Opportunistic Hybrid Communications Systems for Distributed PV Coordination

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The current state of the art grid is sensor starved

At the transmission level, grid operators have no visibility into the current amount of distributed PV generation

At the distribution level, there is the need to have more visibility into DER output and two-way communication (?)

**Objective:** Communicate the state of the grid from the inverter to the system operator
• Full-scale, operational implementation of the opportunistic hybrid communication system:
  o **Hybrid**: various communications pathways, e.g. SCADA, PLC, Zigbee, etc.
  o **Opportunistic**: route messages through each of these systems based on recent data about latency and availability to ensure reliable message passing.
Distributed State Estimation Algorithms for PV System and Distribution System
Real-time, Economic, and Scalable Aggregation of Behind The Meter Information
• PV States: PV inverter AC power output
• Kalman Filter: Temporal dynamic state estimation
  o Multi-rate: Under-sampling of measurements
  o Event-driven: Regular sampling in case of significant event
• Kriging: Spatial estimation at unobserved location
Irradiance Time Series Model at 1-min Resolution

Runway, Kalaeloa Airport

Partial Auto Correlation Coefficient (PACC) for Log(GHI/GHI_{cs}) at Oahu on June 4th, 2011

Auto-Regressive Behavior
AR(p) Model
(Yule-Walker Method)

Partial Auto Correlation Coefficient (PACC) for Log(GHI/GHI_{cs}) at Oahu on June 4th, 2011

GHI at Oahu on June 4th, 2011

GHI
Clear Sky GHI

Normalized GHI at Oahu on June 4th, 2011

1-Sec Data
1-Min Data (from 30 sec average)

Partial Auto Correlation Coefficient (PACC) for Log(GHI/GHI_{cs}) at Oahu on June 4th, 2011

Time lag (minutes)

PACC

95% Confidence Interval

Auto-Regressive Behavior
AR(p) Model
(Yule-Walker Method)
Kalman Filter from AR(p) Model

**Multi-Rate Approach**

- **RMSE**
- **Autoregressive Model Order p**
- **Measurement Update Interval \( \Delta t \) (min)**

**Event Driven Approach**

- **RMSE**
- **log(Clear Sky Index)**
- **Time (Hour)**

- **MREDRI sampling with threshold:0.43926**
- **MR with \( \Delta t : 5\)mins**
- **True**

- **Capture in event driven sampling**

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**Autoregressive Model Order, \( p = 1 \)**

**Multi-Rate and Event Driven Sampling Illustration**

- **RMSE**
- **log(Clear Sky Index)**
- **Time (Hour)**

- **True**
- **MREDRI with Threshold:0.43926; RMSE:0.15087**
- **MR with \( \Delta t : 5\)mins; RMSE:0.18149**
Kalman Filter with Kriging: Spatial LMMSE Estimate

- n GHI sensors: \( S = \{s_1, s_2, \ldots s_n\} \);
- Spatial covariance: \( \mathcal{C}_S \)
- Spatial observation at time t,

\[
y_t = \begin{bmatrix}
y(s_1, t) \\
\vdots \\
y(s_n, t)
\end{bmatrix}
\]

- Observed: \( y(s_i, t) \);
- Unobserved: \( y(s_j \neq i, t) \)
- \( \hat{x}_{t|t} \) from \( y(s_i) \) and Multi-Rate and Event Driven Kalman filter.
- LMMSE: 

\[
\hat{y}(s_{j \neq i}, t) = \frac{C(s_i, s_{j \neq i})}{\sigma^2(s_i)} h^T \hat{x}_{t|t}
\]
• Radial topology
• Ladder iterative (LI) technique\(^1\)
  o State variables: three-phase complex voltages at each node
  o Network reduction
    – Combine nodes connected by zero-impedance lines, such as fuses, switches etc.
  o In each iteration, update node voltage and branch current

Distributed Ladder Iterative State Estimation (DiLISE)

• Automatic Regionalization (Au-Reg) based on spectral clustering [1]
  o The subnetwork in each region is still radial
  o Each subnetwork has its own root, from which the forward sweep starts.

• The master process scans the topology of the network only once before the iterations start

• Voltages and currents are updated asynchronously
  o Computationally more efficient because of no waiting
  o No need for a master process once the iterations start

DiLISE Performance

**Impact of Bad Data**

**Computation Time Reduction by 70%**
Synchronous Integration of PV and Power System States

Perform ADMM [2] based Information Exchange among neighboring clusters

Perform Kalman Kriging in each cluster

Distributed State Estimation for Distribution System

\[
\begin{bmatrix}
\tilde{y}_t^{SYS} \\
\tilde{x}_t^{PV}
\end{bmatrix}
= h(\tilde{x}_t^{SYS}) + \nu_t^{SYS}
\]

Update PV States from Dynamic Estimation

Obtain Power System States from Static Estimation

• Distributed estimation of PV states
• Distributed distribution system state estimation
• Integration of the two to produce actionable information for DSOs/TSOs
Thank You!
Questions and Discussion
Appendices
Reference Test Case A (RTC-A)

- Taxonomy feeder R2-25.00-1 from DOE’s Modern Grid Initiative representing moderate urban environment
- System of 1080 nodes on a distribution feeder
- 10 percent penetration of solar panels
- Fifteen 1-sec irradiance measurements from ground stations (Desoto)
- Power system data determined by the Integrated Grid Modelling System (IGMS)
Integrated Grid Modeling System (IGMS)

- Data collected at 1-min (Trans.) and 6-sec (Dist.) resolution
  - Real and Reactive power
  - Voltage magnitude and phase angle
  - Miscellaneous variables /parameters for sanity checks
- Reference Test Case A current focus for communications development, i.e. as input only
- Future T+D+C simulation environment for ongoing GMLC projects

Opportunistic Hybrid Communication System
Expected features of Opportunistic Hybrid Networks

• **Feasibility**: Extensively use existing infrastructure, minimize new hardware to reduce cost.
• **Interoperability**: Use multiple mixed standardized communication technologies.
• **Scalability**: Accommodate high penetration of distributed PV.
### Alternative Hybrid Networks for NS3 Simulation

<table>
<thead>
<tr>
<th>Hybrid Type</th>
<th>Home Area Network</th>
<th>Neighborhood Area Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hybrid-1</td>
<td>LoWPAN</td>
<td>Ethernet Cable</td>
</tr>
<tr>
<td>Hybrid-2</td>
<td>LoWPAN</td>
<td>WiFi</td>
</tr>
<tr>
<td>Hybrid-3</td>
<td>LoWPAN</td>
<td>WiMax</td>
</tr>
<tr>
<td>Hybrid-4</td>
<td>PLC</td>
<td>Ethernet Cable</td>
</tr>
<tr>
<td>Hybrid-5</td>
<td>PLC</td>
<td>WiFi</td>
</tr>
<tr>
<td>Hybrid-6</td>
<td>PLC</td>
<td>WiMax</td>
</tr>
</tbody>
</table>

**Note:** Reason of LoWPAN instead of well-known Zigbee is Zigbee model can not cooperate with other technologies in NS-3.
Main Challenge: Integrate different technologies and IP address mechanisms into a simulation network.

- Different technology characterized by Phy & MAC layers.
- 6LoWPAN model works as an agent between MAC layer and Network layer, and only supports IPv6. While WiFi mesh and WiMAX only support IPv4.
- Smart meter node is configured with two net devices of two technologies.
- NetRouter app is designed to function as IPv6 to IPv4 tunneling and enable IPv6&4 in a network.
- Customized Client app and Server app are developed for specific smart grid
Tree Topology Hybrid Simulation Model

Note: Unlimited range of Ethernet causes to Tree topology intuitively; For WiMAX, range of 50km can cover up to 10km of NAN (Neighborhood Area Network) with PMP (Point-to-Multiple points) topology.
Note: With range of 30m-1km, WiFi has to be designed as Mesh topology to cover up to 10km of Neighborhood Area Network (NAN).
Hybrid Communication Network: RTC-A Perspective

- # of PV inverters: 52
- # of smart meters: 126
- # of data concentrators: 10
- # of edge router: 1
- # of areas: 10
Hybrid Communication Performance

Average Network Latency vs Packet Size

Average Network Throughput vs Packet Size

Average Network Latency vs Data Rate

Average Network Throughput vs Data Rate
Middleware Framework

- Allows the communication node to adaptively and automatically distribute the data flow to the available links based on their real-time status.
- Not only enhance the QoS of each traffic but also efficiently utilize the existing multiple network resources.
Middleware based Opportunistic Communication
DoS Mitigation through Middleware

Aggregator ↔ Smart Meter
Remote Server ↔ Data Concentrator

Gateway Node: GN
1\textsuperscript{st}-class data flow: 
2\textsuperscript{nd}-class data flow:
DoS attack flow:
Middleware instances are installed in both aggregators and the gateway nodes of the mesh network between the aggregators and the remote servers.
The real-time distributed middleware instances are able to manage data flows of different smart grid application services by exploiting the collaboration of different OSI layers.

The middleware instances belonging to different network devices are able to communicate its neighboring nodes.

The middleware instances have the same structure and functions and the only difference is that the middleware instance installed in end host has an Application Program Interface (API) that can send control commands to the middleware instances installed in the individual gateway nodes in real time.
State-Space Model from AR(p)

- **AR(p) Model**

\[
x_t + [a_1 \ a_2 \ldots \ a_{p-1} \ a_p] \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ \vdots \\ x_{t-p} \end{bmatrix} = w_t; \ w_t \sim \mathcal{N}(0, \sigma_w^2)
\]

- **Define**

\[
w_t = \begin{bmatrix} w_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}; \ \begin{bmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-p+1} \end{bmatrix}
\]

- **State-Space Model**

\[
x_t = \begin{bmatrix} -a_1 & -a_2 & -a_3 & \ldots & -a_p \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \ldots & 1 & 0 \end{bmatrix} x_{t-1} + w_t = F x_{t-1} + w_t
\]

\[
y_t = \begin{bmatrix} 1 & 0 & \ldots & 0 \end{bmatrix} x_t = h^T x_t + v_t; \ v_t \sim \mathcal{N}(0, \sigma_v^2)
\]
PV Power Output Profile for RTC-A

Reference Test Case A Superimposed with DeSoto GHI Sensors

NSRDB

DeSoto, FL Sensor
IDW and Kriging based Spatial Estimation

Observed Locations, \( s_i \in S = \{s_1, \ldots, s_n\} \)

- Oahu, HI (range \( \leq 0.7 \) miles)
- DeSoto, FL (range: 0.7 ~ 4 miles)

Unobserved Locations, \( s_j \notin S \)

\[ \hat{P}(s_j, t) \]

Semivariogram Model Fitting and Kriging

\[ SPI(s_i, t) = \frac{P(s_i, t)}{P_{CS}(s_i, t)} \]

Inverse Distance Weighted (IDW) Average

PV_Lib

NSRDB
Clustering over the Kriged PV power output at RTC-A locations
Kalman Filter

$t$: Discrete time instance
$T$: Sampling interval

Multi-rate and Event Driven Sampling

$t$: Discrete time instance
$T$: Sampling interval
$D$: Decimation factor
$\delta$: Threshold
Kriging

Historical spatial observation

Semivariogram

\[ \gamma(s_i, s_j) = 0.5 \times Var\{y(s_i) - y(s_j)\} \]

LMMSE estimate at unobserved locations

Inverse Distance Weighted Average (IDW)

Given Data

Kriging

• Spatial covariance, $C_{ij} = \text{sill} - \gamma(s_i, s_j)$

• Solve for weights $\lambda_k$,

$$
\begin{bmatrix}
\lambda_1 \\
\vdots \\
\lambda_n \\
\mu
\end{bmatrix} = 
\begin{bmatrix}
C_{11} & \ldots & C_{1n} & 1 \\
\vdots & \ddots & \vdots & \vdots \\
C_{n1} & \ldots & C_{nn} & 1 \\
1 & \ldots & 1 & 0
\end{bmatrix}^{-1}
\begin{bmatrix}
C_{10} \\
\vdots \\
C_{n0} \\
1
\end{bmatrix}
$$

• Kriged estimate at location $s_0$, $\hat{y}(s_0) = \sum_{k \neq 0} \lambda_k y(s_k)$

• Kriging variance,

$$
\hat{\sigma}^2(s_0) = C(0) - 
\begin{bmatrix}
\lambda_1 \\
\vdots \\
\lambda_n \\
\mu
\end{bmatrix} \times
\begin{bmatrix}
C_{10} \\
\vdots \\
C_{n0} \\
1
\end{bmatrix}
$$
Step 1: Solar Power Index (SPI), DeSoto, Fl

- Irradiance and weather data are fed to PV_Lib toolbox [1] assuming 2.5kW capacity
- Sampling interval, $T = 1 \text{ min}$
- Inverter loading ratio = 1.48

Step 2: IDW based Clear Sky AC Power

\[ P_{cs}(s_0, t) = \frac{\sum_{i=1}^{4} P_{cs}(s_i, t)/|s_0 - s_i|^2}{\sum_{i=1}^{n} 1/|s_0 - s_i|^2} \]
Step 3: Exponential Semivariogram Model Fitting

**Exponential Fitting of Semivariogram**

![Graph showing exponential fitting of semivariogram](image)

**Sample**

- **$\gamma(d) = 0.121\{1 - \exp(-0.91d)\}$**

**Oahu, HI**

**$T = 1\text{min}$**

**Exponential model**

\[
\gamma(d) = \begin{cases} 
0, & d = 0 \\
C_0 + C_1\{1 - \exp(C_2d)\}, & d \neq 0
\end{cases}
\]

\[
\gamma(s_i, s_j) = 0.5 \times Var\{y(s_i) \sim y(s_j)\}
\]

**Spatial covariance**, \(C_{ij} = sill - \gamma(s_i, s_j)\)

**Sill**

\(Sill = C_0 + C_1\)
State-Space Model from AR(p)

- **AR(p) Model**

\[
x_t + \begin{bmatrix} a_1 & a_2 & \ldots & a_{p-1} & a_p \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ \vdots \\ x_{t-p} \end{bmatrix} = w_t; \quad w_t \sim \mathcal{N}(0, \sigma_w^2)
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- **Define**

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\]

\[
y_t = \begin{bmatrix} 1 & 0 & \ldots & 0 \end{bmatrix} x_t = h^T x_t + v_t; \quad v_t \sim \mathcal{N}(0, \sigma_v^2)
\]
Utilize $y_t$ for Kalman filter if $\|y_t - y_{t-1}\| \geq \delta$

Else follow the multi-rate measurement update.
Candidate Sensor Selection in Local Neighborhood

**Multi-Rate Kalman Kriging Performance with $\Delta t$: 5 mins**

**MREDRIKK Performance**

$\Delta t$: 5 mins; Threshold: $0.5 \times \text{max(absolute difference)}$

**Candidate Sensors for Observation:** Sensors 2 (DH4) and 3 (DH5)
Automatic Regionalization

• Weighted adjacency matrix design (nodes i and j)
  – Topology Based Similarity (TBS) \( w_{ij} = \begin{cases} 
1, & \text{Nodes } i \text{ and } j \text{ are connected} \\
0, & \text{otherwise}
\end{cases} \)
  – Measurement Based Similarity (MBS) \( w_{ij} = \begin{cases} 
1, & \text{Measurements are available for } i \text{ and } j \\
0, & \text{otherwise}
\end{cases} \)
  – Weighted Measurement Based Similarity (WMBS) \( w_{ij} = \begin{cases} 
\sum_{p \in \mathcal{P}} c_p, \mathcal{P} = \left\{ p \mid \frac{\partial z_p}{\partial x_i} \neq 0 \text{ and } \frac{\partial z_p}{\partial x_j} \neq 0 \right\} \neq \emptyset, & \text{otherwise}
\end{cases} \)
5 Clusters of RTC-A Network

Network Clusters are Different from PV Clusters

PV Statistics Integration

- PV Inverter
- Irradiance Sensor
- Electrically Regionalized
- Local Spatial PV footprint (Correlation Coefficient >80%)
  - (MREDRIKK + ADMM) + DLIA