Analysis of Limited Area Models for Wind Power Prediction

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Abstract:

Allo scopo di migliorare l'accuratezza delle previsioni per impianti rinnovabili di generazione elettrica alimentati da fonte eolica, un nuovo modello NWP (Predizione Numerica del Tempo) è stato testato come input ai modelli statistici sviluppati dall'ENEL.

I campi di previsione forniti dal modello operativo NWP (COSMO-ME) del Servizio Meteorologico dell'Aeronautica Militare sono stati usati e confrontati con un sistema di riferimento interno dell'ENEL, basato su un differente modello NWP, per valutare le prestazioni per le previsioni di energia eolica per il giorno stesso e per il successivo. I test sono stati effettuati su un numero significativo di parchi eolici per verificare l'affidabilità del lavoro. La prestazione di COSMO-ME è molto buona rispetto alla predizione per il giorno stesso, ma sembra sostanzialmente allineata rispetto al modello per quanto riguarda le previsioni per il giorno successivo.

Abstract.

In order to improve the accuracy of wind power predictions, a new mesoscale NWP (Numerical Weather Prediction) model was tested as input to the statistical downscaling models developed by ENEL. Forecast fields provided by the operational CNMCA NWP model (COSMO-ME) were used and benchmarked to a reference ENEL's internal system, based on a different NWP model, to evaluate performance on intraday and next-day wind power predictions. The test has been carried out on a significant number of wind farms in order to assure work reliability. COSMO-ME performance is very good with regard to intraday predictions but seems substantially aligned with the reference model for what concerns the next day predictions.

1 Foreword

Enel Green Power (hereinafter ENEL GP) is the Enel Group Company dedicated to developing and managing energy generation from renewable sources at an international level, with a presence in 17 Countries among Europe, the American continent, Africa and Asia. Enel GP has an installed

capacity of over 10 GW and with more than 740 plants in operation around the world.

Enel Ingegneria e Ricerca (hereinafter Enel E&R) has the mission of serving Enel Group by managing the engineering processes related to the development and construction of power plants. Enel E&R also coordinates and supplements the Group's research activities, ensuring the scouting, development and leveraging of innovation opportunities in all Group business areas, with a special focus on the development of major environmental initiatives.

Enel GP has been working for many years in the field of wind power forecasting, together with Enel E&R, that has been developing renewable-power forecast models for Enel GP plants in the last years.

As the national weather service in Italy, SeMAM – Servizio Meteorologico dell'Aeronautica Militare (Italian Air Force Meteorological Service) has a special responsibility for the general public and industry in the country. SeMAM is a scientific/technical organization whose activities are determined by the Ministry of Defense, with the primary aim to provide meteorological and climatological data, products and services of highest quality for both purposes, support the Italian Air Force and the Nation.

Following WMO – World Meteorological Organization, the meteorological and climatological mission of SeMAM is related with protection of life and property, conservation of the environment, sustainable development and increase of the quality of living and promotion of science and technology. For this reason, all working processes are clearly structured and continuously improved with regard to their efficiency. The global network of National Meteorological Hydrological Services and the partners in Europe secure the daily exchange of meteorological data. Finally, the CNMCA – Centro Nazionale di Meteorologia e Climatologia Aeronautica – is the main operational Centre of SeMAM, where all those processes and observation networks are managed.

2   State of the art

The penetration of renewable energy plants is increasing steadily in the energy sector; as their contribution to the total energy production is becoming more and more relevant, their intermittent operation mode can cause problems of integration in the electrical grid, introducing uncertainty in electrical loads needed by the Transmission System Operators (TSOs) in order to balance the electrical system. In order to reduce this unbalancing as much as possible, TSO, utilities and other renewable-energy producers started years ago to develop tools capable of forecasting the power that could be produced by renewable-energy plants. Typically these tools use weather predictions, statistical and fluid-dynamic models (for wind) in order to provide a quantitative profile of the power that can be produced by one or more renewable-energy plants; the typical time horizon needed is 48-72 hours ahead.

So it becomes extremely useful to be able to forecast the wind power that can be produced by wind farms (and other non-programmable renewable energy sources as well, such as photovoltaic or run-of-the-river hydro), in order to stimulate new wind power installations and in order to bring down the costs for balancing the electrical system, and to bring down the cost of electric energy as well.

3 Wind power forecasting in ENEL

3.1 The Enel forecasting system

In the past years several models for wind power forecasting have been developed by Enel E&R in order to forecast the power production of wind farms owned by Enel GP. This kind of models needs, as driving data, weather forecasts from NWP models. Wind speed and wind direction are the most important parameters to be taken into account, but pressure, temperature and others may also be used in addition to them. Values of such variables, available over a three-dimensional grid of points surrounding the considered wind farm, need to be scaled to the hub height of each farm's turbine. This calculation procedure, known as downscaling, may be performed using a physical approach or a variety of statistical techniques; at Enel E&R both the possibilities have been widely investigated, resulting in the development of consolidated CFD (Computational Fluid Dynamics) and ANN (Artificial Neural Network) models.

A complete forecasting system, based on such downscaling models, has been realized by mid 2010 and since then it has been producing daily predictions for all the so-called relevant (>10MW) Enel GP wind farms, with a 72h time horizon and hourly resolution.

A conceptual scheme of ENEL forecasting system is shown in Figure 1.
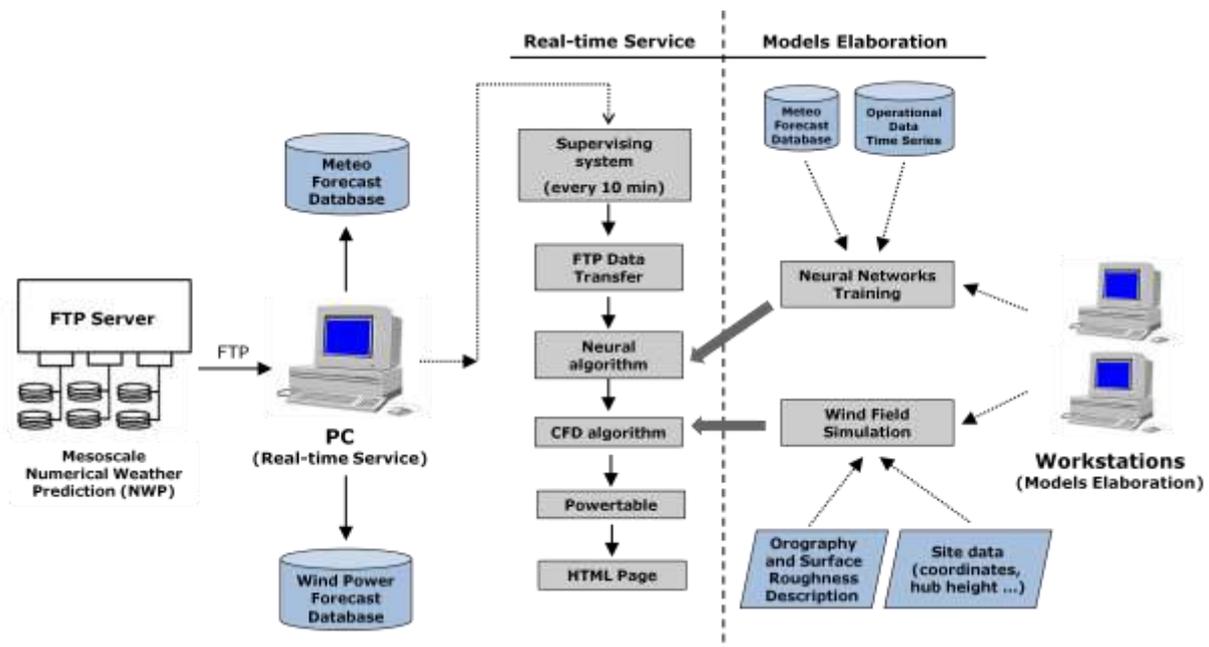
Figure 1 – Architecture of ENEL Forecasting System

Weather predictions, coming from a regional (or mesoscale) model, are downloaded every morning from the Service Provider FTP server. Data are stored and immediately used as input to the CFD and ANN models. The daily wind power forecast (here called "powertable") is then generated and stored to be shared with operational users and for future reference. An optional HTML page may be produced to graphically represent the forecasted power profile, if required. Models used in everyday operation are built as shown on the right, each of them requiring its own appropriate information. In order to be realized, CFD models need orography, surface roughness and land use information, besides to site data regarding turbine position, their hub height, their power curve, rotor diameter and so on. On the other hand, ANN models can work without any information about terrain and wind farm characteristics but need extended time series of NWP variables (wind speed, wind direction, etc.) and time-overlapping operational data from wind farm SCADA (mainly turbine wind speed and power data).

3.2 Regional NWP Models

Weather predictions suitable to wind farm scale are generally provided by regional NWP models, also known as mesoscale or limited area models (scales between two and a few hundred kilometers).

Unlike global models, limited-area models cannot work on their own. They always need to be driven by boundary conditions at the limits of their domains and initial conditions as well. The model's initial state (analysis) must also be specified, using algorithms that combine information from observations and results from a numerical model (short-range forecast) or an interpolation of the global model's instantaneous fields.

Most regional NWP models use nested grids, with a lower-resolution grid covering the full domain and successive higher-resolution grids covering smaller fractions of that domain.

Higher resolution models are the key to the improvement of local weather forecasts, and therefore wind power prediction. For this reason there is a constant effort to make models working on smaller scales, although it is commonly accepted that meteorological processes have a reduced predictability at those levels and that initialization of a high resolution model may require an excessive number of observations. Nevertheless some "external factors" like orographic flow, which is affected by terrain geometry, can be very well modelled even on small scales with only the computational load acting as a limiting constraint.

3.3 Downscaling models and wind-to-power conversion

All the models developed at Enel for wind power prediction basically fall into two groups. When no data from wind plants are available, a CFD

(Computational Fluid Dynamics) model is built from orography maps, local roughness information and turbine data. This kind of model allows to estimate the wind fields over the wind farm area, starting from the values of wind module and direction at a certain point in the space. In practice, these points are selected among those of the three-dimensional model grid of available weather forecasts. The forecasted wind in that point is therefore scaled to the wind turbine hub height and is ready to be converted to power by using the turbine power curve, which is the relation between wind speed and power, as shown in Figure 2.

This is a powerful method to build a model when absolutely no plant data are available but it lacks precision if the model is not calibrated at least with a minimum set of plant measurements of turbine wind speed.

On the other hand, neural network models may be realized quite easily if wind farm data exist, as no other information is required. Furthermore, being inherently calibrated, they also perform very well.
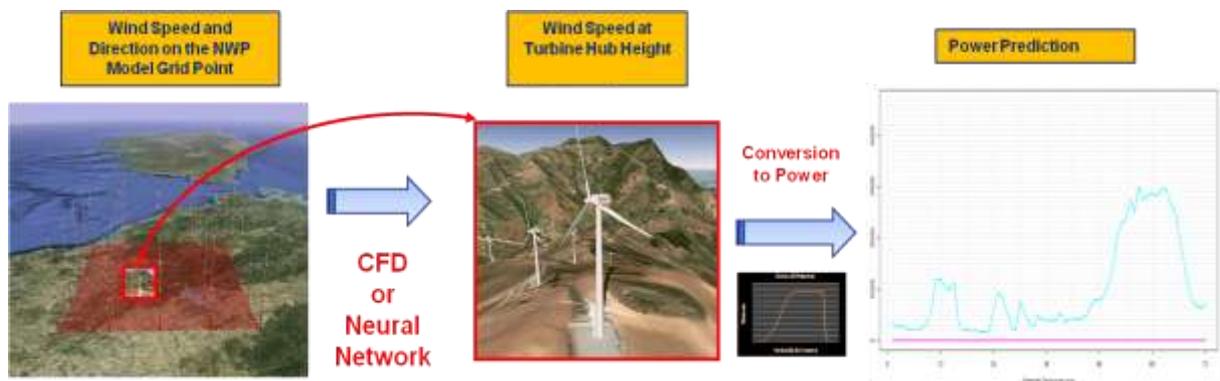

Figure 2 – Statistical or fluid-dynamic downscaling of NWP data for wind power prediction

A typical power curve for a wind generator is depicted in Figure 3. The conversion of available wind power, which is proportional to the cube of the wind speed, into actual power varies nonlinearly, with zero output below a minimum speed threshold (around 3 m/s), a rapid output in growth until the machine attains its nominal power (around 15 m/s), and a constant output above that level until the cut-off speed is attained (around 25 m/s).

Since the power curve is non-linear, the forecast errors relative to wind speed will result in power errors in a peculiar way. Errors at very low speeds are irrelevant since the output is always zero. Errors in the flat region of the power curve (between around 15 and 25 m/s) are also irrelevant as the output is constant. Errors at low-to-moderate speeds (3–12m/s) are highly penalized, as a small error in speed leads to a large error in power. Finally, the worst errors are obtained near the cut-off speed (around 25 m/s), when the system shifts abruptly from maximum output to zero output (or vice-versa).

Surface-layer wind speed and wind direction are directly affected by topographic effects at different scales, thus making wind forecast resolution highly relevant.
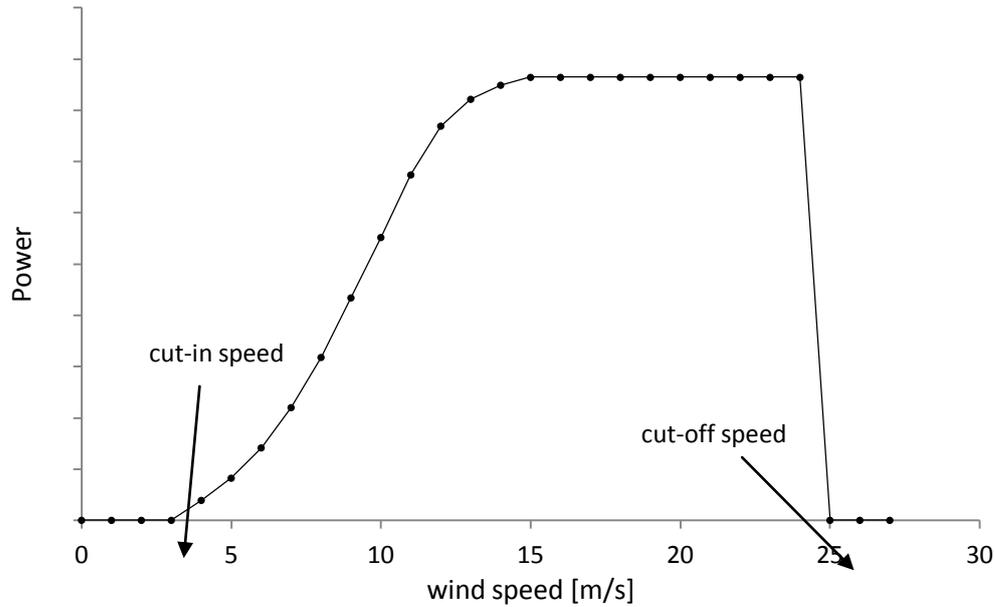
Figure 3 – Typical Wind Turbine Power Curve

3.4 Downscaling models based on artificial neural networks

Neural models developed by ENEL for wind power production have a basic scheme like that depicted in Figure 4. The model is built through neural network training, that is giving, as "examples" to the network, time series of matched input and output variables.
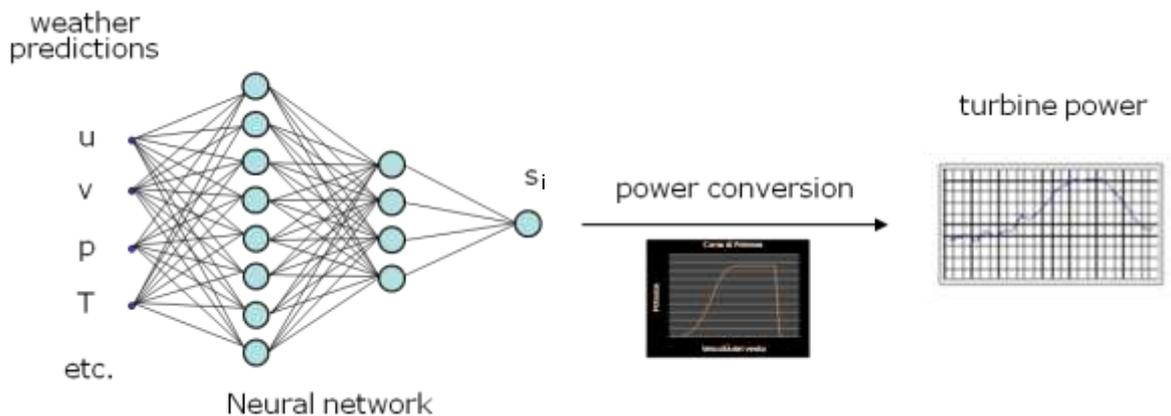

Figure 4 – Neural network for a single turbine

A selection of meteorological variables coming from the mesoscale NWP model grid point is entered as input to the network. Possible parameters to use may be wind speed horizontal components (u, v), pressure (p), temperature (T), and others. The neural network is then trained using, as target, the corresponding values of wind speed measured at the hub height. Once trained, the model will be able to return the appropriate values of wind speed for each turbine (s_i) as function of the input variables (u,v,p,T,etc.):

$$s_i = f(u,v,p,T,etc.)$$

Wind speed needs to be converted to power as described before. Alternatively, a direct training of the neural network using power as target in spite of wind speed is possible. In this case the power curve shown in figure 3 will be embedded in the neural model. In other words, another regression function will result from the training that can be written as follows:

$$P_i = f(u,v,p,T,etc.)$$

where Pi is the power of the i-th wind generator.

After several trials in a variety of situations, the first method (i.e. wind speed training and successive conversion to power) has proved to perform better.

A simplified ANN model may be realized using as target the wind farm aggregated power in spite of the detailed wind speed components for each turbine of the plant. The power data series come from the recordings of actual wind farm energy output realized by the metering systems at the final delivery point. In such cases a CFD model may be realized but it requires long time, availability of another kind of data (detailed terrain description and wind turbine information) and, in any case, even just a few plant data are necessary for a final calibration of the model.
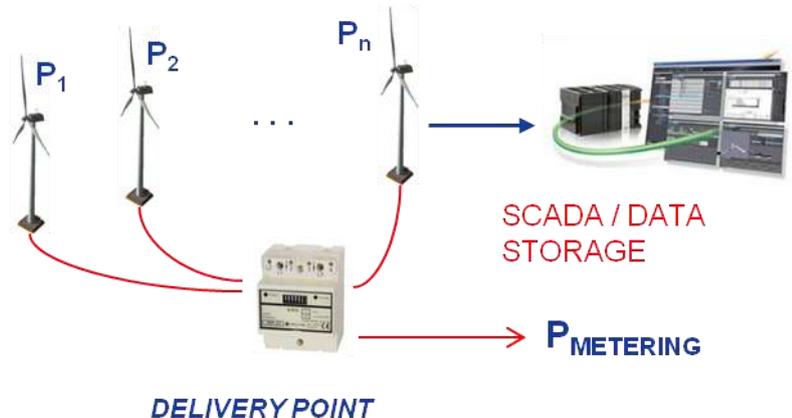

Figure 5 – Power data from Metering System

Power data from metering incorporate mean turbine availability and dispatching commands from TSO, so they require a more frequent update of the model through a re-training on a continuously renewed set of data. Furthermore, they inherently contain all the power curve characteristics, including machine power limitations as well.

The training of a neural network model with metering data is quite easy, so it should certainly be the method of choice in a variety of situations, going from lack of turbine data times series to the need of rapid implementation of a new

model, and finally for testing purpose as in the case of new meteorological data availability. For that reason, this has been applied to the test case described at paragraph 5.

3.5 Model performances and improvement strategies

Model performances, in order to be considered reliable, cannot be referred to spot measures but must be evaluated for the whole forecast horizon, e.g. 25-48 hours for a day-ahead forecast, and must be extended over long periods of time to have statistical significance.

One of the basic criteria for measuring model performance is the Normalized Mean Absolute Error (NMAE), usually expressed as percent. Referring to power this will be:

$$\text{NMAE \%} = 100 \times \frac{\sum |P_P - P_M|}{n} \bigg/ P_{nom}$$

where P_P is the predicted power, P_M is the measured power and P_{nom} is the wind farm (or single turbine) nominal power.

Prediction errors are strongly related to the wind farm terrain complexity. The average value of the NMAE ranges between 8-10% (flat terrain) to 20% (highly complex terrain) as shown in Figure 6, where RIX, Ruggedness Index, is a quantitative measure of orographic complexity.
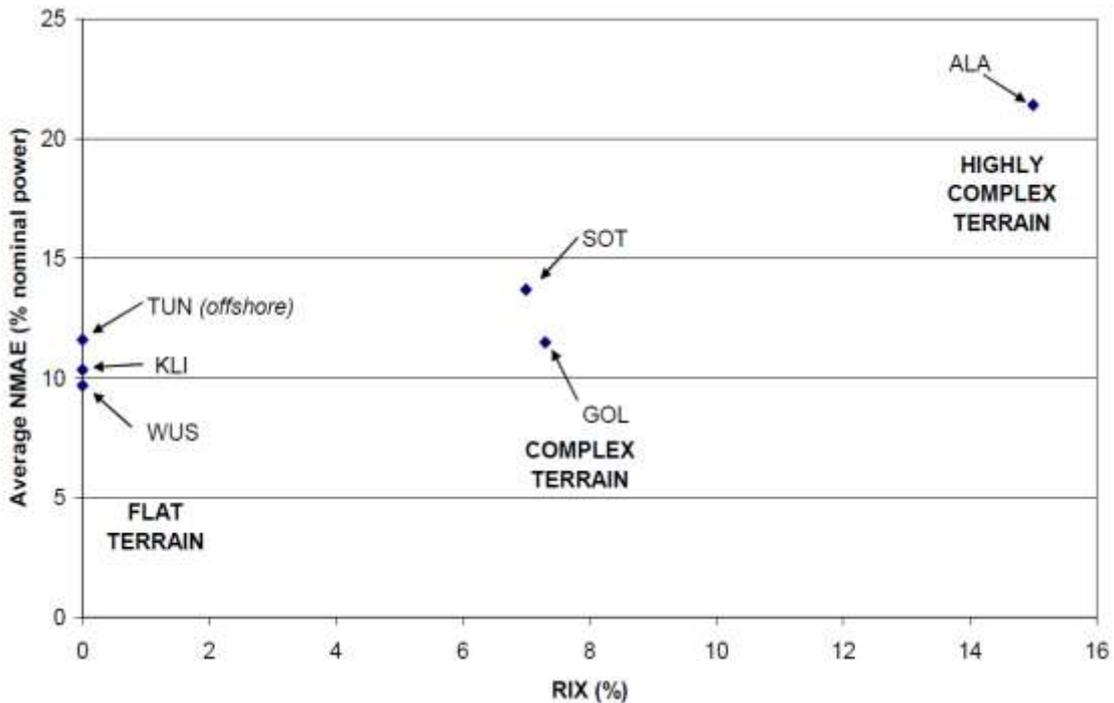
Figure 6 – Average prediction error for 12 hours forecast horizon vs RIX at test cases. Qualitative comparison [10].

As previously stated, weather forecasts in use are already provided by limited area models. While these predictions are considered reliable over the typical scale of weather forecasting, they lack precision when it comes to predicting the wind over the very small area of a wind farm, especially in complex terrain conditions.

So, the first step for improving prediction accuracy appears to go through an increased NWP model resolution.

Another viable approach could be a better initialization of NWP regional models; in this way it should be possible to boost the accuracy of predictions at least for the next day horizon (25-48h lead time).

In the framework of current activities started by ENEL to improve the performances of wind power forecasting, both the strategies are considered valid and are undergoing appropriate test campaigns.

Besides that, having more than one NWP provider will allow to combine forecasts from different models, potentially leading to an improvement of the accuracy, and to increase NWP data availability for the ENEL Forecasting System daily operation.

4   Collaboration with CNMCA

Collaboration between ENEL and CNMCA is aimed at fulfilling some of the targets above described. The use of forecast fields from the CNMCA operational short-range numerical prediction system was tested as input to the statistical downscaling models developed by ENEL.

4.1   The CNMCA operational short-range numerical forecasting system

The CNMCA short-range numerical prediction system is based on the Ensemble Kalman Filter (EnKF) approach [11,12], for the data assimilation component (estimation of the initial conditions), and the COSMO regional model (www.cosmo-model.org) for the prognostic one. The EnKF is an assimilation technique that uses the Monte Carlo approach through an ensemble of forecasts (currently 40+1 members) which allows to include information on the flow-dependent error of day, in particular the Local Ensemble Transform Kalman Filter (LETKF [13]) scheme has been implemented at CNMCA.

The observational dataset operationally ingested comprises 4D radiosonde ascents (RAOB), surface pressure observations from land and sea stations (SYNOP, SHIP, BUOY), manual and automatic aircraft observations, atmospheric motion vectors from Meteosat, European wind profilers, scatterometer winds from METOP/OceanSat2 and AMSU-A/MHS radiances from METOP and NOAA satellites, ATMS radiances from NPP-Suomi.
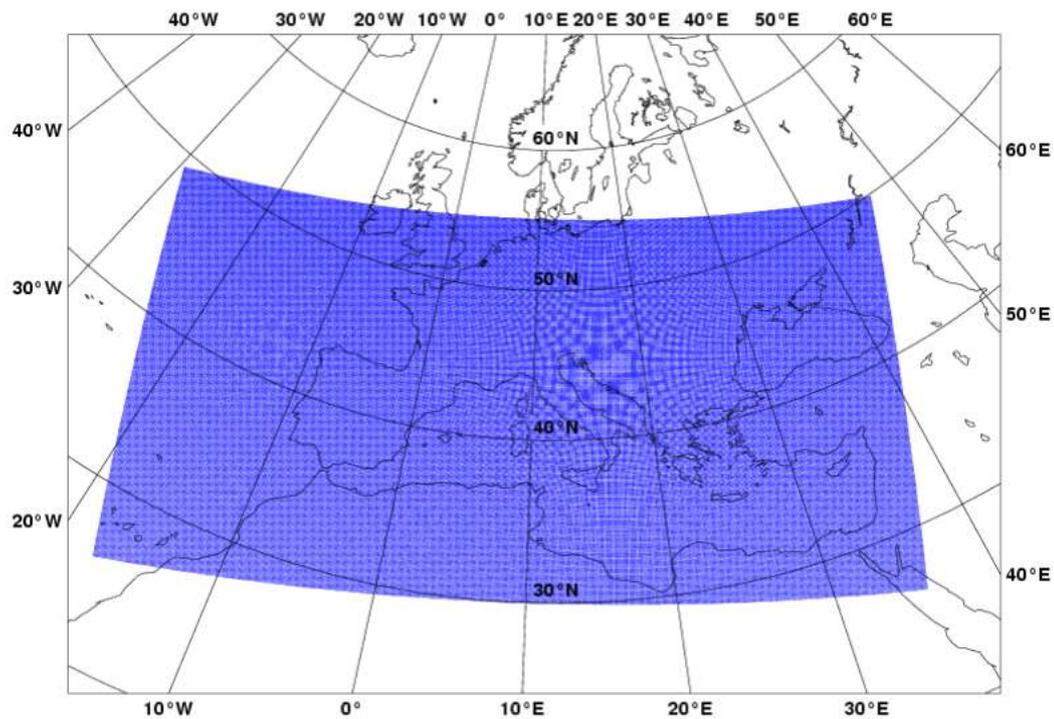
The CNMCA-LETKF data assimilation system is being operationally used twice a day (00 and 12 UTC runs) to initialize the high-resolution non-hydrostatic model COSMO integrated up to 72 hours over the Mediterranean-European region (COSMO-ME, Figure7). The main characteristics of the CNMCA operational NWP system are:

• The system is running on the Mediterranean-European domain having a 0.0625° grid spacing (7 km) and 40 vertical levels. The configuration is defined on a rotated regular grid, the coordinates of rotated North Pole are (47.0,-10.0). Lateral Boundary conditions from IFS (ECMWF-European Center for Medium-range weather forecasts) deterministic run.

• **Figure7: COSMO-ME domain**

5 Case study description and results

COSMO-ME forecasts up to 72 hours, starting at 00UTC, over one year period (that is long enough for wind power purposes), have been provided for testing by CNMCA. The meteorological data set covers an extended grid centered over Sicily, where several ENEL Green Power wind farms are located. The NWP parameters supplied for this test case were wind speed, wind direction, temperature, pressure and Pasquill stability class, but only the first two have been used at this preliminary stage. Time series covered the whole year 2012 and were available for 12 lower vertical levels for each one of the grid points.
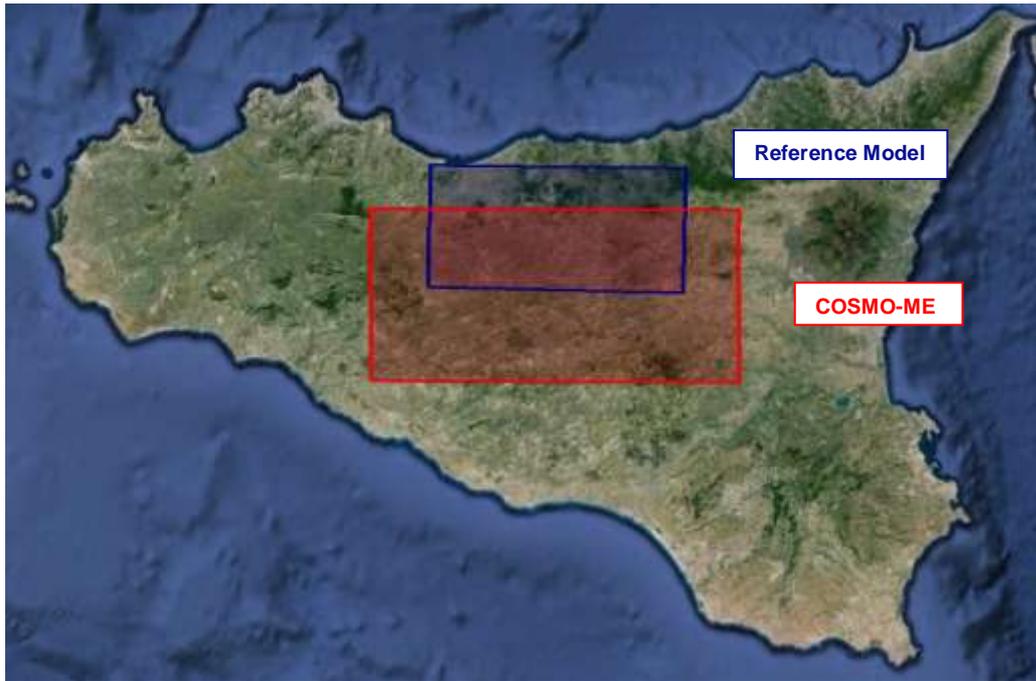
Figure8– Grid areas, extension and position for COSMO-ME and reference model

NWP data from an internal reference model was adopted as benchmark for this analysis, while a time series of registered power values from metering system was used to train the models and to evaluate the prediction errors.

The model chosen here, for an easy preliminary evaluation, was the simple metering-based neural network described before.

The analysis was carried out for six wind farms (hereinafter referred to with Test Site 1, Test Site 2, etc.) so that reliable results could be obtained.

NWP models under test were evaluated for the same day prediction (forecast horizon: 1-24 hours ahead) and for the day-ahead prediction (forecast horizon: 25-48 hours ahead). The two grids for NWP data did not exactly overlap but a sufficient number of grid points were nevertheless available for a first performance comparison. NWP data, in either case, were available for the aforementioned 12 vertical levels whose heights are comprehended approximately between 0 and 1200 m above ground level.

The first eight months of NWP data were used to train the neural models, leaving the last four for the testing phase. ANN models were trained and evaluated in the same conditions for both the NWP data time series.

Results for the intraday prediction are summarized in Table 1 and plotted in Figure 9.

Table 1 – Performance comparison for intraday prediction (training 1 Jan – 31 Aug, testing 1 Sep-31 Dec 2012)

	Reference [%]		COSMO-ME [%]	
	NMAE	CORR	NMAE	CORR

Test Site 1	13.70	0.70	11.78	0.78
Test Site 2	12.15	0.78	10.59	0.81
Test Site 3	9.82	0.79	8.60	0.83
Test Site 4	11.08	0.81	9.49	0.85
Test Site 5	8.80	0.75	7.64	0.80
Test Site 6	11.82	0.76	10.11	0.81

As shown in the table above, COSMO-ME performs very well for all plants. NMAE is always lower and correlation is steadily higher compared to the values obtained for the reference model.
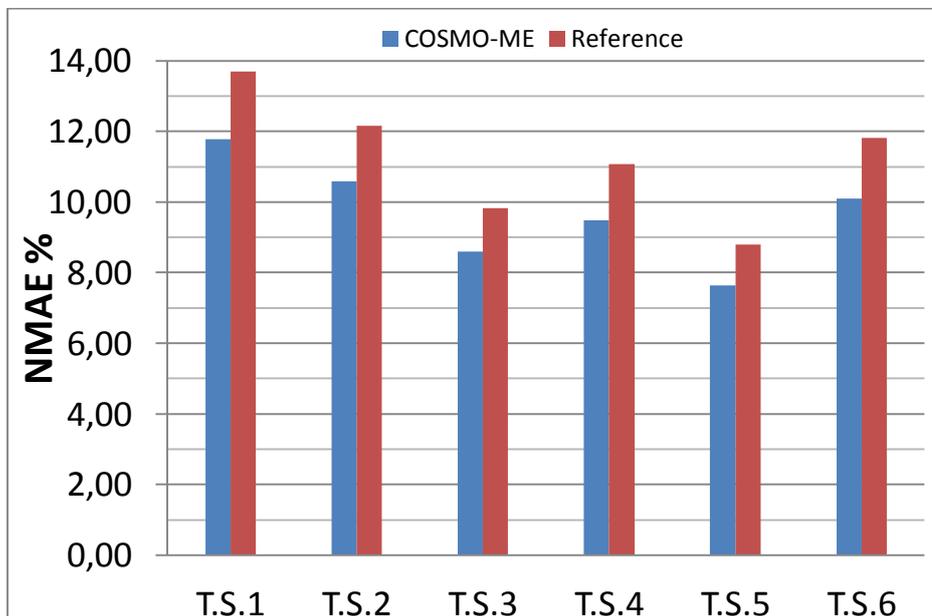

Figure9– NMAE% comparison for the intraday prediction

Results for the next day prediction, reported in Table 2 and Figure 10, seem to get worse compared to the first ones.

Table 2 – Performance comparison for the next day prediction (training 1 Jan – 31 Aug, testing 1 Sep-31 Dec 2012)

	Reference [%]		COSMO-ME [%]	
	NMAE	CORR	NMAE	CORR
Test Site 1	14.19	0.68	13.70	0.72
Test Site 2	12.53	0.74	11.92	0.79
Test Site 3	9.80	0.78	9.78	0.80
Test Site 4	11.25	0.79	11.42	0.80

Test Site 5	8.66	0.77	8.75	0.77
Test Site 6	12.01	0.74	11.54	0.77

Prediction errors, as expected on a longer time horizon, increase for both the reference and COSMO-ME models, but while this growth is minimal and in some cases negligible for the reference model, it shows a rise for COSMO-ME.

The observed behaviour can be explained considering the differences between the compared models. COSMO-ME and the reference model are both area limited models covering the Euro-Mediterranean region, using the same boundary condition from ECMWF-IFS forecasting system. While the numerical core of the models is quite similar, the main difference is the definition of the initial conditions (analysis field): the reference model estimates initial conditions using a method based on Newtonian relaxation (nudging of observations), while the COSMO-ME is initialized by an analysis evaluated through a new method based on the ensemble Kalman filter algorithm (LETKF), that has been proved to perform better than some traditional methods (3DVAR). Moreover in a regional model of such dimensions, the signal coming from the boundary conditions has impact on the forecast starting from the second day, while in the first day of prediction the quality of the initial conditions drives the quality of forecasted field. Because of these considerations it can be concluded that the COSMO-ME model is expecting to perform better at day one because of the better analysis evaluation, while at day two the performances of the two models should be similar because the effects of boundary conditions becomes more important. It can be also observed that the better quality of COSMO-ME forecast is depending on the use of a state-of-the-art data assimilation scheme (LETKF algorithm). The CNMCA is using the new method with encouraging results since 2011. At that time the choice to move from 3DVAR to LETKF algorithm has been pioneering, being the CNMCA the first center using operationally an ensemble-based data assimilation system at regional scale.
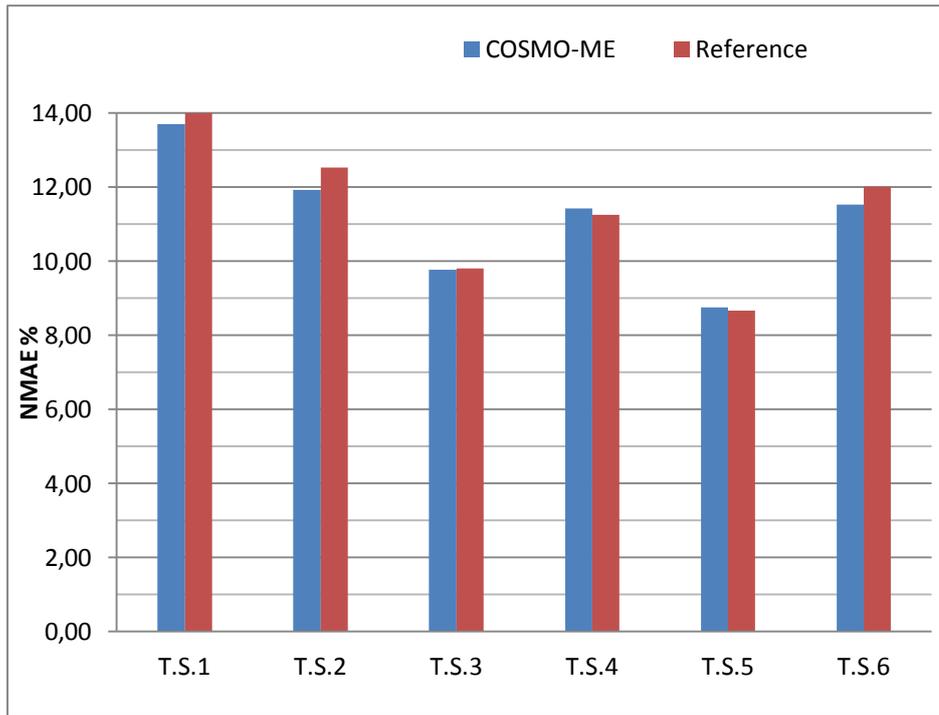
Figure10– NMAE% comparison for the next-day prediction

Another analysis can be carried out in order to compare the performances between the COSMO-ME model and the reference one, regarding the unbalanced volumes of energy.

In order to estimate these unbalanced volumes of energy, the unbalancing index IS can be introduced.

This index represents the percentage of the unbalanced volumes of energy above the franchise level, in respect to the predicted energy.

Herebelow the calculations necessary to obtain this index are shown:

Em = hourly produced energy;
Ep = hourly predicted energy (corrected with the unavailability);
FR = franchise level (0% - 10% - 20%)

On an hourly basis, the following parameters have to be calculated:
$EABS = |Em-Ep|$
$VOL\_BURDEN = If\ (\ EABS>FR*Ep)$ Then $(\ EABS – FR*Ep\ )$ Else (0)

Therefore the unbalancing index IS is calculated as follows:

$$IS = \frac{\sum VOL\_BURDEN}{\sum E_P}$$

where the summation is extended to the whole analysis period.

Herebelow the results for the test sites are presented (calculation basis: Sep-Dec 2012); IS0, IS10 and IS20 are to be intended as the unbalancing indexes calculated with franchise levels respectively equal to 0%, 10% and 20%.

Table 3 – Unbalancing index (calculation basis: 1 Sep-31 Dec 2012; next day prediction)

	Reference [%]			COSMO-ME [%]		
	IS0	IS10	IS20	IS0	IS10	IS20
Test Site 1	58.78	49.42	41.39	47.46	38.24	30.64
Test Site 2	53.09	43.91	36.12	44.65	35.50	27.98
Test Site 3	53.78	44.60	36.82	46.17	37.20	29.82
Test Site 4	48.91	39.80	32.46	41.87	32.84	25.62
Test Site 5	51.94	42.72	35.06	45.43	36.14	28.46
Test Site 6	52.82	43.56	35.64	43.03	33.87	26.51

Results indicate that COSME-ME can ensure lower unbalanced energy volumes compared to the reference model. The unbalancing index is roughly 8% lower for each one of the 3 franchise level considered.

Therefore, while the NMAE for COSMO-ME is just slightly better than the reference (for next-day predictions), COSMO-ME seems to perform considerably better than the reference model in terms of unbalanced energy volumes.

6   Conclusions

COSMO-ME model has been tested as input to ENEL wind power forecasting models and benchmarked against an ENEL internal reference model. COSMO-ME performs better than the reference for the look-ahead horizon 1-24h, while in the horizon 25-48h COSMO-ME's performances seem to be aligned with the reference for the NMAE, but better in terms of unbalanced energy volumes. These results are probably due to the differences in the initial conditions between the two models used in the comparison. In a regional model the initial conditions strongly affect the first forecast steps in a way depending on the domain size and the flow regime. From this experiment it seems that the quality of the initial conditions drives the quality of forecast fields in the first day of prediction, while the boundary conditions has a prevailing impact on the forecast steps starting from the second day.

7   Future Activities

Since COSMO-ME and reference model grids did not overlap completely, a further evaluation has been planned. Longer time series of NWP data (at least 2 years) will be used for this additional trial and model grids will be accurately tuned to cover exactly the same area.

Some investigations will be carried out also for the look-ahead time horizon 49-72h.

Enel is also planning to develop new forecasting models, with different mesoscale models as input.

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