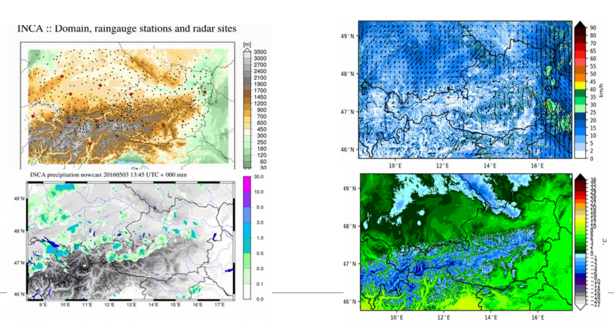
www.zamg.ac.at

ZAMG Zentralanstalt für Meteorologie und Geodynamik

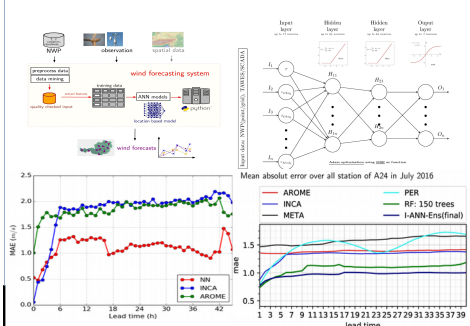
On the impact of machine learning for nowcasting applications

- Traditional nowcasting methods: observation-based Lagrangian extrapolation; persistency; heuristic methods (e.g. INCA), recent developments in NWP based nowcasting systems (e.g. AROME-RUC)
- Data driven approaches that non-linearly combine observation data, NWP, IoT, crowd sourcing data, etc. through machine learning techniques
- ZiANN (ZAMG Interval based Artificial Neural Network) for station based nowcasts (e.g., for wind energy)
- USP (Ultra short range wind and gust speed prediction): frequently updated station based gust nowcasts with SVM
- Gridded precipitation nowcasting by combining extrapolation techniques (INCA) with MLP / CNN

The analysis and nowcasting system INCA (Integrated Nowcasting through Comprehensive Analysis) is operated at ZAMG since many years and is under continuous development. The system is based on blending observations and model output from NWP and provides frequently updated forecasts in the nowcasting range (up to +6 h). Further, it improves numerical weather prediction (NWP) forecasts for up to +48 h through downscaling and bias correction. The basic idea of INCA is to complement and improve high resolution NWP model output using real-time observations, remote sensing data and high-resolution topographic data (Haiden et al. 2011). The INCA system provides near-real-time analyses and forecasts at 1 km x 1 km horizontal resolution for the parameters temperature, humidity, wind, precipitation amount, precipitation type, cloudiness, and global radiation.



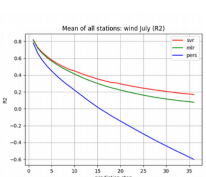
A classical feed-forward ANN has been implemented consisting of one input layer, two hidden layers, and one output layer. The layers are chosen to be dense, i.e., fully connected to the next layer. The input layer consists of 17 input neurons, both hidden layers of 64 neurons each, and the output layer of one neuron, the wind speed forecast. The optimization algorithm needs an objective function, here the mean squared error (MSE) was used. Input features: observed wind speed and direction, temperature, surface pressure, wind speed 10min and 20min before, AROME and ALARO wind forecasts. The ZiANN is an average of ten randomly initialized model runs yielding slightly different wind speed forecasts. The training length is a sliding window approach considering the previous 120 days.



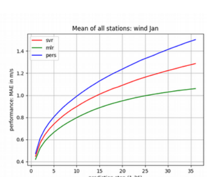
Upper left: Conceptual model and data flow for the ZiANN system.
Upper right: Model configuration of the neural network (one input layer, two hidden layers, one output layer).
Lower left: ZiANN vs. INCA vs. AROME, MAE [m/s] as a function of lead time, averaged over one month.
Lower right: MAE for several experiments, summer month

3. Ultra short range wind and gust speed prediction (USP) with SVM

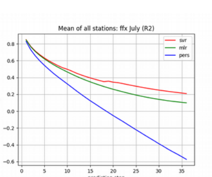
Support Vector Machines (SVMs) are investigated for ultra-short range predictions (0-6 hours ahead) of wind speed and wind gusts. Relevant features for prediction of wind speed and gusts: wind speed, gusts, wind direction, gust direction, sunshine duration, time of day, relative humidity, and mean sea level pressure. For the SVR models a radial basis function is used as kernel function and hyperparameters are optimized individually for each model via gridsearch. 24 TAWES sites (semi-automatic weather station) in different Austrian regions with varying topography and climatology are selected. The SVR model gives good results for both gust and wind predictions and, they perform better in predicting patterns in wind gusts compared to statistical methods (e.g. multiple linear regression model). Improvement of forecasts with SVR compared to MLR forecasts are greater during the summer month than the winter month. SVR models perform better for gust predictions than for wind speed, which might be due to optimization being focused on gust prediction models.



Correlation for wind speed, July 2018, average over 24 stations



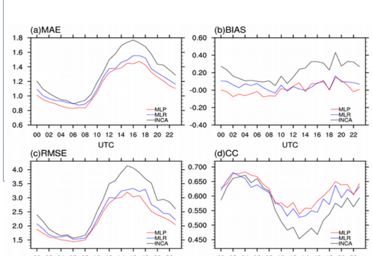
MAE for wind speed, January 2018, average over 24 stations



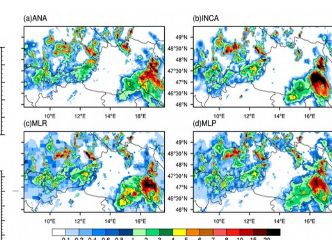
Correlation for gust speed, July 2018, average over 24 stations

4. Precipitation nowcasting: Combining Lagrangian extrapolation with artificial neural networks

A multilayer perceptron (MLP) approach (artificial neural network) for the application of summer precipitation nowcasting over the eastern Alps is developed for hourly precipitation nowcasting. Input features (predictors) include radar-based QPE, extrapolation QPF, convective analyses (CAPE, CIN, MCONV) and three derived radar fields of five C-band radars (MAXCAPPI, ECHOTOP, VIL). The performance of the MLP model application is compared to extrapolation technique (INCA) and a multiple linear regression (MLR). The MLP model yields significant improvements compared to MLR models, with lower MAE, reduced BIAS, lower RMSE, higher CC, higher CSI, and better BS for higher thresholds.



Evaluation of hourly precipitation forecasts by INCA extrapolation, MLR and MLP. (a) MAE, (b) BIAS, (c) RMSE, (d) CC



Case study of 1-h precip nowcast initialized at 16 UTC 30 July 2014, valid at 17 UTC 30 July 2014. (a) Verifying INCA precipitation analysis, (b) INCA extrapolation, (c) MLR, and (d) MLP

Contact: Alexander Kann, Section NWP/Applications, alexander.kann@zamg.ac.at, Tel. +43 1 360 26 / 2322, www.zamg.ac.at
Authors: Alexander Kann, Irene Schicker, Petrina Papazek, Linye Song, Elisabeth Hartel, Yong Wang