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Workshop report: EUMETNET - E-TREND joint workshop on postprocessing, forecasting and nowcasting for renewable energy

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ABSTRACT

From 8 to 10 December 2025, the EUMETNET - E-TREND Joint Workshop on Postprocessing, Forecasting and Nowcasting for Renewable Energy, also known as RenEUCast25, was held at Vrije Universiteit Brussel (VUB). RenEUCast25 was meant as a dedicated event for the exchange of knowledge focused on effective forecasting and postprocessing for the renewable energy sector, and to promote a better understanding of how end users integrate forecasts and current developments in their decision-making processes. Organized by the EUMETNET Postprocessing Module, the Belspo E-TREND consortium (led by the Royal Meteorological Institute of Belgium), the EUMETNET Nowcasting module (led by GeoSphere Austria), and VUB's ETRO.RDI group, it gathered more than 50 participants from both the weather forecasting community and the renewable energy sector. 30 contributions were presented, organized in six different sessions, and including five keynotes. In addition, the event was streamed online with more than 20 additional participants.

1. Introduction

Europe's transition to a net-zero energy system is increasingly underpinned by the growth in renewable energy generation. In 2025, wind and photovoltaic (PV) generation together supplied about 30% of the European Union's electricity, surpassing the output from fossil fuels for the first time (Ember, 2026). Since wind energy and PV energy generation are directly dependent on meteorological conditions (Sweeney et al., 2020), there is an increasing collaboration between the meteorological and renewable energy modeling communities, and end users that make use of renewable energy forecasts, such as Transmission System Operators (TSOs), Distribution System Operators (DSOs), Balance Responsible Parties (BRPs), energy traders and energy service companies.

The joint EUMETNET - E-TREND workshop (RenEUCast 2025), held from 8 to 10 December 2025, was a dedicated event for the exchange of knowledge between these sectors, with presentations from different scientific communities all focused on effective forecasting for the renewable energy sector. Stakeholders were also invited to foster a better understanding of how they make use of forecasts in their decision-making processes. RenEUCast 2025 was organized by the European National Meteorological and Hydrological Services Network (EUMETNET) Statistical Postprocessing module, the E-TREND consortium funded by the Belgian Science Policy Office (BELSPO), led by the Royal Meteorological Institute of Belgium (RMI), the EUMETNET Nowcasting module (led by GeoSphere Austria), and the ETRO.RDI research group of Vrije Universiteit Brussel (VUB). The workshop gathered more than 50 participants, and 30 contributions were presented, organized in six different sessions, and including five keynotes. The event was also streamed online for about 20 additional participants. Table 1 provides an overview of the six scientific programme sessions and their main themes. Below, we summarize the sessions and the discussions that emerged from them.

User requirements identified through the dedicated survey and panel discussion are summarized in Section 7.

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Table 1
Overview of the six scientific RenEUCast 2025 programme sessions and their main themes.

Session	Main themes	Sect.
Operational forecasting application	NWP advances and AI weather models; downstream renewable energy forecasting applications	2
Operation & Decision-making	TSO forecasting use cases, uncertainty-aware forecasting, and Dynamic Line Rating (DLR)	2
Postprocessing	Calibrated ensemble postprocessing; user-informed postprocessing; bounded forecast distributions for wind power and precipitation	3
Nowcasting	AI-based seamless nowcasting; probabilistic very short-term wind power forecasting	4
Wind energy application	Wind-farm flow effects; probabilistic wind power forecasting; AI weather models; offshore ramp events	5
PV energy application	Surface solar irradiance (SSI) nowcasting; day-ahead PV power forecasting; climate change impacts on PV generation	6

2. Operational forecasting and decision making

Decision making in the renewable energy sector is dependent on accurate numerical weather prediction (NWP) forecasts for lead times from a few hours to a few days ahead Sweeney et al. (2020). The accuracy of NWP forecasts and their impact on the decision making process were an important point of discussion during the workshop, with keynotes presented by two TSOs.

2.1. Numerical weather prediction and downstream renewable energy applications

Termonia et al. highlighted the "quiet revolution of NWP" (Bauer et al., 2015), which has slowed down in recent years due to technological issues and challenges related to the hectometric scale, such as predictability issues at hectometric scales and the need for observations at this scale (Lean et al., 2024). Technologies such as Artificial Intelligence (AI) based weather models (Lam et al., 2023) are driving new progress, and for downstream applications in renewable energy forecasting, projects like the Destination Earth Digital Twins (Wedi et al., 2025) can act as catalyst. Nielsen et al. provided in-depth information on how the On-Demand Extremes Digital Twin Renewables Model of ECMWF serves as a "magnifying glass" to study the impact of extreme events. Van den Bergh et al. described examples of how the RMI has taken advantage of national and international collaborations to develop tailored forecasts for the renewable energy sector, within projects such as Be-Forecast (Munters et al., 2025), E-TREND, InStaFlex, and STORM, which have led to developments such as a dedicated storm forecast tool for Elia (Smet et al., 2019, 2023), implementation of a wind farm parametrization within the RMI Alaro model (Van den Bleeken et al., 2025), a new ensemble postprocessing method based on a self-attentive Transformer architecture (Van Poecke et al., 2025) and a verification framework for wind power ramping event predictability in the Belgian Offshore Zone (BOZ) (Meng et al., 2025). Ally et al. connected the use of renewable energy forecasts to decision making in day-ahead power trading and real-time power control for wind farms, using multi-agent reinforcement learning (Ally et al., 2025), while Schicker et al. described how a combination of reanalysis data, forecasts and AI techniques can identify hot spots of adverse weather for the Austrian energy infrastructure (Schicker et al., 2025).

2.2. Forecasting and decision making at TSOs

European TSOs are scaling up their forecasting capabilities. Both Elia (Belgium) and TenneT (Netherlands and Germany) describe the increased importance of accurate forecasting. The growth of offshore wind production, deployment of distributed PV, and evolution towards more electrification have made the behavior of the electricity grid more weather-dependent and unpredictable. Wind energy, PV production and load forecasts are used for reserve dimensioning, project and maintenance planning, balancing and frequency control, short-term adequacy and grid capacity planning. Elia also distributes forecasts to the market. Instead of relying solely on deterministic point forecasts, TSOs are increasingly relying on probabilistic forecasts that capture uncertainty and provide confidence intervals, through e.g. the use of model quantiles and ensemble weather model input.

Concerning operational concerns, Elia noted that Belgium's future offshore build-out towards roughly 6 GW of capacity will cause larger wind ramp events (which cause large fluctuations on the electricity grid), larger imbalances, and more complex reserve requirements. TenneT highlighted that differences between weather models alone can on occasion lead to several GW of variance in solar generation forecasts, which shows the increasing importance of uncertainty forecasting. Estimation of the more extreme quantiles and corresponding high-impact events such as the P90% of a PV generation forecast can be quite valuable. Limited visibility below the transmission interface adds complexity, particularly for DSO-connected solar, wind, and flexible loads "behind the meter". Market behaviors such as price-driven curtailment also introduce new constraints.

To manage this growing complexity and various sources of uncertainty, TSOs are rethinking their forecasting architectures. Elia has developed Predico (Elia, 2024), a performance-based multilateral forecasting market in which multiple forecasters compete and are paid based on accuracy. This has allowed Elia to perform its own ensemble model creation, and the resulting forecast has already demonstrated a roughly eight percent improvement for offshore wind and solar in a proof-of-concept phase. TenneT is moving toward a "meta-forecast" with integration of forecasts from connected parties (such as DSOs), internal providers and external providers, with the aim of selecting the best-performing forecast per day.

Both TSOs are pioneering Dynamic Line Rating (DLR; Michiorri et al., 2015). TenneT-Netherlands's deployment of DLR across 27 lines uses weather-based ampacity estimates to unlock additional capacity during cold and windy conditions. Ongoing challenges include meteorological forecast uncertainty (especially in wind speed and direction), limited sensor placement, hot-spot validation, and the importance of large safety margins to prevent sagging of lines. The advantages of DLR over static line rating have already been demonstrated. There is a further potential that can be unlocked from the use of high-resolution hectometric forecasts, as discussed by Van Oyen et al.

3. Statistical postprocessing

Statistically postprocessed weather forecasts products have long been demanded by industrial users, and included in their own operational workflows. The major difficulty in the weather forecasting context is the miscalibration of ensemble forecasts, limiting the use of these future scenarios for probabilistic inference (Vannitsem et al., 2018, 2021). This is in particular the case for wind forecasts for wind farm operators, but also more generally for all sectors depending on the weather conditions to operate. Effectively conveying the probabilistic information from postprocessing to these stakeholders in a comprehensive manner is a key challenge. In this context, the session focused on user-informed postprocessing: designing ways to present the information to the users according to their specific expectations and needs, depending on the kind of forecast consistency that they expect. In particular, Lake et al. presented a new method to extract information from ensemble forecasts according to these expectations, using clustering techniques to select the 'most-likely' ensemble realisation (Lake et al., 2025).

Another session topic was how to deal with the particular forecast distributions encountered when processing variables related to renewable energies like solar and wind. Bremnes presented a Bernstein Quantile Network (Bremnes, 2020) specifically designed to include wind farm power curves and production capabilities as input, in addition to other predictors such as wind speed. By combining weather forecasts and production information, this method is able to provide directly calibrated probabilistic wind farm power production forecasts.

The postprocessing of precipitation forecasts, like that of renewable energy forecasts, involves specific types of distributions. Two promising research approaches were presented regarding precipitation postprocessing: Groß et al. presented a statistical method based on the zero degree of freedom non-central χ-squared distribution (Groß and Möller, 2024), and Mlakar et al. presented a method based on joint lead time precipitation forecast postprocessing using deep generative models (Mlakar et al., 2024). Both methods are potentially applicable to renewable energy forecasts.

4. Nowcasting

The nowcasting session featured two contributions that addressed complementary aspects of very short-term forecasting for renewable energy: a latent-diffusion-based nowcasting framework and an adaptive Bayesian method for probabilistic wind power forecasting.

De Kock et al. presented RUSH (Rapid Update Short-term High-resolution), an AI-native nowcasting framework based on latent diffusion models (Leinonen et al., 2023; Tomasi et al., 2025) that produces probabilistic 0–24 h forecasts of precipitation at 30-min timesteps on a 1 km grid, with potential future extension to solar nowcasting. RUSH combines observation-driven extrapolation from radar and satellite imagery with large-scale conditioning from ECMWF's AIFS in a single seamless architecture.

Shen et al. addressed probabilistic very short-term wind power forecasting with an adaptive Bayesian method combining the generalised logit transformation with online parameter estimation (Shen et al., 2025). Evaluated across more than 100 wind farms in Great Britain over four years, the proposed method was reported to achieve the lowest average Continuous Ranked Probability Score (CRPS) and highest skill score, while demonstrating greater robustness than alternative adaptive approaches such as Newton–Raphson in sensitivity analysis.

5. Wind energy applications

Wind energy forecasting is a cornerstone of Europe's energy transition, with both offshore and onshore wind contributing to a rapidly growing share of electricity production. As highlighted by Munters et al., the increasing scale of offshore clusters, the coupling between atmospheric processes and turbine-induced perturbations such as wind farm wakes (Palatos-Plexidas et al., 2025), and the operational needs of TSOs and market actors are driving new methodological developments. The session therefore addressed the topic of wind-farm flow effects at farm and cluster scales, and on how these effects can be represented in models that remain useful for forecasting applications. In this context, Delvaux et al. discussed the development of a new multi-layer Atmospheric Perturbation Model (APM; Devesse et al., 2024), and Devesse et al. demonstrated the use of an APM for fast blockage correction (Devesse and Meyers, 2026).

Another topic was probabilistic wind power forecasting, in which the objective is to translate ensemble weather predictions into calibrated predictive distributions of power generation. This is particularly important for operational decision-making because uncertainty information supports reserve planning and imbalance risk management. Particular attention was given to the state-dependent uncertainty introduced by power-curve nonlinearities near cut-in, rated, and cut-out wind speeds, motivating distributional approaches such as quantile-based and generative methods, as discussed by Bruninx et al. (2026).

In addition, the session addressed the growing interest in AI weather models for wind energy applications. Two complementary directions were discussed by Van Poecke et al. and Lerch et al.: incorporating wind power information directly in training to obtain power-relevant atmospheric representations, and parameter-efficient fine-tuning of large pre-trained AI weather models. Key challenges include limited availability of hub-height wind outputs, scarcity of long high-resolution power datasets, and ensuring probabilistic consistency when coupling predominantly deterministic weather forecasts to power prediction frameworks.

Finally, Jones et al. discussed ramp events in offshore wind production in relation to their meteorological drivers and their implications for system operation. Ramp detection based on size-duration thresholds was linked to synoptic-scale systems such as fronts and low-pressure systems, as well as to mesoscale processes such as convection and convergence zones. The discussion emphasised that spatial aggregation reduces variability, but large coherent weather systems can still generate substantial cluster-wide ramps, which reinforces the value of combining meteorological pattern recognition with probabilistic forecasting for wind ramp risk assessment.

6. PV energy applications

Photovoltaic (PV) solar energy is the second pillar of the ongoing decarbonization of the European power grid. PV capacity is growing more rapidly than that of other energy sources, driven by falling PV costs (Nijsse et al., 2023), but the intermittency of surface solar irradiance places additional demands on the spatiotemporal resolution and accuracy of weather forecasts for the successful integration of PV into the energy mix. As illustrated in the keynote presentation by Meyer et al., short-term Surface Solar Irradiance (SSI) forecasts are increasingly important, and regional-scale forecasts are essential because PV capacity is mostly decentralised. For minutes to hours ahead, these high-resolution forecasting demands are addressed typically by satellite-based surface solar irradiance nowcasting models which are in use by early adopters since 20 years, but now gain significantly larger importance in operational weather services due to larger solar energy shares and recently added generative AI-based algorithms (e.g. Carpentieri et al., 2023 and 2025).

Wang et al. developed day-ahead 15-min PV power forecasts based on NWP output post-processed with either EMOS (Ensemble Model Output Statistics) boosting or using LightGBM (Light Gradient-Boosting Machine) with a distributional regression network. Both approaches were reported to provide useful predictive information comparable to a commercial baseline on both statistical and business-oriented metrics, as well as uncertainty information.

Schicker et al. addressed how weather forecasts can be translated into decision intelligence for a grid with high renewable energy penetration, using the hybrid wind-PV sites with limited feed-in capacity as a challenging use case. The proposed forecasting chain combines NWP output with a nowcasting blend including the deep learning-based IrradPhyDNet (Papazek et al., 2023) to obtain site-specific wind and PV power. Combined with accurate PV modelling that accounts for effects such as PV panel tilt (transposition), temperature, and shadowing from wind turbines, these forecasts were shown to enable better scheduling of flexibilities (e.g. home batteries) rather than reactive curtailment. Finally, de Jong et al. presented the impact of climate change on PV energy generation for solar panels in Belgium, using 10 CMIP6 climate model projections (Hou et al., 2021) and a multi-physics energy yield model (Goverde et al., 2017).

Both wind and PV require probabilistic weather forecasts translated into accurate production forecasts, but PV especially brings challenges due to short-term variability, finer spatial scales, and the increasing operational relevance of prosumers and local grid flexibility.

7. User requirements for nowcasting, forecasting, and observations

A short user survey (n = 26) was conducted during a dedicated session on user requirements, with respondents dominated by researchers and developers, and a few forecasters and students. Across answers, the most recurrent general requirements for meteorological (and energy-relevant) observations were: open and easy access, quality control with clear metadata and quality flags, low latency, rapid updates, high temporal resolution, and explicit uncertainty information. Given the limited sample size and respondent composition, these results should be interpreted as indicative rather than fully representative of the broader user community.

Regarding desired observation types, respondents most often asked for radar-based products/data and for access to wind-energy operational measurements, in particular turbine/plant-level SCADA (Supervisory Control And Data Acquisition) data. Additional requests included wind observations closer to hub height, lidar, and more sites.

All respondents supported enhanced cross-border sharing, often noting that exchange should include quality information and metadata, and in some cases also energy production data (e.g., adjacent wind farms). Research-to-operations barriers included data discontinuity and distributional shifts, insufficient operational IT infrastructure, and the need for standardized tool stacks, validation, and production-level engineering support.

The repeated calls for opening up turbine/plant SCADA data directly informed a concrete follow-up action: a perspective statement advocating improved access to SCADA data is being prepared as an outcome of the survey.

8. Summary and conclusions

The RenEUCast workshop 2025 highlighted the growing importance of accurate, high-resolution, probabilistic and user-oriented forecasting for renewable energy applications. Key developments are the move towards (sub-) kilometer-scale modelling and the improved representation of local processes and interactions relevant for wind and solar energy production. Another prominent innovation is the increasing integration of AI-based methods in all parts of the forecasting chain: weather prediction, statistical post-processing, nowcasting, and the translation into user-relevant variables.

In addition, the contributions demonstrated that there is much to be gained from improving alignment between these developments and operational requirements. Improved high-resolution and probabilistic forecasts were shown to translate directly into tangible benefits through applications such as dynamic line rating, allowing real-time increases in grid capacity. The role of weather-forecast-driven decision support is growing, and therefore the value of forecasts needs to be measured in terms of their impact on grid operation and risk management rather than simple statistical scores.

Finally, a user requirements survey indicated that the quality of models and forecasts hinges critically on the availability of sufficient, accurate, and high-resolution operational data. In addition to the valuable ENTSO-E data (the European Network of Transmission System Operators for Electricity), the opening up of SCADA data from wind farms in particular would accelerate the development and validation of advanced forecasting methods, and enable the training of AI-based models. Better forecasts in turn would improve scheduling and planning, leading to a more effective decarbonization of the energy grid.

Overall, the workshop highlighted a shift towards more integrated and application-driven forecasting systems, combining high-resolution modelling, AI methods, and enhanced data availability to support a reliable and efficient transition to a high-renewable, low-carbon energy system.

CRediT authorship contribution statement

Jonathan Demaeyer: Writing – original draft; **Joris Van den Bergh:** Writing – original draft; **Irene Schicker:** Writing – original draft; **Hossein Tabari:** Writing – original draft; **Franziska Schmid:** Writing – review & editing; **Marion Schroedter-Homscheidt:** Writing – review & editing; **Stéphane Vannitsem:** Writing – review & editing; **Lesley De Cruz:** Writing – original draft.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Joris Van den Bergh and Lesley De Cruz report financial support was provided by BELSPO. Jonathan Demaeyer, Stephane Vannitsem and Franziska Schmid report financial support was provided by EUMETNET. Irene Schicker reports financial support was provided by the Austrian Research Promotion Agency. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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