FACULTY OF ENGINEERING

Dynamic Thermal Line Rating: Using the Weather to Increase Transmission Line Capacity

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Outline

- What is DTLR?
- Rating Methods
- DTLR Implementation and Challenges
- U of C DTLR Research Project

Background

As more renewable generation is added to the grid in Alberta

→

Utilities are investigating methods to increase transmission line capacity while minimizing cost

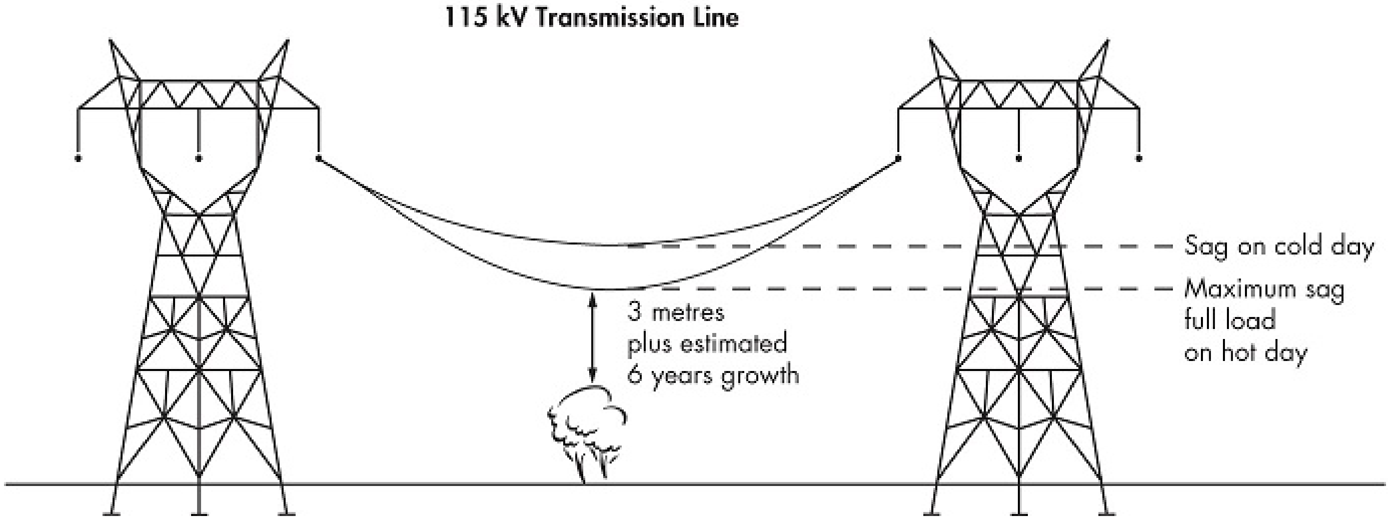
→

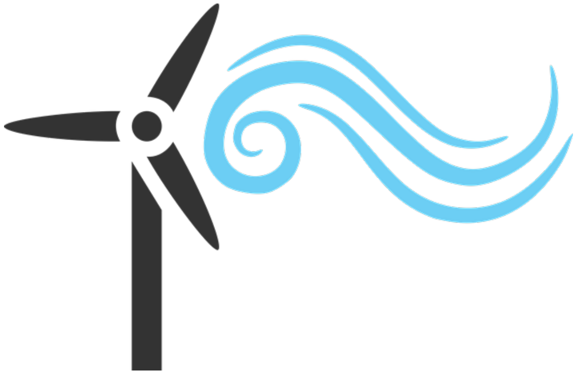
Dynamic Thermal Line Rating (DTLR) is one solution

Types of Line Ratings

- The type of line rating that is used is dependent on the length of the transmission line
  - Thermal limit (short lines – under 80 km)
  - Voltage limit (medium lines – between 80 and 250 km)
  - Stability limit (long lines – over 250 km)
- Dynamic thermal line rating is based on the thermal limit of a line, so is typically only used for short lines

What is Dynamic Thermal Line Rating (DTLR)?





http://www.studyelectrical.com/2016/01/sag-in-overhead-transmission-conductor-lines.html
https://clipartpig.com/download/ThcokA3
https://pixabay.com/en/wind-energy-renewable-energy-wind-2029621/

What is DTLR?

Presently, utilities use:

Reasonable outer-range environmental conditions → IEEE/CIGRE Model → Static Rating

Switching to a DTLR requires:

Weather station data → IEEE/CIGRE Model → Dynamic Thermal Line Rating

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DTLR Benefits

- Increased system visibility
- Reduced aging
- Network planning
- Network reliability
- Increased wind penetration
- Icing and galloping detection
- Maintaining clearance

DTLR Methods

- DTLR can be calculated using either indirect or direct measurements
- Direct measurements include:
  - Conductor temperature
  - Sag
- Indirect measurements include:
  - Line tension
  - Weather conditions
  - Fundamental frequency
  - Electromagnetic waves
  - Synchrophasor data

Sag Methods

- These methods either directly or indirectly measure the position of the line to compare to minimum clearance requirements
- There are commercial products available that can measure/calculate the sag of a line using:
  - Line tension (CAT-1)
  - LiDAR (Lindsey Manufacturing)
  - Fundamental frequency (Ampacimon)
  - Electromagnectic waves (LineVision)

Weather-based Method

- Uses multiple weather parameters as input to a thermodynamic model (IEEE Standard 738-2012) to calculate the conductor temperature
- Weather variables include:
  - Wind speed
  - Wind direction
  - Ambient temperature
  - Solar radiation
- Historical weather data can be used to interpolate or predict the rating

IEEE Model

- IEEE Standard 738:

$$I^2 \mathrm{R}(\mathrm{T}_c) + \mathrm{q}_s = \mathrm{q}_c + \mathrm{q}_r$$

- Where:
  - q_c is the heat removed by convection (air movement)
  - q_r is the heat removed by radiation to surrounding air
  - q_s is the heat gained from solar radiation from the sun
  - $I^2\mathrm{R}(T_c)$ is the heat generated by the electron current flow in the conductor
  - T_c is the core temperature of the conductor

Convection Cooling

- Natural convection (no wind):

$$q_{cn} = 3.645\, p_f^{\,0.5} D^{0.75} (T_c - T_a)^{1.25}$$

- Low wind:

$$q_{c1} = \left[1.01 + 0.0372 \left(\frac{D V_w p_f}{\mu_f}\right)^{0.52}\right] k_f K_{angle} (T_c - T_a)$$

- High wind:

$$q_{c2} = \left[0.0119 \left(\frac{D V_w p_f}{\mu_f}\right)^{0.6}\right] k_f K_{angle} (T_c - T_a)$$

Convection Cooling

- The parameters p_f (air density), μ_f (dynamic viscosity), k_f (thermal conductivity) are dependent on ambient temperature and conductor type
- K_{angle} is a function of the wind direction
- The convection cooling term is a non-linear function of the wind speed

Radiant Cooling

$$q_r = 0.0178 D\varepsilon \left[\left(\frac{T_c + 273}{100} \right)^4 - \left(\frac{T_a + 273}{100} \right)^4 \right]$$

- Radiant cooling is dependent on conductor properties, diameter (D) and emissivity (ε), and temperature, conductor (T_c) and ambient (T_a)

Solar Heat Gain

$$q_s = \alpha Q_{se} \sin(\theta) A'$$

- The solar heat gain can be calculated using the above equation
- The solar heat gain is dependent on absorptivity (α), solar radiation (Q_{se}), elevation and time of day
- Solar radiation can be measured by the weather station

Current Heating

- Current heating is dependent on current and resistance
- Resistance is a function of conductor temperature

$$R(T_c) = R_{ref}(1 + \alpha(T_c - T_{ref}))$$

- Previous research has investigated implementing temperature-dependent resistance in optimal power flow

Transient Equation

- The previous equation is based on steady state
- The transient response for the conductor temperature due to a step change in current is:

$$\Delta T_c = \frac{I^2 R(T_c) - q_c(T_c) - q_r(T_c) + q_s}{mC_p} * \Delta t$$

- The transient response is a function of the heat capacity of the line
- The time constant is 5-15 minutes, depending on the weather conditions used

Ambient-Adjusted Ratings

- Another form of DTLR is to only use changes in ambient temperature
- Can alleviate some of the risk associated with DTLR, as the variations in wind speed/direction are ignored
- Does not have as high of an increase compared to using a full DTLR

Other Methods

- Synchrophasor data can also be used to calculate a DTLR
- Phasor Measurement Unit (PMU) data provides the voltage and current at different points in the grid
- The difference in voltage at two points can be combined with the relationship between resistance and temperature to determine the conductor temperature indirectly

DTLR Implementation

- To implement DTLR on a transmission line, there are three main methods:
  - Find the hottest-spot on the transmission line (limiting span) to determine where to install a device to determine what the minimum rating would be for the entire line
  - Interpolate the rating over the terrain using multiple weather stations and mathematical modeling
    - Idaho National Lab (INL) uses computational fluid dynamics (CFD) to interpolate wind data
  - Install sufficient number of devices to cover desired line

DLTR Prediction

- Difficult to implement DTLR in real-time
- Some commercial DTLR products have prediction capabilities built-in
- Most prediction methods are based on historical weather data
- Time horizon can be 1 hour ahead up to 48 hours ahead
  - The longer the time horizon, the lower the ampacity will be to preserve accuracy

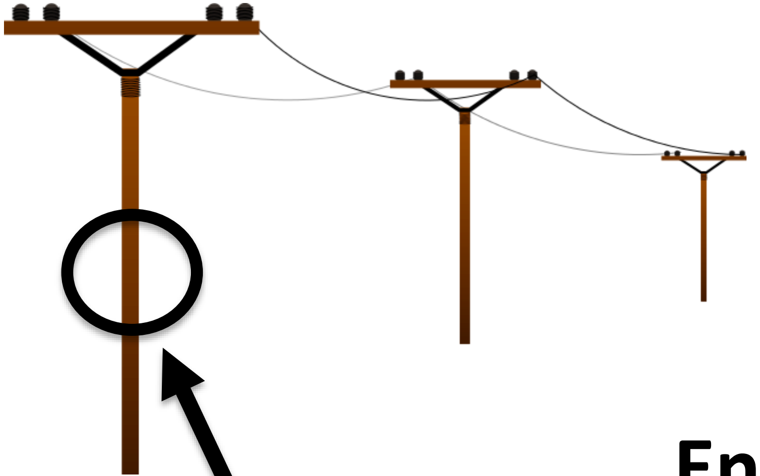
DTLR Challenges

- The limiting span can be difficult to determine
  - Depends on the terrain and predominant wind direction
  - Interpolating weather data can be computationally intensive
  - Installing multiple devices can be expensive, depending on the technology used
- Collecting sufficient weather data
- Communication between devices and EMS
- Integrating a dynamic rating into EMS

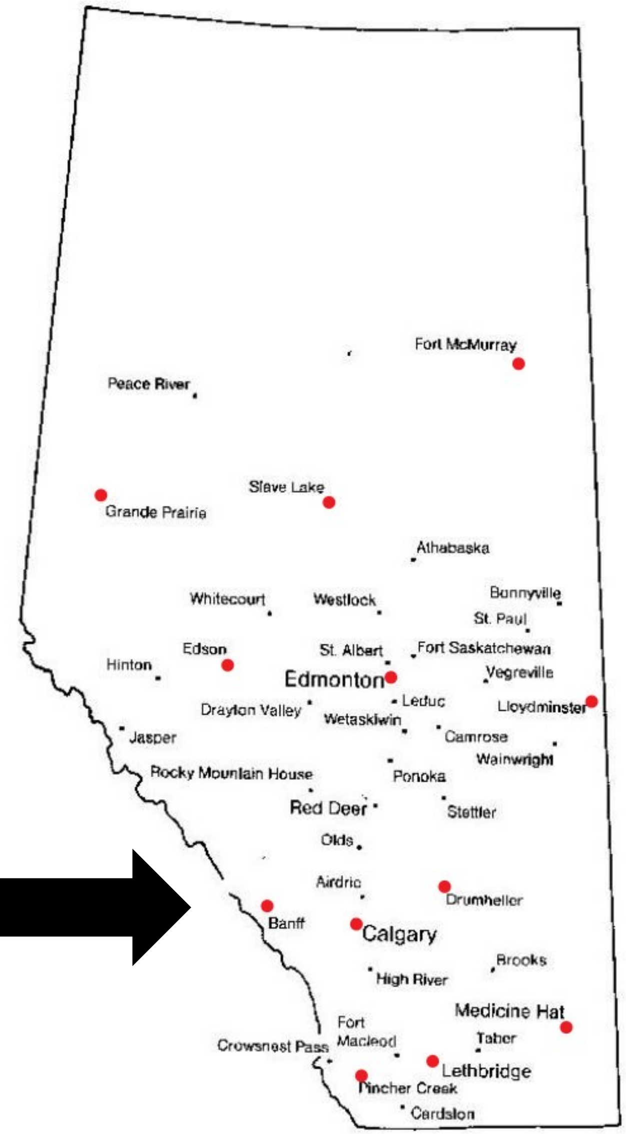
Research Project

- The DTLR Research Project is focused on investigating the implementation of DTLR in Alberta
- Components of the project:
  - Fuzzy DTLR Prediction
  - Transient Impact
  - Spatial DTLR Patterns

Gathering Weather Data



Environment Canada Weather data

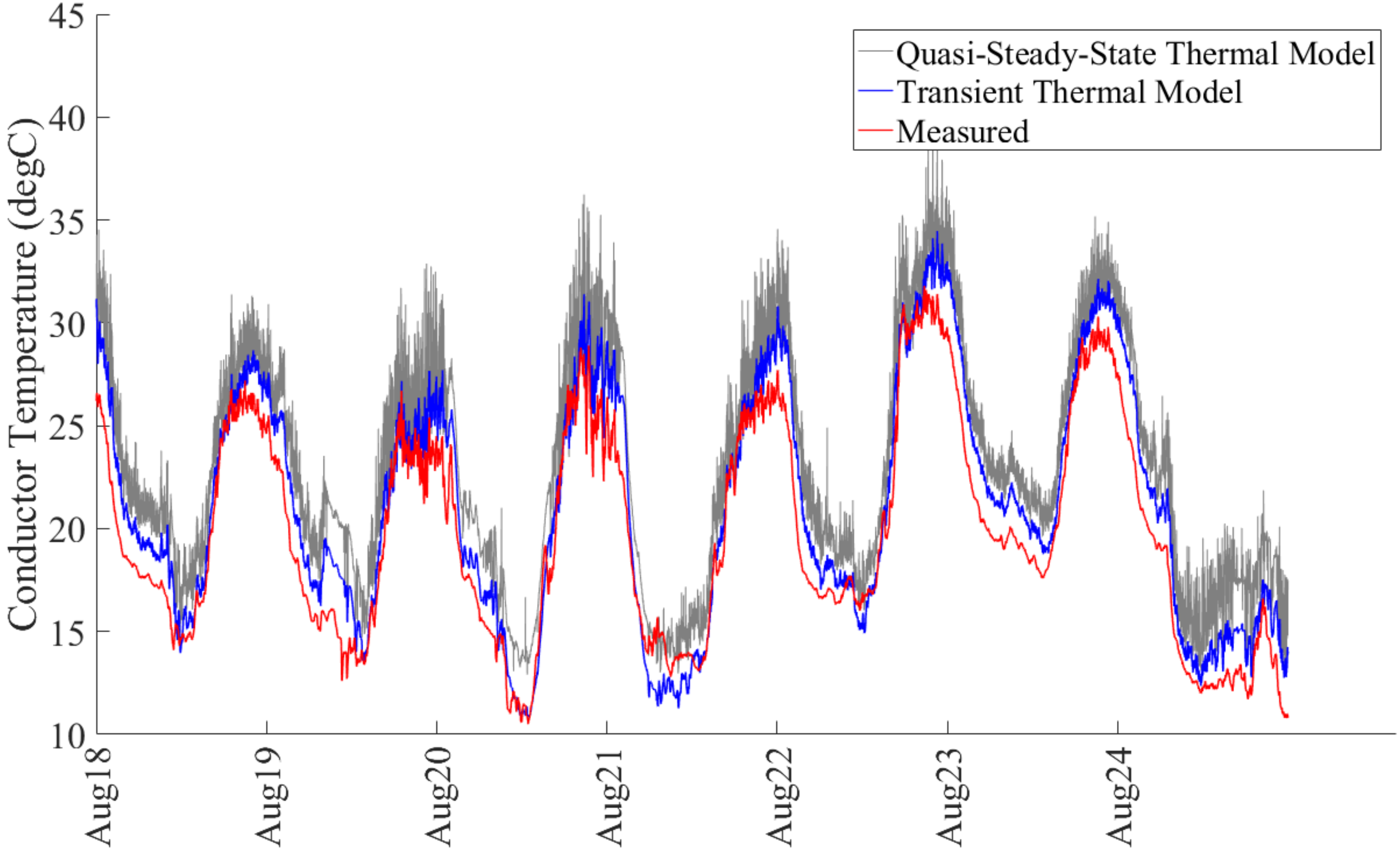


http://weclipart.com/power+lines+clipart
http://clipground.com/weather-station-clipart.html
https://fabulousbydesign.net/printable-map-of-alberta/

Transient Model Validation

- Transient model validated using conductor temperature data from ATCO
- The data was collected using a GE line monitoring relay mounted on a transmission line
- This relay measures the line current, the conductor temperature and the weather conditions

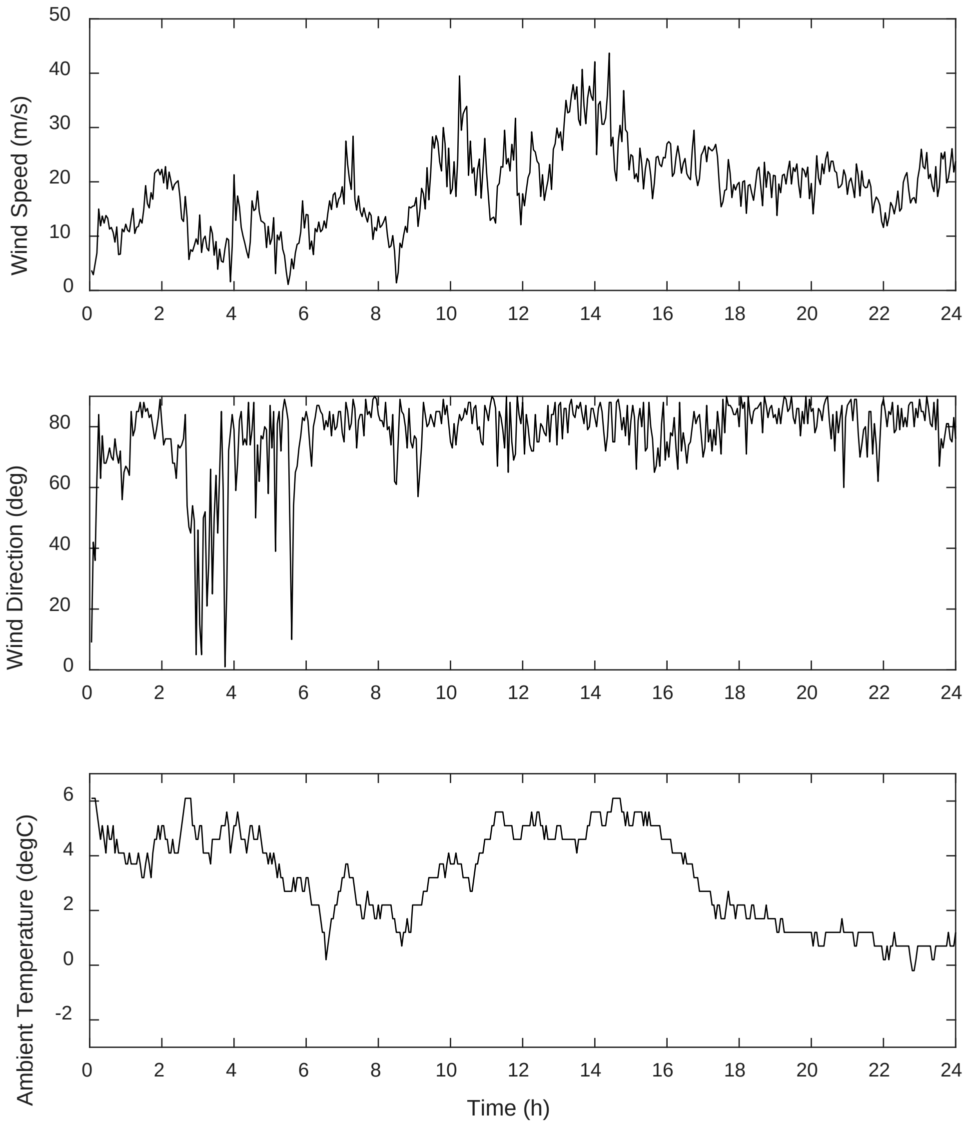
Conductor Temperature Validation



Using DTLR Transient Method

- Investigating the transient thermal impact on transmission lines when environmental conditions drastically change
- Investigating the thermal risk of updating the rating every hour using different confidence levels
- Used 3-minute weather data provided by AltaLink to compare the hourly predicted rating over one winter day to real-time transient conditions

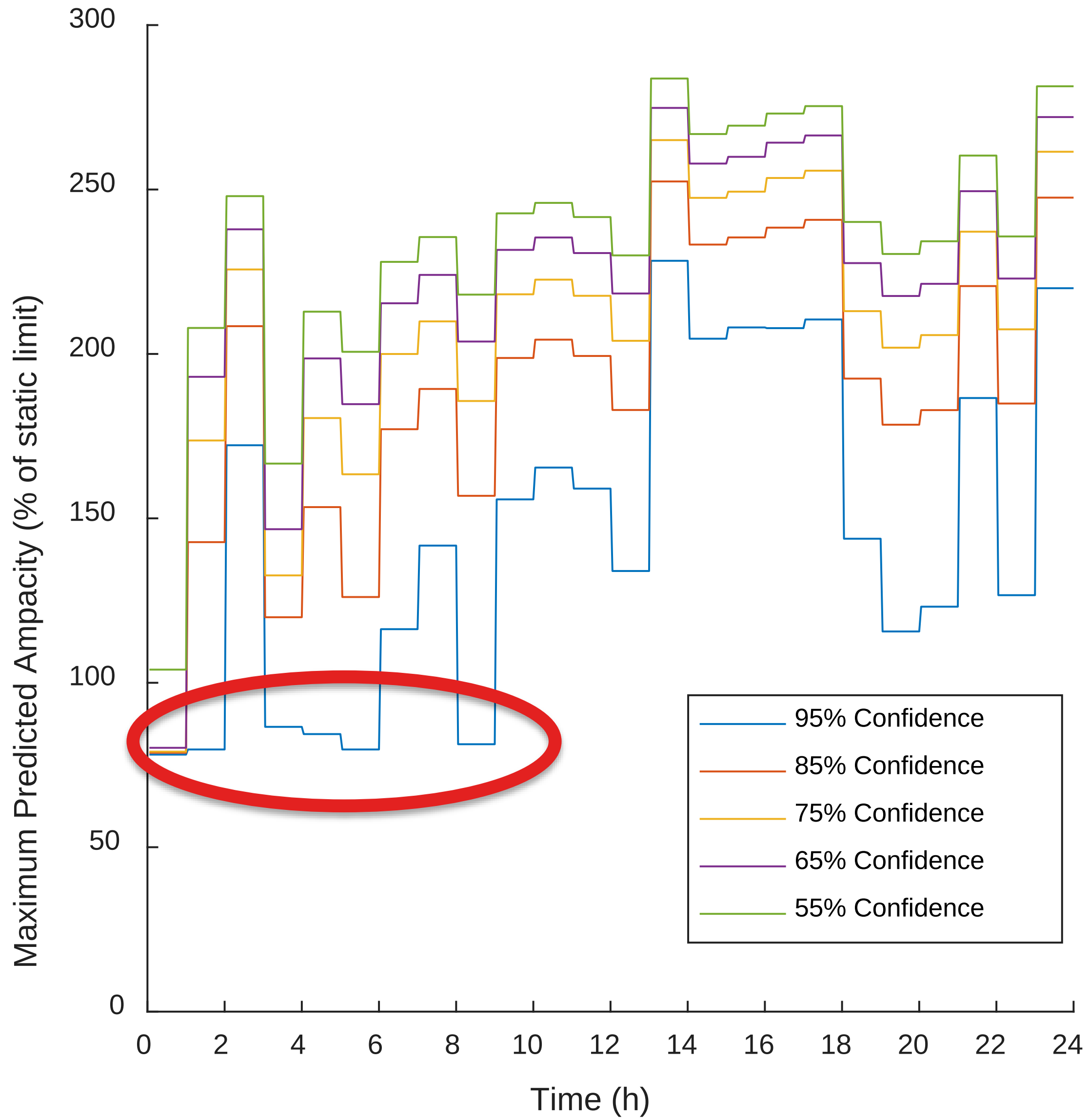
Weather Data



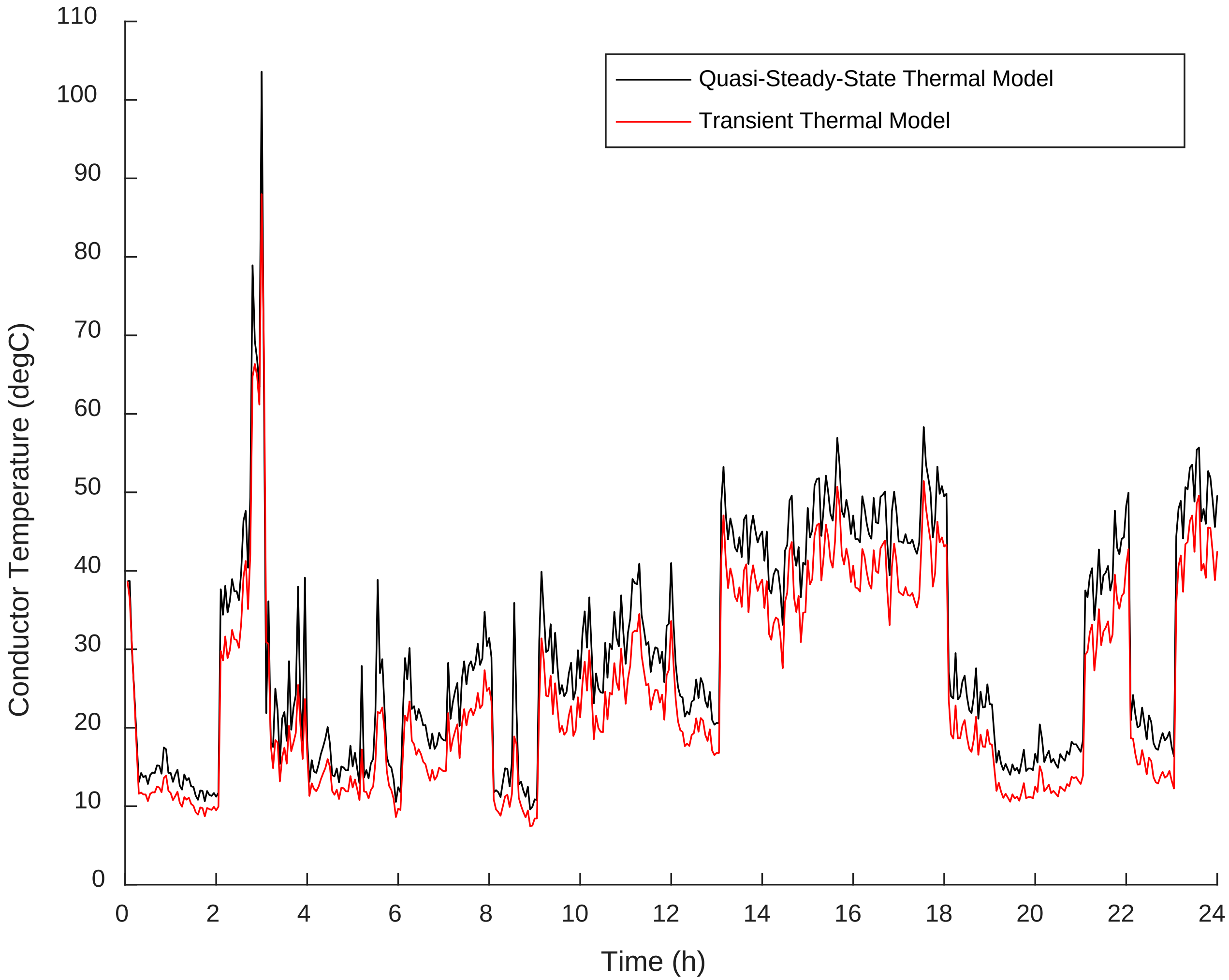
Fuzzy Prediction Model

- A fuzzy clustering model is used for hour-ahead DTLR prediction
- Historical weather data (wind speed, wind direction and ambient temperature) are fed into the model
- A fuzzy model is used to quantify the hourly variations in weather variables
- Different confidence levels are defined based on the desired level of risk

Predicted Ampacity

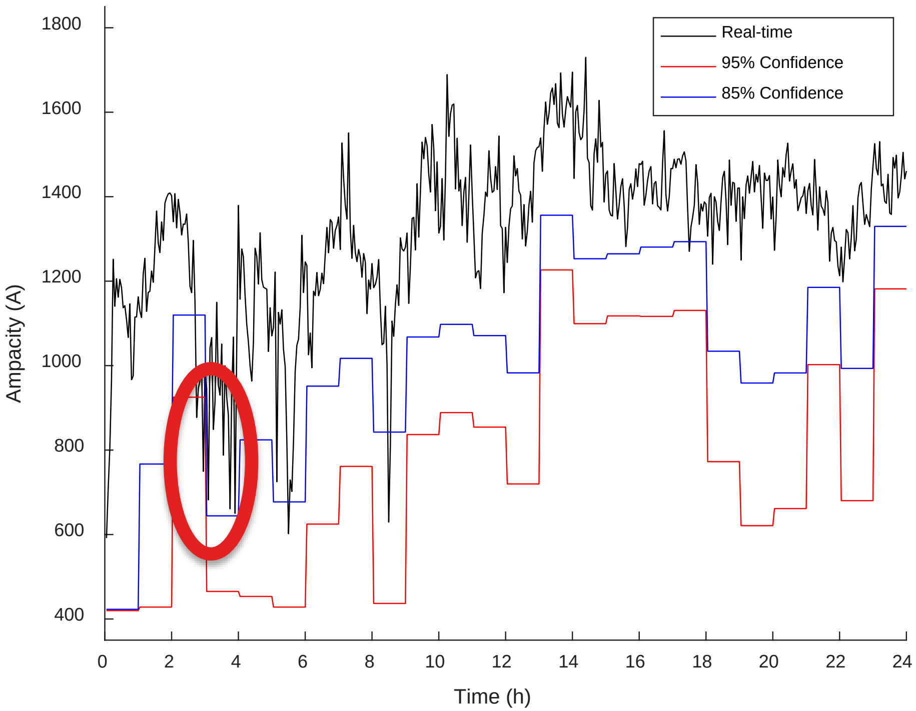


Comparing Transient and Steady-State

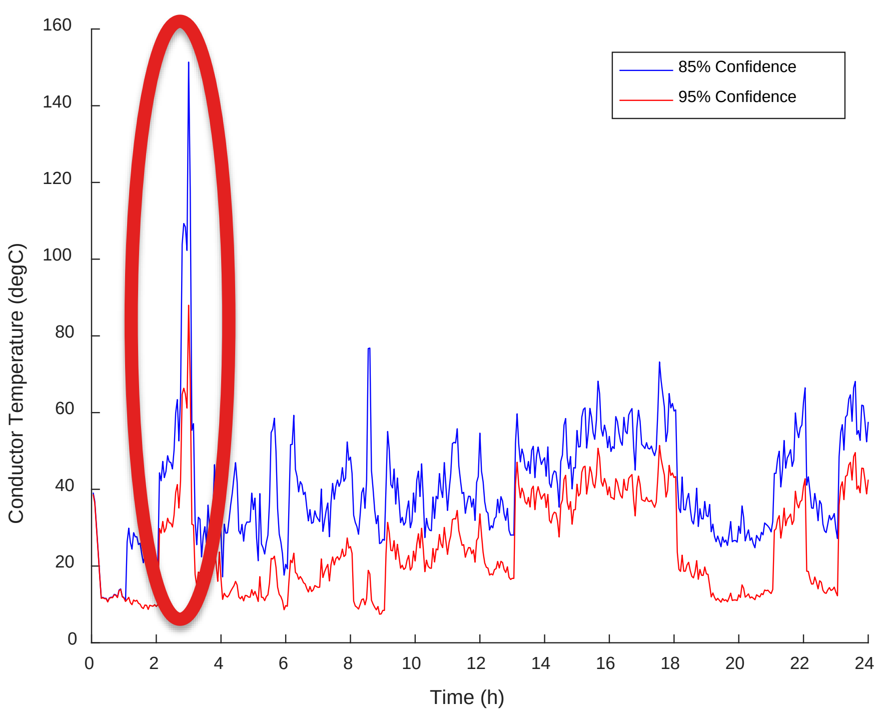


Comparing transient and steady-state conductor temperature calculations using 95% confidence level

Transient Tc for Two Confidence Levels



Comparing real-time ampacity to two different confidence levels



Transient conductor temperature for 85 and 95% confidence levels

Summary of Results

- Transient method is more accurate than using the steady-state method when compared to real-time conductor temperature measurements
- Changes in conductor temperature are mainly dependent on changes in wind speed and wind direction
- Trade-off between excepted risk and ampacity increase

DTLR Patterns

- Is DTLR available when we need it, where we need it?
- Future congestion due to wind isn't necessarily next to the wind farm
- If we add wind farms to Area A, do the weather conditions that produce the power correlate to favorable weather conditions in Area B, where the congestion is?
- How does the potential DTLR increase change over an area?

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Applicability of DTLR in Alberta

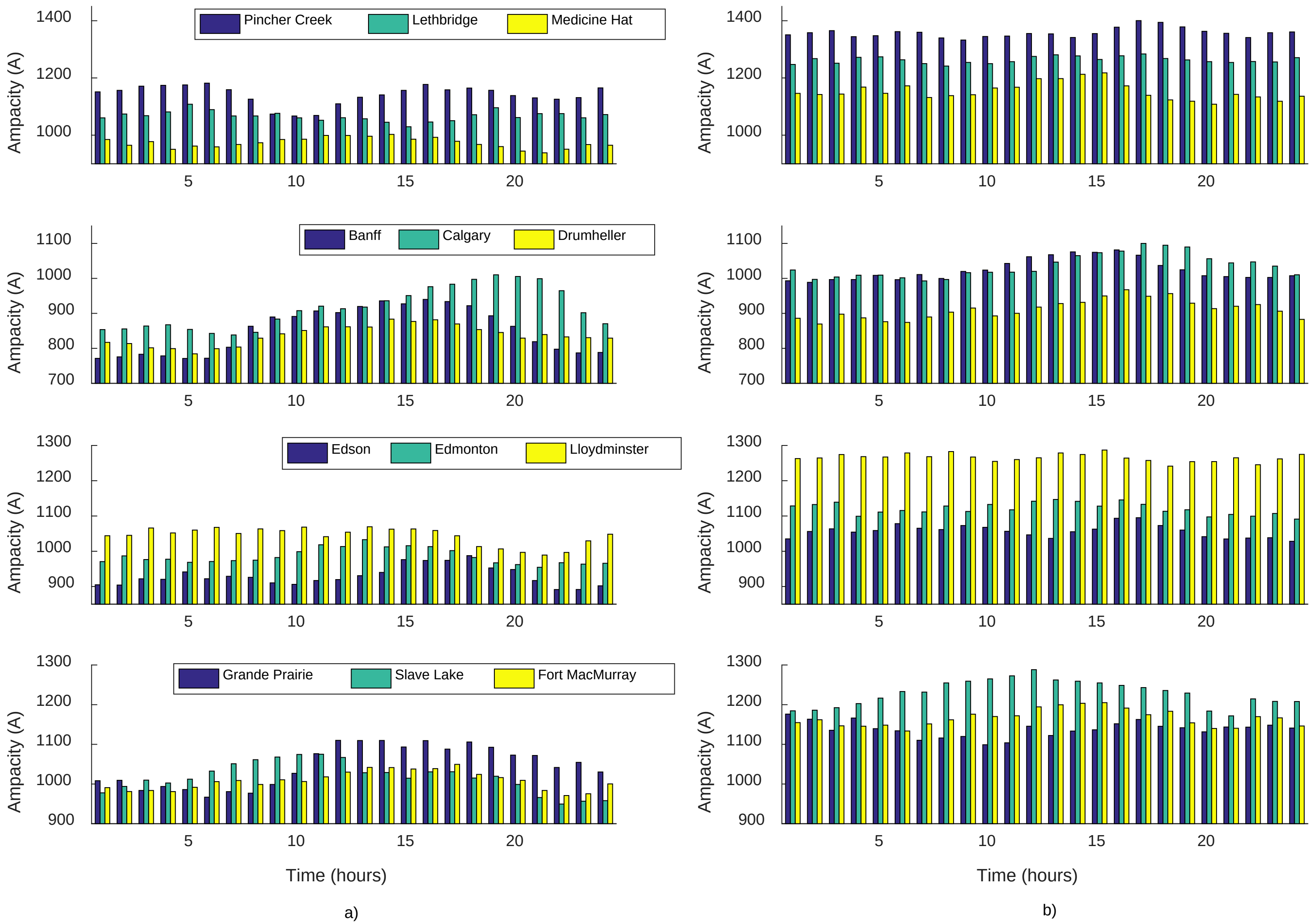
- Purpose is to investigate the applicability of DTLR in different areas of the province
- Spatial Impact
  - 4 different test cases (3 locations each)
- Temporal Impact
  - 4 different locations over 4 different years
- Directional impact
  - 2 different locations, 2 different directions each

Weather Station Locations

Environment Canada Weather data

https://fabulousbydesign.net/printable-map-of-alberta/

Spatial Impact

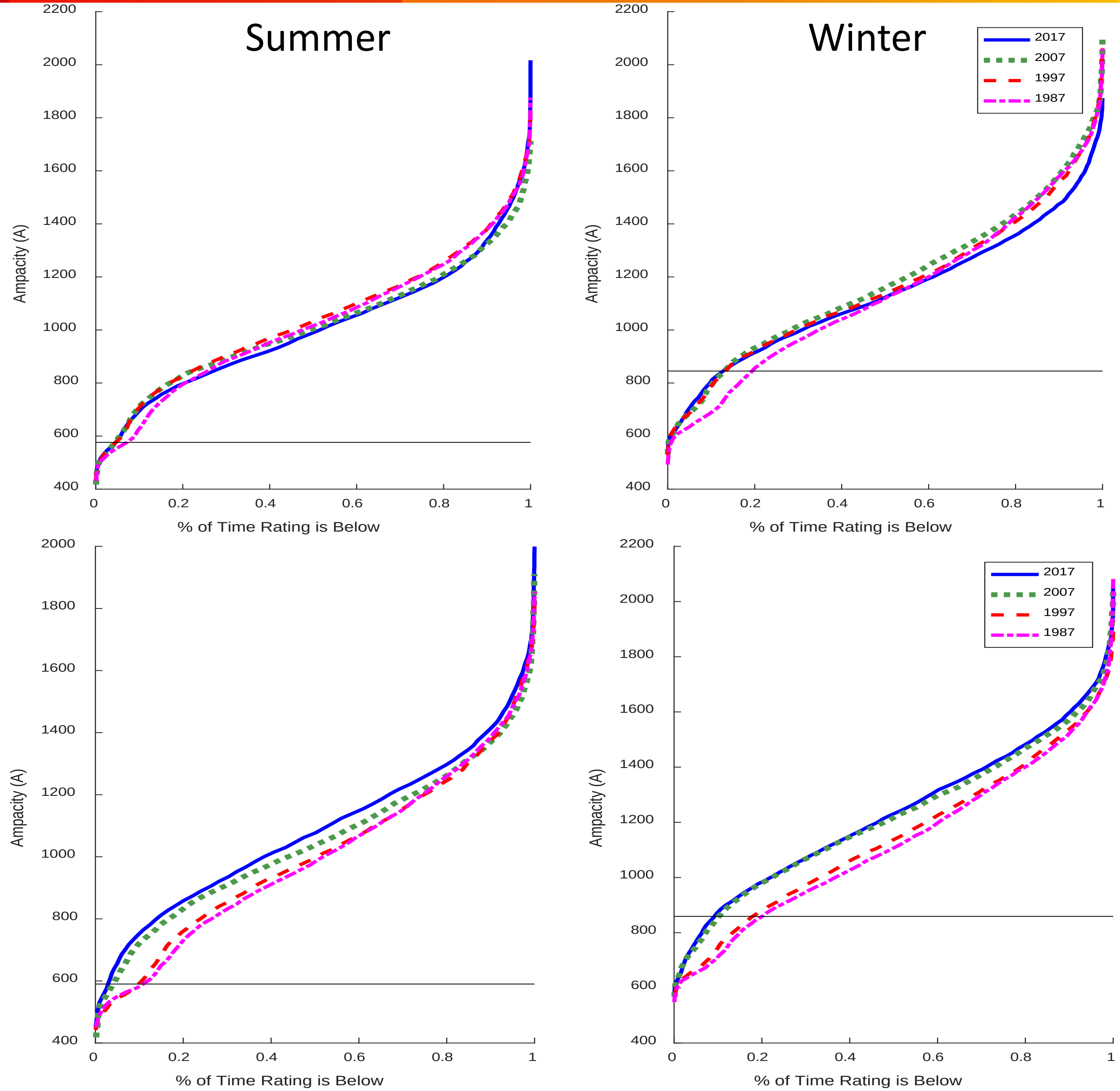


Average Hourly DTLR in Different Locations for a) Summer b) Winter

Temporal Impact

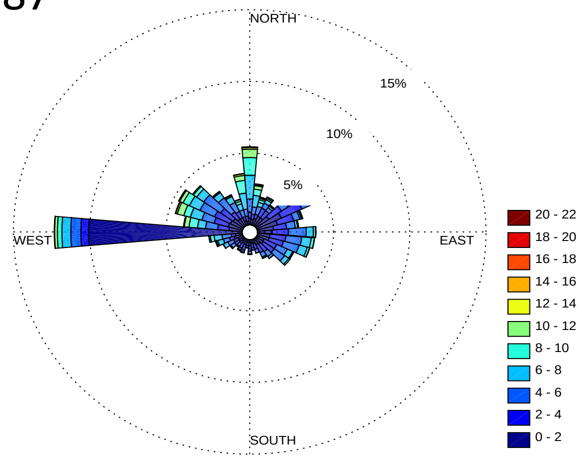
Calgary

Edmonton



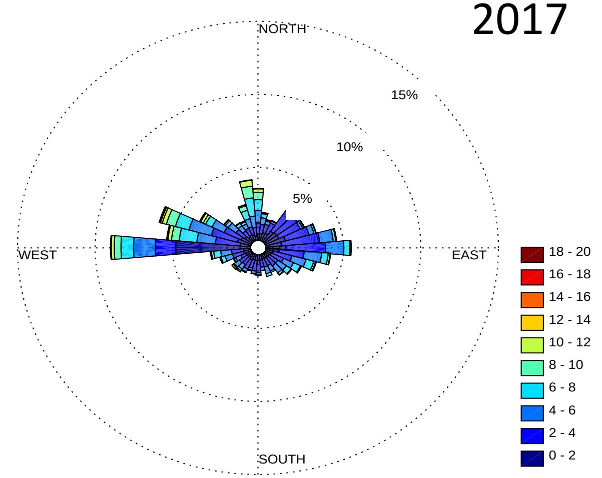
Impact of Line Direction - Calgary

1987

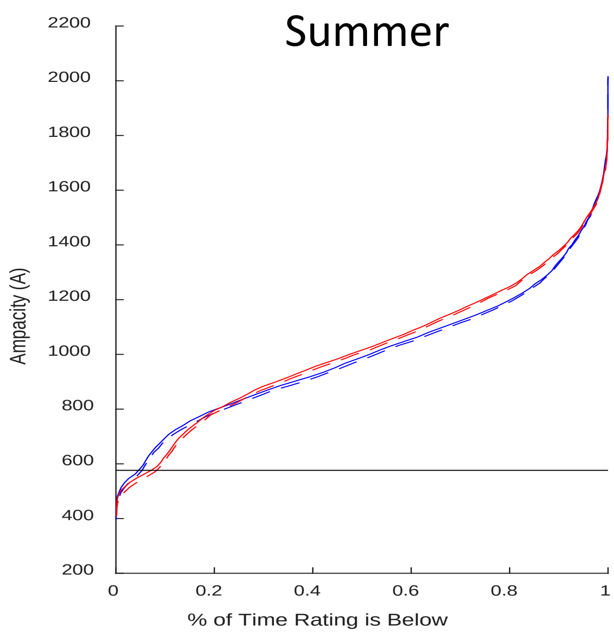


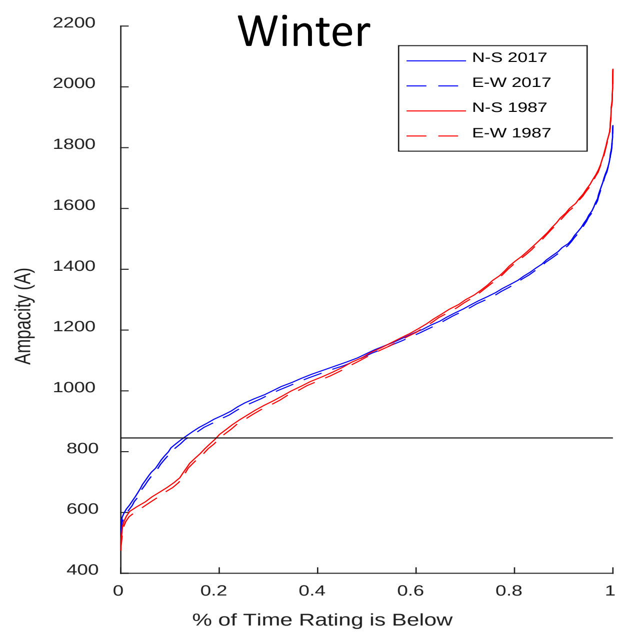
a)

2017



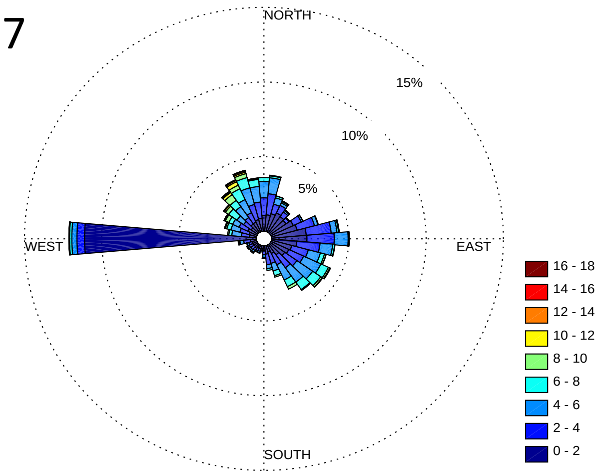
b)





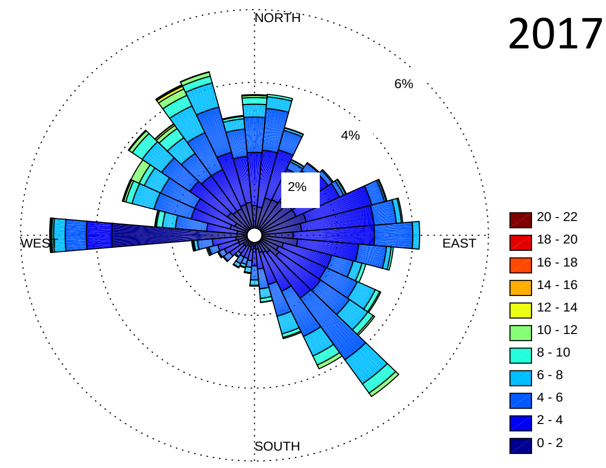
Impact of Line Direction - Edmonton

1987

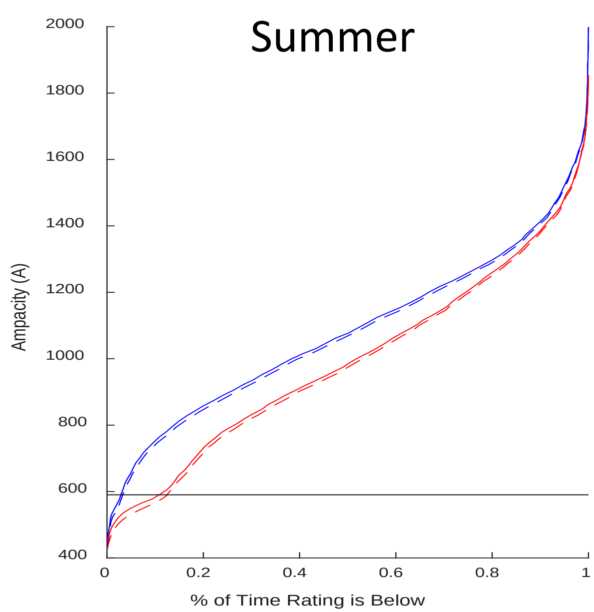


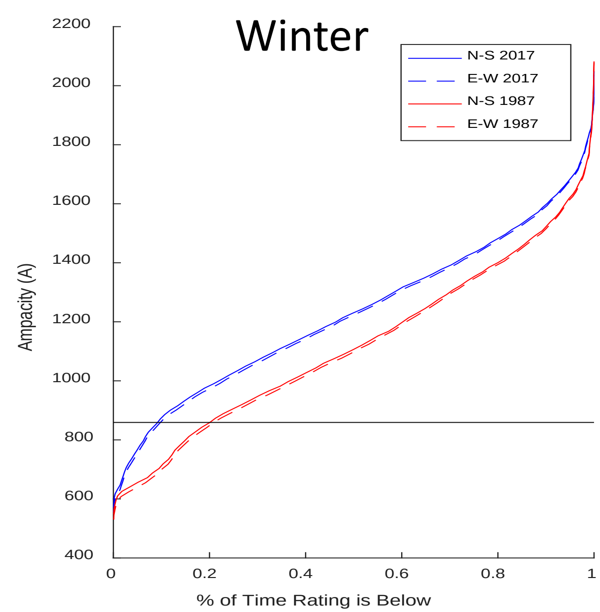
a)

2017



b)





Summary of Results

- The potential increase provided by using a DTLR is dependent on the location and the prevailing weather conditions for each year
- The static limit is not sufficient, as for every test case the static limit was exceeded by 7-20% when using two seasonal limits
- The diurnal patterns for the average hourly DTLR vary based on location
- Changing the line orientation from north-south to east-west makes minimal difference on the overall yearly potential DTLR values

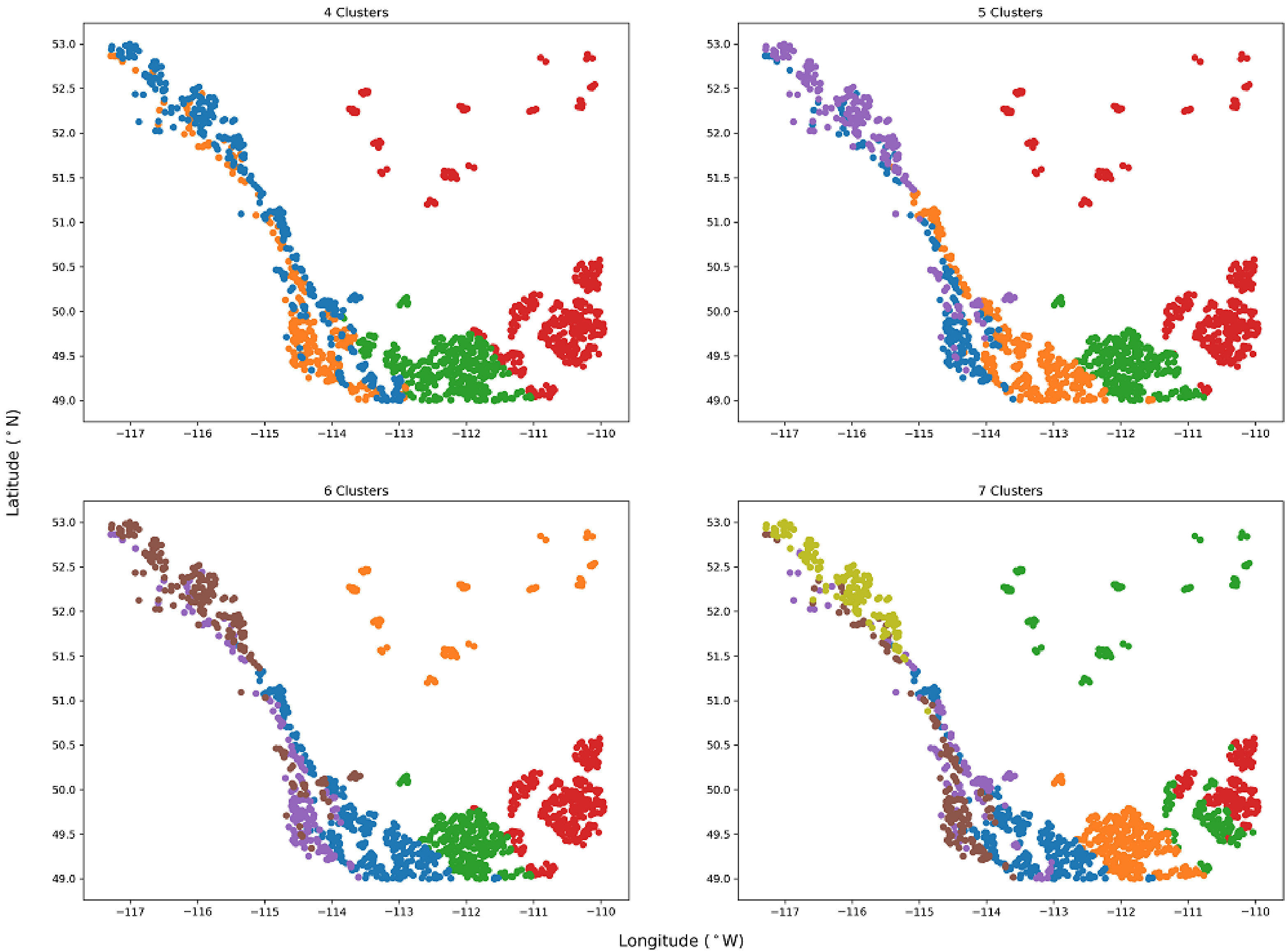
DTLR Clustering Analysis

- Received wind speed and direction data from Pan-Canadian Wind Integration study
- Included 9,570 files of data for Alberta
- Data is sampled every 10 minutes over 2008-10
- Number of data points is reduced based on density of data points
- Fed data into DTLR model
- Clustered DTLR results using k-means clustering

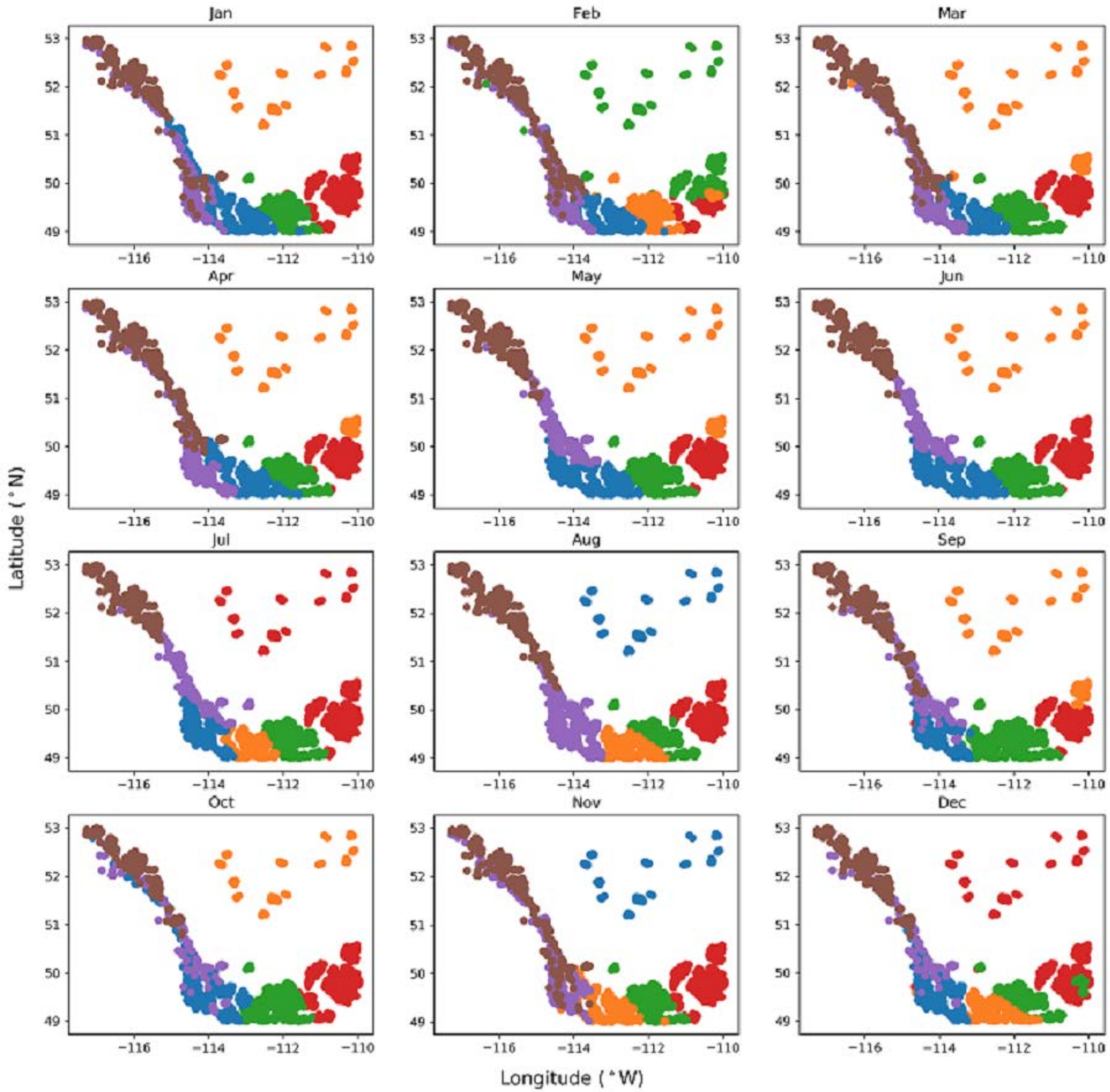
Clustering Method

- K-means clustering is an unsupervised learning method, whose aim is to separate the input data into a specified number of groups with equal variance
- Unsupervised clustering methods are used when the cluster identity of each point is not pre-defined
- K-means clustering is selected for this analysis because of its ability to handle a large number of samples
- One of the challenges with using unsupervised learning models is the need to specify the number of clusters

Cluster Number Comparison



Monthly Cluster Results



Predicting DTLR

Month	DTLR Data			Location Data		
	5	6	7	5	6	7
Jan	96.3	96.7	95.1	92.2	91.8	88.6
Feb	95.9	94.3	94.3	90.2	89.8	87.3
Mar	95.5	97.6	97.1	93.9	94.3	91.8
Apr	98.4	98.0	96.7	94.3	93.9	95.5
May	99.2	99.2	97.6	98.4	98.4	96.7
Jun	98.4	97.6	96.7	97.6	98.0	96.7
Jul	98.8	98.0	97.6	99.2	96.7	96.3
Aug	98.4	99.6	98.0	98.0	98.8	97.1
Sep	95.5	95.1	95.5	92.2	91.8	91.4
Oct	96.3	96.7	94.7	90.2	91.0	89.0
Nov	94.3	94.7	95.5	90.2	87.3	85.7
Dec	97.6	94.7	95.5	97.1	91.0	91.4
Average	97.1	96.9	96.2	94.5	93.6	92.3

Accuracy of DTLR Classification Using Location Data Compared to Historical DTLR For Different Numbers of Clusters

Summary of Results

- Data patterns change based on number of clusters
  - Six clusters are selected for this analysis
- DTLR patterns change for each month
- More distinct clusters based on location during the summer months compared to the winter months
- Prediction accuracy is higher using DTLR data compared to location, but the difference is smaller for the summer months

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Summary

- DTLR is one solution to maximize transmission line capacity while minimizing cost
- Challenges exist in widespread implementation
- Research is being done to investigate using machine learning for temporal and spatial prediction
- More work needs to be done to translate this work into industry practice

Acknowledgment

- I would like to thank NSERC and our industry partners for their support of this project
- I would also like to acknowledge the other contributors to this portion of the project, Soheila Karimi and Dr. Andy Knight, both from the U of C

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