Predictive Analytics Tools for Improving the Electricity Grid Resilience

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Model: Exploit data and physical network components together in time and space

Objective: determine the likelihood of power network outages under *severe weather conditions*

Data: multiple sources (big and heterogeneous)

- measurements from grid
- weather data
- financial data

Challenge: *efficient learning* from big, heterogeneous spatio-temporally integrated network and weather data

Paradigm change: From corrective to predictive handling of resilience

Needed: accurate predictions at three temporal scales (real-time, mid-term, and long-term) from grid and weather measurement big data

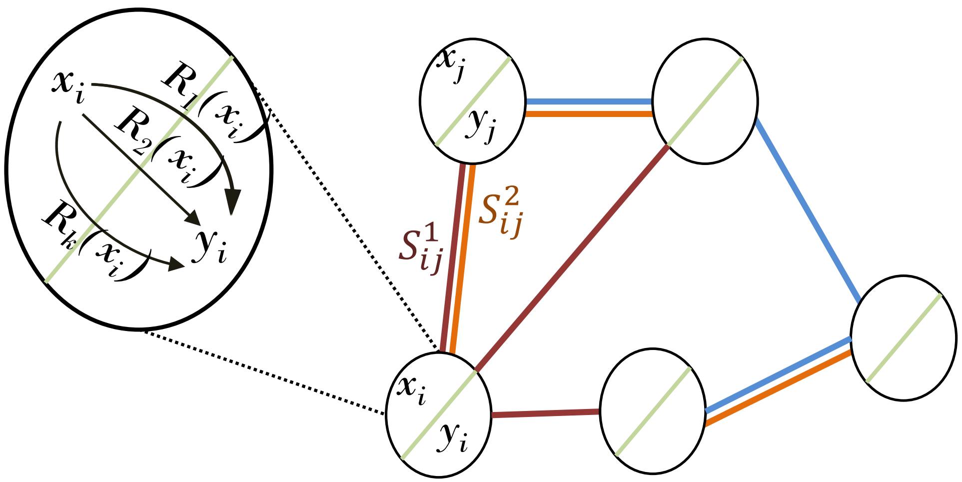
Aims: *innovative tools* for discovering critical knowledge for *improving the electricity grid resilience by:*

- enabling a predictive maintenance strategy continuously across space and time;
- extracting the knowledge required for predicting emergency operating conditions before they occur;
- predicting fault location in real time, and determining strategies to reduce outage duration and restoration time.

Our approach: Structured regression

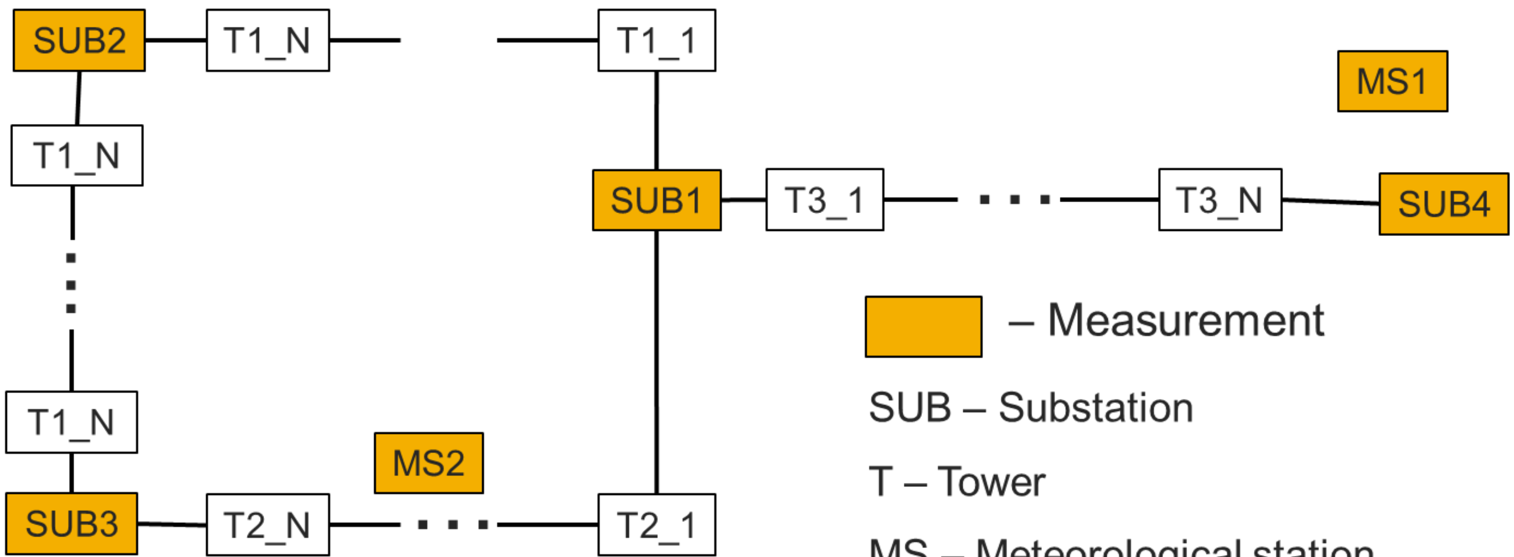
Goal: Prediction of a real valued N-dimensional response $y = (y_1, ..., y_N)$, given:

- explanatory variables $x = (x_1, ..., x_N)$
- **dependencies** between the responses y, represented by a set of networks, each describing one of multiple types of connections among the nodes.



- The regression method should be able to take into consideration **structure represented as various linkage relations** among the nodes (weighted connections)
- The connections are of different nature, each offering partial information, so that the contributions should not be averaged and have valuable information lost

Our approach: Risk Assessment Application



Nodes: X = (Lig_Curr, $\overbrace{\text{Temp, Press, Hum, Prec}}^{\text{From MS}}$, BIL_old)

Y = (BIL_new)

Branches: Impedance matrix

Dokic, T. Dehghanian, P., Chen, P.-C, Kezunovic, M., Medina-Cetina, Z., Stojanovic, J., Obradovic, Z. (2016) “Risk Assessment of a Transmission Line Insulation Breakdown due to Lightning and Severe Weather,” HICS 2016.

Our approach (the main idea): Learning Gaussian Conditional Random Fields

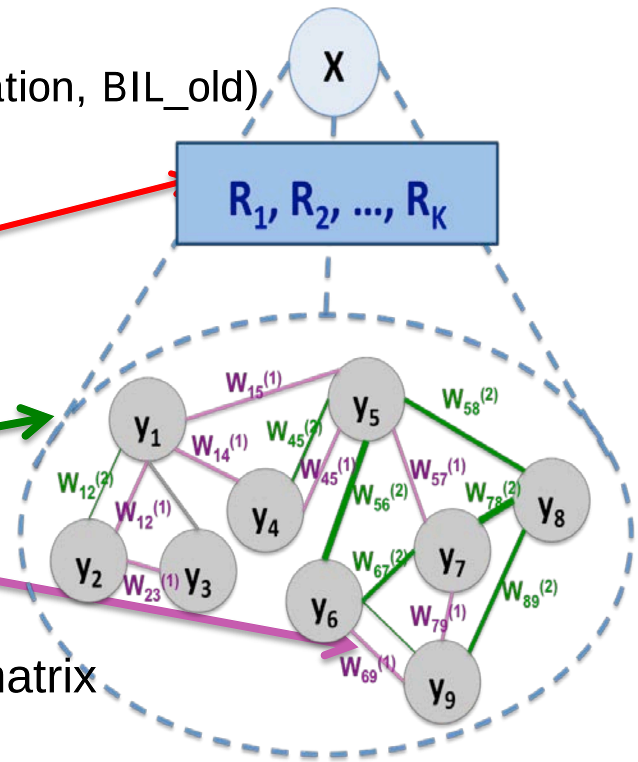
$$P(\mathbf{y}\,|\,\mathbf{x}) = \frac{1}{Z(\mathbf{x},\boldsymbol{\alpha},\boldsymbol{\beta})}\exp\Big(\sum_{i=1}^{N} A(\boldsymbol{\alpha}, y_i, \mathbf{x}) + \sum_{j\sim i} I(\boldsymbol{\beta}, y_i, y_j, \mathbf{x})\Big)$$

Y = (BIL_new)

X = (Lightning Current, Temperature, Pressure, Humidity, Precipitation, BIL_old)

$$A(\alpha, y_i, \mathbf{x}) = -\sum_{k=1}^{K}\alpha_k (y_i - R_k(\mathbf{x}, i))^2$$

$$I(\beta, y_i, y_j, \mathbf{x}) = -\sum_{l=1}^{L}\beta_l e_{ij}^{(l)} S_{ij}^{(l)}(\mathbf{x})(y_i - y_j)^2$$



Branches: S – Impedance matrix

- P(y|x) is **Gaussian** distribution
- **Learning**: *Convex optimization to* find parameters **α** and **β**
- **Inference:** Point estimate of **y** for a given **x** is μ, and uncertainty is Σ, where $P(\mathbf{y}|\mathbf{x}) \sim N(\mu, \Sigma)$

Risk Assessment Results

An automated risk-based early warning system for prediction of insulation breakdown using REAL DATA about the weather and past outages.

While in conventional methods standard BIL is considered to be constant, equal to predetermined manufacturers BIL, our method shows changes to components standard BIL over time due to experienced disturbances.

Prediction of insulator risk is not calculated purely statistically, instead machine learning is used.

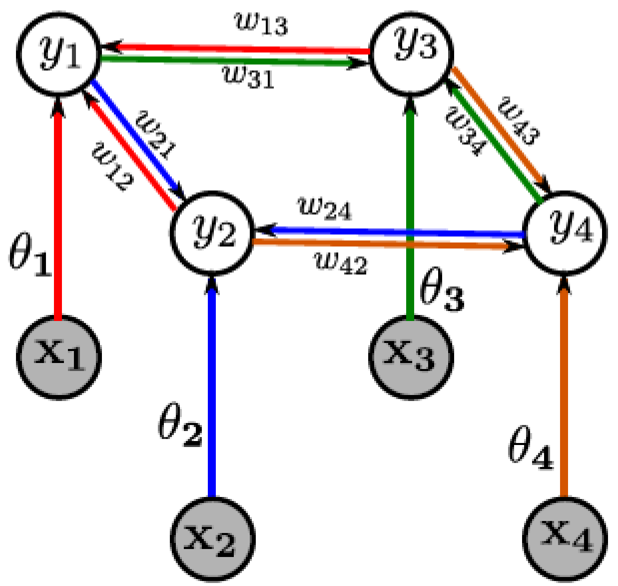
The economic impact assessment that effectively differentiates the impact of different outages on the overall system economic performance has been developed.

Model is capable of predicting risk in case of future lightning strikes using Gaussian Conditional Random Fields structured regression model.

Recent Improvement: Learning Continuous Conditional Dependency Networks (CCDN)

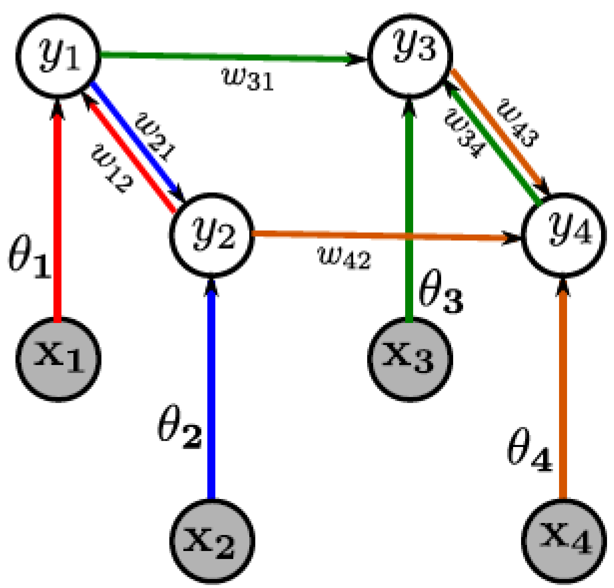
- **[Flexibility]** CCDN is capable of incorporate non-symmetric prior knowledge

CCDN-S: CCDN with symmetric prior knowledge



In spatial data, two nodes are dependent on each other if the are close.

CCDN-N: CCDN with non-symmetric prior knowledge



In spatiotemporal data, besides spatial dependency, one node is also dependent on itself from previous time point.

- **[Structure Recovery]** The entire structure can be discovered from local models
- **[Effectiveness]** Structure learning is convex; we developed effective algorithm for inference

Results: 3 energy related applications

- **Wind Power**: Forecasting wind power on 7 farms over 24 hours in hourly resolution (168 nodes, 4 attributes per node).
- **Precipitation**: Forecasting precipitation amount on 124 stations among U.S. (124 nodes per graph, 9 attributes per node).
- **Solar Energy:** Forecasting solar energy on 98 stations at Oklahoma, (98 nodes per graph, 19 attributes per node).

Learning Time Comparison (Sec.)				
	Wind	Precipitation	Solar Energy	#Parameters
#Nodes (p)	168	124	98	\
GCRF[1]	100.07	83.71	234.38	2
SGCRF[2]	127.44	51.66	178.45	O(p^2)
RLSR[3]	>1000	>1000	>1000	O(l*p^2)
CCDN-S	**47.95**	**13.17**	**19.62**	O(p^2)
CCDN-N	**39.42**	**13.97**	**22.15**	O(p^2)

Forecasting Mean Square Error				
	Wind	Precipitation	Solar Energy	#Parameters
GCRF[1]	0.0593	0.1732	0.0204	2
SGCRF[2]	0.0590	0.1722	0.0201	O(p^2)
RLSR[3]	0.0572	0.1711	0.0206	O(l*p^2)
CCDN-S	0.0697	**0.1670**	**0.0200**	O(p^2)
CCDN-N	**0.0519**	**0.1673**	**0.0201**	O(p^2)

- CCDN is more efficient, and at least as accurate as alternatives

Han, C, Ghalwash, M., Obradovic, Z. “Continuous Conditional Dependent Network for Structured Regression,” AAAI 2017

Thank you

More details:

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