A Cooperative Multi-Agent System for Wind Power Forecasting

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Abstract. In the coming years, ensuring the electricity supply will be one of the most important world challenges. Renewable energies, in particular wind energy, are an alternative to non-sustainable resources thanks to their almost unlimited supply. However, the chaotic nature and the variability of the wind represent a significant barrier to a large-scale development of this energy. Consequently, providing accurate wind power forecasts is a crucial challenge. This paper presents AMAWind, a multi-agent system dedicated to wind power forecasting based on a cooperative approach. Each agent corresponds to a turbine at a given hour, it starts from an initial production forecast and acts in a coopera-tive way with its neighbors to find an equilibrium on conflicting values. An assessment of this approach was carried out on data coming from a real wind farm.

Keywords: Multi-Agent System · Cooperation · Wind energy Forecasting

1 Introduction

Renewable energies are increasing steadily in several countries, in particular wind energy, mainly driven by the cost decrease of wind turbines. In 2017, wind energy represented 5% of the French national electricity production with 12 GW installed. The United Nations Conference on Climate Change COP21 has set a goal of 30% renewable energy in the overall energy supply in the country by 2020, and more precisely, the wind installed capacity should reach 26 GW by 2023 [24].

In a number of countries with significant wind power generation, electricity markets are organized as electricity pools, gathering production and consumption offers in order to dynamically find the quantities and prices for electricity generation and consumption maximizing social welfare. Wind power producers propose energy offers based on forecasts. The market clearing is designed to

https://doi.org/10.1007/978-3-319-94580-4_12

match production offers and consumption bids through an auction process. Since power producers are financially responsible for any deviation from these contracts, improving wind power forecasting accuracy enables to reduce the penalties they incur [20].

Wind power forecasts have been used industrially for over 20 years and this field is approaching technological maturity following a concerted research effort reviewed comprehensively in [8,16]. However, forecast errors are still high and there are several pointers to improve them. This paper focuses on one of the current challenges introduced by the research and industry stakeholders of the International Energy Agency (IEA) Wind task 36: Model the interactions between the wind turbines of a farm [9].

Indeed, the dependencies between the productions of close turbines represent additional information rarely integrated in the wind power forecasting models. In this paper we propose to solve this problem with a cooperative approach which has shown significant results in other applications [2,22].

This paper presents therefore an approach based on Multi-Agent Systems and cooperation to provide wind power forecasts compliant with the farm constraints. It is organized as follows: Sect. 2 introduces the wind power forecasting problem. The Adaptive Multi-Agent Systems approach is described in Sect. 3 and the resulting designed system called AMAWind (**A**daptive **M**ulti-**A**gent System for **Wind** Power Forecasting) is presented in Sect. 4. Finally, the evaluation of the system and the results analysis are detailed in Sect. 5, before concluding.

2 Wind Power Forecasting

2.1 Theoretical Power Curve

According to theoretical studies on wind turbines [15], the power P delivered by a wind turbine follows the equation:

$$P = \frac{1}{2}\rho S C_p v^3 \tag{1}$$

where v is the wind speed, ρ is the air density, S is the rotor surface (the area swept by the blades) and C_p is the power coefficient (the fraction of wind energy that the wind turbine is able to extract).

This function only forms part of the full power curve (the graph representing the wind speed-production relationship). A typical power curve for an operational wind turbine is sketched in Fig. 1 and is made up of 4 parts: (1) below cut-in wind speed (typically between 3 and 4 m/s) where the turbine does not operate, (2) between cut-in and rated wind speed where the power follows (1), (3) above rated wind speed where the power is limited to the turbine's rated power, (4) above cut-out wind speed (usually around 25 m/s) where the turbine is shut down to prevent damage [4].

2.2 Current Forecast Methods

In practice, the relationship between wind speed and power is difficult to model because the conversion process is affected by many external factors such as poor quality wind speed measurements, mechanical wear and blade erosion, among others. Moreover, the wind speed at the exact blades location depends on the topography and the interaction between turbines. In Fig. 1, the observed production of a wind turbine is also plotted as a function of the 100 m high wind speed forecast, the wide disparity of the points demonstrates the difficulty of modeling the relationship.

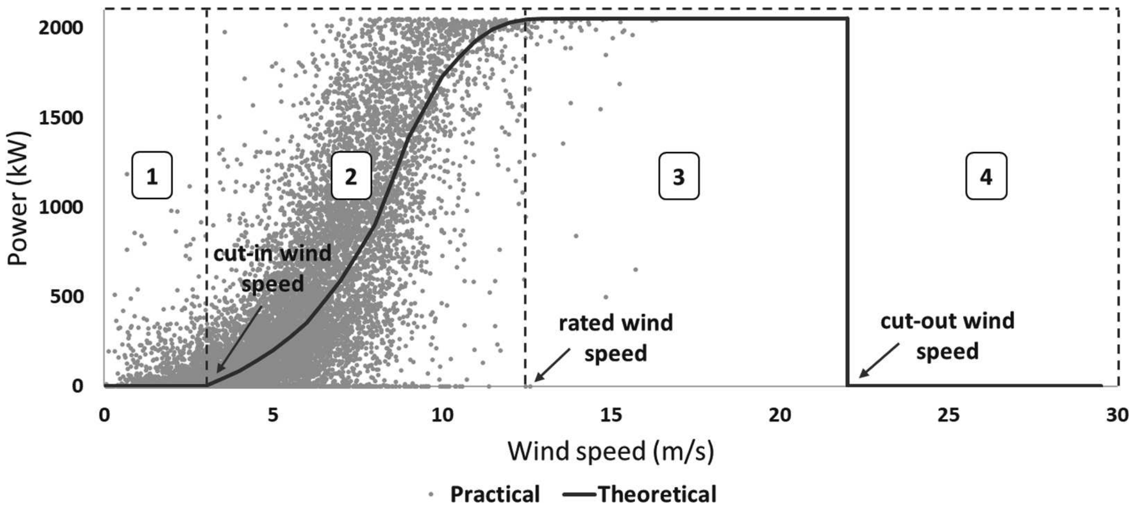


Fig. 1. A theoretical power curve compared with the observed production as a function of the 100 m high wind speed forecast

As a result, power curve models constitute a preliminary approximation of the production but they introduce uncertainty. They are mostly used when a wind speed or production history is not available, e.g. for recently installed turbines.

According to [13], wind power forecasting methods can be basically divided into two distinct categories: (1) Physical approaches based on Computational Fluid Dynamics (CFD) models. (2) Statistical approaches which use previous historical data to train a model representing the relation between wind power and explanatory variables including Numerical Weather Prediction (NWP) and on-line measured data. Hence, either we improve the forecasted wind by modeling the site or we learn from the model errors. Although the first approach is necessary in the absence of measured data on the wind turbine, it is a very specific problem depending on the topography and roughness of the site. Statistical approaches based on machine learning methods such as boosted regression trees [14], neural networks [21] or deep learning [23] are at the forefront of the technology, with gradient boosting methods winning both the 2012 and 2014 Global Energy Forecasting Competitions [11,12]. Despite the performance of these approaches, they do not take into account the information available relating to the relationships between wind turbines.

2.3 Towards a Turbine-Level Forecasting

Due to the low resolution of weather models or a lack of data, wind power forecasts are usually provided at farm scale. In other cases, a production is forecasted for every wind turbine independently and the farm production is obtained by a sum of these forecasts. However, for a single farm, wind turbines productions are very correlated with each other, especially between close turbines. Moreover, since a wind turbine generates electricity from the energy in the wind, the wind leaving the turbine has a lower energy content than the wind arriving in front of the turbine. A wind turbine thus interferes with its neighbors and can cause a production decrease on the turbines located behind it downwind. This phenomenon is called the **wake effect** [17]. This additional information has to be taken into account in the forecast process with the aim of improving the prediction accuracy. Therefore, the problem is to forecast the production at wind farm level by considering local constraints between turbines.

A bottom-up approach has been proposed in [3] to solve this problem. A first forecast is done independently at turbine-level with machine learning algorithms (LASSO, GBM and XGBoost). The farm production is then computed by a weighted sum of the forecasts where weights are determined by linear regression. An improvement can be observed by firstly dividing data by wind direction and then determining weights. However this approach solves the problem in a global way, considering all the turbines together. It does not take into account the local constraints between close turbines.

In this work, a wind farm is considered as a whole system composed of interrelated turbines. Like a mechanical spring system, entities are connected with each other by some constraints. The system evolves towards an equilibrium state globally minimizing the constraints in the system. In this case, an entity tries to comply with the consistency between its forecast and the past observations of its history. Each entity starts from an initial forecast and can modify it in order to make it coherent with the forecasts provided by its neighborhood.

A wind farm is composed of multiple interacting wind turbines within an environment. From this point of view, a Multi-Agent System (MAS) is a suitable system to represent the wind farm structure. Since the relationships between turbines evolve continuously according to weather situations, an adaptive method is required to solve these dynamic constraints. Therefore, the MAS has to be endowed with adaptation capabilities and we focused this study on Adaptive Multi-Agent Systems [5].

3 Adaptive Multi-Agent Systems

An Adaptive Multi-Agent System (AMAS) is a MAS able to adapt to its environment in an autonomous way [5]. In an AMAS, the global function is not hard-coded but emerges from the interactions between the agents composing it. Each agent performs a local partial function and is able to autonomously change its behavior and its relations with the other ones. This ability of self-organization makes the global function evolve and the system becomes able to adapt to disruptions or changes in its environment, it is therefore open, robust and designed in a bottom-up way.

Of course, agents need a criterion to question their behavior and relations, this criterion is what is called "cooperation". Every agent has a cooperative social attitude which makes it always help the most critical agent in its (limited) neighborhood unless itself becomes the most critical one (an agent is benevolent but not altruistic). The criticality of an agent represents its degree of dissatisfaction with respect to its local goal [7]. This domain-dependent criticality value has to be normalized in order to be compared between agents. The actions of the agents aim at minimizing as much as possible the criticality of all the agents in the system without needing any global knowledge.

Despite the fact that this approach is relatively new, recent examples show that these systems can be used to solve complex industrial problems, such as estimation of the state of an electrical network [19], automatic tuning of a combustion engine [2] or optimization of the cooling of photovoltaic panels [10]. Furthermore, the dynamics and uncertainty of data provided as inputs in this wind forecasting problem also confirm the relevance of such a system.

4 AMAWind for Wind Power Forecasting

A weather model provides forecasts on specific coordinates (every 2.5 km horizontally and vertically in our case) called grid points (see Fig. 2) and a wind turbine is directly surrounded by four grid points. Forecasts have to be made considering weather forecast data coming from weather models and production data obtained from the wind turbines of the farm. In this paper, we consider a grid point as the weather forecast database of a coordinate and a wind turbine as the production database of itself. The uncertainty of the weather forecasts, the complexity of the wind speed-production relationship and the interdependence of the wind turbines productions are such that the use of an Adaptive Multi-Agent System is a good candidate to solve the wind turbine production forecast problem.

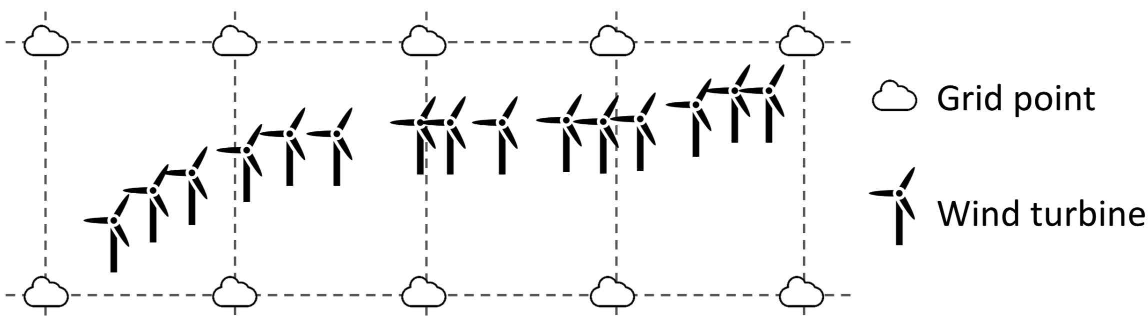


Fig. 2. The layout of the studied wind farm. The weather forecasts are provided at grid points position.

The proposed forecasting system, called AMAWind, is therefore based on an Adaptive Multi-Agent System and was designed in a bottom-up manner by first determining the entities and agents composing this system according to the ADELFE methodology [1].

An active entity, named Grid Point Hour (GPH) entity, is associated with one grid point and one hour and provides weather forecasts for its grid point for the given hour.

An agent, named Wind Turbine Hour (WTH) agent, is responsible of the forecast of a wind turbine production at a given hour (e.g. an agent charged with forecasting for the wind turbine #4 on January 25, 2018 at 08:00 a.m.). The environment of a WTH agent is based on physical closeness: at a given hour, a WTH agent is related to the four closest GPH entities and, at most, the two closest WTH agents (see Fig. 3).

WTH agents and GPH entities have respectively access to their associated wind turbine and grid point history.

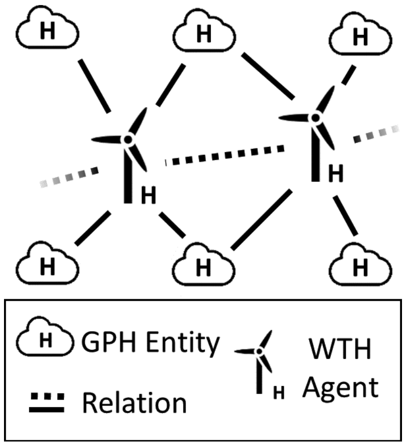


Fig. 3. Agentification

4.1 Agents Behavior

The behavior of an agent follows the classical **Perception-Decision-Action** life cycle. The agent starts with a forecast initialized at the average production of the wind turbine. In each cycle, it can decide to modify it.

Firstly, the agent perceives the current forecast and criticality of its neighbors. It also knows its own forecast and criticality.

Secondly, the agent decides how to change its forecast. These changes are made from the information previously perceived. The agent has three possibilities: to increase, to decrease or not to change its forecast. The increment is fixed at 10 kW. It simulates these different cases and performs the action minimizing the maximal criticality of its neighbors and itself. Even if this action has as a consequence a higher criticality for itself, an agent acts in a cooperative way as described in Sect. 3.

Finally, the agent performs the decided action which possibly changes its forecast, and consequently updates its criticality.

4.2 Criticality

As seen in Sect. 3, the cooperation between agents is mainly based on the concept of criticality. Generally, a criticality C depending on x follows the function:

$$C(x) = \begin{cases} 1 - e^{-k(x-i_1)}, & \text{if } x < i_1 \\ 0, & \text{if } x \in [i_1, i_2] \\ 1 - e^{k(x-i_2)}, & \text{if } x > i_2 \end{cases} \tag{2}$$

where k is a slope factor and $[i_1, i_2]$ is the interval corresponding to the lowest criticality.

The local aim of a Wind Turbine Hour agent is to determine the best forecast and to ensure that this one matches with the ones of its neighbors. Therefore, a high criticality means the forecast does not comply with the constraints imposed by the history. These constraints have to appear in the criticality through the interval $[i_1, i_2]$ chosen in (2). The general process to build the interval from a current weather forecast provided by a Grid Point Hour entity is:

- The weather forecast is compared with the full weather forecasts history of the grid point by means of a Fixed-radius near neighbors search [6]. It consists in looking for the closest entries below a defined threshold according to a similarity measure. In brief, we are looking for the dates where similar weather situations have occurred (e.g. a cold and windy day).
- The powers delivered by the wind turbine corresponding to these dates are extracted from its production history. A set of potential wind power forecasts is thus obtained.
- Finally, the interval is built by selecting the first and third quartiles of this set.

The choice to use an interval simplifies the criticality construction. In the long term, criticality should really represent the distribution of the set of potential wind power forecasts.

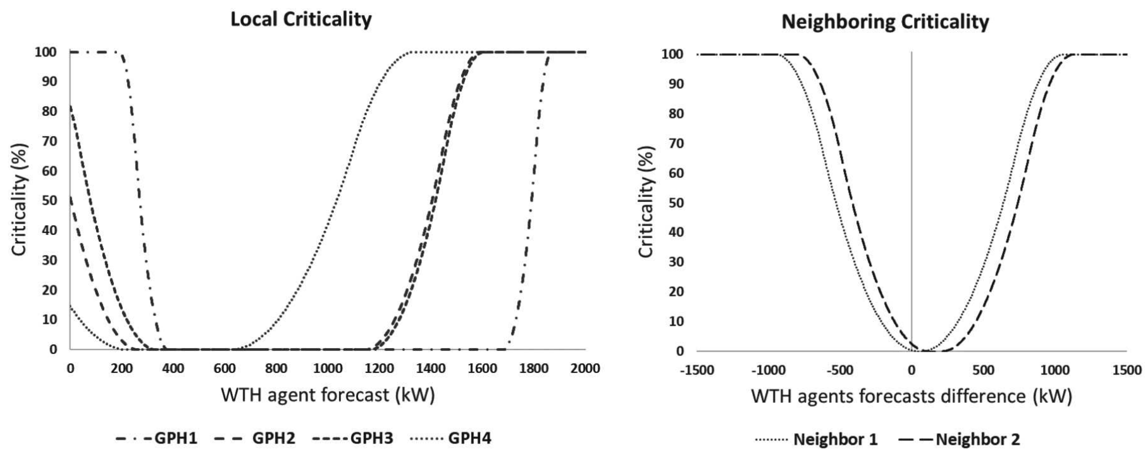
In this paper, the weather situation corresponds to the forecast of the wind speed and the wind direction at a given date. Other indicators indirectly involved in (1) such as temperature, pressure or relative humidity are not used in this work because they have a lesser impact on the production.

The quality of the forecast made by a WTH agent depends on the consistency of its forecast with both its own past productions and the neighboring agents forecast. The criticality is then expressed by considering these two factors and combines two kinds of sub-criticalities (see Fig. 4a and b):

Local Criticality. The forecast made by an agent has to be consistent with the productions observed with a similar weather situation in its history (e.g. the wind turbine rarely produces energy when the weather model forecasts a very light wind). For every pair of WTH agent and GPH entity, an interval is made from the above process. The corresponding criticality is then built with the function (2).

Neighboring Criticality. The forecast has also to be consistent with the ing agents forecasts (e.g. if a wind turbine always produces more amount of power than its neighbor, this constraint has to be taken into account). Indeed, a turbine slows down the wind behind it due to the wake effect and thus interferes with its neighbors. Therefore, a difference appearing in past observations between two wind turbines will be included in the resolution through this criticality. It is built in the same way that the local criticality except that the interval comes from a set of production differences between two wind turbines instead of a set of productions.

The final criticality of a WTH agent corresponds to the maximum between each local criticality and neighboring criticality. This choice enables not to give an advantage to one criticality over the other, they are considered equivalent.



(a) (b)

Fig. 4. Criticality decomposition: local (a) and neighboring (b)

5 Evaluation

The system was implemented and tested on real data coming from a French wind farm. Given that the main goal of this work is to improve forecast quality, we mainly evaluate the system on forecast error.

5.1 Protocol and Data Set

To evaluate forecasts performance two metrics were used: the mean absolute error (MAE) and the root mean squared error (RMSE), two standard measures to evaluate estimator performance. RMSE is an interesting measure in this use case because larger errors have a disproportionately large effect.

These metrics are given by the equations:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|\widehat{y}_i - y_i| \qquad \mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\widehat{y}_i - y_i)^2} \tag{3}$$

where $\widehat{y}_i$ is the forecast and y_i the observation. The NMAE and the NRMSE correspond to the errors normalized by the rated power to have more convenient results.

The wind farm includes 15 lined up turbines. Weather forecasts are provided by the Météo-France AROME high-resolution forecast model from 12:00 a.m. to

06:00 p.m. for the next day (with time horizon from 21 h to 39 h). The experiment covers a large period thanks to a 26-months history of wind power and weather forecasts from 05/2015 to 07/2017.

The model is validated by a k-fold cross-validation. The original sample is partitioned into k equal sized subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining k - 1 subsamples are used as training data. Although this method does not represent the real conditions (learning from more recent data than the validated ones), it enables to give an insight on how the model will generalize to an independent data set. In this case, we chose a 7-fold which corresponds to a validation set of approximately 100 days. At each validation, approximately 28500 agents are created (100 days $\times$ 19 h $\times$ 15 turbines).

The forecasts provided by the agents evolve in the system as long as the overall criticality does not converge towards a value. In practical, we confirm the convergence if the criticality remains constant for 10 successive cycles. When this occurs, the wind power forecasts are extracted and compared to real productions.

5.2 Results and Error Comparison

Table 1 presents the NMAE and the NRMSE computed for the 7 subsamples of the 7-fold validation. The average error is then provided at the end.

Table 1. Results summary

Sample	Forecast method					
	Average production		GBM		AMAWind	
	NMAE	NRMSE	NMAE	NRMSE	NMAE	NRMSE
1	20.66%	23.96%	10.23%	15.62%	10.17%	15.53%
2	22.84%	27.09%	10.78%	17.21%	10.48%	16.78%
3	30.75%	37.94%	14.16%	19.98%	14.13%	19.87%
4	23.73%	29.32%	13.19%	19.39%	13.46%	19.90%
5	18.67%	20.67%	7.27%	11.43%	7.00%	10.73%
6	29.05%	35.36%	14.34%	21.75%	14.23%	21.56%
7	20.09%	23.34%	9.30%	14.18%	9.09%	13.66%
Mean	**23.68%**	**28.24%**	**11.32%**	**17.08%**	**11.22%**	**16.86%**

The *Average production* method consists in using the average production of the turbine as a forecast. This naive method, never used in practice, serves as a reference value. In this experiment, it provides an average NMAE of **23.68%**, twice the errors obtained by the two methods based on weather forecasts.

The *GBM* method (Gradient Boosting Model) is a forecaster commonly chosen in wind power forecasting because it provides correct results without requiring complex tuning. The model was trained and tested on the same data sets and was implemented thanks to the machine learning library Scikit-learn [18].

The cooperative method used in AMAWind provides average results slightly better than the GBM in terms of NMAE and NRMSE (respectively from **11.32%** to **11.22%** and from **17.08%** to **16.86%**). Except for the fourth subsample, the forecasts made by the cooperative approach are more accurate.

Given that the wind power forecast error is highly correlated with the weather forecast error, we observe similar results between methods for the same subsample. The wide disparities between the subsamples (e.g. **7.27%** and **14.34%**) are due to the non-linearity of the wind speed and production relationship. Indeed, as can be seen in Fig. 1, a wind speed deviation before or after the cut-in wind speed will not lead to the same error. Therefore, the sixth subsample depicted a more windy period than the fifth.

5.3 Criticality Analysis

Does a criticality decrease lead to an error decrease? This relation, essential to improve the results with such a system, is not directly implemented. The criticality and behavior definitions have to result to this emerging phenomenon.

The evolution of the average NMAE and criticality for the seven subsamples is presented in Fig. 5a and b which show that the required relation is confirmed by the experiment.

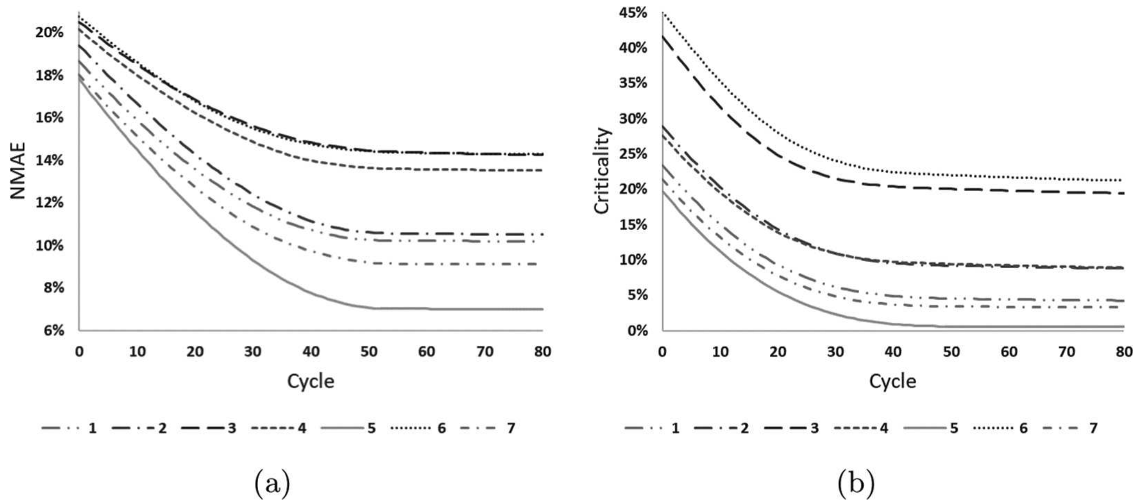


Fig. 5. NMAE (a) and criticality (b) evolution on the seven subsamples

While every criticality decreases in the same way, the errors decrease with different slopes (e.g. the fifth and the seventh). However, for a given subsample, the convergence happens simultaneously for the NMAE and the criticality because an agent would not change its forecast if its criticality reaches a minimum. Moreover, a high final criticality leads to a high final error, e.g. the third and the sixth end at a criticality and error of approximately 20% and 14%. The criticality can therefore be seen as an uncertainty indicator.

In conclusion, the criticality chosen in this work is consistent for the problem because it enables to improve the forecasts.

6 Conclusion

This paper has proposed a wind power forecasting approach based on a cooperative resolution by a Multi-Agent System. We considered the wind farm as a whole system with local constraints between each turbine. We used cooperation as a means to solve the possible conflicts and to obtain a forecast compliant with these constraints.

Resolutions were made locally and showed a decrease of the global forecast error. Despite the basic behavior of the agents, AMAWind provides results slightly better than a commonly used method. These initial outcomes are encouraging but some improvements can be made to the criticality definition and the algorithm used in the initialization.

The future works should take into account temporal dependencies by connecting agents representing the same turbine one hour before and after. Whereas this work focuses on day-ahead forecasting, another potential approach concerns short-term forecasting for the intraday market where temporal dependencies are important.

Acknowledgments. This work is part of the research project Meteo*Swift funded by the ERDF (European Regional Development Fund) of the European Union and the French Occitanie Region and supported by the ANRT (French National Association for Research and Technology). We would also like to thank the CNRM (French Weather Research Centre), our partner in this project.

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