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Weather forecasts for microgrid energy management: Review, discussion and recommendations

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HIGHLIGHTS

- Weather information is a fundamental input for microgrid scheduling.
- A wide variety of weather information has been incorporated into prior microgrid studies.
- The diversity of procedures to implement weather data in microgrid energy management systems are analyzed.
- Discussion and recommendations for future works are conducted.

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ABSTRACT

Meteorological conditions determine the renewable energy generation and, to a lesser extent, the load of microgrids. Weather forecasts are thus necessary to establish optimal plans according to the operational objectives and priorities of each microgid. Weather forecast errors are also responsible for deviations from these plans, thereby being an important source of uncertainty in the scheduling process. Despite this, weather information plays a secondary role in most of microgrid studies. This paper provides a general overview of the use of meteorological data in microgrids, focusing on the implementation of weather forecasts in microgrid energy management systems. Data sources, methodologies, uncertainty approaches and results from a selection of papers with complete information about the forecast context are analysed in detail. Additionally, similarities and differences regarding other energy forecast applications apart from microgrids are discussed. Finally, on the basis of the above, a list of recommendations for future implementations of weather forecasts in microgrid energy management systems is presented.

1. Introduction

A microgrid (MG) is conceived as a small-scale power system comprising a set of loads and distributed energy resources including photovoltaic (PV) panels, wind turbines (WTs), conventional generators and energy storage systems. MGs can operate in both grid-connected and stand-alone modes and have proved to be efficient in smoothing the effects of the intermittent generation associated with renewable energy sources (RES) [1]. They are therefore considered key elements to promote the power system integration of RES and the subsequent reduction of environmental pollutants associated with conventional energy sources. MGs enable local energy management strategies adapted to the particular characteristics of the system (devices, configurations, load patterns or atmospheric conditions of the site), enabling an individualized optimization of the use of energy sources. Such a detailed optimization would become intractable from the viewpoint of the independent system operator (ISO). However, benefited by the regional dispersion of the generation units [2] and the large numbers of connected loads [3], ISO operations and schedules entail a lower degree of uncertainty. In the case of MGs, uncertainty is amplified by the local nature of the problem, and particularly impacts RES and load estimations. In this sense, Olivares et al. associated the first main technical challenge in MG control to the “schedule and dispatch of units under supply and demand uncertainty” [4].

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The scheduling process determines the necessary operations for an optimal MG management, addressing the given objective. This includes minimization of operation costs, maximization of RES, reduction of emissions and assurance of reliability. The schedule is established for a specific time horizon (scheduling horizon) based on predictions of different parameters of interest related to demand, generation or electricity cost. Errors inherent to these predictions produce deviations from the optimal plans and the subsequent worsening in MG operation. Probabilistic or scenario representations are used to describe uncertainty in predictions, and stochastic approaches, as robust optimization [5] or two-stage stochastic optimization [6], are then applied to the determination of the optimal schedule. The rolling horizon strategy also helps in minimizing the uncertainty derived from forecast errors. In this method, only the first steps of the optimal schedule are implemented. Then, a new schedule is recalculated considering the updated data. The implemented operations are thus based on updated information and shorter forecasting horizons, thereby reducing the uncertainty [7].

Weather information is of high value in MG scheduling, since meteorological conditions determine RES generation, and to a lesser extent, the system load. Weather forecast errors, derived from the difficulties in accurately modelling atmospheric processes, are also responsible for a relevant part of uncertainty in MG operation. The characterization of both meteorological context in which MG operates and the weather forecast errors seems to be necessary for an optimal design and validation of the proposed MG management methodologies. Without this, the obtained solutions might be based on ideal representations of the MG working conditions and will not address possible contingencies derived from the operation under real sequences of meteorological scenarios. Despite weather forecasts being referenced as primary inputs in microgrid energy management systems (MEMS), they play a secondary role in MG studies because the main focus is on the electrical, computational or economical aspects of the problem. To illustrate, MG reviews cover control [8,9], architectures [10,11], protection [12,13], storage [14], or computational optimization techniques [15]; but to the authors' knowledge, no review has been conducted for the utilization of weather information in MEMS. Additionally, in studies where weather information is described, there is a general lack of details and uniformity that complicate the interpretation of the approaches, the comparisons among the studies and the extrapolations of results. Thus, the extraction, clarification, and organized description of the meteorological frameworks used in MG research are not a trivial or easy task. In this framework, the main contribution of this review is the analysis of MEMS from a meteorological perspective, in order to clearly define the approaches currently applied to this problem, analysing their pros and cons and providing support for future studies for an efficient implementation of weather forecasts.

This major contribution can be itemized into the following more specific contributions:

- A general contextualization of meteorological data in MG applications, paying special attention to the representativeness of the tested meteorological scenarios.
- A detailed analysis of sources and procedures for the implementation of weather forecasts in MEMS.
- A comparison and discussion of the results regarding additional literature apart from MGs in order to detect strengths and weaknesses in weather forecasts for MEMS.
- Recommendations for an appropriate use of weather forecasts and descriptions of meteorological information in MG energy management studies.

The rest of this paper is structured as follows. Section 2 presents a general overview of the revised papers, providing a context to support the remaining sections. Sections 3 and 4 provide, respectively, a detailed description of the wind and solar forecasts used for MG management based on a restrictive selection of papers. Section 5 is focused on weather forecasts for load predictions. Section 6 synthesizes and discusses the previous sections, completing the information with additional literature beyond MG research. Section 7 provides some recommendations for the application of weather forecasts in MGs and Section 8 contains the summary and conclusions.

2. Preliminary overview

The core of this review comprises about 190 works (from 2014 to the submission date) in which both MEMS and weather forecasts are somehow associated. Approximately 20% of these studies focus on energy policy or very particular aspects that cannot be considered in line with the present review. The remaining papers follow a similar structure: (i) a MG is described, (ii) a methodology for the optimized management of this MG is proposed, and (iii) a test is conducted to corroborate the benefits of the proposed methodology. This set of papers constitutes the preliminary object of our analysis.

Regarding the MGs described in these papers, the grid-connected mode is the most frequent operation mode (65% of studies). Standalone MGs represent 25% of cases, and the remaining case studies tested both modes of operation. There is an important diversity of configurations, as each MG implements different elements for energy generation and/or storage. Battery energy storage system is included in 80% of cases; diesel generators (28%), microturbines (25%), and fuel cells (20%) are other frequently considered elements. Due to its central role in this review, note that RES generation is present in all revised papers. Concretely, wind and solar hybrid systems represent 57% of the described MGs. Solar and wind generation are considered as unique RES in 29% and 14% of cases respectively.

Another relevant aspect regarding the meteorological context is the duration of the tests. The test period was one day or shorter in 50% of the papers. In the solar case, these periods are frequently associated with irradiance profiles of completely sunny days. Under these conditions, the validity of the proposed methodologies for a continuous long-term operation cannot be corroborated, especially of those focused on dealing with uncertainty in RES and load estimations. Thus, robustness against uncertainty must be tested with data from longer periods including partially clouded days and gusty periods, which are the most unfavourable scenarios from the weather forecast viewpoint. Only under these conditions can it be assured that the proposed solutions are appropriate for overcoming the real situations of high uncertainty. Tests longer than one day and shorter than one month are performed in 32% of the revised papers. In these cases, the MEMS is tested in a more significant way, although the possible effects of seasonality are neglected. Again, if the tested periods involve atmospheric stability, the uncertainty derived from weather forecasting errors would not be properly assessed. The remaining studies perform longer tests, covering one year in some cases, in order to assure representativeness in the tested meteorological scenarios is assured.

Regarding forecasts, RES and load predictions are considered in all examined studies. In many cases, the forecasted information also includes other parameters such as electricity prices, building occupancy or charge of electric vehicles. All these forecasts can be classified into four categories depending on the way they are obtained. The following classification will be referenced along the text:

- Arbitrary: The test is based on synthetic data specifically designed for the experiment, with different degrees of similarity with reality.
- Historic: Forecasts are simulated from historical series, which can be treated as perfect forecasts or modified by introducing some variability to simulate errors inherent to real forecasts.
- Local forecasts: They are generated by processing the updated measurements of the system's operation, including meteorological conditions of the site. The implemented forecasting models are typically based on statistical or machine learning approaches.

Historical data are generally used to adjust or train the forecasting model.

- External forecasts: The predictions are directly received from a public or commercial forecast service. In some cases, additional processing for a better adjustment is performed.

The forecast accuracy is typically assessed using statistical estimates such as the mean absolute error (MAE), mean absolute porcentage error (MAPE) and root mean squared error (RMSE), or their corresponding normalized estimates (nMAE, nMAPE and nRMSE) [16]. However, as discussed in Section 6, there is ambiguity in the definition of these estimates. The persistence is used as the benchmark method in many cases.

Weather forecasts are mainly applied to predict RES generation in MGs. Concretely, 58% of the revised papers make explicit the process of obtaining RES generation forecasts from meteorological predictions. In the remaining cases, RES forecasts are assumed to be available, but either the meteorological framework is omitted in the text, or forecasts are obtained by directly processing RES generation data. In the case of load, only few works have accounted for weather considerations. Attending to the above classification, weather forecasts for MGs are mainly local or external. In the case of local forecasts, MEMS is generally supplied with updated meteorological measurements from a nearby station. These data are processed along with additional information of the system to generate the necessary forecasts. Autoregressive models and artificial neural networks (ANNs) are the main options in these cases. Local forecasts are assumed to be appropriated only for short-term horizons, since no information about the atmospheric fronts or synoptic evolution is considered. On the contrary, external forecasts from weather services are used for longer horizons. These predictions are generated using Numerical Weather Prediction (NWP) models, which solve the physical equations associated with the atmospheric processes. Supported by descriptions of the current state of the atmosphere, NWP models can generate gridded predictions of meteorological parameters of several days in advance in steps of 1–3 h. However, the complexity in calculations, and the consequent computational cost, results in a low updating frequency (two or four updates per day) and a lack of local considerations, as is desirable for MG applications. Some weather forecast services also offer ensemble forecasts: a set of single point forecasts that can be used to assess the uncertainty in the predictions. Ensemble forecasts are obtained by slightly varying the parameterizations, boundary and initial conditions of the NWP models so that different possible evolutions of the atmosphere can be calculated. The diversity of the predicted scenarios in a given time horizon informs about the uncertainty associated with the forecasted values at that point.

The already commented deficit of details and uniformity makes difficult an effective comparison among studies necessary to outline the various methodologies and the contexts in which they are applied. Into deeply understand the utilization of weather forecasts in MEMS, a restrictive selection of papers must be conducted. In the following sections, only those studies that provide complete information about the meteorological predictions will be considered. This information must include descriptions of predicted variables, forecast sources, forecasting horizons and, if applicable, processing techniques and uncertainty analysis. Table 1 summarizes this information for each of the selected papers. In some cases, the forecasting horizons are not directly mentioned in the text, but it is assumed that they are adapted to the horizons and temporal resolution of the MG scheduling strategy. Thereby, this information has also been also included in the table. The items labelled with asterisks indicate information that has been inferred from the context: graphs, used algorithms, or referenced works.

3. Wind generation

Wind power forecasts are supposed to be directly available in some studies, therefore avoiding the prediction problem. In these cases, forecasts are simulated by introducing some stochasticity in historical series of wind generation as a way to reproduce the real-life forecasting errors. Despite the meteorological framework being omitted, it is obviously implicit in the wind generation data and the introduced stochasticity, which ultimately represents the uncertainty in wind predictions. However, the absence of explicit information on weather aspects excludes these studies from meteorological analysis. In the remaining cases, wind generation forecasts are obtained by processing real meteorological predictions along with WT models. These models basically implement the typical WT power curves which connect wind speed to wind power. Consequently, wind energy forecasts for MGs are mainly based on wind speed data, although, in some cases, the atmospheric pressure is also considered to include air density estimations [25,51]. NOte that wind direction is not considered in the revised publications; moreover, height extrapolations to estimate the wind speed at the hub height are only detailed in [51].

The information referenced in this section is compiled in Table 1. For clarity, the analysis of the wind forecasts is divided into three aspects of interest for MG energy management applications: the sources and methods, the uncertainty framework, and the results from real case studies.

3.1. Sources and methods

Receiving external information from weather forecast services is one of the two main methods to obtain wind forecasts for MG energy management applications. As commented previously, data from weather forecast services are applied in longest horizons, and consequently, they are specially used in bidding and market applications. Table 1 shows how wind data from external forecasts are applied to scheduling horizons from 12 to 72 h. The Global Forecasting System (GFS) is one of the most used sources of weather forecasts. It has been demonstrated to be a useful tool for wind energy forecasting for ISOs and wind farm operations. GFS data are freely provided by the National Center of Environmental Prediction (NCEP) via a web server, thereby being an interesting solution to be integrated in MEMS. However, the global nature of the GFS data and the coarse resolution of the output grids advise against the direct application of these forecasts in local problems. The Weather Research and Forecasting (WRF) model has been extensively used to refine the GFS grids in order to include local considerations and make the results more usable for energy or environmental applications. A combination of these models (GFS data refined by WRF) was used in [52] to generate wind forecasts for an isolated MG in Huatocondo, Chile. In this case, the WRF output was additionally corrected by a statistical model for a better adjustment to the observed data. The wind forecasts used in [25,51] were also produced by a combination of GFS and WRF, although in this case, the refinement process is carried out by a regional meteorological agency. Updated data, with hourly resolution, are received every 12 h, thereby requiring additional processing to be adapted to the horizons of the MG management strategy. NCEP also provides ensemble forecasts produced by the Global Ensemble Forecasting System. The use of ensemble forecasts allows an uncertainty analysis of the predicted wind conditions with valuable applications for MG stochastic optimization problems, as described in [29]. In this study, after testing the horizons up to 72 h, the authors concluded that a planning horizon of 33 h results in optimal schedules to minimize the expected total cost in grid-connected MGs. Besides the NCEP products, other public and commercial services of wind forecasts have also been cited. In [66], forecasts based on data from the Australian Bureau of Meteorology were used to calculate the optimal purchase of electricity in a grid-connected MG. In [62], a bidding strategy adapted to the Spanish market was tested. The procedure exploited public wind forecasts from the website of the Sotavento experimental wind farm, which, in turn, were specifically generated for the wind farm location by a commercial provider. According

Table 1
Recent works.

Ref.	Year	TIME			WIND				SOLAR			
		Scheduling Horizon	Resolution	Execution Horizon[a]	Variable	Source	Processing	Uncertainty	Variable	Source	Processing	Uncertainty
[17]	2018	24 h	1 h						R, T, P, S, H, Sky Cov	External/Local	Machine Learning	
[18]	2018	24 h	Diverse	5 min	WT gen.	Historic*		Normal	PV gen.	Historic*		Normal
[19]	2018	24 h	30 min	30 min	S	Arbitrary*		Normal				
[20]	2018	4 h	1 h	15 min	WT gen.	Historic		Max–Min	PV gen.	Historic		Max–Min
[21]	2018	24 h	1 h		S	Local	WNN		R	Local	WNN	
[22]	2018	24 h	10 min	10 min	S	Extern/local	FPI	CG	R	Extern/local	FPI	CG
[23]	2018	1 h	1 h		WT gen.	Historic		Normal	PV gen.	Local		Normal
[24]	2018	1 h	1 h		WT gen.	Local		GMM	PV gen.	Local		GMM
[25]	2017	12 h	15 min	15 min*	S, P	External			R, T	External		
[26]	2017	24 h	1 h	1 h					PV gen.	Historic		Max–Min
[27]	2017	24 h	15 min		S	Historic			R, T	Historic		
[28]	2017	48 h	2 min	4 min					R, T	External		
[29]	2017	72 h	3 h	24 h	S	External		Ensemble				
[30]	2017	24 h	1 min	15 min					PV gen.	External		
[31]	2017	24 h	1 min						R, T	Extern/local	ANN	Normal
[32]	2017	24 h	1 h		S	External*		Normal	R, T	Historic		Normal
[33]	2016	1 h	1 h		S	Local	EMD + SBL	Normal	Sky Cover	Local	EMD + SBL	Normal
[34]	2016	24 h	1 h		S	External*		Normal				
[35]	2016	24 h	Non-Uniform	5 min	WT gen.	Historic*		Non-Parametric	PV gen.	Historic*		Non-Parametric
[36]	2016	5 min	5 min		WT gen.	Historic		Hyperbolic	PV gen.	Historic		Hyperbolic
[37]	2016	24 h	30 min		WT gen.	Historic		Uniform	PV gen.	Historic		Uniform
[38]	2016	10 min	10 min		S	Local	ARMA		R, T	Local	ARMA	
[39]	2016	24 h	1 min	10 min					PV gen.	Local	SARIMA	
[40]	2016	24 h	1 h		WT gen.	External		Normal	PV gen.	External		Normal
[41]	2016	6 h	15 min	15 min					PV gen.	Local	SVM	
[42]	2016	3 h	15 min	15 min	WT gen.	Historic	SOWGP					
[43]	2016	1 h	1 h	10 min	S	Local	GA-BP					
[44]	2016	Variable	Variable		WT gen.	Historic*		Normal	PV gen.	Historic*		Normal
[45]	2016	15 min	15 min		S	Local	GA-BP	Max–Min				
[46]	2017	4 h	15/5 min	15/5 min	S	Local	ARIMA + Kalman		R*	Local	ARIMA + Kalman	
[47]	2015	12 h	30 min	30 min	S	Local	ARIMA	Data driven				
[48]	2016	24 h	1 h		S	External*		Normal*	R,T	Historic		Normal*
[49]	2015	24 h	1 h		WT gen.	Historic*		Max–Min	PV gen.	Historic		Max–Min
[50]	2015	24 h	30 min	30 min	WT gen.	Historic		Normal	PV gen.	Historic		Normal
[51]	2015	12 h	15 min	15 min	S, P	External			R, T	External		
[52]	2015	24 h	1 h	1 h*	S	External	WRF + Stat		Clear Sky	Local	Persistence	
[53]	2015	2 h	30 min	30 min	WT gen.	Historic*		Beta	PV gen.	Historic*		Beta
[54]	2015	24 h	10 min	10 min					PV gen.	Local	Persistence	
[55]	2015	36 h	15 min	15 min					Clearness, T, H, Rain	Local/External	Regression	
[56]	2015	24 h	1 h	1 h	WT gen.	Historic			PV gen.	Historic		
[57]	2016	1 h*	1 h*						R, T	External		Normal
[58]	2015	24 h	1 h						R, T	Historic	Struct. Model	Normal

(*continued on next page*)

Table 1 (*continued*)

Ref.	Year	TIME			WIND				SOLAR			
		Scheduling Horizon	Resolution	Execution Horizon[a]	Variable	Source	Processing	Uncertainty	Variable	Source	Processing	Uncertainty
[59]	2015	24 h	1 h	1 h					PV gen.	Historic		Normal
[60]	2014	24 h	1 h						PV gen.	Local	ARMA	
[61]	2014	24 h	1 h		S	External			R, T	External		
[62]	2014	Spanish Intraday Market Timeline			S	External			R	External		
[63]	2014	24 h	1 h						PV gen.	Historic		Uniform
[64]	2014	24 h	30 min						Categories	External		Ocurrence
[65]	2014	24 h	1 h	1 h	WT gen.	Historic		Uniform	PV gen.	Historic		Uniform
[66]	2014	24 h	1 h		S	External		Rayleigh	R	Historic*		Beta
[67]	2014	15 h	1 h						R	External		
[68]	2014	24 h	1 h		WT gen.	Historic*		Weibull	PV gen.	Historic*		Normal

S: Wind speed, P: Atmospheric pressure, R: Irradiance, T: Temperature, H: Humidity.
[a] Only with rolling horizon strategy.

to the timeline of the day-ahead and intraday Spanish markets, forecasting horizons ranging from 3 to 36 h were used in the analysis. In [61], wind forecasts provided by the DTU Wind Energy Department were used in the day-ahead scheduling of a grid-connected MG with the goal of minimizing the use of the energy storage system required to compensate for the deviations derived from forecast errors. This study also illustrated the problem of bidding in the day-ahead market. In this case, forced by the closure of the day-ahead market and the updating period of the weather forecasts, bids and schedules were based on forecasting horizons up to 39 h. In summary, external wind forecasts are mainly applied in bidding strategies, despite the low updating frequency of these data sources, and the market timelines force to work with long forecasting horizons.

Wind predictions can also be obtained by processing local measurements from a nearby station. In this case, a forecasting module is specifically included in the MEMS for this task. As shown in Table 1, this option is associated with scheduling horizons ranging from 10 min to 12 h. The concerned management strategies are focused on reliability, minimization of the operational costs or maximization of wind energy contribution. It is also remarkable that this option is mainly considered in isolated MGs. The forecasting module generally implements a machine learning or an autoregressive model that is trained (or adjusted) using historical series. Bogaraj and Kanakaraj applied an autoregressive moving average (ARMA) model to perform 10-min-ahead schedules focused on assuring the continuous supply to a priority load. The coefficients of the ARMA model were adjusted using a year of observed data [38]. In [47], wind speed was predicted by an autoregressive integrated moving average (ARIMA) model in order to maximize the wind power infeed in an isolated MG. In this case, the model is adjusted using 5000 samples corresponding to intervals of 30 min. Then, the Monte Carlo method was used for scenario generation adapted to the stochastic model predictive control. The ARIMA model, in combination with the Kalman filter algorithm, was also applied to minimize the total operation costs of a combined heating, cooling and power system in a hypothetical building in Naijing, China [46]. In [43], genetic algorithms and backpropagation neural networks were used to perform 1-h-ahead average wind forecasts with the objective of maximizing the utilization of wind energy in an isolated sea water desalination system. The same methodology is used in [45] to assure reliability and optimal scheduling of the different elements in an isolated MG, in this case, based on 15-min-ahead average wind speed forecasts. Dou et al. used the ensemble empirical mode decomposition combined with sparse Bayesian learning to perform 1-h-ahead forecasts with the goal of minimizing costs and gaseous emissions in a grid-connected MG [33]. In [21], wavelet neural networks (WNN) are used to minimize the operational cost of a grid-connected MG based on 24-h-ahead forecast data.

In [22], both external and local wind data were processed using fuzzy predictions intervals (FPI) to generate day-ahead forecasts with a resolution of 10 min for a real MG test bed in Beijing, China. Several optimization methods were considered, obtaining the best results with the particle swarm optimization (PSO) algorithm.

3.2. Uncertainty

Regardless of the predicted variable—wind speed or wind power—or the forecasting process, most revised papers have accounted for the wind power uncertainty, which is assumed to be the result of the wind forecast errors. The treatment of this uncertainty is varied, reflecting that there is not consolidated knowledge in this aspect. Furthermore, there are no differences in the approaches regarding the source of wind forecasts. Table 2 shows relevant information of the uncertainty framework of some of the following studies. Establishing the maximum error bounds is a simple way to deal with this uncertainty. In [49], the 24-h-ahead schedule was determined under the assumption that wind power errors are enclosed in a constant

Table 2
Wind uncertainty.

Ref.	PDF	Horizon				
		5 min	15 min	30 min	1 h	24 h
[49]	Max–Min	–	–	40 %	40 %	
[45]	Max–Min	–	20 %	–	–	–
[19]	Normal	–	–	σ = 50%	σ = 50%	σ = 50%
[34]	Normal	–	–	–	σ = 2%	σ = 2%
[32]	Normal	–	–	–	σ = 15%	σ = 15%
[40]	Normal	–	–	–	σ = 5%	σ = 35%
[18]	Normal	–	–	–	L: σ = 10%	L: σ = 14%
		–	–	–	M: σ = 10%	M: σ = 28%
		–	–	–	H: σ = 10%	H: σ = 56%
[37]	Uniform	–	–	–	L: max = 0%	L: max = 10%
		–	–	–	M: max = 0%	M: max = 30%
		–	–	–	H: max = 0%	H: max = 50%
[65]	Uniform	–	–	–	L: max = 0%	L: max = 10%
		–	–	–	M: max = 0%	M: max = 20%
		–	–	–	H: max = 0%	H: max = 30%
[66]	Rayleigh	–	–	–	σ = 2.1%	σ = 46.4%
[36]	Hyperbolic	σ = 11.9%	–	–	–	–

L: Low, M: Med, H: High.

uncertainty bound of 40%. In [45], the maximum error bound for 15-min-ahead wind speed forecasts was established at 20%. However, the general trend is the application of probability density functions (PDFs) to model the forecast errors. Normal distributions are the most frequent options, although parametrizations differ significantly among studies. This point can be illustrated by comparing references [32,34,40]. These studies used the zero mean normal distribution to represent the wind power forecast errors for 24-h-ahead scheduling with hourly resolution. Despite the coincidence in the chosen PDF and the similar forecasting framework, the standard deviation of the errors was supposed to be below 2% in [34] and 15% in [32]. In [40], the dependence between the error and forecasting horizon was considered. In this case, the standard deviation associated with 1-h-ahead forecasts is established in 5%, being linearly increased until 35% for forecasting horizons of 24 h. In [18], besides the linear increase, different error levels are considered, reaching the standard deviation a maximum value of 56 % for a 24-h-ahead horizon. Other studies refer to an adjustment of the normal distribution considering the expectation and the standard deviation of the errors, but do not provide numerical values of these estimates [33,50]. In [24], the adjustment of parameters is performed every hour according to the last measurements, but it is implicit in a Gaussian mixture model (GMM). In some cases, wind power errors are assumed to be better described by other PDFs.In [37,65], the uniform distribution was used. These studies considered linear dependence between error and forecasting horizon, but associated different magnitudes to this effect: the maximum errors for a 24-h-ahead forecasts achieved 50% and 30%, respectively. In [66], the Rayleigh distribution was chosen and the standard deviation was increased from 2.1% for 1-h-ahead to 46.4% for 24-h-ahead forecasts. The beta distribution was used in [53] considering different parameterizations for different power levels: it was assumed that error variance linearly increases with the predicted power level. In [36], hyperbolic distribution was applied to model the day-ahead wind power forecast errors, assuming a standard deviation of 11.9%, based on the observed errors of the Electric Reliability Council of Texas. Mohammadi et al. considered the Weibull distribution but did not provide any parametrization [68]. Even assuming a normal distribution in wind speed forecast errors, Kou et al. proposed a sparse online warped Gaussian process (SOWGP) to model non-Gaussianity in the wind power predictions [42]. The non-parametric approach based on empirical adjusts was used in [35]. Finally, other approaches avoid the use of PDF to represent wind power uncertainty. In [47], since the normality of the errors could not be confirmed by the Kolmogorov-Smirnov test, a data driven approach without assumptions on the PDF was used to generate probabilistic scenarios. In [29] as well, the uncertainty was described by scenarios, but in this case, they were directly provided by ensemble forecasts. In [22], the fuzzy approach used to solve the problem facilitated the definition of the uncertainty levels, which are defined by the coverage grade (CG).

3.3. Results

Despite the importance given to deviations from schedules caused by forecast errors, only few studies reported the accuracy of the predictions applied in each case study. The errors associated with GFS data refined by WRF in Huatocondo [52] were detailed in [69]. The MAPE associated with wind power errors for 1-h-, 24-h-, and 48-h-ahead horizons were 11.73%, 24.67%, and 27.50% respectively. Marinelli et al. provided the distribution of wind speed errors associated with six months of DTU Meteo forecasts [61], also based on NWP models. The distribution exhibited a bias of 1.0 m/s, a standard deviation of 2.9 m/s, and a non-symmetrical shape with respect to the mean value, which contradicts the generalized application of zero-mean normal distributions. Note that the horizons associated with the represented errors are not clear in the text.

Focusing on local forecasts, Hans et al. evaluated the wind power errors derived from wind speed forecasts using an ARIMA model [47]. The accuracy was assessed by calculating the nRMSE value associated which each predicted series of 24 elements – resolution of 30 min, maximum horizon of 12 h. After the evaluation of 1000 predicted series, they obtained a mean error of 0.035 p.u., showing an improvement of 13% in the results obtained by the persistence method. The error distribution presents a maximum probability in errors around 0 p.u. and a displacement to the positive range in the rest of the errors. In [43], the error analysis was omitted, but it was observed that most of the time the error was below 10% for the next hour average wind speed value, achieving a maximum of 18%. However, it must be taken into account that these values are obtained from a test of four windy hours (wind speed of around 9.5 m/s), and consequently, they may not be representative of the general performance of the model in the site.

4. Solar generation

The survey of solar forecasts for MGs presents important similarities to the wind case. For instance, some studies directly consider solar generation predictions without considering weather forecasts. As in the wind case, these predictions are mostly simulated by introducing some stochastic behaviour in historical series of PV generation with the goal of reproducing the errors inherent to real forecasts. However, unlike the wind case, PV power predictions are also received from forecast services [40,30], or calculated from local power measurements by applying time-series forecasting techniques (autoregressive [39]60, persistence [54], ANN [40]). In all these cases, the weather conditions are implicit in the managed information, but no meteorological variable is directly considered.

In the remaining cases, PV power predictions are explicitly obtained from weather forecasts. PV models are then required to transform the meteorological data into power estimations. These models are based on real PV panels [32,48] or theoretical equations of PV generation [27,38]. Overall, they assume that PV production is fundamentally dependent on irradiance and temperature. Therefore, these are the meteorological parameters typically considered in MEMS. However, in some cases, irradiance is not directly forecasted but inferred from other parameters such as the clear sky index [52], sky cover [33] or sky clearness [55]. Moreover, in [64], the irradiance was estimated from a basic description of the meteorological conditions of the period by using the following three categories: fine, cloudy, and rainy. In [55], besides the sky clearness; temperature, humidity, and rainfall probability were also considered in the PV estimation. The number and diversity of variables involved in PV forecasts indicate another difference between solar and wind cases.

The analysis follows a similar structure to the one performed in the previous section.

4.1. Sources and methods

Solar forecasts are simulated from historical series of irradiance and temperature in some studies. Similar to the above explanation for PV predictions, historical series are transformed in synthetic forecasts by introducing some uncertainty as a representation of the errors that would be present in real weather forecasts. This uncertainty is ultimately translated to the solar production estimations, thereby allowing the assessment of methodologies focused on minimizing the impact of deviations derived from weather forecast errors, one of the main objectives in these studies. For instance, in [58], the tolerance of a grid-connected MG to uncertainties in PV generation forecasts is assessed considering one year of irradiance and temperature registers. Based on irradiance and temperature data acquired at the Oak Ridge National Laboratory (Tennessee, USA), an MG test system is analysed to determine the optimal bidding strategies in the day-ahead market [48] and the islanding capability under different conditions [32]. In [66], different scenarios are generated from a real irradiance profile in order to minimize the operational costs of a grid-connected MG derived from the weather forecast errors.

However, the most extended option is the use of real forecasts, either provided by weather forecast services or generated by forecasting modules embedded in the MEMS. There are even studies in which both sources are considered. For example, the forecasted temperature provided by a weather service and the last hours of measured PV power and irradiance are used as inputs of a three-layer ANN to estimate the day-ahead power reserve of an urban MG [31]. In [55], local weather measurements and external weather forecasts were processed along with technical, time and geographical data by applying regression techniques to predict PV production in an MG test facility at the University of Genoa (Italy). In [17], both local measurements from SCADA and external data from WRF data were combined to accurately forecast the PV generation of a real MG in Beijing, China, by applying different machine-learning algorithms. A similar solar forecast framework was applied in [22], in this case using fuzzy prediction intervals.

As in the wind generation case, data from weather forecast services are used for long scheduling horizons, ranging from 12 to 39 h in the reviewed studies. Again, external forecasts are mainly used in bidding applications. The problems associated with these sources are similar for wind and solar generation: low updating frequency, lack of local features, and necessity of adaptation to the MEMS timeline. References [51,61,62] provide illustrative examples of these issues as they detail forecasting horizons, resolution and updating frequencies. In [51,61], irradiance, temperature and wind forecasts were obtained from the same source. In [62], wind and solar forecasts were received from different sources, the latter being obtained from a commercial provider. Please refer to Section 3 for further details on these studies. If only solar forecasts are needed, it is frequent to filter the predictions associated with the daylight period. In [67], the optimal management of a grid-connected DC MG is supported by irradiance forecasts from Meteo France. The forecasted series have hourly resolution and are received at 3:00 am, but only forecasts from 9:00 am to 6:00 pm are used for MG scheduling, thereby involving horizons from 6 up to 15 h. In [64], the forecasts from the Japan Meteorological Agency were applied in the day-ahead optimal scheduling of a DC MG. The forecasted series comprised of following three categories: fine, cloudy and rainy. A resolution of 3 h implies 8 intervals in a day, but only 4 intervals, covering the period from 6:00 am to 6:00 pm, are considered in the calculations. The case described in [28] is very illustrative about the problems in assimilating data from weather forecast services. The forecasts were generated by the Canada Global Environmental Multiscale NWP model with a maximum horizon of 48 h and hourly resolution. Since the management strategy considers shorter intervals, the received data must be interpolated to be efficiently integrated. Despite is the data being updated every 6 h, they entail a delay of 8 h between the start time of the forecasting process and the online availability of the predictions. This interesting point, which reveals even longer horizons in the use of NWP forecasts, is rarely taken accounted for in MG literature.

Forecasts based on local measurements are used for horizons ranging from minutes to few hours. Statistical and machine learning models are implemented as forecasting engines. In [38], irradiance and temperature forecasts produced by ARIMA models were applied to optimize the energy flow in a stand-alone MG considering horizons of 10 min. In [46], the ARIMA model was complemented with Kalman filtering to be used in rolling horizon strategies with steps of 15 and 5 min and maximum horizon of four hours. In [33] an empirical model decomposition hybridized with sparse Bayesian learning (EMD + SBL) was used for 1-h-ahead forecasts achieving a significant improvement in other approaches based on persistence, wavelet or ANN. Only in [52], local measurements were used for horizons up to 24 h. These predictions were based on the persistence of the clear sky index, but the authors recognized that the approach is only applicable in the special conditions of the desert of Atacama (Chile) [69].

4.2. Uncertainty

As in the wind case, uncertainty in solar estimations has been considered in most of the revised studies. The similarity to the wind case is also applicable to the representations of the forecasting errors. In this sense, normal distribution is the most frequent option to describe these errors, but parameterizations are rarely reported. Adjustments according to the expectation and the standard deviation are commonly referenced, but without providing numerical values (see [52,58] for two examples). Thus, comparisons of the magnitude and characteristics of the considered errors must be made based on few studies. Liu et al. assumed a standard deviation of 15%, which remains constant over the 24-h prediction horizon [32]. Li *et al.* accounted for the increase in errors associated with forecasting horizons. They established a standard deviation of 1.5% for 1-h-ahead predictions, which linearly increased up to 7% for 24-h horizons [40]. In [18], besides the linear increase, different error levels are considered, reaching the standard deviation a maximum value of 56% for a 24-h-ahead horizon. In [48], the normal distribution was associated with both irradiance and temperature errors, with constant standard deviations of 10% and 3% during a 24-h-

Table 3
Solar uncertainty.

Ref.	PDF	Horizon		
		5 min	1 h	24 h
[49]	Max–Min	–	20 %	20 %
[26]	Max–Min	–	10 %	10 %
[48]	Normal	–	σ = 10%	σ = 10%
[32]	Normal	–	σ = 15%	σ = 15%
[40]	Normal	–	σ = 1.5%	σ = 7%
[18]	Normal	–	L: σ = 10%	L: σ = 14%
		–	M: σ = 10%	M: σ = 28%
		–	H: σ = 10%	H: σ = 56%
[63]	Uniform	–	max = 10%	max = 10%
[37]	Uniform	–	L: max = 0%	L: max = 6%
		–	M: max = 0%	M: max = 18%
		–	H: max = 0%	H: max = 30%
[65]	Uniform	–	L: max = 0%	L: max = 8%
		–	H: max = 0%	H: max = 16%
		–	H: max = 0%	H: max = 24%
[36]	Hyperbolic	σ = 11.9%	–	–

L: Low, M: Med, H: High.

ahead period, respectively. Other studies have assumed that forecast errors are well-described by a uniform distribution. Sechilariu et al. modelled solar generation forecasts by considering a random error of 10% during a 24-h-ahead forecasting period [63]. In [37], both a linear increase with the horizon and different levels of prediction errors were considered. For a maximum horizon of 24-h-ahead horizon, the error was assumed to be 6% for the lowest level and 30% for the highest one. Similar considerations were accounted in [65], but in this case, a range of 8–24% was associated with the 24-h-ahead errors. The beta distribution and Monte Carlo method were used to simulate scenarios of solar generation in [53]. The parametrization of the beta function is supposed to be dependent on the power level: higher errors are associated with higher power levels. In [66], the latin hypercube sampling approach was used to generate scenarios according to a linear combination of two unimodal beta distributions. The hyperbolic distribution fitted to the solar errors observed in the Electric Reliability Council of Texas was used in [36]. Besides PDFs, uncertainty was also modeled using a non-parametric approach in [35]. Maximum error bounds were used by Mohan et al. by assuming a constant value of 20% for a 24-h-ahead period [49], and by Li et al., by assuming constant bounds of 10% for the same horizon [26]. In [22], uncertainty levels were expressed by the coverage grade (CG), derived from the obtained fuzzy intervals. The uncertainty framework in [64] had particular elements. As mentioned above, the solar forecasts are provided in three categories (fine, cloudy and rainy) and the uncertainty is estimated according to the observed occurrence of these categories when each of them is predicted.

4.3. Results

Accuracy in solar predictions has been assessed in some of the cited studies. In [61], six months of solar forecasts provided by the Technical University of Denmark (DTU) were analysed. The observed MAE and standard deviation were 34 W/m^2 and 258 W/m^2 respectively. The associated error distribution showed a peculiar shape, which differed from that of common PDFs. However, since the forecasts were associated with different horizons, it was not clear whether the obtained statistics and error distribution referred to a particular forecasting horizon or summarized all the used horizons. In [31], external and local weather forecasts were used, but predictions were evaluated in terms of PV generation. Concretely, a series of day-ahead PV power forecasts of 120 consecutive days was evaluated, each of them being composed of 24 hourly values. The obtained nMAE and nRMSE were approximately 3% and 5.5%, respectively. In [17], the forecasting framework was similar but introducing more meteorological parameters. In this case the yearly average nMAE and MAPE values achieved 0.40% and 4.22%, respectively. The forecasting and validation contexts of the two previous study are comparable to the ones described in [55], except time resolution—15 min instead of one hour—, but the reported errors are significantly higher, achieving an nRMSE[2] of 29% and an MAPE of 11% in the tested period (May 15th to June 15th). This study also illustrates how the forecasting errors are highly dependent on the meteorological conditions. It is shown how forecasted and measured irradiance are very similar for a sunny day, in contrast to the important differences observed for a partially cloudy day. In [39], the errors of 24-h-ahead forecasts using an SARIMA model during a test period of 100 h were assessed. The MG has 12 kW of installed PV power and the obtained average error was 0.75 kW, with a maximum value of 6.21 kW. In [52], the persistence model was used for PV prediction in the Atacama Desert; the performance of the model was evaluated in [69]. The MAPE values associated with solar power forecasts were 8.14%, 11.19%, and 11.35% for 1, 24, and 48-h-ahead horizons, respectively. However, these results must be taken into account carefully, due to the particular climatology of the site (see Table 3).

5. Weather forecast for load estimations

Unlike RES generation, which is almost only determined by the weather conditions, load is also dependant on other factors related to particular MG patterns: building occupancy, seasonality or consumers' behaviour. Thus, weather forecasts for load prediction have even a more pronounced ancillary treatment in MG literature. In fact, only three among the studies compiled in Table 1, make explicit reference to weather data in load estimations. In [31], load predictions were performed by an ANN that processed 48 h of load measurements and 24 h of temperature forecasts provided by a weather service. The procedure is similar in [55], but processing 36 h of load measurements and 36-h-ahead of temperature forecasts. In [57] the outdoor temperature and global irradiance provided by two weather forecast services were used with important focus on thermal loads.

Avoiding the restrictive criteria in the selection of studies for Table 1, more information about the use of weather forecasts for MG

[2] This result can be overestimated since the normalization is obtained by dividing the errors with the mean of the measurements, while in [31] it is done by dividing them with the maximum PV power capacity.

load prediction can be obtained. Sandels et al. tested different parameters for day-ahead predictions of electricity consumption in an office building in Sweden [70]. The dataset included occupancy, indoor and outdoor temperature, daylight level, solar radiation, wind speed,and loads – divided into appliance, ventilation and heat pump (heat or cooling) loads. They found that appliance load is mostly dependent on the occupancy, but ventilation and cooling loads are mainly correlated to the outdoor temperature. Despite the appliance load being higher than the sum of the ventilation and cooling loads most of the year, in the warm months, they were comparable, including moments in which appliance load only represented 30% consumption. The generation of load forecasts for the Faculty of Electrical Engineering (Zagreb, Croatia) based on ANNs was studied in [71]. ANNs were trained considering 49 inputs, including 5 meteorological variables: pressure, humidity, temperature, global, and diffuse irradiance. The results obtained using these 49 variables were similar to the ones obtained by excluding global and diffuse irradiance. In other test the selection of variables was heuristic, and only temperature and pressure were considered as weather variables. In this case, the results were worse, indicating some relevant information from humidity data.

On a larger scale, load forecasting for district energy management was studied in [72]. The study was based on data obtained from the main campus at the University of Texas, comprising 160 buildings. Consumption was divided into electrical, cooling, and heating loads, in order to calculate their correlation coefficients with temperature (0.8, 0.8, and −0.8, respectively) and with humidity (−0.3, −0.2, and 0.2). These parameters, along with time information (hour of the day, day of the week and month) were used as exogenous inputs in a non-linear autoregressive model. If only weather variables were considered, day-ahead predictions and observed data would show R^2 coefficients higher than 0.9 for cooling and heating loads, and higher than 0.7 for electrical loads. These results can be improved if time information is also considered, achieving R^2 coefficients higher than 0.9 in all cases and indicating the dependence of electrical load on the occupancy patterns. In [73], different load forecasting methods for MG management on the district scale were analysed. Consumption data from 94 households in Lodz, Poland were compiled from January 2012 to December 2012, along with astronomical and meteorological data provided by a weather service. The tested weather variables were relative humidity, atmospheric pressure, precipitation, surface air temperature, wind speed and wind chill temperature. Data were divided depending on the type of the day (workday, Saturday, Sunday or holiday) and the variables found with significant correlation were daytime, daily average surface air temperature and daily average of relative humidity. Yuce et al. also studied the demand forecasting problem on the district scale [74]. Principal component analysis and multiple regression analysis were used in the selection of variables. Among the 23 analysed parameters, only 12 were selected for the proposed ANN model, five of which related to the meteorological conditions: outdoor air temperature, outdoor humidity, outdoor air pressure, wind speed, wind direction and visibility.

In summary, the above studies confirmed the dependence of load on weather conditions. The outdoor temperature seems to be the most crucial weather parameter, and the ventilation, heating and cooling, seem to be the more weather-dependant loads. However, as commented previously, meteorological data are not considered for load predictions in most MG studies.

The load forecasts for MGs are generated using statistical and machine learning models, of which persistence [25,60,75,76], autoregressive [38,39,46,47], and ANN models [45,55] are the most frequently used. Regarding uncertainty, normal distribution is by far the most used approach for describing the load forecasting errors, although it is remarkable that, unlike RES generation, perfect forecasts are considered in many studies [42,48,56]. In the load case, neither the models nor the uncertainty framework are determined by the meteorological information and, therefore, a deeper analysis of these elements is beyond the scope of this study.

6. Discussion

The previous sections described a wide variety of approaches for implementing weather forecasts in MEMS. Despite this diversity, some general ideas are present in the revised literature. In the following subsections, these ideas are expounded and complemented with additional information from other publications, some of which are beyond the scope of the MG field:

6.1. Variables

Wind power forecasts for MGs are based on wind speed data, except for of few cases in which other meteorological parameters are considered. Note that wind direction is not considered since is a common input for other wind power forecasting models besides MG applications [77]. The absence of height extrapolations in wind speed estimations is also noticeable. Typically, measured or gridded data from NWP are provided at 10 m above ground level, but hub heights can be significantly higher, especially in the WT lying in the range of MW. Therefore, wind forecasts should be corrected as these height extrapolations could involve an important increase in the available wind energy. Regarding solar forecasts, it seems that irradiance and temperature are the most important variables although, in this case, the input parameters are more diverse. Rashkovska et al. provided interesting information in this aspect [78]. They tested different meteorological variables, from both local measurements and forecast services, for a proof-of-concept PV forecasting module focused on MG applications. Measured data (including humidity, precipitation, wind speed and direction) were analysed, finding the best R^2 values for irradiance (0.887) and air temperature (0.244). Additionally, NWP data from weather forecast services were considered (including humidity, temperature, and UV-index), but finally only cloud cover was used as external information for the proposed forecasting module. It is also remarkable that wind data are frequently considered in applications of solar power forecasting besides MGs, because of its effects on PV module temperature [79].

Historical measurements of PV or WT power were used in more than 40 % of studies to simulate RES generation forecasts. The effects of weather forecast errors were generally modelled by introducing a stochastic component in these series—in most cases described by common PDFs—. This is a practical alternative if meteorological information is unavailable and the research focus is on certain MG aspects not particularly affected by deviations of RES forecasts. However, these results must be carefully considered in the assessment of scheduling strategies to be implemented in real-life MEMS, specially of those focused on dealing with uncertainty. As discussed in Sections 6.3 and 6.6, weather forecast errors show a complex dependency on the forecasting models, forecast horizons, and atmospheric and geographical conditions. In addition to this complexity, WT and PV models also introduce particular deviations in the error distributions. For instance, according to the WT power curves, some intervals of wind speed involve similar wind power output. Thus, wind speed forecast errors within these intervals do not involve errors in wind generation, *i.e.* certain wind speed errors are not translated to wind generation errors. This fact motivated the use of a sparse online warped Gaussian process (SOWGP) in [42] (commented in Section 3.2) and also explains the non-conventional distribution of wind power errors observed in [47] (commented in Section 3.3). Consequently, the assumption of a fixed, well-defined probabilistic distribution to model the RES forecast errors in a given MG is in contrast with the diversity of atmospheric scenarios and the variety of elements involved in the forecasting process. Thus, results from simulations of RES forecasts based on PV and WT generation data cannot be considered analogous to the ones obtained from real forecasts obtained based on meteorological variables.

6.2. Sources

As shown in Table 1, data from weather services are used in horizons longer than 12 h and forecasts from local measurements are used in horizons up to 24 h. According to recent reviews of irradiance forecasting, the use of NWP data is recommended for horizons longer than 3 h, and predictions based on local data in horizons shorter than 6 h [80,81]. In wind power reviews, the limit is also established for few hours [77,82]. In this sense, forecasts based on local measurements are probably used in excessively long horizons in MG applications. However, the use of data from weather forecast services introduces other problems: data require adaptation, entail low updating frequency, and involve additional delays resulting from the computation process. As commented above, the latter point was not well addressed in the revised MG studies (except in [28]), since the data delivery time was adopted as reference time for the forecasting horizon. Thus, the computation time associated with the forecasting process was not considered. Furthermore, computation time differs among different NWP models, and therefore the delivery time cannot be used as an uniform reference. This issue is well addressed in other studies focused on energy forecasting models [83]. Finally, note that some MG studies included both NWP and local data in order to exploit the best of each source.

6.3. Errors vs. horizons

Some studies consider errors constant in time, but it is accepted that forecast errors seem to increase with the horizon. The dependency between errors and horizons is generally modelled by a linear relation: errors are supposed to be null in the present and linearly increase reaching values of up to 56% for wind and solar generation in 24-h-ahead horizons. An illustrative visual example of the consequences of this assumption in the generation of probabilistic scenarios is provided in [40]. The linear relation between errors and horizons represents an excessive simplification in most of cases. In [17], the forecast errors associated with NWP and local data processed using machine-learning techniques were analysed showing a logarithmic relation with the forecasting horizon. Additionally, the errors also exhibited an important seasonal component. In [84], the solar predictions generated by the Australian Bureau of Meteorology and post processed with machine-learning techniques were analysed in a period of 11 days; including sunny, partially clouded and cloudy days. The results showed how the square correlation coefficient strongly decreases in the first three hours, remaining almost stable around 0.65 beyond that point. It is also shown how 2-h-ahead predictions in sunny days are more accurate than 30-min-ahead predictions in cloudy periods. This point demonstrates that, besides the time horizon, the evolution of the errors is affected by other variables related to atmospheric stability. Thus, future situations of stability (such as wind calm periods, sunny days or absence of fronts) can imply more accuracy than present situations of high variability. The ensemble forecasts generated by NWP models are a valuable tool in this sense, since they can describe these situations. Their application in renewable energy forecasting has received increased interest in recent years [85]. The use of ensemble forecast in MGs was considered in [86,29]. According to the latter study, ensemble forecasts benefit the MG management for planning horizons up to 33 h.

6.4. Wind errors vs. solar errors

Wind forecasting errors are frequently considered to be higher than solar ones. The wind-to-solar standard deviation ratio ranged from one [32] to five [40] in the studies in which both RESs were considered. These differences are compatible with real observations reported in some publications. Neves et al. analysed the forecast errors observed in an isolated MG in the Corvo Island by using the persistence model [87]. They reported annual MAPEs of 19% and 73% for solar and wind power forecasts, respectively. The already cited study of Huatocondo, Chile [69] reported comparable MAPE values for 1-h-ahead horizons. For 24 and 48-h-ahead horizons, wind errors become double than the solar ones.

6.5. Error metrics

One of the main problems in comparing forecast results from different MG studies is the absence of standardization of error metrics. Thus, similar acronyms are frequently associated with different estimates, and similar estimates are sometimes applied to series of different characteristics, *i.e.* series including a specific forecasting horizon or series including different forecasting horizons. This ambiguity is particularly noticeable in the normalized estimates—such as nMAE or nRMSE—, which, depending on the study, are obtained by dividing with the mean of the measurements [55], installed capacity [17], or number of elements of the series [31]. Even in some cases, there are contradictions between the definition of the estimates and the way in which they are reported; for instance, defining absolute errors but providing relative ones. These problems are detected not only in MG research, but also in other energy disciplines, such as solar forecasting [88] or building energy models [89], and demand a cautious interpretation of results.

6.6. Error descriptions

There is a general lack of agreement regarding the characteristics of the forecasting errors, which indicates the lack of consolidated knowledge in this aspect. Parametric approaches, based on PDFs, are commonly used to describe these errors. Normal distribution is the most used option, although uniform and beta distributions are also frequent. A wide diversity of parameterizations can be found in each case. Non-parametric approaches based on empirical adjusts, ensemble forecasts or maximum error bounds are occasionally used. This variety of uncertainty descriptions is enclosed not only to the MG context but also general applications of RES generation, as reflected in solar forecasting [79], and especially in wind forecasting reviews [82,90]. Some studies have analysed the wind and solar forecast errors pointing to similar conclusions. Zhang et al. made a thorough analysis of 1-h-ahead and day-ahead solar forecast errors considering different spatial scales, from one power plant with a 100-MW capacity to the whole Western Interconnection including 1,007 solar plants with an aggregated 64,495-MW capacity [16]. The observed error distributions differ depending on the scale (larger areas involve lower errors) and forecasting horizons (shorter horizons involve lower errors). Additionally, they corroborate that the shape of the distributions depend on the given hour of the day and month, revealing the complexity in the structure of solar errors. Similar conclusions about wind energy can be found in [91]. In this study, the wind power error distributions observed in six different ISOs with installed wind capacity ranging from 130 MW to 26,000 MW were compared. The study showed how the shape of the distributions differs depending on the scale, spatial dispersion, seasons, forecasting horizons, hour of the day and wind power level. Topography [92] and meteorological situations [93] have also been related to the observed error distributions in single wind farms. Hodge *et al.* perfectly summarized of all the above mentioned points [94]. They concluded that forecast error distributions depend on the area, the forecasting methodology, and the considered time scale and, consequently, recommended a preliminary analysis of each problem to properly define the distribution of errors and to select the best way to model them. However, in most MG studies, the uncertainty descriptions are arbitrary or based on other studies that not necessarily perform similar experiments regarding area, forecasting models, horizons, etc.

6.7. Challenges

Simply stated, the main weather forecast challenge involves improving the accuracy to benefit the MG operation. Regarding data from NWP, they are beyond the action of MEMS. Institutions and companies in charge of each weather forecast service are responsible for continuously upgrading the models to improve the results. In this sense, increasing the spatial and temporal resolutions would benefit the implementation of NWP data in MEMS. In the MG's range of action, the improvement in weather forecasts comes from the enhancement of local measurements and the optimization of the processing techniques. For instance, solar forecasting for MG applications has mainly focused on day-ahead predictions with resolutions ranging from ten minutes to one hour. These horizons and periods are not efficient in the description of the possible variations in sky coverage, thereby involving important deviations between the forecasted and measured values in each interval (see [55,95] for two illustrative examples). However, the real complexity of the problem is revealed when the MG is monitored at high sampling frequency. Then, the extreme variability in solar power resulting from cloud motion can be captured, showing variations of up to 80% in few seconds, which can last for hours on partially clouded days [96,97]. Owing to this variability, undesirable power flows can be produced [97] and PV smoothing techniques are required to make the generation more dispatchable [98]. Thus, there is an increasing interest in ultra-short-term solar forecasts including the sub-second range. The use of new instrumentation as all-sky cameras and new processing methods will be necessary to face this task [99]100. Similar problems are associated with wind forecasting for MGs (see [52] for an illustrative example). In this case, the LIDAR would represent an instrument analogous to all-sky cameras, as it provides high frequency snapshots of the surrounding wind fields [101]. However, the cost of this instrumentation seems to be disproportionate with the related economic benefit in the context of MGs. A more realistic option to obtain similar information lies in the application of nowcasting techniques based on information sharing among nearby MGs. This solution is also in line with recent proposals of big data applications for MG energy management [102]. Yang et al. indicated that the development of solar sensor networks will be fundamental in future applications of solar forecasting [88]. In the case of wind, a high density of measurement points can produce regional descriptions comparable to NWP data, but increasing the updating frequency up to minutes [103]. Muller et al. also pointed the potential of multiple sensor networks to monitor the local weather in urban environments, which is the main niche of MGs [104]. The aggregation of information from different MGs to decrease the forecasting errors was studied in [105], but focusing on trading energy in the market, not representing an improvement in the individual errors associated with each MG.

7. Recommendations

The previous literature revision and discussion allow the definition of some guidelines for an efficient use of weather forecasts for MG applications. Addressing the commented lack of uniformity in this aspect, the following recommendations can also represent a preliminary attempt of standardization that will be necessary in future MG developments, as suggested in [106]:

- Use of real forecasts: Real forecasts provide the real context in which MG strategies and results should be validated. Synthetic forecasts generated by introducing some stochasticity in historical series lead to a simplified and more predictable problem, since the simulated forecasting errors are assumed to obey a certain rule that is simple and arbitrary in most cases. The main problem in the use of external forecasts is the cost of a forecast service which may not be justified in the case of MGs. The main problems in the use of local forecasts are related to the availability of representative meteorological data, and the implementation of a forecasting model to generate predictions. However, these drawbacks can be easily overcome in most cases since forecasts from GFS are freely available all over the world and data from nearby meteorological stations are generally accessible in most areas. As mentioned above, in the latter case, applying a simple forecasting model to obtain real predictions seems a more realistic and easier-to-implement option than assuming a behaviour of the forecasting errors which, almost certainly, do not reflect the real working conditions of the MG.
- Long test periods: A test period of one year is desirable. Since this condition can involve serious computational inconveniences, sequences of at least three or four consecutive days with different meteorological situations—including the most unfavourable ones—should be considered.
- Sources: NWP data from weather forecast services must be applied in horizons longer than six hours, and predictions from local data in shorter horizons. To ensure maximum utilization of each source, the implementation of both external and local forecasts is desirable in typical 24-h-ahead scheduling applications. In this sense, the rolling horizon strategy can be an excellent option, as it distinguishes between the scheduling and execution horizons which generally are above and below the limit, respectively.
- Uncertainty: The uncertainty should be studied in each case as the error distribution depends on the local conditions, forecasting model, forecasting horizon, meteorological situations, or the considered period (season, month, or hour of the day). The use of ensemble forecasts of NWP models is a suitable choice to obtain real forecasts and uncertainty estimations simultaneously.
- Report: The use of weather forecasts for MGs should be described by clearly indicating the data sources (local data, weather forecast services, historical series), time information (horizons, resolution), and if applicable, processing techniques (forecasting models, local adjusts, adaptation to MEMS), the uncertainty analysis (models, parameterizations, error dependences), and observed forecasting errors (if real information is available). Including one paragraph or small subsection with this information could help in the contextualization of the problem and the interpretation of the results. Note that descriptions of NWP data should include the delay associated with the forecasting process.
- Error Metrics: The formulae that define the error estimates should be provided to clearly define the calculation associated with each acronym. Subscripts can be used to overcome the above commented ambiguity of acronyms. Thus, the involved forecasting horizons can be indicated, providing a distinction between estimates associated with a specific forecasting horizon—MAE_{1h}, MAPE_{24h}, RMSE_{10min}—and estimates associated with a range of forecasting horizons—MAE_{1h-24h}, MAPE_{1h-6h}, $\text{RMSE}_{10min-4h}$. In the case of normalized estimates—e.g. nMAE or nRMSE—, the expression per unit (p.u.) could be used to discern whether a normalization is conducted by dividing the power errors with the maximum installed power or with the mean of the measurements.
- Load forecasts: MGs with significant presence of heating, ventilation, and cooling loads should introduce, at least, outdoor temperature forecasts to improve demand predictions. Humidity estimations can also be valuable in this case.
- Variables: Wind power forecasts should consider wind direction as it has been demonstrated to be relevant in wind prediction. Wind speed height extrapolations are essential in accurate wind power estimations, as WT hubs and forecast heights are generally different, and this can imply important deviations.

8. Summary and conclusion

The present study reviewed the use of weather forecasts for microgrid energy management related to recent publications in the discipline. The use of renewable energy sources in all examined microgrids was verified. It has also been confirmed that dealing with possible deviations from plans resulting from forecasting errors is a main objective of the proposed energy management strategies. Therefore, meteorological information should be a primary input for microgrid scheduling problems. Despite this fact, and as a first result of the literature review, it is observed that the meteorological component plays a secondary role in a significant part of the studies, with the meteorological information provided in these papers being scarce, dispersed and occasionally incoherent or not fitted to meteorological standards. Thus, for a proper analysis of the elements and methodologies involved in the use of weather forecasts in MG problems, a restrictive selection of studies was conducted. The selected works provided a complete characterization of the forecast framework, including sources, methodologies, horizons, objectives, uncertainty and results. Based on these elements, a detailed survey was conducted for wind, solar and load forecast applications for microgrids, evincing and outlining the diversity of elements, cases and approaches involved in these problems. Additionally, this information was contextualized in relation to other literature on weather and renewable energy forecasts, discussing their similarities and differences on different aspects related to the use of the information, treatment of errors and uncertainty, and main challenges in the topic. Finally, the following recommendations for future research and real applications are suggested, such as use of real forecasts, long test periods, appropriate use of data sources and metrics, or standardized descriptions.

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