Integration of ARIMA and Software Models for Wind Speed Forecast and Noise Map Prediction in a Wind Farm

Claudio Guarnaccia, Joseph Quartieri and Carmine Tepedino

Abstract— Wind turbine installation for electricity production is growing all around the world. The large energy demand, in fact, together with the environmental issue, leads to the promotion of renewable energy sources, with low (or zero) polluting impact. Wind turbines represent a sustainable solution, especially in areas with strong wind speeds and low density of obstacles. Anyway, there is a problem of annoyance related basically to noise production and landscape degradation. Regarding noise, it is almost evident that the greater is the wind speed, the larger is the noise emission, because of higher rotation speed of the blades and higher aerodynamic noise. Of course higher wind speed corresponds also to larger electricity production, thus a compromise must be found between energy and noise. For this reason, models able to exploit the relation between wind speed and noise map in the surrounding area of any wind farm, represent a strong tool to help policy makers in monitoring operating wind farms and in designing turbines placements.

In this paper, the wind turbine noise issue is faced by different point of view. After presenting the noise maps in a wind farm in Italy, produced in the framework of a predictive software, in different wind speed and directivity conditions, a seasonal ARIMA model is presented. This model is used to predict wind speeds, to be given as input of the software for noise map drawing. This method will show that, starting from the time series of wind speeds in the wind farm area, strong information about the noise levels map can be obtained by means of accurate modelling of the area under investigation.

Keywords—Wind turbines, Acoustical noise level, Predictive Model, ARIMA model, Noise map.

I. INTRODUCTION

ENERGY production is one of the most important problems of this century, that is characterized by the large use of fossil fuels and by global warming. To cope this problem alternative solutions have been sought, such as green and renewable energies. In this complex scenario of the sustainable development, the wind turbine power source is an important component.

Wind power has been used for different purposes through the ages, but only recently the wind turbines are developed specifically to generate electricity. According to the Global Wind Energy Council report of 2009, approximately at the end of 2008 there were 120800 MW of wind energy capacity installed around the world [1]. The new global total for wind power production at the end of 2015 was 432419 MW [2]. During 2015 12800 MW of wind power were installed in the EU, that represents an increase of 6.3% on 2014 installation.

This strong growth implies also the raise of environmental problems due to the installation of wind farms. The most relevant effects are the landscape visual disturbance and the noise annoyance. The latter is usually referred to few sensitive receivers, since the turbines are generally installed in country side and/or in the higher part of hills or mountains close to villages. For these reasons, very often a careful noise investigation prior the installation is not performed, leaving the problems to possible legal procedures started by the inhabitants of the area. More about noise effects on human health can be found in [3, 4].

Several studies in literature regard wind turbine noise problem. One of the aim is to help producers and policy makers in the site choice, giving them tools to predict the noise that could be produced by different positions and configurations of wind farm. Persson Waye and Öhrström [5] proposed an experimental study in order to support the hypothesis that different sound properties can be related not only to the operating condition of the wind farm, but also to the perception and annoyance for wind turbine noise.

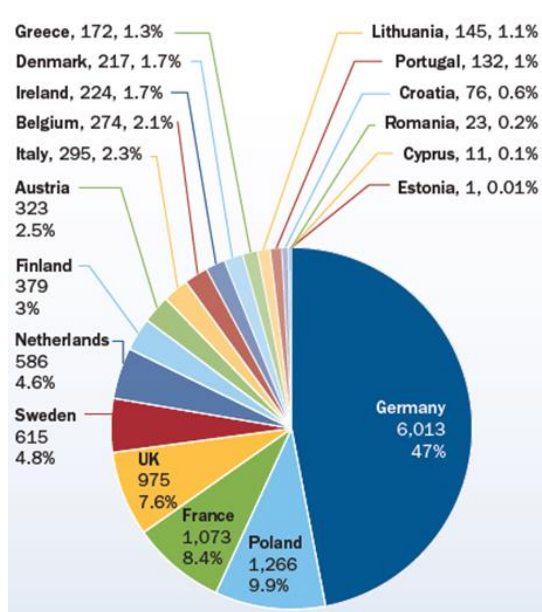

Fig. 1: EU member state market share for new wind energy capacity installed during 2015 (MW) [2].

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A relevant result of this experiment, which consisted in recording and compare the noise produced by five wind turbines in terms of reported perception and annoyance, was that the different turbines gave different annoyance perception, although the equivalent A-weighted SPL were the same. These subjective sound characteristic can be very relevant for perception and annoyance, especially at low background noise levels. More subsequent studies enforced this result and suggested that the presence of sound characteristics subjectively described as lapping, swishing, and whistling are responsible for the differences in perception and annoyance between the sounds [6]. In [7-10], some of the authors implemented a simple analytical model, able to give the propagation of the acoustic intensity level as a function of the horizontal distance from the tower, resulting in a Lorentzian function, with a maximum level in correspondence of the tower (minimum distance source-receiver) and an inflection point. In the same papers, the authors also pursued the drawing of noise maps of the wind farm installed in Postiglione (Italy), highlighting some of the peculiarities of the area under study. The noise maps drawing technique has been adopted with success by some of the authors also in other scenarios, mainly related to transportation infrastructures (see for instance [11-19]).

In this paper, after presenting the sources in a wind turbine (section II), the authors describe the implementation of a wind farm in Italy in a noise predictive software (section III and IV). The resulting models give interesting information about the noise map and propagation in a country side area. In addition, the directivity of the source is implemented in the software, giving new results and map features.

The main parameter that drives the prediction is wind speed. This value, in fact, fixes the power level of the turbine and influences the emissions of the wind farm. When it is not possible to measure this parameter or when the wind farm is still under designing, a forecasting model of the wind speed is needed. Classical deterministic models are not always adequate to describe the behavior of highly random phenomena such as wind. For instance, in [20-27], deterministic Time Series Analysis (TSA) models are successfully implemented by the authors for various purposes, such as acoustical noise, CO concentrations, electricity absorption forecasts and missing data imputation. Regarding wind speed prediction, literature presents different models (for instance [28-31]). In this paper, to have reliable predictions of wind speed, a stochastic linear model is proposed, based on the analysis of a univariate time series given by the hourly average wind speed in the region of interest. This model, briefly described in section III and applied in section V, will furnish the input values for noise mapping by means of software application. This "prediction chain" can be adopted to predict noise maps, having as input basically just the time series of wind speed, the geometry and the features of the area under investigation. Of course, the proposed technique can be implemented both in operating wind farm, to assess noise impact on existing buildings, or to design the best placement for turbines, minimizing the noise at the surrounding receivers.

II. Noise Sources in a Wind Turbine

There are many types of noise that can be generated by wind turbine operation: tonal, broadband, low frequency, and impulsive. They are caused by turbine components, interaction of wind turbine blades with atmospheric turbulence, interaction of wind turbine blades with disturbed air flow around the tower of a downwind machine. In addition, they could be originated when the turbine blade encounters localized flow deficiencies due to the flow around a tower. Thus, the noise can be classified into mechanical noise and aerodynamic noise, according to the source.

The mechanical noise is generated by the mechanical components of the wind turbines during their operation. The sources of this noise are mainly: gearbox, generator, yaw drives, cooling fans, auxiliary equipment. The hub and tower could act as loudspeakers, transmitting the mechanical noise and radiating it. The noise is directly propagated from the component surface or interior, into the air.

The aerodynamic noise is the largest noise produced by the wind turbine operation and is correlated to the rotors speed. It could by classified into two groups: inflow turbulence noise, airfoil self-noise. These noises depends on the atmospheric turbulence and on the interaction between blades and wind.

A more detailed analysis of wind turbine noise can be found in [32].

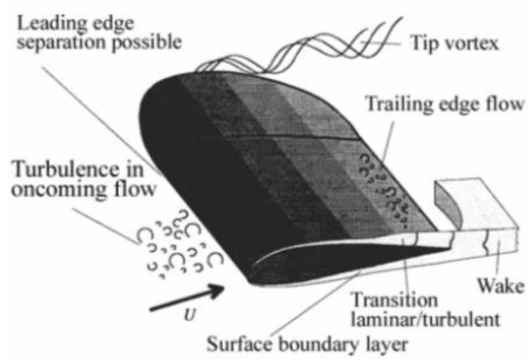

Fig. 2: Schematic of flow around rotor blade [8].

III. Mathematical and Software Tools

In this section, the authors present the mathematical and software tools used to produce the final predictive model.

A. Predictive software and preliminary model description

The noise map of the wind farm is produced in the predictive software CadnaA® (produced by DataKustik) framework. In this subsection, the preliminary model presented in [7-10] is recalled, to highlight the resources of this software. This preliminary model describes the source "wind turbine" in different operating condition, varying the geometry of the source, its power level and directivity.

The software algorithm is based on "Angle Scanning" and inverse "ray-tracing" principles. The area under study can be divided in many small surfaces in which a receiver is placed at a variable height (in our case is 2 m), obtaining the calculation grid. From each grid element, many rays with a full angle coverage (omni directive) are released and these rays, potentially after many reflections, intercept the noise source. The attenuation of the sound wave is given by the path length of the single ray. In addition, specific receivers can be inserted in the map, with the possibility to export the results in a worksheet.

The first step consists in the software simulation of a single pointlike source, without directivity. This means that the source emits in the full solid angle. The parameters of the simulations are resumed in Tab.1 and the resulting noise map is reported in Fig. 3.

Table 1: Simulation and calculation grid parameters.

L_W	98,0 dBA
Height of the source	70 m
Evaluation grid height	2 m
Receivers height	4 m
Distance between receivers	10 m

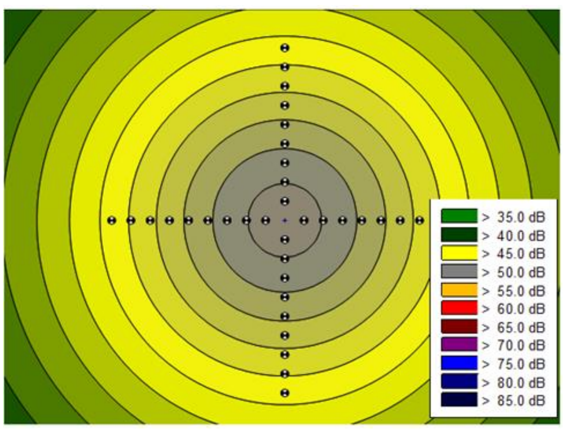

Fig. 3: CadnaA® noise map (values are in dBA) for a pointlike source with Lw=98 dBA, height=70 m.

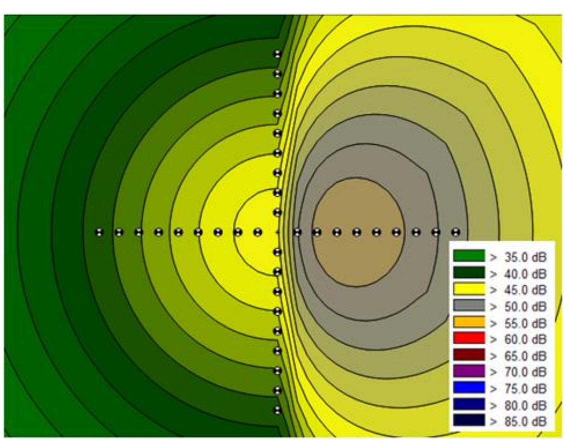

Fig. 4: CadnaA® noise map (values are in dBA) for a pointlike source with Lw=98 dBA, height=70 m with high directivity.

In order to obtain a more accurate noise map, the directivity of the source, due to the wind speed and direction, can be taken into account. Such a purpose is pursed giving, as an input in the source parameters, the directivity vector. Thus, a new simulation with the same parameters resumed in Tab. 1, is performed, assuming that the favourite direction of noise is west. The noise map obtained is shown in Fig. 4, in which is clearly shown the shift of the maximum point in the wind direction, with respect to the previous map. This result leads to the conclusion that, in addiction to orography and other features of the source and of the area, also the directivity is important to obtain accurate noise maps of the wind farm.

B. *ARIMA model*

The ARIMA models are Time Series Analysis (TSA) predictive models, largely adopted in many branches of scientific and economic literature. The authors already implemented deterministic TSA models for prediction of acoustical noise [20,21], CO concentration [22] and electrical energy absorption [23,24], such as for imputation of missing data [25-27]. In any case, the key point is the possibility to predict the observable with a low number of inputs and to any time in the future (with respect for instance to Artificial Neural Network).

A very powerful class of stochastic linear model is the multiplicative seasonal ARIMA (Auto Regressive Integrated Moving Average), that will be adopted in this paper. In general, a multiplicative seasonal ARMA(p,q)x(P,Q)$_s$ model with seasonal period *s*, is defined as a model with AR characteristic polynomial $\phi(x)\Phi(x)$ and MA characteristic polynomial $\theta(x)\Theta(x)$, [33], where:

$$\begin{cases} \phi(x) = 1 - \phi_1 x - \phi_2 x^2 - \cdots - \phi_p x^p \\ \Phi(x) = 1 - \Phi_1 x^s - \Phi_2 x^{2s} - \cdots - \Phi_P x^{Ps} \end{cases} \tag{1}$$

$$\begin{cases} \theta(x) = 1 - \theta_1 x - \theta_2 x^2 - \cdots - \theta_q x^q \\ \Theta(x) = 1 - \Theta_1 x^s - \Theta_2 x^{2s} - \cdots - \Theta_Q x^{Qs} \end{cases} \tag{2}$$

The ARMA model becomes ARIMA(p,d,q)x(P,D,Q)$_s$ once the *d*-th difference of the data is performed. This difference is done to achieve the stationarity of the series (see section V).

This kind of models strongly depends on recent data (close to prediction period), both in parameters calibration and forecasting. This means that parameters evolve on time, according to changes in the process, and are able to recognize possible variations in the slope of the time series. This is the main difference between these models and the deterministic ones adopted in the previous papers by the authors, in which the coefficients were constant and did not allow to appreciate variations on time.

IV. Simulations of the Noise Produced in a Wind Farm

In this section, a wind farm will be implemented in the predictive software CadnaA®. The software allows to simulate the entire area under study, implementing the real orography and features of the terrain, the wind turbines (as the pointlike sources described in the previous section), together with any other relevant element, such as roads, buildings, foliage, etc.. After implementing the model, a noise map is produced, giving immediate information about the noise impact in the area, according to the different conditions considered in each simulation.

A. Description of the wind farm

The wind farm under study is located in Taverne Vecchie, in the town of Postiglione, province of Salerno (Italy). The map of the area, taken from Google maps© and then implemented in the software CadnaA, is shown in Fig. 5.

The wind farm is composed by 12 turbines Vestas V52. The height of the hub is 65 m from ground level.

The turbines are placed quite close to the town of Postiglione, that is a small village of about 2500 inhabitants. The area is rural and composed of small hills. Few roads, with quite low traffic flows, surround the wind farm. The noise produced by these roads can be negligible in the noise map drawing.

B. Description of the simulation parameters

As already stated in previous sections, each wind turbine is implemented into the software as a pointlike source. The value of the acoustic power assigned to each turbine is related to the wind speed in each hour. The acoustic source power as a function of the wind speed is reported in Fig. 6 [34]. The calculation is performed on a grid having 2x2 m^2 elements. In each grid element, a virtual receiver, with height of 4 m, is placed and used to draw the map of the levels in the entire area. Of course, all the items in the map have been inserted with their relative height with respect to the terrain. The orography was implemented considering the height points given by the map of the area. Fig. 7 reports the 3D view of the wind farm. This figure shows the presence of turbines in the hill landscape and their relative heights. It is easy to notice how the orography of the terrain modifies the distance between sources and receivers, as will be highlighted by noise maps.

C. Simulations of the noise map without source directivity

The first simulations have been run neglecting the source directivity, i.e. assuming an isotropic emission of the wind turbines. In order to highlight the variation during a typical winter time day, hourly average wind velocities have been set, extracting information from online weather databases. Each wind speed corresponds to a source power level, as reported in Tab. 2. Once the power levels have been fixed, noise maps can be calculated for each different wind speed (i.e. for each different source power level). Results are reported in Figg. 8-15.

Looking at the resulting noise maps, it is evident that there is a strong influence of the orography of the terrain, that changes the distances between sources and receivers, according to the slope of the hill. In addition, it can be noticed that when the wind speed is basically constant, the noise map does not change.

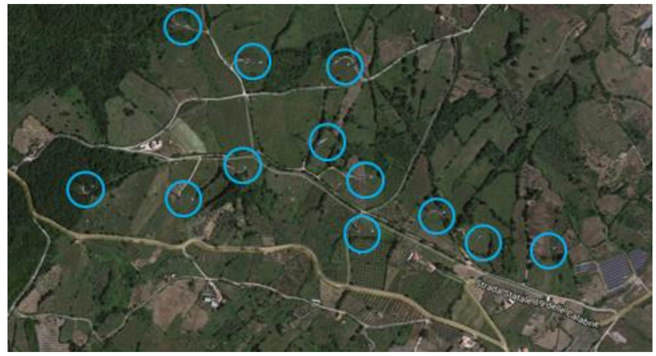

Fig. 5: Map of the area of Taverne Vecchie, Postiglione (Salerno, Italy) (Google Maps©). The turbines are highlighted by the light blue circles.

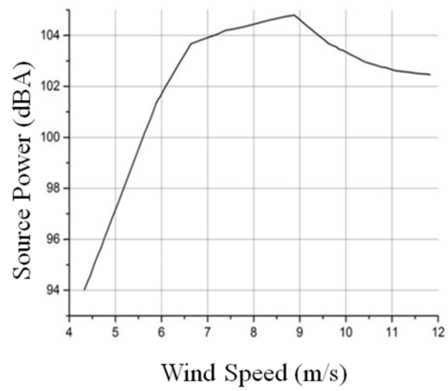

Fig. 6: Source power level as a function of the wind speed of a turbine Vestas V52, with height of the hub 65m [34].

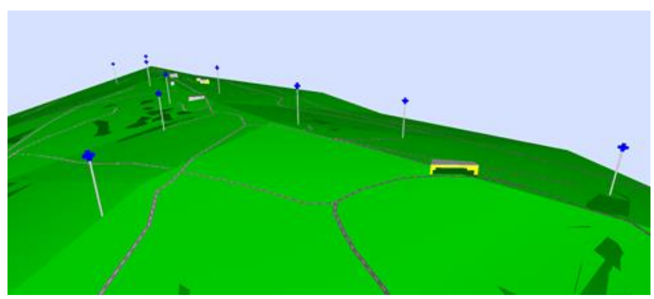

Fig. 7: 3D view of the wind farm area of Taverne Vecchie, implemented on CadnaA®. The blue crosses are the pointlike sources simulating the wind turbines.

Table 2: Simulation parameters.

Hours	Wind speed [m/s]	Lw [dBA]	Hours	Wind speed [m/s]	Lw [dBA]
01 AM	5.3	98.3	01 PM	9.2	104.3
02 AM	6.1	102	02 PM	8.9	104.6
03 AM	6.4	102.8	03 PM	8.3	104.6
04 AM	7.2	104	04 PM	7.5	104.2
05 AM	7.5	104.2	05 PM	6.4	102.8
06 AM	8.1	104.4	06 PM	6.4	102.8
07 AM	8.6	104.7	07 PM	5.6	100.1
08 AM	9.2	104.3	08 PM	5	97.4
09 AM	9.4	104	09 PM	5.3	98.3
10 AM	9.4	104	10 PM	5	97.4
11 AM	9.4	104	11 PM	5.3	98.3
12 AM	9.4	104	12 PM	5.3	98.3

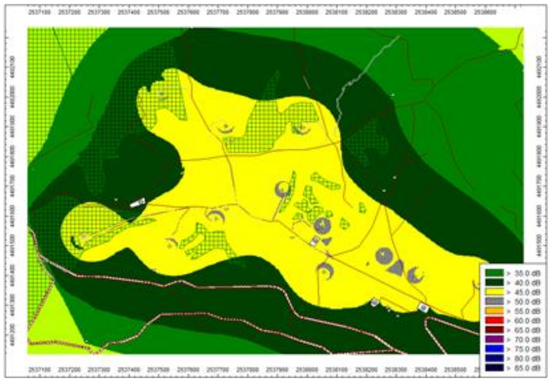

Fig. 8: Noise map of the wind farm area. Source Power Level: 98.3 dBA. Hours: 01 AM, 9PM, 11PM, 12PM.

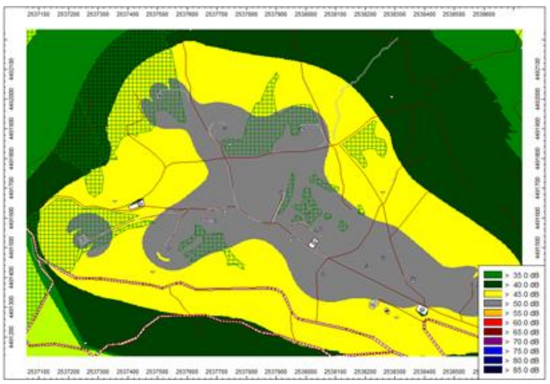

Fig. 9: Noise map of the wind farm area. Source Power Level: 102.2 dBA. Hours: 02 AM.

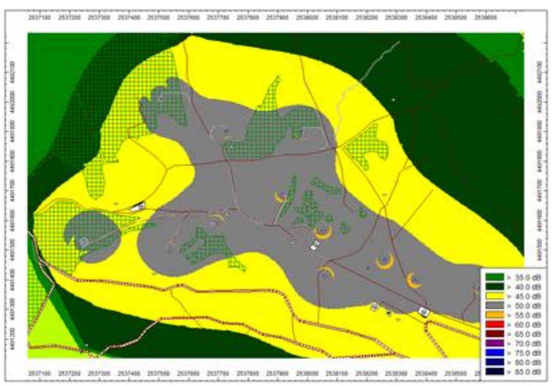

Fig. 10: Noise map of the wind farm. Source Power Level: 102.9 dBA. Hours: 03 AM, 5 PM, 6 PM.

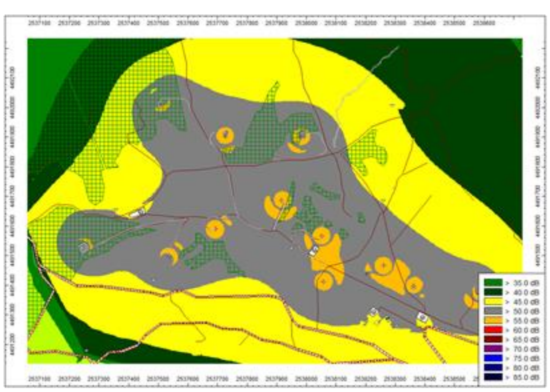

Fig. 11: Noise map of the wind farm area. Source Power Level: 104.2 dBA. Hours: 05 AM, 01 PM, 04 PM.

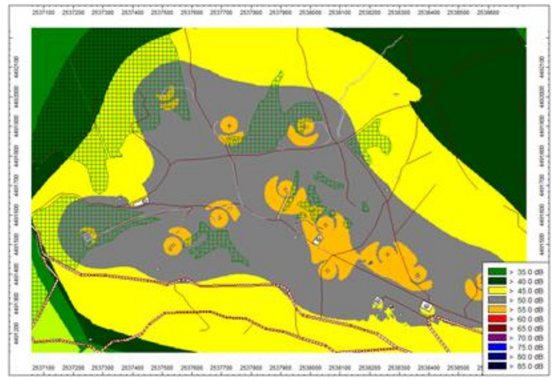

Fig. 12: Noise map of the wind farm area. Source Power Level: 104.7 dBA. Hours: 07 AM, 02 PM.

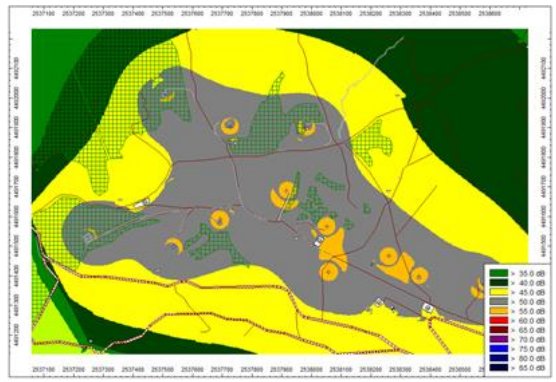

Fig. 13: Noise map of the wind farm area. Source Power Level: 104 dBA. Hours: 04 AM, 09 AM, 10 AM, 11 AM, 12 AM.

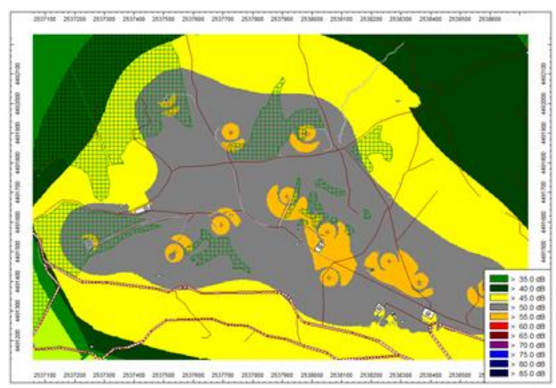

Fig. 14: Noise map of the wind farm area. Source Power Level: 104.6 dBA. Hours: 3 PM.

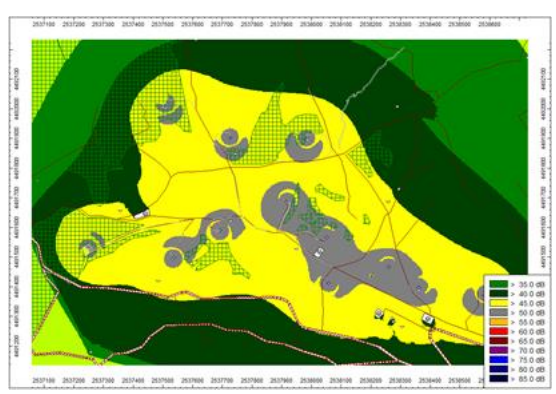

Fig. 15: Noise map of the wind farm area. Source Power Level: 100.1 dBA. Hours: 7 PM.

New simulations have been executed, to perform a comparison with the noise maps produced in presence of directivity (see next subsection), considering a different wind speeds set, in a day of the week in which variation in the wind direction were recorded. The parameters used in the new simulations are resumed in Tab. 3. In this case, the wind direction has not been used.

Resulting noise maps are reported in Figg. 16-19, and, in Fig. 20, the 3D view of the area is showed.

It is interesting to notice that, of course, the higher levels are obtained close to the turbines and for higher wind speeds. In addition, outside the wind farm area, the noise rapidly decreases.

Table 3: New simulation parameters.

Hours	Wind velocity [m/s]	Direction	L_{WA} [dBA]
01am-02am	5.28	W	98.3
03am-05am	5	WSW	97.4
06am-08am	4.7	W	96
09am-11am	5	W	97.4
12pm-2pm	5.28	WNW	98.3
3pm-5pm	3.6	WNW	93.4

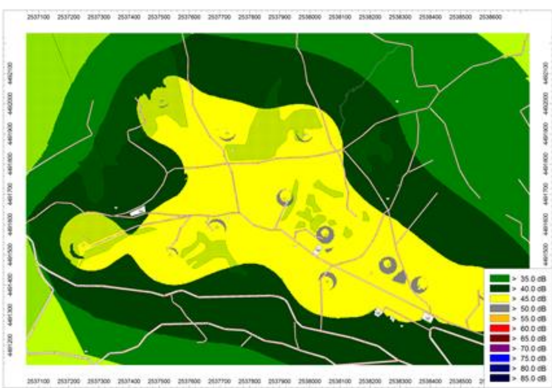

Fig. 16: Noise map of the wind farm area. Source Power Level: 98.3 dBA.

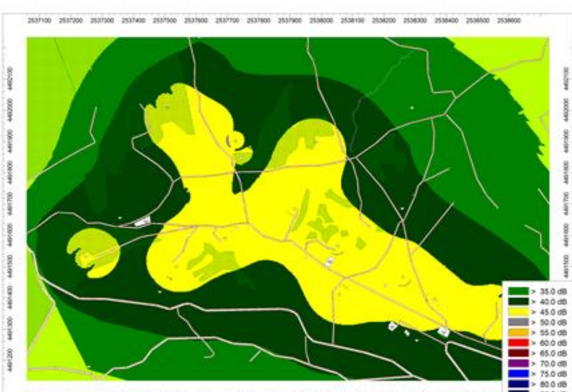

Fig. 17: Noise map of the wind farm area. Source Power Level: 97.4 dBA.

Fig. 18: Noise map of the wind farm area. Source Power Level: 96 dBA.

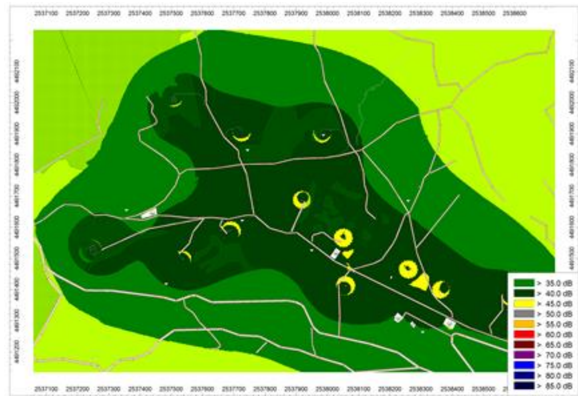

Fig. 19: Noise map of the wind farm area. Source Power Level: 93.4 dBA.

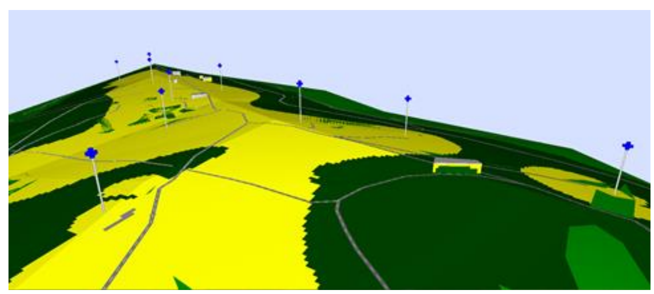

Fig. 20: 3D noise map of the wind farm area obtained in CadnaA®. The Source Power level is 97.4 dBA.

D. Simulation with the directivity of the sources

In this subsection, simulations with the directivity of the noise source are presented, assuming that this feature of the turbine depends on the wind direction.

Let us recall that turbines have an internal engine able to orient the nacelle to maximize the rotor speed and, consequently the energy production. This means that the turbine rotates according to the wind direction.

The parameters of the simulations with directivity are the same of Tab.3.

In order to obtain a realistic noise map, wind speed data of a typical day of the winter months were used. The choice was a day with a moderate variation of the wind direction, to see how noise maps change. It is important to underline that, usually large changes in the wind direction correspond to high values of the wind speed. In this cases the turbines do not operate, for preventing mechanical damages.

Resulting noise maps are reported in Figg. 21-26, and, in Fig. 27, the 3D view of the area is showed.

It is evident that the directivity change very much the noise map simulations, influencing the higher values zones position. Again, wind speed is the most influent parameter in noise production.

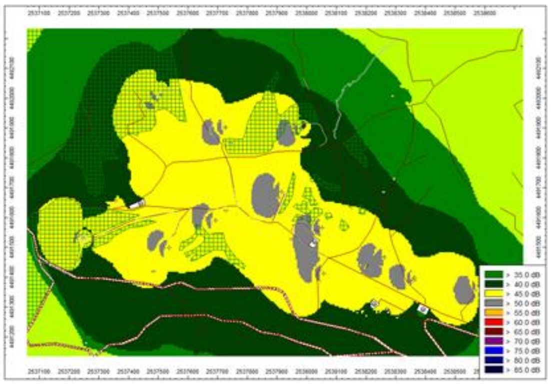

Fig. 21: Noise map of the wind farm area. Source Power Level: 98.3 dBA, with a preferred direction: West.

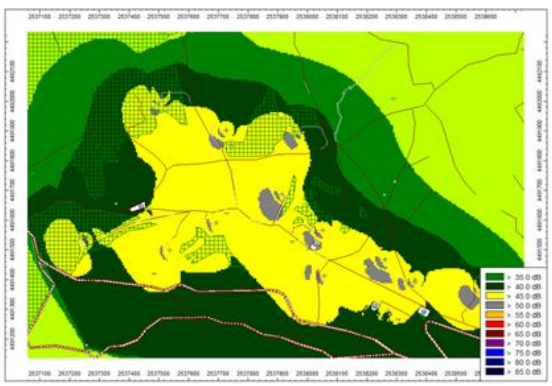

Fig. 22: Noise map of the wind farm area. Source Power Level: 97.4 dBA, with a preferred direction: WSW.

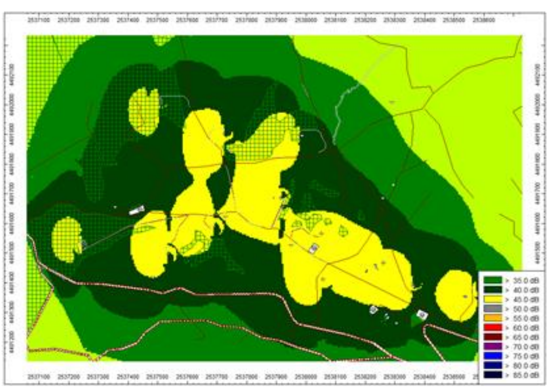

Fig. 23: Noise map of the wind farm area. Source Power Level: 96 dBA, with a preferred direction: W.

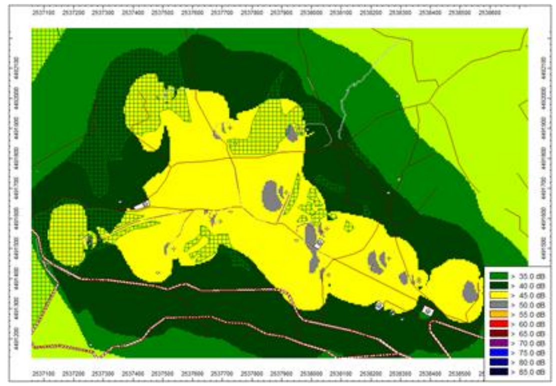

Fig. 24: Noise map of the wind farm area. Source Power Level: 97.4 dBA, with a preferred direction: West.

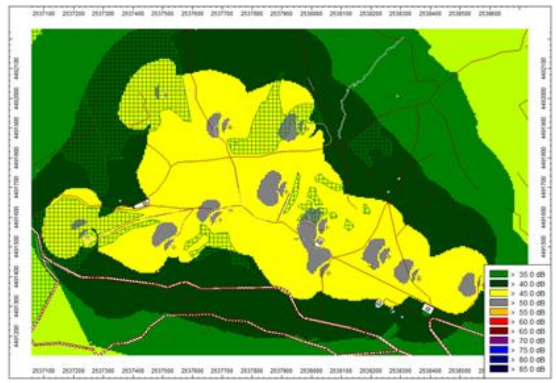

Fig. 25: Noise map of the wind farm area. Source Power Level: 98.3dBA, with a preferred direction: WNW.

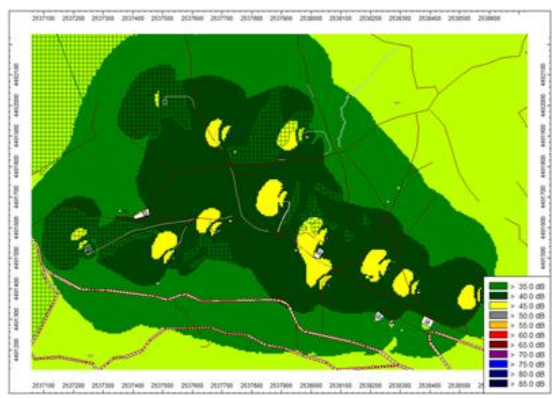

Fig. 26: Noise map of the wind farm area. Source Power Level: 93.4 dBA, with a preferred direction: WNW.

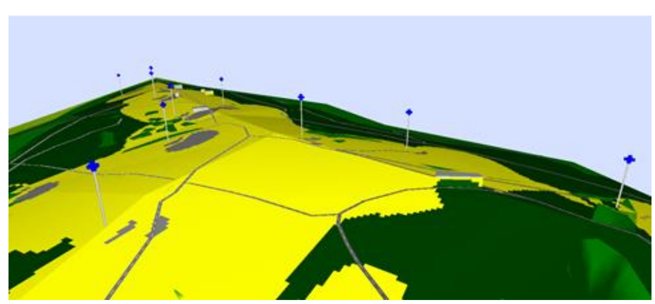

Fig. 27: 3D noise map of the wind farm area obtained in CadnaA®. The source power is 97.4 dBA with directivity.

V. Prediction of Wind Speed by ARIMA Model

In this section, a seasonal ARIMA model is adopted to predict the wind speed. Since this parameter is an essential input for noise map drawing, the more precise is the predictive model, the more effective will be the noise prediction.

For calibrating the model, a dataset of wind speed in the area of the wind farm was needed. Due to the absence of a weather station with open access data, the simulation was done on data available on the web [35]. From this website, hourly wind speed data related to one week (from 1 p.m. of July 21 to 3 a.m. of July 28, that are 159 data) have been downloaded. Since these data were given in km/h and for ground level, they have been converted in m/s and transformed to value at 65 m (i.e. the height of the wind turbine nacelle). The latter transformation has been performed according to the wind speed power law formula [36]:

$$u = u_r \left(\frac{z}{z_r}\right)^{\alpha} \quad , \tag{3}$$

in which u is the computed wind speed, z is the height at which the wind speed is required and z_r is the reference height, i.e. the one in which the wind speed u_r is given.

The roughness has been chosen equal to 0.18, according to a country side terrain with very low density of buildings and obstacles.

Once the wind speed dataset is ready, a calibration dataset of the first 135 periods has been set and used to build the model. The last 24 data have been kept apart, to be used in the validation phase (see Fig. 28, in which the solid black line represents the calibration data and the dashed red line is the validation dataset).

Since the calibration data are not normally distributed, a one-step difference is performed to achieve a stationary and normal dataset. In addition, the autocorrelation function of the data is evaluated as a function of the lag. A daily seasonality has been exploited in the differenced data, since the 24 hours lag has a significant autocorrelation (see Fig. 29).

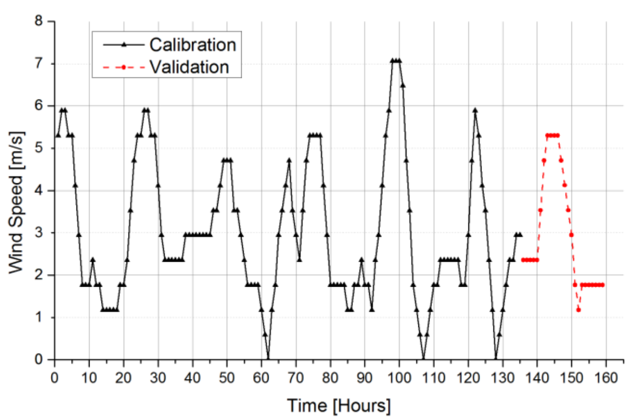

Fig. 28: Wind speed data (hourly mean) in Postiglione during July 2016 [32]. The dataset is divided in 135 calibration data (black solid line) and 24 validation data (red dashed line).

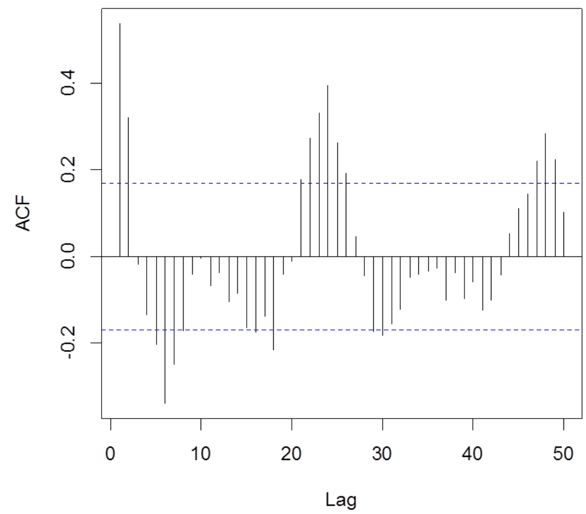

Fig. 29: Correlogram of the wind speed series after performing the first order difference. The value of autocorrelation coefficient is plotted as a function of the lag.

For these reasons, a seasonal ARIMA model, with 24 hours lag and first order difference, seems to be the appropriate choice. In order to choose the best model, a ranking of the possible models has been produced in the R framework, according to the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion). The results are reported in Table 4, were the models are sorted by BIC value.

Since the SARIMA(1,1,0)x(1,0,1) model minimizes both the AIC and BIC, it is reasonably the best choice for this dataset.

Model parameters were estimated in the R framework, using the maximum likelihood method, and the results are reported in Table 5.

Table 4: Table of the seasonal ARIMA models tested on the wind speed time series. The models are ordered by the best value of the BIC and AIC specification methods. *N* is the number of parameters.

Rank	p	d	q	P	D	Q	N	BIC	AIC
1	1	1	0	1	0	1	3	221.99	213.39
2	1	1	1	1	0	0	3	221.99	213.39
3	0	1	0	0	0	2	2	225.46	219.72
4	0	1	2	0	0	0	2	225.46	219.72
5	0	1	0	1	0	2	3	229.23	220.63
6	0	1	2	1	0	0	3	229.23	220.63
7	1	1	0	0	0	2	3	229.23	220.63
8	1	1	2	0	0	0	3	229.23	220.63
9	0	1	1	0	0	2	3	230.32	221.72
10	0	1	2	0	0	1	3	230.32	221.72
11	0	1	1	1	0	2	4	234.13	222.66
12	0	1	2	1	0	1	4	234.13	222.66

Table 5: Estimated coefficients and standard errors for the SARIMA(1,1,0)x(1,0,1) model. The seasonal lag *s* is 24.

	ar1	sAR1	sMA1
Coefficients	0.4048	0.9961	-0.9338
Standard Errors	0.0822	0.0358	0.2981

With these coefficients, a model diagnostic can be performed in the calibration dataset, in particular by means of residual analysis. The residual (error) is defined as:

$$e_t = A_t - F_t \quad , \tag{4}$$

in which A_t is the actual observed wind speed and F_t is the forecast.

The statistics of residuals are resumed in Table 6 and the histogram is reported in Fig. 30. It is evident that the error distribution is normal, with mean zero and low standard deviation. These results are consistent with the theoretical assumptions of the model.

Once the model has been calibrated and the parameters evaluated, prediction of wind speed can be performed in the following hours. These forecasts are compared with the 24 validation data and the results of the comparison are reported in Fig. 31. It is evident that the prediction is affected by a delay. This is a common feature of autoregressive models, as reported in [33].

The statistics of the error in the validation phase, that can be assumed as model performance indicators, are resumed in Table 7. The mean of the error is -0.62 m/s, showing a slight overestimation of the forecast. Of course mean and standard deviation worsen with respect to calibration data residuals analysis, since in that case the data used for the error computation are the same used in the estimation of the parameters of the model.

Table 6: Summary of statistics of the errors in the calibration data set, 135 data.

Mean [m/s]	Std.dev [m/s]	Median [m/s]	Min [m/s]	Max [m/s]	skew	kurt
0	0.48	0	-1.44	1.49	0.25	0.47

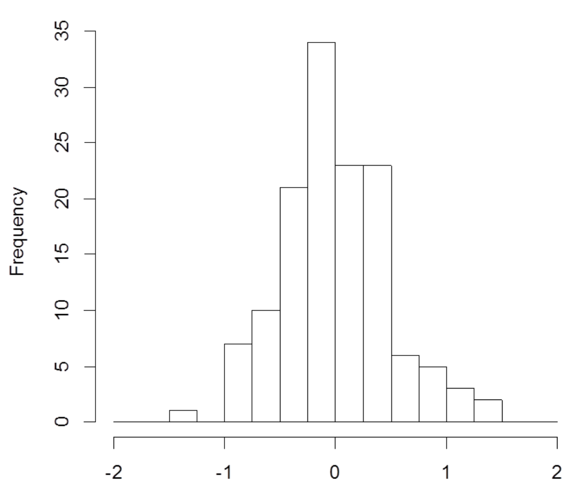

Fig. 30: Frequency histogram of the errors calculated on the 135 calibration data.

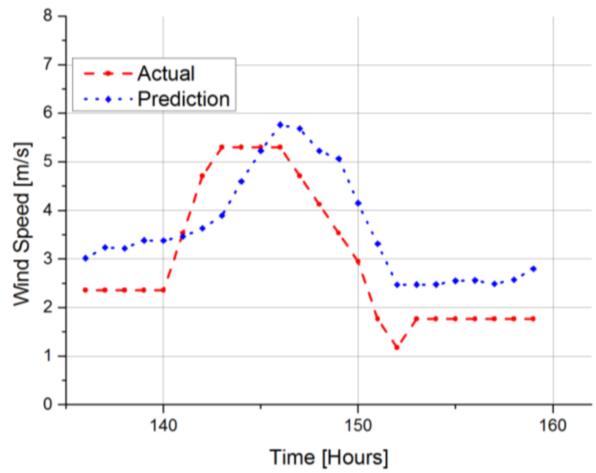

Fig. 31: Wind speed in the 24 validation hours. The red dashed line shows the actual data, the green dotted line shows the prediction. All the data are hourly mean in meters per second.

Table 7: Summary of statistics of the errors in the validation data set, 24 data.

Mean [m/s]	Std.dev [m/s]	Median [m/s]	Min [m/s]	Max [m/s]	skew	kurt
-0.62	0.76	-0.8	-1.55	1.41	1.28	0.78

A. Noise map of the area with predicted wind speed

Once the wind speed has been predicted in a given time range (in our case 24 hours), the wind farm noise map can be evaluated according to the software model presented in section IV and to the wind conditions obtained with the SARIMA model.

In this paper, the authors present the noise map related to the average wind speed in the time range that goes from 7 a.m. to 7 p.m., i.e. the "day" range defined in the EU directive [37]. This value is 4.46 m/s and, according to the procedure described in subsection IV.B, is related to a sound power source of 94.6 dBA. The resulting noise map is presented in Fig. 32.

In addition, the noise map related to the maximum value of wind speed predicted by the model (5.76 m/s, measured at 2 p.m.), and consequently related to the maximum value of sound power level (100.7 dBA), is presented in Fig. 33.

Of course the maximum prediction of wind speed leads to higher noise values in the map. Still the orography influences the propagation and, again, a directivity could be implemented, to take into account wind direction.

Let us also underline that, once the area is modelled in the software, the procedure presented in this paper can be applied anytime, to predict wind speed, and thus noise map, in the following 24 hours. This prediction can be used to tune the operating time of the turbines, in order to reduce the noise impact on surrounding buildings.

Fig. 32: Noise map of the wind farm area, with average wind speed predicted by the SARIMA model. Source Power Level: 94.6 dBA.

Fig. 33: Noise map of the wind farm area, with maximum wind speed predicted by the SARIMA model. Source Power Level: 100.7 dBA.

VI. Conclusions

In this paper the authors faced the problem of the noise produced by a wind farm by means of predictive software approach and Time Series Analysis models for wind speed forecast. The modelling of a wind park placed in Postiglione (Italy) in the framework of the software allowed to run various simulations, with different wind speeds and directions. Results showed that the operation of the turbines produces a noise map that is clearly influenced by the position of each turbine with respect to the hill slope. In fact, even though wind speed is the most influent parameter in noise production, basically because it fixes the source power level, the orography of the terrain represents an important feature in the noise propagation, since it affects the distance between sources and receivers. The introduction of directivity of the source, related to wind direction and, consequently, to sound propagation, led to significant variations in the noise map. In particular the shape of the sound field is modified, introducing, as expected, a shift of the noise levels in the direction of the wind.

In the second part of the paper, a stochastic linear model based on the analysis of an univariate time series composed by the hourly average wind speed in the region of interest is presented. In particular, a seasonal ARIMA model for wind speed prediction has been selected. The parameters have been evaluated on a calibration dataset of 135 wind speed data and the forecasts have been compared with 24 validation data. The diagnostic of the model, performed with a residuals analysis, confirmed the theoretical assumptions (zero mean and normal distribution) in the calibration dataset and showed good performances in terms of error statistics, in the validation phase. In this phase, a slight overestimation and a short delay (typical of autoregressive models) with respected to observed data were exploited by the forecasts. Let us also remind that the prediction time range is 24 hours, that is, in some sense, more powerful with respect to one step ahead prediction.

Finally, the predicted wind speed values have been used as input in the software model described above, in order to produce noise maps related to the chosen wind conditions.

The procedure described in this paper, merging wind speed and noise map predictions, is useful to evaluate the noise propagation in the area of the wind farm with any wind speed and direction condition and furnishes a tool to help policy maker in wind turbine placement choice or wind farm design.

This study can be further developed, for instance considering wind speed distribution, such as the authors performed in [38] for vehicles speed affecting road traffic noise, or considering a Poisson process counting the number of exceedances of a given value of the wind speed (that could be the turn on value of the turbine), such as the authors did in [26,27,39,40] for noise threshold surpassing.

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