Dealing with Uncertainty
An Empirical Study on the Relevance of Renewable Energy Forecasting Methods
Motivation
Motivation

**GENERAL**
- Traditional demand-focus in the energy forecasting community
- Great variety of solution proposals but few reliable benchmarks
- Domination of time-intensive Trial-and-Error optimization approaches

**SCIENCE VIEW**
- Low objective comparability of concurring methods based on literature and dissimilar data sets
- Unlikely successful re-implementations due to limited access to crucial information
- Forecasting competitions are rare and time-intensive

**INDUSTRY VIEW**
- Customers demand robust proves of achievable overall forecast quality for their specific problems
- Complex solutions for individual tasks can scare away normal users
- Experts hardly accept simple black-box tools
Research Questions

**Scientific Relevance**

1. How strong is the scientific interest in renewable energy forecasting methods?
2. Which methods are the preferred research topics?
3. Can the most promising directions be identified?

**Practical Relevance**

4. Which methods are currently implemented in the available software products?
5. What are the commonly used quality evaluation criteria?
6. What do users expect of such solutions?
Scientific Relevance
Methodology

**STEP 1: DETERMINE TOTAL LITERATURE POPULATION**

- Online search in *IEEE, ScienceDirect, SpringerLink* and *WileyOpenLibrary* databases
- Valid publications are book chapters, conference papers and journal articles (2005 – 2015)
- Search query "error AND forecasting AND renewable AND wind AND solar AND method AND NOT production AND NOT demand"

**STEP 2: DEFINE REDUCED SAMPLE DATA SET**

- Articles published in renewable energy journals (2010 – 2015)
- Only the highest two quantiles (Q1 and Q2) of *SCImago Journal Rank Indicator* are considered
- Manually revised abstracts
Quantitative Analysis

**TOTAL PUBLICATIONS**
- Preferred channels are journal articles (48.8%) and conference papers (37.8%)
- Average growth of 48.8% p.a.
- Positive trend and peak in 2015

**SAMPLE DATA SET**
- 93 results from search
- 83 articles from 9 journals after manual revision
- 10% of total population represented in the sample

### Table: Sample Data Set

<table>
<thead>
<tr>
<th>Rank</th>
<th>Symbol</th>
<th>Title</th>
<th>SJRQ</th>
<th>SJR</th>
<th>Articles</th>
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<td>RE</td>
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</table>
**Quantitative Analysis**

**Proposed Stand-Alone Model Classes**
- Dominated by Machine Learning (30%), Hybrid Models (29%) and multivariate Stochastic Time Series Models (23%)
- Physical Models (11%) and univariate Stochastic Time Series Models (5%) under-represented

**Proposed Combination Types**
- Dominated by Machine Learning (40%) and multivariate Stochastic Time Series Models (34%)
- Physical Models (20%) are more frequently used
- Univariate Stochastic Time Series Models (4%) under-represented

<table>
<thead>
<tr>
<th>Combination Type</th>
<th>Physical Model</th>
<th>Stochastic Time Series</th>
<th>Univariate</th>
<th>Multivariate</th>
<th>Similar-Days</th>
<th>Machine Learning</th>
<th>Hybrid Model</th>
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<td>Stand-alone Model</td>
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<td>1</td>
<td>0</td>
<td>2</td>
<td>20</td>
<td>0</td>
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<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>17</td>
<td>1</td>
<td>20</td>
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<td>[\Sigma]</td>
<td>22</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>37</td>
<td>1</td>
<td>46</td>
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</tbody>
</table>
Quantitative Analysis

TEMPORAL EVOLUTION OF PROPOSED METHODS

- No significant changes in observation period (2010 – 2015)
- Machine Learning and multivariate STS alternate
- Positive trend for Physical Models
Qualitative Analysis

Typical Evaluation Problems

- Qualitative evaluation only considers forecast accuracy
- No standardized accuracy measure
- Heterogeneous use cases and experimental settings
- No industry benchmarks available

Proposed Standard Evaluation Protocol [Madsen+04]

- Use MAE, RMSE, MBE measures and/or Skill Scores (SS)
- Apply normalization
- Compare against naïve predictors

Qualitative Analysis

RESULTS

+ RSME (65.1%), MAE (47.0%) and MBE (27.7%) are frequently used
+ Between 0 and 8 simultaneously used error measures per publication (average 2.6)

- Popular combinations are RMSE-MBE (24.1%), RMSE-MAE (22.9%) and RMSE-MAPE (14.5%), only 8% combine RMSE-MAE-MBE
- 20% use tailor-made or undefined error measures
- 26% apply normalization on data or error values
- 32% include naïve benchmark predictors
- 8.4% use NREL data set

Only 1 publication matches all criteria!
Practical Relevance
Methodology

**SOFTWARE USER QUESTIONNAIRE**
- Targeting users of energy forecasting software
- 56 utility companies contacted
- 13 associations and organizations contacted
- 8 questions aiming at:
  1. Forecast appliance
  2. Underlying energy source
  3. Output evaluation criteria
  4. Additional parameters of interest
  5. Market role

Response rate 30%

**SOFTWARE PROVIDER QUESTIONNAIRE**
- Targeting energy forecasting software providers listed on German market report
- 29 software companies contacted
- 14 questions aiming at:
  1. Forecast appliance
  2. Underlying energy source
  3. Implemented methods
  4. Additional parameters of interest
  5. Company characteristics

Response rate 21%
Feedback from Software Providers

**Solution Scope**

- Demand and -price forecasting (37.5% each), 25% for renewable energy
- Handles both conventional and renewable energy sources
- Equally suited for all forecasting horizons

**Implemented Methods**

- Similar-Days (29%), followed by Machine Learning and Stochastic Time Series models (24%).
- Hybrid (14%) and Physical models (10%) less relevant
- Named algorithms are: *Multi-variate Regression, Neural Networks, k-nearest Neighbors and Support Vector Machines*
Feedback from Software Users

**Solution Scope**
- 43% use forecasting software
- Focus on demand forecasting (50%), supply (30%) and prices (20%)
- Supply forecasts mostly for renewable energy sources (73%)
- Equally suited for all forecasting horizons

**User’s Expectations**
- Benefits are increased supply stability, balancing cost estimation and production site identification
- Requirements are appropriate statistical output evaluation measures, robustness of the models and low maintenance efforts

<table>
<thead>
<tr>
<th>Factor</th>
<th>Important</th>
<th>Irrelevant</th>
<th>Abstention</th>
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</thead>
<tbody>
<tr>
<td>Increased supply security</td>
<td>76.5%</td>
<td>5.9%</td>
<td>17.6%</td>
</tr>
<tr>
<td>Avoidance of overproduction</td>
<td>64.7%</td>
<td>17.6%</td>
<td>17.6%</td>
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<tr>
<td>Use of smart grid applications</td>
<td>35.3%</td>
<td>41.2%</td>
<td>23.5%</td>
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<tr>
<td>Improved demand-site management</td>
<td>58.8%</td>
<td>23.5%</td>
<td>17.6%</td>
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<tr>
<td>Balancing energy cost estimation</td>
<td>70.6%</td>
<td>17.6%</td>
<td>11.8%</td>
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<tr>
<td>Production site analysis</td>
<td>64.7%</td>
<td>23.5%</td>
<td>11.8%</td>
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</table>

<table>
<thead>
<tr>
<th>Requirement</th>
<th>Important</th>
<th>Irrelevant</th>
<th>Abstention</th>
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</thead>
<tbody>
<tr>
<td>Statistical error measures</td>
<td>92.9%</td>
<td>7.1%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Technical performance</td>
<td>85.8%</td>
<td>7.1%</td>
<td>7.1%</td>
</tr>
<tr>
<td>Robustness / Adaptability</td>
<td>92.9%</td>
<td>7.1%</td>
<td>0.0%</td>
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<tr>
<td>Application usability</td>
<td>71.4%</td>
<td>21.4%</td>
<td>7.1%</td>
</tr>
<tr>
<td>Maintenance efforts</td>
<td>92.9%</td>
<td>7.1%</td>
<td>0.0%</td>
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<tr>
<td>Graphical result representation</td>
<td>64.3%</td>
<td>35.7%</td>
<td>0.0%</td>
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<tr>
<td>Manual output pre-processing</td>
<td>71.4%</td>
<td>21.4%</td>
<td>7.1%</td>
</tr>
</tbody>
</table>
Feedback from Software Users

**Output Evaluation Criteria**
- Not limited to accuracy
- Mainly MAPE (24%) and Standard Deviation (20%), followed by MAE and RMSE (16% each)
- Over- and underestimations less important

**Market Role**
- Transmission System Operator (25%), Supplier (20%), Generator (20%) and Network Operator (10%)
- 15% Others (e.g. planning, construction)
- 10% no classification

<table>
<thead>
<tr>
<th>Scientific Literature</th>
<th>Software Providers</th>
<th>Software Users</th>
</tr>
</thead>
<tbody>
<tr>
<td>65% RMSE</td>
<td>25% SD</td>
<td>24% MAPE</td>
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<tr>
<td>47% MAE</td>
<td>21% MAPE</td>
<td>20% SD</td>
</tr>
<tr>
<td>28% MBE</td>
<td>21% RMSE</td>
<td>16% RMSE</td>
</tr>
<tr>
<td>25% MAPE</td>
<td>13% MAE</td>
<td>16% MAE</td>
</tr>
<tr>
<td>20% Others</td>
<td>13% Others</td>
<td>2% Others</td>
</tr>
</tbody>
</table>
Summary
Summary

**Scientific Relevance**
- Unabated interest for more than one decade
- Small but increasing research field in the energy forecasting domain
- Dominating methods are Machine Learning, Hybrid- and multivariate Time Series Regression models
- RMSE is preferred error measure

**Practical Relevance**
- Available commercial solutions focus on energy demand and -price forecasting
- Quality is determined by maintenance efforts, robustness and output accuracy
- Dominating methods are univariate Similar Days, Machine Learning and Time Series Regression models
- MAPE is preferred error measure
Dealing with Uncertainty

An Empirical Study on the Relevance of Renewable Energy Forecasting Methods

Robert Ulbricht, Anna Thoß, Hilko Donker, Gunter Gräfe and Wolfgang Lehner