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Minute-Scale Wind Forecasting Using Lidar Inflow Measurements

Elliot Simon
PhD Defence
24 June, 2019
Outline

- Background and motivation
- Project objectives
- Experimental results
  1. WAFFLE
  2. Østerild Balconies
  3. LASCAR
- Outlook and conclusions
Our reality

- Energy is a critical resource
- Global transition towards clean and affordable energy systems
- Money to be made!
Wind power

- Industry is rapidly maturing to become competitive and efficient
- Wind supplies 4% (global) 14% (EU) and 44% (Denmark) of electricity demand
- Wind is leading renewable in new installed capacity
Important considerations (1)

- Atmospheric conditions dictate production ($\text{Production}$)
- Winds are highly variable (seasonal patterns, weather, turbulence, land effects)
- Variability of wind $\rightarrow$ variability in energy production
- Power grid requires constant balance (production = consumption)
- System level storage not feasible (at the moment)
Important considerations (2)

- Grid and markets not devised for high variability and uncertainty
- Grid failures are catastrophic
- Real-time power balancing is expensive! (Reserve capacity, ancillary services, demand response)
- Market designs are changing to accommodate renewables (e.g. 5/15/30-minute contracts in EPEX & AEMC)

2003 blackout: 55 million without power
Why do we need minute-scale wind forecasts?

- Predicting energy production
  - Support schemes being phased out
  - Financial risk from forecast errors
  - Grid planning and operation

- Large-scale and extreme event detection/response

- Collective wind farm control
Wind farm control

- Production gains and fatigue load reductions
  - Wake steering
    ~5% AEP increase \cite{fleming2017}
  - Dynamic induction control
    ~1.5% AEP increase \cite{gebraad2015}

- Flow models and controllers require knowledge of conditions
  - Sensitive to wind direction input!

**Wake steering**

![Wake steering diagram](image-url)
Wind variability on very-short timescales

- 35 days of 1 Hz active power measurements from 850 kW V52 wind turbine
- Change in active power (% capacity) over selected time frames
Forecasting approaches on minute-scale

- Numerical weather prediction (physical modelling e.g. WRF) not applicable
  - Lack knowledge of boundary conditions
  - Computationally not feasible

  → Persistence – everything stays the same, next value = previous value
  → Statistical time series modelling – inferring patterns from past observations

- Maybe we can do better?
- Use remote sensing to look ahead and anticipate what’s coming
Remote sensing

- Measurement technique using radio/light/sound waves to observe phenomena at a distance
- Common examples: ranging radar, mapping lidar

- Doppler remote sensing adds velocity information
- Doppler wind lidars are compact, commercially available, well established, and scatter off atmospheric aerosols
- Scan head allows great flexibility in measurement setup
- Measurements are radial! (velocity component along line-of-sight)

Source: Vasiljevic (2014)
Scanning lidar measurement techniques

- Takes time to scan. Everything is a tradeoff!
- Plan position indicator (PPI)
  - Fixed elevation angle, azimuth sweep (full/partial)
- Doppler beam swing (DBS)
  - Fixed points (4 orthogonal and optional vertical beam)
  - Opposing pairs used to reconstruct horizontal winds
PhD project objectives

- Explore and document potential applications of minute-scale forecasts for wind energy
- Interface with forecast users and providers to survey existing practices and encourage community dialogue
- Perform field experiments to obtain observational data needed to build and evaluate remote sensing based forecast models
- Implement and test novel forecast methods using lidar observations which adhere to the constraints of real-time usage
- Benchmark the lidar forecast method’s skill to other commonly used methods
- Reflect on the potential benefits and drawbacks of a real-world fulfillment of such a system
Experiments introduction

- Three field experiments performed using pulsed scanning lidars (DTU Long-Range WindScanners)
- All campaign data is released for public access (CC BY 4.0)
- Not a solo effort! Big thank you to everyone who contributed 😊
Experiment 1: WAFFLE

(Wind Analysis of Fronts and Large Events)
WAFFLE experiment (Risø)

- Short feasibility study (3 weeks) for exploratory analysis and investigating advection-based flow transport
- Single ground-based scanning lidar deployed, scanning upwind (west)
- Beam elevated at 3° to clear vegetation and intersect met-mast sensors

Data access: Simon and Lea, 2019a
WAFFLE methodology (1)

- Far point used to forecast wind speed at close point

- Forecast horizon of 70 s derived from mean advection time between positions
WAFFLE methodology (2)

- Wind reconstruction performed using IVAP cosine fitting method (Liang, 2007)
- Measurements height-normalized using empirical wind profile power law ($\alpha=0.14$)
  - (No inputs required beyond wind speed and height)
- 2-day period with neutral/near-neutral stability and westerly winds chosen
- Wind power transformation using generic power curve model
WAFFLE scan-shift method

- Upwind position at present time used to predict delayed downwind signal using time-of-flight
- Phase error apparent in time series and lagged cross-correlation

![Graph showing Advection delay](image)
Performance evaluation metrics

- MAE (mean absolute error)
  \[ MAE(y, \hat{y}) = \frac{1}{n} \sum_{i=0}^{n-1} |y_i - \hat{y}_i| \]

- RMSE (root mean squared error)
  (larger errors are penalized disproportionately to smaller ones)
  \[ RMSE(y, \hat{y}) = \sqrt{\frac{1}{n} \sum_{i=0}^{n-1} (y_i - \hat{y}_i)^2} \]

- General linear model fit
  - Slope
  - Intercept
  - \( R^2 \) coefficient of determination
WAFFLE forecast evaluation (wind speed)

Persistence forecast (m/s)

Lidar scan-shift forecast (m/s)

$y = 0.939x + 0.514$
$R^2 = 0.932$
$n = 2770$ mins
$MAE = 0.401$ m/s
$RMSE = 0.527$ m/s

$y = 0.95x + 0.429$
$R^2 = 0.957$
$n = 2770$ mins
$MAE = 0.327$ m/s
$RMSE = 0.427$ m/s
WAFFLE forecast evaluation (wind power)
WAFFLE key results

- Scan-shift significantly outperforms persistence benchmark
- 20% (30%) improvement in RMSE for wind speed (power) forecast
- Persistence skill decreases as wind speed increases
- Inclined measurement plane is not ideal for correlating far distances and height normalization has limitations
  - Valdecabres (2018) would sympathize
Experiment 2: Østerild Balconies
Balconies experiment (Østerild)

- Full scale (4 month) measurement campaign in coastal western Denmark
- Scanning lidars mounted at height to met-towers (50 m and 200 m AGL)
- PPI scans provide 2D cross-sections of the horizontal wind field with no height change over distance

Data access: Simon and Vasiljevic, 2018
Balconies methodology

Forecast position

Upwind measurements
(100 m – 7 km)
Balconies data processing

- Simple and quick wind retrieval method introduced

- Cup anemometer measurements from same height used as reference signal
- Sampling rate of both instruments matched using moving average
- Data sources synchronized to align timestamps
Balconies upwind space-time correlations (1)

Upwind lidar measurements shifted and cross-correlated to reference signal.
Balconies upwind space-time correlations (2)
Balconies forecasting model

- Available lidar measurements (100 m - 7 km upwind scalar wind speeds) used to predict 1-60 min ahead wind speeds at met-mast
- Direct multi-step forecast model (separate models for each time step)
- Rolling walk-forward training and prediction architecture (assimilates latest observations to update model weights at each step)
- Optimization using Stochastic Gradient Descent Regression (SGDR)
  - Includes regularization penalty to perform feature selection and counter overfitting
  - Allows online learning (partial fitting to previously trained model)
  - Quick and suitable for very large datasets

- All details and flowcharts in the thesis!
Balconies forecast evaluation
Balconies weather front event
Balconies key results

- Horizontal scan configuration corrects prior measurement concerns
- Space-time correlations demonstrate sharp discernable peak up to 2-3 km upstream
- Theoretical and empirical wind field advection shows good agreement within this range
- RMSE reduction of 21% (1-min ahead), 11% (5-min), 9% (10-min), 7% (30-min), 6% (60-min) over (10-min average) persistence
- At least some coherent structures able to be seen and their propagation tracked

- But the atmosphere isn’t a 1-Dimensional conveyor belt!
Experiment 3: LASCAR

(LAS Campaign At Risø)
LASCAR experiment (Risø)

- Full scale (4 month) measurement campaign along inland fjord
- Rooftop lidar performed rapid PPI scans up to 4 km
- Ground based lidar performed DBS profiling

Data access: Simon and Lea, 2019b
LASCAR forecast approach

- Most spatial information is lost through wind reconstruction/retrieval
  - Can we preserve this?
- Investigate 2D space-time forecasting methods from computer vision
How can we apply this?

- Convolutional recurrent neural networks used for image sequence prediction (spatial features and time are key attributes)

- What does this look like in a real product?
Inspiration from computer vision
LASCAR forecast model (1)

• 2-D convolutional LSTM neural network
• Same online learning approach as before
• Trained on Google Cloud Compute instance (1x Tesla P100 GPU) using tensorflow

• Sequence of last 5-mins of upwind PPI scans used to forecast following 5-mins conditions at downstream position (DBS lidar profiles)
• Multiple output strategy (one model for all time steps)
• Wind vectors (u and v) are output to give both speed and direction predictions
• Benchmarked against persistence, ARI(5,1) and ARIMA(5,1,1) models
LASCAR forecast model (2)

- 12 hour continuous period with inflow direction
- Re-projected polar to Cartesian coordinates
- Scaled values (0-1) according to:

\[ X_{\text{max}} = \bar{X} + 4\sigma^2 \]
\[ X_{\text{scaled}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \]
LASCAR forecast evaluation

Wind speed forecast

Wind direction forecast

Relative improvement of Lidar-ANN model compared with:

<table>
<thead>
<tr>
<th>Wind speed</th>
<th>Wind direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Persistence (%)</td>
<td>ARIMA (5,1,0) (%)</td>
</tr>
<tr>
<td>0.22</td>
<td>3.30</td>
</tr>
<tr>
<td>0.43</td>
<td>19.68</td>
</tr>
<tr>
<td>0.65</td>
<td>18.71</td>
</tr>
<tr>
<td>0.87</td>
<td>18.77</td>
</tr>
<tr>
<td>1.08</td>
<td>18.35</td>
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<tr>
<td>1.30</td>
<td>17.17</td>
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<tr>
<td>1.52</td>
<td>16.62</td>
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<tr>
<td>1.73</td>
<td>16.50</td>
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<td>1.95</td>
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<td>18.37</td>
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<td>2.60</td>
<td>18.86</td>
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<tr>
<td>2.82</td>
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</tr>
<tr>
<td>3.03</td>
<td>17.04</td>
</tr>
<tr>
<td>3.25</td>
<td>16.26</td>
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<tr>
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<tr>
<td>4.12</td>
<td>1.30</td>
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<tr>
<td>4.77</td>
<td>-57.58</td>
</tr>
<tr>
<td>4.98</td>
<td>-98.38</td>
</tr>
</tbody>
</table>
LASCAR key results

- Space-time features from sequences of PPI scans applied in forecasting model
- Coherent patterns retain discernable features up to 3 km and up to 5-minutes ahead
- ANN-lidar method outperformed 2/3 benchmarks (persistence & ARI(5,1))
- ANN-lidar method performed best up to 30s ahead
- Similar performance gains over persistence to previous study (18% lower RMSE)
- ARIMA(5,1,1) model performs remarkably well!
Outlook and broad conclusions

• We can do better than persistence (at least in simple terrain)
  – Order of 20% to 5% RMSE improvement, depending on lead time
• Lidar regression models may not deliver broad overall value compared with time series models using ‘free’ existing data
  – Measure and save high-frequency data!
• Real value of lidar forecasting system lies in detecting large scale events where NWP misses entirely, or gets the scale and timing wrong
• Advection assumption likely only holds in simple terrain / offshore
  – WESC 2019: Ines Würth
    Experiences, Challenges and Opportunities of Lidar-Based Minute-Scale Forecasting in Complex Terrain
Thank you for joining!

Please get in touch if you have anything to discuss:
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Balconies

Data flowchart

Forecast model (partial fit)

Forecast model (rolling re-training)
LASCAR

Data filtering

- Input lidar measurements
  - Parse timestamps and convert to local time
- Filtering
  - Drop partial scans
  - CNR filter
  - Radial speed filter
  - Line-of-sight filter
  - Range gate filter
- Reproject Polar to Cartesian
- Scale 2-D scan image
- Copy lags to new axis
- Reduce sample size by lags and leads
- Processed dataset
  - Shape = (time, lags, x_dim, y_dim, channels)

Model implementation

- In-sample PPI scans
  - T + 5 mins to T PPI scans
- In-sample DBS measurements
  - T to T + 5 mins DBS measurements
- Feature scaling
  - T to T + 5 mins DBS measurements
- Train model
  - Model prediction
  - Real time prediction
  - Inverse scaling
  - Calculate wind speed and direction
  - Forecast output
    - u-component
    - v-component
    - wind speed
    - wind direction

Neural network architecture

- Input layer
  - Shape = (1, 23, 106, 294, 1)
- ConvLSTM2D
  - 16 5x5 filters
  - (1, 23, 106, 294, 16)
- TimeDistributed MaxPooling2D
  - (2x2)
  - (1, 23, 53, 147, 16)
- ConvLSTM2D
  - 32 5x5 filters
  - (1, 23, 53, 147, 32)
- TimeDistributed MaxPooling2D
  - (2x2)
  - (1, 23, 26, 73, 32)
- TimeDistributed Flatten
  - (1, 23, 60736)
- Two channel Multi-step output
  - (1, 23, 2)
Practical recommendations

• Measure inflow with lowest elevation angle possible
• Simplified application specific instrument (e.g. long-range fixed beam adaptation)
• Use only 1 system (no dual/triple Doppler)
• Use radial speeds directly, or simple wind retrieval methods
• Faster sampling rate is more important than spatial resolution
• Use dynamic filtering to increase data availability
Extensions of this work

• Use real-time inflow measurements to correct pre-run NWP forecasts
• Develop classification system for identifying and tracking large-scale events
• Integrate upstream measurements into wind farm flow models
• Dynamically adapt scan pattern depending on conditions
• Include uncertainty estimates for probabilistic output
• Extend measurement range (e.g. up to 30 km with LMWT or SmartWind radar)