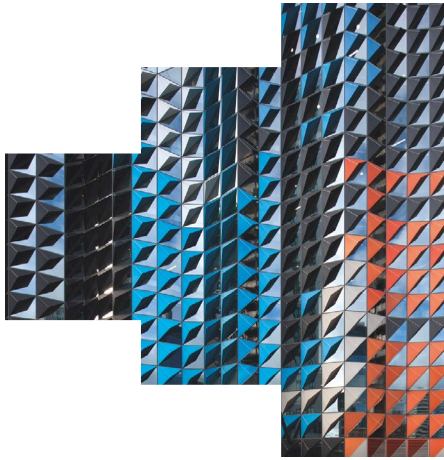
Probabilistic Modelling of Aggregated Renewables for Power System Stability Assessment



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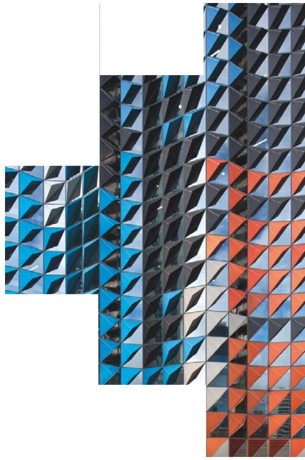
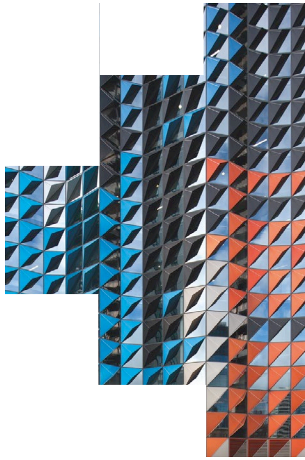
Presentation Outline

- Brief overview
- Significance of this research
- Algorithms and Procedures
- Simulations and Results
- Observations and Future works



Power Systems of the Future

- Increased contribution of **intermittent Renewables** generations
- Plant cycling, less synchronous inertia
- Consistently changes the current power system analysis
  - New types of **generations** (Wind, solar PV, fuel cell)
  - **Loads** (such as Electric Vehicle, Battery storage)
  - Converter-connected smart home **appliances**
- Higher **variability** and **uncertainty**
- **Wind power generation** has experienced a dramatic rise in the last decade
- Large Wind Farm consisting of **tens and even hundreds** of wind turbines



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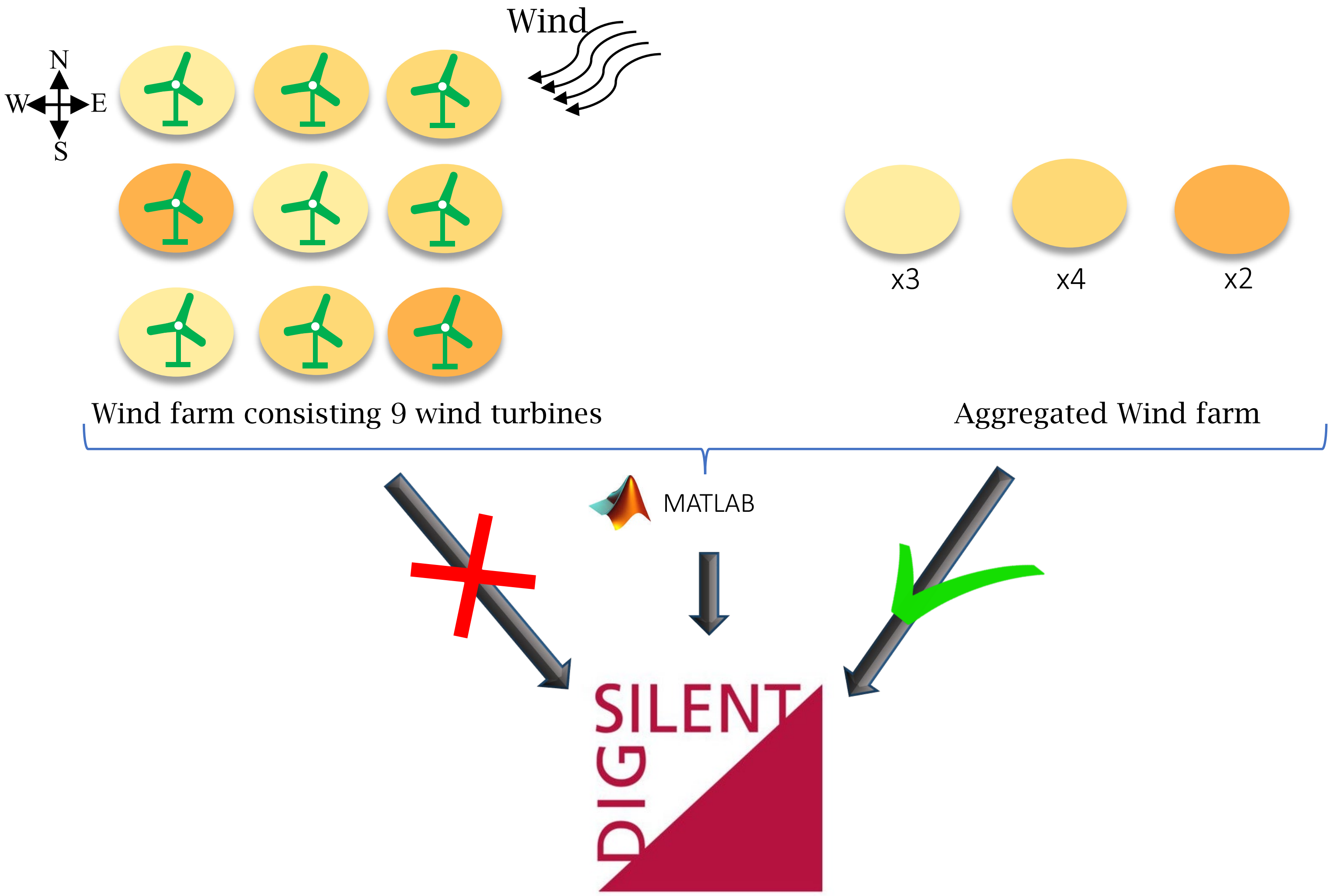
Why Probabilistic Aggregation

- Combining the probability functions for individual components/units with correctly propagated uncertainty, is known as probabilistic aggregation
- Unreasonable to build a **detailed model** of a wind farm **dynamic studies**
    - Complex mathematical model
    - Simulation time
- Power generation of a wind farm changes frequently as the **wind speed and directions** change
- Wind is a variable energy resource, deterministic models often **do not lead to a reliable solution**
- System stability measures could take **minutes to hours, even weeks** depending on the number of nodes

Wind Farm Aggregation- Example



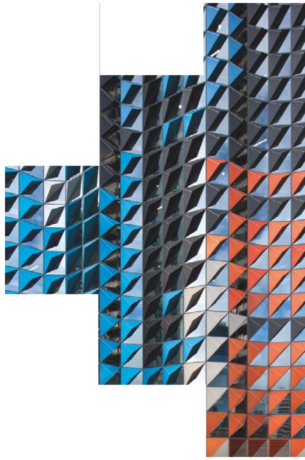
Stage I

Stage II

Objectives of This Research

What would be an appropriate methodology to investigate the impact of **renewable generations** on **power system stability** in a **transmission network** connected with the **wind farm?**

- **Probabilistic clustering framework** to represent the most recurring aggregated WF model throughout the whole year
- Applying **four clustering algorithms** to compare and establish the best-performed clustering technique with varying wind speed and direction
- Assessing the power system's **small disturbance, frequency, and voltage stability**



Stability analysis of interconnected power system integrated with wind generation

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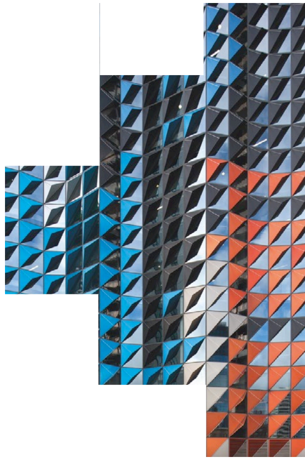
Probabilistic Clustering of Wind Farm

- **“Probabilistic clustering”** is defined in the context of probabilistically determining the recurring (mostly occurred) group of clusters (among a large number of clusters) of wind turbines based on their individual wind speed and direction within a timeframe (such as in one year)
- The **‘probability’** is used once the clustering algorithm determines the clustering of wind turbines
- Different wind turbines may fetch **different wind speeds** within a wind farm due to wakes
- Abrupt change of wind speed and direction) may require **frequent readjustment** of clustering or modelling parameters



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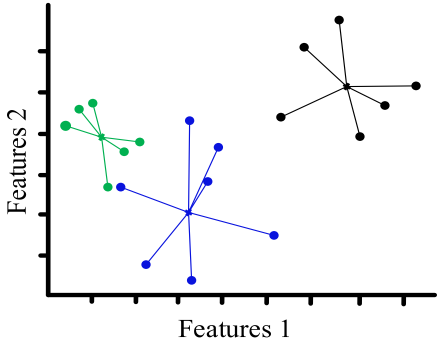
Clustering Algorithms

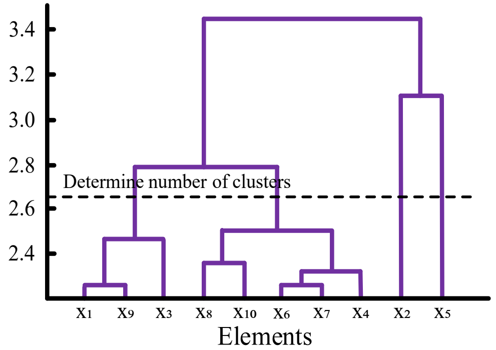
K-means Clustering

$$D(c) = \sum_{i=1}^{N} (x_c - x_i)^2 ||^{½} \qquad (1)$$



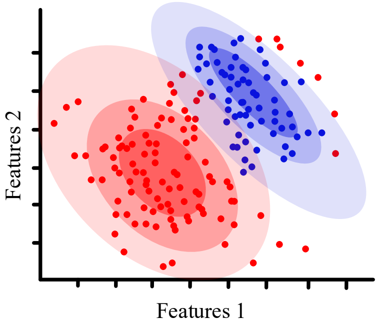
Hierarchical Clustering

$$D_{r,s} = \min\left(dist\left(x_{ri}, x_{sj}\right)\right) \qquad (2)$$



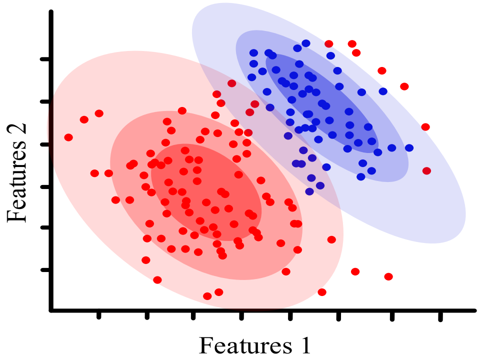
Fuzzy c-means Clustering

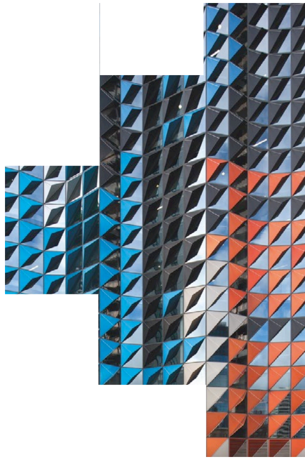
$$D_m = \sum_{j=1}^{N} \sum_{i=1}^{k} (\mu_{ij})^m \left| |X_i - C_j| \right|^2 \qquad (3)$$



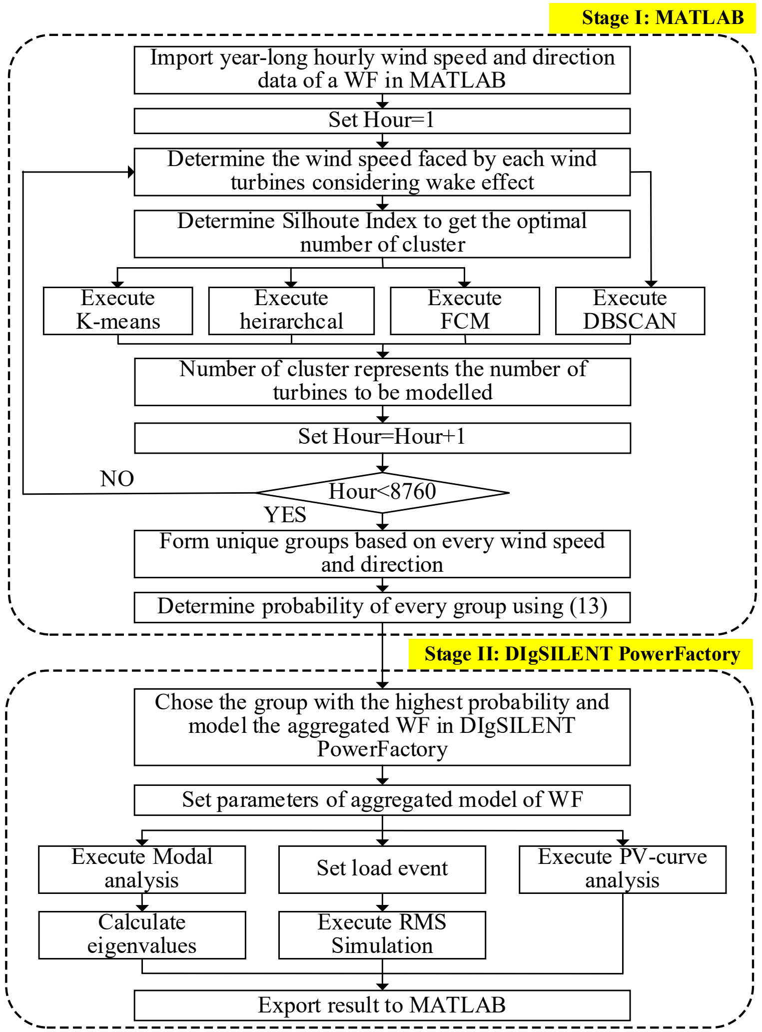
$$\mu_{ij} = \left[\sum_{j=1}^{N} \left[\frac{\left| |X_i - C_j| \right|}{\left| |X_i - C_j| \right|} \right]^{\frac{2}{m-1}} \right]^{-1}$$

Density-based spatial clustering of applications with noise (DBSCAN)





Computational Procedure



Data collection and processing

- Wind speed and direction are recorded in 15 minutes time interval
- **MATLAB** is used to determine the wind speed faced by each turbine (Wake Effect Model)
- Filtering is used to eliminate the inconsistent data

Classification by using clustering algorithms

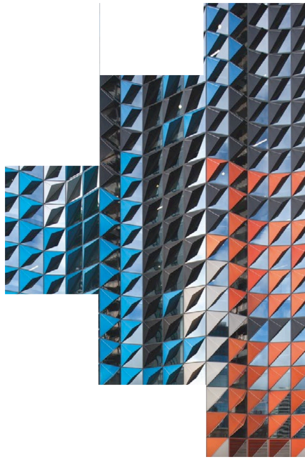
- K-means clustering
- Hierarchical clustering
- Fuzzy c-means clustering
- DBSCAN

Equivalent probabilistic wind farm model

- Determine the unique group of clusters
- Probability of occurrence of each unique group

Stability Analysis

- Modelling in **DIgSILENT PowerFactory**
- Small-disturbance stability, frequency stability, voltage stability



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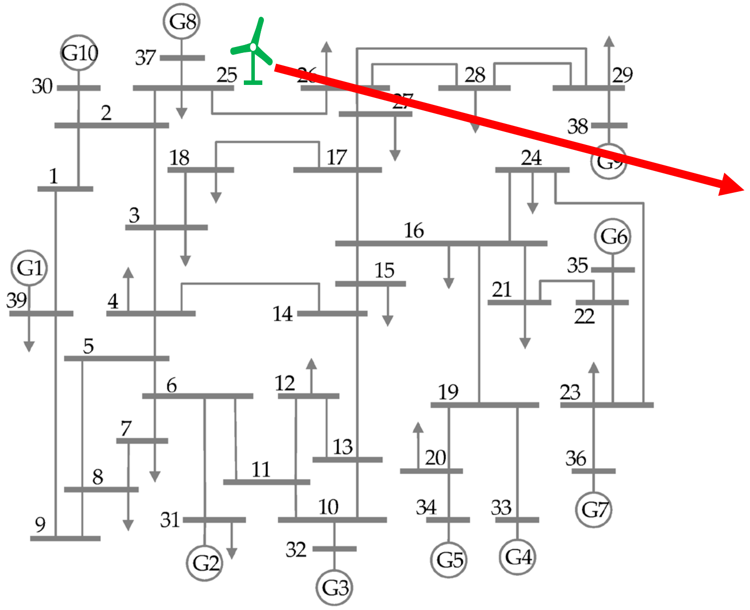
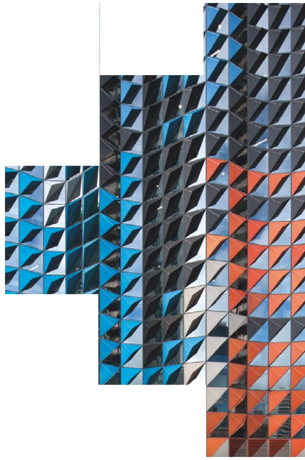
Test System Modelling



IEEE 39 bus New England Test Systems



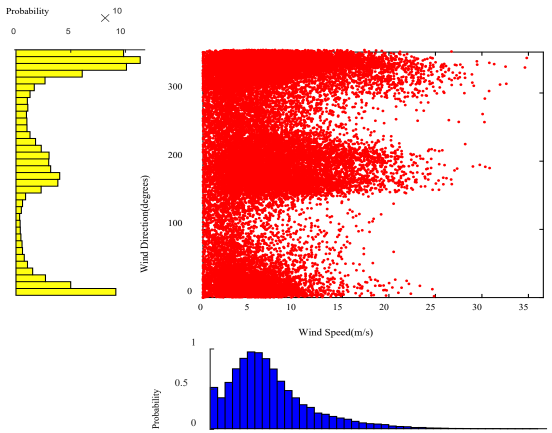
Power System Stability Indices:

- Small-disturbance stability
  Damping of critical oscillatory mode
- Frequency stability
  Frequency nadir
- Voltage stability
  Loadability (load margin)

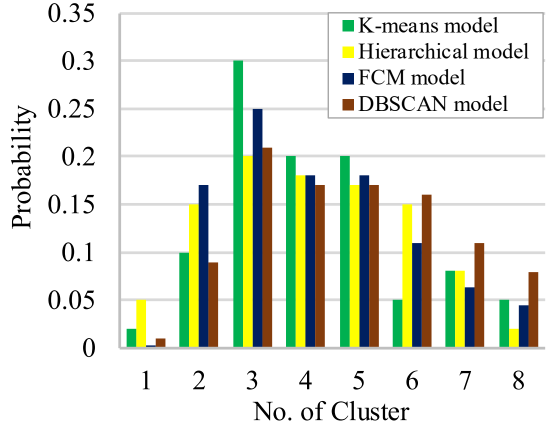
Clustering Output

Turbines of WF in clusters based on the wind speed and direction

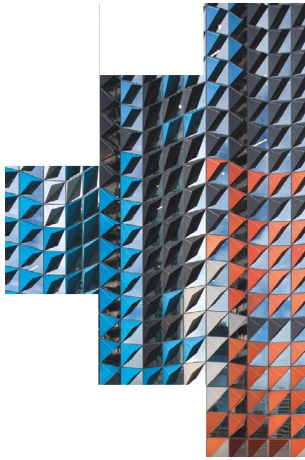
Hour	Clusters								No. of cluster
	c1	c2	c3	c4	c5	c6	c7	c8	
1	25	20	28	27					4
2	60	40							2
3	22	10	22	14	12	20			6
4	11	11	16	10	12	10	12	18	8
⋮	--	--	--	--	--	--	--	--	-
⋮	--	--	--	--	--	--	--	--	-
⋮	--	--	--	--	--	--	--	--	-
⋮	--	--	--	--	--	--	--	--	-
8758	27	44	29						3
8759	29	25	46						3
8760	22	23	21	12	22				5



Wind speed and direction distribution



Probability of number of clusters



Probabilistic Clustering Output

Probability of cluster for each group

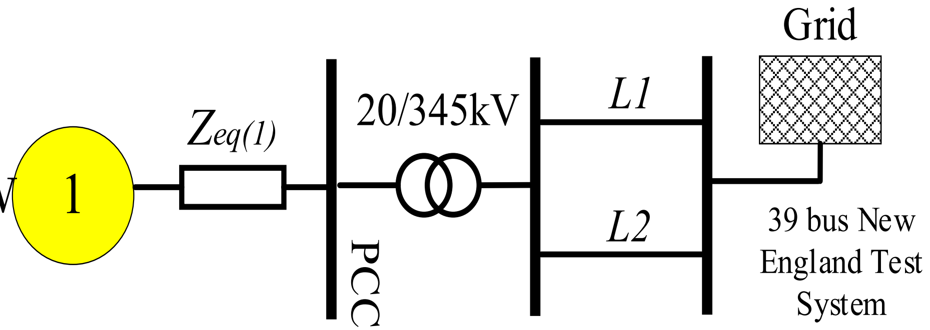
$$G_p = \sum_{w_d \in W_{(d)}} \cdot \sum_{w_s \in W_{(s)}} \cdot \sum_{c_s \in C_{(al)}} P_{w_d, w_s, c_s} \qquad (1)$$

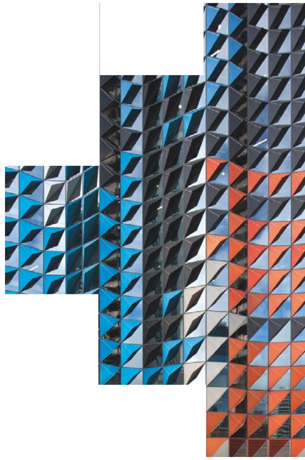
Wind Condition : 7 m/s from 180°
Total Power: 68.89 MW

Unique Group	K-means model	Hierarchical model	Fuzzy c-means model	DBSCAN model
Group 1	27:44:29	26:45:29	23:40:29	26:44:30
Group 2	33:29:28	31:28:41	37:41:22	26:29:35
Group 3	31:26:43	31:43:26	24:39:37	37:26:37

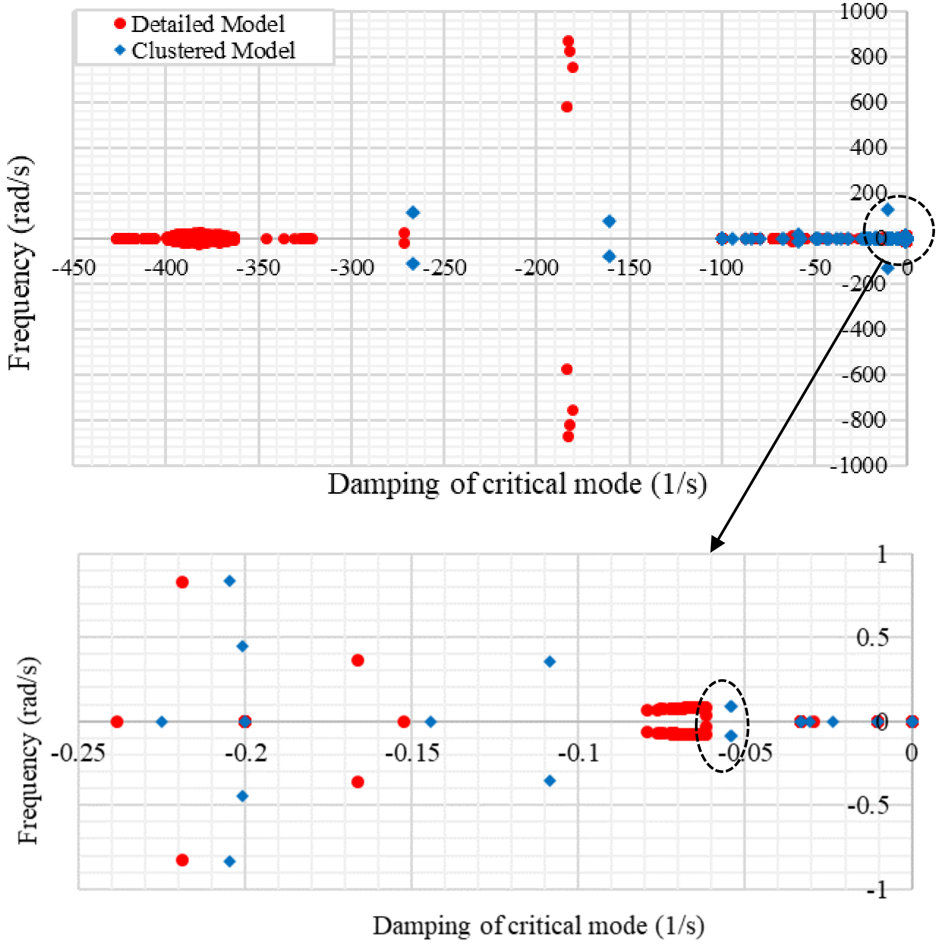
Single-unit model of wind farm model

68.89 MW





Eigenvalues with a Sample Data



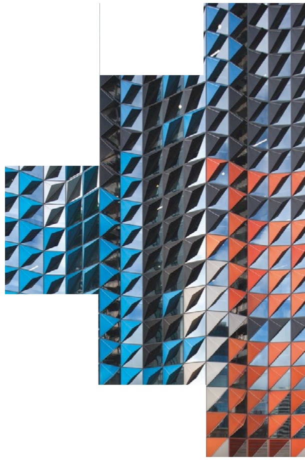
Zoomed in figure

Descriptions	Detailed Model	Aggregated Model
Turbines	100	**3**
Eigenvalues	3267	**366**
Simulation time	680s	**68.8s**

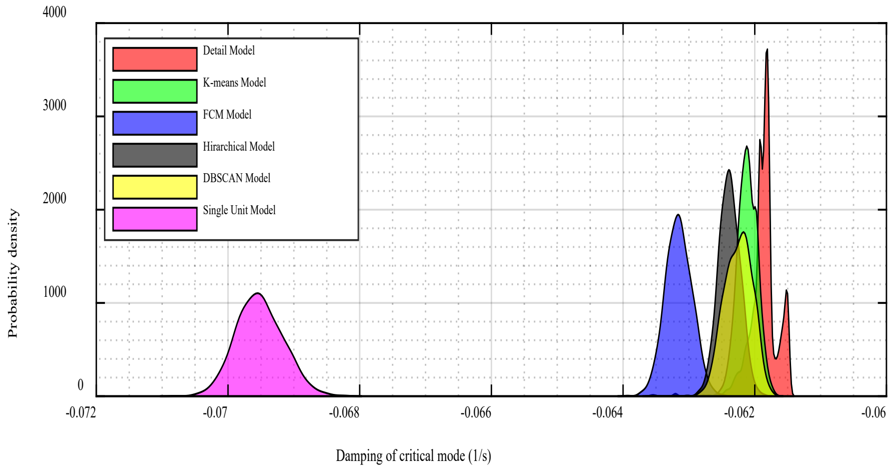
- The critical eigenvalues for-

  Detailed model: $-0.0618 \pm j0.816$

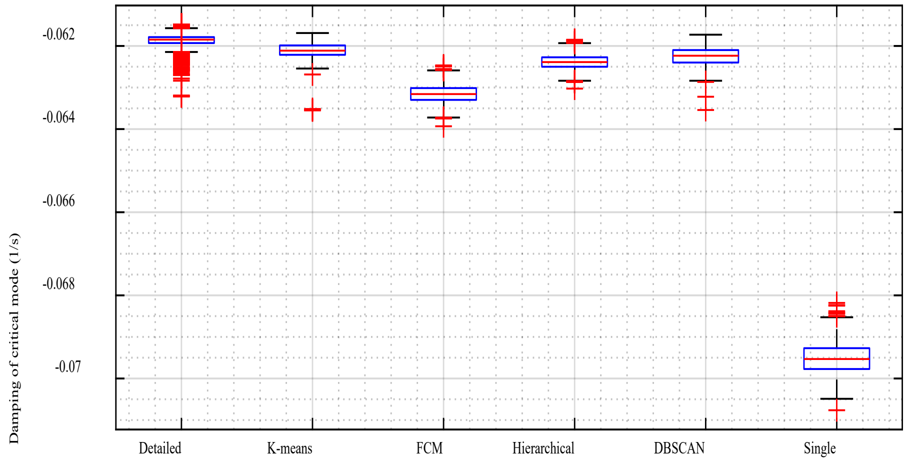
  Clustered model: $-0.0559 \pm j0.822$



Damping with Various Model of Wind Farm

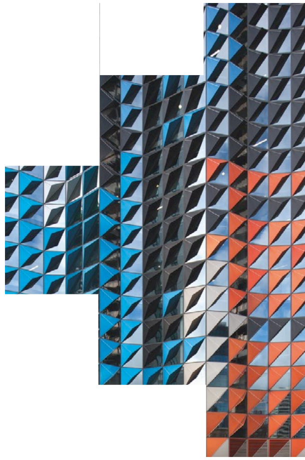


Histogram *pdf* of damping of critical mode with various models of WF



Box plot of damping of critical mode with various models of WF

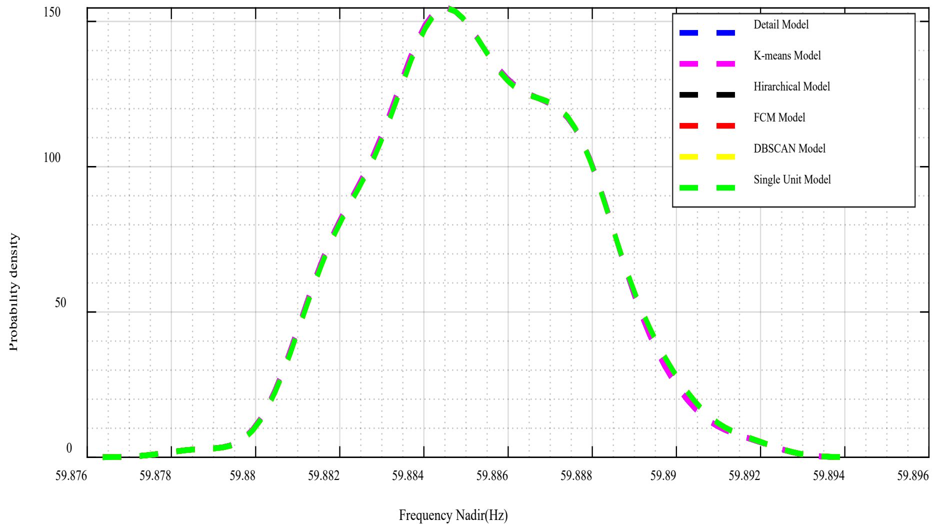
- Presenting **8760** number of damping in *pdf*
- Damping of critical mode is similar to the detailed model of WF
- **K-means** algorithm produces the closest damping with the detailed model
- Single-unit model produces distant *pdf* with the detailed model



- Box plots present the statistical median
- The algorithms ranking are:

K-means > DBSCAN > Hierarchical > FCM

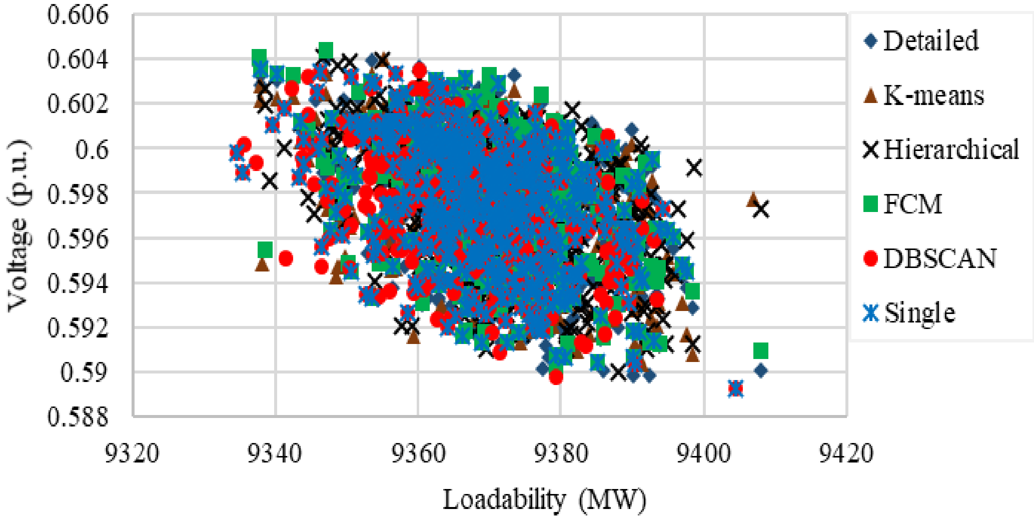
Frequency Nadir with Various Models of Wind Farm



Kernel smoothing *pdf* of frequency nadir with various models of WF

- Load event (10% increment on load 15)
- RMS simulation is conducted for 40s
- Similar frequency response with various model of WF
- *pdf* of frequency nadir are similar regardless the WF model

P-V Nose Points with Various Model of Wind Farm



Spreads of P-V nose points with various models of WF

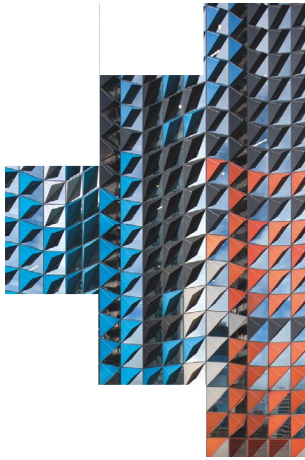
- Presenting 8760 number of P-V nose points
- The nose points are concentrated in a narrow region
- Variation of model of WF is disregarded
- Capable of capturing the similar load margin

Efficiency of Probabilistic WF Clustering Models

Efficiency Measure of Different Models of WF Based on a **Single Simulation Time**

WF Model	Small-disturbance stability	Frequency stability	Voltage stability
Detail model	660s	858s	1.8s
Aggregted models	68.8s	78s	0.2s
Single-unit model	49s	56s	0.15s

- Aggregated WF models are 10-13 times faster in simulation time (better efficiency)



Accuracy Measure of Different Models of WF Based on **RMSE** of 8760 Simulation

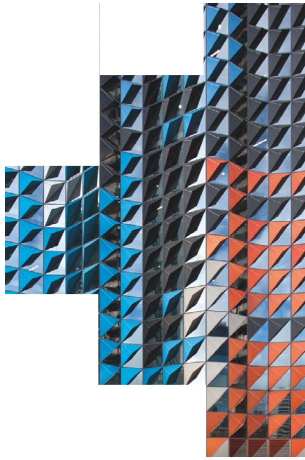
WF Model	Small-disturbance stability	Frequency stability	Voltage stability
K-means	0.0163		
Hierarchical	0.0361		
FCM	0.0231	0.00153	0.0019
DBSCAN	0.0200		
Single-unit	0.0875		

- K-means > DBSCAN > Hierarchical > FCM

Observations and Future Works

Observations:

- A methodology for probabilistically aggregating large WF using clustering algorithms in order to assess power system stability
- Aggregated wind farm model is still able to capture the similar dynamic responses to detailed model
- Stability simulations can be performed using aggregated wind farm model while preserving the same level of accuracy



Future works:

- No clustering algorithms are perfect that could generally apply to all types of power system studies
- More number of wind farms can be considered to justify the strategy

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Thank you