

ENERGISE Program Kickoff

DOE Award #: **DE-EE0008003**

U.S. DEPARTMENT OF
ENERGY

Energy Efficiency &
Renewable Energy



DEEP SOLAR
Data DrivEn Modeling and Analytics for Enhanced
System Layer Implementation

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Project Team

Name	Role	Main Responsibilities (High level tasks/sub-tasks)
Viktor K. Prasanna (USC)	PI	<ul style="list-style-type: none">• Work closely with the team members to meet the milestones and deliverables within budget and schedule• Co-ordinate and host the kick-off meeting, quarterly review meetings and annual meetings• Technical lead on developing predictive analytics and real-time control software
Rajgopal Kannan (USC)	Co - PI	<ul style="list-style-type: none">• Work closely with the students<ul style="list-style-type: none">• Machine learning algorithms• Software development of forecasting models• Stochastic analysis and optimization
Valentino Tiangco (SMUD)	Subcontractor	<ul style="list-style-type: none">• Utility guidance on interconnection standards, distribution grid issues and interoperability requirements• Utility perspective on distributed generation and renewable energy programs

Project Team

USC

- ❖ Viktor K. Prasanna
- ❖ Rajgopal Kannan
- ❖ Ajitesh Srivastava
- ❖ Athanasios Rompokos
- ❖ Atila Orhon
- ❖ Chi Zhang
- ❖ Chung Ming Cheung
- ❖ Sanmukh Rao Kuppannagari



SMUD

- ❖ Valentino Tiangco
- ❖ Elaine Sison-Lebrilla



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- ❖ Modeling and Optimizations to Enable Deep Solar Penetration
 - > 100% relative to peak
 - > 250% relative to day time minimum load

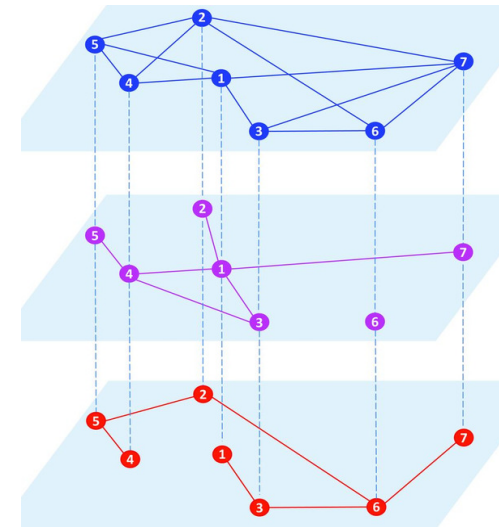
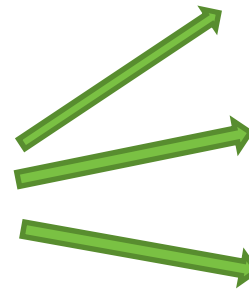
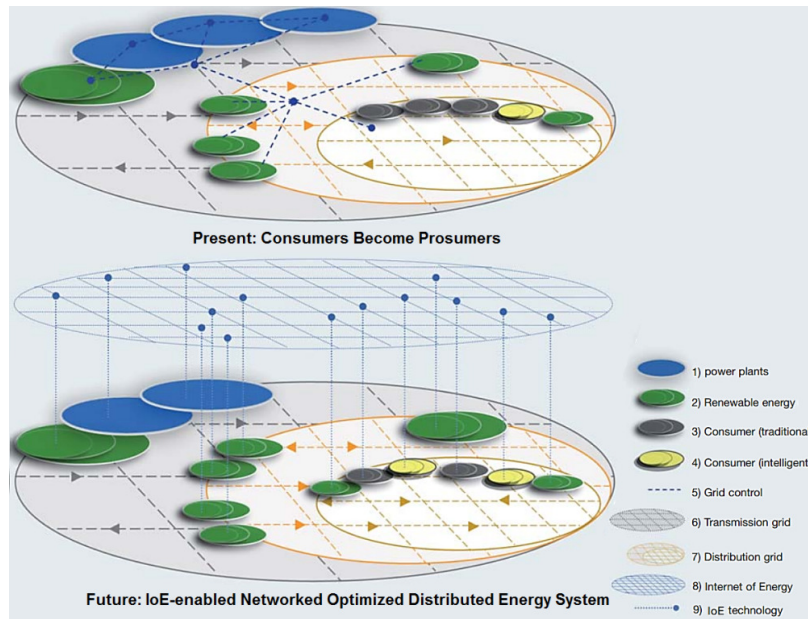
- ❖ Fast Data Analytics for Real-time Operations
 - Grid Size: 1000 to 1 million node
 - Response time: <1 min for short term, < 5min for long term planning

- ❖ Software for Situational Awareness & Operational Planning
 - Preparation for spontaneous condition changes

- ❖ Fast, robust predictive analytics for accurate load and generation **prediction**
- ❖ Real time scalable **optimization** framework for smooth grid operation
- ❖ Dynamic “**What-If**” Scenario Analysis for operational planning

- ❖ Live Energy Map (LEM)
- ❖ Predictive Analytics
- ❖ Optimization Framework
- ❖ Data Modeling, Forecasting & Imputation
- ❖ Parallelization for Real-Time ESL Control

Live Energy Map (LEM)



❖ Problem definition

- Effective representation of energy components

❖ Challenges

- Granularity, support for fast analytics, scalability

❖ Approach

- Multilayered heterogeneous, directed, time varying, labeled **network representation** to capture the physical, communication, logical network, etc., to fully express essential grid attributes
- “Incremental” and “evolving” graph analytics algorithms for **real-time** computation of effect of change in a node or a link on the entire system

❖ Problem definition

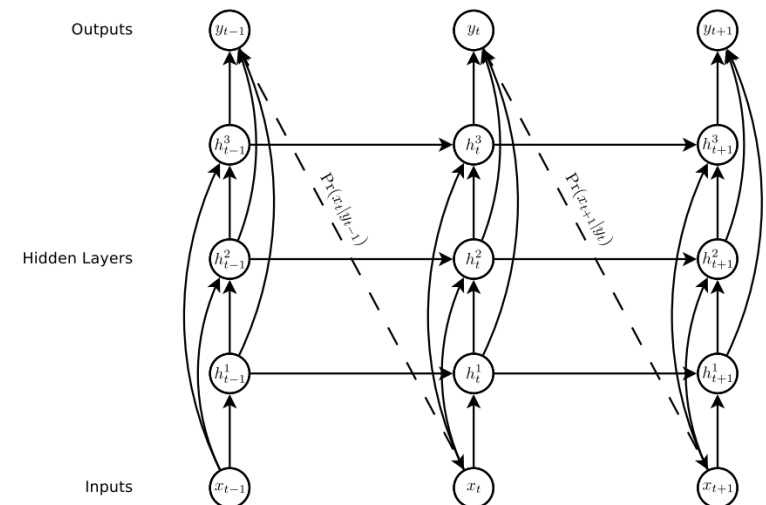
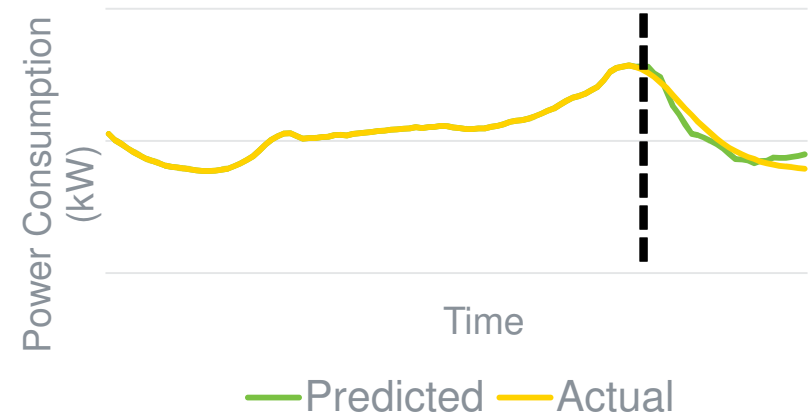
- Solar generation prediction
- Short term load forecasting

❖ Challenges

- Missing data
- Various time granularity of data

❖ Approach

- Model distribution of data with **mixture models**
- **Granger-causality** Graph representation to capture the node dependency
- **Recurrent Neural Networks**



❖ Problem definition

- Supply Demand matching in each interval
- Minimize cost of grid operations

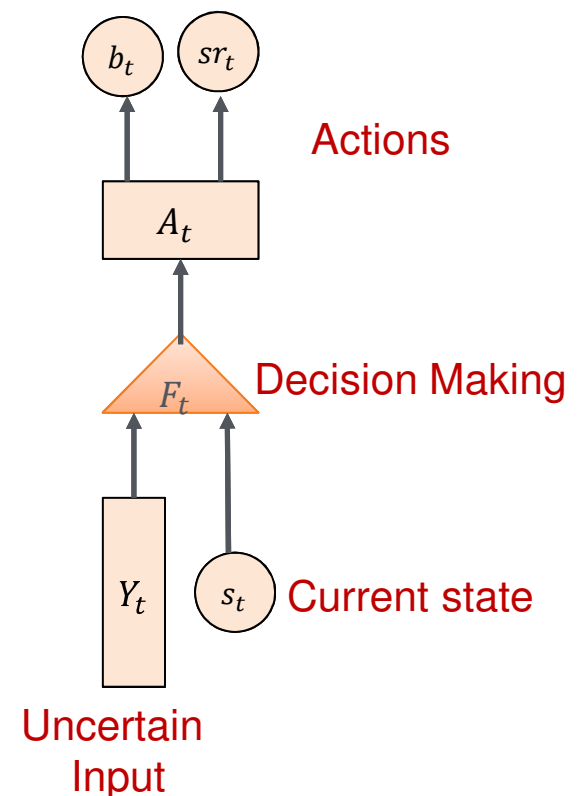
❖ Challenges

- Uncertainty in solar output due to weather conditions
- Error prone prediction

❖ Approach

- Markov Decision Process based sequential decision making framework to minimize expected cost under input uncertainty

Sequential Decision Making
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❖ Problem definition

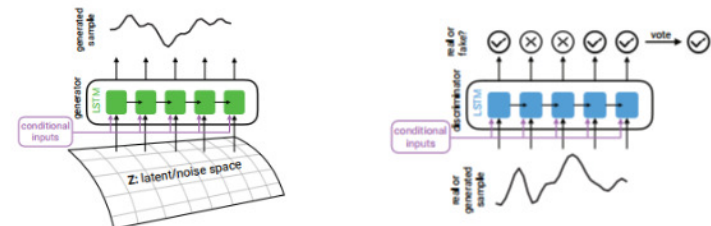
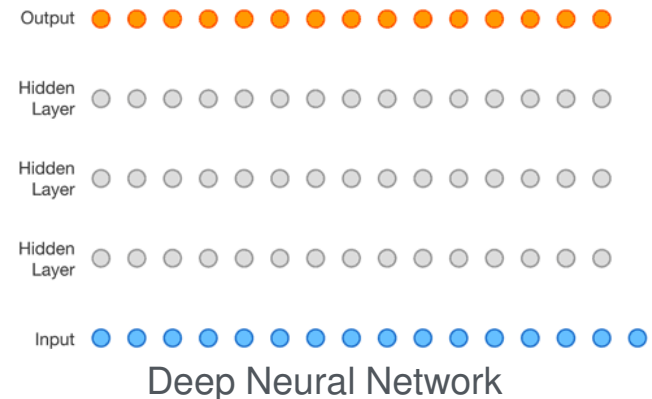
- Arbitrary Horizon Forecasting
- Synthetic Data Generation

❖ Challenges

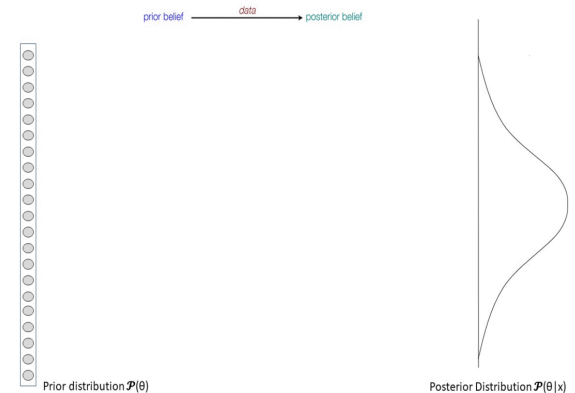
- Computational Complexity – need parallel and efficient extensions to State-of-the-art models
- Models that learn from small datasets

❖ Approach

- Fully Visible Belief **Neural Networks**
- Generative **Adversarial Networks**
- **Markov Chain Monte Carlo** (MCMC)



Generative Adversarial Networks



MCMC Metropolis-Hastings algorithm

❖ Problem definition

- Real time operation of Dynamic Scenario Analysis toolkit to meet ENERGEISE response time targets

❖ Challenges

- ML algorithms parallelization
- Computational complexity of optimization algorithms

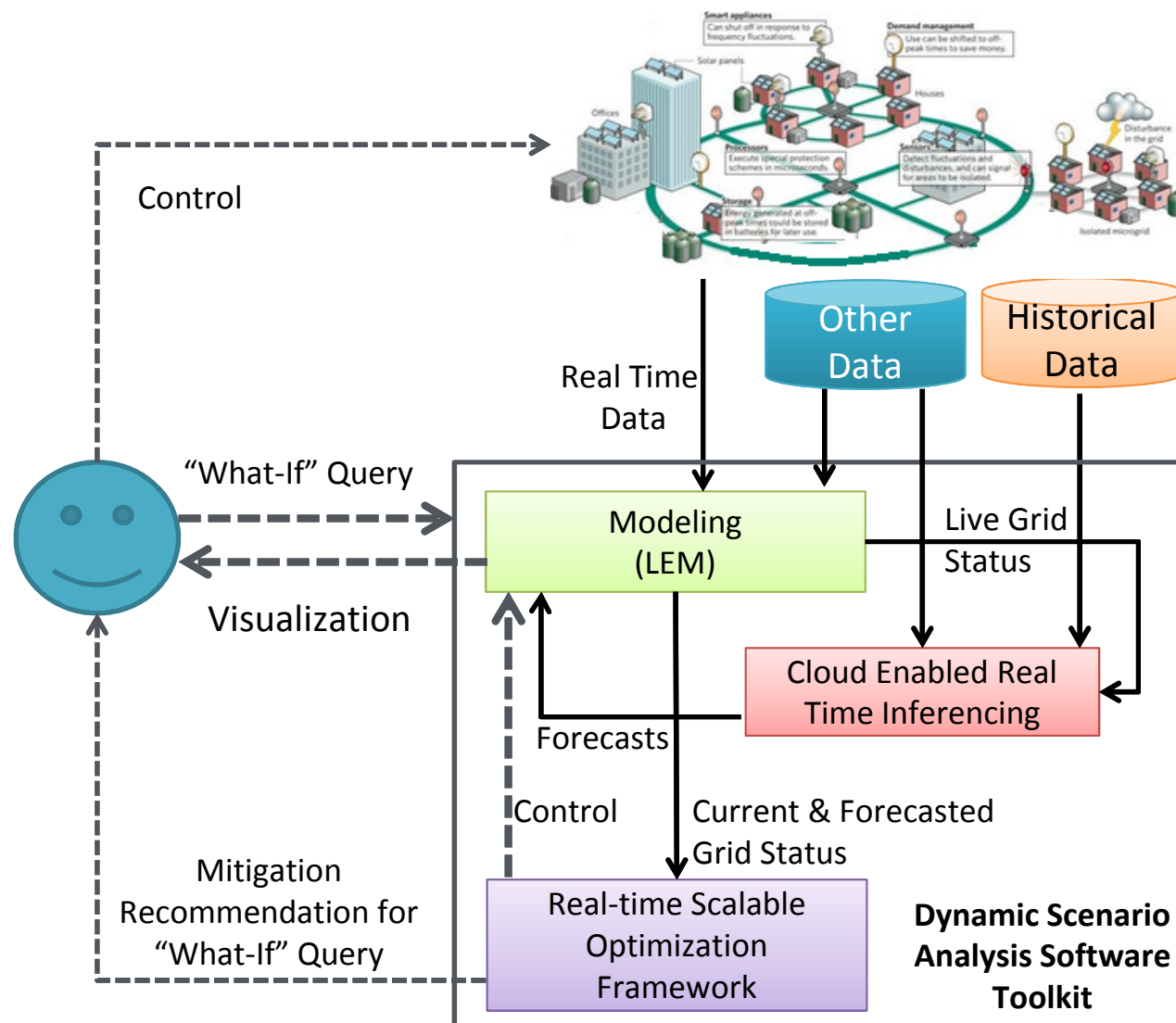
❖ Approach

- Partitioning the LEM representation of distribution network (graph representation)
- Develop cloud enabled parallel algorithms

Project Architecture

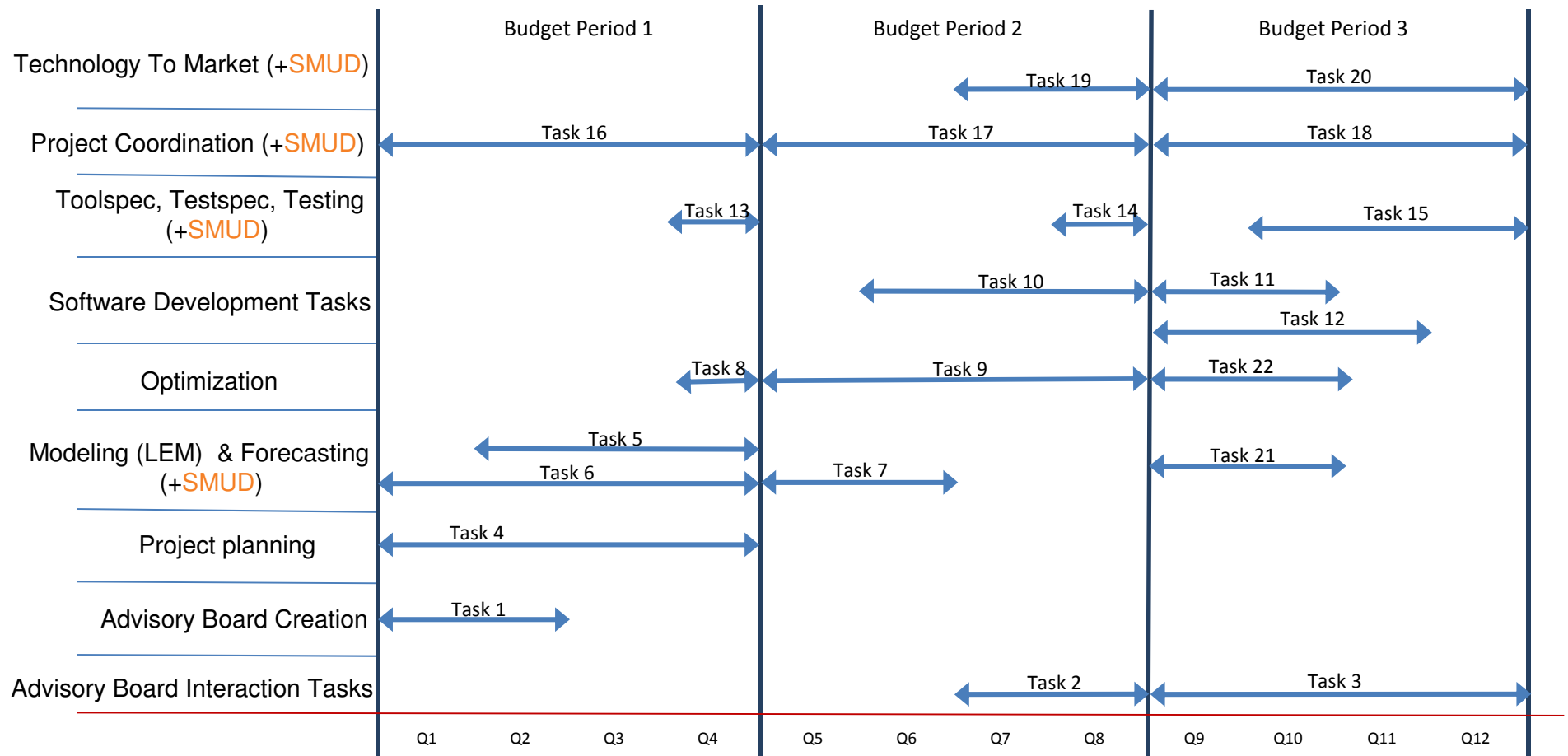
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Main Project Tasks/Subtasks

TIMELINE



- ❖ Development of a mockup of Proof-Of-Concept (POC) software for LEM
- ❖ Development of accurate load/generation forecasting models
- ❖ Development of a functional Dynamic Scenario Analysis Software Toolkit with integration of the LEM, forecasting and optimization algorithms
- ❖ Functionality and scalability demonstration of the Dynamic Scenario Analysis Software Toolkit (+SMUD)

❖ Budget Period 1

- Report on forecasting model
- Draft Market Transformation Plan
- Cybersecurity and Interoperability Plans (+SMUD)
- IP Agreement Plan

❖ Budget Period 2

- Report on the Dynamic Scenario Analysis Software Toolkit integrated with the LEM, forecasting and optimization algorithms
- Report on the requirements of the market
- Updated Cybersecurity and Interoperability Plans (+SMUD)
- Updated Market Transformation Plan

❖ Final Deliverable

- Functionality and scalability demonstration of the Dynamic Scenario Analysis Software Toolkit (+SMUD)

High Risks & Mitigation

Risk	Mitigation Strategy
LEM model accuracy	Development & testing using network and operational data from SMUD
Forecasting models accuracy	Validation using network and operational data from SMUD
ESL software scalability	Task development on parallel algorithms Methods implementation in a cloud-enabled software platform
ESL meets ENERGISE metrics	Enhancement of ESL's computational capability Design changes based on testing

- ❖ Fast graph-theoretical optimization algorithms minimizing protection cost while ensuring situational awareness
- ❖ Remove/Mitigate cloud computing model risks
- ❖ Interaction with SMUD and advisory committee
- ❖ Follow established interface standards to develop interoperable software

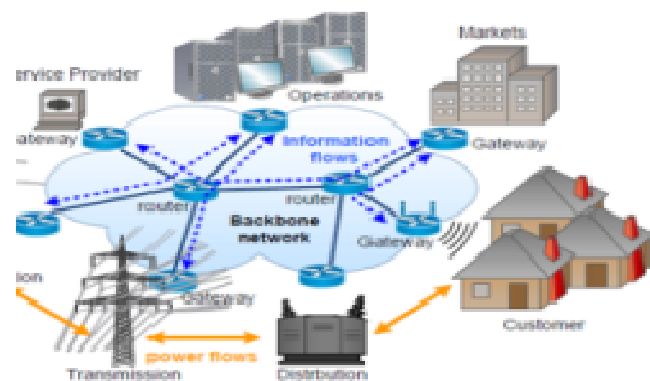
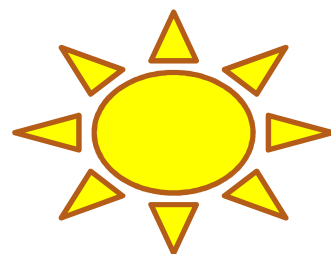
To Appear in ACM BuildSys '17, Submissions to ISGT '18.

- ❖ **“Temporal Ensemble Learning of Univariate Methods for Short Term Load Forecasting,”** C. Cheung, R. Kannan, V. K. Prasanna
 - Novel ensemble learning method partitioning with temporal features
 - **11.2%** and **30%** decrease in mean absolute percentage error for kernel regression and support vector regression respectively
- ❖ **“Optimal Net Load Balancing in Smart Grids with High PV Penetration,”** S. Kuppannagari, R. Kannan, V. K. Prasanna
 - Unified solar and load curtailment framework
 - Linearly in number of nodes and intervals, Bounded Error Guarantee: $(1 + \epsilon)$ factor
- ❖ **“NO-LESS: Near Optimal Curtailment Strategy Selection Algorithm for Net Load Balancing in Micro Grids,”** S. Kuppannagari, R. Kannan, V. K. Prasanna
 - Curtailment selection with fairness and strategy switching overheads
 - Bounded Error Guarantee: $(1 + \epsilon)$ factor
- ❖ **“Risk Aware Net Load Balancing in Micro Grids with High DER Penetration,”** S. Kuppannagari, R. Kannan, V. K. Prasanna
 - Sequential decision making for storage scheduling for net load balancing under prediction uncertainty

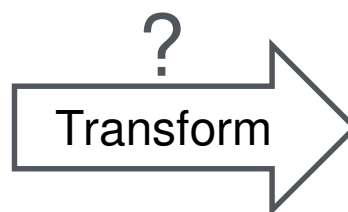
Concluding Remarks

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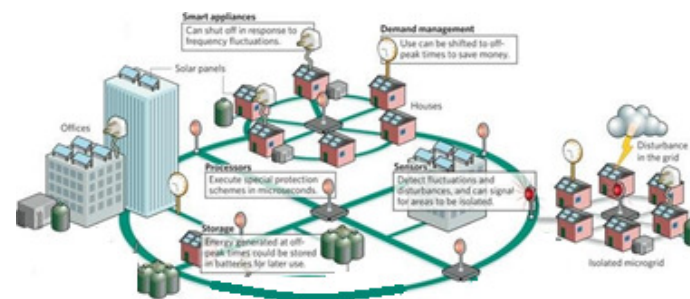
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Today



Data Science
Smart Grid
Parallel Computing



2030, Cognitive Grid

DEEP SOLAR: deepsolar.usc.edu
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