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Joint modelling of wind power and hydro inflow for power system scheduling

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Abstract

This paper concerns the joint modelling of wind power and hydro inflow for long-term power system scheduling. We propose a vector autoregressive model applied to deseasonalized series to describe the joint generating mechanism of wind and inflow. The model was applied to daily and weekly bivariate time series comprising wind and inflow from seven regions in Norway. We found evidence of both lagged and contemporaneous dependencies between wind and inflow, in particular, our results indicate that wind is useful in forecasting inflow, but not the other way around. The forecasting performance of the proposed VAR models was compared to that of independent AR models, as well as the persistence forecasts. Our results show that the VAR model was able to provide better forecasts than the AR models and the persistence forecast, for both the daily and weekly time series.

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Keywords: Forecasting; hydro inflow; power system scheduling; wind power; vector autoregressive model

1. Introduction

Integration of high shares of wind generation in hydro dominated power systems, such as Norway, can substantially alter the conditions for long-term generation scheduling. For example, consider the case of wind and hydropower facilities owned by the same producer and located within the same transmission constrained area. In such cases the long-term hydropower scheduling should be coordinated with the variable and uncertain wind production in order to avoid or minimize energy losses (in the form of spillage or wind curtailment)[1]. In turn, the question of how to model the stochastic wind and inflow processes in long-term scheduling models come forward. This work concerns the joint modelling of wind power and hydro inflow for power system scheduling.

The number of forecasting methods proposed for wind power and inflow separately are numerous. More than three decades ago Brown et al.[2] proposed to use autoregressive time series models in wind speed and wind power forecasting. Since then, a great number of studies concerning wind speed and/or power predictions have emerged in the literature. We refer to the reviews by Giebel et al.[3] and Jung and Broadwater[4] for a comprehensive coverage of the various approaches to wind power forecasting. With regards to inflow forecasting we mention the extensive

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forecasting study conducted in [5], which compared 10 different time series models applied to 30 monthly river flows. A stochastic inflow model which has been implemented in hydro scheduling models currently used by several hydropower producers in Norway is described in Gjelsvik et al.[6].

Several authors have studied the correlations and complementary characteristics of wind and hydro, e.g. [7,8], however, there are few studies on joint modelling of the two stochastic processes. Souto et al.[9] presented a high-dimensional multivariate time series model for forecasting and simulation of monthly wind and hydro inflow in the Brazilian power system. It is, however, hard to judge the quality of the proposed model based on this study, since a benchmark is not included.

The present work was highly motivated by the need for a proper stochastic representation of wind and inflow in scheduling models based on the Stochastic Dual Dynamic Programming (SDDP) algorithm [10]. Helseth et al.[11] presented an SDDP-based scheduling model that treated wind power as a stochastic variable. The stochastic wind-energy model employed suffer from some weaknesses, as the authors clearly point out, in that it assumes wind and inflow are independent and that it ignores possible autocorrelations.

We propose to first properly deseasonalize wind and inflow series individually, and then use a vector autoregressive (VAR) model to describe the dynamics and inter-dependence structure of wind and inflow. The advantage of a VAR model is first of all its flexible and simple structure which makes it ideal for forecasting and simulation [12], which in turn makes it practically useful in power system applications. For example, such a model can be used internally to generate scenarios for wind and inflow in stochastic scheduling models based on the SDDP algorithm. Secondly, VAR models also allows for easy interpretation of the individual and joint dynamics of wind and inflow, which in it self may contribute to insight relevant for a range of applications, such as wind integration studies, transmission planning and power system analysis.

The methodology is applied to daily and weekly wind and inflow series from seven regions covering Norway. Our primary concern is the VAR models' ability to forecast future values of wind and inflow. We evaluate the models' step-ahead forecasting performance out-of-sample by considering both deterministic (point) and probabilistic (distributional) forecasts. As a benchmark to judge whether the model is successful or not, we use the persistence forecast for comparison. Furthermore, to assess whether there is any gain in joint modelling, as opposed to modelling wind and inflow as two independent processes, we also include individual AR-models for comparison. To numerically measure the performance and rank the competing forecast methods we use the Energy Score [13].

The remainder of this paper is structured as follows. Section 2 describes the data used in this study and summarizes the exploratory data analysis. The deseasonalization method and the (vector) autoregressiv models are described in Section 3. Section 4 presents the results and finally, Section 5 ends this paper with a conclusion.

2. Data and exploratory analysis

2.1. Wind and inflow data

The wind data series used in this work are based on NCEP Reanalysis data [14] provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their web site at http://www.esrl.noaa.gov/psd/. The Reanalysis data set contains wind speeds from 1948-today with a temporal resolution of six hours and a spatial resolution of 2.5 degrees in both longitude and latitude. For the purpose of this study, it is important to use time series of sufficient length in order to properly capture seasonal effects and the potential dependence structure. Alternative data series with finer spatial resolution are typically only available for a few years (¡10 years), and are therefore not considered here. A two-dimensional linear interpolation has been applied to get wind speeds at seven selected sites in Norway, see Figure 1. Hourly wind speed values were derived by linear interpolation of the 6-hourly values and then converted to normalized wind power using a regional power curve developed in the TradeWind project [15]. The data processing was carried out by SINTEF Energy Research and the hourly wind power series were made available to the authors upon request.

Inflow data were provided by the Norwegian Water Resources and Energy Directorate, available on their web site at http://www.nve.no/no/Vann-og-vassdrag/Data-databaser/Historiske-vannforingsdata-til-produksjonsplanlegging-/. The complete data set contains average daily inflow [m^3/s] from the period 1958-2013 for 82 sites, which is used to describe the inflow to the Norwegian hydropower system. Seven inflow series are chosen for this study based on their proximity to the selected wind coordinates (Figure 1). The inflow series are 'Karpelv' (Region 1), 'Skogsfjordvatn'

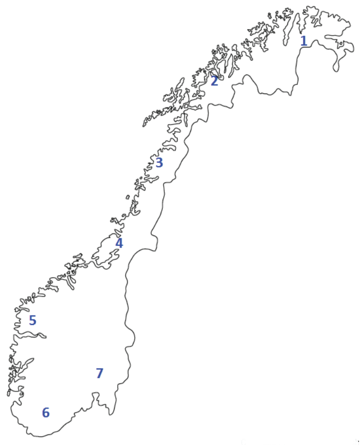

Fig. 1: Selected locations in Norway for wind power time series considered in this study.

(Region 2), 'Berget' (Region 3), 'Krinsvatn' (Region 4), 'Fetvatn' (Region 5), 'Aardal' (Region 6) and 'Kraakfoss' (Region 7).

We consider average daily and weekly wind power and inflow time series in this work, calculated from the available data by block averaging. These are relevant time scales for long-term power system scheduling. Currently, a stochastic time resolution of one week is commonly used in long-term models, e.g. [6]. However, considering the fluctuating nature of wind, a finer time resolution might be needed as the share of wind generation increase.

Each year contains exactly 365 daily observations and 52 weekly observations. The extra observation in leap years is omitted from the data series. For the weekly series, the average value of the last week of each year is taken over the last eight days in the year. This was done to ensure proper handling of seasonal effects. We have used the common period of available wind and inflow data from 1958-2013.

2.2. *Exploratory analysis*

The pattern and general behavior of the wind and inflow series was first examined from the time plots, which suggested that all series considered exhibited seasonal variations within the annual cycle. Further investigation of the sample weekly means and standard deviations showed that generally, both the mean and standard deviation was varying from season to season. Consequently, the series are nonstationary and must therefore be deseasonalized before an autoregressive moving average (ARMA) model can be considered for the data. When both the mean and standard deviation varies with season, the following deseasonalization method is appropriate:

$$z_t = \frac{a_t - \mu_t}{\sigma_t}, \tag{1}$$

where a_t denotes a seasonal time series, and μ_t and σ_t are the seasonal mean and standard deviation at time t, respectively. Notice that for a time series with period S it is understood that $\mu_{t+S} = \mu_t$ and $\sigma_{t+S} = \sigma_t$.

We found no evidence of long-term trends in any of the data series considered in this study. The time plots of deseasonalized series indicate approximately constant location and variance over time, without systematic changes. The resulting series z_t are therefore assumed to be (weakly) stationary.

For each deseasonalized wind and inflow series, we investigated the sample autocorrelation (ACF) and partial autocorrelation (PACF) plots as a first step in the process of ARMA model identification. We observed a typical autoregressive (AR) signature for all cases. Although the exact autocorrelation structure varied (e.g. persistence extends over more lags for daily than for weekly data) the general observation was that the ACF damps out slowly while the PACF cuts off after a certain (small) number of lags, indicating that no moving average terms are needed [16]. Based on this, we consider only AR models in the following.

Finally, a test for independence was carried out by considering the correlation between 'prewhitened' wind and inflow series. If this correlation is significantly different from zero, the two processes can not be considered independent [17]. The prewhitened series were obtained as the residuals from fitting AR(1) models to deseasonalized data. The correlation was significant for all wind and inflow series within the same region, and also across regions in many cases. The general tendency found was that correlation decrease with increasing distance between regions.

3. Methodology

This section first describes the method used to estimate the seasonal mean and standard deviation, needed for seasonal adjustment. Then, the uni- and multivariate autoregressive models for nonseasonal time series are presented.

3.1. Deseasonalization by harmonic regression

Since much of the total variation in daily and weekly wind and inflow series are driven by seasonal effects, it is important to capture this seasonality in a proper way in order to arrive at a good forecasting model. Using the seasonal sample mean and standard deviation in Equation (1) is a common way to deseasonalize data [18]. However, when we are dealing with weekly and daily time series this method will result in a very high number of deseasonalization parameters and consequently the risk of overfitting. To reduce the number of parameters needed to model the seasonality we use harmonic regression to estimate the seasonal mean and standard deviation.

Consider a univariate seasonal time series with period S consisting of T successive daily or weekly values denoted by $a_t, t = 1, 2, ..., T$. To estimate the seasonal mean μ_t we fit

$$a_t = \alpha^{(0)} + \sum_{k=1}^{K_\mu} \left[\alpha_k^{(1)} \sin(\frac{2\pi kt}{S}) + \alpha_k^{(2)} \cos(\frac{2\pi kt}{S}) \right] + u_t, \tag{2}$$

where $\alpha^{(0)}$ is the overall mean and $\alpha_k^{(1)}$ and $\alpha_k^{(2)}$, $k = 1, ..., K_\mu$, are the harmonic coefficients. K_μ is the number of harmonics used to capture the seasonal pattern. Finally, u_t is a zero-mean error term with variance σ_t^2. An estimate of the seasonal mean at time t is then given by

$$\hat{\mu}_t = \hat{\alpha}^{(0)} + \sum_{k=1}^{K_\mu} \left[\hat{\alpha}_k^{(1)} \sin(\frac{2\pi kt}{S}) + \hat{\alpha}_k^{(2)} \cos(\frac{2\pi kt}{S}) \right] \tag{3}$$

where $\hat{\alpha}^{(0)}, \hat{\alpha}_k^{(1)}, \hat{\alpha}_k^{(2)}$ are the least-squares estimates.

The variance σ_t^2 is also allowed to vary with season, and is estimated by the regression

$$\hat{u}_t^2 = \beta^{(0)} + \sum_{k=1}^{K_\sigma} \left[\beta_k^{(1)} \sin(\frac{2\pi kt}{S}) + \beta_k^{(2)} \cos(\frac{2\pi kt}{S}) \right] + v_t, \tag{4}$$

where $\hat{u}_t^2$ denotes the squared residuals, $(a_t - \hat{\mu}_t)^2$, obtained from the fitting of (2) and v_t is a zero-mean error term. The estimated seasonal variance is then given by

$$\hat{\sigma}_t^2 = \hat{\beta}^{(0)} + \sum_{k=1}^{K_\sigma} \left[\hat{\beta}_k^{(1)} \sin(\frac{2\pi kt}{S}) + \hat{\beta}_k^{(2)} \cos(\frac{2\pi kt}{S}) \right]. \tag{5}$$

The deseasonalized series $z_t = (a_t - \hat{\mu}_t)/\hat{\sigma}_t$ can then be obtained.

The number of harmonics K_μ and K_σ needed to properly model the seasonal mean and variance will depend on the series at hand, but usually only a few harmonics are needed to capture the seasonal pattern in weather driven processes [19]. We follow the recommendations in Hipel and McLeod[18] and determine the number of harmonics K_μ and K_σ using model selection criteria. We use the Bayesian Information Criterion (BIC) [20], and the approach is to fit a set of candidate with the number of harmonics between 0 and 6, and select the model which minimizes the BIC value.

3.2. Autoregressive models

Subsequent to deseasonalization we model the dynamic correlation structure using standard (vector) AR models for stationary time series [16]. For a univariate time series z_t, a general AR model of order p (AR(p)) can be written

$$z_t = \sum_{\ell=1}^{p} \phi_\ell z_{t-\ell} + \varepsilon_t, \tag{6}$$

where $\phi_\ell;\ \ell = 1, ..., p$ are the autoregressive coefficients, which reflect the short-term memory of the process, and ε_t is a white noise process, having zero mean, zero autocorrelation and constant variance.

For the multivariate case, the vector-autoregressive (VAR) model generalizes the univariate AR model to describe the joint generation mechanism of the variables involved [12]. Now, let $\mathbf{z}_t = (z_t^{(1)}, z_t^{(2)}, ..., z_t^{(m)})'$ denote an $(m\times 1)$ vector of time series variables. The VAR model expresses each variable as a function of its own lagged values and lagged values of all of the other variables involved, plus an error term. A general VAR model of order p (VAR(p)) can be represented as

$$\mathbf{z}_t = \sum_{\ell=1}^{p} \mathbf{\Phi}_\ell \mathbf{z}_{t-\ell} + \boldsymbol{\varepsilon}_t, \tag{7}$$

where $\mathbf{\Phi}_\ell;\ \ell = 1, ..., p$ are $(m\times m)$ coefficient matrices and $\boldsymbol{\varepsilon}_t$ is an $(m\times 1)$ white noise vector process. That is, the error vector has zero mean and autocorrelation, and a time invariant covariance matrix $\mathbf{\Sigma}$. The parameters were estimated using ordinary least squares (OLS).

For the purpose of probabilistic forecasting and simulation, we need a description of the error distribution. Since both the wind and inflow distributions generally deviates from normality, we rather rely on the properties of the observed residuals obtained from the model fitting than to impose distributional assumptions on the error term. After the VAR (AR) model of appropriate order have been fitted to the deseasonalized data, a set of estimated errors are available that constitute the multivariate (univariate) error distribution. Simulated values and predictive distributions for wind and inflow can then be constructed from the model by random sampling from the empirical error distribution.

The appropriate order for each of the VAR and AR models are selected based on the BIC, using the following approach. VAR(p) models with $p = 1, , p_{\max}$ were fitted to data and the BIC calculated. The model VAR(p^*) which attains the minimum BIC value was selected. Then, for wind and inflow separately, AR(p) models with $p = 1, , p^*$ were fitted and the order which minimizes BIC was selected. Thus, the AR models for wind and inflow may have different order p, but the order of either model cannot exceed the order of the corresponding VAR model. This allows for a fair comparison in the forecasting evaluation.

4. Results

In this study, we considered VAR(p) models for daily and weekly bivariate time series, each comprising wind and inflow from the same region (see Figure 1). The reason for using bivariate models was to better enable inferences on the relationships between wind and inflow, and we chose series from the same region to limit the scope of the analysis. However, the methodology could readily be used for higher dimensional data series and for data series across regions when this is relevant.

Model estimation was conducted using observations from 1958-2008, while the remaining five years (2009-2013) were kept for out-of-sample forecast evaluation. Since no systematic long-term trends were found in the data, the last five years should provide a sufficient basis for evaluation and comparison.

The appropriate VAR order was determined for each case using BIC as described in section 3.2. We set $p_{\max} = 4$ for both daily and weekly series, which based on inspection of the PACF plots was considered to be sufficiently high for all series and both time scales. For the daily time series a VAR(3) model was selected for regions 1, 4, 5 and 6, while a VAR(4) model was chosen for regions 2, 3 and 7. For the weekly series, a VAR(1) model was selected for all regions.

The following subsection summarizes the most important findings from the fitting of the VAR models. Then, the forecasting performance of the VAR models is evaluated by comparison to the persistence forecast, and further to independent AR models.

4.1. Model inferences

The results from fitting bivariate VAR(1) models to weekly data are reported in Table 1. The vector of deseasonalized time series variables contains wind and inflow from the same region, such that index 1 refers to wind and index 2 to inflow. The t-statistic was used to test the significance of individual parameters at the 5% level and nonsignificant parameters are shown in italic font. As can be seen, the estimated autoregressive coefficients vary in magnitude between the different sites, and the lag-1 autocorrelation for weekly series is stronger for inflow than for wind. This was expected, since wind fluctuates more rapidly than inflow. What is interesting to notice is the estimated values of the autoregressive coefficient ϕ_{21}, which describe the dependence between current inflow and the lag-1 value of wind. With the exception of region 1 and 7, ϕ_{21} is significantly positive for all regions, ranging from 0.074 in region 3 to 0.169 in region 4. In contrast, the parameter ϕ_{12} which describe the dependence between current wind and lag-1 inflow is not significant for the majority of cases. The exceptions are region 5 and 6, however, these estimates are only barely significant and for all practical purposes likely to be negligible. The modelling results for the weekly series show that wind can be useful in forecasting inflow, but not the other way around.

Table 1: Estimated autoregressive parameters and corresponding standard errors from the fitting of VAR(1) models to weekly data.

	ϕ_{11}		ϕ_{12}		ϕ_{21}		ϕ_{22}	
Data series	Value	SE	Value	SE	Value	SE	Value	SE
Region 1	0.144	0.019	*-0.015*	*0.019*	*0.008*	*0.014*	0.696	0.014
Region 2	0.175	0.020	*0.030*	*0.020*	0.157	0.016	0.550	0.016
Region 3	0.199	0.020	*0.026*	*0.019*	0.074	0.020	0.409	0.019
Region 4	0.229	0.021	*-0.010*	*0.020*	0.169	0.020	0.280	0.020
Region 5	0.213	0.020	0.052	0.020	0.095	0.019	0.363	0.019
Region 6	0.185	0.021	0.050	0.021	0.140	0.019	0.414	0.019
Region 7	0.240	0.019	*0.021*	*0.017*	*0.032*	*0.017*	0.612	0.015

Model results for the daily case (not shown) are more involved and not so easy to interpret due to the higher model order (e.g. [12]). However, by considering only the lag-1 autoregressive coefficient matrix the same dependence structure could be observed for the daily case; wind was useful in forecasting inflow but not the other way around.

The contemporaneous correlation was generally not very strong, although it was substantially stronger for the weekly than the daily case. The estimated covariance, i.e. the cross-terms of the error covariance matrix, ranged from 0.008 to 0.097 for daily series, and from 0.032 to 0.367 for weekly series.

Finally, note that a diagnostics check was carried out for all the estimated models to ensure the model residuals approximately demonstrate the behavior of a white noise process. Visual inspection of the graph of the residuals suggested that the property of zero mean and constant variance was fulfilled, and no systematic variation could be observed. The sample autocorrelation function was also examined and showed no evidence of serial correlation in the residuals. On this basis, there was no reason to doubt the assumption that the fitted models are appropriate.

4.2. Forecasting performance

Step-ahead deterministic (point) and probabilistic forecasts were constructed and evaluated out-of-sample. The probabilistic forecasts take the form of discrete predictive distributions constructed from the estimated model, by random sampling from the empirical error distribution. We used 5000 random draws, such that the predictive distribution can be seen as an ensemble forecast with 5000 members. Forecast performance was measured using the Energy Score (ES) which assess both the reliability and sharpness of the forecast distribution [13]. For point forecasts the energy score reduces to the Eucliden error (EE). To rank and compare the competing forecast methods, we calculated the mean ES and EE over all forecast-observation pairs.

First, we compared point forecasts from the VAR models for each region with the corresponding persistence forecasts. The persistence forecast simply takes the most recent observation at hand as the point forecast. Since we are dealing with seasonal data, the persistence is adjusted accordingly, such that the persistence forecast for time t amounts to the deviation from the seasonal mean observed at time $t-1$ added to the seasonal mean at time t. Figures 2 and 3 display the percentage improvement in mean EE for VAR forecasts over the persistence forecasts for the daily and weekly cases, respectively. It can be seen that the VAR forecasts outperform the persistence forecasts in all cases (regions) and on both the daily and weekly time scale. These results confirm the VAR models' forecasting ability and, moreover, underline the importance of accounting for serial correlation.

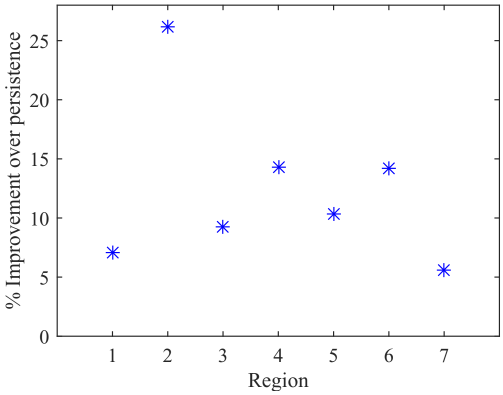

Fig. 2: Percentage improvement in mean Eucliden error (EE) for VAR over persistence for step-ahead daily forecasts.

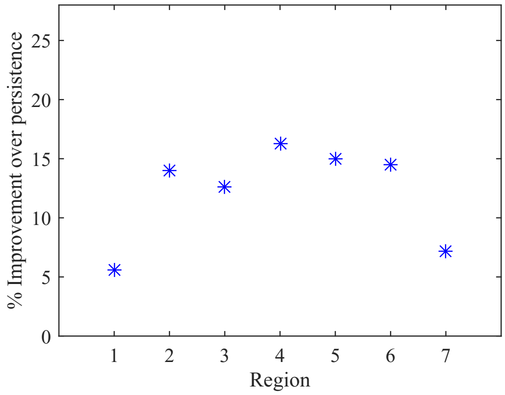

Fig. 3: Percentage improvement in mean Eucliden error (EE) for VAR over persistence for step-ahead weekly forecasts.

Secondly, we investigated whether the VAR models were able to provide better forecasts than independent AR models. The forecasting performance for both deterministic and probabilistic forecasts are summarized in Table 2, which reports the percentage improvement in mean EE and ES achieved by the VAR models compared to the AR models. With the exception of region 1, the VAR models performed better than the AR models in all cases on both time scales. The percentage improvement in ES ranges from 0.2% to 4.4%, depending on the region and time scale. Notice also that the improvements in the mean EE tends to be higher than the mean ES, which indicates that the predictive distributions from the VAR models are not necessarily sharper than those of the AR models. Given that the contemporaneous correlation is generally weak, this is not so surprising. Most likely the improvements in forecasting performance by VAR modelling can be attributed to the explanatory power of lagged values of wind in forecasting inflow, represented by the parameter ϕ_{21}. It can be seen from Tables 1 and 2 that the improvements generally increase with higher estimated values of ϕ_{21}. For example, for region 1 and 7 the forecasting performance of VAR and AR are approximately equal, and for these cases ϕ_{21} are statistically zero.

Table 2: Summary of forecasting performance for VAR models compared to AR models, in terms of percentage improvement in mean Euclidean error (EE) and mean Energy Score (ES).

	Daily		Weekly	
Data series	EE	ES	EE	ES
Region 1	-0.4	-0.5	-0.2	-0.2
Region 2	0.3	0.4	3.1	2.7
Region 3	3.6	3.4	0.7	0.6
Region 4	4.5	3.3	3.8	3.9
Region 5	4.9	3.6	1.9	1.9
Region 6	6.2	4.4	3.1	2.9
Region 7	1.9	1.3	0.4	0.2

5. Conclusions

Vector autoregressive (VAR) models based on deseasonalized data have been constructed to describe the joint generating mechanism of wind and inflow time series from seven regions in Norway. The purpose of the models is to aid in decision making problems concerning power system scheduling.

We found evidence of both lagged and contemporaneous dependencies between wind and inflow, in particular, our results indicate that wind is useful in forecasting inflow but not vice versa. Forecasts from the VAR models were shown to be substantially better than the persistence forecasts, which proves its forecasting ability. Furthermore, the improvements in VAR forecasts compared to AR forecasts suggest that a joint modelling approach should be used to better characterize the stochastic wind and inflow processes. Even though the results presented in this paper pertains to the Norwegian case, the methodology could be useful also for other systems with substantial shares of hydropower and wind.

Finally, we would like to underline that there is a difference between forecast *quality*, as addressed in this work, and forecast *value* [21]. When forecasts are used as a basis for decision support it is important to investigate whether or not forecast improvements also yield benefits to the users of the decision making models for which the forecasts serve as input. Work is underway to evaluate these aspects in the context of a coordinated wind-hydro scheduling problem.

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