37th IAEE International Conference: Energy & the Economy

Stochastic Modelling of the Feed-in of Wind Using a Second Order Markov Chain

New York City, June 15-18, 2014
Thiemo Pesch, Hans-Josef Allelein, Jürgen-Friedrich Hake
The Transformation of the Energy System

Exemplary case: German Energy Concept

- GHG emissions reduced by 40% until 2020, 55% 2030 and 80% 2050 compared to the levels of 1990
- Total primary energy supply cut into halves by 2050
- Electric power consumption reduced by 10% until 2020
- Share of RES in electricity generation up to 50% until 2030
- Phase out of nuclear power by the end of 2022

- Significant increase of fluctuating and non-dispatchable generation from RES
- Less conventional power plants in the market
Uncertainties of the Feed-in of Wind

- Large parts of the wind feed-in can drop out in a very short period of time.
- Likewise, electricity generation from wind can increase drastically within short time.
- This leads to growing uncertainties in the electricity system.

One approach to address these uncertainties in energy system models is the stochastic modelling of wind using Markov Chains.

Gross generation capacities in Germany

- Wind feed-in Dec 24-31, 2012
Outline

1. Introduction
2. Modelling the Second Order Markov Chain
3. Conditioning of Wind Feed-in Time Series
4. Application Analysis for Wind Feed-in in Germany
5. Conclusion
Characteristics of Markov Chains

- Time- and amplitude-discrete stochastic process
- Break down of the range of values in defined number of discrete states
- Assignment of every value of the time series to the corresponding state
- Determination of transition probabilities between the states based on the ex-post data
- The number of considered previous values determines the order of the Markov Chain, i.e. a second order Markov Chain has two lags
- The amount of transition probabilities increases exponentially with the order of the Markov Chain
- Applicable for time series with any probability distribution
- One requirement is weak stationarity of the ex-post time series data
- Deterministic components of the time series such as trends or periods therefore need to be removed
Approach for Modelling the Markov Chain

1. Conditioning of input data
   - Removing deterministic trends and seasonalities
   - Ensuring weak stationarity of the input data for the Markov Chain

2. Determination of transition matrix
   - Configuration of the number of states (n) and considered previous values (particularly the second lag)
   - Determination of the transition probabilities and generation of the nxnxn matrix

3. Generation of synthetic time series
   - Determination of the starting values for the Markov Chain
   - Calculation of the following values using a random generator that takes the transition probabilities into account

4. Conditioning of output data
   - Conversion of discrete states to corresponding values
   - Restamping the removed trends and seasonalities

5. Analysis of statistical parameters
   - Determination of the statistical parameters of the synthetic time series such as arithmetic mean, deviation and probability distribution
   - Comparison of synthetic and original time series characteristics
Determination of the Transition Probabilities

- Example for the determination of the transition probabilities
  - Discretisation in 3 states
  - First lag at t-1; Second lag at t-10

```
<table>
<thead>
<tr>
<th>State</th>
<th>1</th>
<th>1</th>
<th>1</th>
<th>2</th>
<th>2</th>
<th>2</th>
<th>3</th>
<th>3</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time step t</td>
<td>-10</td>
<td>-9</td>
<td>-8</td>
<td>-7</td>
<td>-6</td>
<td>-5</td>
<td>-4</td>
<td>-3</td>
<td>-2</td>
</tr>
</tbody>
</table>

2nd lag

<table>
<thead>
<tr>
<th>Lag 2: State 1</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 1: State 1</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Lag 1: State 2</td>
<td>0.05</td>
<td>0.95</td>
<td>0.00</td>
</tr>
<tr>
<td>Lag 1: State 3</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

1st lag

<table>
<thead>
<tr>
<th>Lag 2: State 2</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 1: State 1</td>
<td>0.96</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td>Lag 1: State 2</td>
<td>0.02</td>
<td>0.97</td>
<td>0.01</td>
</tr>
<tr>
<td>Lag 1: State 3</td>
<td>0.00</td>
<td>0.07</td>
<td>0.93</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lag 2: State 3</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 1: State 1</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Lag 1: State 2</td>
<td>0.00</td>
<td>0.97</td>
<td>0.03</td>
</tr>
<tr>
<td>Lag 1: State 3</td>
<td>0.00</td>
<td>0.06</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Discretised time series

<table>
<thead>
<tr>
<th>State</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time step t</td>
<td>-10</td>
<td>-9</td>
<td>-8</td>
</tr>
<tr>
<td>Lag 1: State 1</td>
<td>0.96</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td>Lag 1: State 2</td>
<td>0.02</td>
<td>0.97</td>
<td>0.01</td>
</tr>
<tr>
<td>Lag 1: State 3</td>
<td>0.00</td>
<td>0.07</td>
<td>0.93</td>
</tr>
</tbody>
</table>
```

Institute of Energy und Climate Research
IEK-STE: Systems Analysis and Technology Evaluation
Outline

1 Introduction
2 Modelling the Second Order Markov Chain
3 Conditioning of Wind Feed-in Time Series
4 Application Analysis for Wind Feed-in in Germany
5 Conclusion
Wind feed-in time series for Germany with sampling time of 15 minutes (2010-2012)
Division by the monthly installed capacities to derive the specific feed-in per kW
Resulting time series does not fulfil weak stationarity due to periodic components

Original wind feed-in time series

Task

- Determination and filtering of periodic components since weak stationarity is a requirement for Markov Chains
### Seasonal Index for Every Quarter of an Hour

- **Determines monthly based periods with consideration of daily oscillation**
- **Column: Month**
- **Rows: Time of day (every quarter of an hour)**
- **High feed-in: summer afternoons and winter nights**
- **Low feed-in: summer mornings/ evenings and winter middays**

#### Seasonal component

![Seasonal component chart](chart.png)

---

Institute of Energy und Climate Research
IEK-STE: Systems Analysis and Technology Evaluation

IAEE 2014 | June 15-18, 2014
Thiemo Pesch | Slide 11
Conditioned (Filtered) Time Series

- Removing yearly and daily oscillations with multiplicative decomposition
- The resulting time series only contains the non-deterministic residuals and fulfils weak stationary

Deseasonalised wind feed-in time series

Result
- Modelling with Markov Chain now possible
Effect of Varying the Second Lag

- Synthetic time series with a second lag of 2
  - Since the second lag is very close to the first lag, state transitions occur less often
  - The results are too few fluctuations in the synthetic time series and ramps that are not steep enough

- Synthetic time series with a second lag of 10
  - Due to the greater distance of the second lag to the first lag, much more state transitions occur
  - The form of the synthetic time series fits much better to the original time series with respect to the steepness of ramps and the fluctuations

- The shape of the synthetic time series is mainly influenced by the choice of the second lag
Effect of Varying the Number of States

- Too few states distort the distribution function
- The more states there are, the more ex-post data is needed
The best results for the wind feed-in in Germany were obtained by choosing lag 10 as the second lag and 55 states.

### Statistical Parameters

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Variance</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original time series</td>
<td>0.173</td>
<td>0.021</td>
<td>0.003</td>
<td>0.851</td>
</tr>
<tr>
<td>Synthetic time series</td>
<td>0.167</td>
<td>0.019</td>
<td>0.000</td>
<td>0.833</td>
</tr>
<tr>
<td>Difference</td>
<td>-0.006</td>
<td>-0.002</td>
<td>-0.003</td>
<td>-0.019</td>
</tr>
</tbody>
</table>
Conclusion

- The rising share of wind in electricity generation leads to growing uncertainties in the system since the feed-in can vary drastically within short time.

- One approach to address these uncertainties in energy system models is the stochastic modelling of wind using Markov Chains.

- Markov Chains are easy to implement and well suited to generate synthetic time series that show the same statistical parameters as the original time series.

- Of main importance for the quality of synthetic time series is the appropriate choice of the second lag and the number of states.

- In the case of Germany, the best results were obtained by using a second lag of 10 and a discretisation with 55 states.

- With synthetic time series it is possible to analyse a multitude of different situations and scenarios regarding the feed-in from wind.

- They can also be used as input for further approaches to address uncertainty in energy system models, e.g. scenario trees.