Mohsen A. Jafari

Industrial and Systems Engineering
Center for Advanced Infrastructure and Transportation (CAIT)
&
Laboratory for Energy Smart Systems (LESS)

Our Research Program

Application areas:

- Distributed Energy Resources (DER)
  - Sizing and location
  - Optimization (day-ahead and real time)
  - Islanding and resiliency
  - Applications (frequency regulation, cost savings, carbon footprint,
  - Portfolio planning and management
  - Smart communities and cities
  - Utility perspective and the future of power grid
  - Energy data analytic
  - Asset management
  - EV integration and charging infrastructure
  - EV and energy storage
- Demand Side Management (DSM)
  - Building energy management and zero net
  - Distributed control of Heating and cooling assets
  - Near real time response and asset degradation
  - Energy asset management (O&M)
- Smart Manufacturing
- Intelligent Transportation Systems
  - Advanced driver assistance systems
  - The use of floating vehicle data and driver safety experience for safety mapping of roads

Common Research Theme of our Research Program

- Control and automation
- Data analytic

- Total of 24 Ph.D. graduates between 1995 – present
- Currently 5 Ph.D. students; 2 M.S. students, and 2 undergraduate students, and 2 engineering staff

Collaborators:

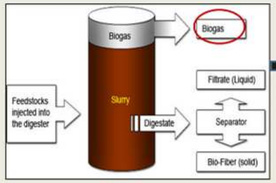
- Siemens, DNV GL Energy, IBM, Quanta, Anhui Keli,
- Public agencies and cities/townships
- University of Cambridge – UK
- Poly-technique Milan – Italy
- University of California – Irvine

Funding Sources:

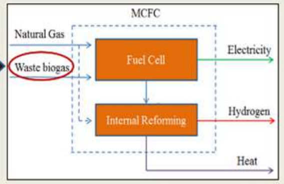
DOD, DOT, DOE, CEC, FHWA, Siemens, DNV-GL Energy, University Transportation Center (UTC/FHWA), NJ Board of Public Utility, internal, Qatar National Research Foundation

Distributed Energy Resources (DER)

Tri-generation to power wastewater & fuel hydrogen vehicles

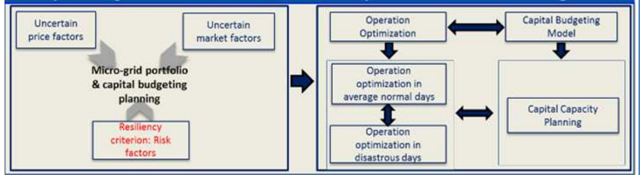


Basic Anaerobic digestion process in wastewater treatment plants
Reference:
http://www.phase3dev.com/biomass_plant_provider.html

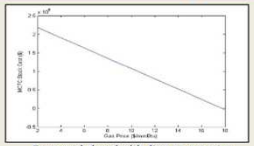


Schematic figure of Molten carbonate fuel cell (MCFC) hydrogen tri-generation

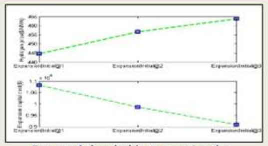
Incorporating Risk in Micro-Grid Portfolio Optimization and Planning



Optimal investment timing under market and price uncertainties



Expected thresholds line to exercise the initial investment option



Expected thresholds to exercise the expansion investment option

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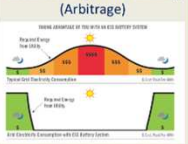
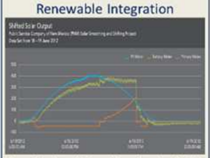
Electric Energy Time Shifting (Arbitrage)



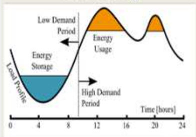
Source: Available at "http://oregonbest.org/news-events/news/item/news/News/action/detail/story/nortooic-flow-battery-slashes-energy-storage-costs/"

Renewable Integration



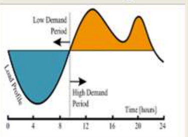
Source: Solar Energy Shifting and Power Smoothing, Available at "http://www.ecoult.com/case-studies/pnm-nm-usa-solar-power-smoothing-and-energy-shifting/"

Peak Shaving



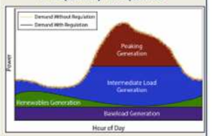
Source: "A Numerical and Graphical Review of Energy Storage Technologies" by S. Sabihuddin, November 2014

Load Leveling



Source: "A Numerical and Graphical Review of Energy Storage Technologies" by S. Sabihuddin, November 2014

Capacity for Regulation and Frequency Response



Source: "Grid Energy Storage", U.S. Department of Energy, December 2013

Generation Capacity Deferral

Source: Asset Deferral, Available at: http://www.imtdon.com/energy-storage-solutions/renewable-energy-developers/

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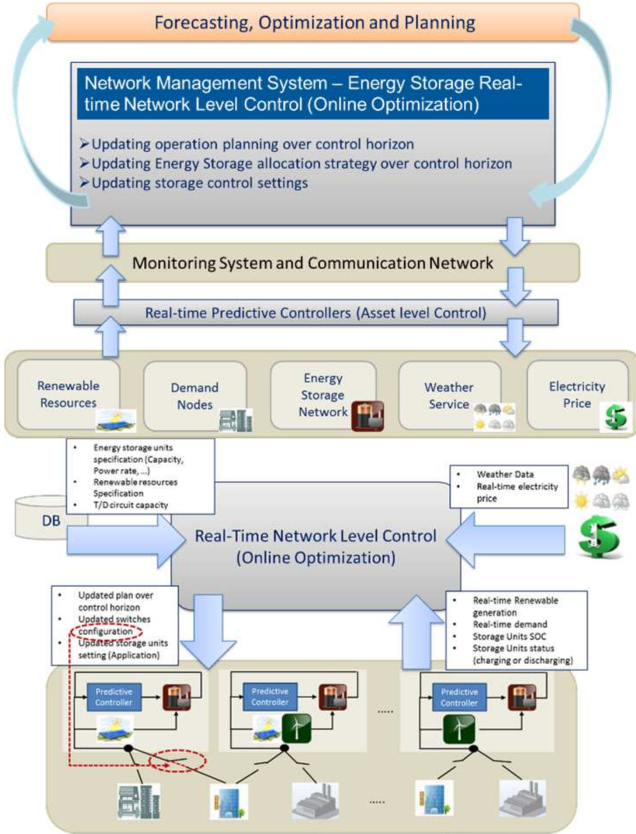
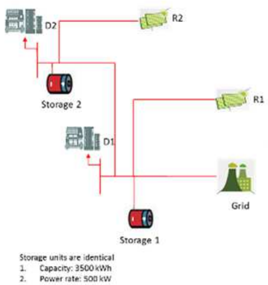
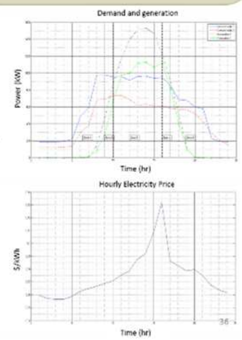
Multi-layer Planning and Control of Energy Storage Networks







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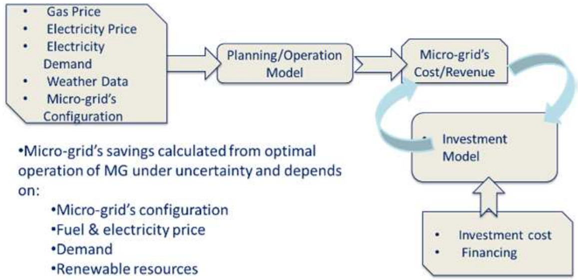
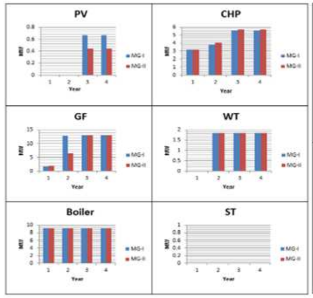
Distributed Energy Resource Portfolio Optimization – Reliability/ resiliency /sustainability

- Portfolio: Gas-fired, PV, Wind Turbine, Energy storage & Sell-back, ...
- Uncertainty in Investment
  - Gas price
  - PV and Storage capita; cost
- Uncertainty in Planning/Operation
  - ✓ Electricity demand
  - ✓ Electricity price
  - ✓ Solar intensity and wind speed

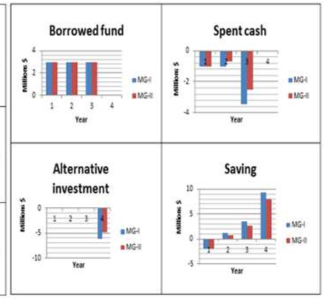


•Micro-grid's savings calculated from optimal operation of MG under uncertainty and depends on:

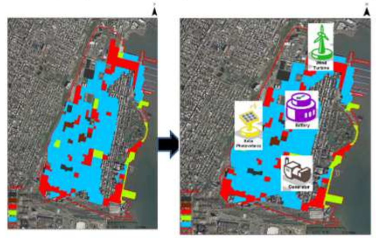
- •Micro-grid's configuration
- •Fuel & electricity price
- •Demand
- •Renewable resources



Micro-grid optimal incremental portfolios with resiliency criterion (MG-I) and without resiliency criterion (MG-II)



Micro-grid optimal expected financial activities with resiliency criterion (MG-I) and without resiliency criterion (MG-II)



Case study: 100-year flood zone are in city of Hoboken, New Jersey

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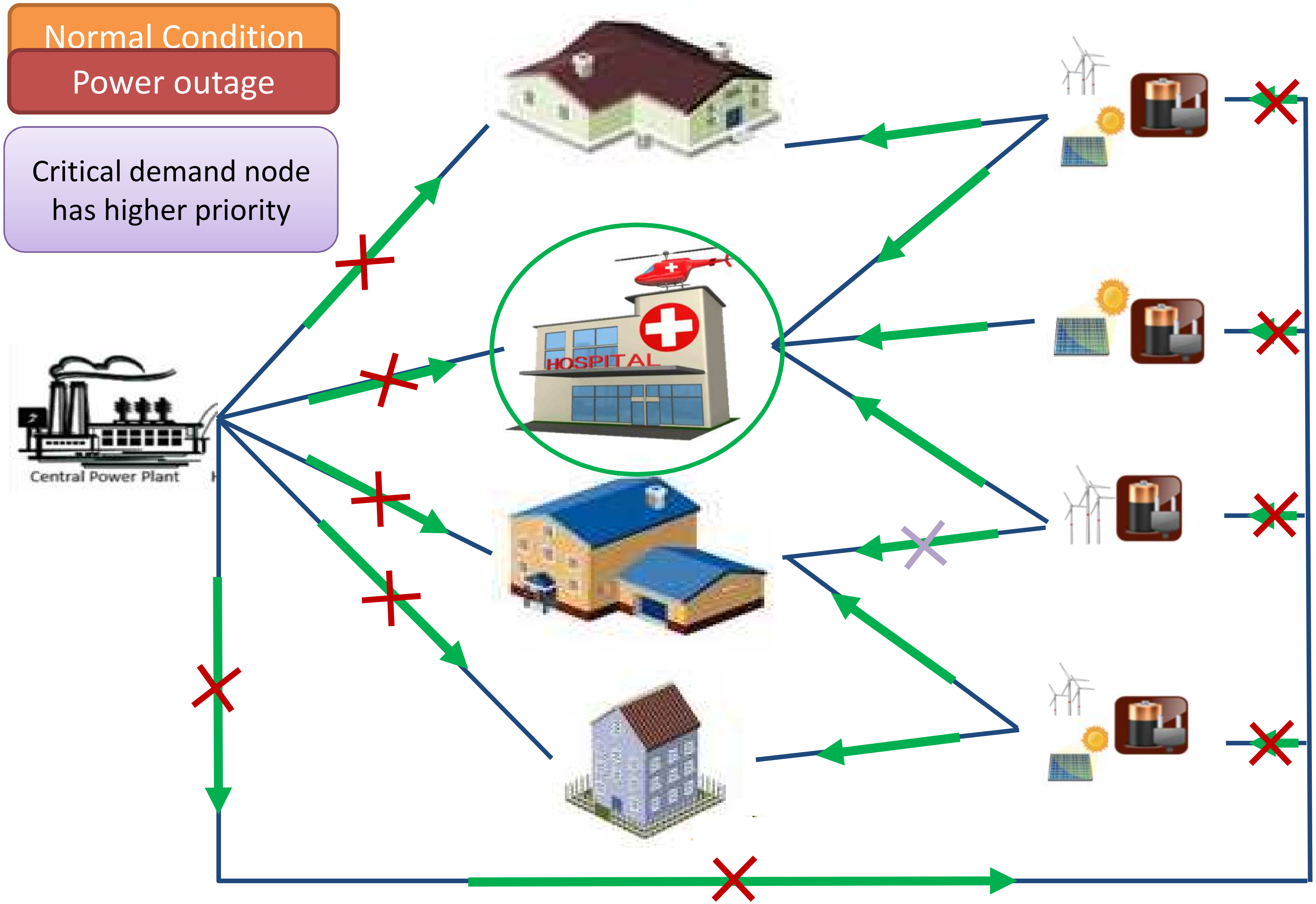
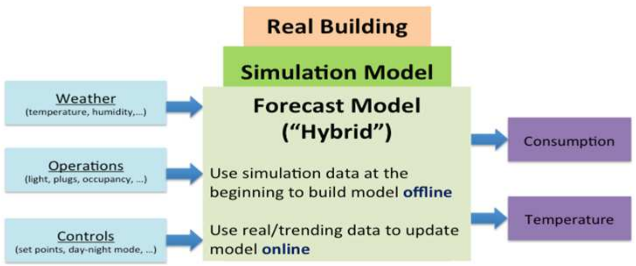
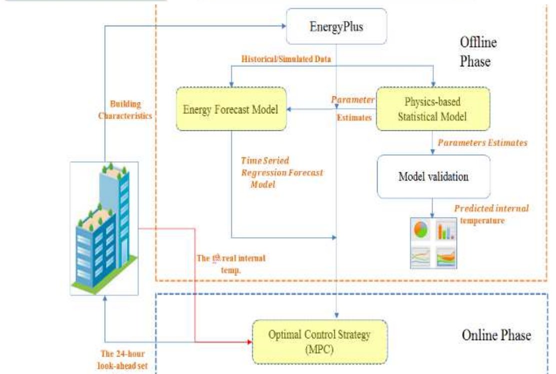
DER Planning for Resiliency Planning

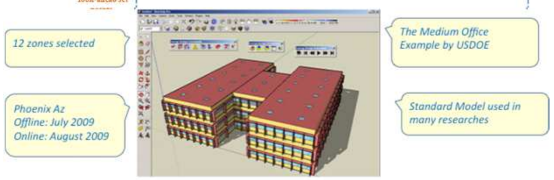


DSM for Built Environment

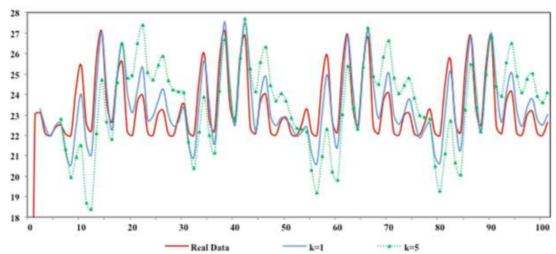
Building Energy Forecast and MPC control



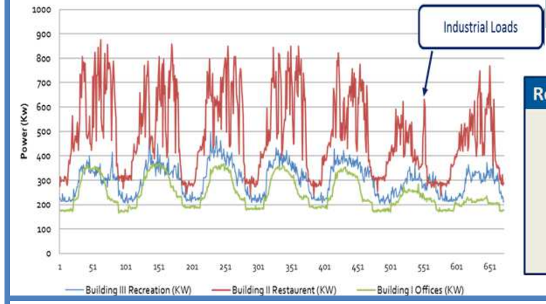




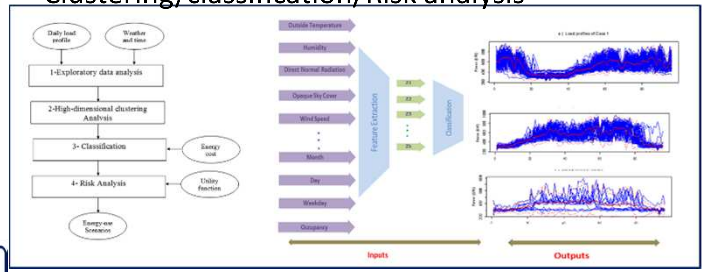
$$\hat{T}_{in}^{t+k}(i) = \hat{T}_{in}^{t+k-1}(i) + \hat{\alpha}_i^k R^{t+k-1}(i) + \hat{\varphi}_i^k \left(\hat{T}_{in}^{t+k-1}(i) - \hat{T}_{ext}^{t+k-1}(i)\right)$$



Demand Response and avoiding Demand Charges in Industrial Systems

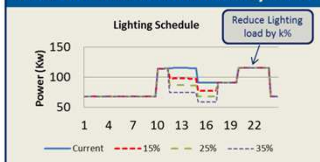


Clustering/classification/Risk analysis



Risk based control

Reduction in industrial load by reducing lighting loads



	% reduce in total lighting load							
	0%	10%	15%	20%	25%	30%	35%	50%
Class 1	200.67 **0.0%**	199.00 **0.8%**	198.33 **1.2%**	197.50 **1.6%**	196.67 **2.0%**	195.83 **2.4%**	194.33 **3.2%**	192.67 **4.0%**
Class 2	270.33 **0.0%**	268.33 **0.6%**	267.33 **1.0%**	266.33 **1.3%**	265.50 **1.6%**	264.67 **1.9%**	263.50 **2.5%**	262.50 **3.0%**
Class 3	433.75 0.0%	430.75 0.7%	429 1.1%	427.5 1.4%	426 1.8%	425 2.0%	423.75 2.3%	422.5 2.6%
Total Expected Energy Cost	262.9 **0.0%**	261.0 **0.7%**	260.0 **1.1%**	259.0 **1.4%**	258.2 **1.8%**	257.3 **2.1%**	256.1 **2.5%**	254.9 **2.9%**

Community Bottom up Dynamic Modeling – Planning & control

With the increasing penetration of PEVs, **load patterns change** and the magnitude depends on whether or not households utilize advanced controls/charging schedules.

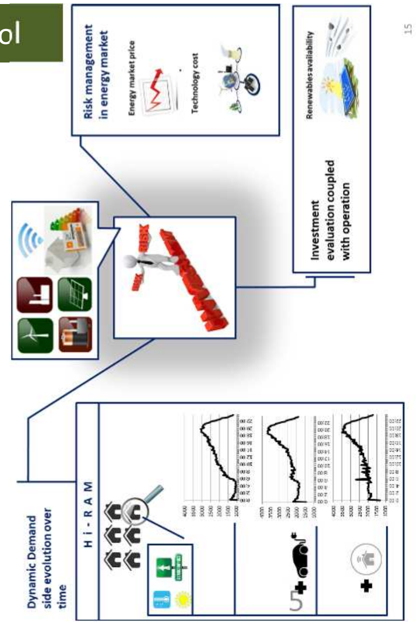
Smart homes and technological solutions certainly **change demand patterns** and will impact DER sizing in short and long terms.

Using average loads/time series forecast models from historical data, may lead to investment decisions that **fail to correctly oversee these changes.**

- A dynamical **High** Resolution Adaptive Model (**Hi-RAM**); captures load under a discrete set of configurations and design choices that pertain to behavioral patterns and technological solutions
(at individual household levels)

- A stochastic DER portfolio investment model in the form of MINLP that optimizes cash flow over & beyond planning horizon.
- Cash flows include operational savings due to DER investment.

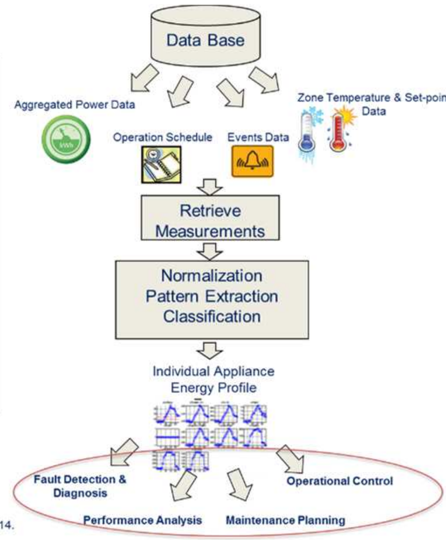
High-resolution data without relying on historical data
Impact of different technologies (e.g. PEV, Advanced BMS)
Implementation of DSM



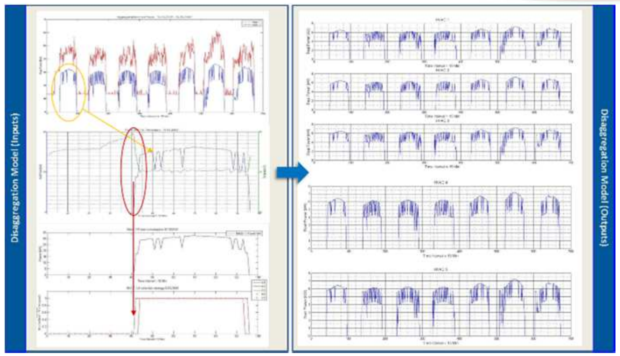
DMS for Built Environment

Load Disaggregation – Buildings & communities

- About 40% of the total energy used in the United States is consumed by the building sector. [1]
- Data analytics of metering data allows auto identification of the consumption of an individual appliance:
  - Tailored energy feedback at no extra cost
  - Improved energy and performance efficiency
  - New business opportunities in long and short term planning/scheduling



[1] Annual Energy Review 2014, Energy Information Administration, 2014.



Community based collaboration to reduce quantity risk (CfD measure)

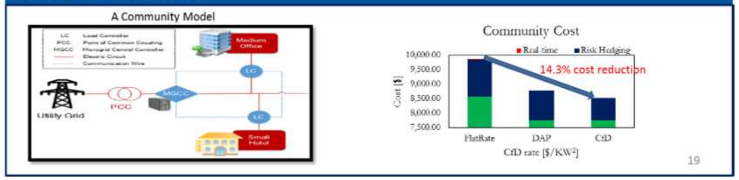
Load forecasting/Day-ahead planning/ Real-time tracking

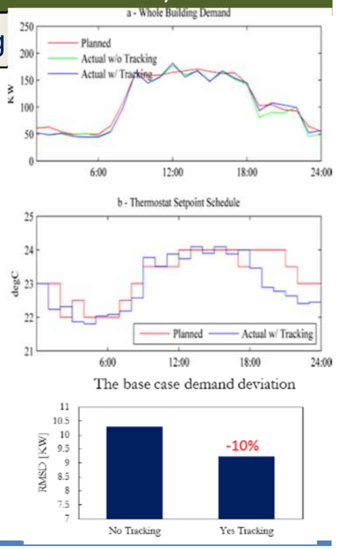
- Major sources:
  - Weather
  - Human behavior
- Well recognized and accounted for in:
  - Demand forecast
  - Load scheduling
  - Grid operation
  - Market strategy
- Treated as
  - given or can be estimated
  - Uncontrollable

- Causes quantity risk
- Quantity risk is hedged by raised retail price
- Two consequences:
  - More electricity cost
  - Unfair cost share (paying for someone else's fault)

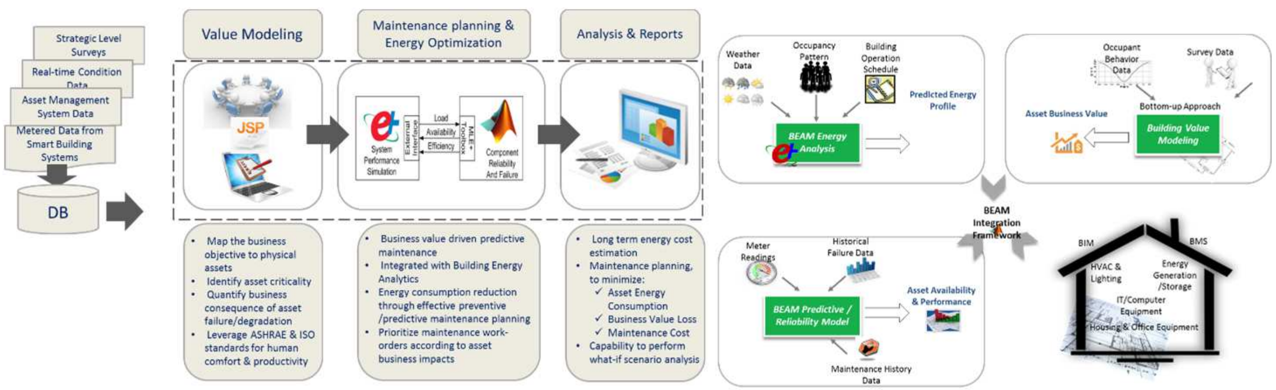
- **Proposed Approach**
  - Cost-for-Deviation (CfD)
  - Customers plan demand schedules first, and follow their schedules in real-time
  - Buildings can track their usage and coordinate with other buildings in their community to reduce deviations and spot prices.
  - Assuming dynamic pricing

CfD Reduces Risk/Cost





Building Energy Asset Management (BEAM)

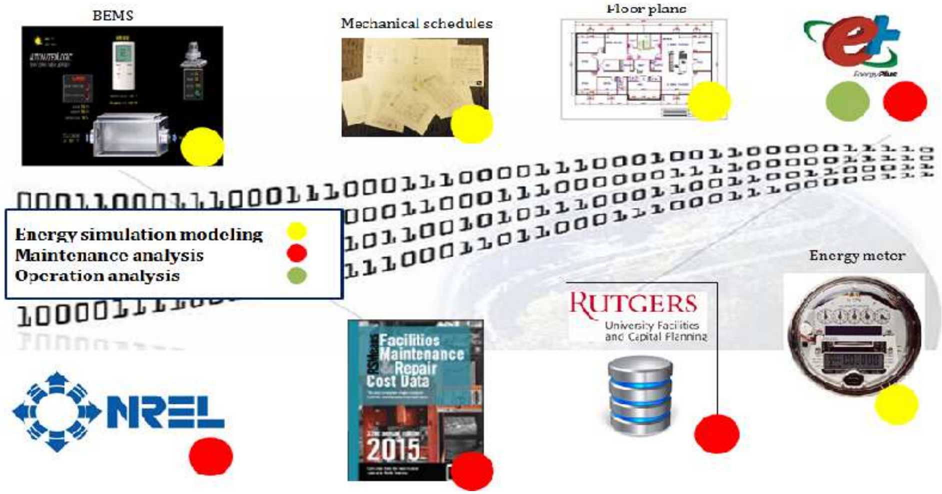


Next Generation BEAM will integrate device and equipment simulations with cloud computing and IOT for optimal short and medium term maintenance planning and operation control.

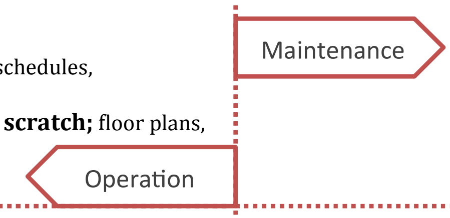
O&M for building complexes

- Operational planning (hourly)
  - ✓ Estimation of hourly HVAC consumption
  - ✓ Hourly HVAC set point schedule
  - ✓ Load shifting capability
  - ✓ Evaluation of different schedules (e.g., on/off, always on, set-back)
  - ✓ No need for online energy simulation in optimization framework

- Maintenance planning (annually)
  - ✓ Assigning best maintenance actions to HVAC assets (possible sets of action: reactive maintenance, preventive maintenance, replacement, repair) considering current health and age condition of assets
  - ✓ Annual building performance measure (the percentage of time that the internal temperature is in the pre-defined band-gap)
  - ✓ Expected numbers of assets failure
  - ✓ Electricity & maintenance cost (present value) under different O&M Strategies & Initial Conditions
  - ✓ Annual cost savings under different O&M Strategies & Initial Conditions



Option1: Available Bldg. energy model
Option2: BMS systems; HVAC Meter data, occupancy schedules, external temperatures, zonal internal temperatures
Option3: Constructing Bldg. energy model from scratch; floor plans, mechanical & occupancy schedules, list of assets, HVAC meter data

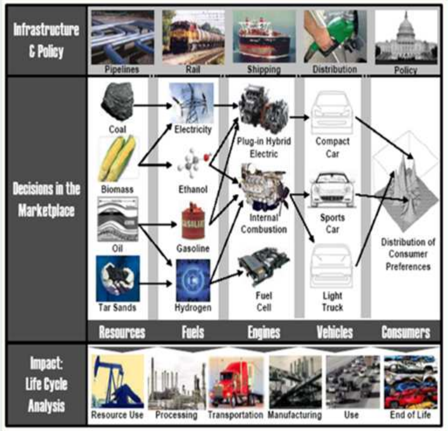


Infrastructure

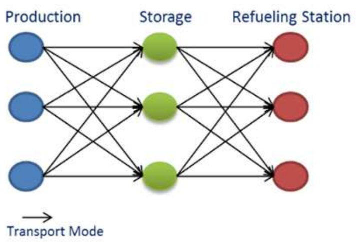
Hydrogen Fueling Infrastructure

- How to design and plan a sustainable regional infrastructure for hydrogen fuel supply chain network under uncertain demand and in what capacity and location in macro and micro level.
  - The hydrogen supply chain consists of hydrogen production plants, storage facilities and delivery modes.
- How to estimate the potential demand for fuel cell vehicles based on different household attributes such as income, education etc.

Transportation Energy Infrastructure



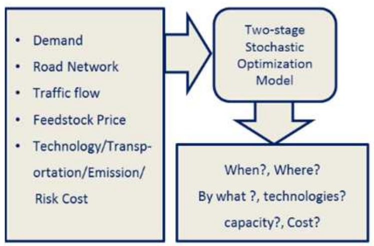
Source: Material Use, Infrastructure Change, and Environmental Impacts for Alternative Fuels and Vehicles by Lave, Hendrickson, Matthews, Michalek and W. Michael Griffin .http://gdi.ce.cmu.edu

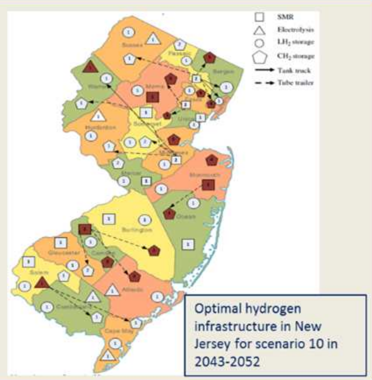


Social Cost

Social cost categorized by four perspectives

- **Economy**
  - Capital Cost
  - Operating Cost
- **Ecology**
  - Emission cost
- **Energy**
  - Energy Consumption cost
- **Risk**





Optimal hydrogen infrastructure in New Jersey for scenario 10 in 2043-2052

- Electric vehicle charging networks
  - Planning
  - Charging sequencing control
- Parking lots as energy storage
- Transforming underprivileged communities to clean energy communities
- Value generation from statewide energy storage (completed in summer 2016)
- Value generation from statewide CHP-FC (ongoing)

Cyber Physical Simulation Platform for Smart communities

Motivation

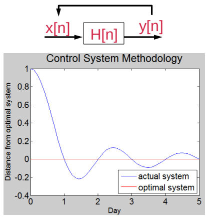
Net-Zero energy communities are being established all over the world, and require advanced operational controls and maintenance plans supported by data and innovative technology. While many models have been established for individual smart grid components, accurately predicting the behavior of a system that combines renewable technologies with multiple buildings is a challenge necessary for implementing Net-Zero communities on a larger scale.

Goals

1. Build a cyber-physical testbed that achieves Net-Zero energy for a given community
2. Accurately portray the behavior of multiple renewable energy technologies
3. Make dynamic decisions in real-time using customizable forecast models
4. Design testbed to model and optimize any community

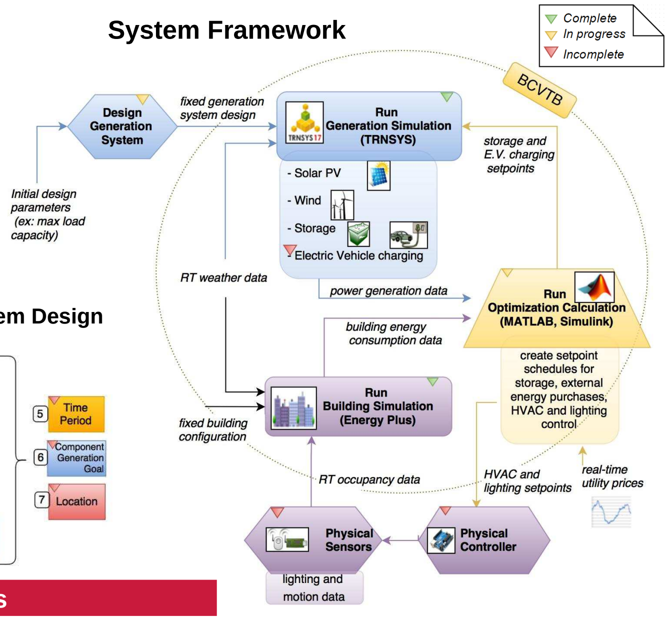
Methodology

Control Theory

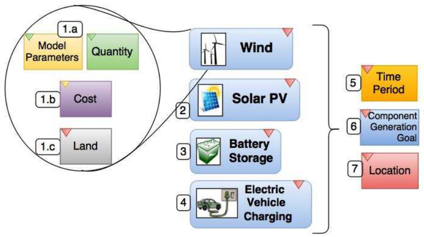


For each daily iteration, the forecast model overshoots but eventually reaches the optimal system behavior

System Framework



Choosing Generation System Design

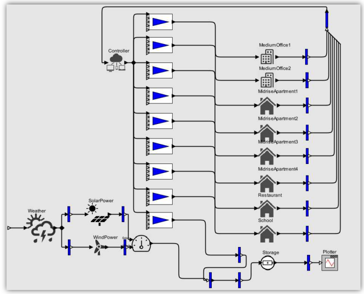


Challenges

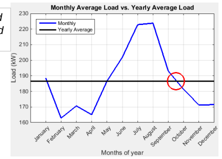
- Integrating TRNSYS with BCVTB
- Developing heuristic generation system design methodology
- Initially simulating real-time building occupancy data without using physical sensors
- Creating dynamic user-friendly interface that allows easy alteration of system design and forecast models
- Scaling and accuracy verification

Results

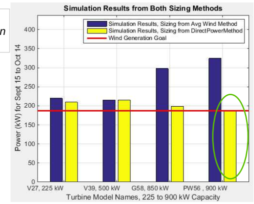
Layout of Testbed in BCVTB Interface

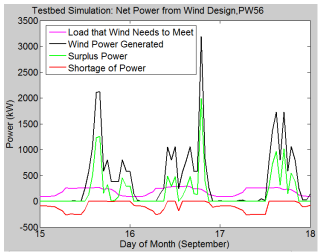


Best representative time period is Sept 15 to Aug 14 month and is fixed for subsequent design



Turbine model that best meets energy generation goal is PW56





Net zero energy: Surplus power – Shortage power ~= 0 ✓

Conclusions

- Test bed established:

Buildings: (based on D.O.E. models)	Renewable Generation:
• 2 medium offices • 4 midrise apartments • 1 full-service restaurant • 1 primary school	• 4 PowerWind 900kW 56m diameter wind turbines • 120x130 silicon PV solar farm • 400x400 batteries, 16.7kW capacity

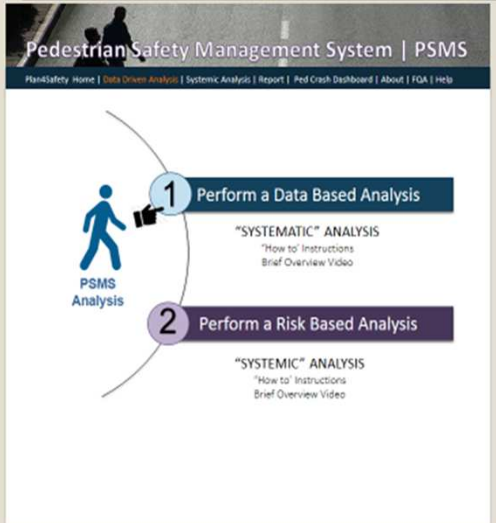
- Test bed achieves distributed building control based on onsite generation
- Wind design finds best turbine model and quantity from available commercial options

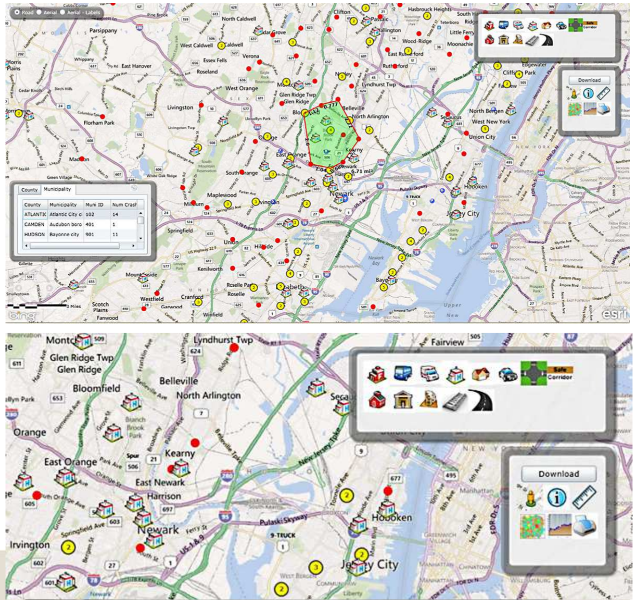
	Generation	Consumption	Whole System
✓ Phase 1: Setup	• Simulate basic wind, solar, and storage system using TRNSYS	• Design building geometry with Google Sketchup • Create deterministic occupancy models of typical buildings using Energy Plus	• Energy Plus to BCVTB integration • TRNSYS to BCVTB integration
✓ Phase 2: Development Part 1	• Wind farm design	• Create additional building models	• Create forecast models • Incorporate utility electricity prices

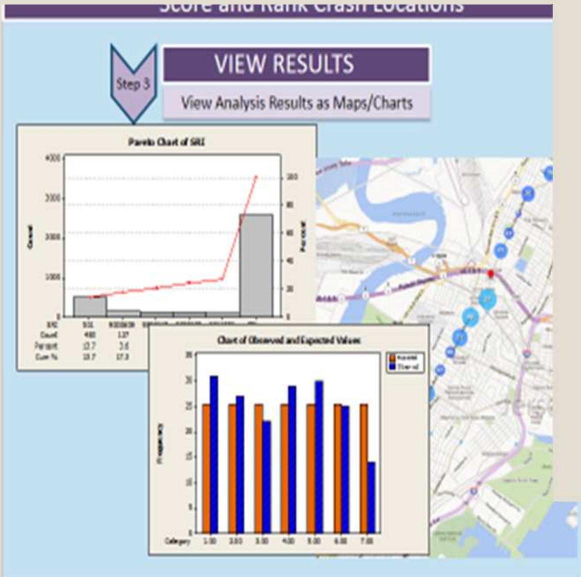
Future Work

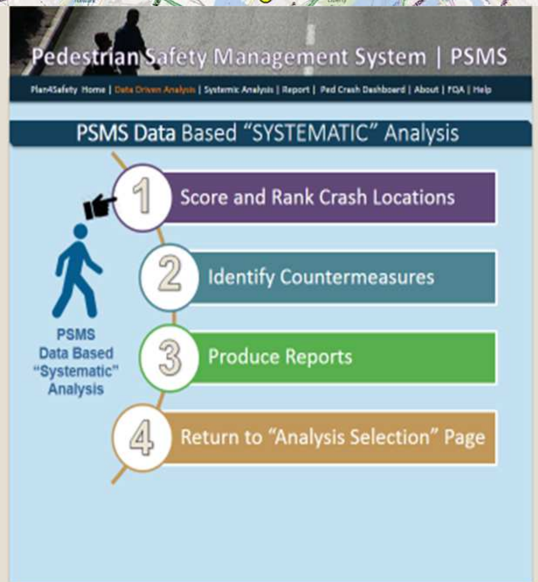
	Generation	Consumption	Whole System
Phase 2: Development Part 2	• Solar farm design • Battery storage design • electric vehicle charging simulation and design	• Use lighting and motion sensors to collect real building occupancy data	• Create storage/HVAC/lighting set-point schedules
Phase 3: Testing	• Design combined generation system with load balancing and cost minimization	• Improve control logic that acts in physical building	• Create test plan: vary parameters, analyze results, develop design trends • Run whole system in real time • Achieve net zero energy
	Achieve net zero energy		

Plan4Saefty (P4S) – A Tool For Systematic Analytics









A Short Overview Of P4S Predictive Analytics (1)

Historical Database

- Crash Records
- Traffic Volume Data

$X_1(t)$ $X_2(t)$ .... $X_k(t)$

Predictive Model

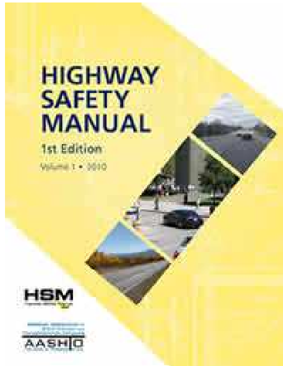
$Y_i(t)$ = Average Crash Frequency For site *i* at time t

Z_1 Z_2 .... Z_n

How to find a good model?

Roadway (Engineering) Database:

- length of segment, lane width, shoulder width, shoulder type, roadside hazard rating, presence or absence of horizontal curve, curve characteristics, Lighting, Speed Limit and ....



- **Based on AADT and Roadway Length**
- **Models were developed by data from specific states**

Adjust the calculated SPF predicted value for base conditions to actual or proposed conditions

Adjust SPF to reflect local conditions: Climate , Driver populations , Animal populations , Crash Reporting System.

Improve crash estimations by combining predicted data with historical data

Inputs → SPF → Crash Modification Factor → Calibration Factor → Empirical Bayesian Method → **Average Crash Frequency**

$$N_{predicted} = SPF \times (CMF1 \times CMF2 \times \ldots) \times C$$

$$N_{expected} = w \times N_{predicted} + (1-w) \times N_{observed}$$

A Short Overview Of P4S Predictive Analytics (2)

Poisson Model (popular model)

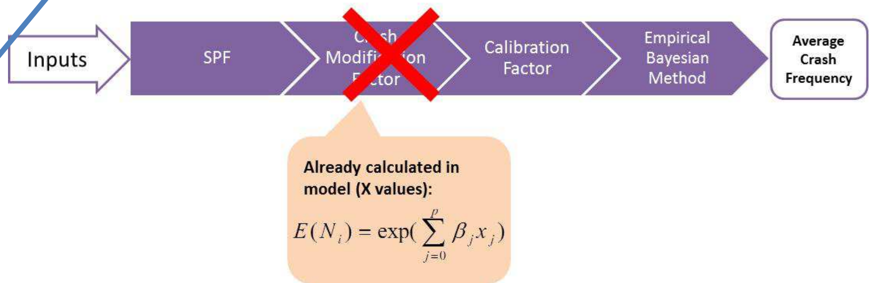
$N_i(t)$: # of crashes in site i and year t

$$f(N_i(t),\lambda_i) = e^{-\lambda t}\frac{(\lambda_i t)^{N_i(t)}}{N_i(t)!}$$

$$E(N_i(t)) = \exp(\sum_{j=0}^{p}\beta_j x_j)$$

Average crash at site i and year t

Roadway characteristics and traffic information



Negative binomial model

Assume that the Poisson parameter is random variable (with gamma distribution)

$$f(N_i(t)\,|\,x_i,\lambda_i,\nu,\delta) = \int_0^\infty e^{-\lambda_i}\frac{(\lambda_i)^{N_i}}{N_i!}.G(\lambda_i\,|\,\nu,\delta)\,d\lambda_i$$

$$f(N_i\,|\,x_i,\nu,\delta) = \frac{\Gamma(\nu+N_i)}{\Gamma(\nu)\Gamma(N_i+1)}\left(\frac{\delta}{1+\delta}\right)^{\nu}\left(\frac{1}{1+\delta}\right)^{N_i}$$

$$f(N_i\,|\,x_i,\alpha,\delta) = \frac{\Gamma(N_i+1/\alpha)}{\Gamma(1/\alpha)\Gamma(N_i+1)}\left(\frac{1}{1+\alpha\mu_i}\right)^{1/\alpha}\left(1-\frac{1}{1+\alpha\mu_i}\right)^{N_i}$$

$$E(N_i) = \mu_i = \exp(\sum_{j=0}^{p}\beta_j x_j)$$

Multiple Data Streams

Static Data
Roadway conditions, traffic signals, etc.

Dynamic data

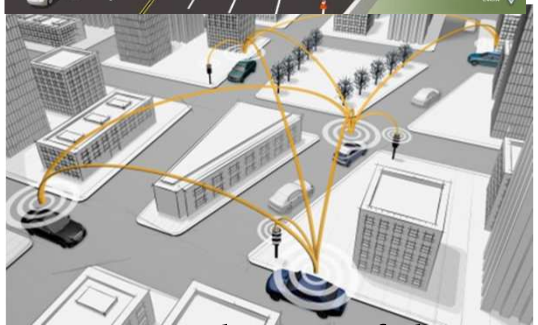
Weather & roadway conditions real time

Weather data and roadway condition
can be reported near real time by sensors, vehicles, and roadway sensors.

Near miss, IOT & roadway sensors

Crashes are rare events and crash based safety solutions are reactive; Near real time near miss data and unsafe driving conditions can protect vulnerable users, e.g., pedestrians and bicycles.

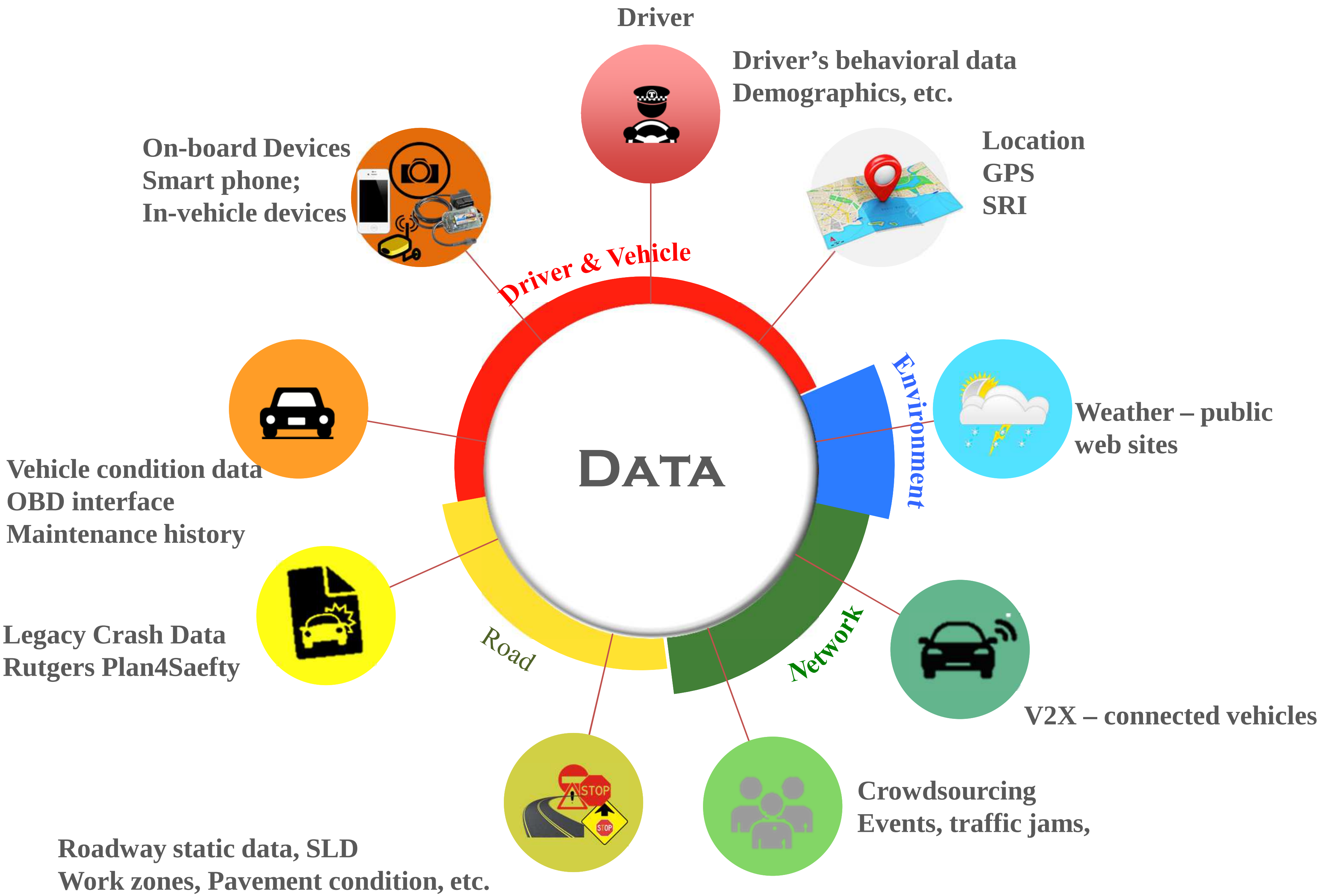
Traffic flow data V2V,V2I & crowdsourcing



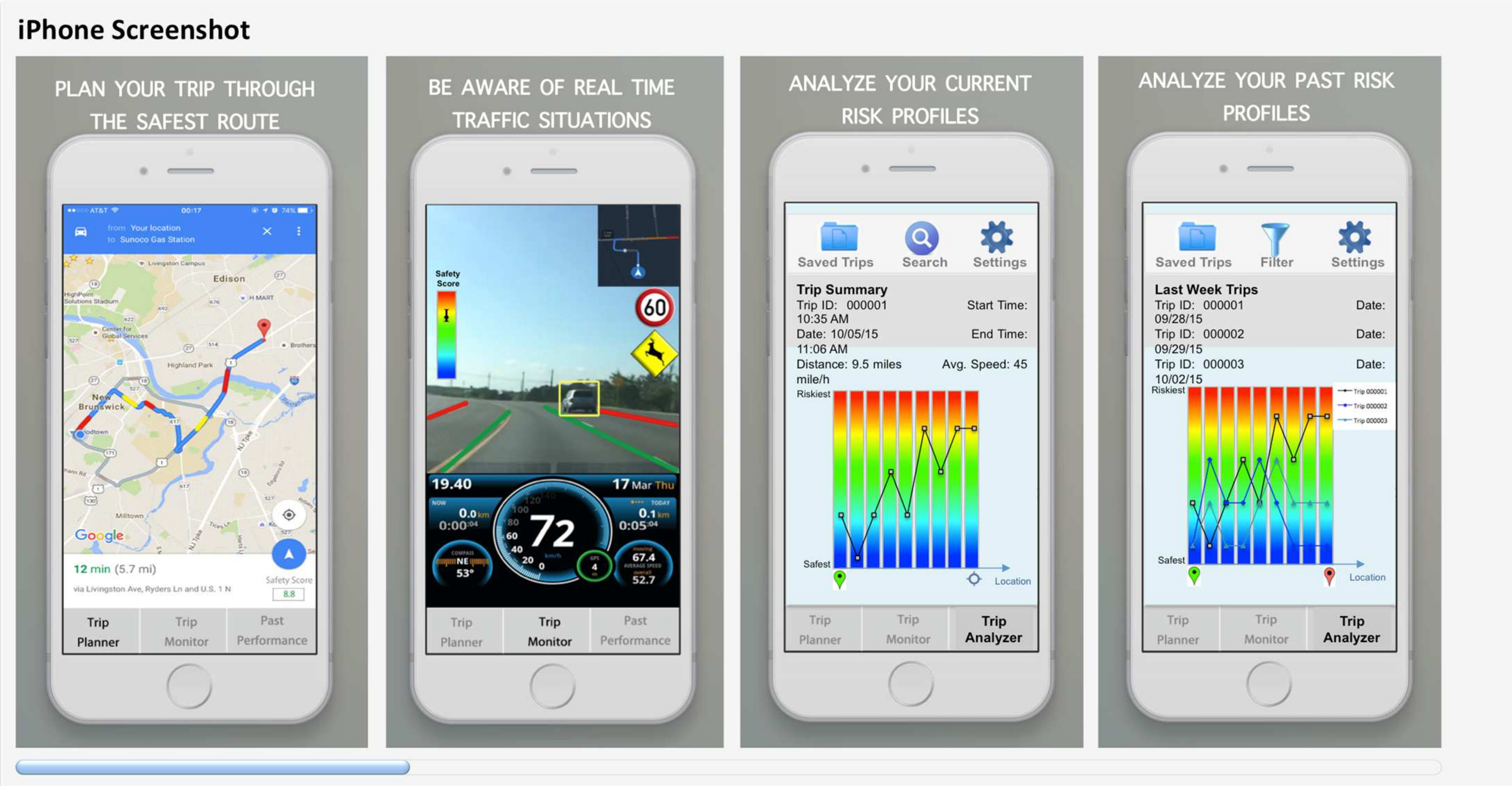
Warnings & real time unsafe driving conditions generated between vehicles and between vehicles and infrastructure;

Naturalistic Driving Data

Holistic data fusion approach will becomes possible soon …



Onboard Smart Device APP …



- ❑ Instantaneous safety alerts and risk heat maps
- ❑ Safety risk profiles for current trip – from start to current location/time
- ❑ Historical safety profiles
- ❑ Safe route maps

Safe route mapping technology …

Towards vision ZERO
To bring road safety information to drivers and traffic authorities in real time
To evaluate safety countermeasures in much shorter time periods
Real time road safety conditions for autonomous driving