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Machine learning methods for predicting energy demand/production based on hydro-meteorological input

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Reliable predictions of the energy demand and production could be a gainful information for the management and integration of renewable energy sources. Especially in periods of water deficits or surplus this information could be beneficial for example for the planning of the hydro-power production of the upcoming days, weeks and months. Thus several different Machine Learning (ML) methodologies have been tested for predicting the energy demand and production in the near future and for deriving predictive uncertainties based on the information of hydro-meteorological data. The methods analysed include the Multivariate Linear regression (MLR) and Multivariate Adaptive Regression Splines (MARS) approach and Quantile Regression (QR) models. The QR models cover classical QR models, Quantile Regression Neural Network (QRNN), Quantile Random Forest (QRF) and Deep Learning Quantile Regression (DLQR).
Daily measurements of temperature, precipitation, global-radiation and wind-speed, as well as information of weekdays and holidays are taken as input variables for calibrating the demand model. Additionally for the production model the information of the surface runoff (simulated by the usage of a hydrological model taking the observed/forecasted meteorological variables as input) of the analysed region has been included. The same input information necessary for the calibration of these models are available from hydro-meteorological forecasts and could be used to predict future energy demands/productions including predictive uncertainties. Different skill scores have been tested for verifying the predictions and first results for coupling the ML techniques with monthly weather forecasts will be shown for the southern Switzerland (Canton of Ticino). The emphasis and novelty of this study is the derivation of predictive uncertainties based on ML approaches and the usage of ensembles of monthly weather forecasts for the estimation of future energy demands and productions.