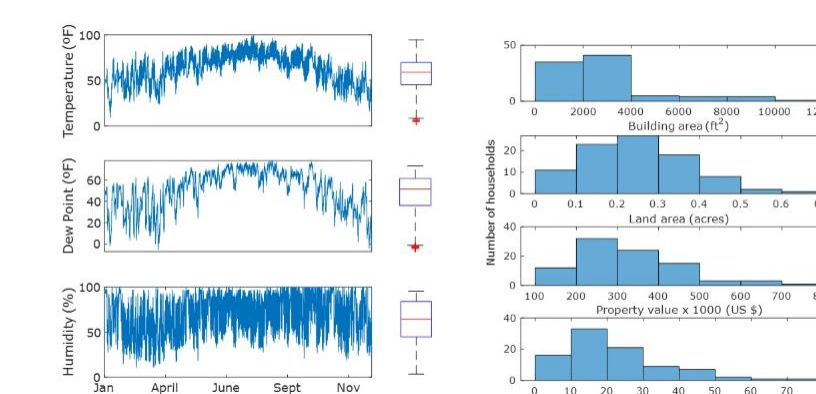
## Methodology

### 1. Clustering:



### 2. Types of Predictors:

- Previous demand and seasonal (DS) variables
- Weather (W) data
- Characteristics of the households (CH)



### 3. Size of data sets

- Individual or multiple meters

### 4. Machine Learning methods:

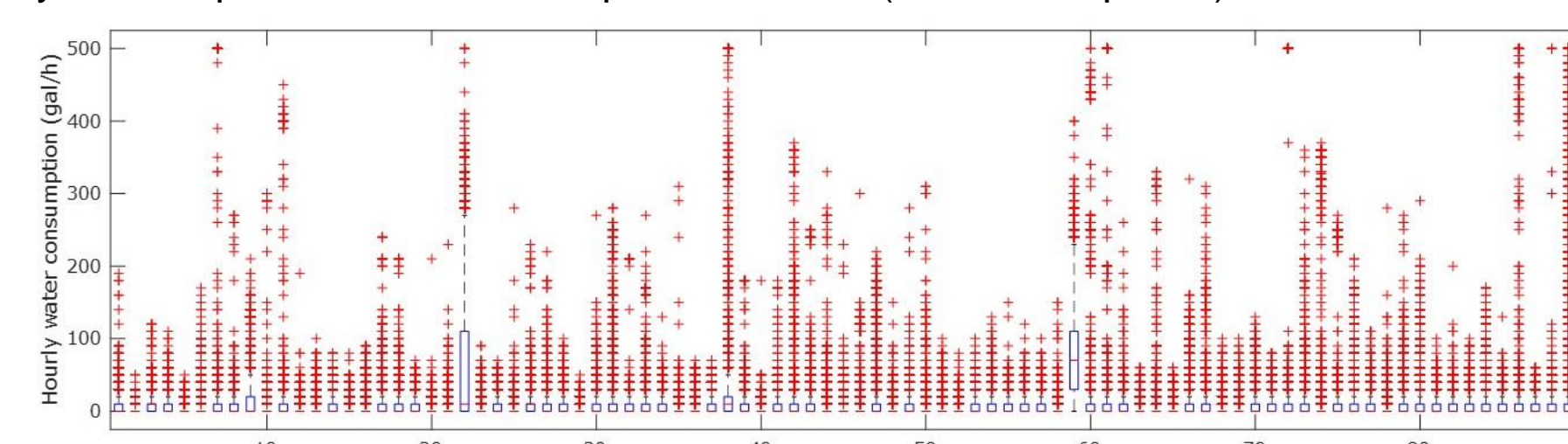
- Random Forest
- Art Neural Network
- Support Vector Machine

### ML hyperparameters:

- Number of trees
- Leaf size
- Number of hidden layers
- Number of neurons
- Box constraint
- Bandwidth margin
- Kernel function scale

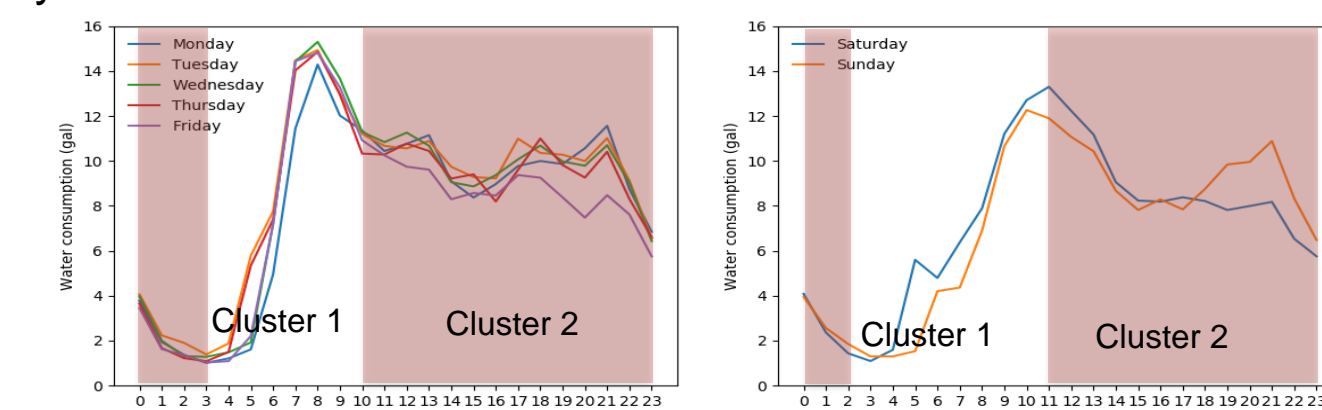
## Application and Results

- Data were retrieved from a set of 90 smart meters located throughout the town of Cary, NC
- The meters reported hourly consumption for a 12-month period in 2017 (8,760 data points)

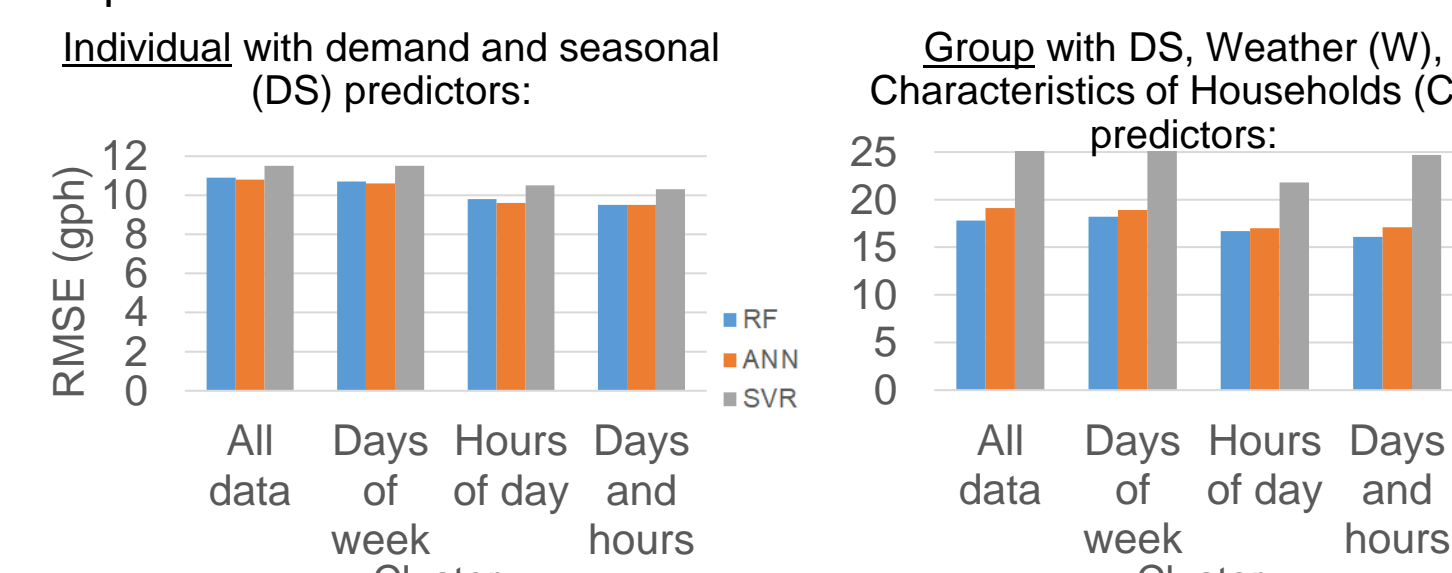


Smart meters have a volumetric resolution of 10 gph for battery-saving purposes.

- Clusters identified for weekdays and weekends



- RMSE: Individuals and Group models:

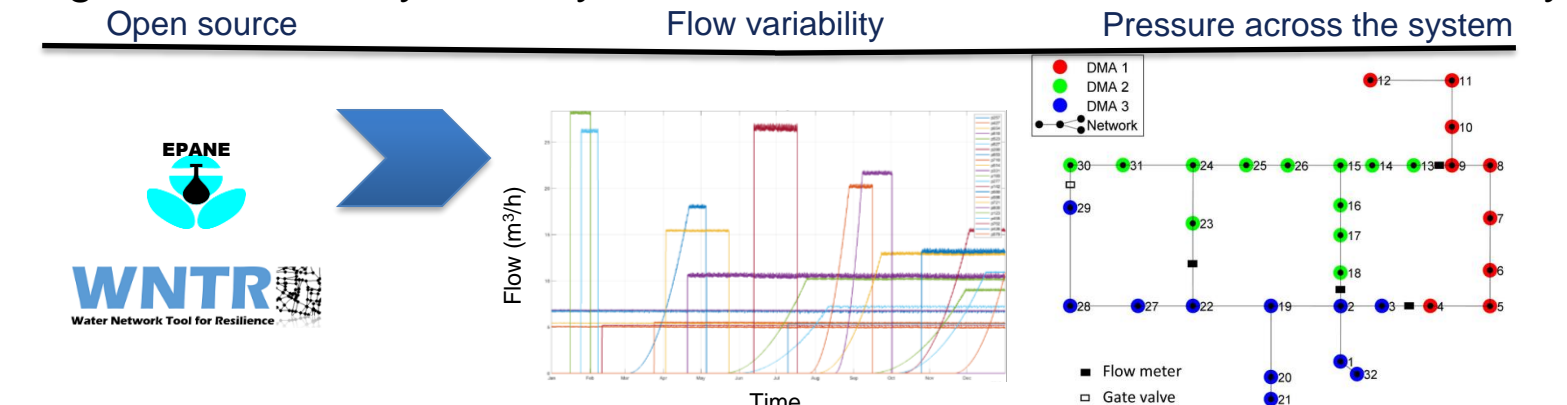


References:  
 Pesantez, J. E., Berglund, E. Z., & Kaza, N. (2020). Smart meters data for modeling and forecasting water demand at the user-level. *Environmental Modelling & Software*, 125, 104633.

## Water Systems Operation

### Leak localization using a simulation optimization model

Modeling and data analysis of hydraulic models and sensor data from water systems



**Objective** → To localize leaks in WDS using data from pressure sensors and demand from smart meters

## Methodology

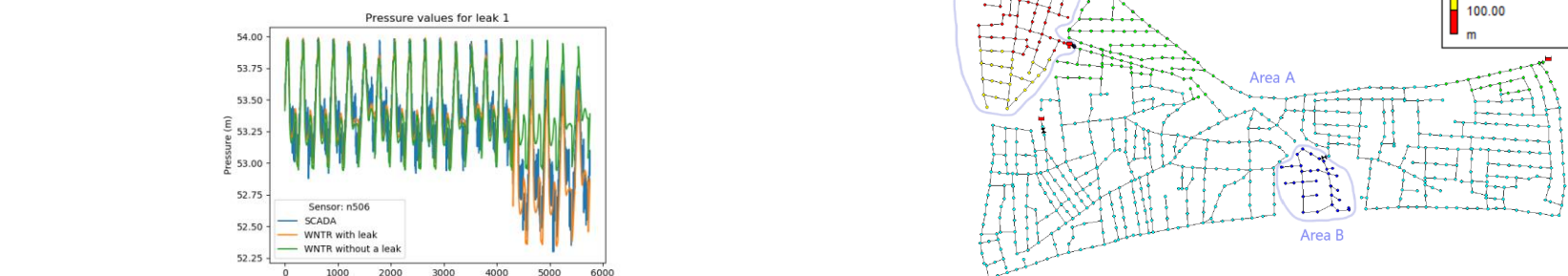
Data analysis from sensors + Hydraulic simulation = Optimization

**Modeling leaks on piped systems**

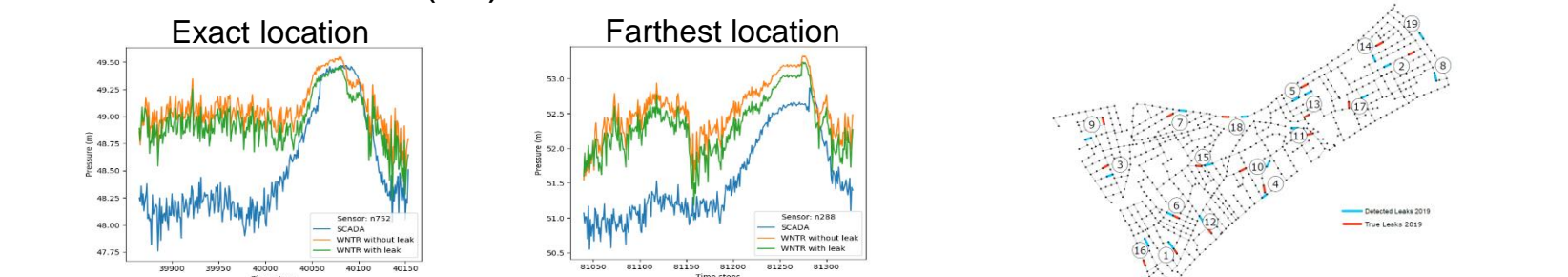
- Leakage model: power law  $q = cp^{\alpha}$
- Leak flow  $q$ , Leakage exponent  $\alpha$ , Leak coefficient  $c$ , pressure
- simulated pressure with leaks  $y_{sim}(x) = Ax + y_{sim}(0)$
- vector of leak coefficients  $x$ , leak sensitivity matrix, simulated pressure with no leaks  $y_{sim}(0)$

## Application and Results

- L-Town calibrated model: 782 junctions, 905 pipes, 1 pump. Serving 10,000 people
- Pressure values from 33 sensors across the network with a 5-minute time step for 2018 and 2019
- AMI demand data for each customer in Area C

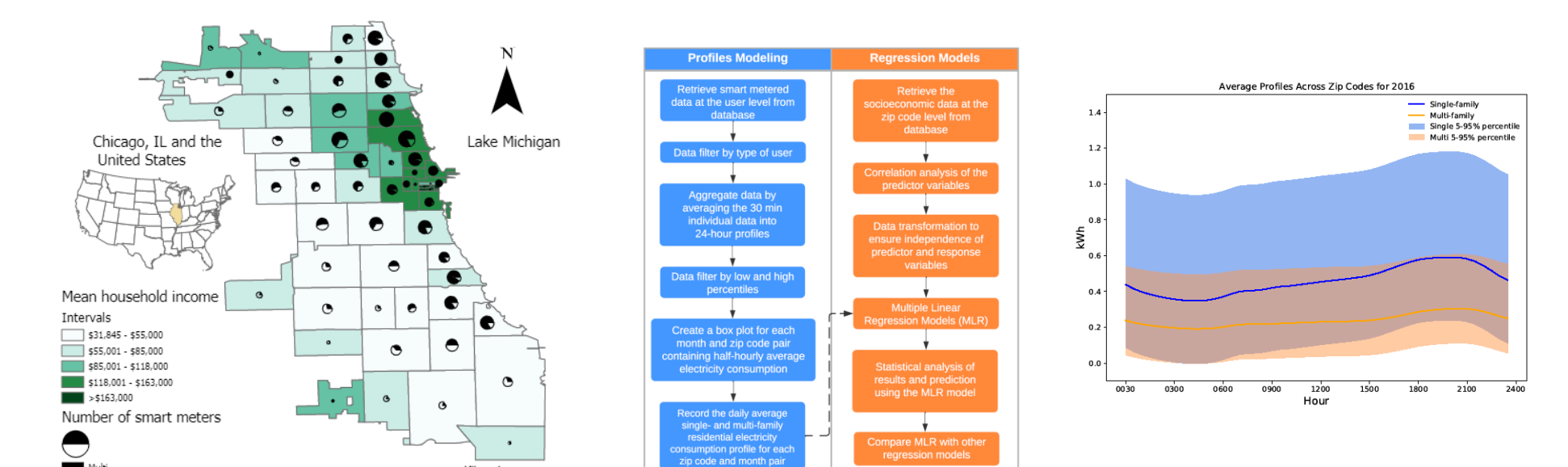


- We found all the leaks (19) that started in 2019 with an average distance of 185 meters

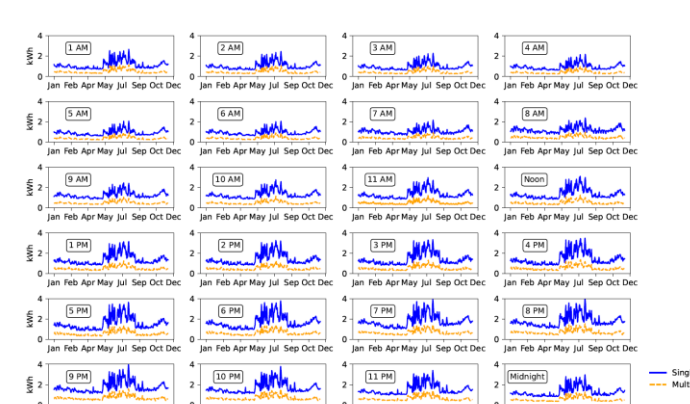


## Ongoing Projects

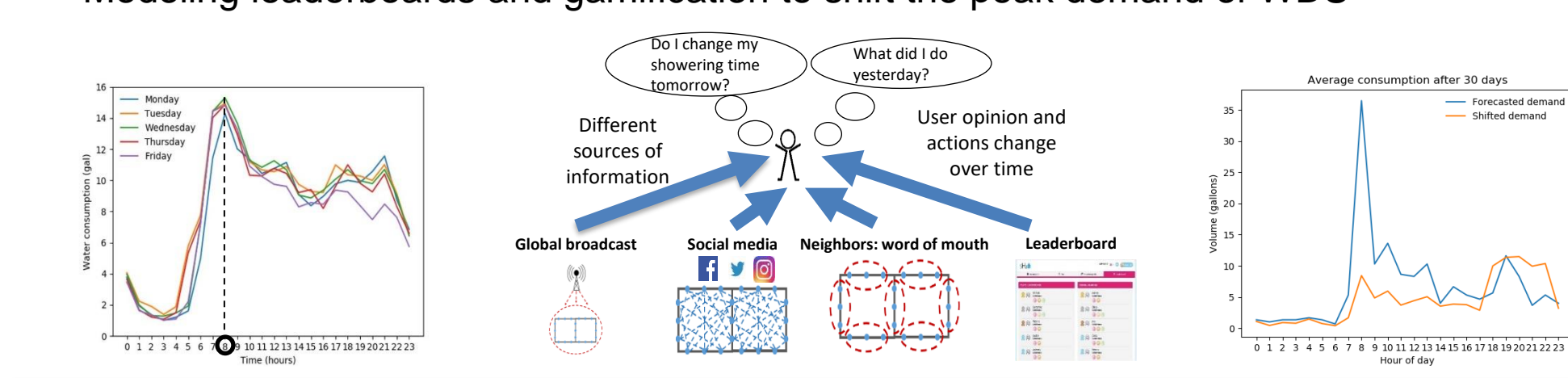
- Predicting single- and multi-family residential electricity consumption for the City of Chicago



- Using smart metered data to forecast electricity demand in a diverse urban environment



- Modeling leaderboards and gamification to shift the peak demand of WDS



## Acknowledgments

