Informatics and Analytics for Integrated Energy Systems

Madhav Marathe
Email: mmarathe@vbi.vt.edu
Phone: 540 808 3292
Network Dynamics and Simulation Science Laboratory (NDSSL)
Biocomplexity Institute of Virginia Tech
& Dept. of Computer Science
Virginia Tech

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NDSSL: http://bi.vt.edu/ndssl
Biocomplexity Institute: http://bi.vt.edu

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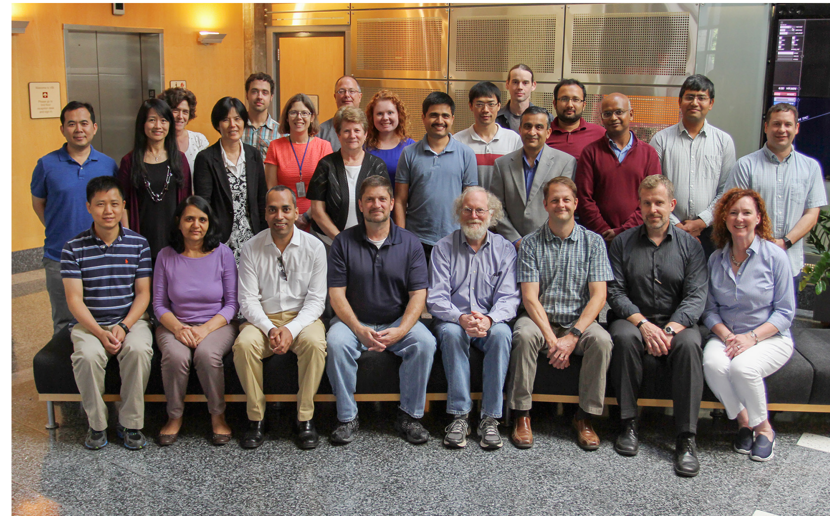

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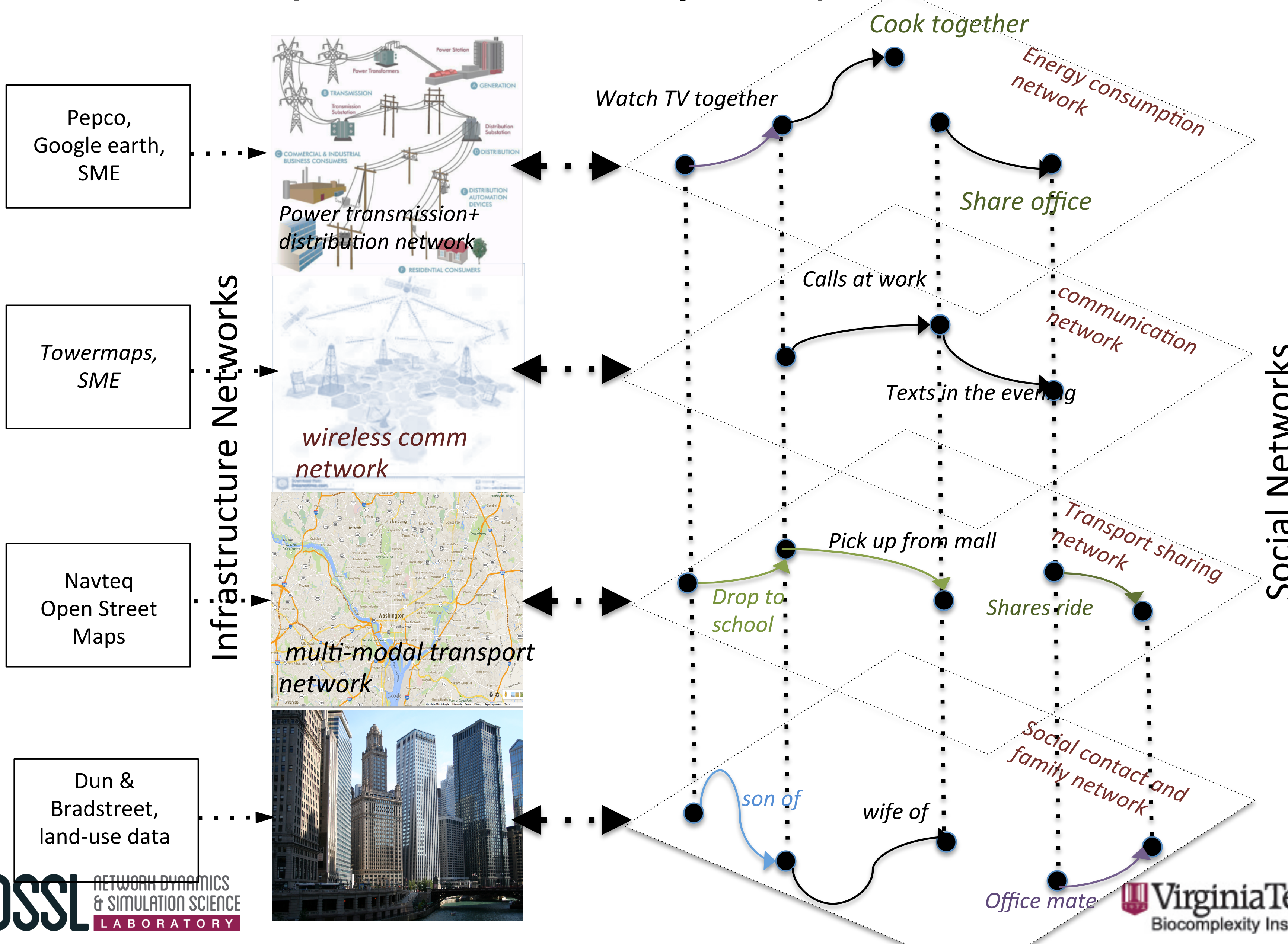
Integrated Energy Systems

- Modernization of the energy systems is underway and poses technical and social challenges
- Integrated energy systems involves more than just power grid representation
  - Coupled with social networks
    - Individual activities and behavior has significant impact on power system demand and performance
    - Changes in demand based on real time pricing
    - Adoption of green technologies and impact
  - Coupling with different infrastructures and markets
    - Transport: Impact of electrical vehicles and V2G
    - Communication: Increasing use of communication infrastructure
    - Markets; Power markets at different spatio-temporal scales

Inter-dependent Socially Coupled Networks



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Hypothesis: N*ext-generation energy systems networks cannot be* ***effectively*** *designed, analyzed and controlled in isolation from the social, economic, sensing and control contexts in which they operate.*

Advances in ICT and AI can help

- **Proliferating digital devices** that, by ubiquitous and varied measurements and interaction with the end users and the underlying energy system, **can provide context-rich information and services.**
- **New data analytics and machine learning** techniques can lead to driven **first principles modeling and analytics capabilities** to support the energy systems modernization program.

Computational Modeling of Integrated National Energy Systems (MINES)

- Integrated HPC-enabled high-resolution models of synthetic power networks
  - Detailed representations of all the constituent elements of the electrical grid: generation, transmission, end users
- A modeling framework to represent urban environments and the embedded social network comprising end users, their interactions and movements,
  - Realistic demand and response behaviors for consumers, system operators and individual companies.
- Applications areas include
  - study of interdependencies among infrastructures
  - vulnerabilities and resilience; electricity market analysis
  - renewable and distributed energy generation

Section

INTEGRATED HPC-ENABLED HIGH-RESOLUTION MODELS OF SYNTHETIC POWER NETWORKS

Data Sources/Methods Used

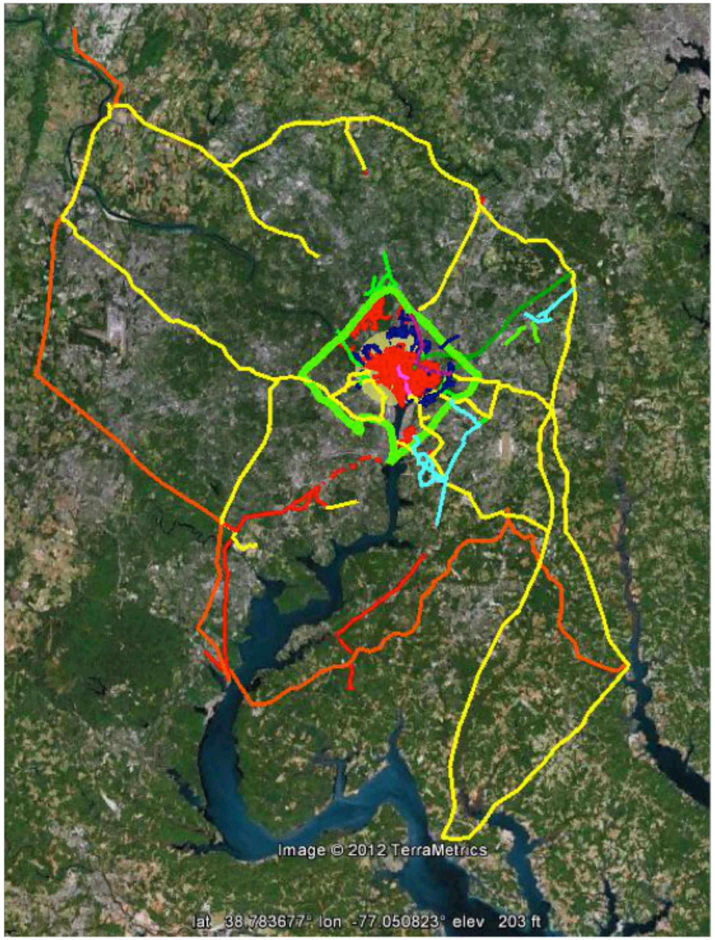
- Public reports from different public utility companies and local governmental agencies
  - High level factsheets from Pepco on generation capacity, main generators, number of substations, total transmission and distribution line statistics
  - Overall energy consumption
  - Streetlamp locations
- Tracing power lines on Google earth
  - Identify lines based on overhead clearing, which can be visually identified by experts
  - Domain expertise in connecting different networks
- Use of the power system simulation software, PSSE, to determine how the grid interconnects within the greater DC area

Data Sources

Name	Description	Type
Electricity generation	http://205.254.135.24/state/state-energy-rankings.cfm?keyid=33&orderid=1	Open Source
Electricity Consumption	http://www.eia.gov/state/seds/hf.jsp?incfile=sep_sum/plain_html/rank_use_per_cap.html	Open Source
Distribution network	Tracing power lines on Google earth, identify lines based on overhead clearing	Discussion with subject matter expert, ECE-VT
Transmission network	Transmission 2000 data, power system simulation software to find grid interconnects	Commercial, ECE-VT

Power Network Synthesis

- The transmission and distribution grid geospatially determined using Google Earth & power system simulation software, PSSE, to determine how the grid interconnects within the greater DC area.
- The major transmission lines (500kV, 230kV, 138kV, and 115kV) bring large amounts of power into the city from the Baltimore Gas & Electric (BG&E), Potomac Electric Power Company (PEPCO), and Dominion Virginia Power (DVP) systems.
- This power is brought into urban parts of the city through underground subtransmission & distribution level circuits (69kV, 34.5kV).
- Almost all the distribution network within the region are underground, with overhead distribution lines feeding power to customers further outside the urban areas.



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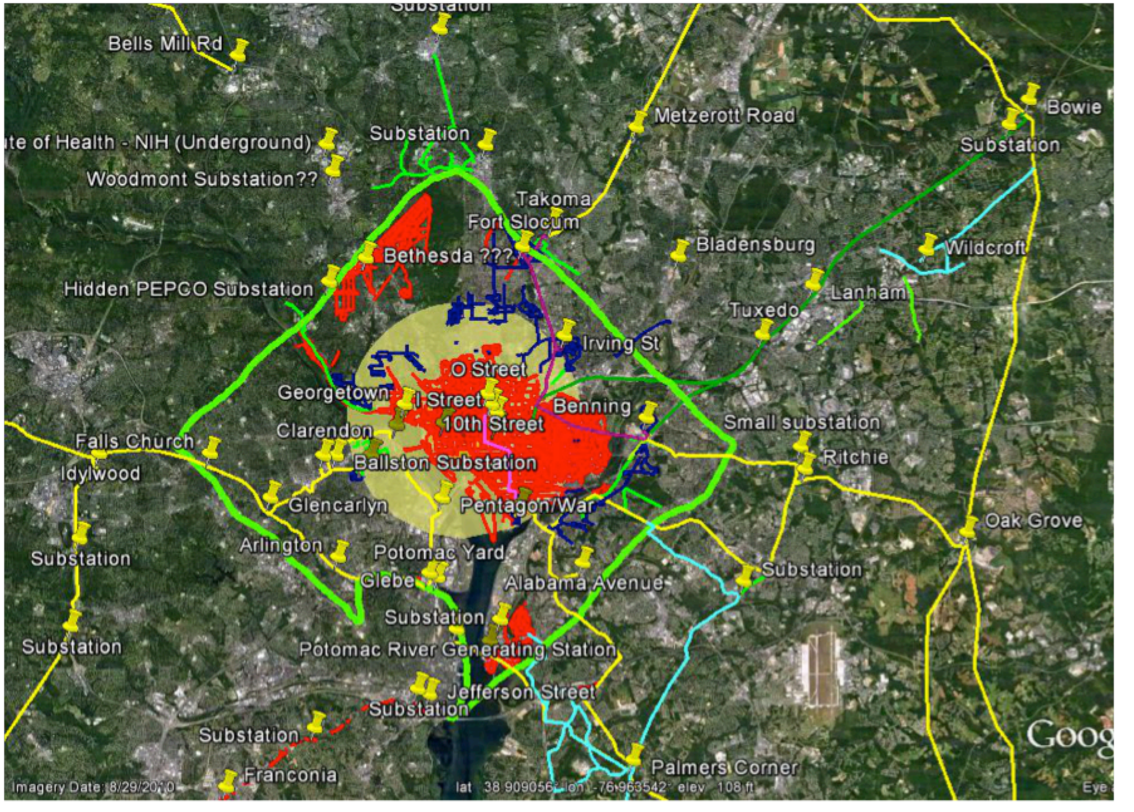
Incorporating Substation Locations

- Identifying specific substations using openly available information
- Provides estimate as to how the power is brought into the city for consumption &
- Where the major load centers and tie lines are located.



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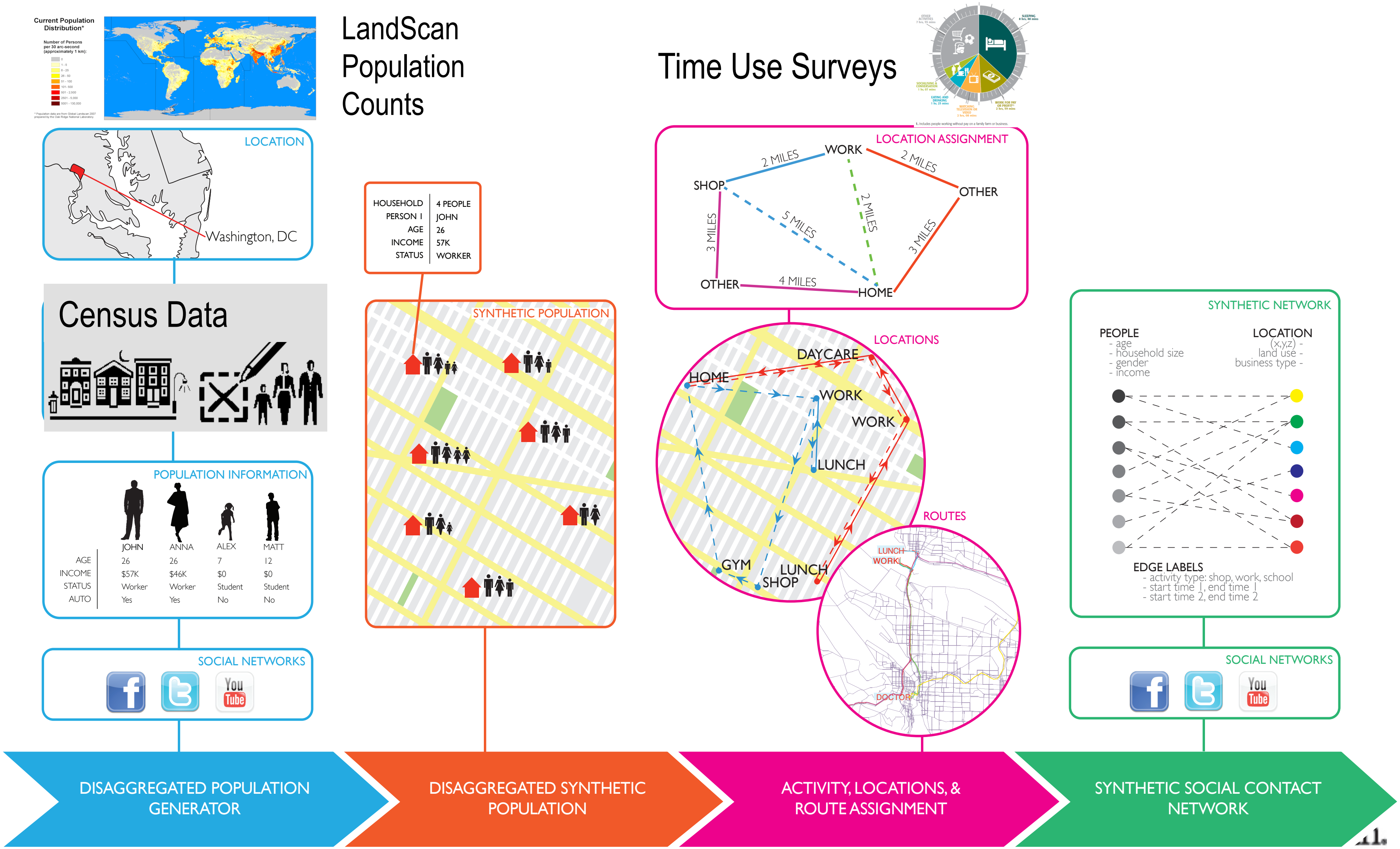
SYNTHETIC SOCIAL SYSTEMS

Synthetic populations, infrastructure, networks and multi-networks

- A statistically accurate, augmentable representation of agents (people, infrastructure elements, things)
  - in a given area with associated demographic, physical, social and behavioral attributes
  - **Anonymity and Privacy preserved**
- Synthetic infrastructure and social networks
  - Capture the interaction between individuals and infrastructure elements
  - Multi-networks capture the interaction between individuals and infrastructures across networks

Constructing synthetic multi-scale social contact networks at scale



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Data sources – general and specific

- **Activity locations:**
  - LandScan
  - D&B
  - InfoGrid
  - NAVTEQ/HERE POIs
  - OSM POIs
  - Wikipedia
- **Residence locations:**
  - LandScan
  - NAVTEQ/HERE
  - OSM

- **Activity template data**
  - NHTS
  - MTUS
  - ATUS
  - Custom surveys
  - Country similarity measure (matching algorithm)
- **Administrative boundaries**
  - GADM
  - NAVTEQ/HERE
  - OSM
  - US Census
  - ADC Worldmap

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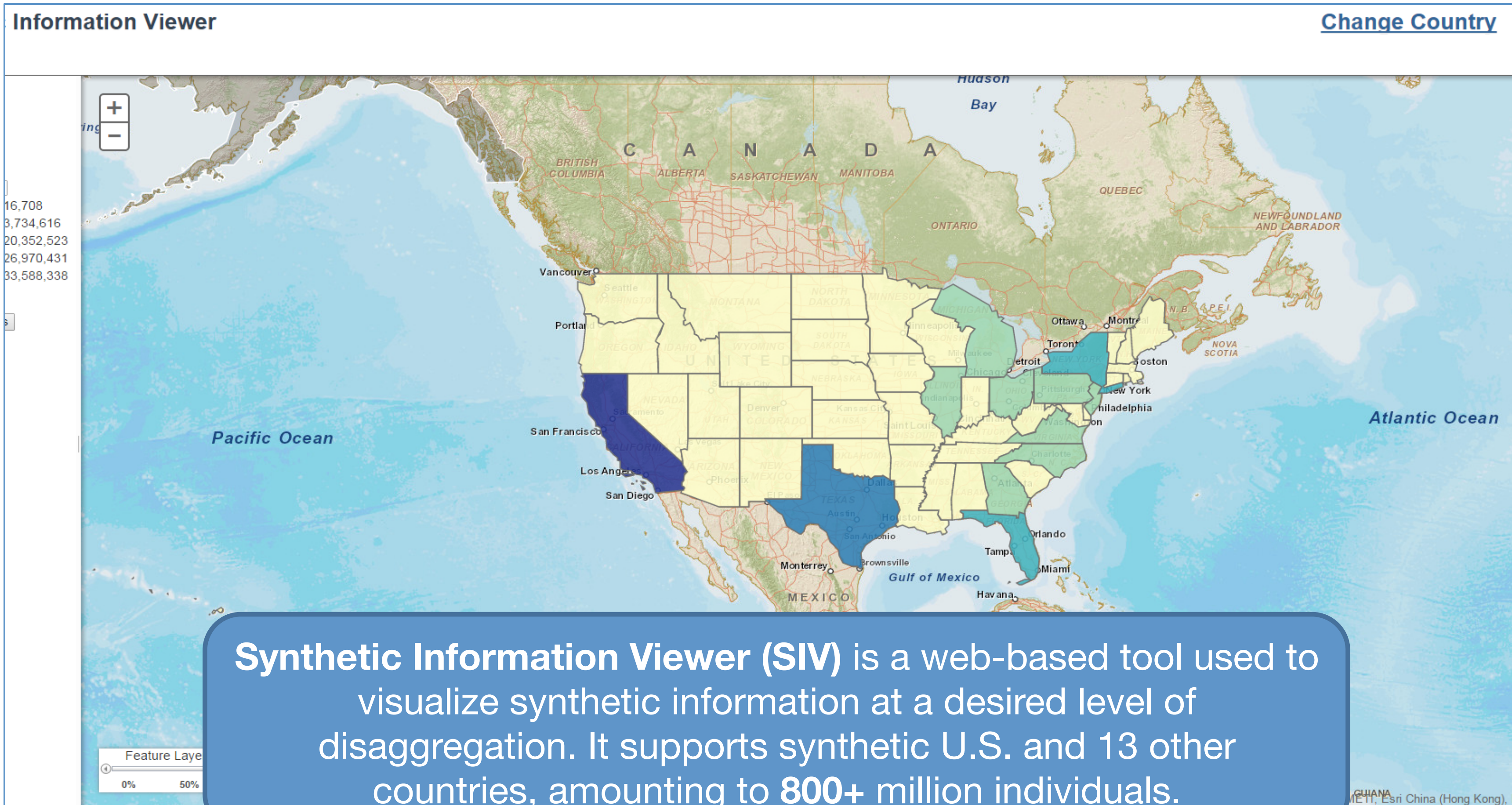
Global Synthetic information: A big data challenge

2 GB/M people Storage	7Billion Synthetic individuals	28+Billion Interactions	40+ Databases
220 countries synthetic populations and networks constructed	50K+ Files in which data is stored	5 Days Compute time	8TB Storage

First data driven global synthetic populations and proximity networks

Synthetic Information Viewer (SIV)



Synthetic Information Viewer (SIV) is a web-based tool used to visualize synthetic information at a desired level of disaggregation. It supports synthetic U.S. and 13 other countries, amounting to **800+** million individuals.

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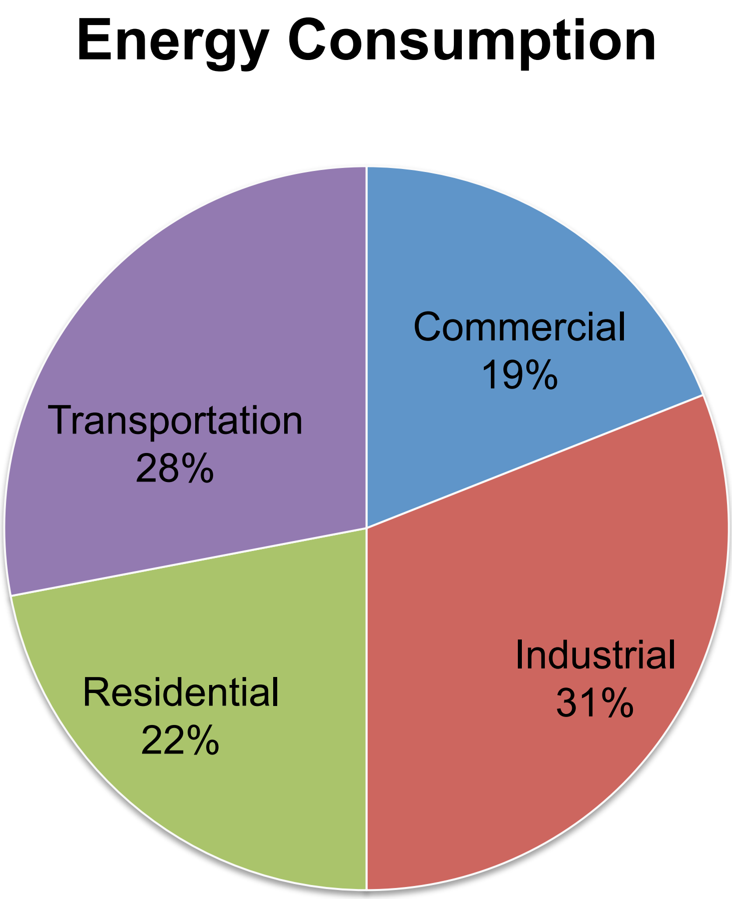
DISAGGREGATED MODELS OF RESIDENTIAL AND COMMERCIAL ENERGY DEMAND

Motivation: Demand Side response

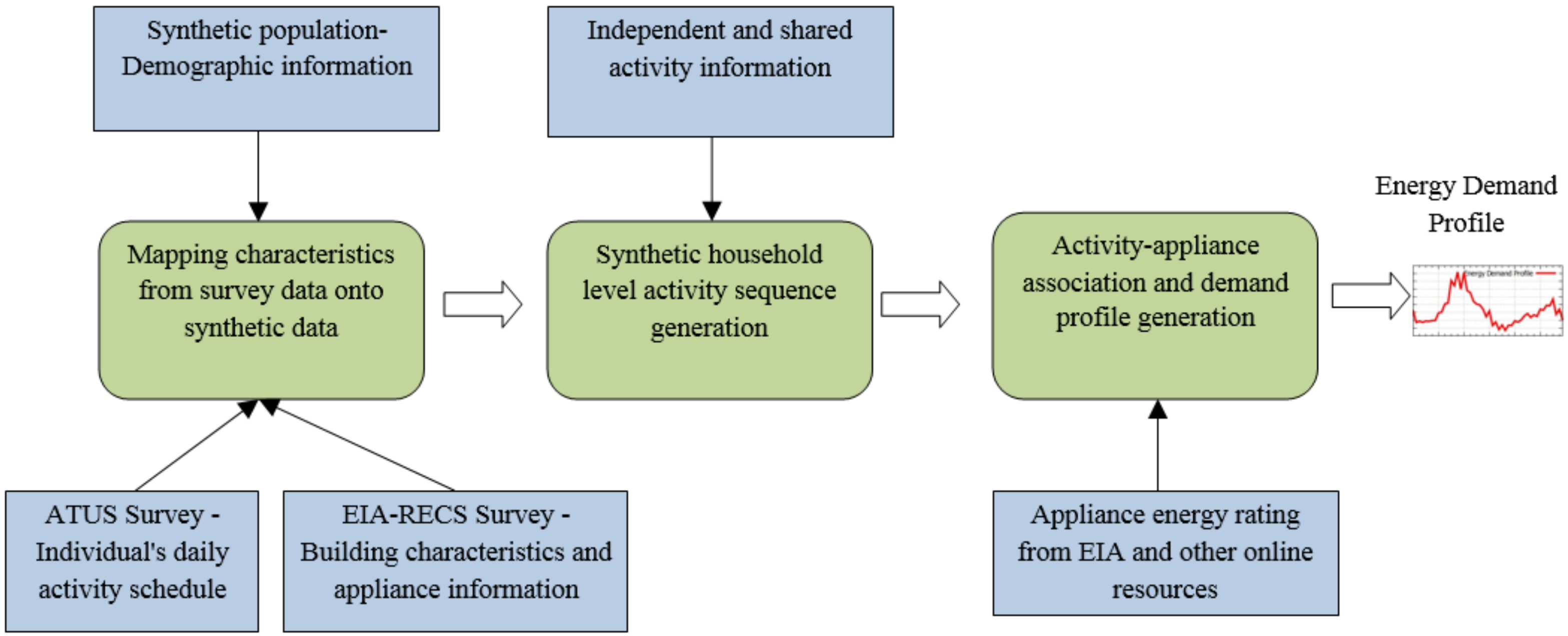


- Commercial and residential buildings together account for ~40% of energy consumption.
- Energy consumption in these sectors is, in large part, a function of the activities of the residents, customers, and employees of these buildings.
- Consumption may change as appliances become more efficient or people begin to take more energy-saving measures.
- This calls for the need for a highly detailed model of energy consumption.

Figure Source: US Annual Energy Consumption Outlook - 2012

Synthesizing household level daily energy demands

Data from multiple sources is combined in one common architecture to generate time varying, individualistic demand profiles.



Residential Energy Consumption: Data

Data	Type	Description
ATUS	Survey	Contains activity diaries over a 24 hour period for 13,260 respondents.
EIA-RECS	Survey	Contains detailed household-level characteristics and associated energy consumption
Synthetic Population	Generated as described	Contains household level and individual level demographics representing Washington-DC area.

Activity Name	Appliances Used	Energy rating (watts)	Usage (%)
Laundry	Washer, Dryer	{234, 670}	{.45, .55}
Dish washing	Dishwasher	1200	1
Cooking (mid-day)	Microwave	500	.5
Watching TV	Television	220	1
Computer usage	Compute	160	1
Cooking (morning)	Stove, Coffee maker, Microwave, Toaster Oven, Blender	856	{.35, .05, .5, .05, 0, .05}
Cooking (night)	Stove, Coffee maker, Microwave, Toaster Oven, Blender	940	{.35, .05, .45, .05, 05, .05}

Modeling Workflow

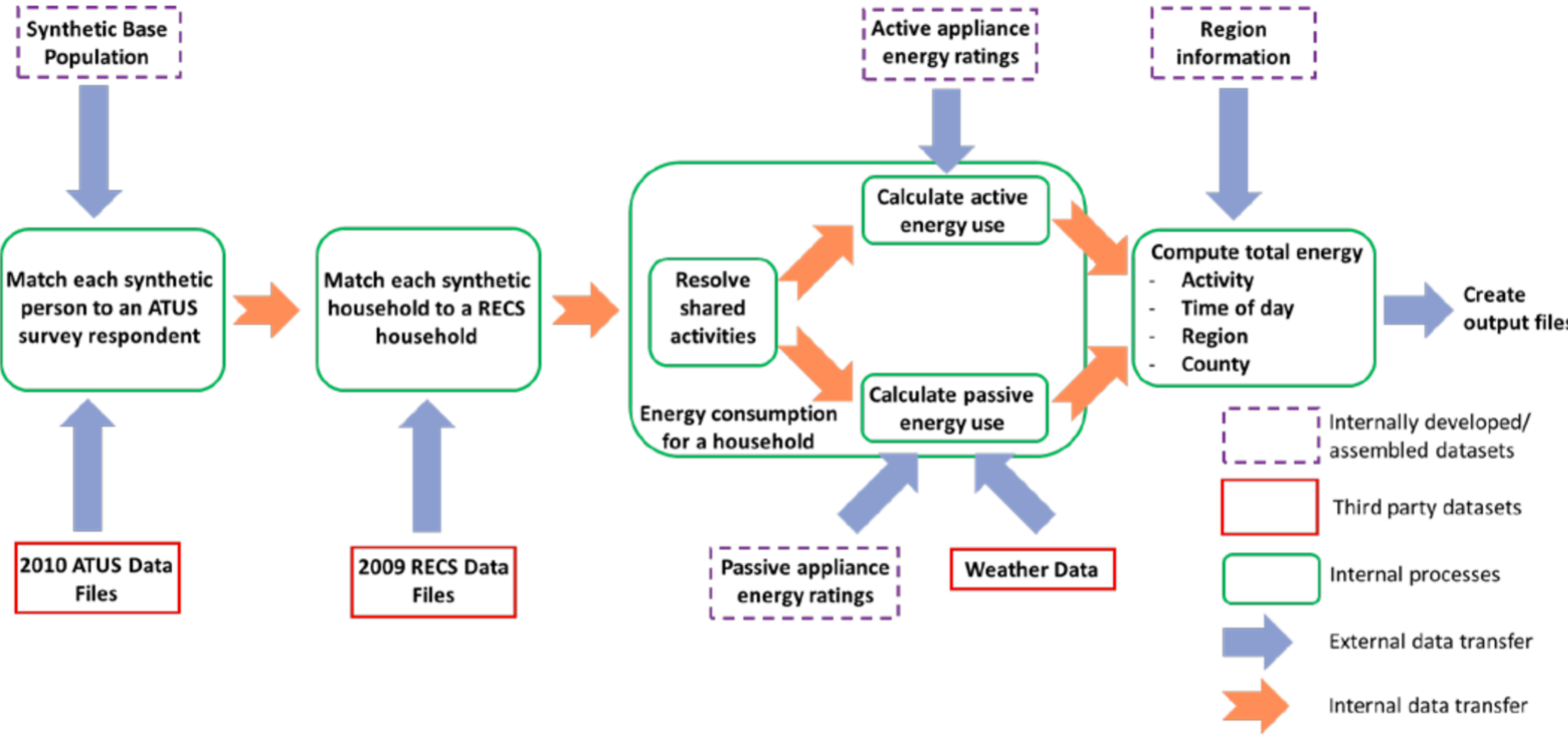


Fig. 2. Modeling framework to generate energy demand model for residential buildings

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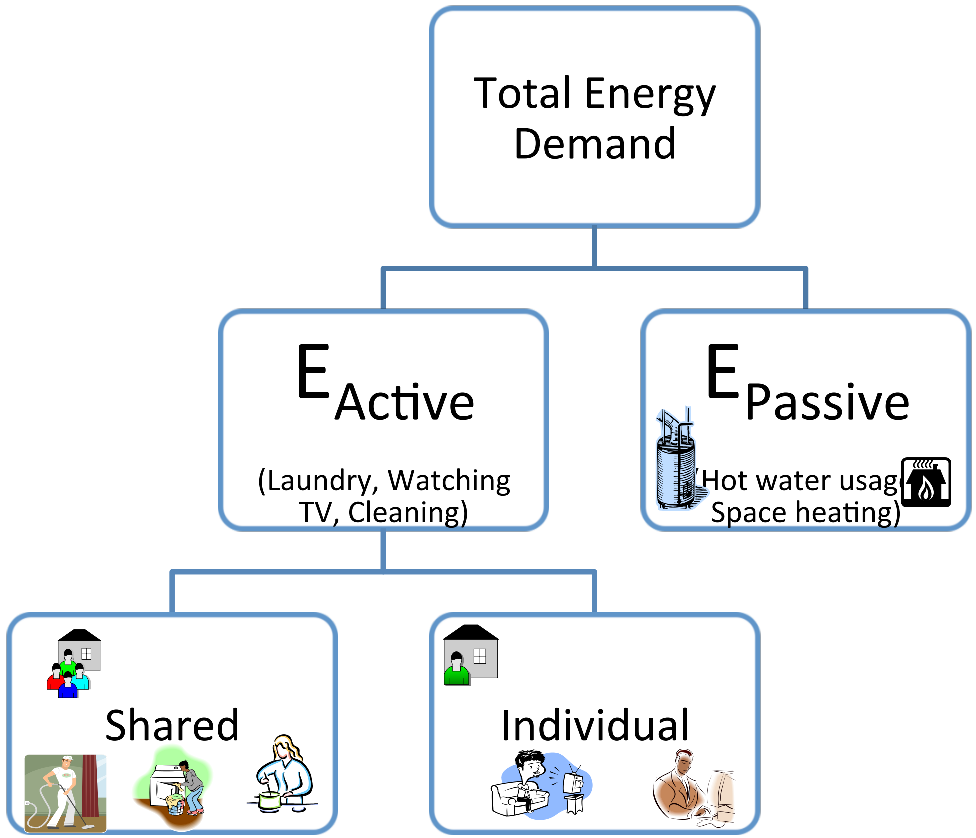
Residential Energy Consumption

We further break down the activities that take place at home.

We categorize the energy consumption of a residential building into two major groups: active energy consumption varies as a function of the activities of the household members. Passive energy consumption is mainly due to temperature regulation, refrigeration, etc. and does not vary with individual activities.



- Laundry
- Washing dishes
- Watching TV*
- Cooking
- Cleaning

- Computer use
- Checking email

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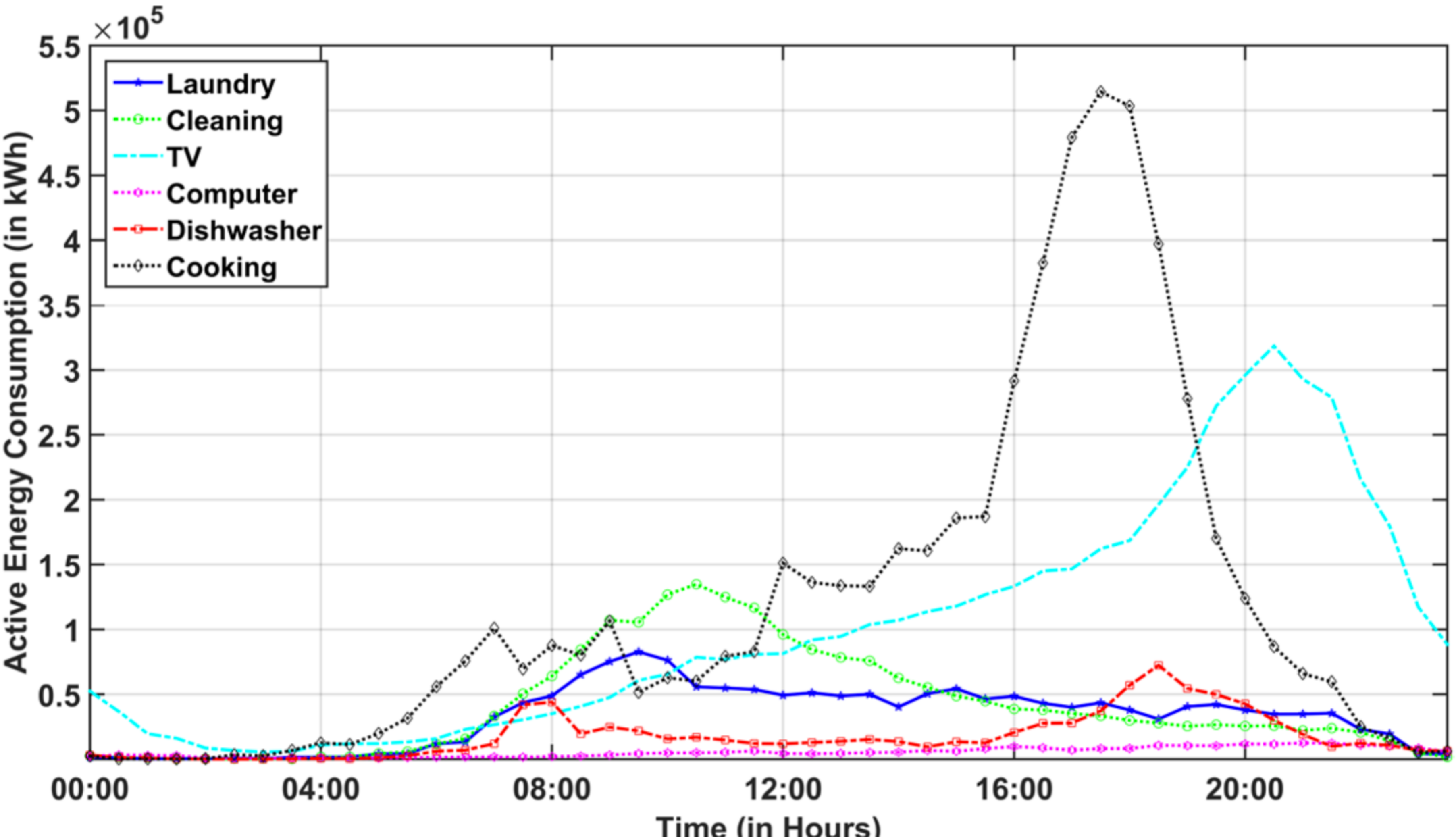
Usage pattern in a typical house



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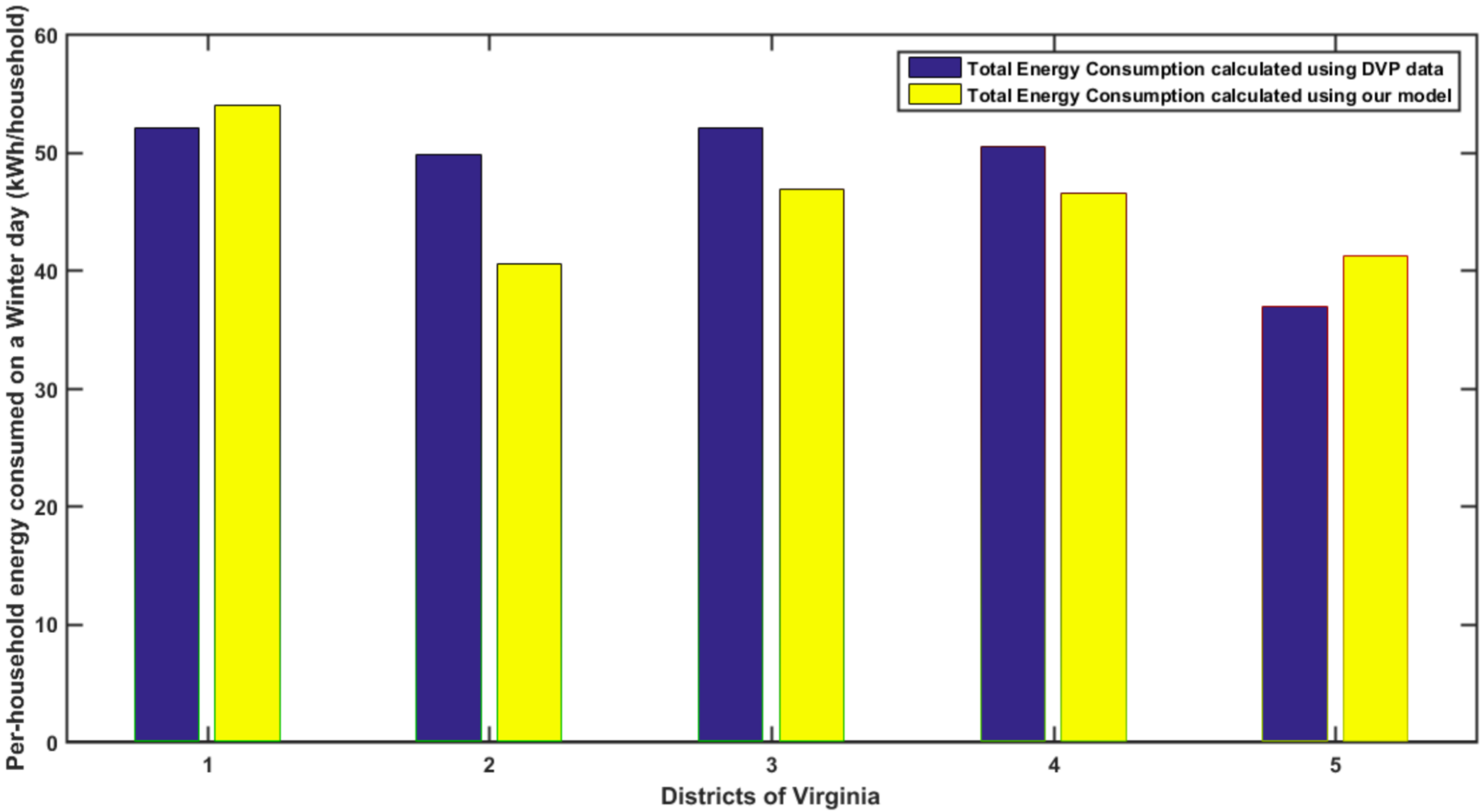
Validating the model



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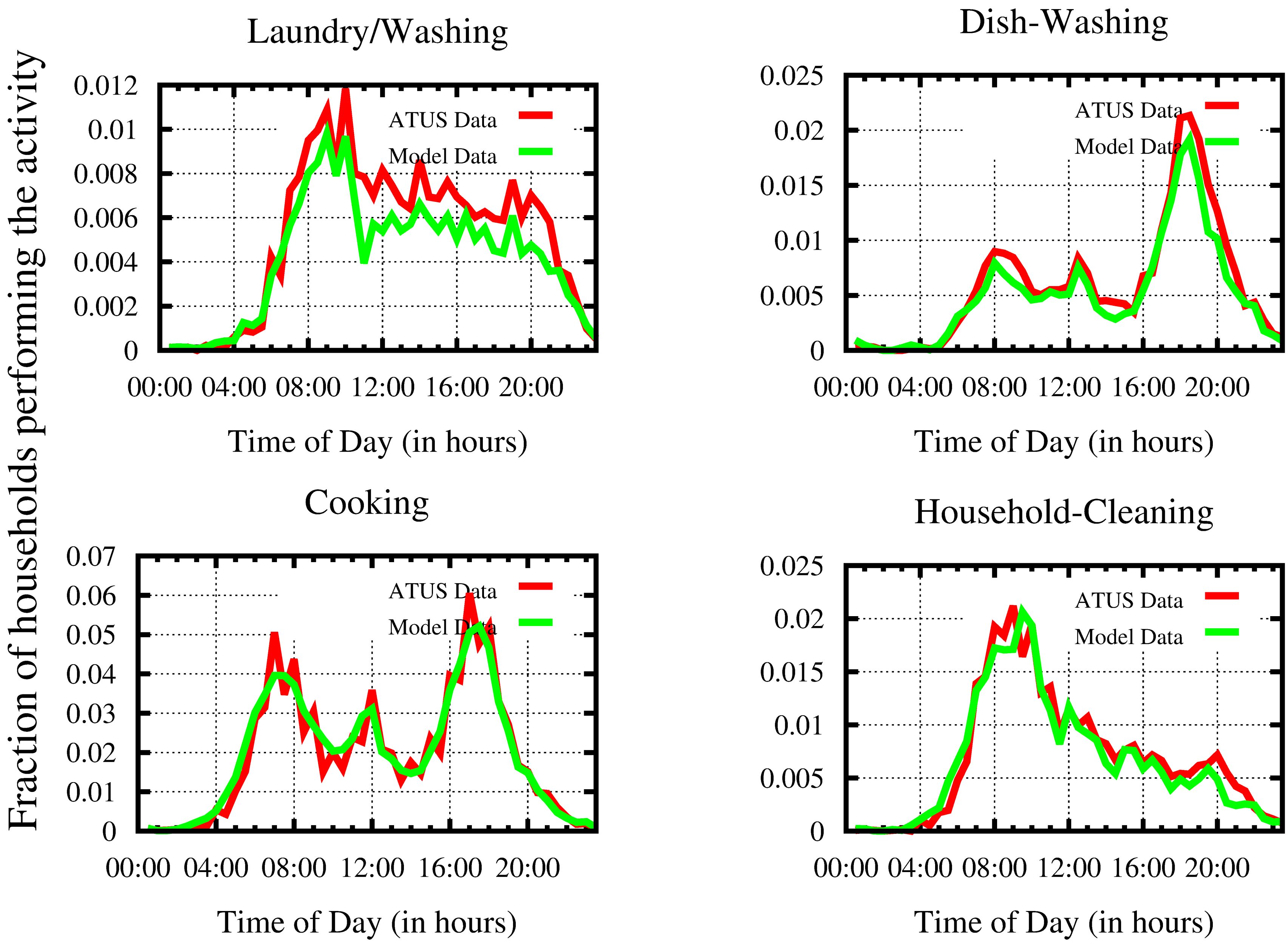
Residential Energy Consumption: Results



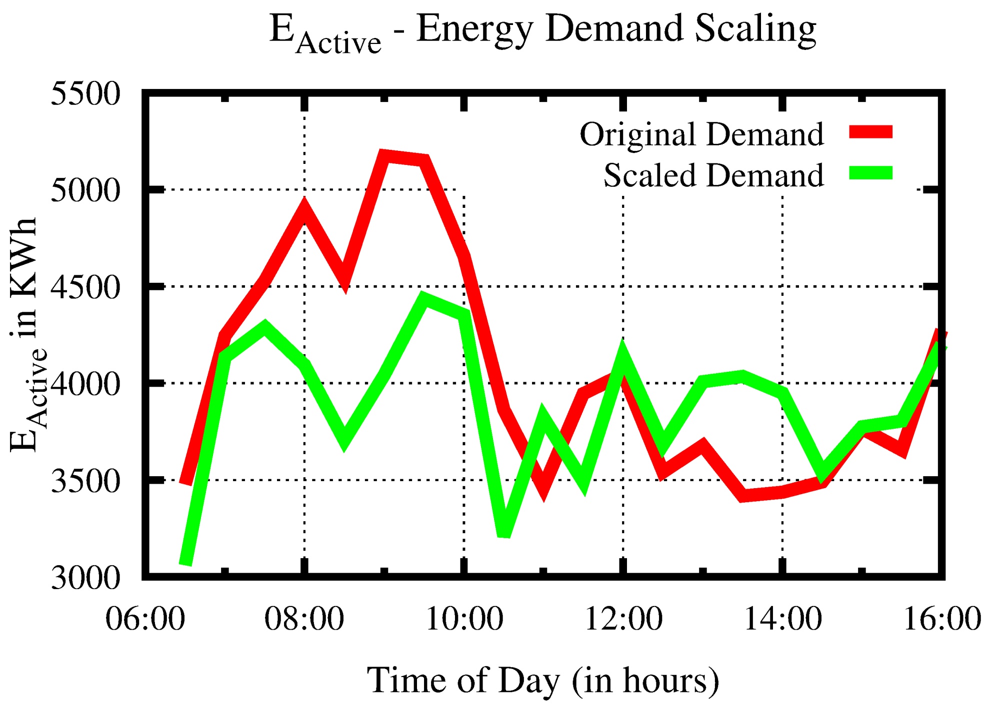
Section

APPLICATIONS

Applications of synthetic demand modeling

- Placing energy storage devices to support bidirectional flow and net metering
- What levels of renewable penetration will make it necessary to update the electrical infrastructure?
- How to nudge consumers to move load from peak hours to off-peak hours?
- How can we improve grid resiliency?
- How can we protect the grid from cascading failures within and across infrastructures?

Case Study: Energy Demand Scaling



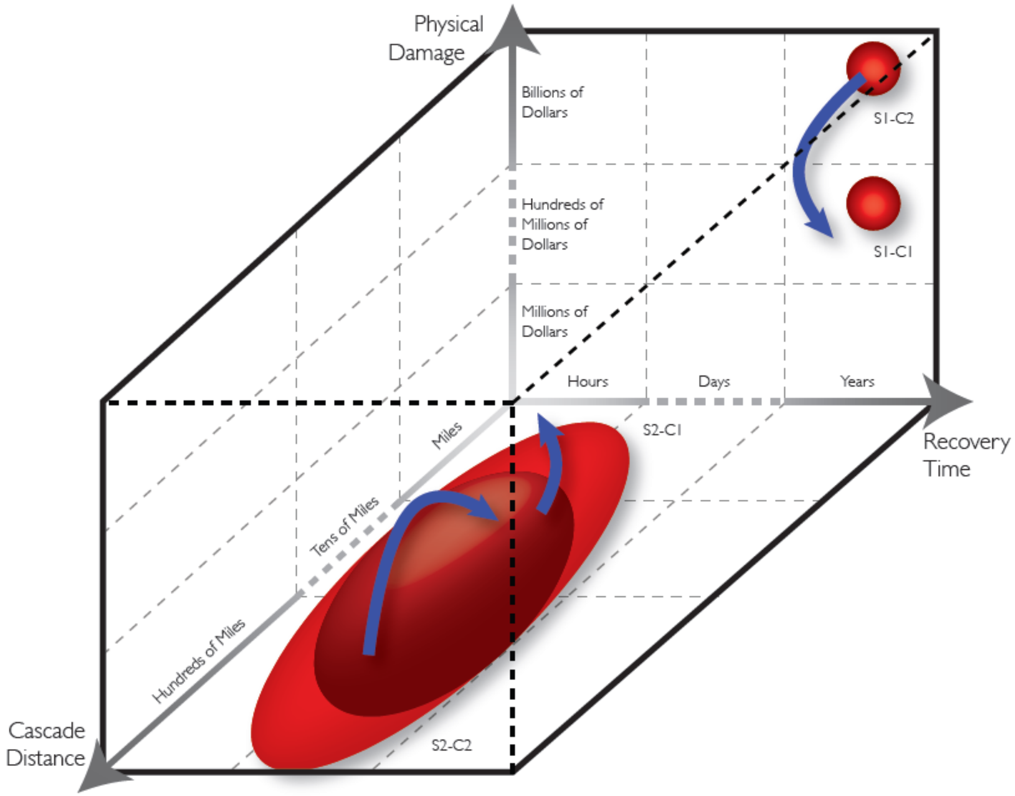
- We selected about 20% of households and shifted their cleaning and washing activities from peak to off peak time periods
- We saved about 4.5 MWh of energy at peak time

Section

2. CASCADING FAILURES IN POWER NETWORKS

Power networks, cascades and resiliency

- Development of dedicated theory and analysis for power networks.
- Scenarios:
  - S_1: NPS-1
  - S_2: A coordinated, targeted attack on the major generating substations Sub-scenarios:
  - C_1: protection system works perfectly
  - C_2: protection system within a certain distance of the attack is compromised.



Broad Results

1. Scenario 1 is unlikely to cause large cascading failure of the grid, highlighting the role of protection devices and the local structure of the power grid;
2. Scenario 2 can lead to widespread cascading failures even though the physical damage to the infrastructure is minimal;
3. For both scenarios, using smart devices like phasor measurement units (PMUs) already present in the field and placing relays at strategic locations inside EMP-proof boxes, can considerably reduce the damage.

Broad insights

- The physical damage to electrical infrastructure and corresponding outage probabilities depend on
  - urban geography, structure and geography of the power infrastructure, location of impact and the prevailing weather patterns.
- Substantial immediate effects of IND
  - Might not be **possible** to restore power for months because of resulting environmental contamination, and lack of spare capacity and components
- Islanding becomes important
- Demonstrates need for developing realistic and integrated representations of the underlying interdependent system

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Key Factors Considered

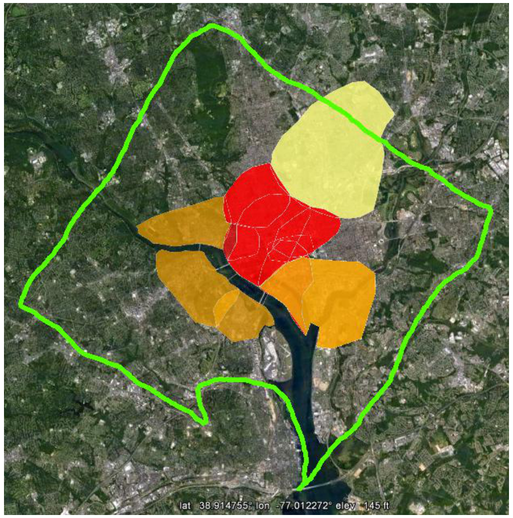
- Outage region and to what extent?
- How many control centers, substations, transformers have been destroyed, and impact of cascading failures?
- Resources available for restoration, e.g., spare transformers
- Secondary effects: impact on communication, health, transportation
- Number and location of control centers, transformers, generating units in the DC region.
- Distribution network
- Total peak time load, generation capacity of the DC region

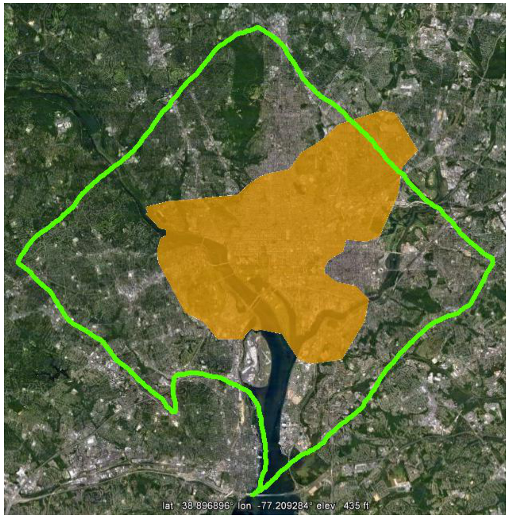
Dynamic Analysis on synthetic power system

- Dynamic analysis by simulation of tripping
  - Steady state model reduction using PSSE
  - Transient analysis of the eastern grid (PEPCO service area)

- System response emulation for 100 sec
  - Final frequency at which local grid settled was found to be lower than the base frequency

Estimated Long Term Power Outage Area





- Probability of damage to individual substations

Aggregated outage area

- ■ / ■ ■ High/medium/low: probability of damage
- Long-term outage area devised by geographically relating the location of substations in the city with the blast damage zones.
- Loss of a substation has a much more widespread impact on power delivery to the customers.

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Estimated Cost of Damage to Electrical Infrastructure

- Factors considered in cost assessment
  - Estimate of substation damage costs
  - Estimate of distribution line costs
- Cost of damaged substations is $96.4m, and distribution system including underground network is $705m.
- Total loss in load is 889.1 MW. At avg. price of $93 per MWh, value of energy lost is $27.78m

Section

3. SMART CITIES APPLICATION

Electric vehicle (EV) charging station placement

- Transportation infrastructure contributes 26% of carbon emissions in the US
- Well accepted approach for reducing emissions: adoption of EVs and hybrid vehicles
- Challenge: limited cruising distance
  - Need to provide charging stations
- Where do we deploy charging infrastructure?

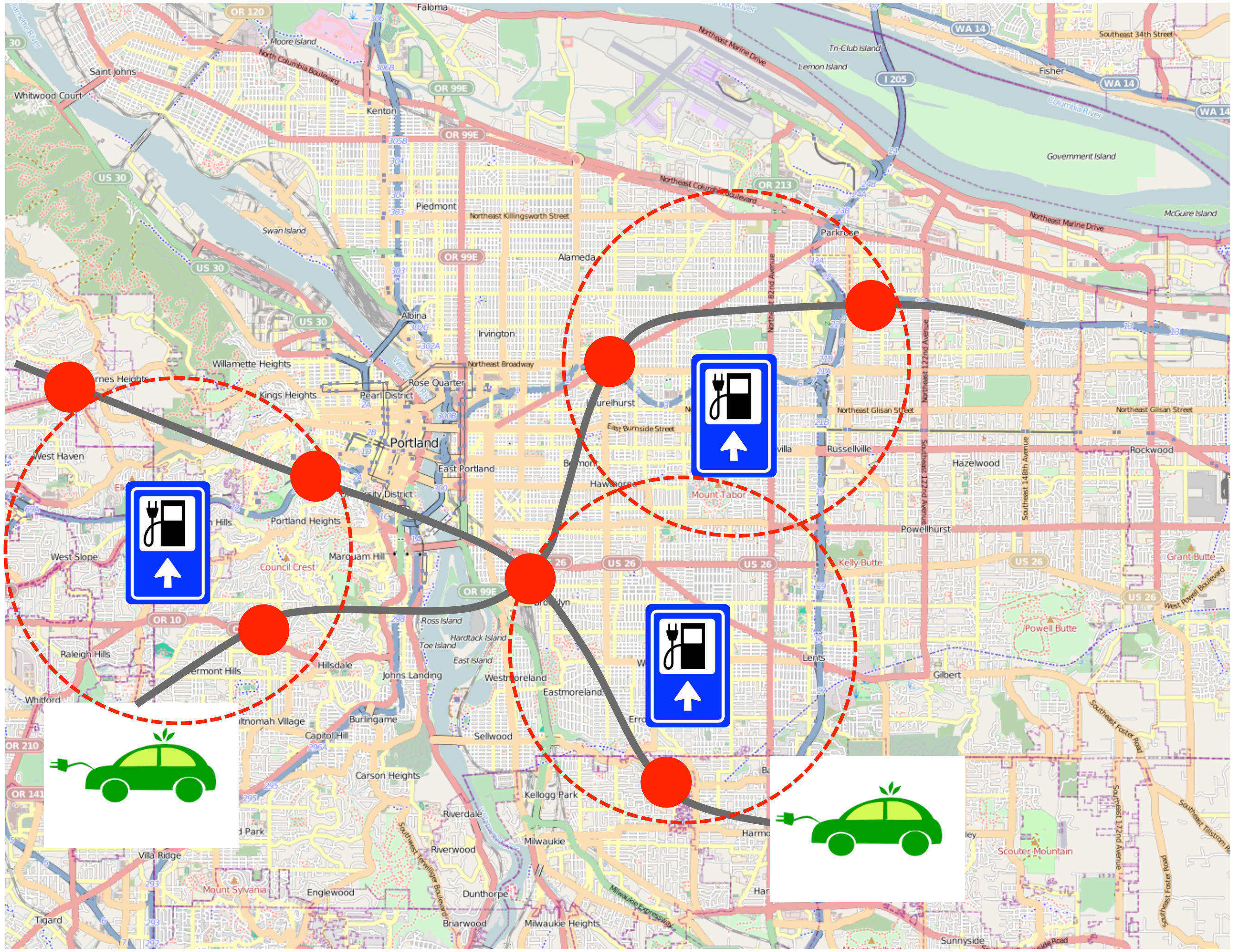
EV charging infrastructure

- Different kinds of charging stations:
  - Level 0: charging at home
    - 4.5 miles of range per hour of charge (Nisan Leaf)
    - 22 hours for full charge
  - Level 1: 240V supply
    - 26 mile of range per hour
    - ≈ $2000
  - Level 2: DC fast charging
    - 40 miles of range per 10 min
    - ≈ $100,000
- Where should different kinds of charging stations be installed?

EV Charging Station Problem

- User demand
  - Relatively small fraction currently has EVs (<2%)
  - Might grow to 10% in a few years
  - Need to be able to serve current users and growing demands
- Typical scenario
  - Users park EV and leave it for charging
  - Should have enough charge to allow for next trip
- Objectives of interest:
  - Distance to charging station from activity location
  - Alternative transportation from charging station
  - Activity duration needs to be taken into account

Formalizing the problem



For each potential location

- Fraction of battery level that gets charged for EV
- Depends on activity duration

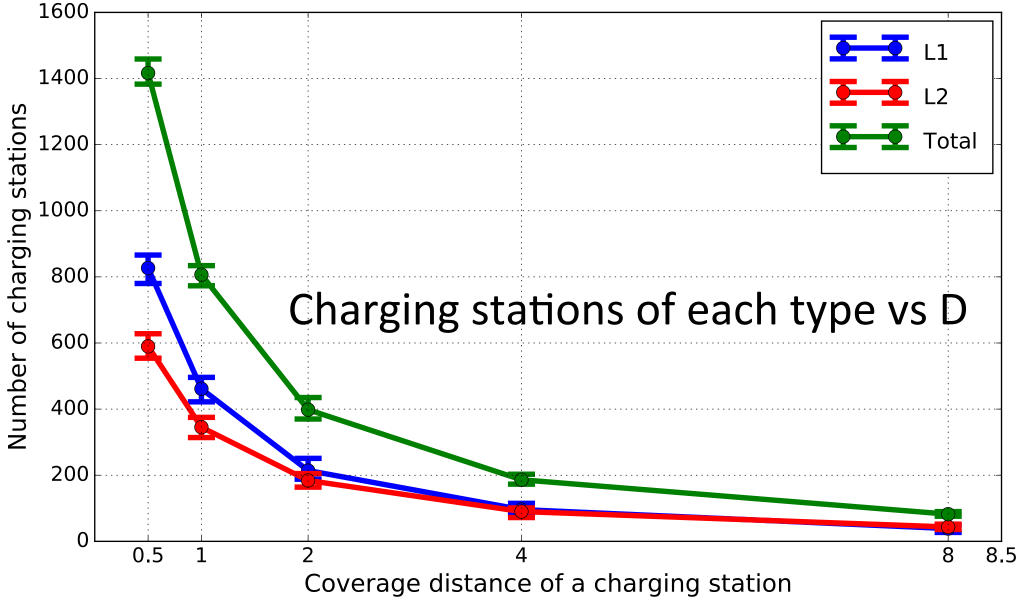
Solve as a facility location problem

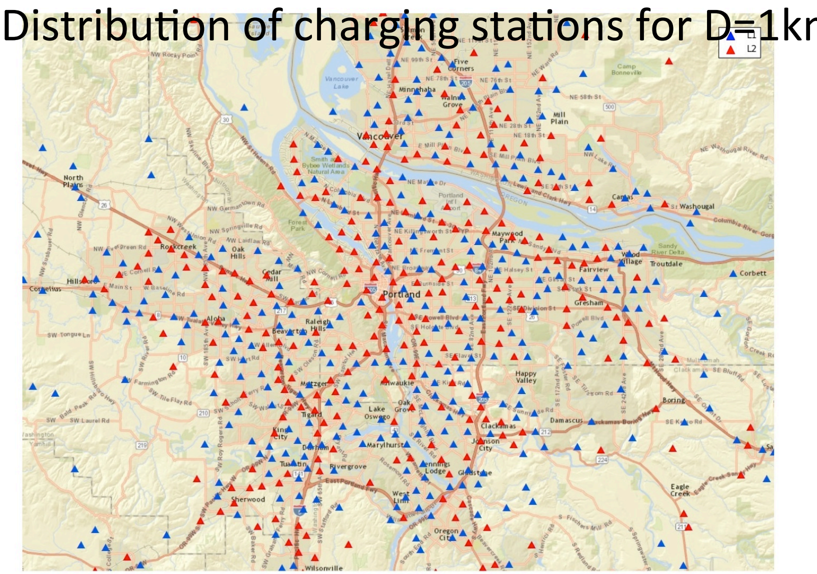
A case study

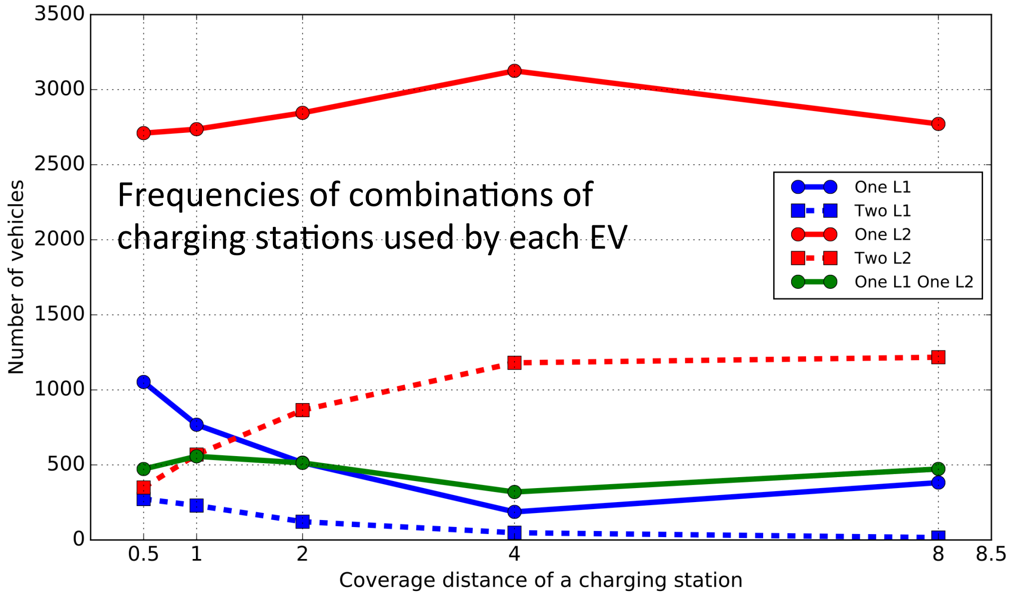
Population	**Over 1.6 million**
#activities per person	~5
Population with EVs	~0.2% of the population
#potential locations for charging stations	~3700

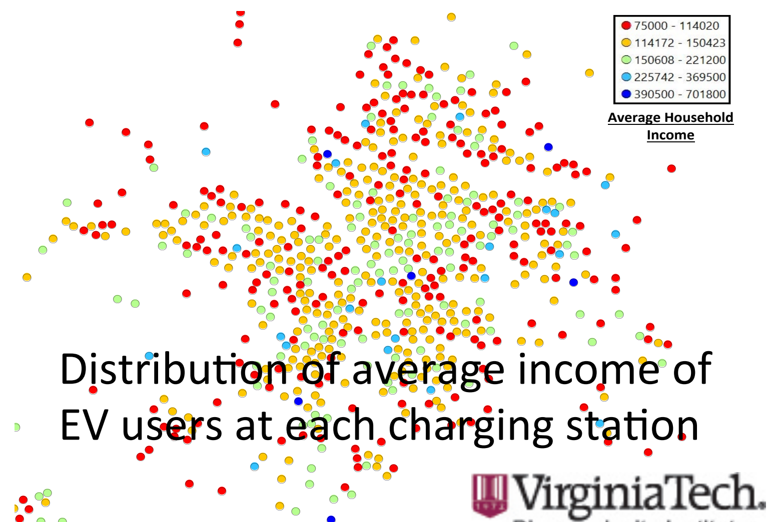
- Currently low adoption rate
- Specific demographics from literature
  - Urban trendsetters (18-35), high income levels
  - Middle-aged families with high income
  - Seniors (60-75) with high income
- In general, can vary adoption rates and other demographics

Results









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Summary

- Synthetic and detailed representation of integrated system can be useful in addressing important problems arising in designing smart grids
- ICT Technologies including Big-data and machine learning techniques can be developed to provide new insights and solutions to emerging problems arising in the design and deployment of next generation energy systems

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Section

ADDITIONAL SLIDES

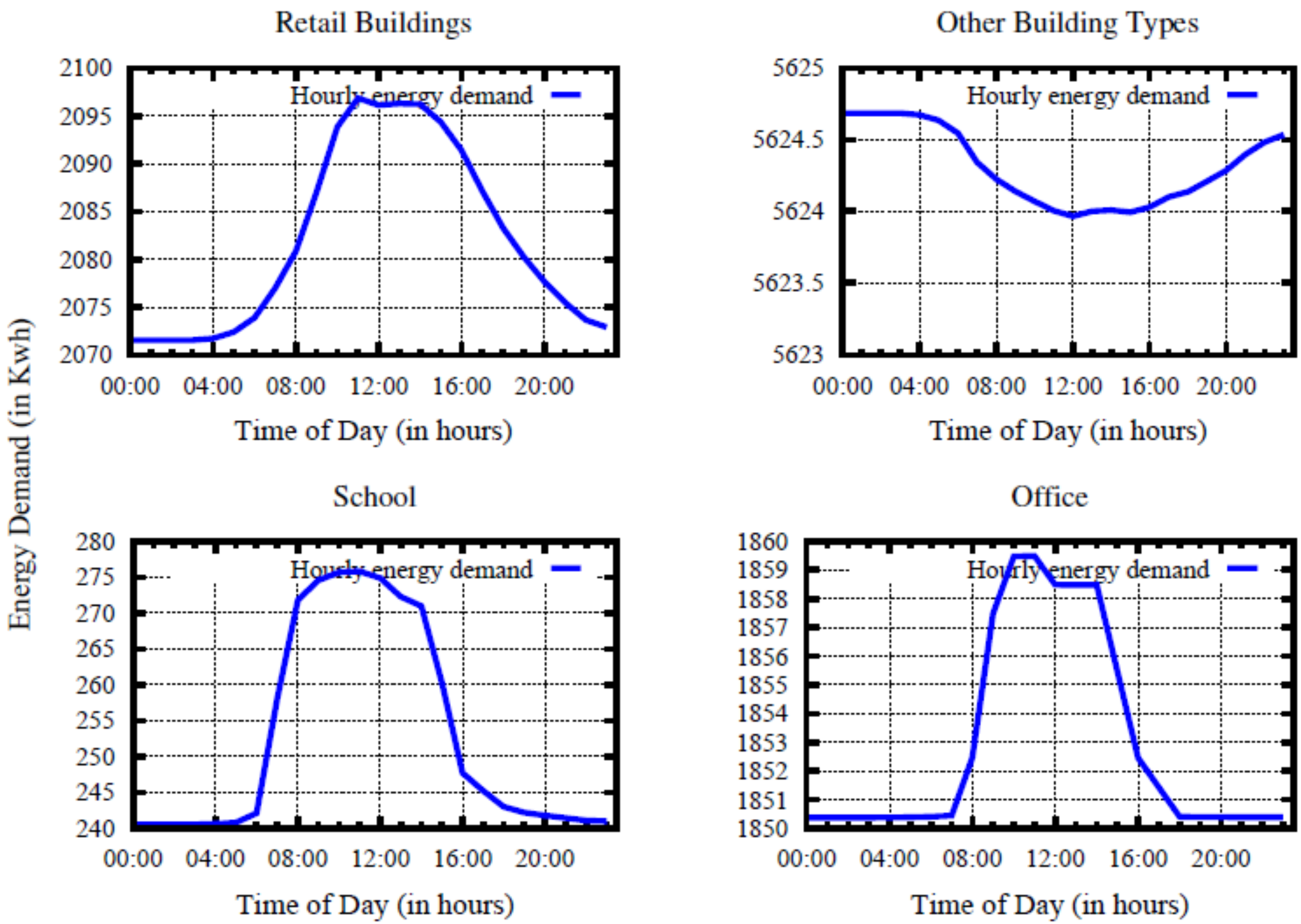
National planning scenario 1

- Unannounced 10 kt detonation of an Improvised Nuclear Device (IND)
- 16th and K Street, Washington DC
- 11:15am May 15th, 2006

Modernizing today's energy systems

- Energy system modernization poses very large scale, evolving and interdependent scientific, policy and design challenges that test the limits of current understanding.
- A national effort is underway to architect and build the next generation power grid ("smart grid"), harness renewable energy sources and reduce its carbon footprint while expanding generation and distribution capacities

Commercial Energy Consumption: Results



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