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GLOBAL MICROCASTING SERVICE GMS

YIELD STUDY 2010

For 13 German Wind Farms

Mag. Vojko Daneu, Dipl.- Inf. Carsten Albrecht,
AL-PRO GmbH & Co. KG, Dorfstrasse 100, D- 26532 Großheide, Germany
E-Mail: vojko.daneu@al-pro.de, carsten.albrecht@al-pro.de,
Tel.: +49 (0) 4936 6986-0, Fax.: +49 (0) 4936 6986-46
www.al-pro.de

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1 Introduction

There is a high demand in the wind energy industry for detailed and accurate wind and weather forecasts for multiple applications:

- The growing “free” energy market has opened new market opportunities for operators but requires and accurate wind and/or yield forecasts to optimize financial returns.
- Effective grid management requires realistic planning of the feeding capacity of each single wind farm and is heavily dependent on the wind and weather conditions at the wind farm site.
- Down time during the construction of wind farms increase costs and can be directly related to weather conditions on site.

Accurate forecasting is essential for the operation and maintenance of wind farms and is crucial in resource scheduling during wind farm construction. Precise wind forecasts also substantially improve daily farm yield predictions.

One main difference in requirements between a “standard” weather forecast and a forecast service specialized for wind energy is that the latter has to be as precise as possible at one particular location – the wind farm. Another key requirement is the need for detailed forecast information in the atmospheric boundary layer, in particular wind and gust values.

Mesoscale weather forecasting methods typically have a resolution of several kilometres. This resolution is not precise enough; especially in complex terrain conditions were very small scale variations in the wind flow have a significant impact on the wind farm yield.

Weather Central LLC, provider of the world’s most-viewed on-air, online, print, mobile and enterprise weather solutions, has partnered with AL-PRO, a global leader in wind energy consulting and planning, to create GMS – GLOBAL MICROCASTING SERVICE – a hyper-local forecasting engine with a complete set of forecasting solutions designed for the wind energy industry.

GMS has been designed to deliver hourly resolved wind, energy yield and other weather forecast information with the highest possible accuracy for several days ahead of the present.

A study was developed to validate the quality of GMS, to further develop the GMS key features and to improve their accuracy. A 3 month study was carried out during the first 3 months of 2010. A total of 13 wind farms located throughout Germany participated.

This report contains the analysis results, quantifies the accuracy of the GMS wind speed and wind energy yield forecasts and the capability of various GMS features to improve those forecasts.

2 Introducing the Global Microcasting System GMS

2.1 General Concept

GMS consists in the following key components:

2.1.1 Weather Central's GMS MicroCast™ Model

GMS MicroCast™ is a cutting-edge forecasting system that has been tuned to detect local fluctuations in wind patterns due to microclimates and topographical influences within the GMS project area.

2.1.2 GMS FARM YIELD PREDICTOR

The GMS FARM YIELD PREDICTOR computes the influence of wake-effects within a wind farm and incorporates the results in the forecast. It also simulates the intra hourly wind fluctuations, which tend to have a large influence on the energy yield.

2.1.3 GMS MICROCOUPLING

GMS MICROCOUPLING combines the GMS MicroCast™ model with a high resolution Computational Fluid Dynamic (CFD) flow model, enabling wind forecasts with exceptional resolutions of 20-30 meters.

2.1.4 GMS SMART LEARNING

GMS SMART LEARNING improves the forecast accuracy by using neural networks. A neural network consists of a network of simple processing elements (artificial neurons) which can exhibit complex global behaviour, determined by the connections between the processing elements and element parameters. In a neural network model, simple nodes are connected together to form a network of nodes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow.

Neural networks require a carefully selected training period. In the case of wind forecasting, neural networks are trained to comparing the actual and yield data at the turbine site with the forecasted values. The training period should include all the predominant weather conditions that occur at the site to enable the maximum learning effect.

2.2 GMS Products

Unlike weather forecasts that rely on averages taken over large areas, GMS can be applied to small geographic areas. GMS is available in 3 different products to suite varying needs:

1. GMS BASIC offers a detailed, elevation-based, hourly wind forecast ideal for near-term applications such as maintenance planning.
2. GMS PREMIUM features GMS MICROCOUPLING, the key to turbine-specific wind forecasts for existing wind farms, as well as modeling for terrain and obstacle induced wind effects. An automated warning option provides advanced alerts of upcoming low or high wind conditions. It also features GMS SMART LEARNING, the neural network algorithm that learns from forecast deviations and corrects them automatically. GMS PREMIUM is uniquely suited for wind farm construction management and for the operation of wind farms.
3. GMS FARM YIELD incorporates the features of GMS PREMIUM and adds power-based algorithms that provide modeling specific to each make and model of wind turbine. GMS FARM YIELD features the GMS YIELD PREDICTOR which simulates intra-hourly wind fluctuations and turbine wake effects. It offers a detailed yield forecast for wind farms based on individual turbines or a combined yield estimate summary.

3 Methodology

This paper describes a 3 month correlation study designed to qualify the relationship and accuracy of the GMS Suite of products for wind farms. Actual measurement data from 13 wind farms located in Germany were compared with the GMS Farm Yield forecast data for these farms. All participating wind farms are located in simple to semi-complex terrain.

The focus of this GMS yield study was to analyse and report on the following five tasks:

- Determination of the accuracy of the GMS MicroCast™ (6 km resolution) wind speed forecasts.
- Determination of the accuracy of the energy yield forecasts using the GMS FARM YIELD PREDICTOR.
- Evaluation of improved forecast results based on the implementation of GMS SMART LEARNING.
- Evaluation of the effect of a refined GMS MicroCast™ model (1 km resolution) on the accuracy of the wind speed forecasts.
- Evaluation of improved forecast results based on the implementation of GMS MICROCOUPLING.

The initial preparatory work of this GMS forecast project comprised of the GMS MicroCast™ wind model set-up and the wind farm set-up in WindPRO [13] with the calculation of the GMS FARM YIELD PREDICTORs for each wind farm.

The terrain within one study site, “Hartenfelser Kopf” can be considered as semi-complex terrain. Due to the site complexity, GMS MICROCOUPLING was used for this site using enhanced micro modeling with WindSim [14].

The GMS yield study ran for a 3 month period, starting on the 1st of January 2010 and was completed on March 31st, 2010. In addition to publishing the forecasts on an access restricted web page on the internet (www.gms-alpro.com), all forecast files were archived for the subsequent neural network training steps and the final analysis.

The first neural network training was performed in early February using the data recorded in January. Several network architectures were tested on the first month’s data to determine the best network architecture to reduce the standard error between the measured and forecasted wind energy yield values. The training of the neural networks was repeated early in March, using the recorded data for the previous 2 month period. The increased data recording and forecasting time provided a better chance to find the optimum network architecture.

The analysis of the yield study itself passes through a couple of processing steps using proprietary software tools [15] developed by AL-PRO. Forecast files and actual measurement data for each turbine were used as inputs for the programs. Various combinations of input data with different recording periods and different settings (with or without the use of neural networks and/or CFD coupling) were used in the analysis to understand their influence on the accuracy of the forecasts.

The following parameters have been determined during the analysis:

- Coefficient of determination between forecast and measurement values
- Scale and offset of the regression line
- Standard error and the relative standard Error
- Mean bias.

Out of these, the coefficient of determination (r^2), the standard error (SE) and the relative standard error (RSE) were selected to describe the analysis results within this report.

The r^2 statistic in this study is the square of the sample correlation coefficient between the outcome and the values being used for prediction. r^2 is a statistic that will give some information about the goodness of fit of the model – it is a measure of how well the regression line approximates the actual data points. The values of r^2 vary from 0 to 1 and an r^2 of 1 indicates that the regression line perfectly fits the data – therefore correlates 100%. A zero on the other hand would mean no relationship exists between the forecast and the observation.

The standard error SE in [m/s] is considered to be the most important parameter to describe the accuracy of the wind speed forecast in this study. SE describes the difference between the forecasted and observed wind speed. It is computed as follows:

$$se = \sqrt{\sum_{i=1}^{n} (fc_t - obs_i)^2}$$ (fc = forecasted value; obs = observed value)

An equally sound method to describe the accuracy of the wind energy yield forecast is the relative standard error RSE in [%]. RSE is simply the standard error of the yield, computed as described above, divided by the nominal power of the wind farm and expressed as a percentage. RSE has to be computed to make the results of the study comparable between wind farms with different nominal powers.

To prevent the results of the analysis from being too lengthy, only a fraction of the large amount of evaluation results have been compared among each other and presented in this report. Comparisons and visualizations of the energy yield of a complete farm have therefore been worked out instead of each single wind energy converter (WEC). Also wind velocities for a single WEC from each wind farm have been used for comparison and visualization. Finally, the forecast periods 1, 5 and 8 (i.e. the forecast hours 1-6, 25-30 and 43-48) have been presented in this report.

4 Participants and Sites

A total of 7 energy companies and wind farm developers took part in the study, providing 10 minute to 1 hour actual measurement data from 13 German wind farms over a 3 month period. The measurement data consisted of wind speed and wind direction values as well as wind energy yield values and a flag value indicating normal or restricted WEC working conditions. For one wind farm also Temperature values were available whereas another wind farm could not deliver wind direction data during the study period.

The following companies participated in this study:

- E.ON Climate & Renewables
- Energiequelle GmbH
- ENOVA Energieanlagen GmbH
- HELIOTEC Betriebs- und Verwaltungsgesellschaft mbH
- juwi Wind GmbH
- Landwind Verwaltungs GmbH & Co. KG
- WestWind Service GmbH & Co. KG

The wind farm sites are located in central and northern Germany in relatively flat regions with simple terrain conditions. “Ems-Emden” in Lower Saxony is a single turbine site located in near shore conditions whereas “Salzhemmedorf” and “Hartenfelser Kopf” are located in semi-complex terrain conditions.

Operator	Wind Farm Name	WECs	Hub Height	Lat	Lon
E.ON	Dargelütz	11 x E-70	105 m	53.4928°	11.8461°
E.ON	Treue	4 x V-90	85 m	52.1820°	10.9973°
Energiequelle	Gallun	5 x V-90	105 m	52.2427°	13.5866°
ENOVA	Börger-Breddenberg	7 x E-66/18.70	98 m	52.9382°	7.59874°
ENOVA	Ems-Emden	1 x E-112	108 m	53.3329°	7.21116°
HELIOTEC	Kuhschnappel	1 x E-48/8.48	78 m	50.8152°	12.6345°
HELIOTEC	Pegau	2 x E-70 E4	113 m	51.1811°	12.2372°
juwi Wind	Hartenfelser Kopf	12 x E-70 E4 and 1 x E-82	113,5 / 138 m	50.6109°	7.76445°
juwi Wind	Wörrstadt	5 x E-82	138 m	49.8300°	8.13820°
Landwind	Salzhemmendorf	5 x E-82	108 m	52.0788°	9.65635°
Landwind	Söllingen	15 x GE 2.3	100 m	52.0780°	10.9484°
WestWind	Barenburg	3 x E-82	138 m	52.6422°	8.77434°
WestWind	Twistringen	8 x E-66/18.70	85 / 86 m	52.77641°	8.643928°

Tabel 4.1: Wind farm data

Image 4.1: Overview of the wind farm locations in Germany

5 Results

5.1 General Remarks

The main emphasis of this yield study was to evaluate the quality of the GMS forecasts and the implementation of the GMS FARM YIELD PREDICTOR, GMS SMART LEARNING and GMS MICROCOUPLING on the 6 km resolution GMS MicroCast™ forecasts as well as evaluating the quality of the 6 km resolution GMS MicroCast™ forecasts themselves. In a second evaluation step, a comparison between the 6 km and 1km resolution GMS MicroCast™ forecasts was made to determine if here was an improvement in forecast accuracy.

The GMS yield study basically worked well as planned and was on schedule. Nevertheless there had been some organisational, data related and most notably weather related setbacks to the study. January and February had unusual weather conditions, a remarkable hard winter over all Europe with severe icing conditions and storms including cyclone "Xynthia" that arrived at the end of February. Despite these occurrences, both months were characterized by unusually low wind speed periods with atypical winds from the east and north-east. As a consequence of the icing conditions, the operation of many WECs was constrained and if detected, a flag value was set within the corresponding data files. Flagged data was then filtered to exclude these measurement values from the analysis and thus preventing distortion of the analysis results. As a consequence, more than two weeks of measurement data from the wind farm “Hartenfelser Kopf” had to be excluded from the analysis due to heavy icing conditions.

Another challenge was that some study participants had difficulties in verifying the correct operational status of their WECs. In the course of the analysis, it was discovered that some wind farms showed implausible behaviour during limited time periods. For example, the measurement values of one wind farm showed that all the WECs were running at full load with the exemption of one WEC, but yet all WECs were registered as running in unrestricted operation mode.

Besides a concerted effort to find and exclude implausible data, there is a high probability that data flaws due to the impact of undetected icing of anemometers and blades as well as other undetectable data flaws might have found their way into the analysis.

Furthermore, WEC number 3 from the wind farm “Wörrstadt” worked in restricted mode during the entire study period. As it was not possible to correct the onsite configuration parameters, all the data for WEC number 3 was replaced with the data of WEC number 4 which worked normally. That simplification is justifiable due to the modest topographical characteristics of the landscape within and around the small wind farm and due to the small distance of approximately 250 m between the two turbines.

The operator of the wind farm "Söllingen" initially encountered some problems supplying data and therefore measurement data was only available for February and March.

Due to missing or unusable measurement data from the wind farms "Hartenfelser Kopf" and "Söllingen", some concessions had to be made during the analysis with regard to the selected evaluation periods and the wind farm data that was used. The summarized evaluation of all the wind farms for example or the evaluation of the forecasts using 11 weeks of trained neural networks had to be completed without the data from the wind farms "Hartenfelser Kopf" and "Söllingen".

To test and adjust the GMS settings for the study, measurement data for December 2009 from the wind farm "Twistringen" was made available for this study, thus enabling a start of GMS forecasting on the 4^{th} of December. With the extended dataset from the wind farm "Twistringen", a three month trained neural network (from 04.12.2009 to 04.03.2010) was applied to the measurement data for a period of slightly more than 3 weeks (from 05.03.2010 to 31.03.2010). The evaluation results are also outlined in the following chapters.

Generally, all results in this report are presented in bar graphs and described with brief statements. The charts show three bars in three different colours for each wind farm. The green bars represent the parameter values for period 1 (i.e. for the forecast hours 1-6), the yellow bars for period 5 (i.e. for the forecast hours 25-30) and the orange bars for period 8 (i.e. for the forecast hours 43-48) of a 48 hour forecast cycle.

5.2 Main results

5.2.1 Quality of the 6 km resolution GMS forecasts

5.2.1.1 Average RSE values of the wind energy yield forecasts (01.03.10 – 31.03.10):

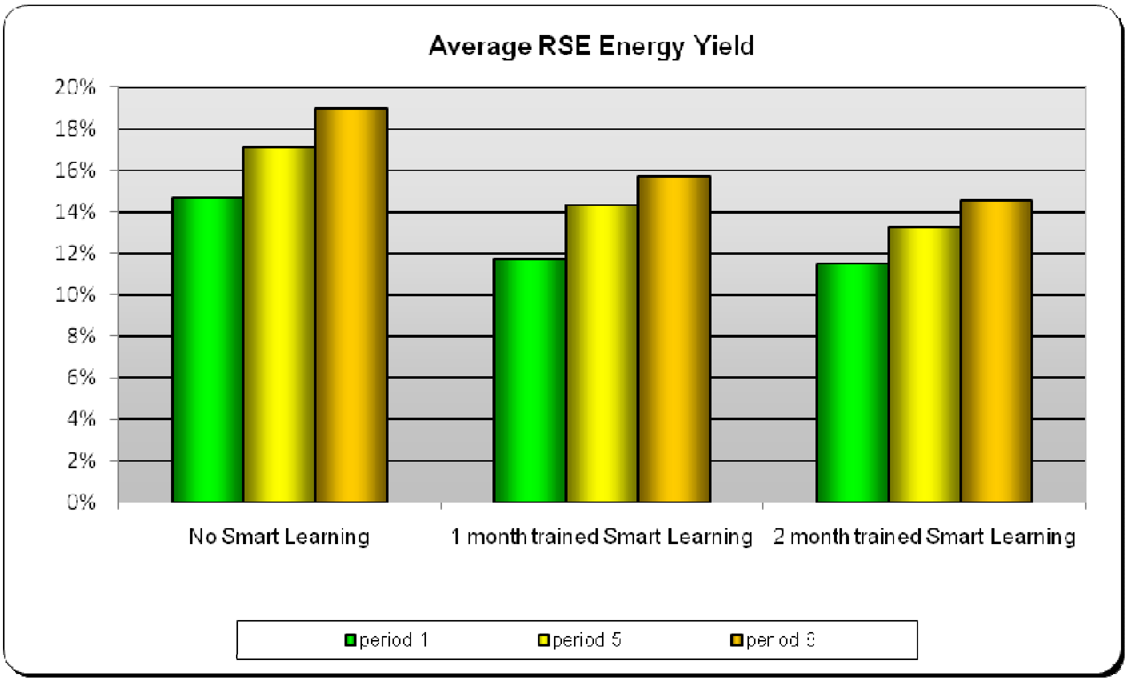


Image 5.2.1.1: Average RSE values of the wind energy yield forecasts of all wind farms apart from wind farm Söllingen and Hartenfelser Kopf for the time frame 01.03.10 - 31.03.10

The original average wind energy yield forecasts of the GMS FARM YIELD PREDICTOR (applied on the GMS MicroCast™ model with 6 km resolution) of all wind farms (except wind farms Söllingen und Hartenfelser Kopf) and without the implementation of any GMS forecast enhancement method show mean RSE values of **14.6%**, **17.1%** and **19.0%** for the periods 1, 5 and 8 respectively.

These values improve with the use of a 1 month trained neural network by 19.9% to a value of **11.7%**, by 16.4% to a value of **14.3%** and by 17.4% to a value of **15.7%** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS FARM YIELD PREDICTOR forecasts with the forecasts using a 2 month trained neural network shows an improvement of RSE by 21.2% to a value of **11.5%**, by 22.8% to a value of **13.2%** and by 23.2% to a value of **14.6%** for the periods 1, 5 and 8 respectively.

5.2.1.2 Average SE values of the wind speed forecasts (01.03.10 – 31.03.10):

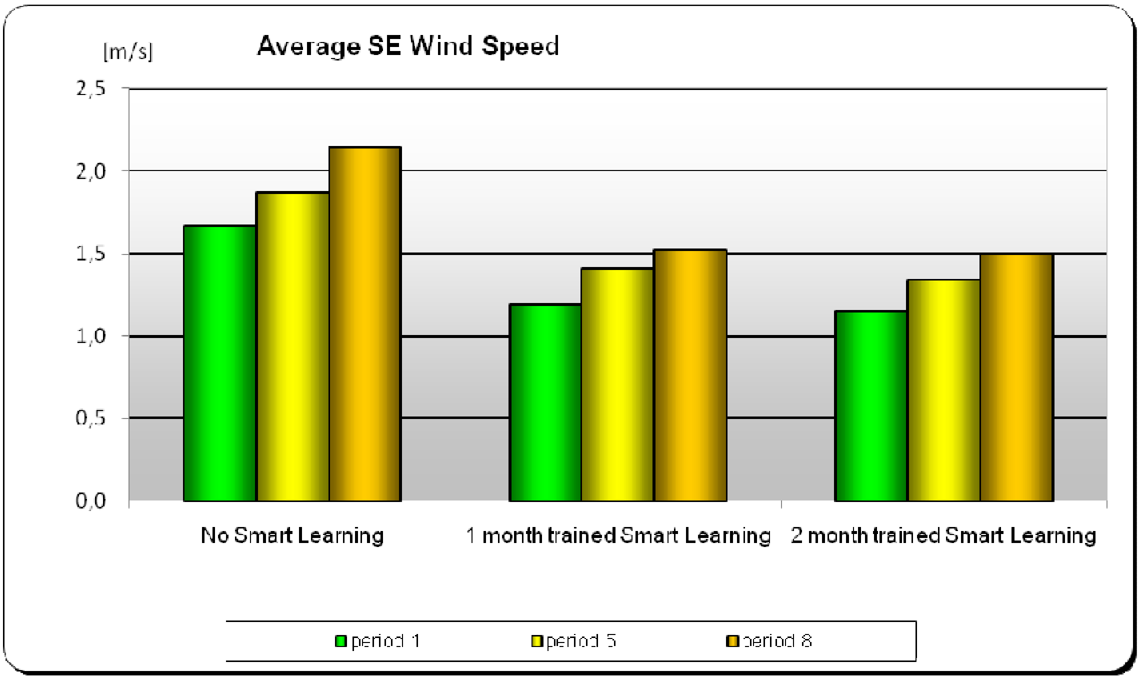


Image 5.2.1.2: Average SE values of the wind speed forecasts of all wind farms apart from wind farm Söllingen and Hartenfelser Kopf for the time frame 01.03.10 – 31.03.10

The original average wind speed forecasts of the GMS MicroCast™ model with 6 km resolution of all wind farms (except wind farms Söllingen und Hartenfelser Kopf) and without the implementation of any GMS forecast enhancement method show mean SE values of **1.67**, **1.87** and **2.14 m/s** for the periods 1, 5 and 8 respectively.

These values improve with the use of a 1 month trained neural network by 28.1% to a value of **1.20 m/s**, by 24.6% to a value of **1.41 m/s** and by 29.0% to a value of **1.52 m/s** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS MicroCast™ forecasts with the forecasts using a 2 month trained neural network shows an improvement of SE by 31.1% to a value of **1.15 m/s**, by 28.3% to a value of **1.34 m/s** and by 30.4% to a value of **1.49 m/s** for the periods 1, 5 and 8 respectively.

5.2.1.3 Average r^2 values of the wind speed forecasts (01.03.10 – 31.03.10):

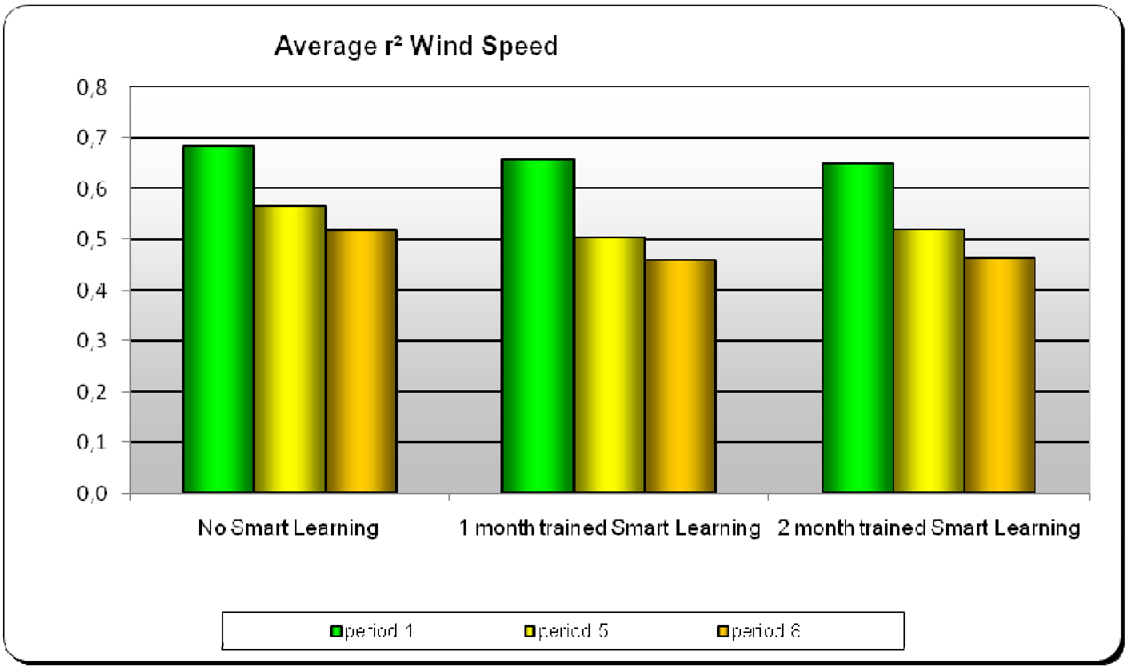


Image 5.2.1.3: Average r² values of the wind speed forecasts of all wind farms apart from wind farm Söllingen and Hartenfelser Kopf for the time frame 01.03.10 – 31.03.10

The original average wind speed forecasts of the GMS MicroCast™ model with 6 km resolution of all wind farms (except wind farms Söllingen und Hartenfelser Kopf) and without the implementation of any GMS forecast enhancement method show mean r^2 values of **0.68**, **0.57** and **0.52** for the periods 1, 5 and 8 respectively.

These values decrease with the use of a 1 month trained neural network by 2.9% to a value of **0.66**, by 12.3% to a value of **0.50** and by 11.5% to a value of **0.46** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS MicroCast™ forecasts with the forecasts using a 2 month trained neural network shows a decrease of r^2 by 4.4% to a value of **0.65**, by 8.8% to a value of **0.52** and again by 11.5% to a value of **0.46** for the periods 1, 5 and 8 respectively.

5.2.1.4 Average r^2 values of the wind energy yield forecasts (01.03.10 – 31.03.10):

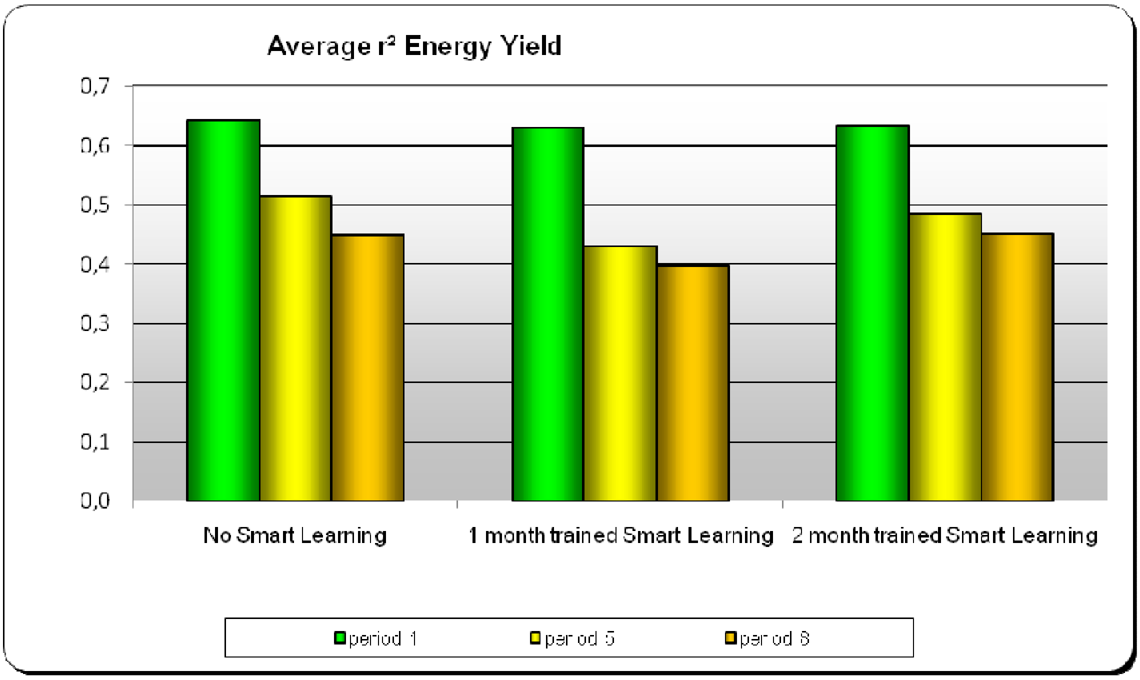


Image 5.2.1.4: Average r² values of the wind energy yield forecasts of all wind farms apart from wind farm Söllingen and Hartenfelser Kopf for the time frame 01.03.10 – 31.03.10

The original average wind energy yield forecasts of the GMS FARM YIELD PREDICTOR (applied on the GMS MicroCast™ model with 6 km resolution) of all wind farms (except wind farms Söllingen und Hartenfelser Kopf) and without the implementation of any GMS forecast enhancement method show mean r^2 values of **0.64**, **0.51 and 0.45** for the periods 1, 5 and 8 respectively.

These values decrease with the use of a 1 month trained neural network by 1.6% to a value of **0.63**, by 15.7% to a value of **0.43** and by 11.1% to a value of **0.40** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS FARM YIELD PREDICTOR forecasts with the forecasts using a 2 month trained neural network shows a decrease of r^2 by 3.9% to a value of **0.49** for period 5 but no significant change for the periods 1 and 8.

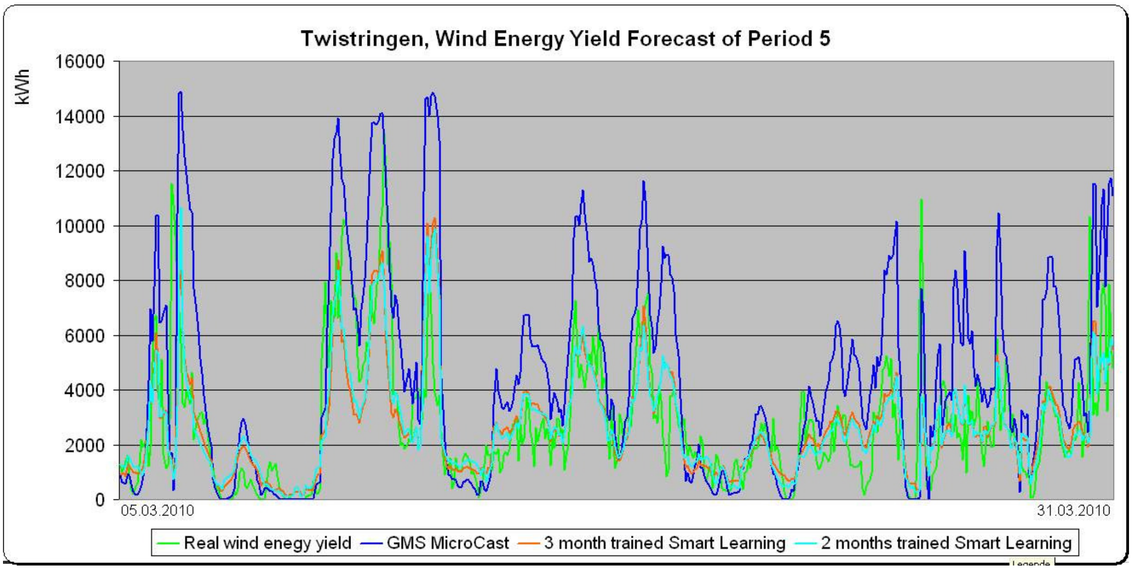
5.3 Discussion of the Main Results

The accuracy of the GMS wind speed and wind energy yield forecasts have been quantified with the coefficient of determination (r^2), the standard error (SE) and the relative standard error (RSE).

r^2 gives some information about the goodness of fit of the model (measuring how well the regression line approximates the actual data points). The values of r^2 vary from 0 to 1. Better yet and more expressive are the SE and RSE parameters to describe the quality of a forecast!

5.3.1 Overall forecast quality

GMS was able to provide yield forecasts with a relative standard error of approximately 13 % for one day ahead after a training period of only 2 month for GMS SMART LEARNING! This result is the most remarkable as it was achieved in a period where most of the wind farms were producing, but very rarely or never reached rated power, which is the most difficult range to forecast. The forecast quality is impressively shown in the following graph displaying the time series for the Twistringen wind farm:



This diagram can be found in the appendix (8.3.11.5) as well. It impressively shows the overall quality of the forecast and in particular the improvement of GMS SMART LEARNING. It also highlights the fact that no full load periods occurred during the entire month (full load would be slightly above 14 MW for this wind farm).

5.3.2 GMS SMART LEARNING

The mean r^2 values of the wind speed forecasts slightly deteriorated using the GMS MicroCast™ model with 6 km resolution and of the wind energy yield forecasts using the GMS FARM YIELD PREDICTOR. This is an expected result since the short training period did not allow a neural network architecture to be selected and implemented that potentially could improve the correlation. Such an improvement could be expected if a network with the ability to correct forecasted events in time is used.

The strength of GMS SMART LEARNING becomes apparent with the evaluation of the mean SE and RSE values of the wind speed and wind energy yield forecasts. The mean SE values of the wind speed forecasts derived from the GMS MicroCast™ model with 6 km resolution and without the implementation of any GMS forecast enhancement method range for all considered periods from roughly 1.6 to 2.2 m/s. The implementation of GMS SMART LEARNING (using one month and two months trained neural networks) clearly improves the GMS MicroCast™ results by approx. 25 – 31 %. The differences between 1 month and two months trained neural networks in this case are marginal (image 0). The individual evaluation of wind farm

„Twistringen“ furthermore again shows no significant improvement of the SE values if a three months trained neural network is applied on the GMS MicroCast™ forecasts (image 8.3.11.3).

The mean RSE values of the wind energy yield forecasts derived from the GMS FARM YIELD PREDICTOR (applied on the GMS MicroCast™ model with 6 km resolution) without the implementation of any GMS forecast enhancement method range for all considered periods from roughly 14 to 19 %. The implementation of GMS SMART LEARNING (using one month and two months trained neural networks) clearly improves the GMS FARM YIELD PREDICTOR results by approx. 16 – 23 %. The rate of improvement in this case increases with the length of the training period of the neural networks (image 5.2.1.1). The individual evaluation of wind farm „Twistringen“ on the other hand again shows no significant improvement of the RSE values if a three months trained neural network is applied on the GMS FARM YIELD PREDICTOR (image 8.3.11.4).

Overall, the evaluation shows that already with a one month training period, significant improvements can be achieved. The results improve with a longer training period, as expected, but do not show further improvements in the same range. The reason for this probably is that due to the short overall training period only quite simple neural networks were set up for GMS SMART LEARNING to avoid over training. With longer periods more sophisticated networks also using further input values like temperature, pressure, dew point etc. can be set up. It is reasonable to expect further improvements from this.

5.4 Discussion

5.4.1 GMS MICROCOUPLING

The validation of GMS MICROCOUPLING was not possible in the course of this study, as no single wind farm was located in complex terrain. “Hartenfelser Kopf” is the only wind farm in the study that can be considered as semi-complex. GMS MICROCOUPLING was implemented on the GMS MicroCast™ (6 km resolution) forecasts for this site. Evaluation of the results became even more difficult as the wind farm was heavily affected by icing due to the untypical hard winter in Germany.

GMS MICROCOUPLING showed little or no effect on the r^2 values of the wind speed and wind energy yield forecasts. In contrast clear, deteriorations of the SE and RSE values could be observed with maximum values of 20.0 and 41.2% respectively (images 8.4.1.1 – 8.4.4.1).

This in fact is an expected result, due to the following fact: the GMS MicroCast™ forecast which is the basis for the MICROCOUPLING trended to over predict the wind speed. As it gives the average wind speed of a 6x6 km area and the wind farm is erected on a hill, therefore at a spot where you can expect wind speeds above this average, the MICROCOUPLING must lead to a even higher over prediction – but better representing the variations from turbine to turbine. The overall bias could easily be corrected with GMS SMART LEARNING. Unfortunately, due to the extremely short data period that could be used from this wind farm, it was not possible to implement this.

GMS MICROCOUPLING has been tested in more complex terrain situations over Southern Europe in the meantime, where GMS PREMIUM forecasts are operational and showed clear improvements compared to the pure GMS MicroCast™.

5.4.2 GMS MicroCast™ 1 km downscale

The implementation of a 1 km downscaled GMS MicroCast™ was not originally planned at the beginning of this study. However, the ability to test this additional service to improve the forecast quality came up during the study.

No improvements of the forecast accuracy could be realized by this approach. Refining the model resolution resulted in a slight deterioration of the mean r^2 values of the wind speed forecasts by approx. 2 – 10% and of the wind energy yield forecasts by approx. 8% for period one and two (images 5.1.5 and 5.1.6 respectively).

A slight deterioration could also be observed evaluating the mean SE and RSE values of the wind speed and wind energy yield forecasts respectively. Mean SE values deteriorated by approx. 1-2% and mean RSE values by approx. 0-3% (images 5.1.7 and 5.1.8).

5.5 Conclusion

This GMS yield study can be considered as extraordinarily successful. The results showed that GMS forecast quality is very impressive and provided keys to areas were improvements can be made to the system.

The GMS MicroCast™ 6 km implementing GMS SMART LEARNING with a short training period of only two month's provided a forecast with a relative standard error of only about 13 %. This is especially remarkable as this result was achieved with a training period with highly untypical weather patterns and for a forecasting period with wind farms operating in partial load conditions nearly all the time, which is the most difficult to forecast.

The study also brought up questions for further research, for instance, it is not clear yet why the 1 km downscaling deteriorates the forecast quality. This has to be further examined and studied.

The collected data can and will be used for further analysis, e.g. ramp forecasting ability of the system, which was beyond the scope of this study, and is available to the participants for their own analysis.

6 Acknowledgement

AL-PRO GmbH & Co. KG is grateful to the firms that participated in this study. The participants made the study possible and allowed AL-PRO to refine the analysis routines while providing a meaningful evaluation of the GMS product suite.

We hope that the results contained within this study prove beneficial to the participants and others.

7 References

7.1 Bibliography

[1] European Wind Atlas (1989); Nils G. Mortensen, Ib Troen, Erik Lundtang Pertersen; Risø National Laboratory, Denmark

[2] Technische Richtlinien für Windenergieanlagen, Teil 6: Bestimmung von Windpotenzial und Energieerträgen, Revision 7, 10.09.2007; Fördergesellschaft Windenergie e.V.

[3] Meso scale modeling with a Reynolds Averaged Navier-Stokes Solver (1998); A. R. Gravdahl, 31th IEA Experts Meeting – State of the Art of Wind Resource Estimation, Risö.

[4] Wind field simulations at Askervein hill (1999); J. Leroy; Technical report VECTOR_9910_100.

[5] WindSim – Flow Simulations in Complex Terrain (2000); A. R. Gravdahl, K. Harstveit; 5th German Wind Energy Conference, Wilhelmshaven.

[6] Power prediction and siting – When the terrain gets rough (2002); A. R. Gravdahl, S. Rorgemoen, M. Thogersen; The World Wind Energy conference and Exibition, Berlin.

[7] Wind Modeling in Mountains, Intercomparison and Validation of Models (2003); B. Schaffner, A. R. Gravdahl; European Wind Energy conference and Exibition, Madrid.

[8] Verifikation des dreidimensionalen CFD-Strömungsmodells WindSim anhand von Testfällen in der Region Hochsauerland (2004), Bericht Nr. WS-130304-272-CA; Carsten Albrecht; AL-PRO

[9] WindSim in Complex Terrain: test case Castronovo, Sicily, C. Albrecht, M. Klesitz; WindSim User Meeting, Tønsberg, 2005.

[10] An introduction to boundary layer meterology, Roland B. Stall, 1988.

[11] Long term correlations of wind measurements with neural networks; C. Albrecht, M. Klesitz, Wind Power Asia Beijing, 2006

[12] Everitt, B.S. (2003) The Cambridge Dictionary of Statistics, CUP. ISBN 0-521-81099-x.

7.2 Used software

[13] WindPRO, Version 2.6.1.252 Jan. 2009, EMD International A/S, Denmark

[14] WindSim, Version 4.9.1, WindSim AS, Norway

[15] Matlab 7.5.0.342 (R2007b), The MathWorks, Inc.

[16] Microsoft Office Excel 2003 (11.6113.5703) SP 1, Microsoft Corporation

[17] WAsP, Wind Atlas Analysis and Application Program, Version 8.1, Build 8.01.0057, Risø National Laboratory, Denmark

8 Annex with Results in Detail

8.1 Effects of the grid refinement of the GMS MicroCast™ model from 6 km to 1 km on the forecast quality

8.1.1 Average r^2 values of the wind speed forecasts and of the wind energy yield forecasts (19.02.10 – 31.03.10):

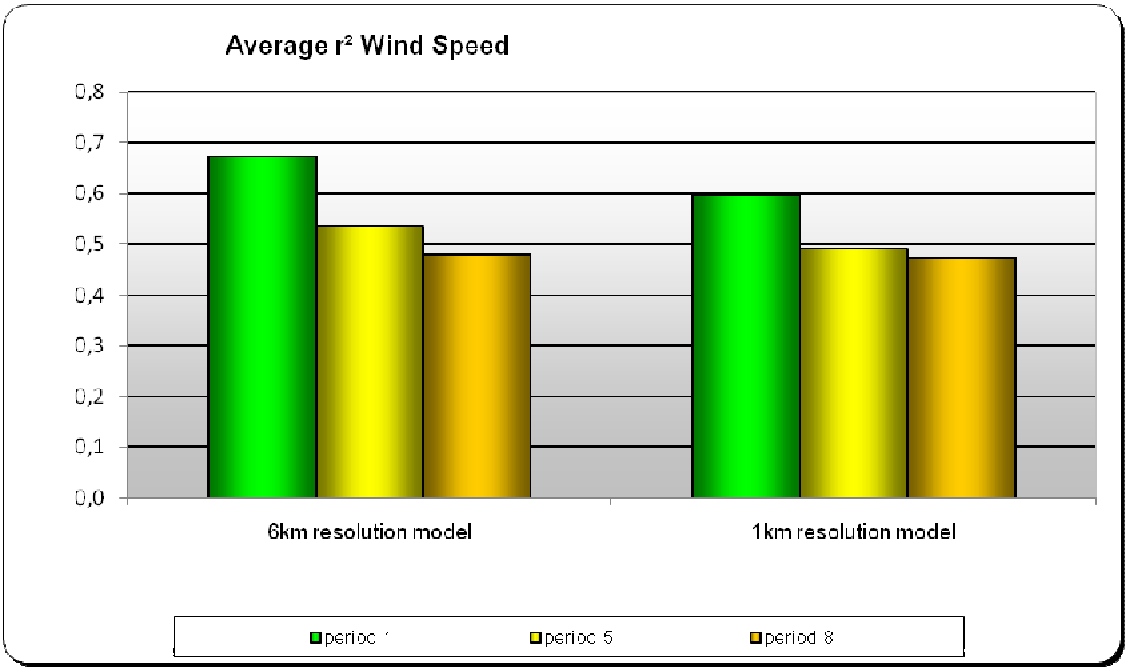


Image 8.1.1.1: Average r² values of the wind speed forecasts of all wind farms for the time frame 19.02.10 – 31.03.10

The average wind speed forecasts of the GMS MicroCast™ model with 6 km resolution and without the implementation of any GMS forecast enhancement method show mean r^2 values of **0.67**, **0.54** and **0.48** for the periods 1, 5 and 8 respectively.

These values decrease with the model refinement to 1 km resolution by 10.4% to a value of **0.60**, by 9.3% to a value of **0.49** and by 2.1% to a value of **0.47** for the periods 1, 5 and 8 respectively.

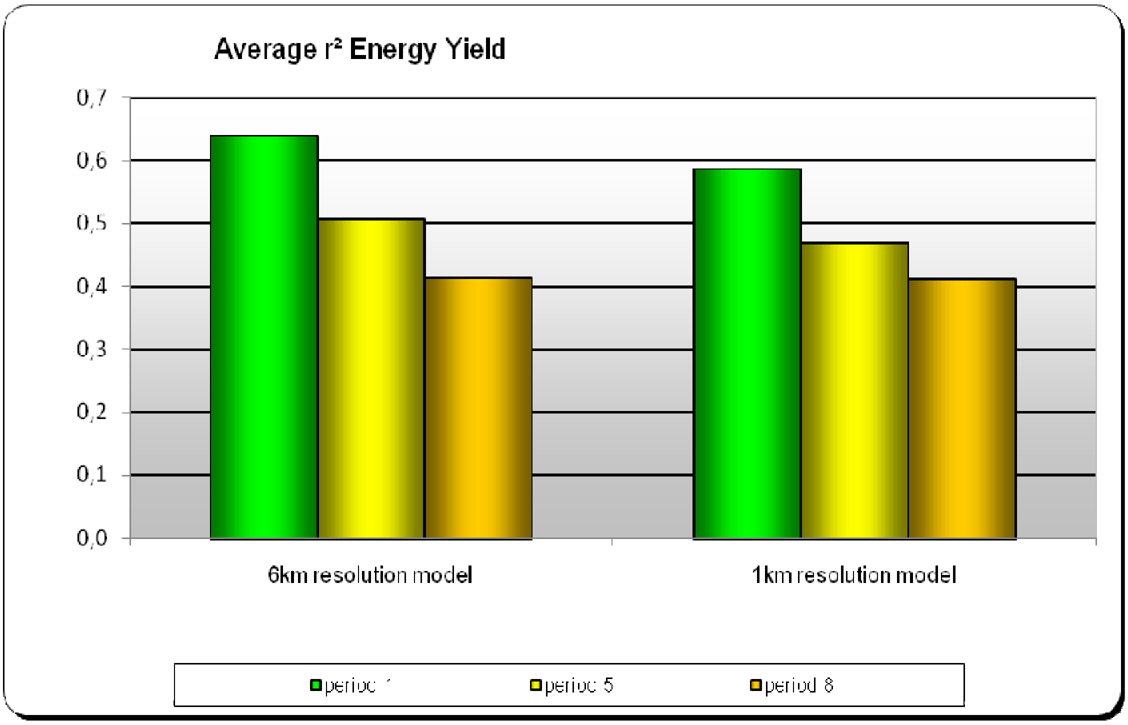


Image 8.1.1.2: Average r² values of the wind energy yield forecasts of all wind farms for the time frame 19.02.10 – 31.03.10

The average wind energy yield forecasts of the GMS FARM YIELD PREDICTOR (applied on the GMS MicroCast™ model with 6 km resolution) without the implementation of any GMS forecast enhancement method show mean r^2 values of **0.64**, **0.51** and **0.41** for the periods 1, 5 and 8 respectively.

These values decrease with the model refinement to 1 km resolution by 7.8% to a value of **0.59** and equally by 7.8% to a value of **0.47** for the periods 1 and 5. Period 8 shows no difference between the 6 km and 1 km forecasts.

8.1.2 Average SE values of the wind speed forecasts and RSE values of the wind energy yield forecasts (19.02.10 – 31.03.10):

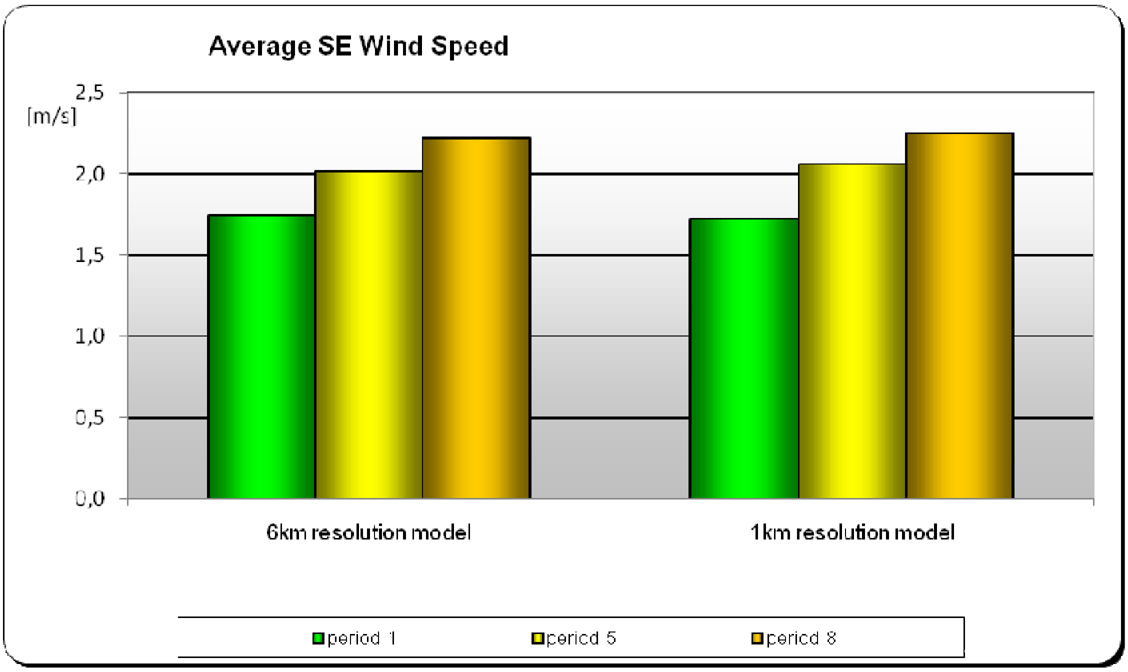


Image 8.1.2.1: Average SE values of the wind speed forecasts of all wind farms for the time frame 19.02.10 – 31.03.10

The average wind speed forecasts of the GMS MicroCast™ model with 6 km resolution and without the implementation of any GMS forecast enhancement method show mean SE values of **1.75**, **2.02** and **2.22 m/s** for the periods 1, 5 and 8 respectively.

These values deteriorate with the model refinement to 1 km resolution by 1.7% to a value of **1.72 m/s**, by 2.0% to a value of **2.06 m/s** and by 1.4% to a value of **2.25 m/s** for the periods 1, 5 and 8 respectively.

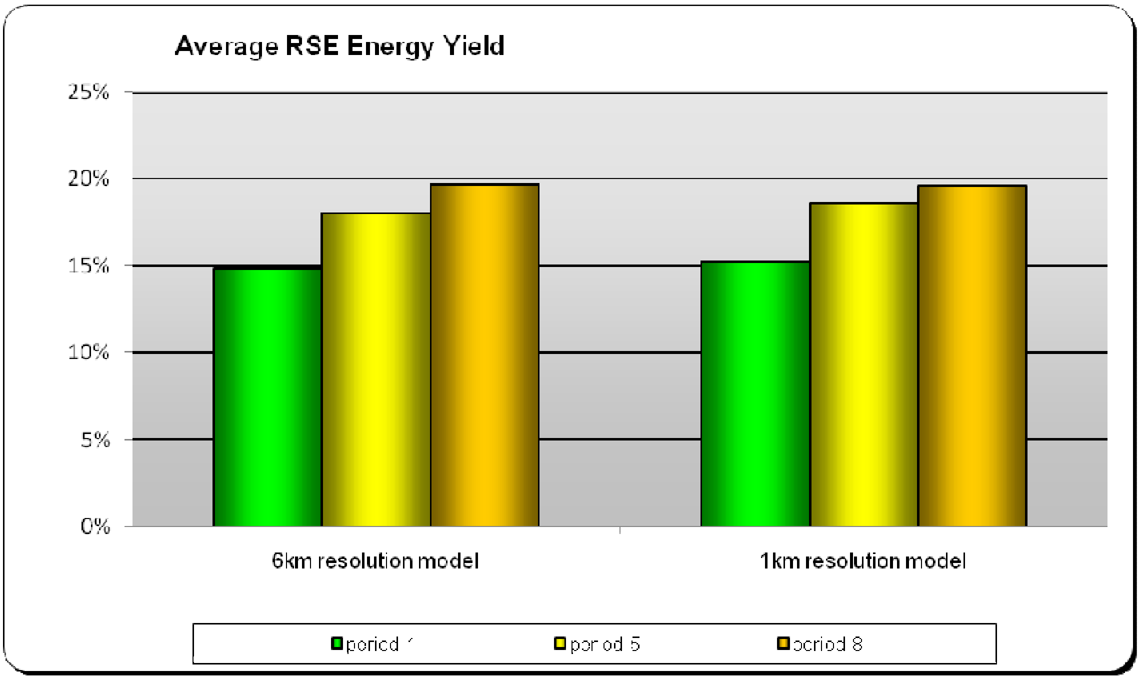


Image 8.1.2.2: Average RSE values of the wind energy yield forecasts of all wind farms for the time frame 19.02.10 – 31.03.10

The average wind energy yield forecasts of the GMS FARM YIELD PREDICTOR (applied on the GMS MicroCast™ model with 6 km resolution) without the implementation of any GMS forecast enhancement method show mean RSE values of **14.8%**, **18.0%** and **19.7%** for the periods 1, 5 and 8 respectively.

These values deteriorate with the model refinement to 1 km resolution by 2.7% to a value of **15.2%**, by 3.3% to a value of **18.6%** and by 0.5% to a value of **19.6%** for the periods 1, 5 and 8 respectively.

8.2 Implementation of GMS SMART LEARNING to improve the accuracy of the GMS MicroCast™ (6 km resolution) wind speed forecasts

8.2.1 r^2 of the wind speed values (01.03.10 – 31.03.10) <u>without</u> the use of a neural network:

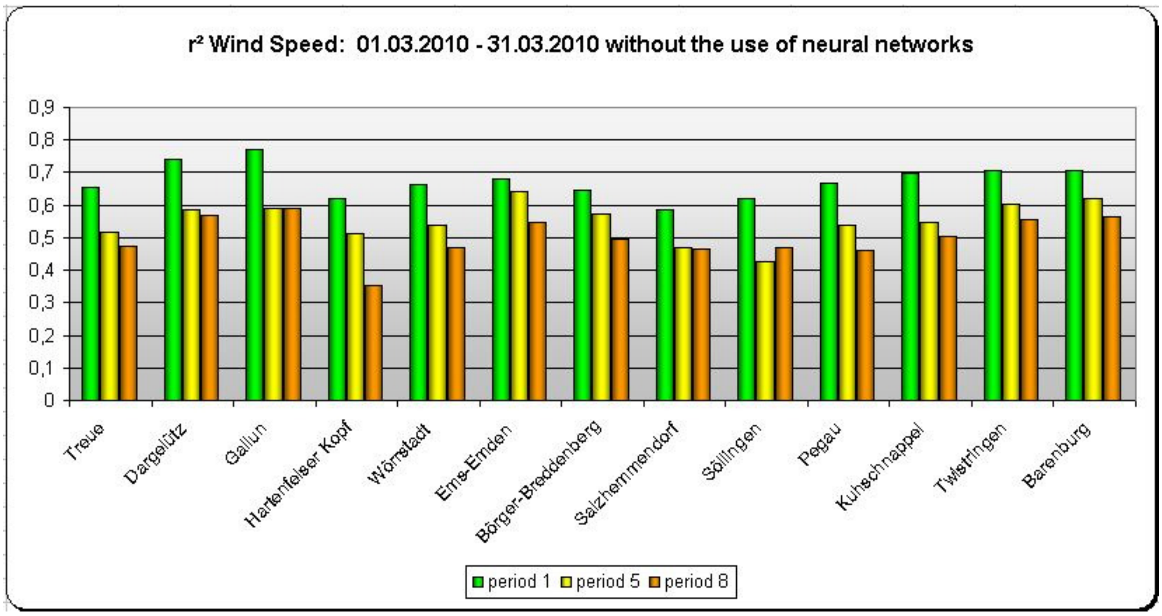


Image 8.2.1.1: r² values (01.03.10 - 31.03.10) without the use of neural networks

The wind speed forecasts of the GMS MicroCast™ (6 km resolution) model show r^2 values between **0.77** and **0.59** for period 1. r^2 values generally drop towards values between **0.64** and **0.43** for period 5 and towards values between **0.59** and **0.35** for period 8.

8.2.2 r^2 of the wind speed values (25.03.10 – 31.03.10) without the use of a neural network:

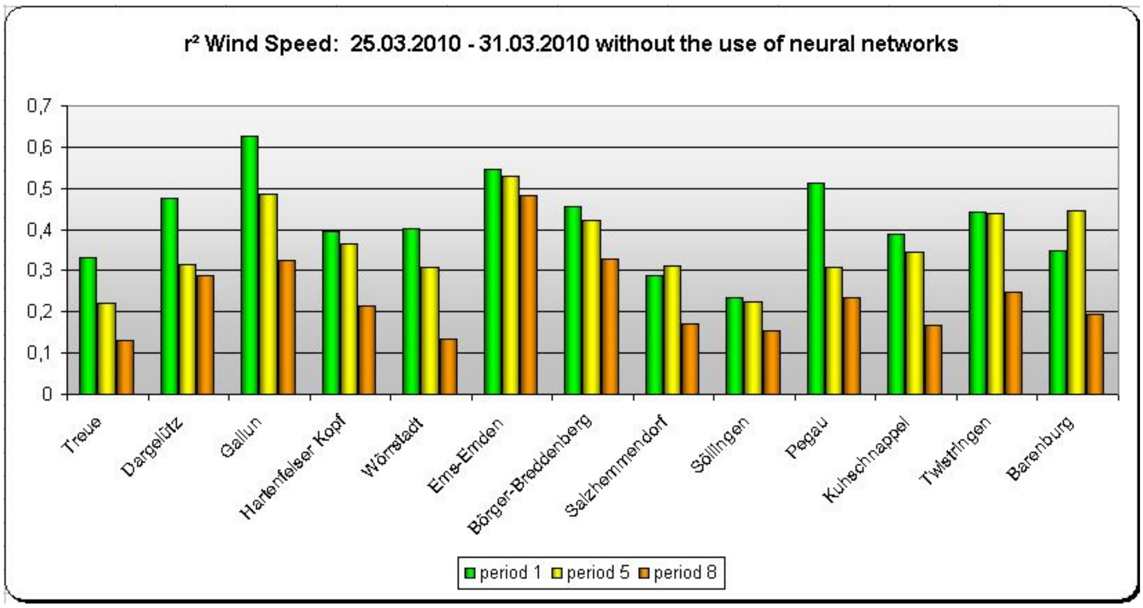


Image 8.2.2.1: r² values of the wind speed values (25.03.10 - 31.03.10) without the use of neural networks

The wind speed forecasts of the GMS MicroCast™ (6 km resolution) model show r^2 values between **0.63** and **0.23** for period 1. r^2 values generally drop towards values between **0.53** and **0.22** for period 5 and towards values between **0.48** and **0.13** for period 8.

8.2.3 r^2 of the wind speed values (01.03.10 – 31.03.10) using a 1 month trained neural network:

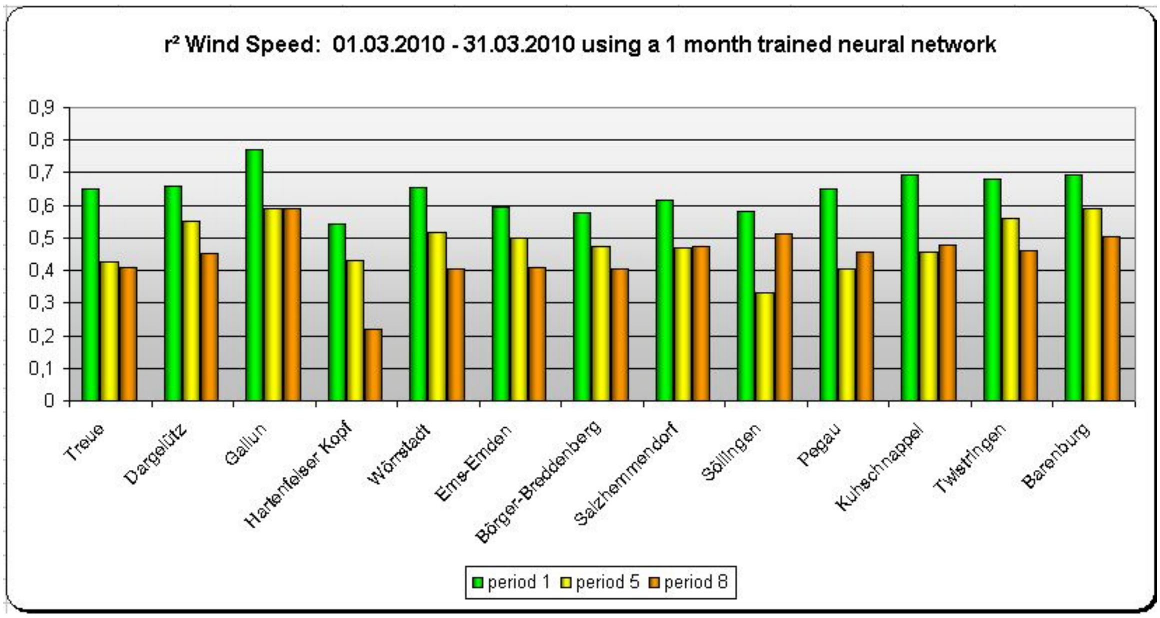


Image 8.2.3.1: r² values of the wind speed values (01.03.10 - 31.03.10) using a 1 month trained neural network

The wind speed forecasts computed with GMS SMART LEARNING show r^2 values between **0.77** and **0.54** for period 1. r^2 values generally drop towards values between **0.59** and **0.33** for period 5 and towards values between **0.59** and **0.22** for period 8.

8.2.4 r^2 of the wind speed values (01.03.10 – 31.03.10) using a 2 months trained neural network:

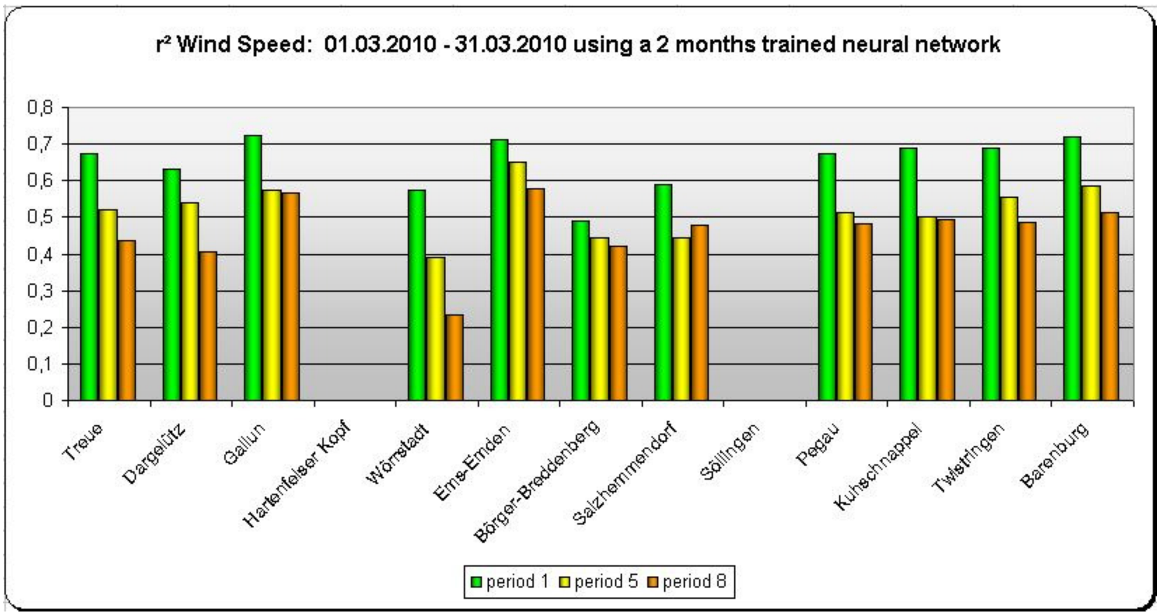


Image 8.2.4.1: r² values of the wind speed values (01.03.10 - 31.03.10) using a 2 months trained neural network. The implementation of a 2 months trained neural network for the wind farms Hartenfelser Kopf and Söllingen was not possible due to missing or unusable data of January

The wind speed forecasts computed with GMS SMART LEARNING show r^2 values between **0.72** and **0.49** for period 1. r^2 values generally drop towards values between **0.65** and **0.39** for period 5 and towards values between **0.58** and **0.23** for period 8.

8.2.5 r^2 of the wind speed values (25.03.10 – 31.03.10) using a 2,75 months trained neural network:

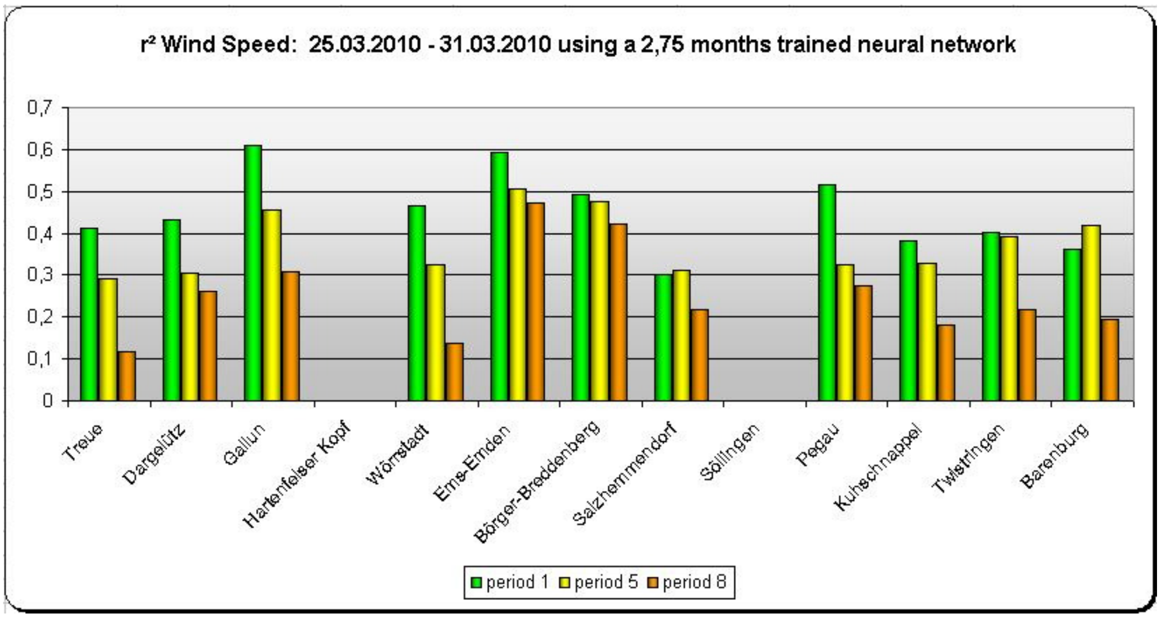


Image 8.2.5.1: r^2 values of the wind speed values (25.03.10 - 31.03.10) using a 2,75 months trained neural network. The implementation of a 2,75 months trained neural network for the wind farms Hartenfelser Kopf and Söllingen was not possible due to missing or unusable data of January

The wind speed forecasts computed with GMS SMART LEARNING show r^2 values between **0.61** and **0.30** for period 1. r^2 values generally drop towards values between **0.51** and **0.29** for period 5 and towards values between **0.47** and **0.12** for period 8.

8.2.6 SE of the wind speed values (01.03.10 – 31.03.10) <u>without</u> the use of a neural network:

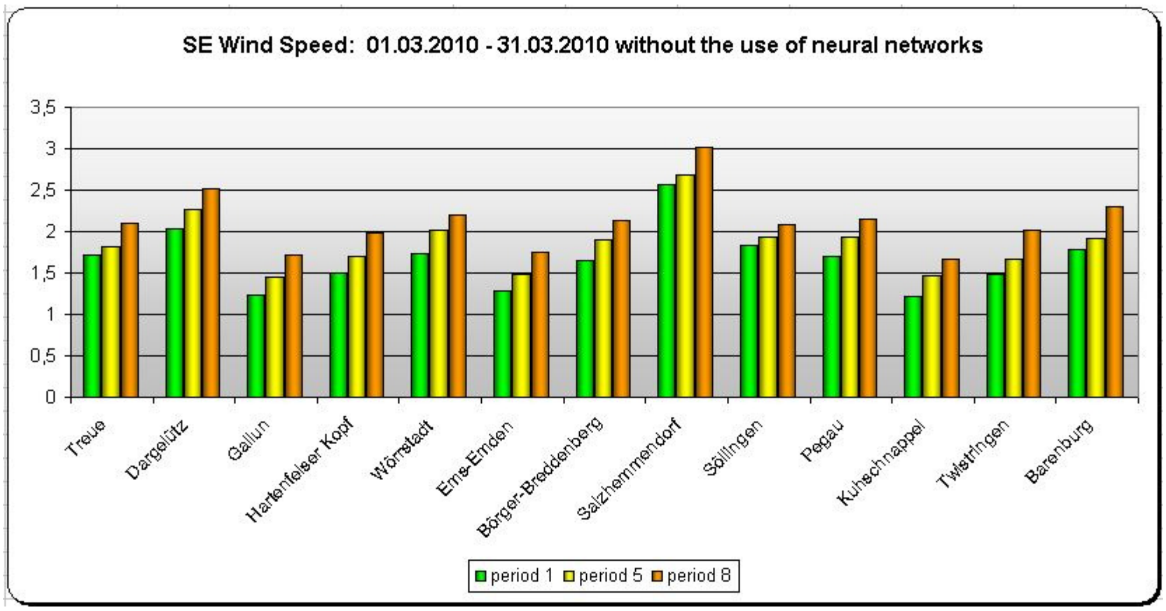


Image 8.2.6.1: SE values of the wind speed values (01.03.10 - 31.03.10) without the use of neural networks

The wind speed forecasts of the GMS MicroCast™ (6 km resolution) model show standard errors with values between **1.22** and **2.57** for period 1. The standard error uniquely increases towards values between **1.45** and **2.69** for period 5 and towards values between **1.66** and **3.02** for period 8.

8.2.7 SE of the wind speed values (25.03.10 – 31.03.10) without the use of a neural network:

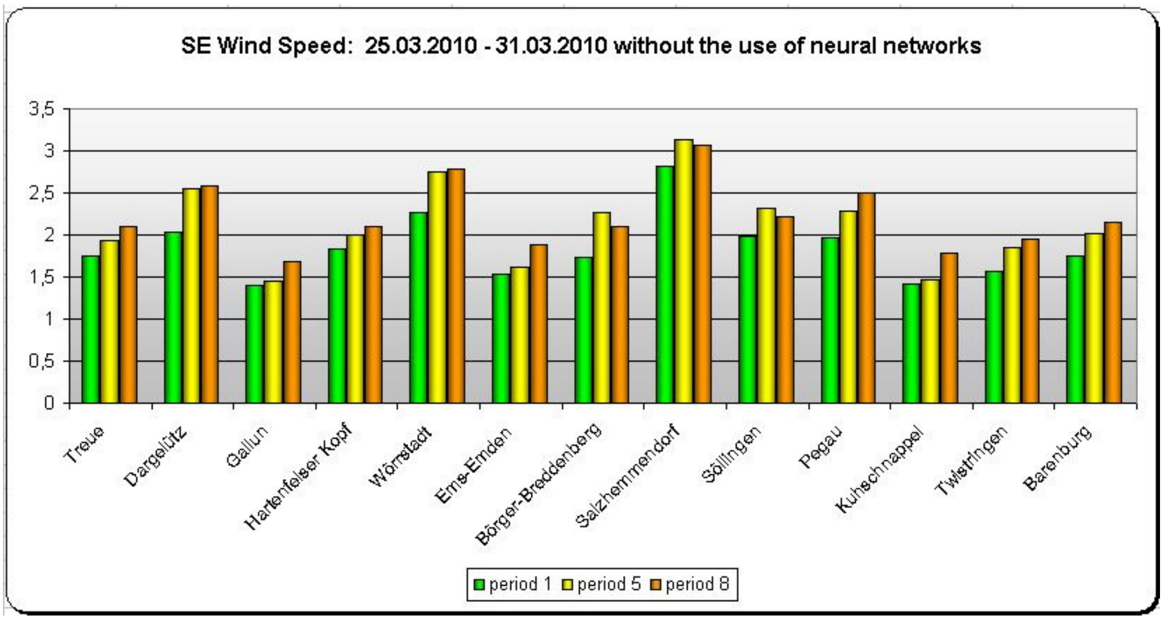


Image 8.2.7.1: SE values of the wind speed values (25.03.10 - 31.03.10) without the use of neural networks

The wind speed forecasts of the GMS MicroCast™ (6 km resolution) model show standard errors with values between **1.40** and **2.81** for period 1. The standard error generally increases towards values between **1.45** and **3.14** for period 5 and towards values between **1.68** and **3.07** for period 8.

8.2.8 SE of the wind speed values (01.03.10 – 31.03.10) using a 1 month trained neural network:

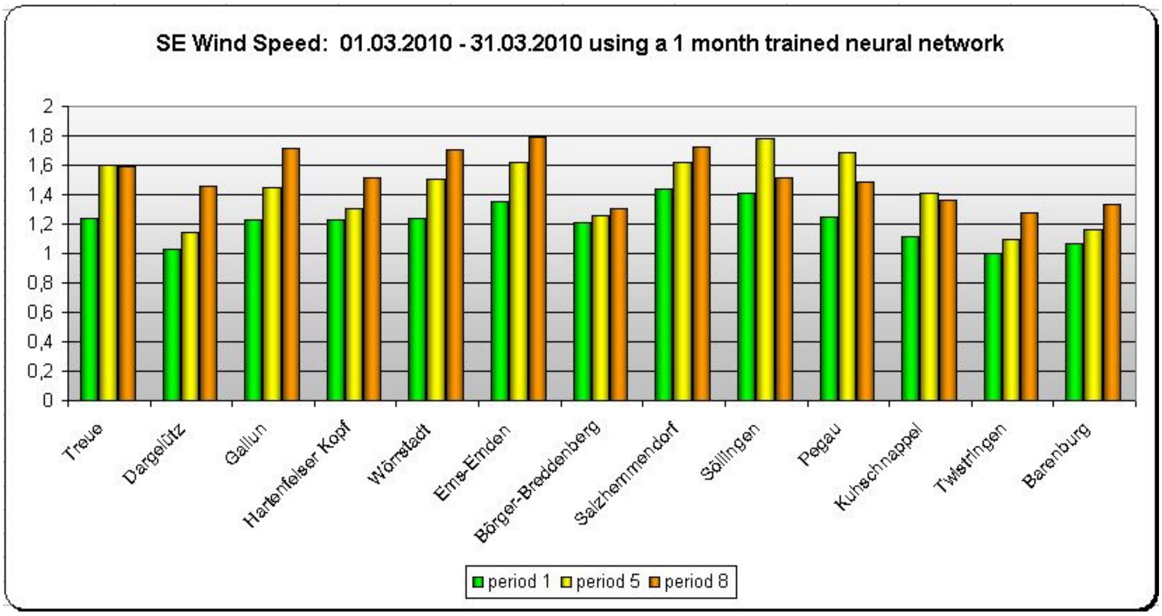


Image 8.2.8.1: SE values of the wind speed values (01.03.10 - 31.03.10) using a 1 month trained neural network

The wind speed forecasts computed with GMS SMART LEARNING show standard errors with values between **1.00** and **1.44** for period 1. The standard error generally increases towards values between **1.09** and **1.78** for period 5 and towards values between **1.28** and **1.79** for period 8.

8.2.9 SE of the wind speed values (01.03.10 – 31.03.10) using a 2 months trained neural network:

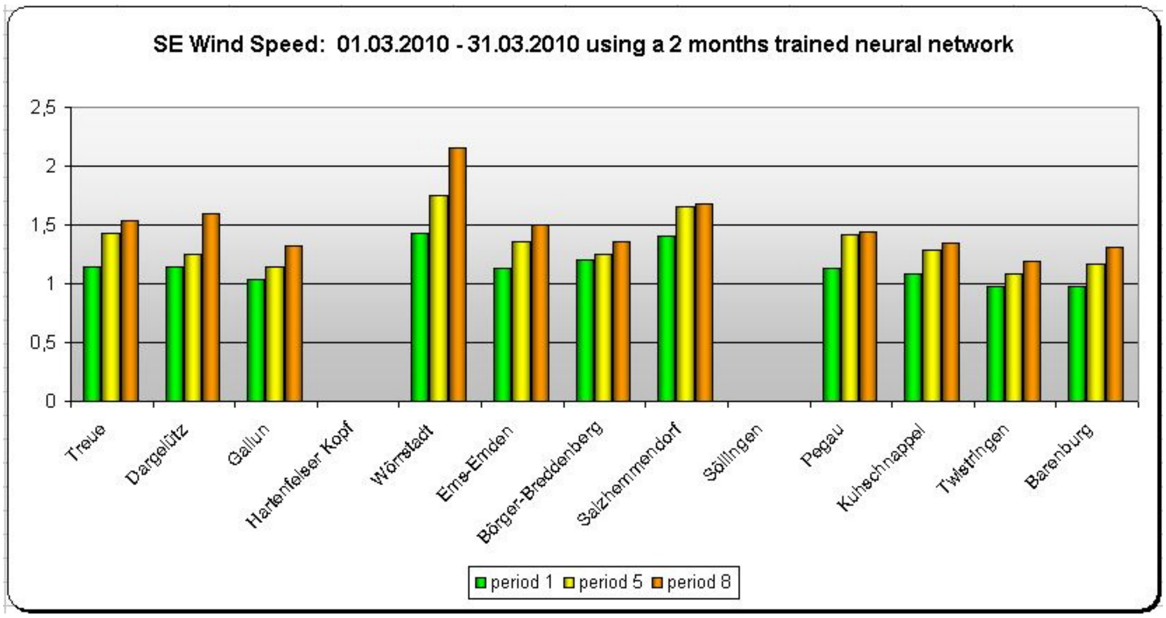


Image 8.2.9.1: SE values of the wind speed values (01.03.10 - 31.03.10) using a 2 months trained neural network. The implementation of a 2 months trained neural network for the wind farms Hartenfelser Kopf and Söllingen was not possible due to missing or unusable data of January.

The wind speed forecasts computed with GMS SMART LEARNING show standard errors with values between **0.97** and **1.43** for period 1. The standard error uniquely increases towards values between **1.09** and **1.75** for period 5 and towards values between **1.19** and **2.15** for period 8.

8.2.10 SE of the wind speed values (25.03.10 – 31.03.10) using a 2,75 months trained neural network:

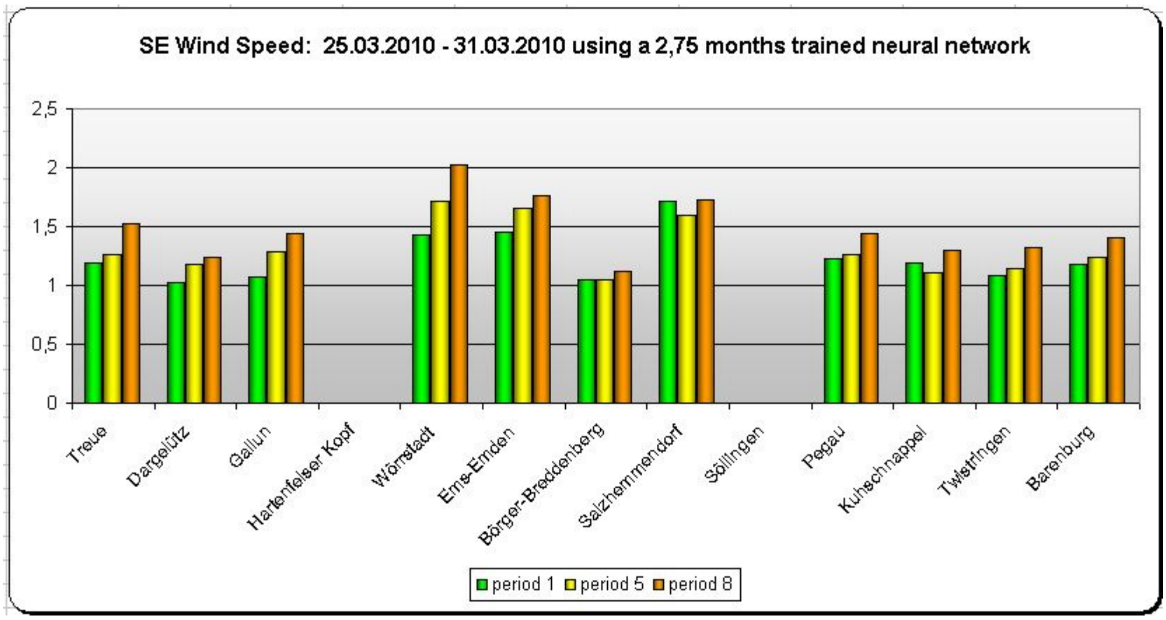


Image 8.2.10.1: SE values of the wind speed values (25.03.10 - 31.03.10) using a 2,75 months trained neural network. The implementation of a 2,75 months trained neural network for the wind farms Hartenfelser Kopf and Söllingen was not possible due to missing or unusable data of January.

The wind speed forecasts computed with GMS SMART LEARNING show standard errors with values between **1.03** and **1.72** for period 1. The standard error generally increases towards values between **1.04** and **1.71** for period 5 and towards values between **1.12** and **2.02** for period 8.

8.3 Implementation of GMS SMART LEARNING to improve the accuracy of the energy yield forecasts (as obtained with the GMS FARM YIELD PREDICTOR)

8.3.1 r^2 of the wind energy yield values (01.03.10 – 31.03.10) without the use of a neural network:

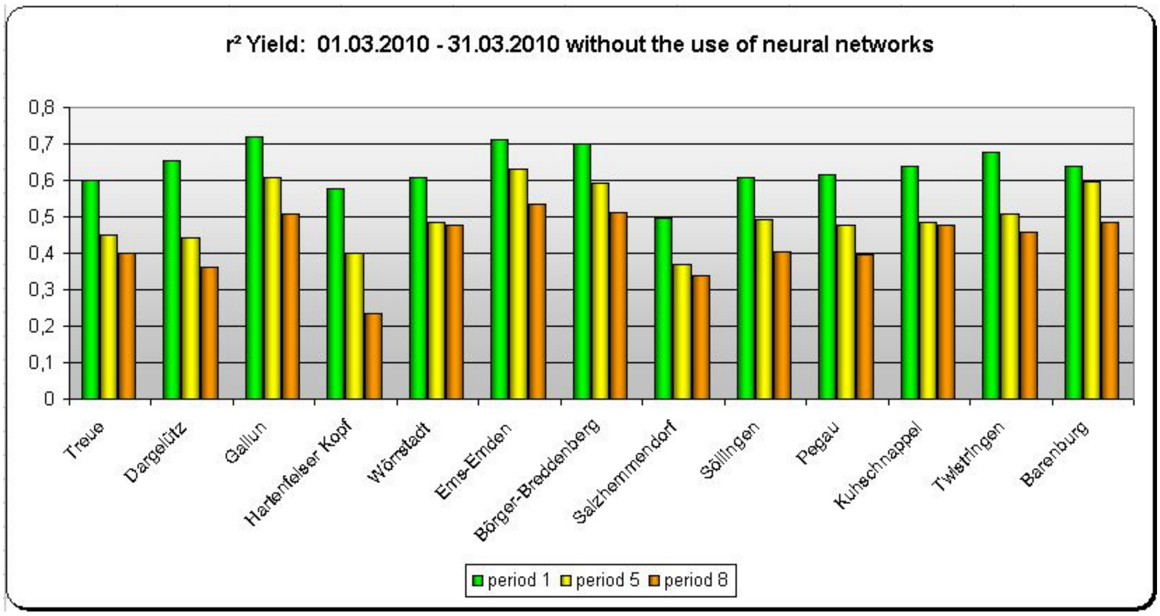


Image 8.3.1.1: r² values of the wind energy yield values (01.03.10 - 31.03.10) without the use of neural networks

The wind energy yield forecasts based on the implementation of the GMS FARM YIELD PREDICTOR show r^2 values between **0.72** and **0.49** for period 1. r^2 values uniquely drop towards values between **0.63** and **0.37** for period 5 and towards values between **0.54** and **0.23** for period 8.

8.3.2 r^2 of the wind energy yield values (25.03.10 – 31.03.10) <u>without</u> the use of a neural network:

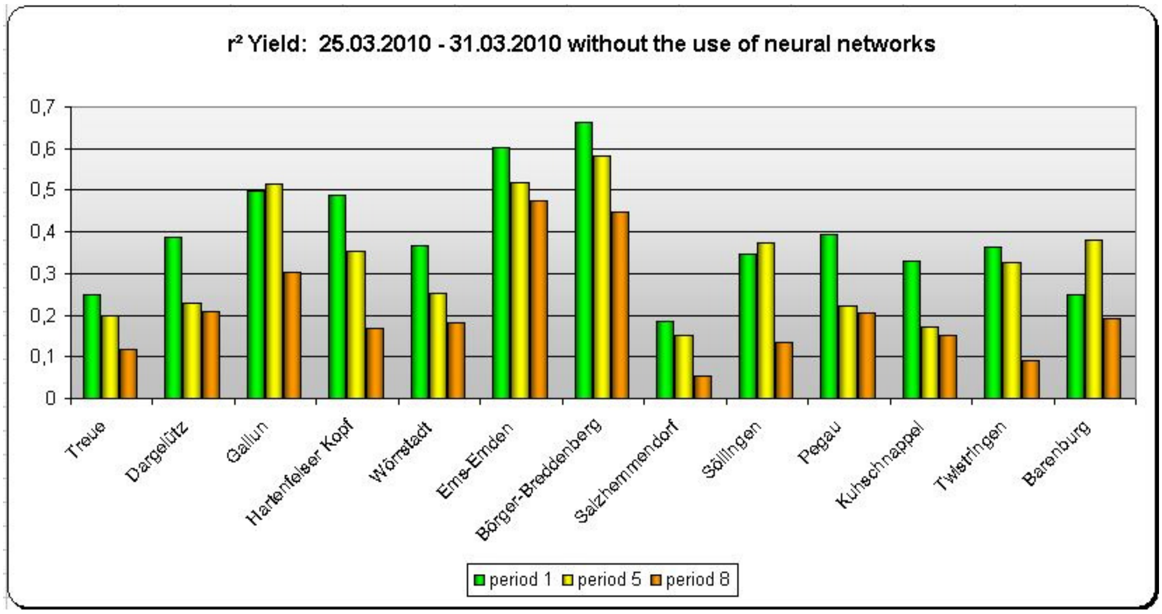


Image 8.3.2.1: r² values of the wind energy yield values (25.03.10 - 31.03.10) without the use of neural networks

The wind energy yield forecasts based on the implementation of the GMS FARM YIELD PREDICTOR show r^2 values between **0.66** and **0.19** for period 1. r^2 values generally drop towards values between **0.58** and **0.15** for period 5 and towards values between **0.47** and **0.05** for period 8.

8.3.3 r^2 of the wind energy yield values (01.03.10 – 31.03.10) using a 1 month trained neural network:

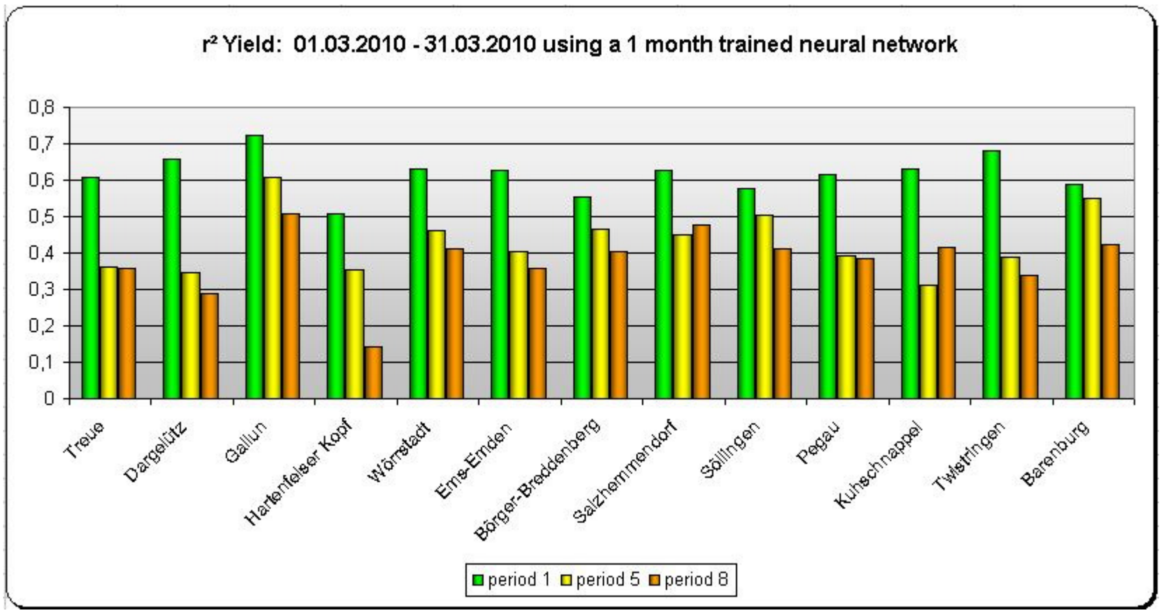


Image 8.3.3.1: r² values of the wind energy yield values (01.03.10 -31.03.10) using a 1 month trained neural network

The wind energy yield forecasts computed with GMS SMART LEARNING show r^2 values between **0.72** and **0.51** for period 1. r^2 values generally drop towards values between **0.61** and **0.31** for period 5 and towards values between **0.51** and **0.14** for period 8.

8.3.4 r^2 of the wind energy yield values (01.03.10 – 31.03.10) using a <u>2 months</u> trained neural network:

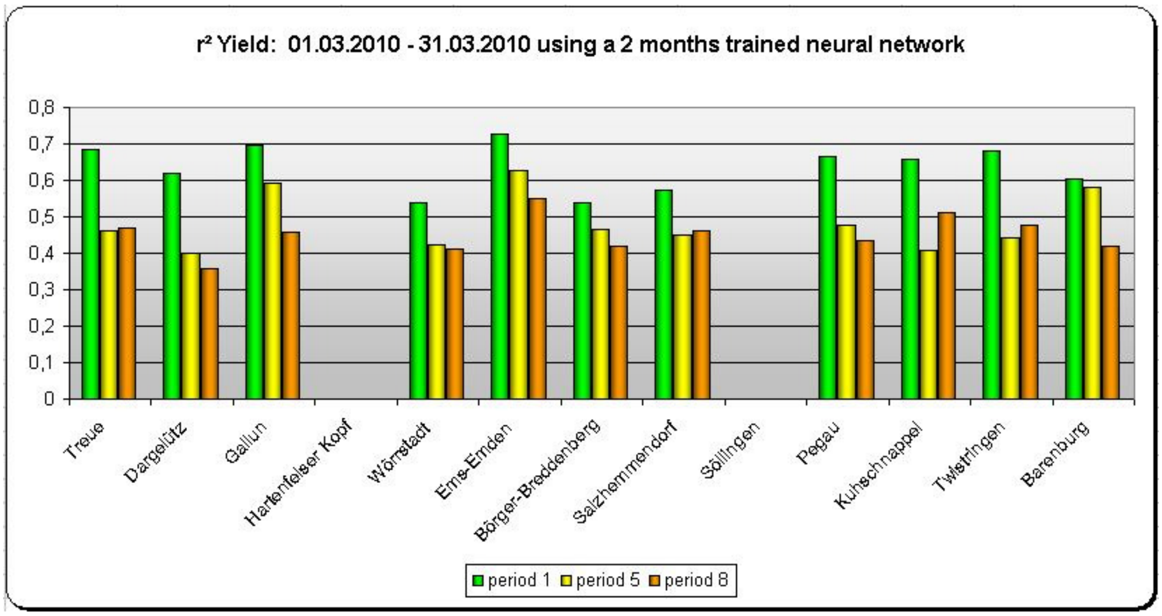


Image 8.3.4.1: r^2 values of the wind energy yield values (01.03.10 -31.03.10) using a 2 months trained neural network. The implementation of a 2 months trained neural network for the wind farms Hartenfelser Kopf and Söllingen was not possible due to missing or unusable data of January

The wind energy yield forecasts computed with GMS SMART LEARNING show r^2 values between **0.73** and **0.54** for period 1. r^2 values generally drop towards values between **0.63** and **0.40** for period 5 and towards values between **0.55** and **0.36** for period 8.

8.3.5 r^2 of the wind energy yield values (25.03.10 – 31.03.10) using a 2,75 months trained neural network:

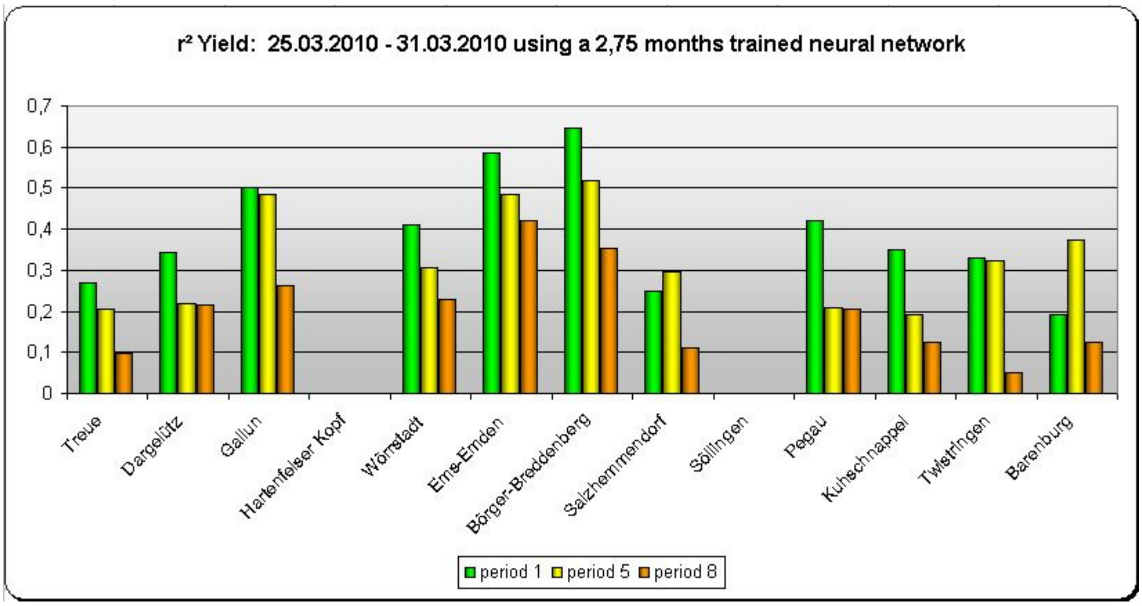


Image 8.3.5.1: r^2 values of the wind energy yield values (25.03.10 - 31.03.10) using a 2,75 months trained neural network. The implementation of a 2,75 months trained neural network for the wind farms Hartenfelser Kopf and Söllingen was not possible due to missing or unusable data of January

The wind energy yield forecasts computed with GMS SMART LEARNING show r^2 values between **0,65** and **0,19** for period 1. r^2 values generally drop towards values between **0,52** and **0,19** for period 5 and towards values between **0,42** and **0,05** for period 8.

8.3.6 RSE of the wind energy yield values (01.03.10 – 31.03.10) without the use of a neural network:

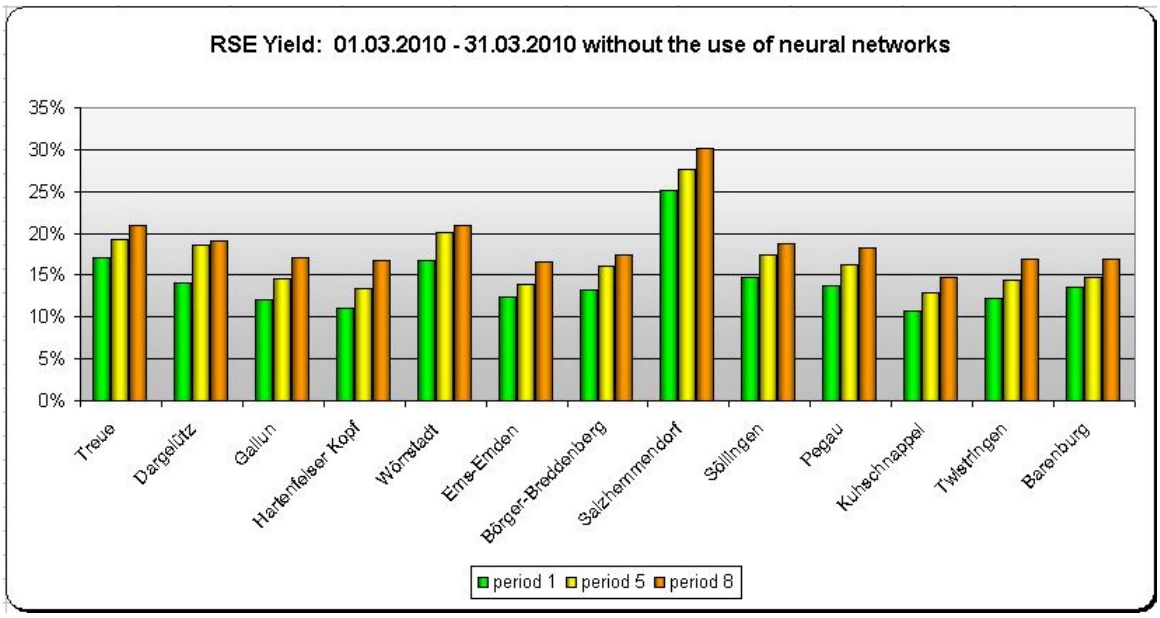


Image 8.3.6.1: RSE values of the wind energy yield values (01.03.10 - 31.03.10) without the use of neural networks

The wind energy yield forecasts based on the GMS MicroCast™ (6 km resolution) model show standard errors with values between **11%** and **25%** for period 1. The standard error uniquely increases towards values between **13%** and **28%** for period 5 and towards values between **15%** and **30%** for period 8.

8.3.7 RSE of the wind energy yield values (25.03.10 – 31.03.10) without the use of a neural network:

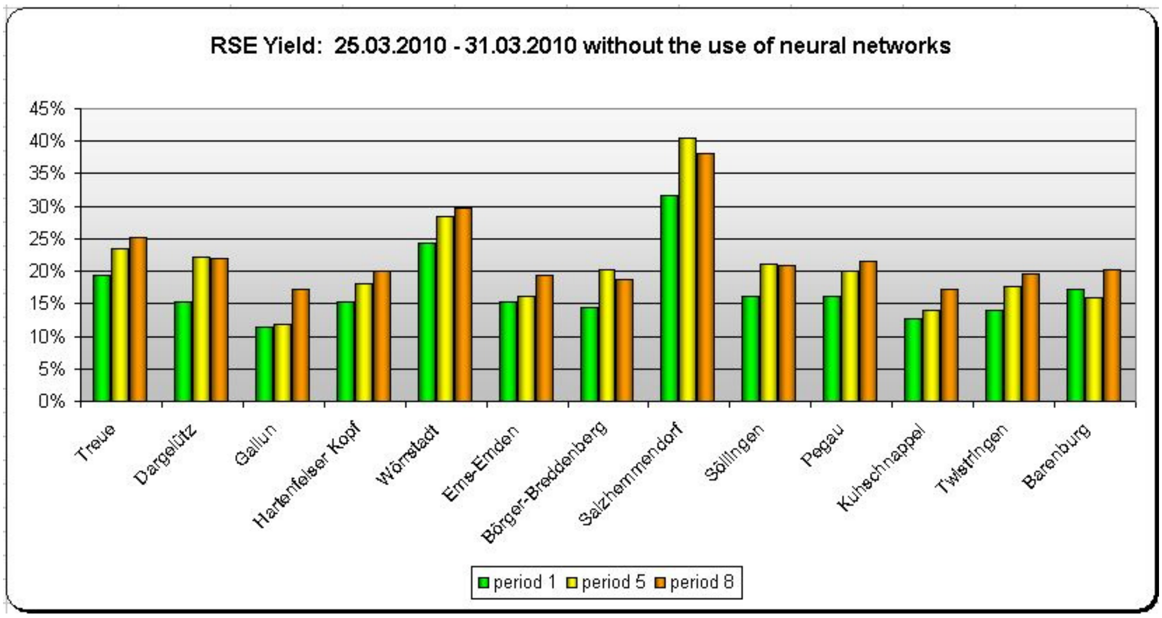


Image 8.3.7.1: RSE values of the wind energy yield values (25.03.10 - 31.03.10) without the use of neural networks

The wind energy yield forecasts based on the GMS MicroCast™ (6 km resolution) model show standard errors with values between **12%** and **32%** for period 1. The standard error generally increases towards values between **12%** and **40%** for period 5 and towards values between **17%** and **38%** for period 8.

8.3.8 RSE of the wind energy yield values (01.03.10 – 31.03.10) using a 1 month trained neural network:

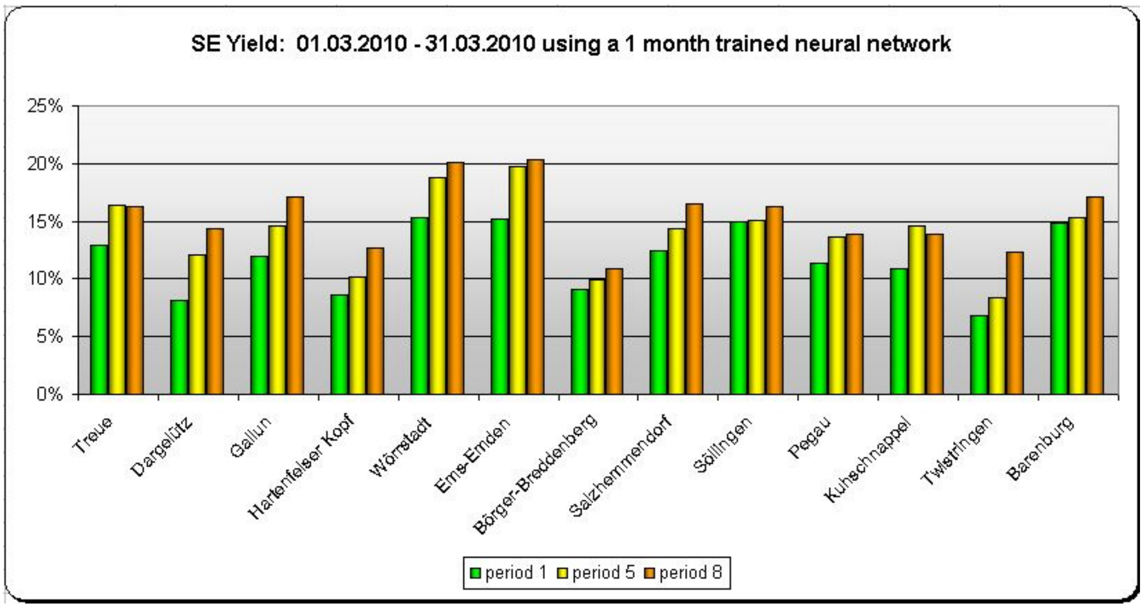


Image 8.3.8.1: RSE values of the wind energy yield values (01.03.10 -31.03.10 using a 1 month trained neural network

The wind energy yield forecasts computed with GMS SMART LEARNING show relative standard errors with values between **7%** and **15%** for period 1. Relative standard errors generally increase towards values between **8%** and **20%** for period 5 and towards values between **11%** and **20%** for period 8.

8.3.9 RSE of the wind energy yield values (01.03.10 – 31.03.10) using a 2 months trained neural network:

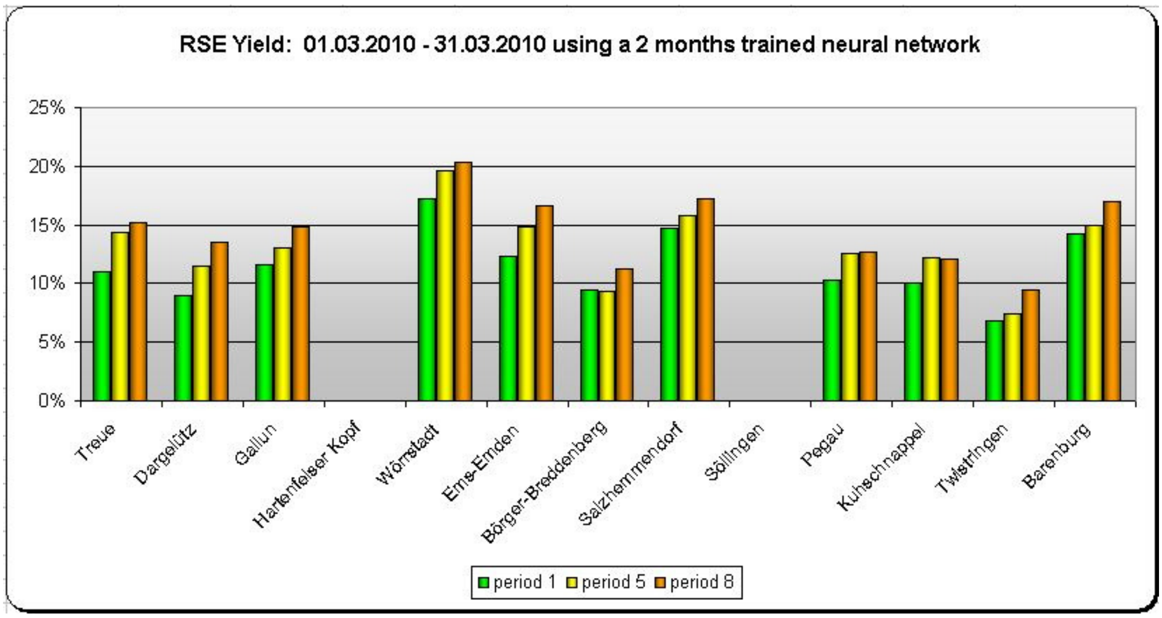


Image 8.3.9.1: RSE values of the wind energy yield values (01.03.10 - 31.03.10) using a 2 months trained neural network. The implementation of a 2 months trained neural network for the wind farms Hartenfelser Kopf and Söllingen was not possible due to missing or unusable data of January

The wind energy yield forecasts computed with GMS SMART LEARNING show relative standard errors with values between **7%** and **17%** for period 1. Relative standard errors generally increase towards values between **7%** and **20%** for period 5 and towards values between **9%** and **20%** for period 8.

8.3.10 RSE of the wind energy yield values (25.03.10 – 31.03.10) using a 2,75 months trained neural network:

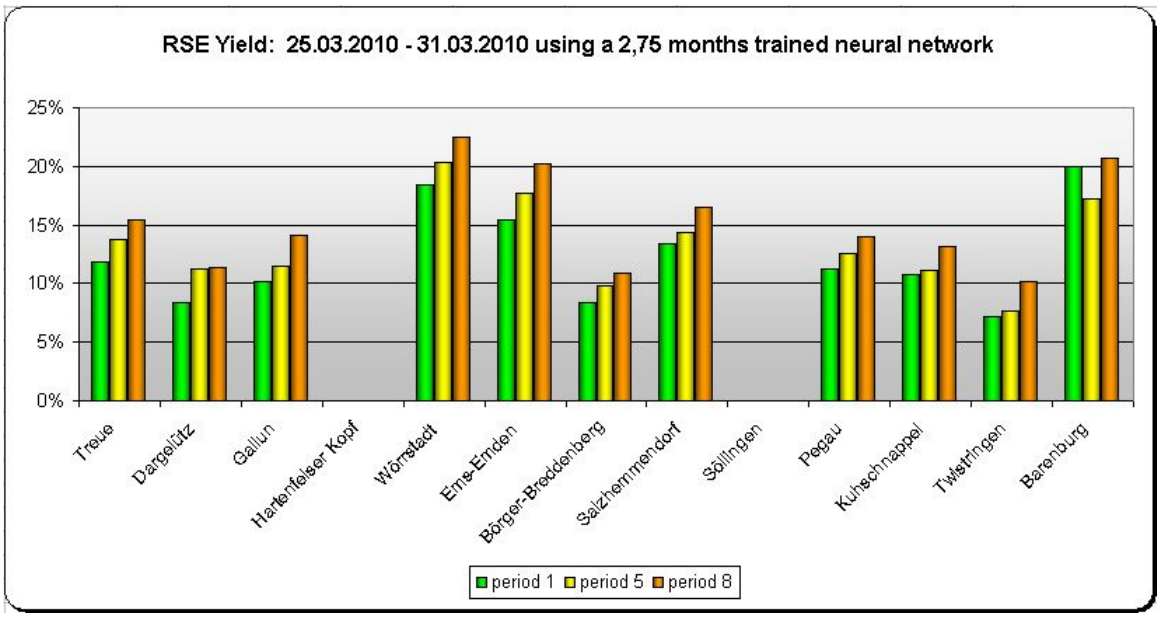


Image 8.3.10.1: RSE values of the wind energy yield values (25.03.10 - 31.03.10) using a 2,75 months trained neural network. The implementation of a 2,75 months trained neural network for the wind farms Hartenfelser Kopf and Söllingen was not possible due to missing or unusable data of January

The wind energy yield forecasts computed with GMS SMART LEARNING show relative standard errors with values between **7%** and **20%** for period 1. Relative standard errors generally increase towards values between **8%** and **20%** for period 5 and towards values between **10%** and **22%** for period 8.

8.3.11 Application of GMS SMART LEARNING with different training time frames at the Twistringen site

As described before, for the Twistringen site, data for almost the whole month of December was available. Therefore, GMS SMART LEARNING could be evaluated with one additional month of training data beside the standard evaluation.

8.3.11.1 r^2 values of the wind speed forecasts (05.03.10 – 31.03.10):

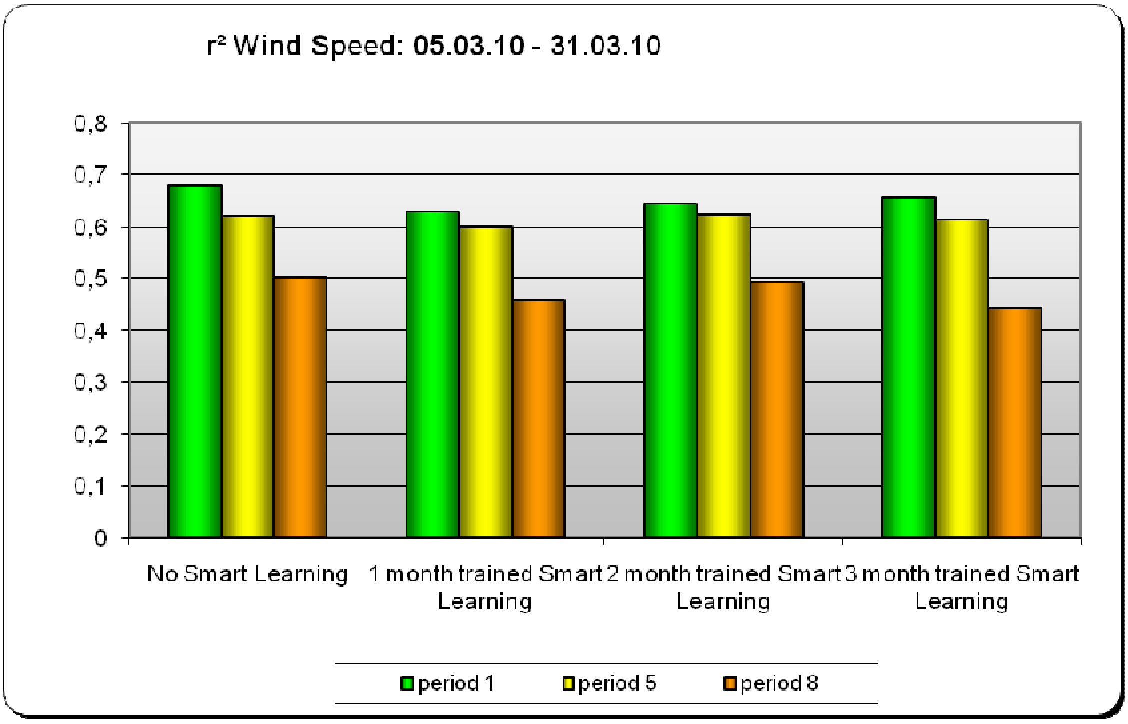


Image 8.3.11.1: r² values of the wind speed forecasts of wind farm Twistringen for the time frame 05.03.10 – 31.03.10

The original wind speed forecasts of the GMS MicroCast™ model with 6 km resolution and without the implementation of any GMS forecast enhancement method show r^2 values of **0.68**, **0.62** and **0.50** for the periods 1, 5 and 8 respectively.

These values decrease with the use of a 1 month trained neural network by 7.4% to a value of **0.63**, by 3.2% to a value of **0.60** and by 8.0% to a value of **0.46** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS MicroCast™ forecasts with the forecasts using a 2 month trained neural network shows a decrease of r^2 by 5.9% to a value of **0.64** for period 1, no change for period 5 and a decrease of r^2 by 2.0% to a value of **0.49** for period 8.

The comparison of the original GMS MicroCast™ forecasts with the forecasts using a 3 month trained neural network shows a decrease of r^2 by 2.9% to a value of **0.66**, by 1.6% to a value of **0.61** and by 12.0% to a value of **0.44** for the periods 1, 5 and 8 respectively.

8.3.11.2 r^2 values of the wind energy yield forecasts (05.03.10 – 31.03.10):

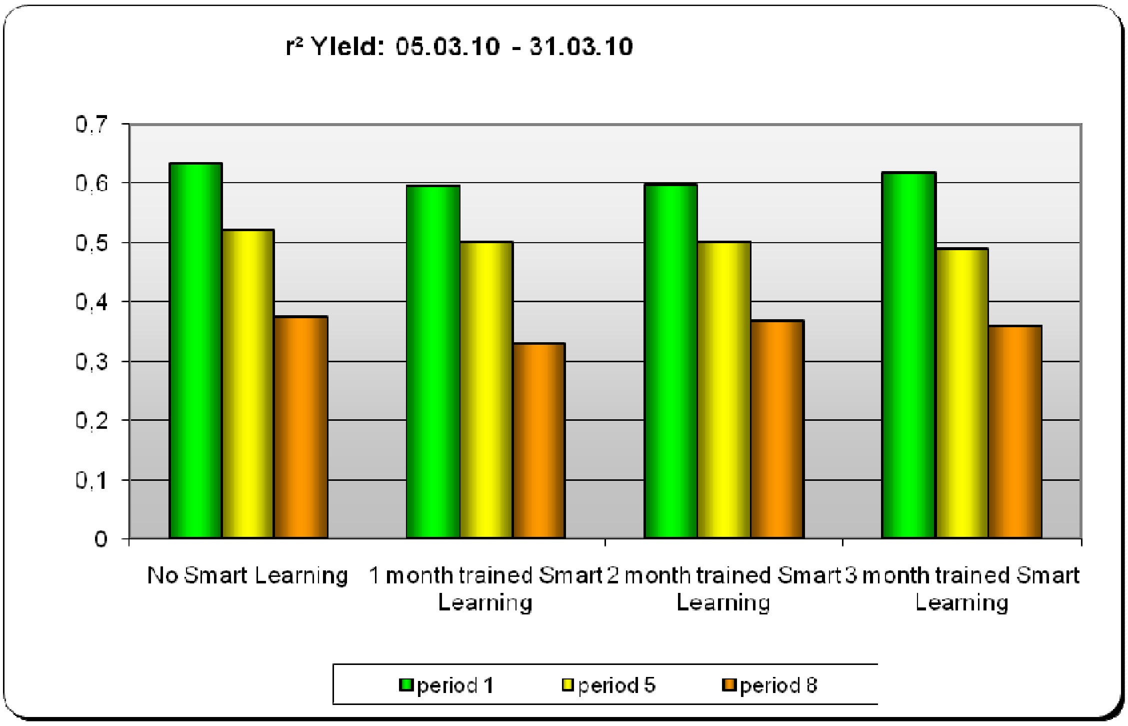


Image 8.3.11.2: r^2 values of the wind energy yield forecasts of wind farm Twistringen for the time frame 05.03.10 – 31.03.10

The original wind energy yield forecasts of the GMS FARM YIELD PREDICTOR (applied on the GMS MicroCast™ model with 6 km resolution) without the implementation of any GMS forecast enhancement method show r^2 values of **0.63**, **0.52** and **0.37** for the periods 1, 5 and 8 respectively.

These values decrease with the use of a 1 month trained neural network by 4.8% to a value of **0.60**, by 3.8% to a value of **0.50** and by 10.8% to a value of **0.33** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS FARM YIELD PREDICTOR forecasts with the forecasts using a 2 month trained neural network shows again a decrease of r^2 by 4.8% to a value of **0.60** and by 3.8% to a value of **0.50** for the periods 1and 5. Period 8 shows no change to the original forecasts.

The comparison of the original GMS FARM YIELD PREDICTOR forecasts with the forecasts using a 3 month trained neural network shows a decrease of r^2 by 1.6% to a value of **0.62**, by 3.8% to a value of **0.49** and by 2.7% to a value of **0.36** for the periods 1, 5 and 8 respectively.

8.3.11.3 SE values of the wind speed forecasts (05.03.10 – 31.03.10):

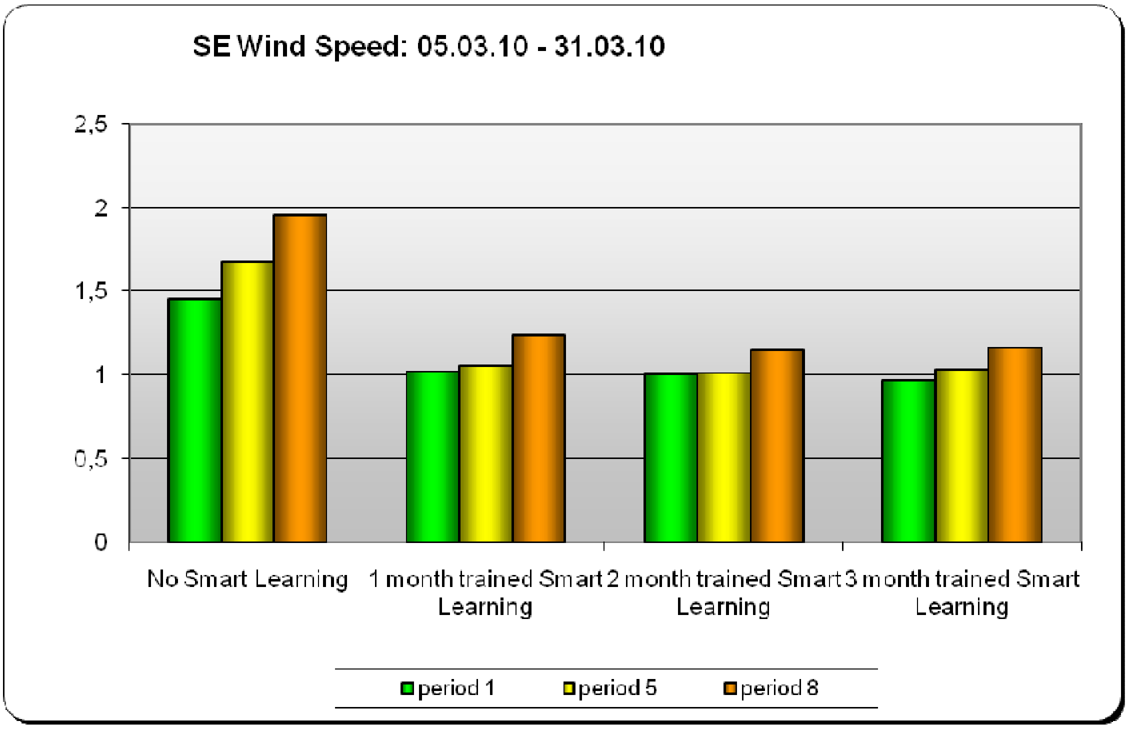


Image 8.3.11.3: SE values of the wind speed forecasts of wind farm Twistringen for the time frame 05.03.10 – 31.03.10

The original wind speed forecasts of the GMS MicroCast™ model with 6 km resolution and without the implementation of any GMS forecast enhancement method show SE values of **1.45**, **1.68** and **1.95 m/s** for the periods 1, 5 and 8 respectively.

These values improve with the use of a 1 month trained neural network by 29.7% to a value of **1.02 m/s**, by 37.5% to a value of **1.05 m/s** and by 36.4% to a value of **1.24 m/s** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS MicroCast™ forecasts with the forecasts using a 2 month trained neural network shows an improvement of SE by 31.0% to a value of **1.00 m/s**, by 39.9% to a value of **1.01 m/s** and by 41.0% to a value of **1.15 m/s** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS MicroCast™ forecasts with the forecasts using a 3 month trained neural network shows an improvement of SE by 33.1% to a value of **0.97 m/s**, by 38.7% to a value of **1.03 m/s** and by 40.0% to a value of **1.17 m/s** for the periods 1, 5 and 8 respectively.

8.3.11.4 RSE values of the wind energy yield forecasts (05.03.10 – 31.03.10):

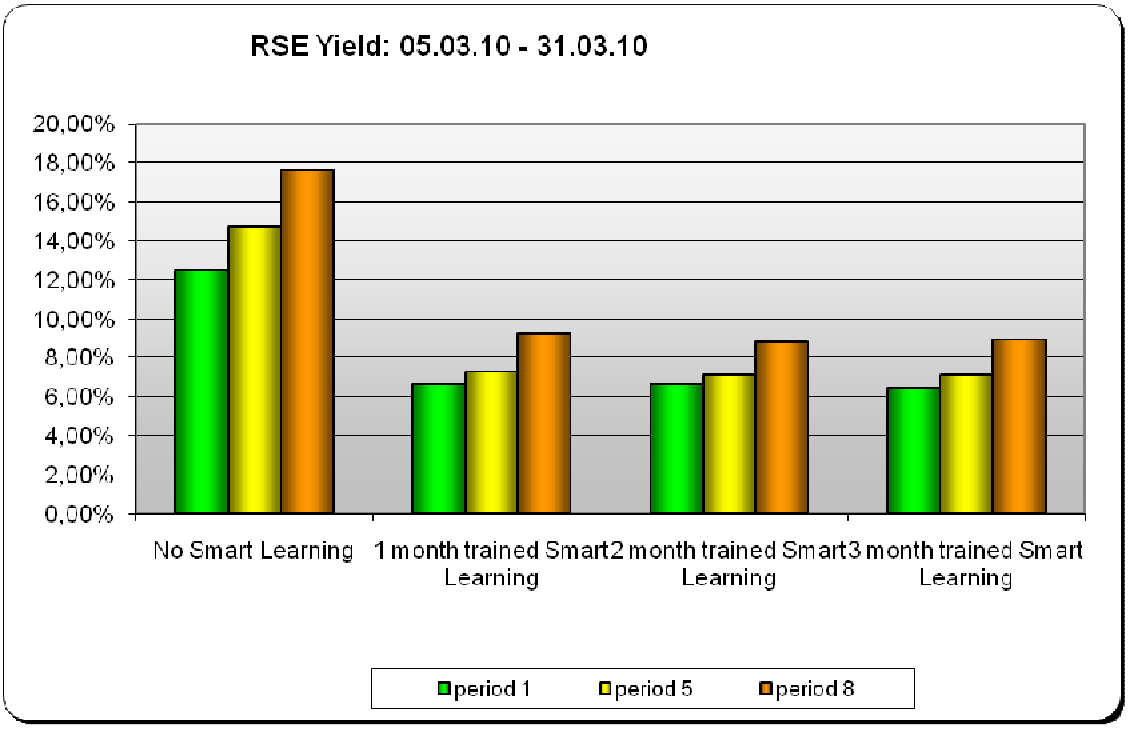


Image 8.3.11.4: RSE values of the wind energy yield forecasts of wind farm Twistringen for the time frame 05.03.10 – 31.03.10

The original wind energy yield forecasts of the GMS FARM YIELD PREDICTOR (applied on the GMS MicroCast™ model with 6 km resolution) without the implementation of any GMS forecast enhancement method show RSE values of **12.5%**, **14.7%** and **17.6%** for the periods 1, 5 and 8 respectively.

These values improve with the use of a 1 month trained neural network by 47.2% to a value of **6.6%**, by 50.3% to a value of **7.3%** and by 47.7% to a value of **9.2%** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS FARM YIELD PREDICTOR forecasts with the forecasts using a 2 month trained neural network shows a decrease of RSE by 46.4% to a value of **6.7%**, by 51.7% to a value of **7.1%** and by 49.4% to a value of **8.9%** for the periods 1, 5 and 8 respectively.

The comparison of the original GMS FARM YIELD PREDICTOR forecasts with the forecasts using a 3 month trained neural network shows an improvement of RSE by 48.0% to a value of **6.5%**, again by 51.7% to a value of **7.1%** and as well by 49.4% to a value of **8.9%** for the periods 1, 5 and 8 respectively.

8.3.11.5 Time series graphics Twistringen

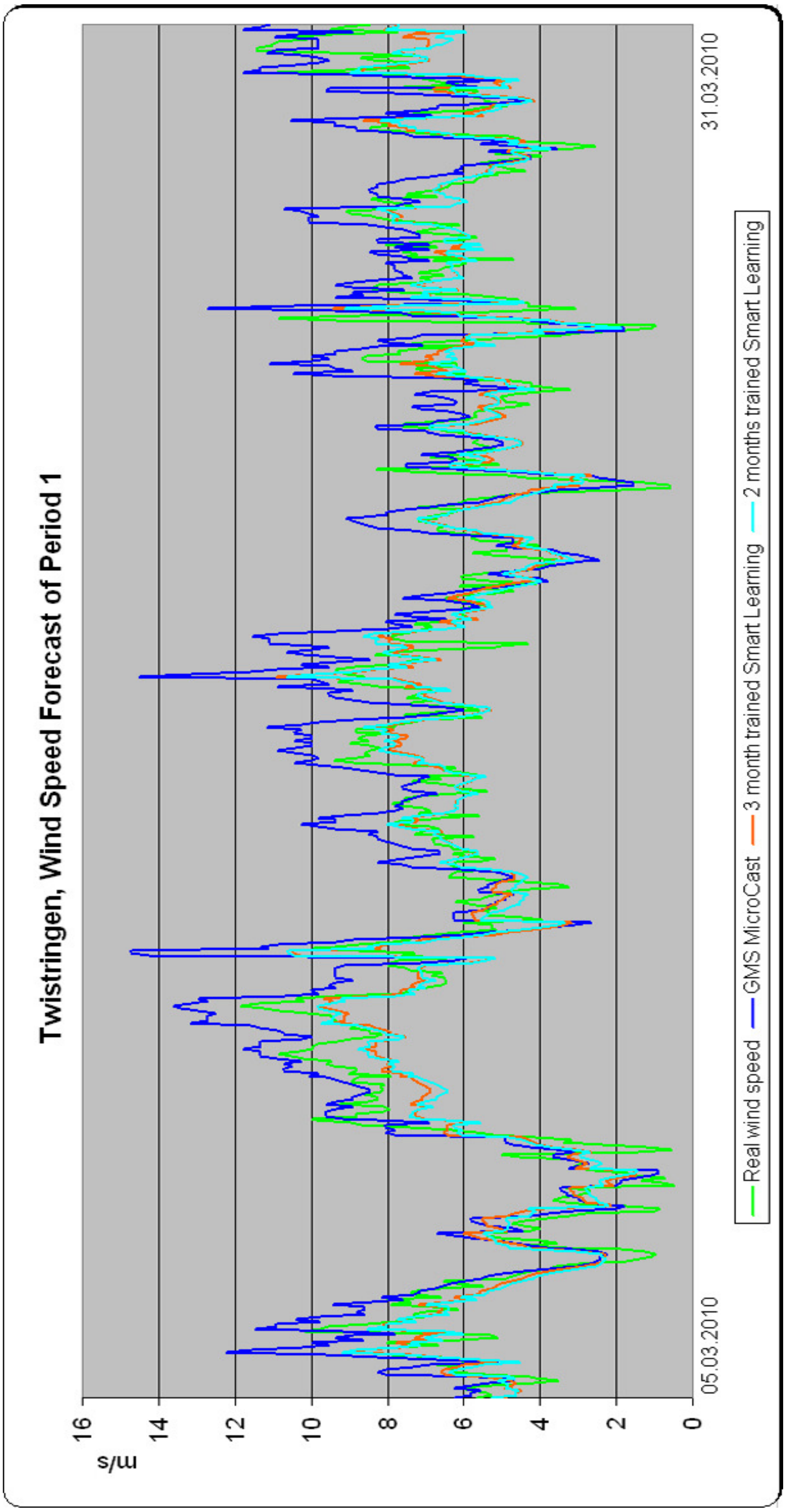


Image 8.3.11.5: Time course of the measured wind speed, of the GMS MicroCast™ wind speed forecasts and of the forecasts with 2 and 3 months trained neural networks of wind farm Twistringen for the time frame 05.03.10 – 31.03.10 and period 1.

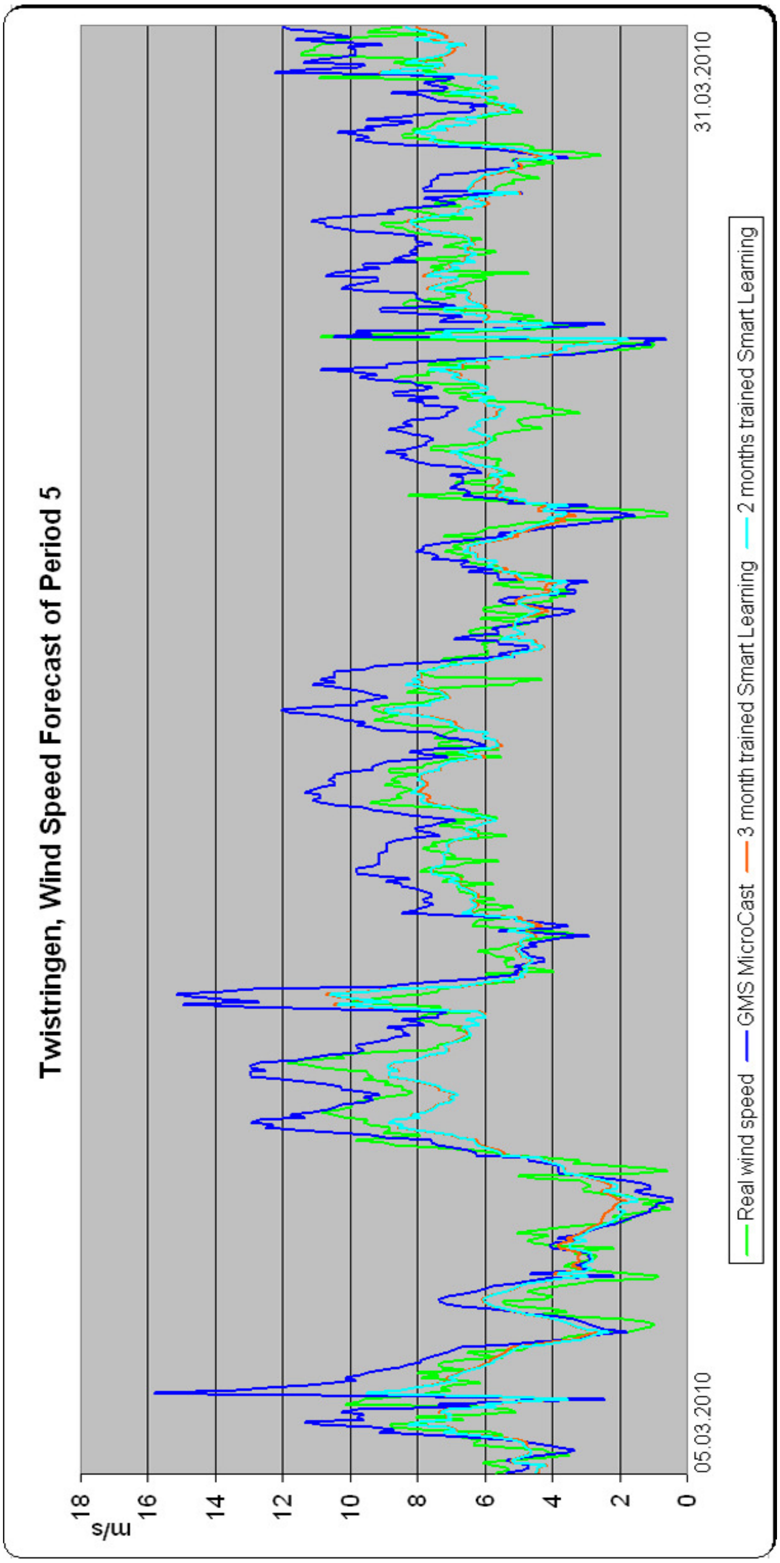


Image 8.3.11.6: Time course of the measured wind speed, of the GMS MicroCast™ wind speed forecasts and of the forecasts with 2 and 3 months trained neural networks of wind farm Twistringen for the time frame 05.03.10 – 31.03.10 and period 5.

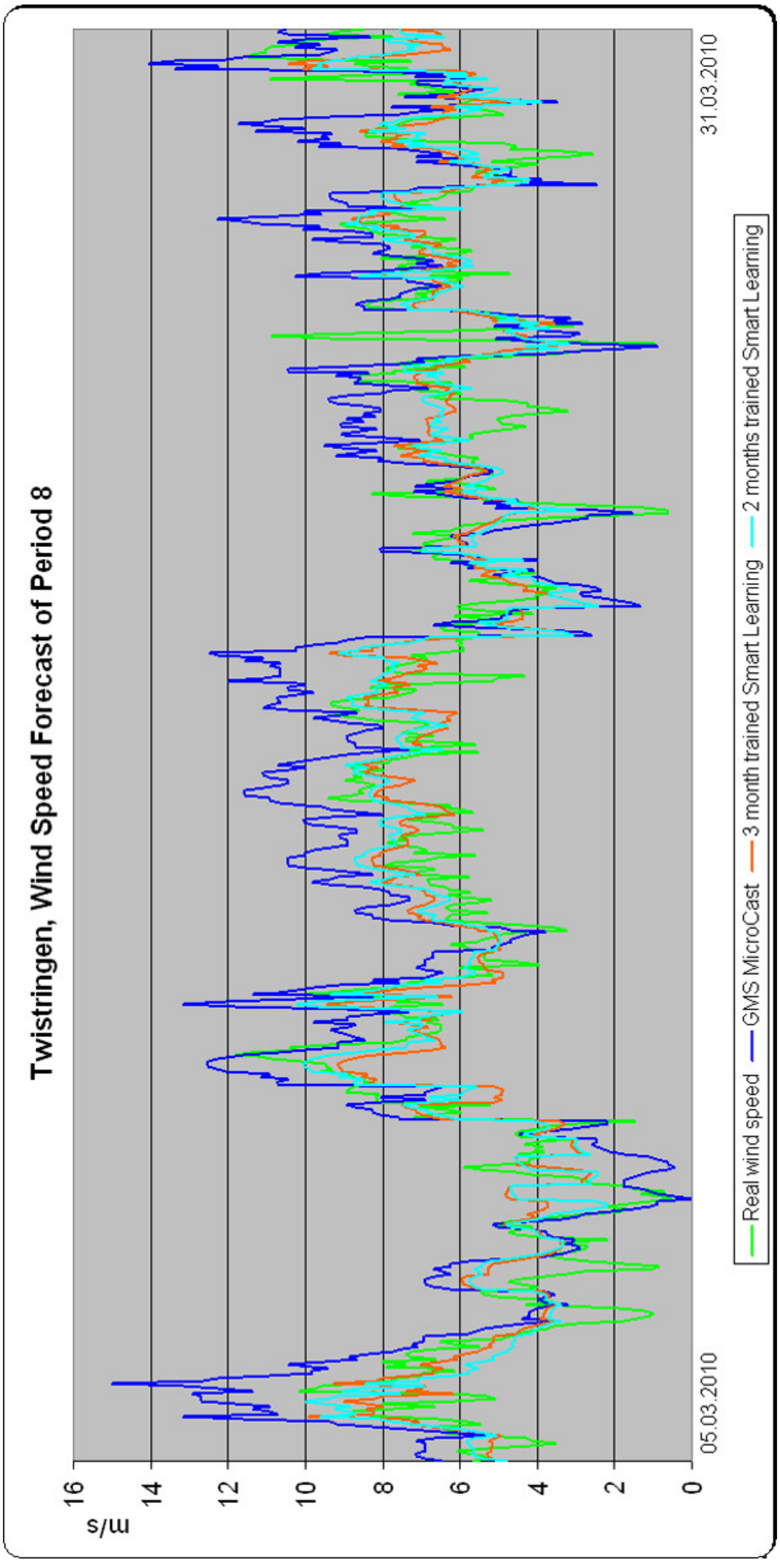


Image 8.3.11.7: Time course of the measured wind speed, of the GMS MicroCast™ wind speed forecasts and of the forecasts with 2 and 3 months trained neural networks of wind farm Twistringen for the time frame 05.03.10 – 31.03.10 and period 8.

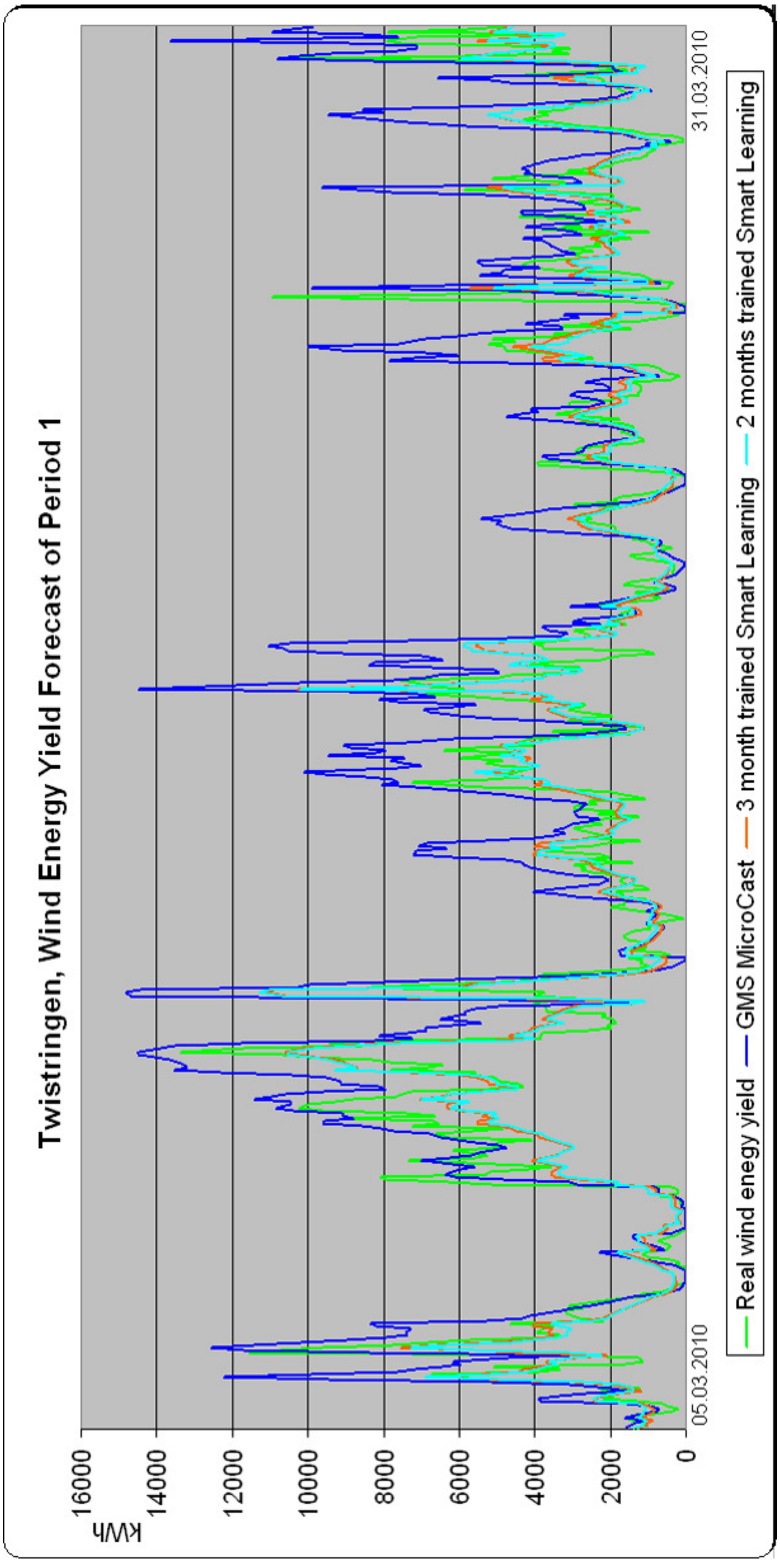


Image 8.3.11.8: Time course of the measured wind energy yield, of the GMS FARM YIELD PREDICTOR wind energy yield forecasts and of the forecasts with 2 and 3 months trained neural networks of wind farm Twistringen for the time frame 05.03.10 – 31.03.10 and period 1.

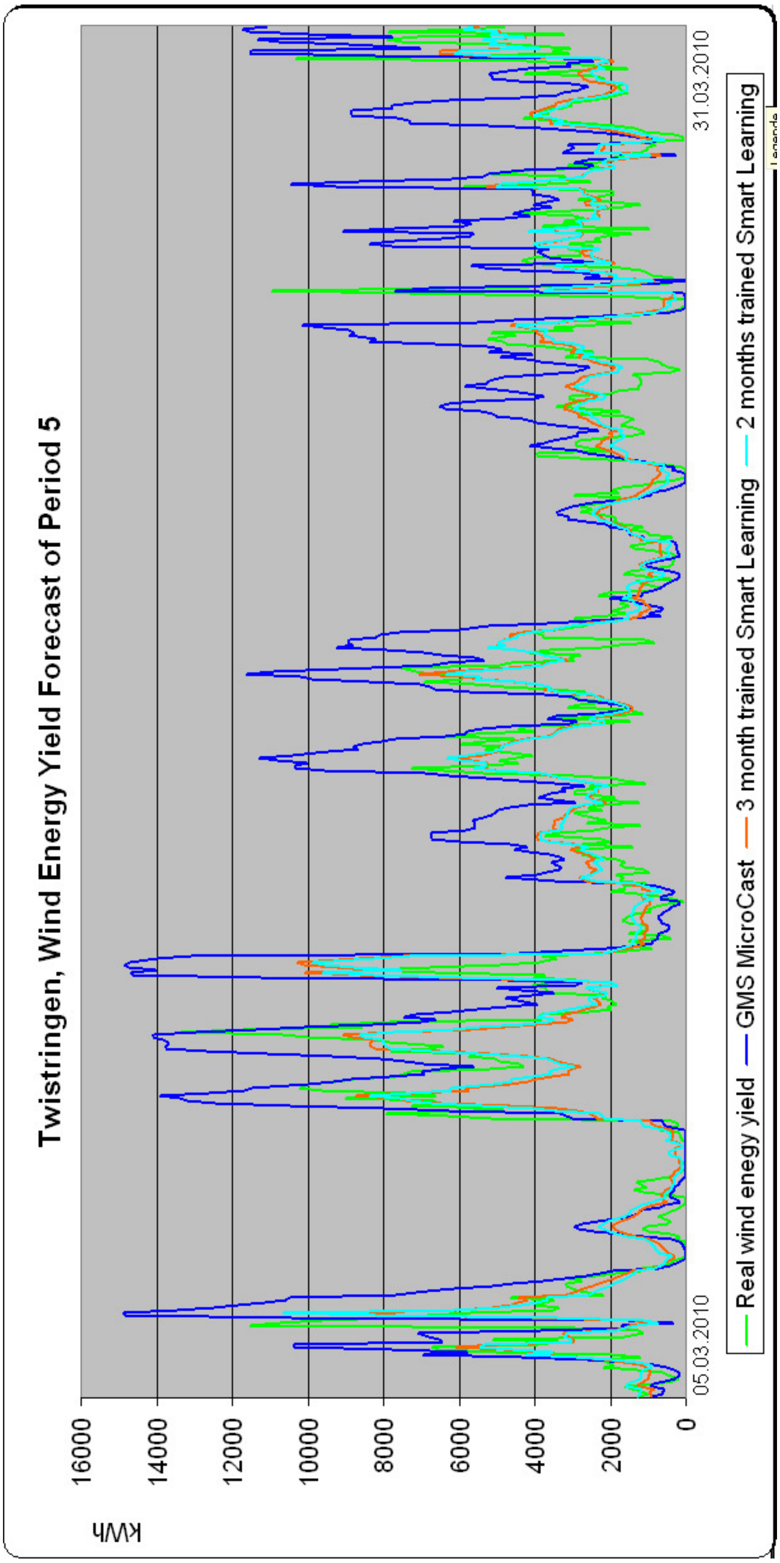


Image 8.3.11.9: Time course of the measured wind energy yield, of the GMS FARM YIELD PREDICTOR wind energy yield forecasts and of the forecasts with 2 and 3 months trained neural networks of wind farm Twistringen for the time frame 05.03.10 – 31.03.10 and period 5.

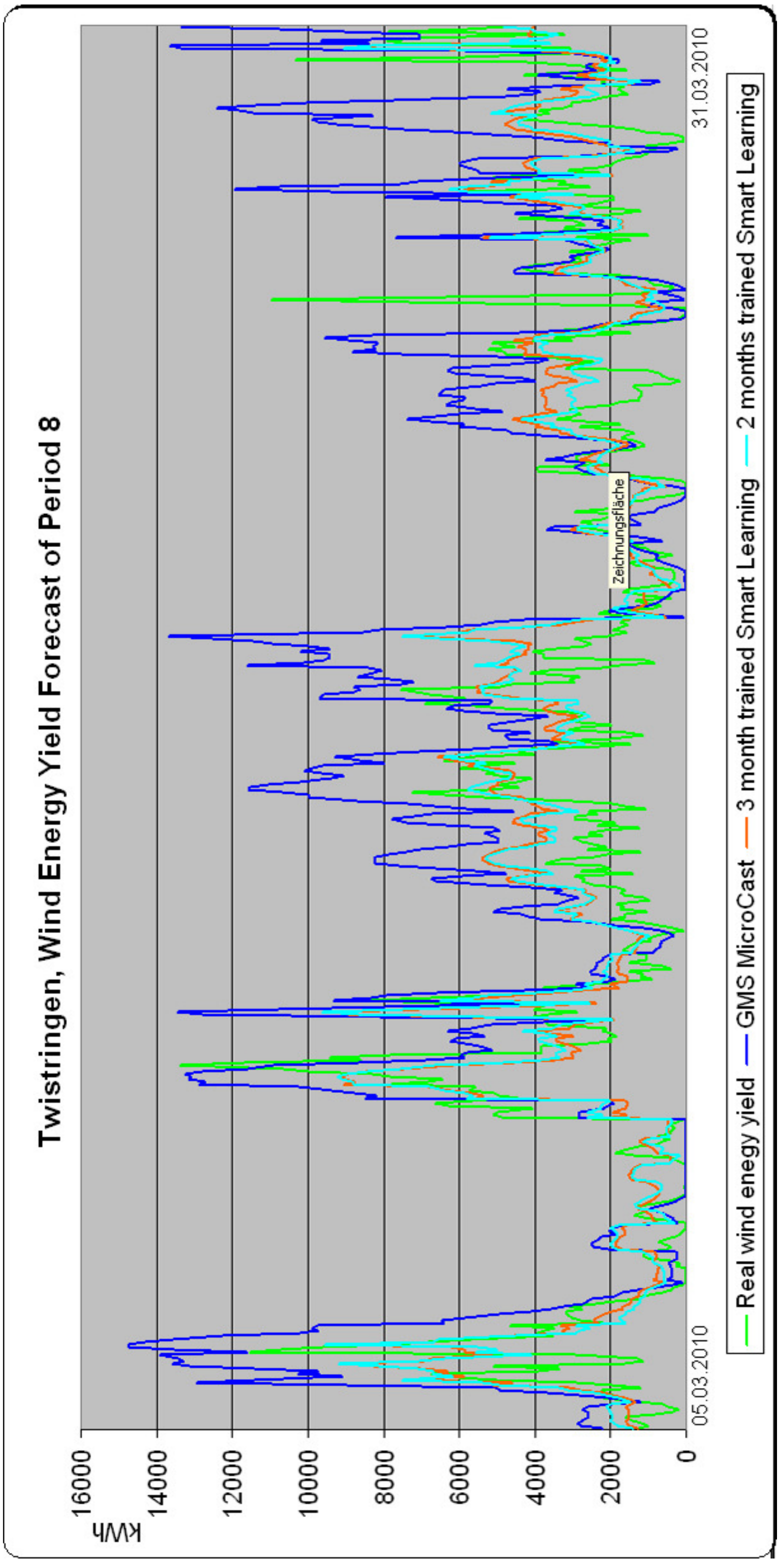


Image 8.3.11.10: Time course of the measured wind energy yield, of the GMS FARM YIELD PREDICTOR wind energy yield forecasts and of the forecasts with 2 and 3 months trained neural networks of wind farm Twistringen for the time frame 05.03.10 – 31.03.10 and period 8.

8.4 Implementation of GMS MICROCOUPLING to improve the accuracy of the GMS MicroCast™ (6 km resolution) wind speed forecasts for wind farm "Hartenfelser Kopf"

8.4.1 r^2 of the wind speed values for selected time frames implementing GMS MICROCOUPLING:

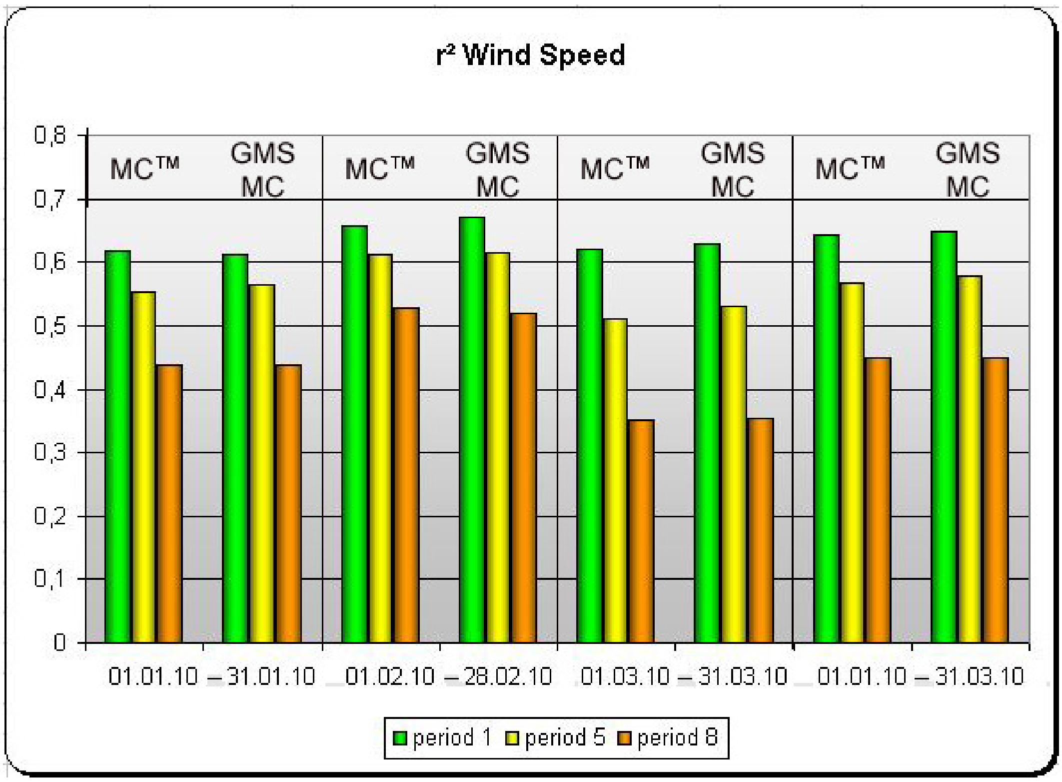


Image 8.4.1.1: r^2 of the wind speed values for selected time frames implementing GMS MICROCOUPLING (MC™ = Micro Cast™, GMS MC = GMS Microcoupling)

The implementation of GMS MICROCOUPLING shows little or no effect on the r^2 values of the wind speed forecasts. Deteriorations of r^2 by 1.6 – 4.5% and improvements of r^2 by 1.5 – 3.9% can be observed.

8.4.2 r^2 of the wind energy yield values for selected time frames implementing GMS MICROCOUPLING:

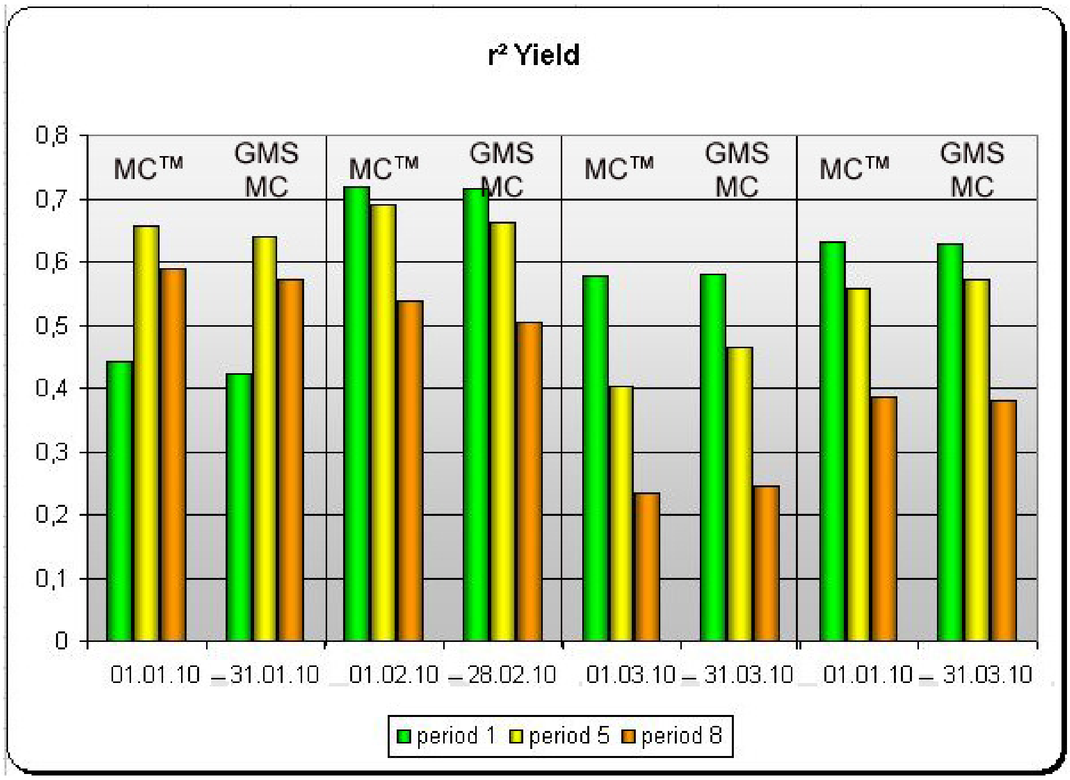


Image 8.4.2.1: r² of the wind energy yield values for selected time frames implementing GMS MICROCOUPLING (MC™ = Micro Cast™, GMS MC = GMS Microcoupling)

The implementation of GMS MICROCOUPLING shows little or no effect on the r^2 values of the wind energy yield forecasts. Deteriorations of r^2 by 3.0 – 7.4% and improvements of r^2 by 1.8 – 4.3% (with the exception of period 5 of the time frame 01.03.10 – 31.3010 which shows an improvement of 17.5%) can be observed.

8.4.3 SE of the wind speed values for selected time frame implementing GMS MICROCOUPLING:

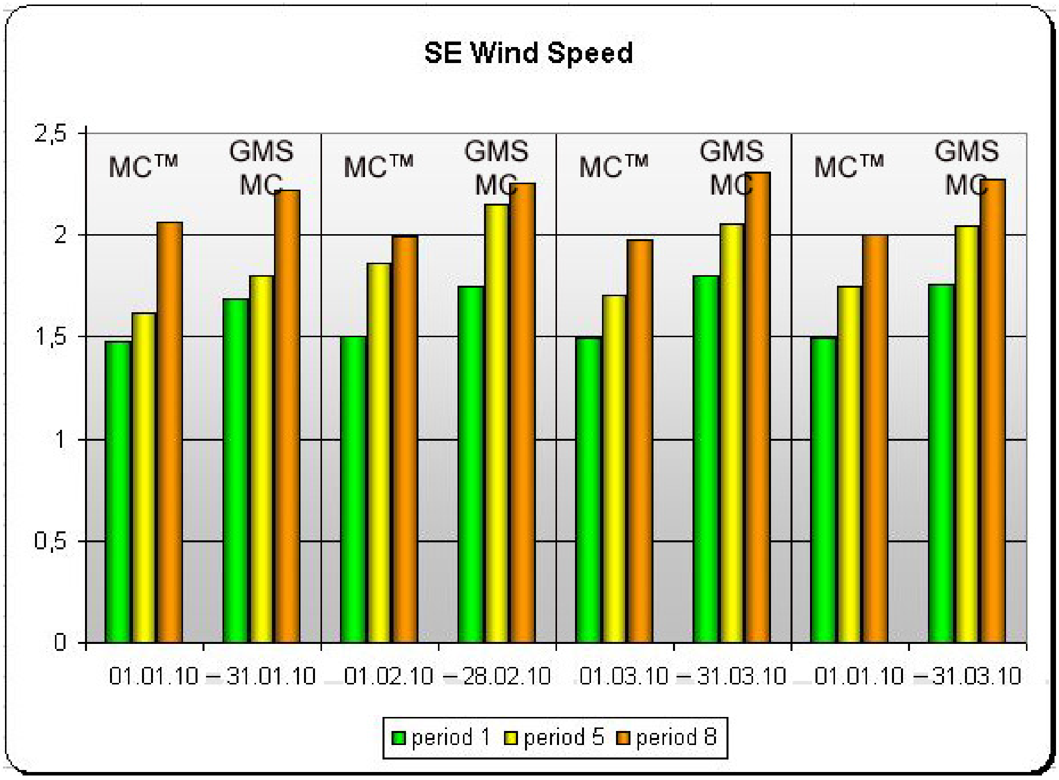


Image 8.4.3.1: SE of the wind speed values for selected time frame implementing GMS MICROCOUPLING (MC™ = Micro Cast™, GMS MC = GMS Microcoupling)

The implementation of GMS MICROCOUPLING results in clear deteriorations of the SE values of the GMS MicroCast™ forecasts by 7.8 – 20.0% for all selected time frames and periods.

8.4.4 RSE of the wind energy yield values for selected time frames implementing GMS MICROCOUPLING:

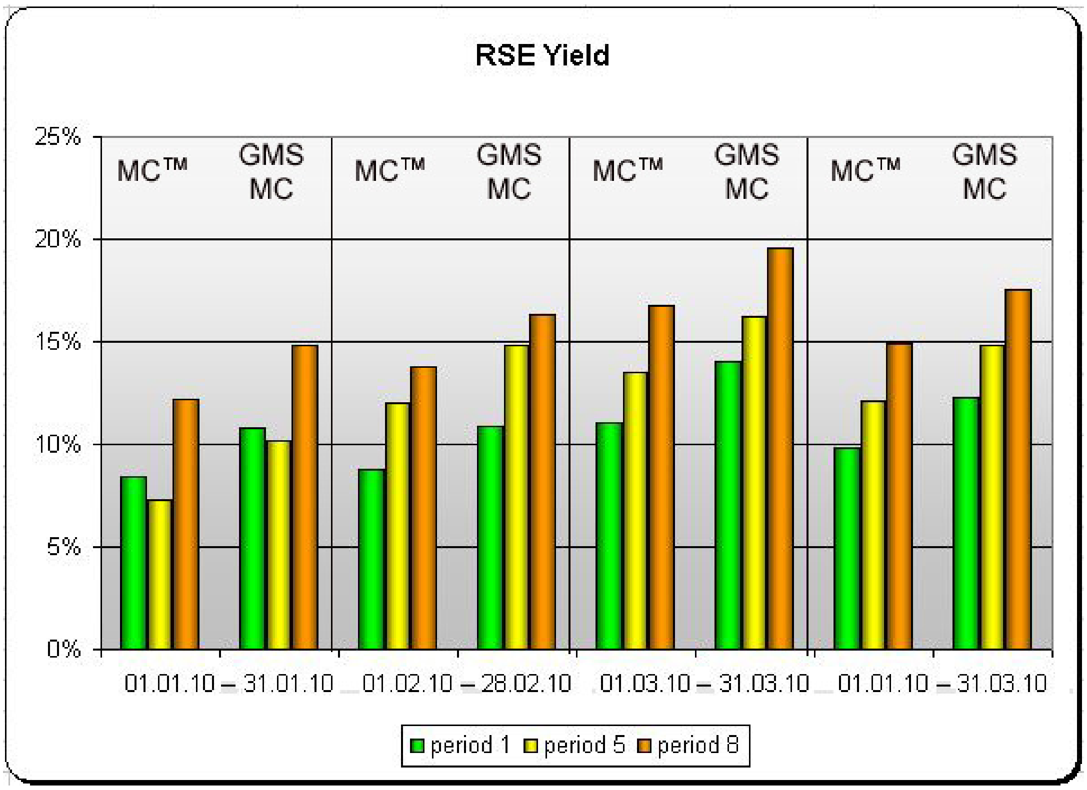


Image 8.4.4.1: RSE of the wind energy yield values for selected time frames implementing GMS MICROCOUPLING (MC™ = Micro Cast™, GMS MC = GMS Microcoupling)

The implementation of GMS MICROCOUPLING results in clear deteriorations of the RSE values of the GMS FARM YIELD PREDICTOR forecasts by 16.6 – 41.2% for all selected time frames and periods.

8.5 Accuracy of the GMS MicroCast™ (6 km resolution) wind speed forecasts

8.5.1 r^2 of the wind speed values (01.01.10 – 31.03.10):

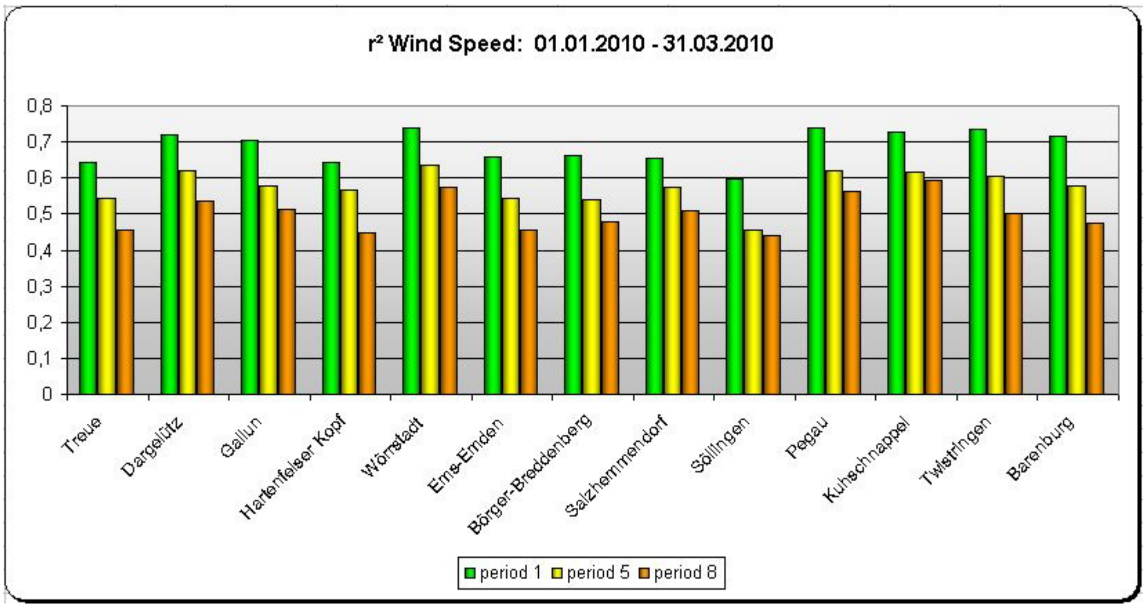


Image 8.5.1.1: r^2 of the wind speed values (01.01.10 - 31.03.10). Söllingen: r^2 of the wind speed values (01.02.10 - 31.03.10)

The wind speed forecasts of the GMS MicroCast™ (6 km resolution) model show r^2 values between **0.74** and **0.60** for period 1. r^2 values uniquely drop towards values between **0.64** and **0.46** for period 5 and towards values between **0.59** and **0.44** for period 8.

8.5.2 SE of the wind speed values (01.01.10 – 31.03.10):

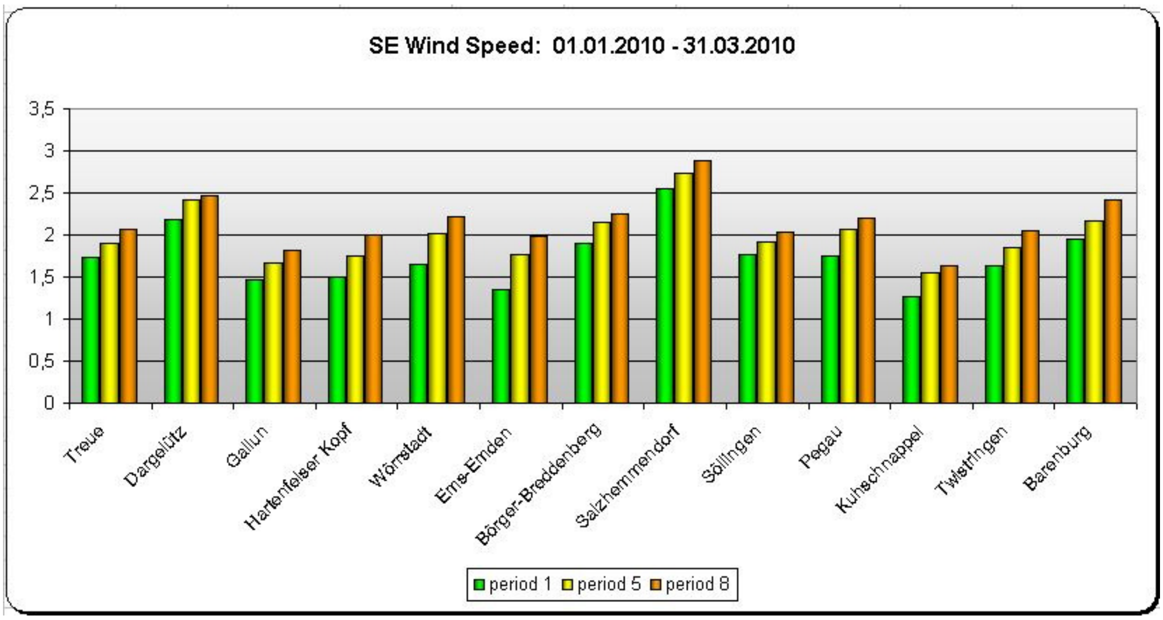


Image 8.5.2.1: SE of the wind speed values (01.01.10 - 31.03.10). Söllingen: SE of the wind speed values (01.02.10 - 31.03.10)

The wind speed forecasts of the GMS MicroCast™ (6 km resolution) model show standard errors with values between **1.27** and **2.55 m/s** for period 1. The standard error uniquely increases towards values between **1.55** and **2.74 m/s** for period 5 and towards values between **1.63** and **2.88 m/s** for period 8.

8.6 Accuracy of the energy yield forecasts using the GMS FARM YIELD PREDICTOR on the GMS MicroCast™ wind speed forecasts (6 km resolution)

8.6.1 r^2 of the wind energy yield values (01.01.10 – 31.03.10):

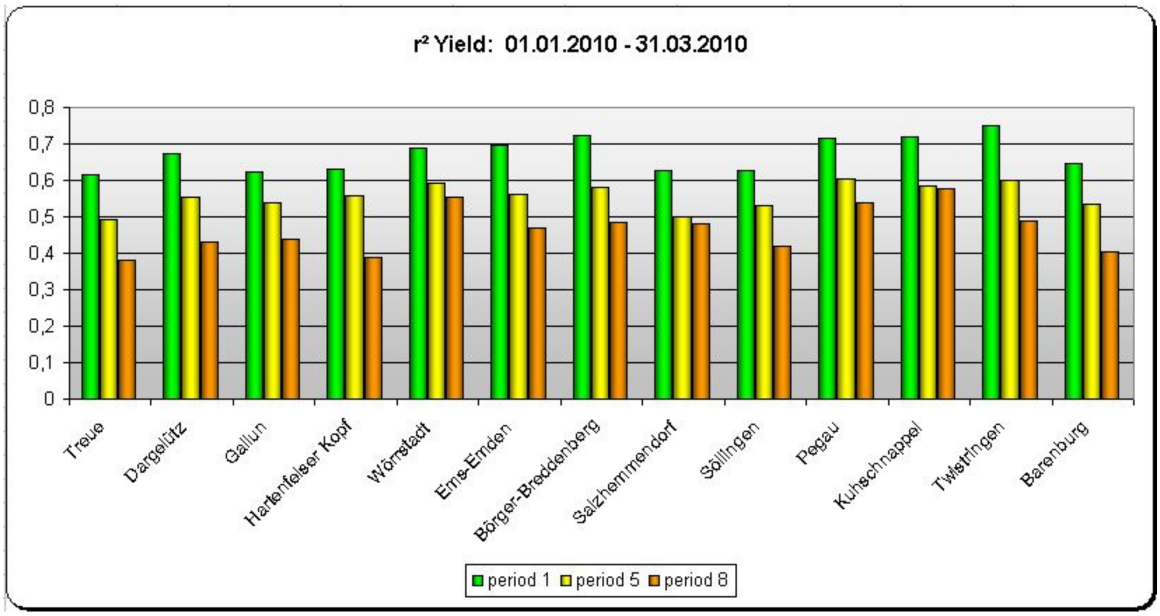


Image 8.6.1.1: r^2 of the wind energy yield values (01.01.10 - 31.03.10). Söllingen: r^2 of the wind energy yield values (01.02.10 - 31.03.10)

The wind energy yield forecasts based on the implementation of the GMS FARM YIELD PREDICTOR show r^2 values between **0.75** and **0.62** for period 1. r^2 values uniquely drop towards values between **0.60** and **0.49** for period 5 and towards values between **0.58** and **0.38** for period 8.

8.6.2 RSE of the wind energy yield values (01.01.10 – 31.03.10):

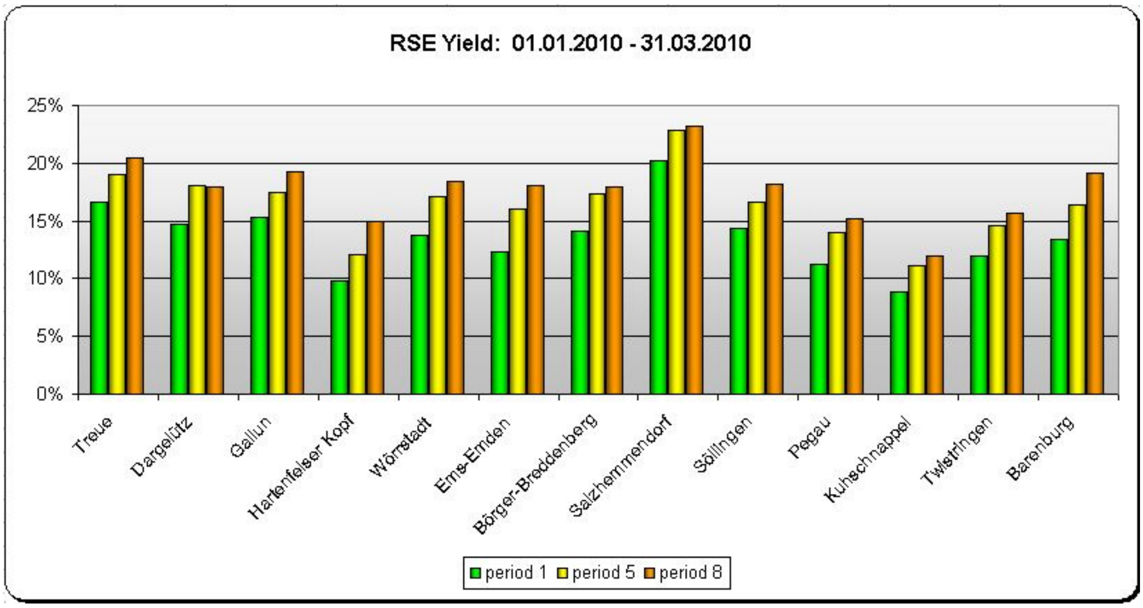


Image 8.6.2.1: RSE of the wind energy yield values (01.01.10 -31.03.10). Söllingen: RSE of the wind energy yield values (01.02.10 - 31.03.10)

The wind energy yield forecasts based on the implementation of the GMS FARM YIELD PREDICTOR show relative standard errors with values between **9%** and **20%** for period 1. Relative standard errors generally increase towards values between **11%** and **23%** for period 5 and towards values between **12%** and **23%** for period 8.

8.7 Refinement of the MicroCast™ model from 6 km down to 1 km resolution to improve the forecast accuracy

8.7.1 r^2 of the wind speed values (19.02.10 – 31.03.10) of the 6 km MicroCast™ model:

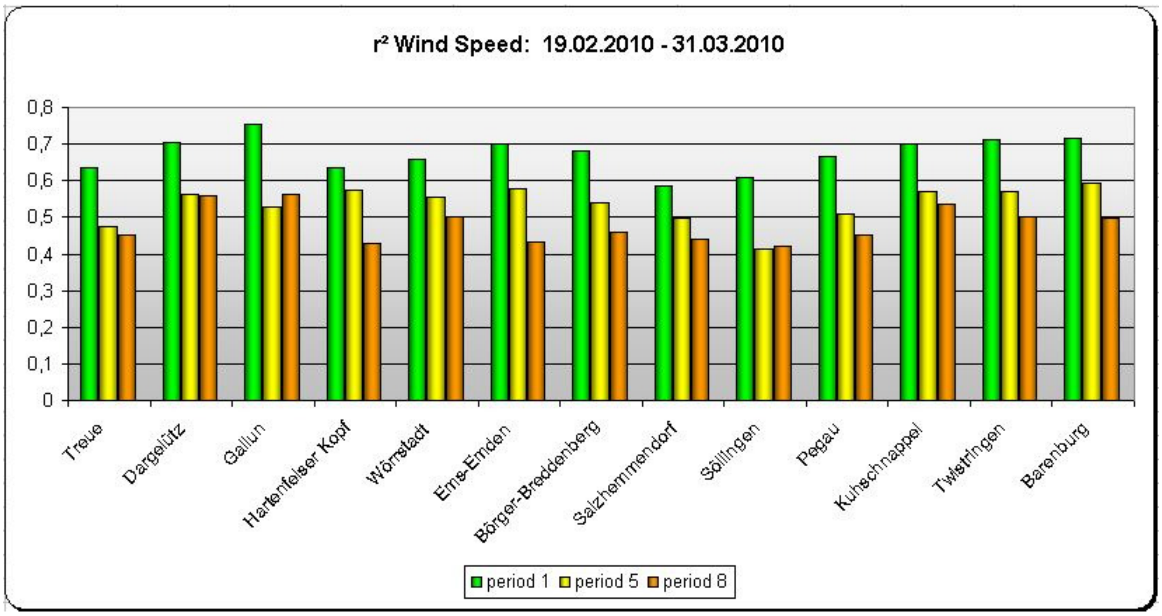


Image 8.7.1.1: r² of the wind speed values (with a 6 km GMS MicroCast™ model) (19.02.10 - 31.03.10). Kuhschnappel and Pegau: r² values (23.02.10 - 31.03.10). Hartenfelser Kopf: r² values (12.03.10 - 31.03.10).

The wind speed forecasts of the GMS MicroCast™ (6 km resolution) model show r^2 values between **0.75** and **0.59** for period 1. r^2 values generally drop towards values between **0.59** and **0.41** for period 5 and towards values between **0.56** and **0.42** for period 8.

8.7.2 r^2 of the wind speed values (19.02.10 – 31.03.10) of the 1 km MicroCast™ model:

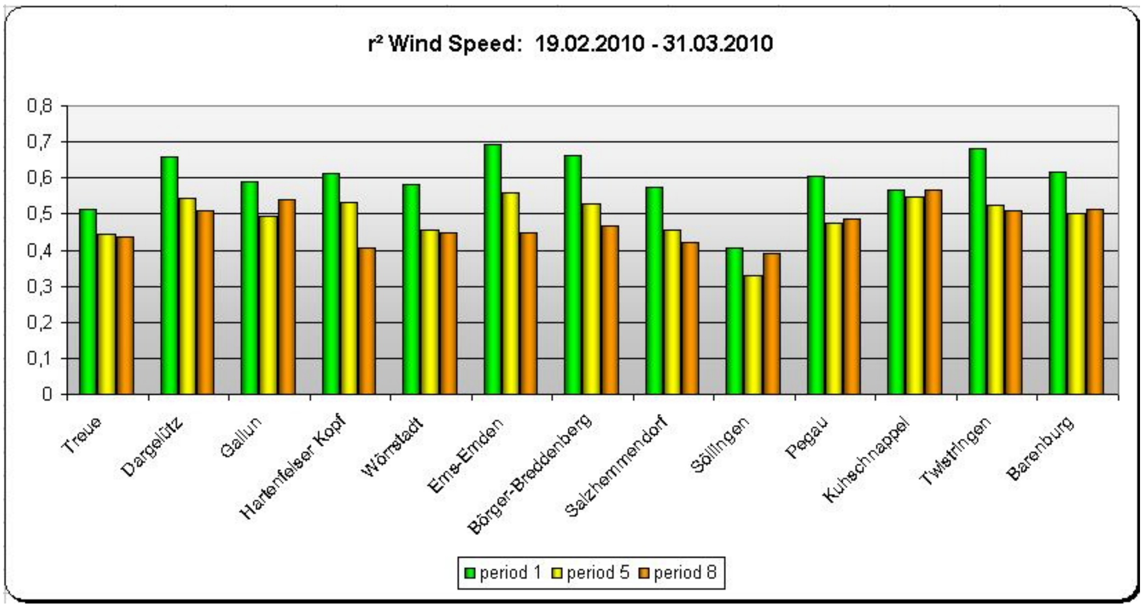


Image 8.7.2.1: r^2 of the wind speed values (with a 1 km GMS MicroCast™ model) (19.02.10 - 31.03.10). Kuhschnappel and Pegau: r^2 values (23.02.10 - 31.03.10). Hartenfelser Kopf: r^2 values (12.03.10 - 31.03.10).

The wind speed forecasts of the GMS MicroCast™ (1 km resolution) model show r^2 values between **0.69** and **0.40** for period 1. r^2 values generally drop towards values between **0.56** and **0.33** for period 5 and towards values between **0.57** and **0.39** for period 8.

8.7.3 SE of the wind speed values (19.02.10 – 31.03.10) of the 6 km MicroCast™ model:

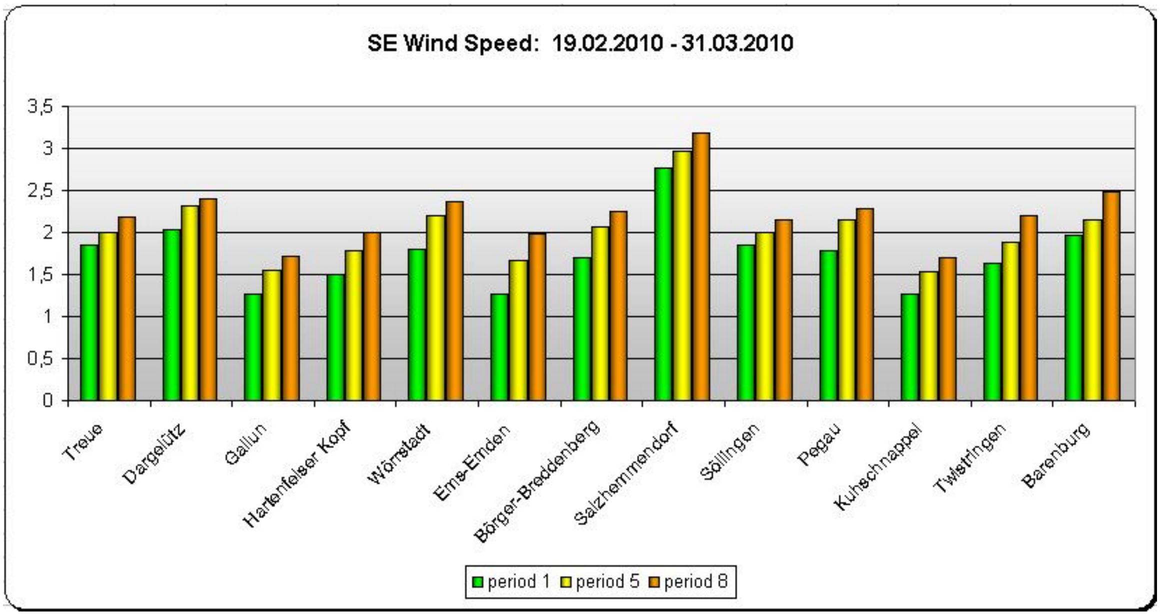


Image 8.7.3.1: SE of the wind speed values (with a 6 km GMS MicroCast™ model) (19.02.10 - 31.03.10). Kuhschnappel and Pegau: SE values (23.02.10 - 31.03.10). Hartenfelser Kopf: SE values (12.03.10 - 31.03.10).

The wind speed forecasts of the GMS MicroCast™ (6 km resolution) model show standard errors with values between **1.26** and **2.77 m/s** for period 1. The standard error uniquely increases towards values between **1.53** and **2.97 m/s** for period 5 and towards values between **1.70** and **3.19 m/s** for period 8.

8.7.4 SE of the wind speed values (19.02.10 – 31.03.10) of the 1 km MicroCast™ model:

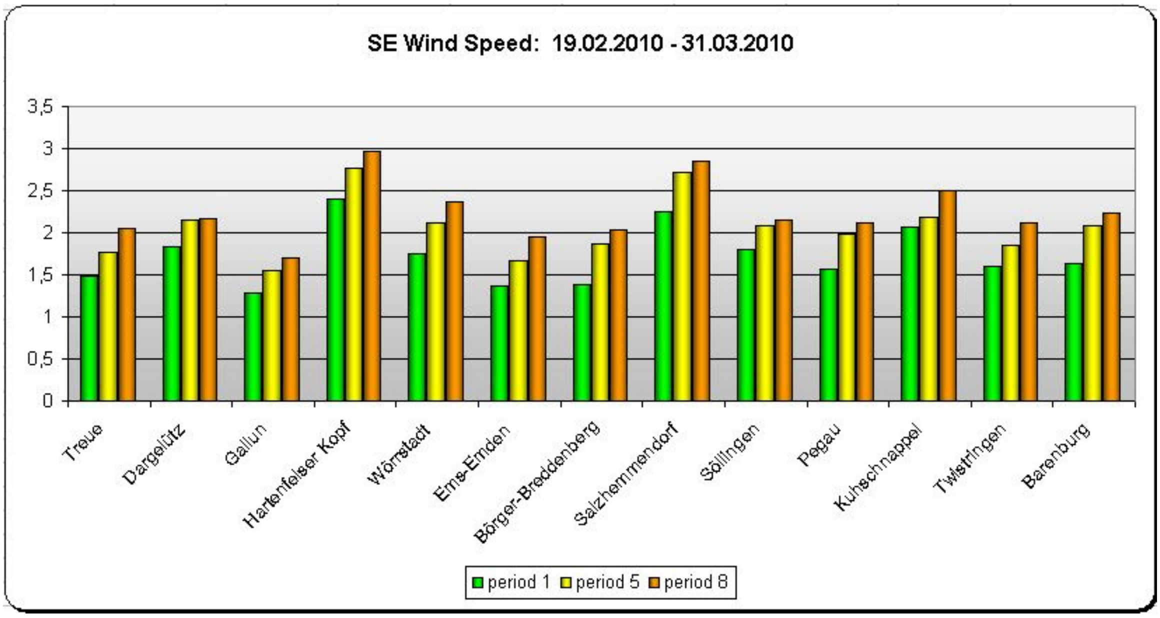


Image 8.7.4.1: SE of the wind speed values (with a 1 km GMS MicroCast™ model) (19.02.10 - 31.03.10). Kuhschnappel and Pegau: SE values (23.02.10 - 31.03.10). Hartenfelser Kopf: SE values (12.03.10 - 31.03.10).

The wind speed forecasts of the GMS MicroCast™ (1 km resolution) model show standard errors with values between **1.29** and **2.41 m/s** for period 1. The standard error uniquely increases towards values between **1.55** and **2.77 m/s** for period 5 and towards values between **1.70** and **2.97 m/s** for period 8.

8.7.5 r^2 of the wind energy yield values (19.02.10 – 31.03.10) of the 6 km MicroCast™ model:

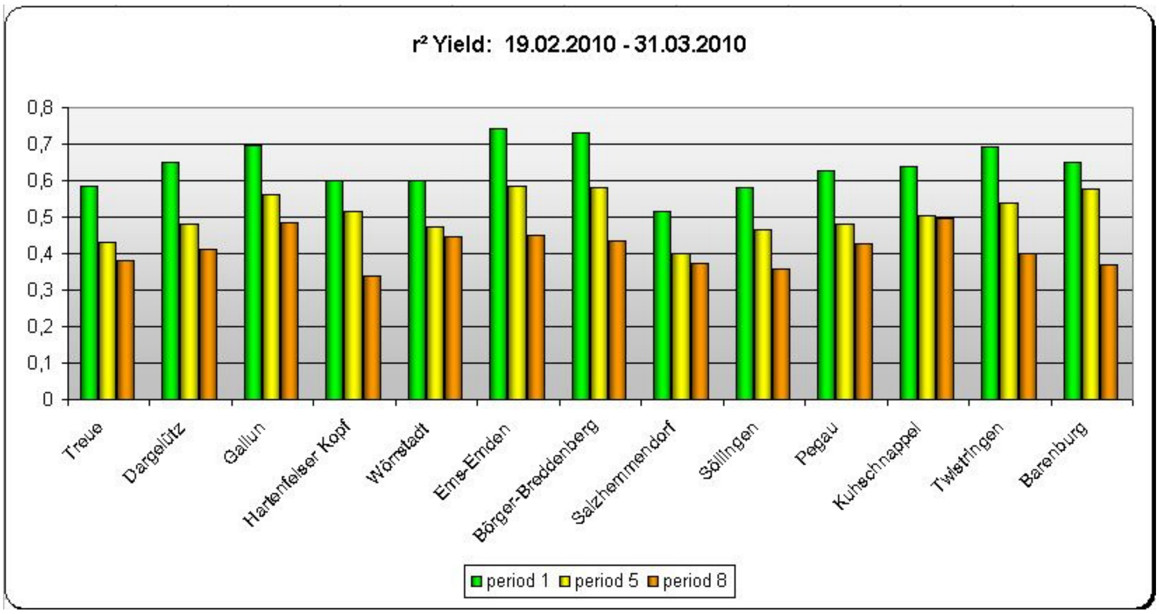


Image 8.7.5.1: r^2 of the wind energy yield values (with a 6 km GMS MicroCast™ model) (19.02.10 - 31.03.10). Kuhschnappel and Pegau: r^2 values (23.02.10 - 31.03.10). Hartenfelser Kopf: r^2 values (12.03.10 - 31.03.10).

The GMS FARM YIELD PREDICTOR wind energy yield forecasts based on the GMS MicroCast™ (6 km resolution) forecast data show r^2 values between **0.74** and **0.52** for period 1. r^2 values uniquely drop towards values between **0.59** and **0.40** for period 5 and towards values between **0.50** and **0.34** for period 8.

8.7.6 r^2 of the wind energy yield values (19.02.10 – 31.03.10) of the 1 km MicroCast™ model:

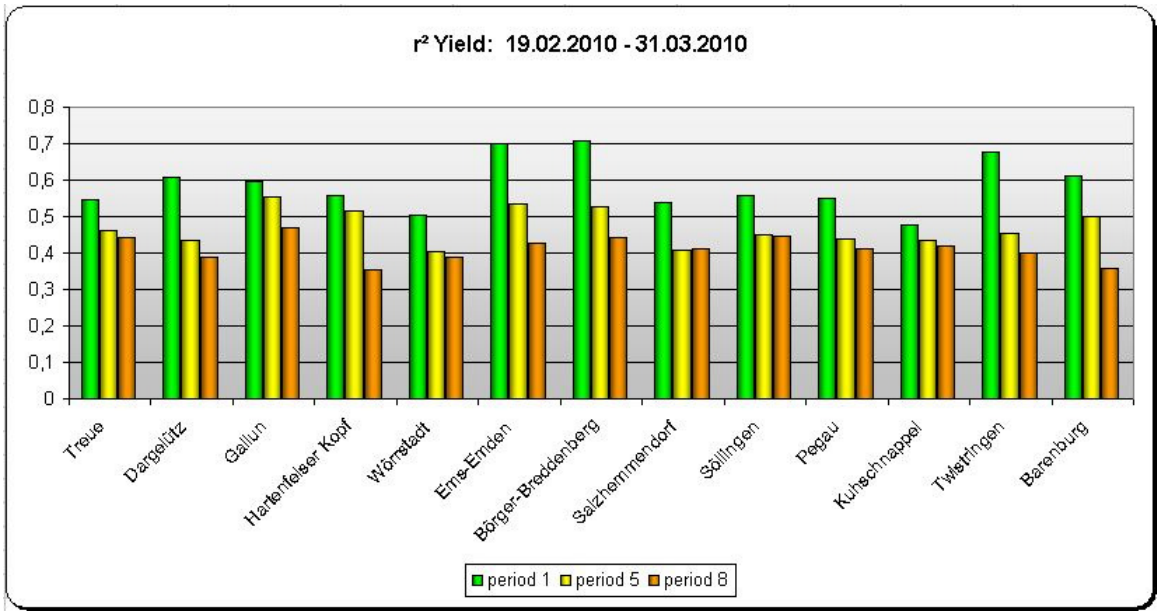


Image 8.7.6.1: r^2 of the wind energy yield values (with a 1 km GMS MicroCast™ model) (19.02.10 - 31.03.10). Kuhschnappel and Pegau: r^2 values (23.02.10 - 31.03.10). Hartenfelser Kopf: r^2 values (12.03.10 - 31.03.10).

The GMS FARM YIELD PREDICTOR wind energy yield forecasts based on the GMS MicroCast™ (1 km resolution) forecast data show r^2 values between **0.71** and **0.48** for period 1. r^2 values uniquely drop towards values between **0.55** and **0.40** for period 5 and towards values between **0.47** and **0.35** for period 8.

8.7.7 RSE of the wind energy yield values (19.02.10 – 31.03.10) of the 6 km MicroCast™ model:

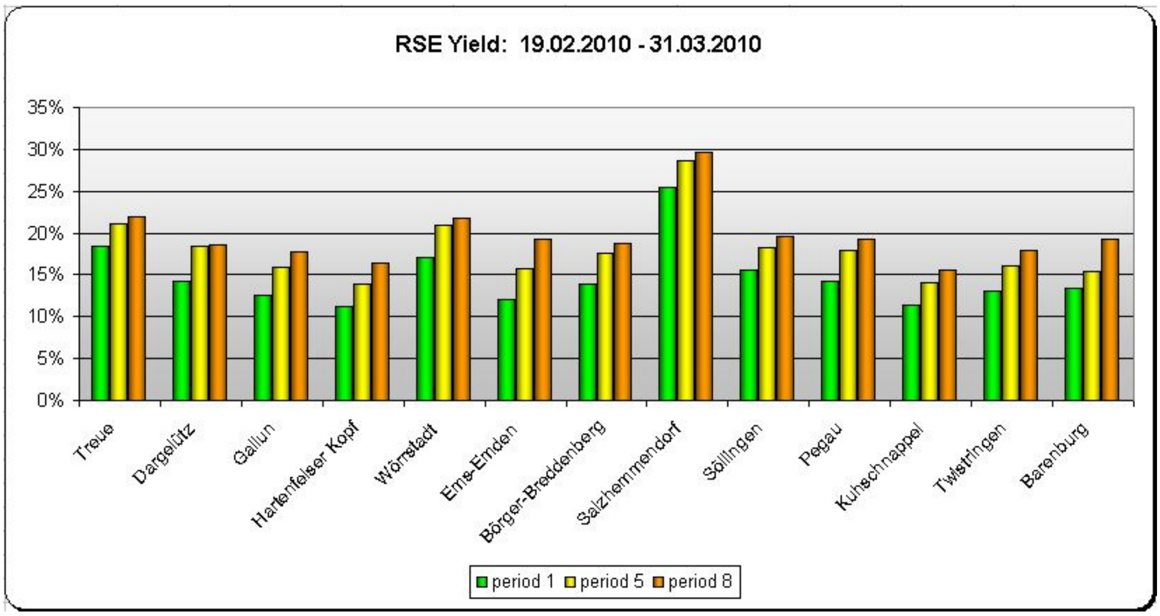


Image 8.7.7.1: RSE of the wind energy yield values (with a 6 km GMS MicroCast™ model) (19.02.10 - 31.03.10). Kuhschnappel and Pegau: r^2 values (23.02.10 - 31.03.10). Hartenfelser Kopf: r^2 values (12.03.10 - 31.03.10).

The GMS FARM YIELD PREDICTOR wind energy yield forecasts based on the GMS MicroCast™ (6 km resolution) forecast data show standard errors with values between **11%** and **26%** for period 1. The standard error uniquely increases towards values between **14%** and **29%** for period 5 and towards values between **16%** and **30%** for period 8.

8.7.8 RSE of the wind energy yield values (19.02.10 – 31.03.10) of the 1 km MicroCast^{TM} model:

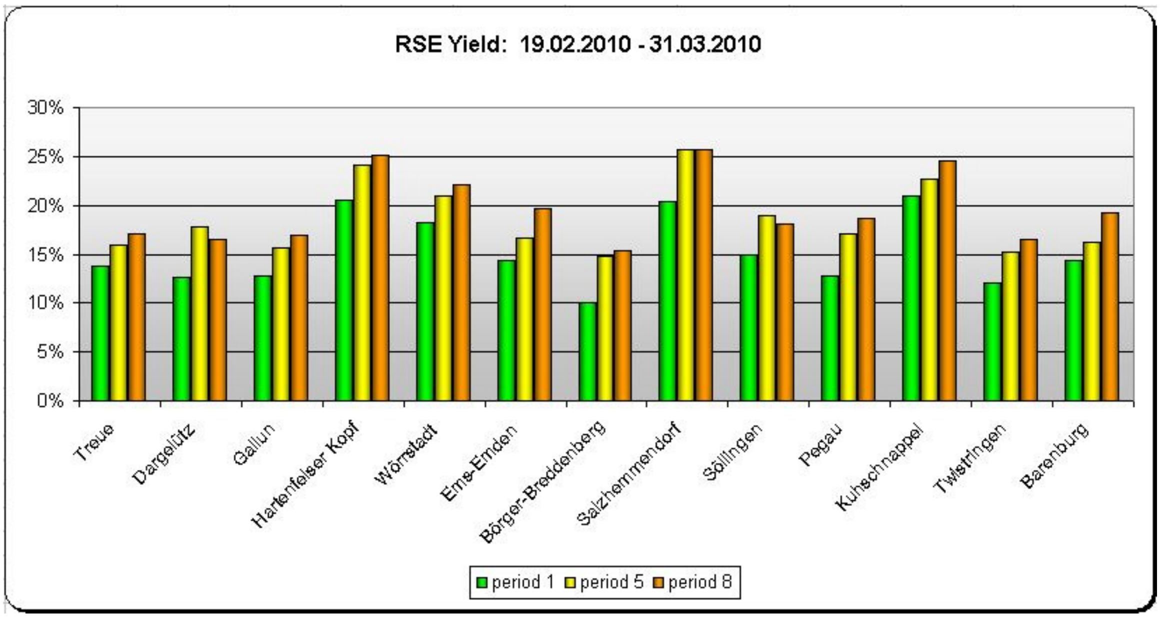


Image 8.7.8.1: RSE of the wind energy yield values (with a 1 km GMS MicroCast™ model) (19.02.10 - 31.03.10). Kuhschnappel and Pegau: r² values (23.02.10 - 31.03.10). Hartenfelser Kopf: r² values (12.03.10 - 31.03.10).

The GMS FARM YIELD PREDICTOR wind energy yield forecasts based on the GMS MicroCast™ (1 km resolution) forecast data show standard errors with values between **10%** and **21%** for period 1. The standard error generally increases towards values between **15%** and **26%** for period 5 and towards values between **15%** and **26%** for period 8.