Microgrid Operational Planning using Deviation Clustering within a DDDAS Framework

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Outline

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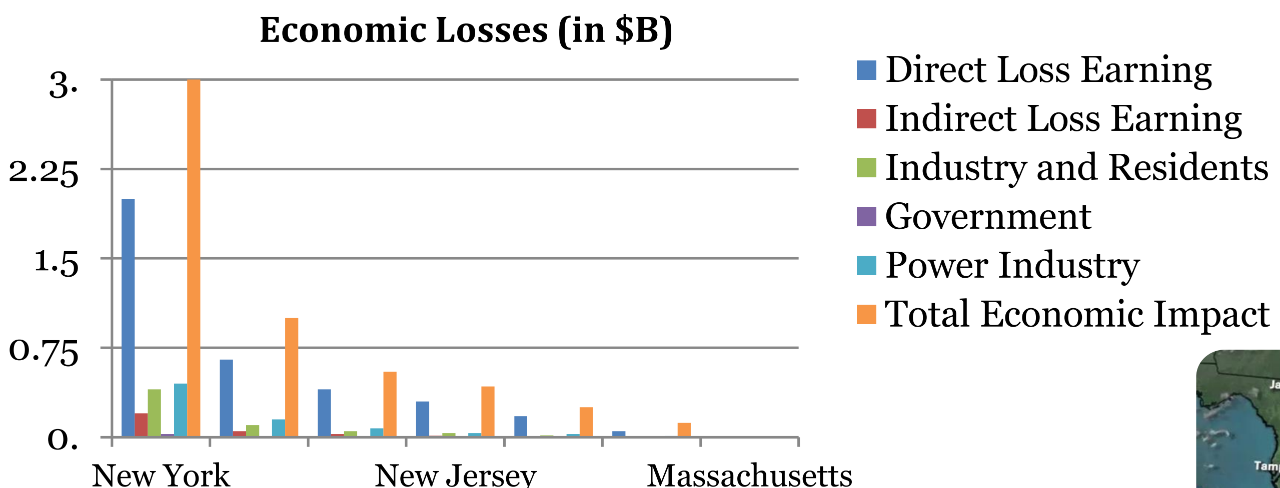
- Challenges in Power Dispatch Problem
- Previous Work from the Literature
- Dynamic Data-Driven Application Systems (DDDAS) for Microgrid Planning
  - Agent–based Modeling of a Microgrid System
  - External and Sensory Data Collection
  - Deviation Clustering (DC) for Load Estimation
  - Rule-based Policy (RBP) for Conditional Responses
  - Microgrid Dispatch Model
- Experimental Results
- Conclusion and Future Work

Motivation and Significance

- California Forest Fire[1] , 2020: Affected – > over 290k acres, Death toll – 6
- Dorian in The Bahamas[2] , 2019: Affected –> 30% population, Death toll – 30
- Florence in Carolinas[3] , 2018: Affected –> ¼ mill, Death toll – 50 , Cost – $22B
- Irma in Florida[4], 2017: Affected –> 6.7 mill people, Death toll – 134, Cost – $50B
- USA and Canada[5], 2003: Affected –> 55 mill people



Challenges in Power Dispatch

Objectives : Min Cost & Emissions
Constraints: Power Balance

To produce electricity economically, environmentally, reliably, and securely

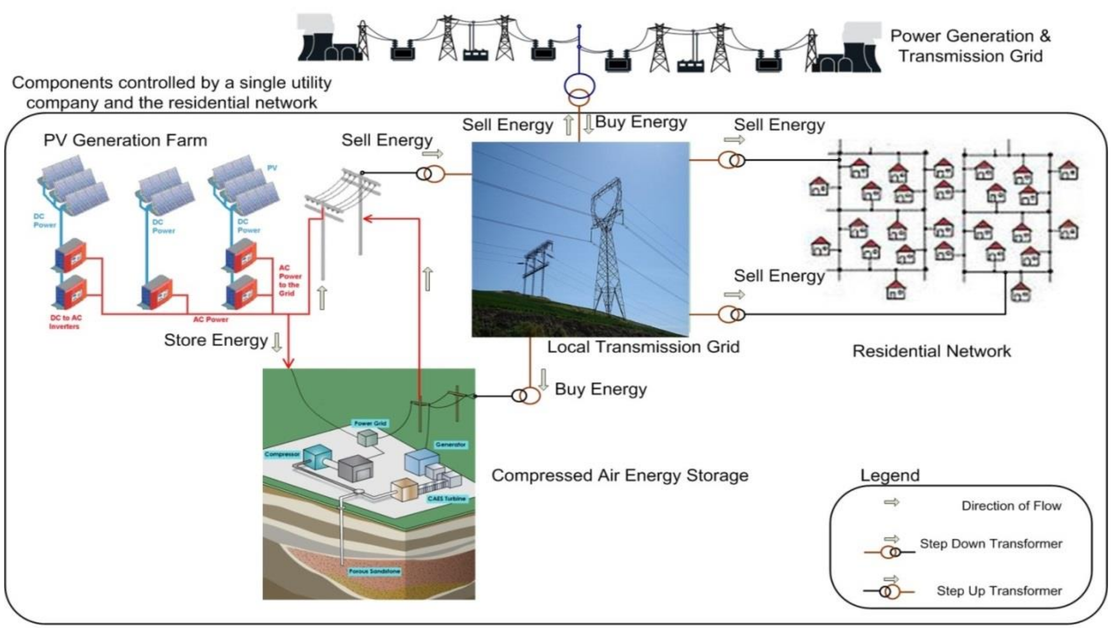
...about power networks

- large # of variables, nonlinearities, and uncertainties
- operate at various scales
- resources => more distributed
- generation =>more intermittent
- system => more conducive to demand-response

...about dispatch control

- changing demands
- very large range for solution space
- Intense and time-critical information exchange
- significant burden on computational resources

(processing of massive datasets)

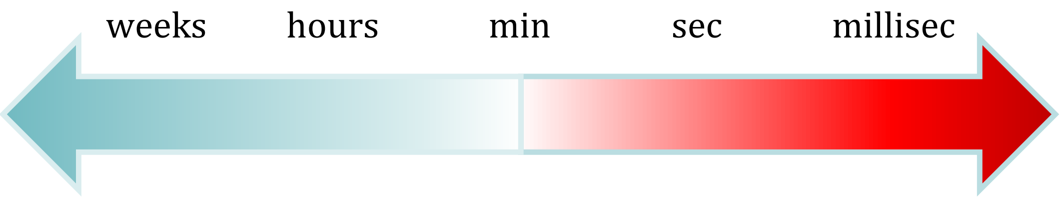


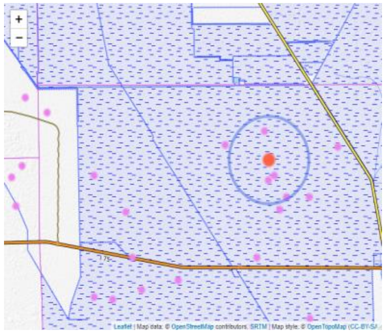
Impact of Load Profile on Dimensionality

Clustering Techniques

- **K-means** - on spatial data to aggregate similar load profiles and achieve accurate long-term load forecasts based on land usage or location

- **Load Characteristics** - to reduce complexity of communication between microgrid & consumers.

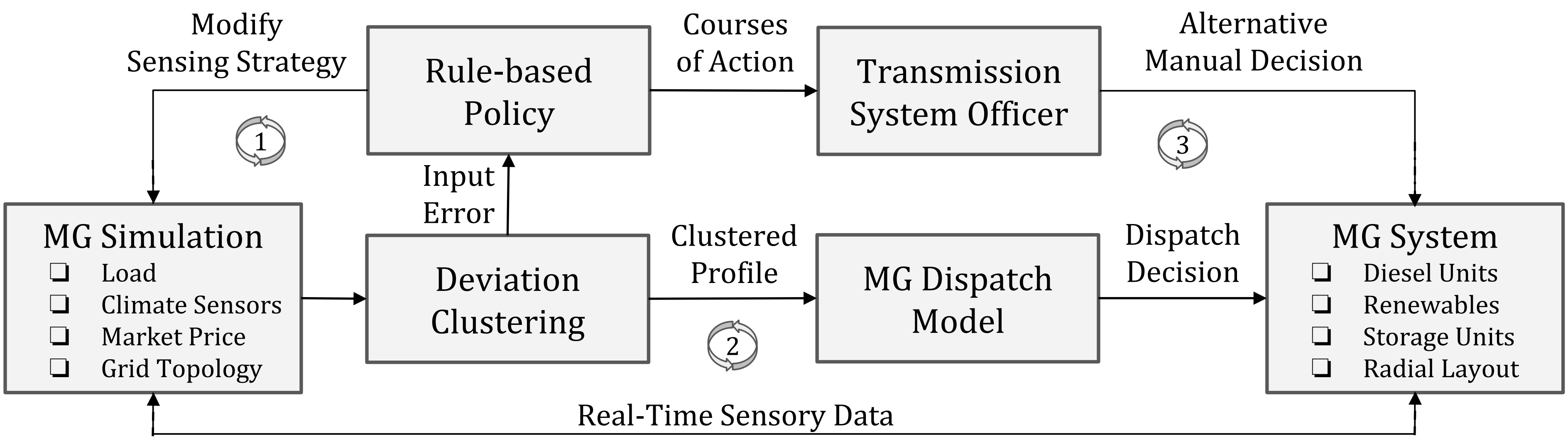




Key Finding from Literature

- Studies throughout literature note a relationship between scale of a power dispatch model & number of blocks that define its planning horizon

DDDAS Framework for Real-time Power Dispatch



- DDDAS is a paradigm utilizes symbiotic behavior between executing application & measurement data to develop two-way feedback loop
- Cycle 1: DDDAS ascertains how data should be harvested as MG simulation receives near real-time data from MG system
- Cycle 2/3: Rule-based Policy choses between TSO or solver’s dispatch solution

Agent–based Modeling of a Microgrid System

Agent-based Models

Load / Demand

$$F_t \sim N(\mu_t, \sigma) \;\; where\; \mu = PD \times PF_t \;\; and\; \sigma = 0.05\mu$$

Market Price

$$f(x;\, \mu, \lambda) = \left[\frac{\lambda}{2\pi x^3}\right]^{1/2} exp\left(\frac{-\lambda(x-\mu)^2}{2\mu^2 x}\right)$$

Solar Power

$$PV_t = FF \cdot V_t \cdot I_t$$

$$V_t = V_{oc} - k_v\left[T_t^{cell} - 25\right]$$

$$I_t = SI_t \left(I_{sc} + k_i\left[T_t^{cell} - 25\right]\right)$$

$$T_t^{cell} = T_t^{amb} + \frac{(T^{nom} - 20)}{0.8} \cdot SI$$

Wind Power

$$W_{out} = \begin{cases} & if\; v_w < v_{ci} \\ P_w \times \dfrac{v_w - v_{ci}}{v_r - v_{ci}} & if\; v_{ci} \le v_w \le v_r \\ P_w & if\; v_r \le v_w < v_{co} \\ 0 & if\; v_w \ge v_{co} \end{cases}$$

External Weather Data

T_t^{amb} **: Ambient Temperature**

Normal $f(x; \mu, \sigma)$

$$\frac{1}{\sqrt{2\pi\sigma^2}} exp^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

SI_t**: Solar Irradiance**

Beta $f(x)$

$$\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}$$

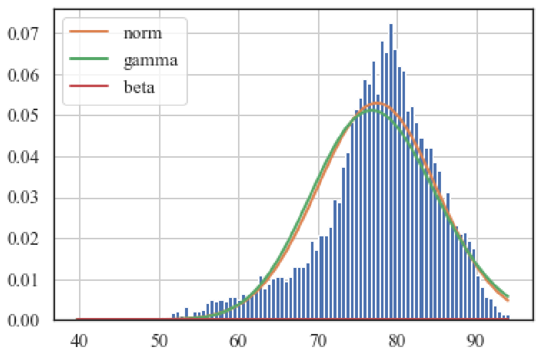
v_w**: Wind Speed**

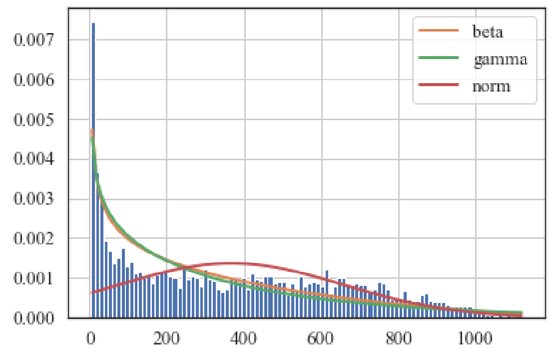
Gamma $f(x; \alpha, \beta)$

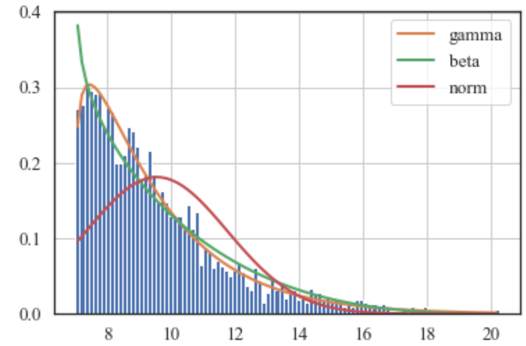
$$\frac{x^{\alpha-1}}{\beta^\alpha \Gamma(\alpha)} exp^{\left(-\frac{x}{\beta}\right)}$$

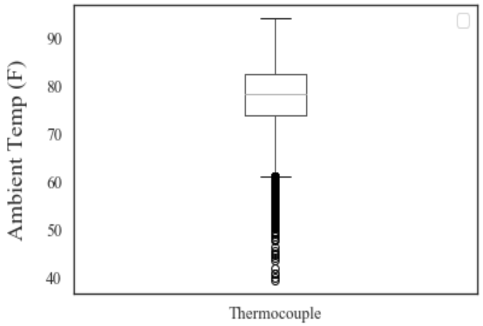
External and Sensory Data Collection

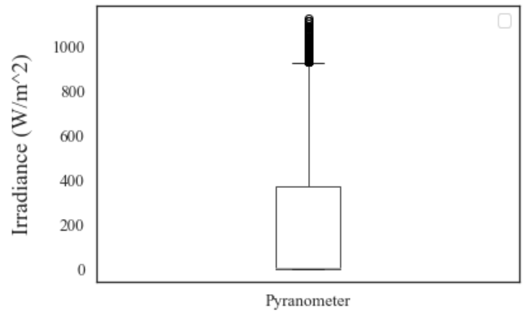
Data Source: External weather (June 2019-20) from FAWN[6]











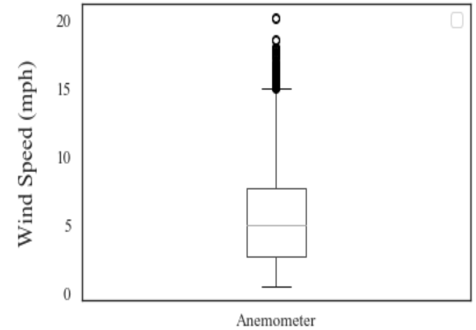


Table 1:
Data Statistics

	Ambient Temperature	Solar Irradiance	Wind Speed
Distribution	Normal - $f(x;\mu,\sigma)$	Beta - $f(x)$	Gamma - $f(x;\alpha,\beta)$
Minimum	39.41	0	0.44
Maximum	94.3	1,126.25	20.23
Square Error	0.004	0.00002	0.19

Deviation Clustering for Load Estimation

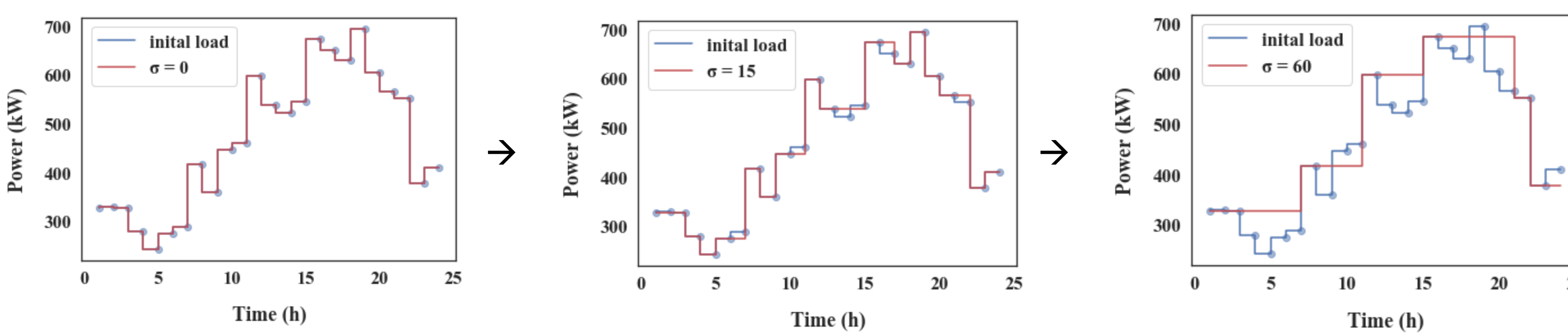
- Deviation Clustering (DC) is a load estimation technique
- Chronologically groups according to a tunable standard deviation (σ)
- Addresses large solution space challenge in dispatch control
- Reduces initial load profile into subgroup called blocks

Table 2:

Pseudo code for Deviation Clustering (DC) Algorithm

Input: x load profile, σ threshold
1. Initialize counter
2. Initialize an empty array (no load profile)
3. Add first element of x to empty array
4. Conduct a pairwise comparison between elements of x
5. If pair's standard deviation is < σ, cluster load
6. Else add current element from x to begin a new cluster
7. Conduct another pairwise comparison on x
8. If elements in pair are not equal, increase counter

Output: clustered load profile, new planning horizon in blocks



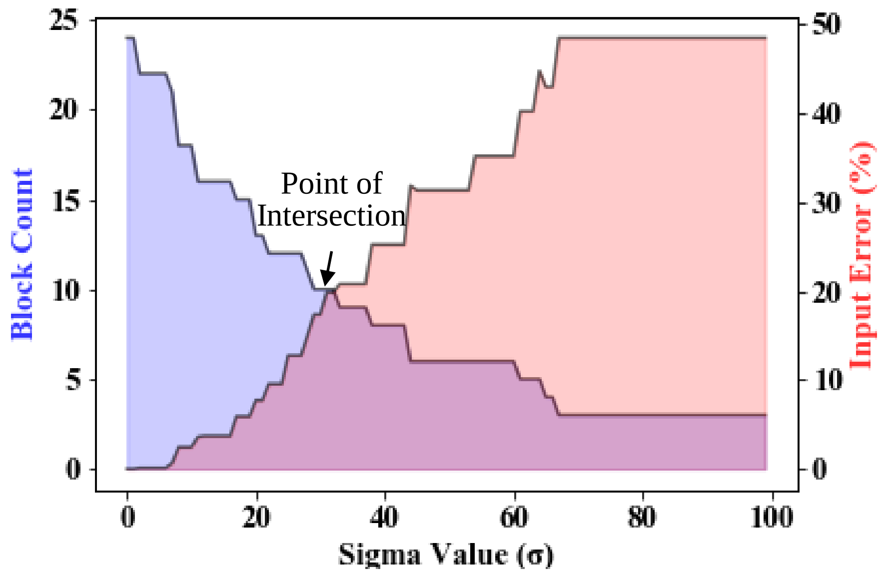
Deviation Clustering for Load Estimation (con'd)

Performance Indicators

$$Block\ Count(BC) = \frac{1}{t} \cdot \frac{24\ hours}{day}$$

$$Input\ Error(IE) = \sum_{t \in 24} \frac{|D_t - D_t^*|}{D_t} \cdot 100$$

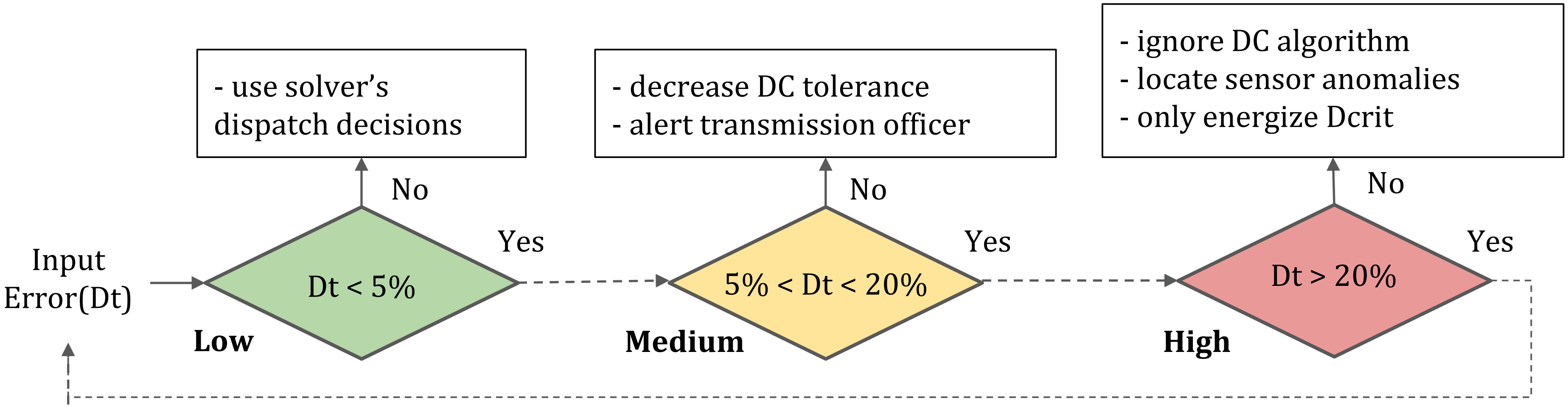
- BC ~ model's scale
- IE ~ level of distortion in



Tradeoff analysis between reducing planning horizon (block count) and retaining initial information (input error) at various sigma values (σ)

- Indicators help track tradeoff of DC on initial load profile
- There is no tradeoff between indicators at point of intersection (POI)
- A rule-based policy is developed based on this limitation

Rule-based Policy for Conditional Responses



Rule-based policy embedded into operational framework where (Dt) is input error after clustering and (Dcrit) is a subset of initial load reflecting public safety facilities

- Rule-based policy is grouped into 3 abnormality levels determined by POI
- Abnormality source may be natural (weather) or unnatural (system intrusion)
- Transmission system officer can tune (σ) and steer response toward low or high
- Dynamic property of DDAS improves MG simulation impromptu response

Microgrid Dispatch Model

Multi – Objective Optimization:

$$min\ z = \sum_{t=1}^{24}\left[\sum_{i=1}^{I} x_{it}\ RI_{it} + \sum_{j=1}^{J}(u_{jt}\ CI_j + \sum_{k=1}^{2} g_{jt}^{k}\ CS_j) + U_{lb}\ v_t + b_t U_r\right] \qquad \text{(Cost w/ DSM)}$$

$$min\ z = \sum_{t=1}^{24}\sum_{j=1}^{J}\sum_{k=1}^{2} g_{jt}^{k}\ ES_j^k + u_{jt}\ EI_j \geq \epsilon_k \qquad \text{(Emissions)}$$

Subject to.

- Active power balance constraint
- Operating segments for linearized diesel and emissions function constraints
- Ramp-up and -down constraints
- Load shedding / Peak shaving constraints
- Islanding and main grid coupling constraints

Extensions [10]

- State of charge considering charging and discharging constraints
- Rate of Change of Frequency for distributed energy resources
- Effect on nominal frequency on microgrid system

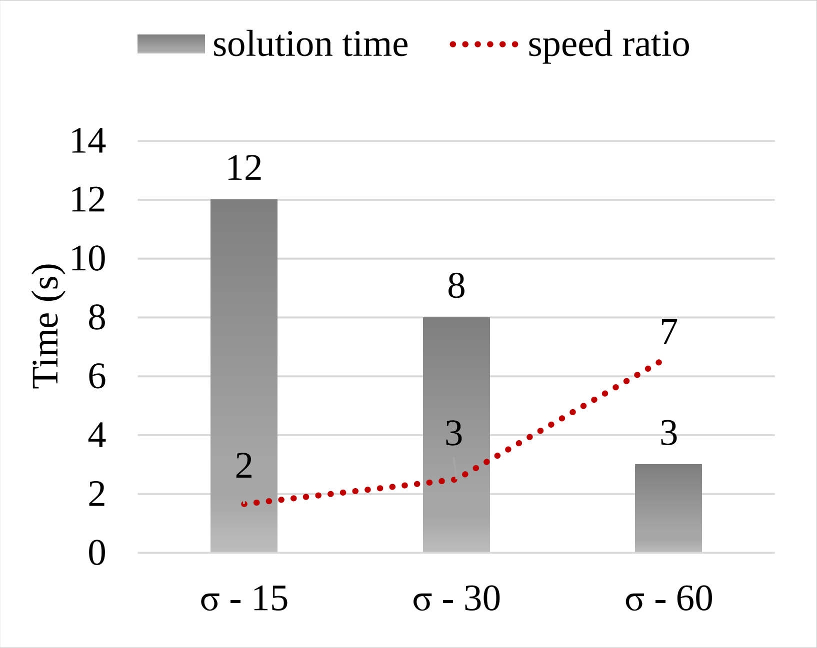
Experimental Results

Performance Indicators

$$Speed\ Ratio(SR) = \frac{solve\ time - solve\ time^*}{solve\ time}$$

$$Output\ Error(OE) = \sum_{Z\in 2} \frac{|x_z - x_z^*|}{x_z}$$

- SR ~ method's efficiency
- OE ~ level of distortion out



Deviation clustering's effects on solution time for microgrid dispatch model.

Table 3:
Results Summary

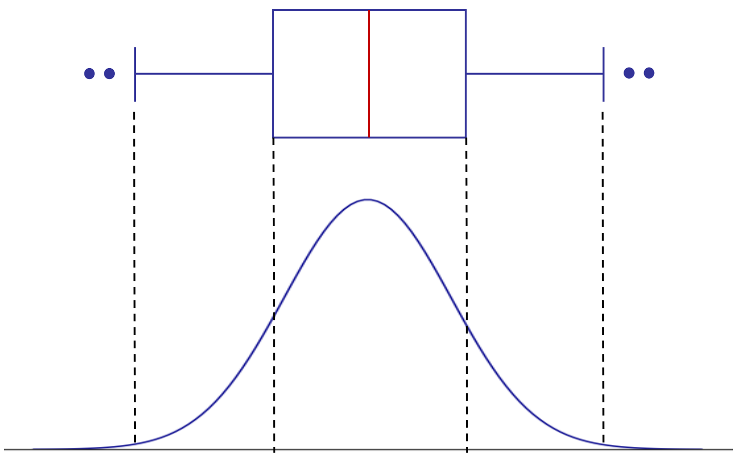
Load Profile	Block Count	Input Error	Speed Ratio	Output Error
Sigma = 0	24	-	-	-
Sigma = 15	16	3.7	2	2.8
Sigma = 25	13	7.744	2.4	3.6
Sigma = 30	10	17.4	3	7.23
Sigma = 45	8	25.22	5	8.2
Sigma = 60	6	35.2	7	9.6

Future Work

Transition to Robust Optimization

- Randomness from controlled by Rule-based Policy -> Data-driven Scenario Selection
- Relaxing assumption is test point is analogous to a potential scenario in an optimization problem
- Developing hybrid relationship for Data–driven Scenario Selection ($Level^{Factor} = All\ Scenarios$)
- Level derived from quartiles of Box plot & Probability derived from PDF of each factor w/ randomness
- Unlikely scenarios generated by outliers are omitted from scenario set unless they map to extreme weather events

Box plot – PDF Overlay



Analogous Terminology

Design of Experiments	Optimization	Simulation
Factors	Parameters	Input
Response	Objective Function	Output
Treatment Combination	Scenario	Replication
Levels	Sensitivity	Fidelity
Risk	Optimality Gap	Confidence Interval

Questions

Thank you!