Resilient Distributed Control of Multi-Microgrid Systems During Failure of Communication Infrastructure

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COARE

COMPUTING & ARCHIVING RESEARCH ENVIRONMENT

HPC

Processing of large data sets.
High-speed calculations and analysis.
3,120 cores with 10Gbps network speed.

STORAGE SERVICE

Repository of scientific data.
Short- to long-term data archiving support.
Storage can handle large quantity of files (GB to TB).

SCIENCE CLOUD

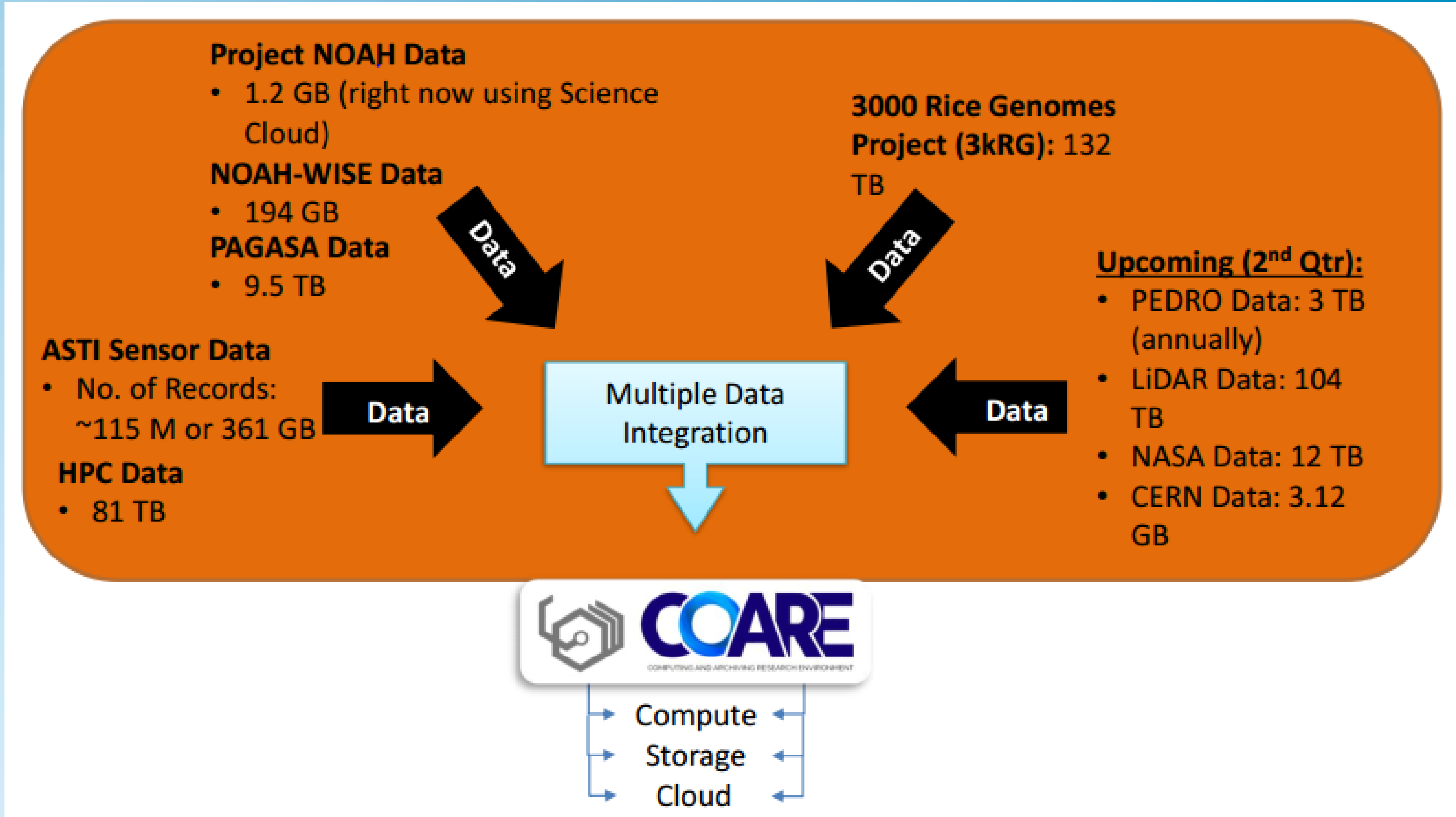
Delivers cloud-based services to researchers and students.
Enables private sharing of data among specific groups.
Provisioning of Virtual Machines.

DATA CATALOG

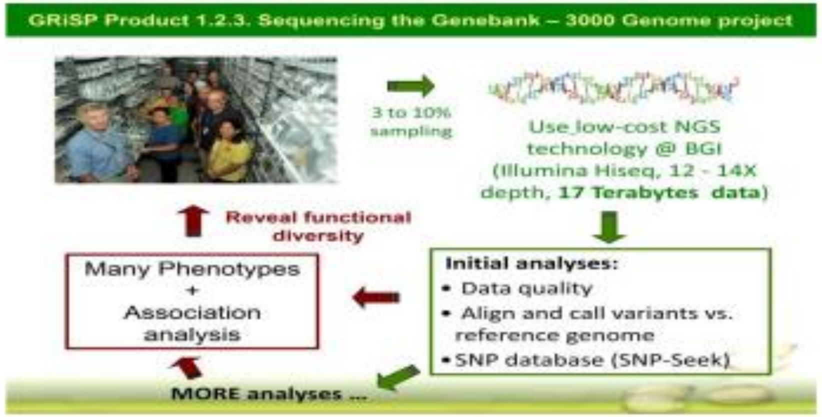
Web portal for data gathered from CoARE research collaborations.
Publicly accessible data sets.
Supports open data for research and decision-support purposes.

OTHER SERVICES

Additional computational services from CoARE.
Strategic Consultancy service.
Porting and Software Installation Service.


Project NOAH Data
• 1.2 GB (right now using Science Cloud)
NOAH-WISE Data
• 194 GB
PAGASA Data
• 9.5 TB
3000 Rice Genomes Project (3kRG): 132 TB
Upcoming (2nd Qtr):
• PEDRO Data: 3 TB (annually)
• LiDAR Data: 104 TB
• NASA Data: 12 TB
• CERN Data: 3.12 GB
ASTI Sensor Data
• No. of Records: ~115 M or 361 GB
HPC Data
• 81 TB
Data
Data
Data
Data
Multiple Data Integration
COARE
Compute
Storage
Cloud

Project NOAH makes use of ASTI's sensor data (1500++) in their modeling and visualization activities. These data are stored in CoARE's data repository.



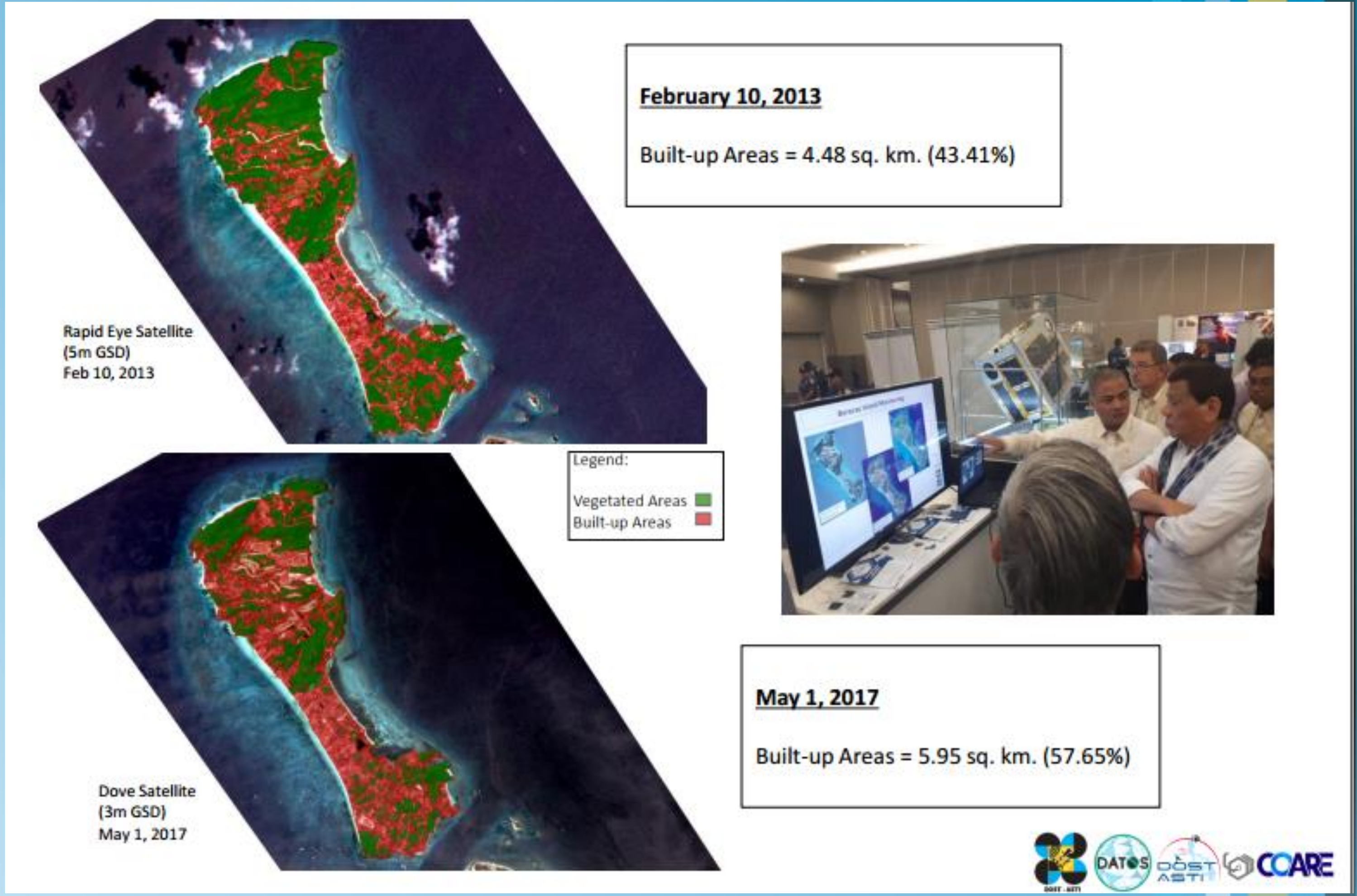
Hosting of IRRI's 3,000 Rice Genome (3KRG) dataset with over 120TB of data which are publicly available.

APPLICATIONS RUNNING ON COARE:

- Flood modelling (Gerris)
- Molecular Dynamics (NAMD)
- Numerical Weather Prediction Modelling (WRF, CCAM)
- Climate Modelling (RegCM)
- Bioinformatics Pipeline (BWA, GTK)
- Storm Surge Modeling (Gaussian)
- OGC Services (WMS, WFS)

Other users:
- **PAGASA - numerical modeling**
- **NOAH-WISE/ASTI – Operational WRF**

Remote Sensing and Data Science (DATOS) Help Desk

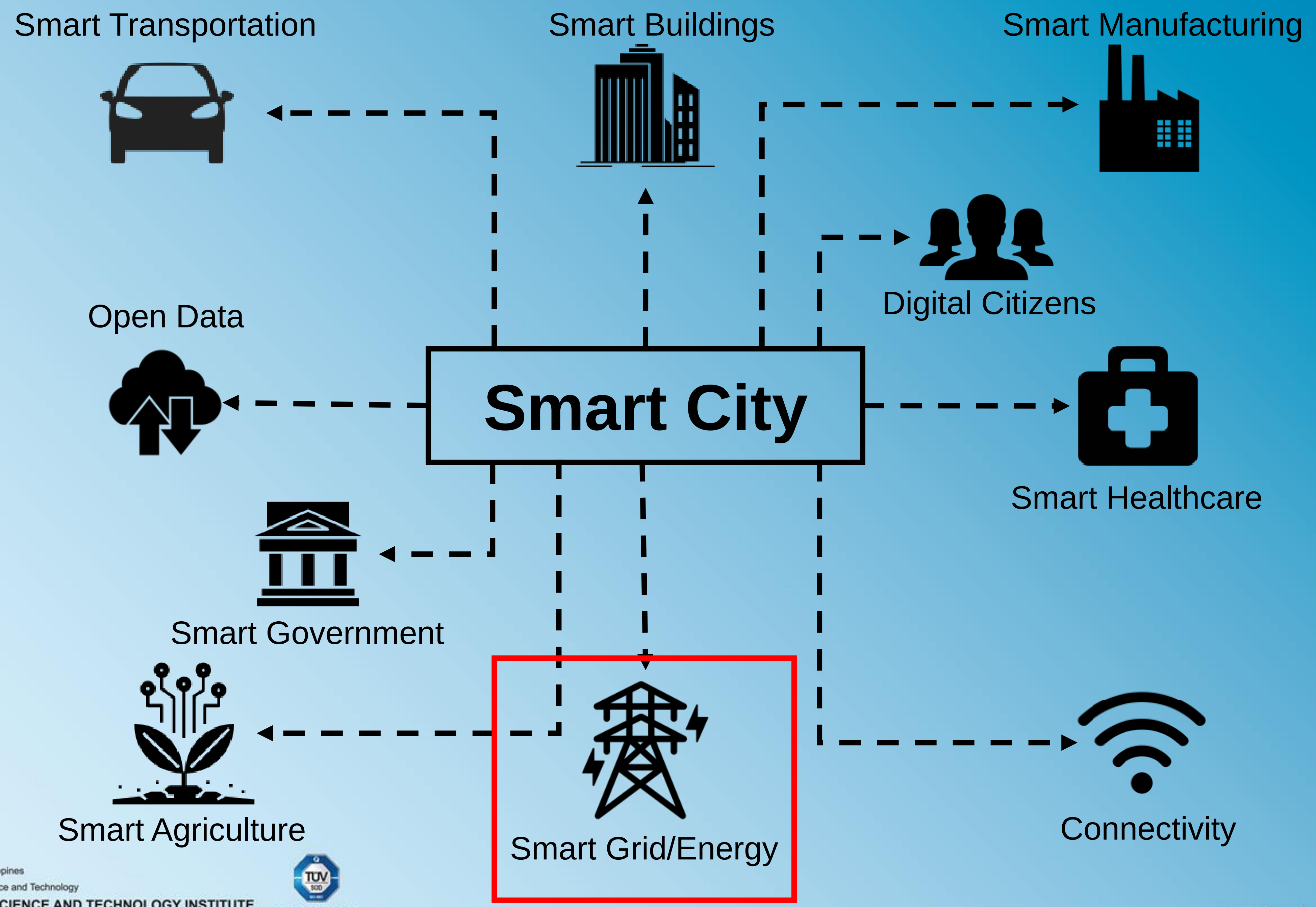


Boracay Monitoring

Smart Streetlights

Outline

I. Introduction
II. Smart Grids in Smart Cities
III. Applications of Artificial Intelligence in Smart Grids
IV. Resilient Distributed Control in Multi-Microgrid Systems
V. Results
VI. Conclusion



Smart Transportation
Smart Buildings
Smart Manufacturing
Digital Citizens
Open Data
Smart City
Smart Healthcare
Smart Government
Smart Agriculture
Smart Grid/Energy
Connectivity

Smart Grid's Role in Smart Cities

- "Backbone" of smart cities
- Energy sustainability
- Reliability and efficiency
- Robustness and resilience of power systems

Challenges on complexity, uncertainty and huge volume of information [2]

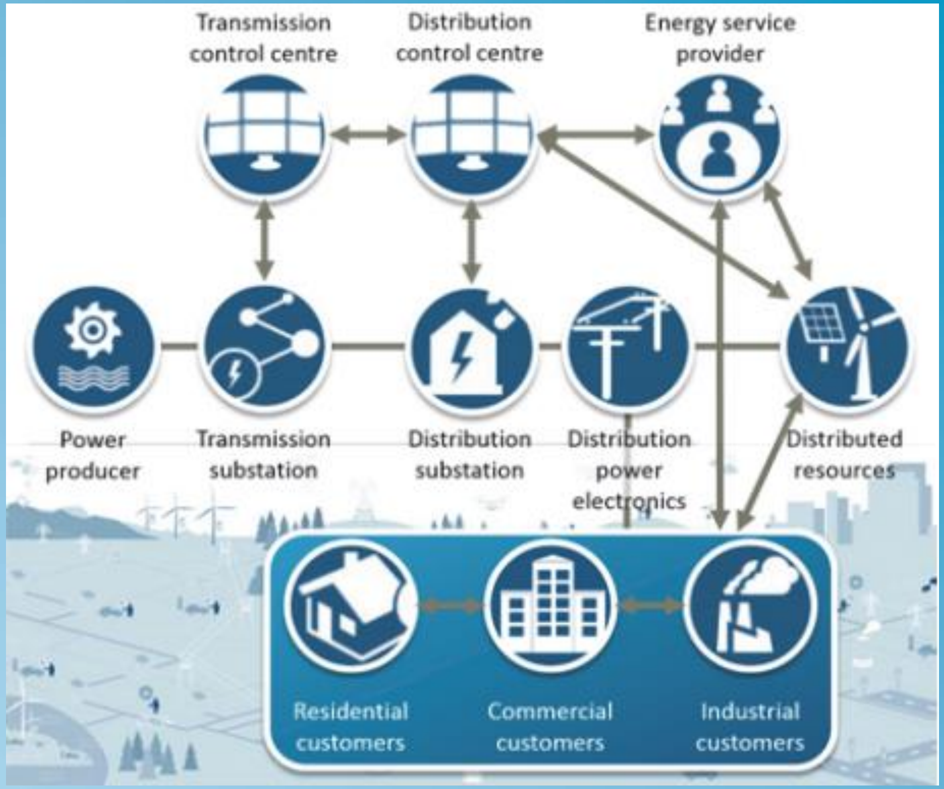


Fig. 1: Smart Grid via IoT platform [1]

[1] http://www.powel.com/about/feature_stories/sensors-and-the-iot/ accessed on 25th March 2019.
[2] Zhang, D., Han, X., & Deng, C. (2018). *Review on the research and practice of deep learning and reinforcement learning in smart grids. CSEE Journal of Power and Energy Systems, 4(3), 362–370.*

Artificial Intelligence in Smart Grids

Deep Learning

Reinforcement Learning

Deep Reinforcement Learning

Field	Challenges that may be solved through AI
Load Prediction/Forecasting	Improvement of prediction accuracy from big datasets and weather forecast systems
Microgrid	Energy management, operation and control uncertainties and partial observation
Demand Response	Customer's flexibility analysis, Nonintrusive Load Monitoring (NILM), Direct Load Control (DLC)
Anomaly Detection	Detection based from data of measurement devices, aerial vehicles, inspection robots
Power System Analysis and Control	Data-driven analysis and control based from measurement units
Cyber Security	Detection of malicious attacks and false data injection
Renewable Generation Prediction	Improvement of prediction accuracy based on big datasets

[3] Zhang, D., Han, X., & Deng, C. (2018). Review on the research and practice of deep learning and reinforcement learning in smart grids. CSEE Journal of Power and Energy Systems, 4(3), 362–370. doi:10.17775/cseejpes.2018.00520

Improving Reliability of Power Systems through Multi-Microgrid Systems

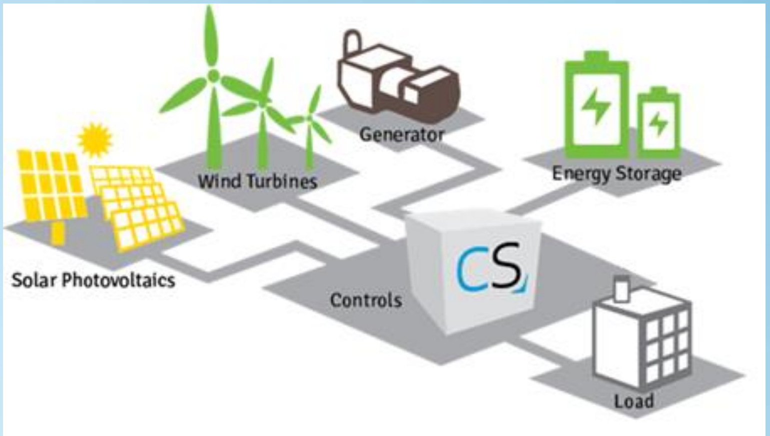
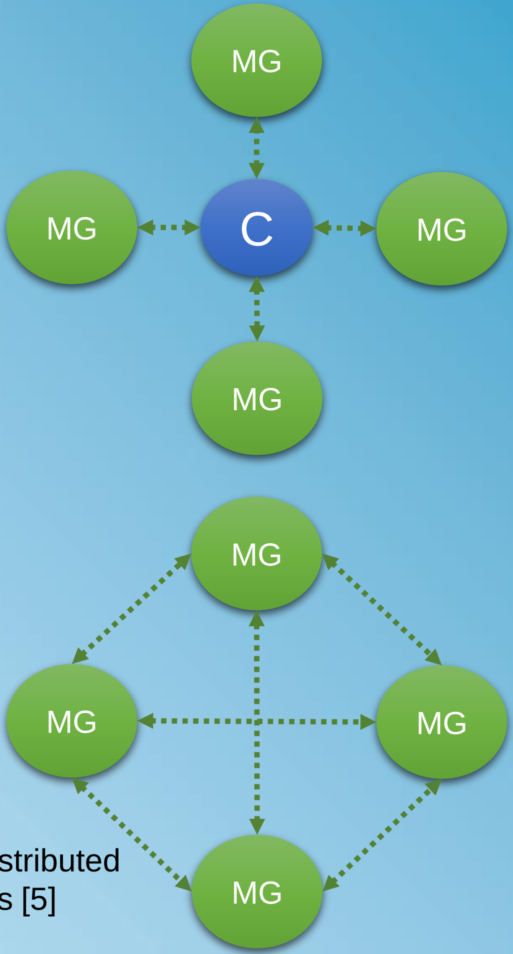


Fig. 2: Microgrid (MG) System [4]



Centralized [5]

✔ Easier System Monitoring
✗ Single-Point Failure
✗ Heavy Computational Burden

Distributed [5]

✔ No Single-Point Failure
✔ Reduced Computational Burden
✔ Flexible (plug-and-play)
✗ Complex Communications

Fig. 3: Centralized and Distributed Control configurations [5]

Communication Failure compromises system operation

[4] Sustainnovate, “Navigant Research: Majority of World’s Microgrids Are Now Remote Ones”
[5] Dagdougui, Hanane, et.al., Decentralized Control of the Power Flows in a Network of Smart Microgrids Modeled as a Team of Cooperative Agents, IEEE Trans. Control Systems Technology

Resilient Distributed Control of Multi-Microgrid Systems

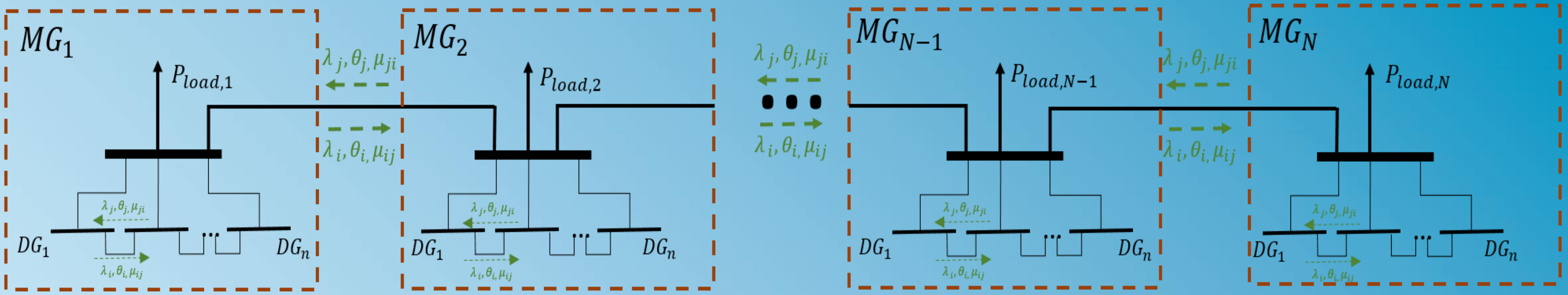


Fig. 2: Multi-Microgrid System Diagram

- Primary Control
  - tries to meet the least cost operation of the system using predicted values of missing parameters

$$\min_{P_G} \sum_{i \in \Omega_N} C_i\left(P_{G_i}\right)$$

- Secondary Control
  - minimizes ENS (energy not served) in the system:
  - ensures supply-demand balance in the system

$$\min_{P_G, \theta_i} \sum_{i \in \Omega_N} ENS_i^{\,2} = \min_{P_G, \theta_i} \sum_{i \in \Omega_N} \left(P_{G_i} - P_{L_i} - \frac{\theta_i - \theta_j}{X_{ij}} \right)^2$$

[6] Asarias, Fredmar N., and Michael Angelo A. Pedrasa. "Resilient distributed generation dispatch in multi-microgrid systems." *2017 IEEE Innovative Smart Grid Technologies-Asia (ISGT-Asia)*. IEEE, 2017.

Prediction of Missing Information

- Marginal Cost estimate, $\lambda_{j,est}(k)$
  - Naïve – previous observed state
  - Historical Averaging

$$\lambda_{j,est}(k) = \frac{1}{N}\sum_{n=1}^{N}\lambda_{j_n}(k)$$

  - Forecast using Time Series ARIMA models – ARIMA (p, d, q)

$$y_t' = \mu + \phi_1 y_{t-1}' + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$$

y_t'- estimate	ϕ_p - AR coefficient
μ – constant	θ_q - MA coefficient
y_{t-n} - lags	e_{t-n} - error residual

  - AI (Machine Learning, Deep Learning) *

- Bus Angle estimate, $\theta_{j,est}(k)$
  - With real-time line flow reading

$$\theta_{j,est}(k) = \theta_i(k) + P_{line,ij}(k) \cdot X_{ij}$$

  - Lagrange Multiplier for line flow estimate, $\mu_{ji,est}(k)$

$$\mu_{ji,est}(k) = \mathrm{P}\left(\mu_{ji}(k) - \delta\left(\overline{P_{ij}} + P_{line,ij}(k)\right)\right)$$

[7] Asarias, Fredmar N., and Michael Angelo A. Pedrasa. "Resilient Distributed Control of Multi-Microgrid Systems During Failure of Communication Infrastructure." *2018 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*. IEEE, 2018.

Results

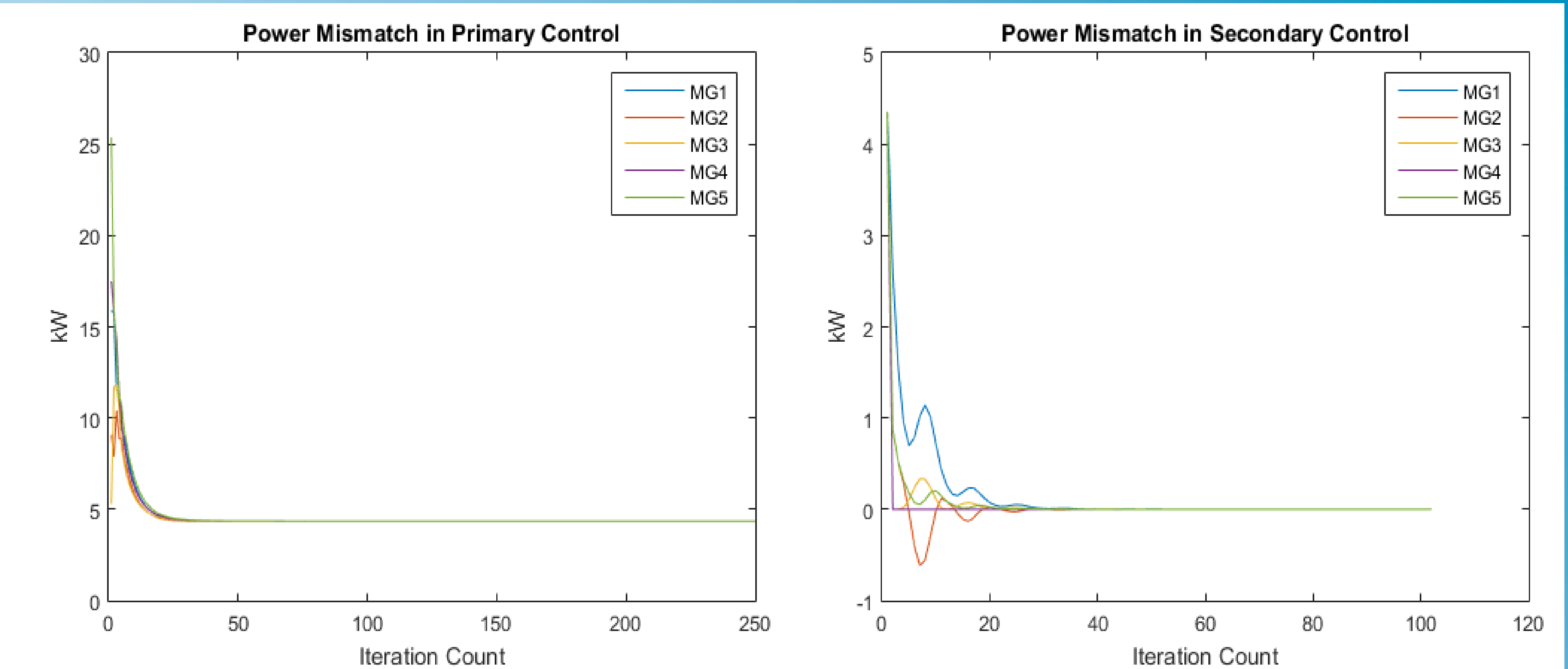


Fig. 5: Comparison of power mismatch. (a) Primary Control, (b) Secondary Control

- Around 4.35kW power deficit in each microgrid (21.75 kW in total)
- Zero power mismatch in all microgrids

Results

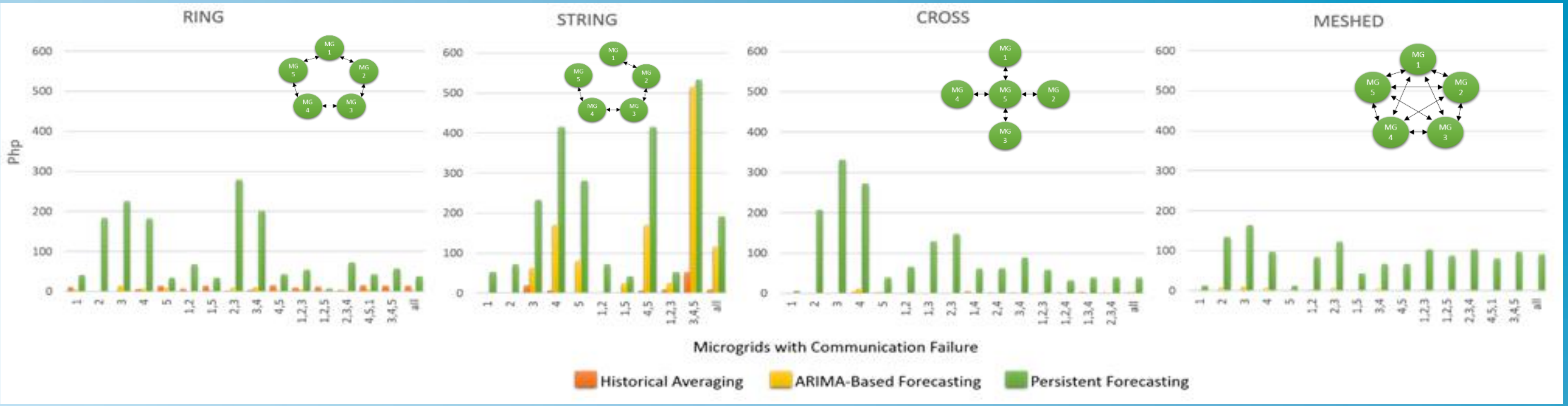


Fig. 6: Cost of Information Loss of Different Network Configurations and Time-Series Estimation Methods

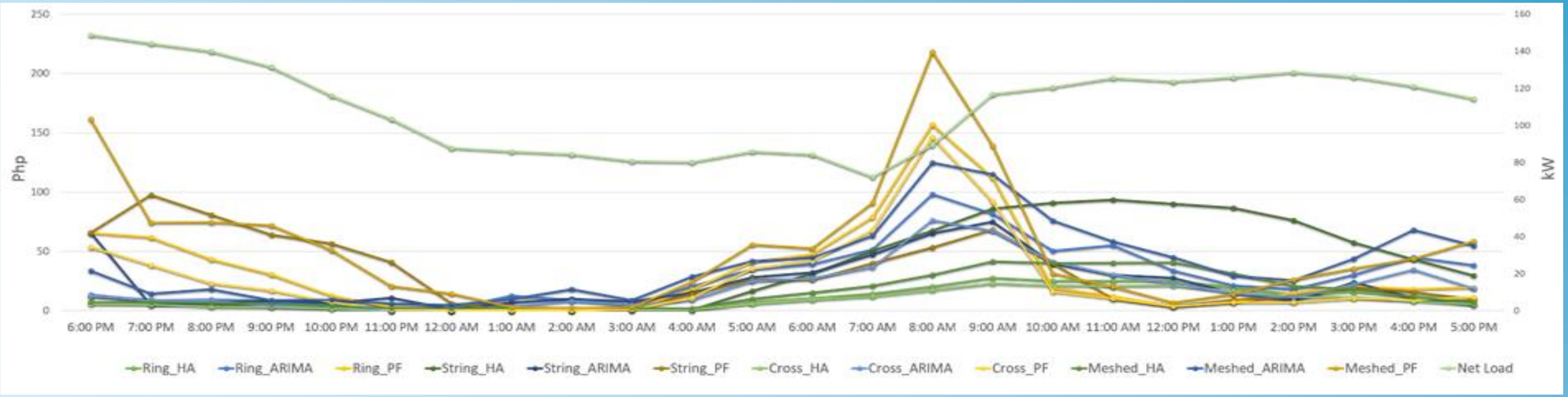


Fig. 7: Average Cost of Information Loss of different network configurations using the three estimation methods

Smart Grids in the Philippines

- **“Resilient Electricity Grids”**
  - Collaborative project between University of the Phillippines Diliman and University of California Berkeley
  - Application of data science and machine learning for the resilience of electricity grids
  - Research Opportunities for AI
    - Event detection (faults, attacks, islanding)
    - Electricity theft detection
    - Interruptible Load Program
    - Load Forecasting

Fig. 8: Micro-synchrophasor /uPMU (micro phasor measurement unit)
Image source: www.powerstandards.com

PMU Deployment

Conclusion

- Shift in paradigm in the power grid framework, control and operation (from load-following to supply-following)
- Data-driven power grids through massive deployment of measurement units
- Smart grids are one of the areas with great potential application of Artificial Intelligence (DL, RL, DRL)
- Many AI researches on smart grids are still in their initial stage

Thank you

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