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Advances in Wind Power Modeling

Merging Research and Market Experience

Thesis submitted for the degree of Philosophiae Doctor

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This work stays proof that I sometimes swim against the current
To Oriol

Preface

This thesis is submitted in partial fulfillment of the requirements for the degree of *Philosophiae Doctor* at the University of Oslo. The research presented here was conducted primarily at the University of Oslo and used the expertise from Refinitiv, an LSEG business, under the supervision of professor Fred Espen Benth and associate professor Salvador Ortiz-Latorre. The application of this work was possible thanks to the static data provided by Refinitiv.

The thesis is a collection of three papers, presented in chronological order of writing. The papers are preceded by an introductory chapter that relates them to each other and provides the motivation and context for this work. The first paper is written in collaboration with professor Fred Espen Benth. In the last two papers I am sole author.

Acknowledgements

I sometimes swim against the current and the present thesis is an example of this. There has been a long way since the time I used to like Mathematics in primary school to today. I am the product of a competitive Romanian educational system up to high-school level, a holistic Spanish academic system up to Bachelor level, an inspiring Belgian research environment, and a supportive Norwegian learning and research environment from Master to PhD level. But, above everything, I am the reflection of so many inspiring persons and positive experiences that I gathered throughout the years. I would like to take this opportunity to be grateful to some of them.

First of all, I am deeply thankful to my supervisor, professor Fred Espen Benth, for being such a valuable support during this project and beyond. His teaching skills, research insights, support and career advice have been paramount to accomplishing this thesis and evolving professionally. I am grateful to professor Salvador Ortiz-Latorre for his support in some of the inflexion points of this project.

I grew up professionally in the energy industry by being part of the great Thomson Reuters and, lately, Refinitiv family. I am profoundly grateful to the whole Power Research team. In particular, I would like to thank Petter Vegard Hansen and Jørund Haartveit for their support to the current research, as well as for providing me with the resources to learn and evolve professionally.

It is said that if an idea is not scary enough it means it is not bold enough. I took on the challenge of working on a PhD project together with my full-time job almost without being fully aware of the amount of effort it would entail. I took this challenge...because it had to be done. And because someone very dear kept reminding me that I have to follow my path, through thick and thin. During all this journey, I have received your confidence, drive and unconditional support. It goes beyond words to say that this thesis would not exist today without you and your strength. When the quest became exhausting, you were there to remind me that we must always conclude what we started. Thank you, Oriol, for being the guiding light along the way.

I am profoundly grateful to my family in Bucharest, whose values, initial education and support gave me a precious start in life. Your warm safe cocoon, yet the strive to overcome myself were two key elements that accompanied me during my education and far beyond. I appreciate every single effort you made to support me and, ultimately, give me the opportunity to choose what I would like to do in life. I hope one day I can make you proud.

I hold very dear my years in Romania and the teachers I had the enormous luck to have. I am especially grateful to my Mathematics teacher, professor Mihaela Andreescu from Mihai Viteazul National College. From your inspiring classes I took with me your passion and curiosity for this science. You led those of us interested in Mathematics to the boundaries of what we knew and let us challenge ourselves by revealing us small bits of mysteries. "Those of you who will take a Mathematics degree will understand this later", I remember you saying.

Also, I would like to thank my English teacher from Mihai Viteazul National College, professor Ana-Maria Rampelt. You infused us with the sense of structure and logic in everything we write. Thank you for your passion and dedication to improving our English writing skills. This rendered the writing process of this thesis much smoother.

I was extremely lucky to have many more inspiring teachers in Romania. I would like to extend my gratitude to professors Gilda Gebaila, Georgeta Murzea, Rodica Alexandru and Cavy Meca.

During my academic incursion, I had the opportunity to work with extremely valuable persons and professionals. To professor Marta Folgueira López from Universidad Complutense de Madrid I owe my beginnings in research. I am deeply indebted for the confidence deposited in me ever since I was a first year Bachelor student and for the friendship thereafter. I am extremely grateful to professor Véronique Dehant from the Royal Observatory of Belgium for her warm welcome into the world of international scientific research. Through your personal example I understood the beauty and freedom of research.

While working on this thesis, I received the moral support of several dear persons from Bucharest, Ibiza, Brussels, Madrid and Oslo.

To the readers of this thesis, you have in front of your eyes the work of ant:

"An ant cannot turn a mountain upside down, but it can move it, slowly, piece by piece" (Marin Preda)

Mihaela-Alexandra Puica
Oslo, February 2022

Dedicație

Uneori înot împotriva curentului, iar teza de față este un exemplu. Am parcurs un drum lung de la momentul in care a început să îmi placa matematica si până în ziua de astăzi. Sunt produsul sistemului de educație competitiv românesc până la liceu, al mediului academic spaniol până la licență, a unui mediu de cercetare inspirațional belgian și a sistemului academic si de cercetare protector norvegian la masterat si doctorat. Dar, mai presus de toate, sunt reflexia atâtor oameni care m-au inspirat si a atâtor experiențe pozitive. Vreau, cu această ocazie, să le fiu recunoscătoare câtorva persoane.

În primul rând, îi sunt foarte recunoascătoare conducătorului meu de doctorat, profesorului Fred Espen Benth, pentru sprijinul acordat de-a lungul acestui proiect și, in general, de-a lungul carierei de până acum. Calitățile pedagogice, sugestiile științifice și sfaturile de carieră au fost extrem de importante in dezvoltarea mea profesionala. De asemenea, îi mulțumesc coordonatorului secundar de doctorat, profesorului Salvador Ortiz-Latorre pentru sprijinul acordat in punctele de inflexiune ale acestui proiect.

Am crescut profesional in domeniul energiei făcând parte din familia Thomson Reuters, ulterior, Refinitiv. Îi sunt recunoscătoare întregii echipe care se ocupă de Electricitate in cadrul Refinitiv. In special, aș vrea să le mulțumesc lui Petter Vegard Hansen și lui Jørund Haartveit pentru sprijinul acordat proiectului meu și, totodata, pentru că mi-au pus la dispoziție multe resurse pentru a mă dezvolta profesional in domeniul energiei.

Se spune că dacă o idee nu te sperie înseamnă că nu este suficient de îndrazneață. Mi-am lansat provocarea unui doctorat, pe lângă serviciul full-time aproape fără să fiu conștientă de efortul pe care acesta îl implica. Am făcut-o pentru că...trebuia să o fac. Și pentru că cineva foarte drag imi amintea tot timpul că trebuie sa îmi urmez calea si, orice ar fi, să fiu doctor în matematică. De-a lungul acestei călătorii, mi-ai acordat încrederea, suportul necondiționat si puterea ta. Este de prisos să spun ca această teză nu ar fi existat astăzi fără tine și determinarea ta. Când lucrul devenea epuizant, îmi aminteai ca ceea ce se incepe trebuie terminat. Mulțumesc, Oriol, pentru că ai fost farul pe acest drum.

Le sunt profund recunoscătoare parinților si sorei mele din București, ale caror valori, 7 ani de acasă și sprijin mi-au dat un start in viață de neprețuit. Cuibul vostru și, în același timp ambiția de a mă autodepăși sunt doua elemente-cheie care m-au însoțit de-a lungul drumului academic si mă vor însoți mereu. Apreciez fiecare efort pe care l-ați făcut ca să mă susțineți și, in definitiv, ca să pot avea libertatea de a face ceea ce îmi doresc in viață. Sper ca într-o zi să fiți mândri de mine. Vă multțumesc, dragă familie.

Mă gîndesc cu drag la anii din România și la profesorii care mi-au marcat existența. Îi sunt in special recunoscătoare profesoarei mele de matematică de la Colegiul Național "Mihai Viteazul", doamnei Mihaela Andreescu. Din experiența orelor dumneavostră am rămas cu pasiunea și curiozitatea dumneavoastra pentru această știință. Pe cei interesați de matematică ne puneați in fața limitelor noastre de liceeni și ne dadeați mici crâmpeie din ce ar putea fi dincolo de ceea

ce știam. Îmi amintesc când ne spuneați: "Cei care o să dați la Matematică o să înțelegeți asta mai târziu". Multțumesc, doamna profesoară.

De asemenea, aș vrea să îi mulțumesc profesoarei de engleză a Colegiului National "Mihai Viteazul", Ana-Mariei Rampelt. Ne-ați inculcat un profund simț al logicii și al structurii in tot ceea ce scriem. Vă mulțumesc pentru pasiunea cu care mi-ați îmbunătățit abilitatea de a scrie in engleză. Grație acestui lucru, redactarea tezei de față a fost un proces cu mult ușurat.

Am avut norocul de a întalni mulți alți profesori care m-au inspirat. Vreau, cu această ocazie, să le mulțumesc profesorilor Gilda Gebăilă, Georgeta Murzea, Rodica Alexandru și Cavy Meca.

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Cititorilor acestei teze, sunteți în fața lucrării unei furnici:

"O furnică nu poate răsturna un munte, dar îl poate muta din loc, încet, bucată cu bucată" (Marin Preda)

Mihaela-Alexandra Puica
Oslo, februarie 2022

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Algunas veces nado a contracorriente y la presente tesis es un ejemplo de ello. He recorrido un largo camino desde los 6 años cuando me empezaron a gustar las matemáticas hasta hoy en día. Soy el producto del sistema educacional competitivo de Rumanía hasta instituto, del sistema académico holístico de España hasta el grado, de un ámbito inspirador de investigación en Bélgica y de un sistema académico y de investigación protector de Noruega hasta el máster y doctorado. Pero, sobre todo, soy el reflejo de tantas personas inspiradoras and y de tantas experiencias positivas. Me gustaría aprovechar esta oportunidad para agradecer a un par de personas clave.

Antes que nada, le estoy profundamente agradecida a mi director de tesis, al profesor Fred Espen Benth, por todo su apoyo durante el proyecto y más allá de éste. Tus cualidades didácticas, tus consejos académicos y profesionales han sido muy importantes para levar a cabo esta tesis y en mi desarrollo profesional. Asimismo, le estoy agradecida a mi co-director de tesis, el profesor Salvador Ortiz-Latorre por su apoyo en los puntos de inflexión de este proyecto.

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Dicen que si una idea no nos da respeto es porque la idea no es suficientemente temeraria. Me comprometí a trabajar en una tesis doctoral junto a mi trabajo a jornada completa sin estar del todo consciente del esfuerzo que ello requiere. Me comprometí a ello...porque tenía que hacerlo. Y porque alguien muy querido me recordaba que, pese a todo, yo tenía que seguir mi camino y ser doctora en matemáticas. En todo este viaje, he recibido tu impulso, confianza y apoyo incondicional. Sobran las palabras para decir que sin ti y tu fuerza, esta tesis nunca hubiera exisitido. Cuando la búsqueda científica se volvía agobiante, estabas ahí para recordarme que lo que se empieza se acaba. Gracias de corazón, Oriol, por ser la luz en mi camino.

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En mi incursión académica, he tenido la oportunidad de trabajar con personas muy valiosas, tanto como calidad humana, como profesional. A la profesora Marta Folgueira López de la Universidad Complutense de Madrid le debo mis comienzos dentro de la investigación. Le estoy muy agradecida por haber confiado en mí desde que era una alumna de primer curso de la Facultad de Ciencias Matemáticas. Su amistad es muy valiosa para mí. Le estoy muy agradecida también a la profesora Véronique Dehant del Real Observatorio de Bélgica por su calurosa acogida dentro de la investigación internacional. He conocido, con el ejemplo personal, la belleza y la libertad de la investigación.

A lo largo del presente proyecto he recebido el apoyo moral de muchas personas queridas de Bucarest, Ibiza, Bruselas, Madrid y Oslo.

A los lectores de esta tesis, estáis ante el trabajo de una hormiga:

"Una hormiga no puede volcar una montaña, pero la puede mover, despacio, pedazo a pedazo." (Marin Preda)

Mihaela-Alexandra Puica
Oslo, febrero de 2022

List of Papers

Paper I

M. Puica and F.E.Benth "A Spatio-Temporal Model for Predicting Wind Speeds in Southern California". *Submitted for publication: Communications in Statistics-Case Studies and Data Analysis.*

Paper II

M.Puica "On an Hourly Spatio-Temporal Model for Wind Speed Prediction: Applications to Southern California". *Submitted for publication: Journal of Applied Statistics*

Paper III

M.Puica "Improvements in Wind Power Prediction by Considering Locational Wind Speed Estimates: A Critical Analysis". *Submitted for publication: Energy Systems.*

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Chapter 1

Introduction

Energy security lies undoubtedly at the forefront of our social and economic lives. Accelerated by power market deregulations, climate policies, electrification or geopolitics, the discussion about security of energy supply is part of nearly all governmental agendas. Renewable energy sources receive increasingly more attention as they are a cheap way to produce electricity while offsetting our CO2 emissions. In particular, since the end of the 19th century[1], wind has been recognized as a source of energy. As of the end of 2020, the International Renewable Energy Agency (IRENA) reports a total wind power capacity worldwide of 732 GW[2], the equivalent of 732 nuclear reactors. By 2025, the International Energy Agency (IEA) expects 65-100 GW of new wind additions to come [34].

However, wind power poses an important challenge to the electricity transmission system operators and to power market participants. As an intermittent source of energy, wind may imply difficulties to balance supply and demand and maintain grid stability. This is the reason why in many developed markets, this source of energy may still be curtailed[3]. In this context, accurate wind power forecasting becomes imperative.

The present thesis is the result of 6 years of power market research within a leading global power analytics company and nearly 10 years of experience within Applied Mathematics. Since its inception, the main goal of this research has been to merge market experience with complex techniques from Statistics and Time Series Analysis. Thus, we set ourselves the aim of refining our understanding of wind power forecasting using high-quality market data while never losing sight of the real industrial concerns. Therefore, throughout this thesis, we will gradually approach the problem by way of 3 articles studying wind speeds with a daily resolution, then down to an hourly resolution and, finally, to a refinement of wind power supply forecasting. These studies have been performed in a real-life setting, taking the case of Southern California as an example.

More precisely, with this research we make the following contributions:

- We propose an original spatio-temporal model for wind speeds with a daily and hourly resolution.
- We provide a novel technique of downscaling wind speed data to new locations of interest via kriging. We do this an an original manner, by

[1] 1891: the Danish scientist Poul La Cour is known to develop the first electricity-generating wind turbine

[2] Value reported for the end of 2020, retrieved from https://www.irena.org/Statistics/View-Data-by-Topic/Capacity-and-Generation/Statistics-Time-Series

[3] The act of limiting the access of the wind power to the public grid

first modeling the temporal behavior of wind speed, then by spatially optimizing the time series parameters.

- Our time series approach of hourly wind speed data opens the way to more complex models. First, we model seasonality by way of Fourier and a set of indicator functions. Then, we work with ARMA-GARCH or ARMA-GJR-GARCH models.
- We offer an application of multilinear cokriging to tackle the challenge of the spatial variability of seasonality in wind speeds.
- During the computation process, we discover the need for recovering invertibility in ARMA processes. We bring up the less discussed matter of transforming the polynomial roots of such a process and then making the process statistically identifiable with its original version.
- We study the anisotropic behavior of wind speeds.
- We build an original wind power prediction model that starts from the phenomenological equation (Betz law) and extends via power curves to a whole market area. The model is simple yet comprehensive.
- Our problem formulation makes use of market data in a unique way. We start from data in a gridded format that we eventually aim to direct towards wind farm locations. None of the choices of data in this study is fortuitous. We use all data insights that an average market participant has. We add the expertise acquired by working with a wide range of dataset types.
- We offer a wealth of programming scripts specially developed for this study. No built-in packages were used during the spatial study or the simulation phase, but they were rather tailor-made for the study.

In the sequel, we shall introduce our work in the following way. In Section 1.1, we discuss successively the importance of such a research for the industry and academia. Section 1.2 discusses more in depth the contributions of this study in the market and academic context. During Section 1.3, we explain the process of this scientific quest, going through the usage of data to the breadth and depth of coding. With Section 1.4, we provide a technical background on ordinary kriging and its extension to multilinear cokriging. In Section 1.5, we briefly introduce the ARMA and GARCH processes. With Section 1.6, we offer a general account on power curves. Section 1.7 details on the spatio-temporal analysis of daily wind speed data. With Section 1.8, we extend this to the hourly data. Section 1.9 eventually discusses the improvements that a targeted wind speed forecast brings to the forecasting of wind power generation. Trial and errors are intrinsic to scientific research. We continue this chapter by reviewing how we responded to our goals, as well as to the mistakes made along the way in Section 1.10. In Section 1.11 we draw the limits and assumptions of our study as well as ways of bridging them. Finally, with Section 1.12, we discuss further applications of our research. We also look beyond those at future research directions in wind power modeling from a market and research-relevant perspective.

1.1 Motivation for the study

1.1.1 Market Perspective

According to the IEA, renewables are expected to surpass coal supply in the generation mix by 2025 [34]. This is likely to happen as the aging coal power fleet will be retiring gradually and more wind and photovoltaic projects are being commissioned. However, this assumption also relies on the fact that the penetration of wind power into the grids will increase. The latter becomes possible if the grid flexibility is improved but also if the transmission system operators and market actors can work with more accurate wind predictions.

Given its highly variable nature, wind power faces the challenge of grid integration. For this reason, more project deployment is not necessarily synonymous to more wind power covering demand. Capacity factors are, to a certain extent, a measure of such flexibility. They represent the generation as a percentage of the total installed capacity. For instance, data from the U.S Energy Information Administration show that the capacity factors for wind power at country level have been rather stagnant around 35% during 2016-2019, below hydroelectricity [5]. This is even lower for Germany's onshore wind installations, around 22% [33].

Supply anomalies can be one of the reasons for low capacity factors. When windmills produce a high amount of power, imbalances in the grid frequency may occur. To avoid this from happening, the excess of power is prevented from entering the grid and the producers are paid to stop their turbines, a process called curtailment. The California Independent System Operator (CAISO) is known to have one of the highest curtailments of renewables among all deregulated markets. Albeit being only 6% of the total generation curbs, the curtailment of wind power amounts for significant power volumes. Fig 1.1 shows that this attained 73 GWh in 2016, the equivalent generation of a nuclear reactor running continously for 3 days.

As an alternative to curtailment, the German system operators have been notorious for massive power exports. However, this has caused several debates in the market, as these exports were taking all the capacity of the gridlines and could endanger the grid stability of their neighbours. So was the case for Poland or Norway's NO2 price area. When high amounts of wind generation are forecasted in Germany, the latter limits its transmission capacity to avoid any grid issues.

In addition, there might be sudden wind curtailments due to other reasons than grid stability. For instance, the windmills are equipped with automatic breaking systems that stop them from spinning when wind exceeds certain values (i.e. cut-out values). There might also be other causes for curtailment not necessarily related to wind per se. For example, in the aftermath of the extreme cold-spell that hit Texas in February 2021 producing blackouts, it was shown,

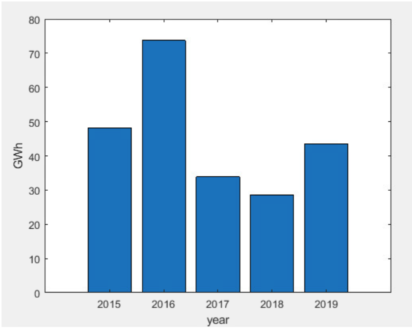


Figure 1.1: CAISO: Total yearly wind power curtailment (Data sourced from CAISO Renewables Watch)

among other disruptions, that windmills stopped producing power because of frozen blades.

All the generation anomalies discussed earlier produce system imbalances that ultimately incur costs. A technical report from the National Renewable Laboratory (NREL) in the United States shows that if both the day-ahead and 4-hours ahead wind power predictions would improve by 40% in California, the production costs would decrease by 2.34%, in a range of 2-100 million dollars ([55]).

For the market participants, avoiding imbalances is paramount. Whether they are present on the physical or speculative side of the market, traders would put their bids for the day-ahead by keeping constant watch on the status of renewable power. Together with the unplanned power plant outages, these are two of the most important factors to watch during a trading session.

All these aspects considered, the improvements in wind power forecasting are deemed very important to the power markets. This is broadly recognized by the transmission system operators, including those in North America, which started adopting central wind power forecasting since 2004. The pioneer was CAISO and the program is called Participating Intermittent Research Programme (PIRP). Thereby, intermittent generators pay a certain amount of money per produced MWh and are required to install telemetry equipment. With the collected data, CAISO hires an external vendor that would forecast its intermittent generation. As of 2009, the aggregated day-ahead root-mean squared error of this forecast was below 15% ([44]). In addition to the centralized forecasts, there also exist private vendors that compete in providing accurate and updated wind power forecasts throughout the trading session.

1.1.2 Academic Perspective

Already by the end of the 70's, the Pacific Northwest National Laboratory highlighted the importance of wind levels forecasting for a correct system scheduling strategy [12]. Ever since, the academic studies on this topic started to provide more and more refined models. The vast literature on the topic of wind power modeling touches on different aspects.

Studying many geographical areas to assess their wind generating potential is one direction of research. Without attempting to be comprehensive, we can cite such studies for Ireland ([28]), Tangiers ([43]), Navarre ([53]) or Sicily ([10]).

Perhaps the widest study direction is given by the quest for more power prediction accuracy. Thereby, many different types of models have been tested. Several reviewing studies agree on 4 general classes of models : physical, statistical, spatial correlation and AI models ([11, 12, 36]). The physical methods are based on atmospheric considerations and use numerical weather predictions such as WRF[4] ([7]), HIRLAM[5] ([38]), ERA Interim[6] ([3]) or ERA5[7] ([46]). The statistical methods comprise, for instance, AR/ARMA models ([47, 53]), Kalman filters ([8]) or methods of statistical moment matching ([52]). In addition to these, the ARMA-GARCH model with different variations has been employed in the current project ([45, 46]).

Kriging is the technique underlying our studies of wind speeds ([47], [46]). This is categorized as a spatial statistical method. Another method within the same area is the constant delay method ([15]).

The class of AI models is very comprehensive and includes, among others, artificial neural networks ([15]), empirical mode decomposition ([2, 25]) or neuro-fuzzy networks ([56]). These models usually employ a wide range of explanatory variables, including but not limited to meteorological inputs.

A third problem approached by several research studies is that of complex terrains. Costa et al. (2008) [12] calls for more studies in this area that would enhance accuracy and computational feasibility. Throughout the present research, we have included a detailed case study from Southern California which includes several areas with complex terrains such as Mojave Desert (around 35°lat; -118°lon) and San Jacinto Mountains (around 33.5°lat;-116.5°lon). Fig 1.2 depicts an example of kriging predictor results for monthly averaged wind speeds. The presence of complex terrains becomes apparent for the two mentioned areas. Thus, the models we developed hereby represent also our attempt to approach the challenge of complex terrains.

1.2 Contributions of the study

1.2.1 Market Context

In the context of the power market concerns discussed above, our study answers four main needs.

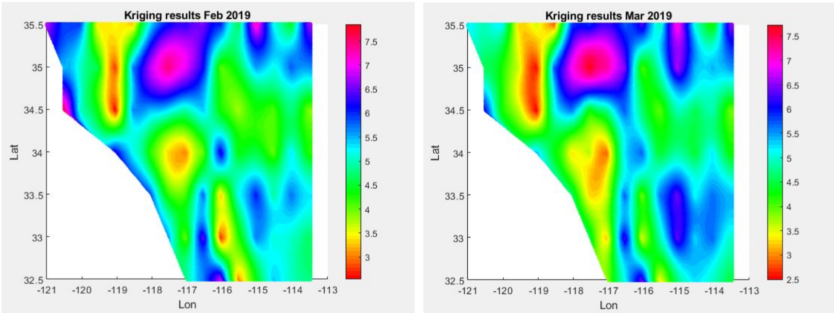
Firstly, we propose a time series model able to predict wind speeds 1 to several hours ahead. This is relevant to the transmission system operators and

[4]Weather Research and Forecasting

[5]High Resolution Local Area modeling

[6]Reanalysis dataset from the European Center for Medium-Range Weather Forecast (ECMWF)

[7]The most recent reanalysis dataset from ECMWF



(a) (b)

Figure 1.2: CAISO: Kriging predictor results for wind speeds February 2019 (a) and March 2019 (b)

market participants for the aforementioned reasons. Our model is better than the persistence model[8] in root mean square error (RMSE) terms by nearly 7% in the immediacy of Mojave Desert and San Jacinto Mountains. For an intraday trader, assessing wind changes hour-on-hour is paramount for determining the direction of the traded contract.

Secondly, the model forecasts wind speeds in unvisited locations where the real wind farms are located. This tackles the data dissemination problem. As wind farm producers do not publicly disclose their production data with an hourly resolution, training any model based on farm-specific data is unfeasible. Therefore, our spatio-temporal model solves this problem by making statistical assumptions and thus reaching the wind farm locations (see map in Fig 1.3).

Benchmarked against ERA5 reanalysis data, our 1-hour ahead model gives very good results. Fig 1.4 displays the ERA5 observations within the 95-5 percentile prediction interval of the 1-hour ahead forecast for Palm Springs (located in the valley of San Jacinto Mountains). In Chapter 3 we will perform more in-depth benchmarks of the model.

This is important because locational wind speed forecasts improve the overall grid-wide generation forecast by up to 3.6%. In Chapter 4, we explore these improvements extensively.

Thirdly, by producing grid-wide forecasts we answer the need of market participants. Indeed, knowing how much wind power will be produced in the whole market area gives insights into the direction of the system price.

The fourth aspect is connected to the use of market data. From this perspective, our model represents also a showcasing of how market actors can make the most out of their data. We employ high-quality data based on which we train and validate our models. Starting from past EC operational hourly

[8] Trivial model whereby the wind speed for the next hour is the same as the wind speed of the current hour

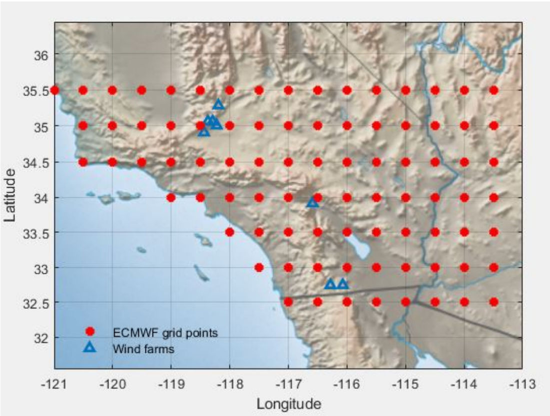


Figure 1.3: Map of gridded (known) and farm (unknown) points

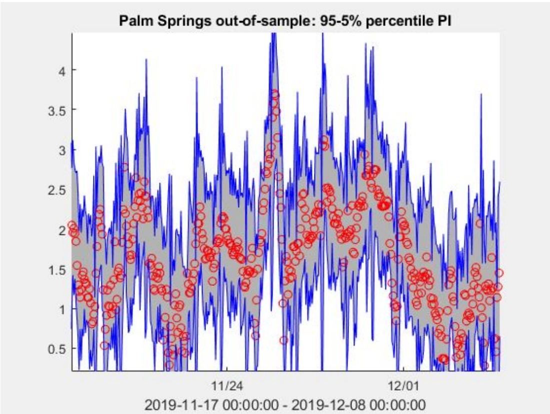


Figure 1.4: Prediction intervals for 1-hour ahead out-of-sample forecast in Palm Springs

forecasts[9] in grid format, we train a spatio-temporal model that we eventually validate through actual measurements coming from the meteorological aviation reports (METAR). We also test our model against ERA5 reanalysis data, which is the output of the numerical weather prediction model implemented by the European Center for Medium-Range Weather Forecast.

1.2.2 Academic Context

The academic interest of the project stems from the mathematical tools employed, the original models deployed and the critical points raised in this process.

[9]Weather forecast published by the European Center for Medium-Range Weather Forecast (ECMWF)

Our choice of wind speed model is a hybrid between the physical, statistical, and spatial correlation models discussed earlier. We propose complex time series models in each grid point from Fig 1.3. These are comprised of seasonality and ARMA terms for the mean, on the one hand, and seasonality together with GARCH or GJR-GARCH for the variance, on the other hand. Next, we derive a model for new locations by applying kriging on the time series parameters. With this, we reconstruct time series models in unvisited sites. To the best of our knowledge, such an application of spatio-temporal modeling is an innovation.

The kriging procedure entails two different processes. On the one hand, when we have one parameter for each grid point, we solve the ordinary kriging optimal parameters for new locations. This is possible under the assumption of intrinsic stationarity, meaning (1) constant mean region-wise and (2) variogram between two points depending solely on the distance between them ([13]). On the other hand, when each grid point is characterised by a seasonality profile, we perform multilinear cokriging. This assumes that the seasonality factor in a new site at a certain instance in time depends on the seasonality factors in all the remaining locations at all times. Such an application of multilinear cokriging is explained in detail in Chapter II.

Prior to obtaining kriging predictors, we evaluate the effect of anisotropy on wind speeds. More precisely, we study spatial variations in certain directions with a 15°tolerance angle. We do not find a clear sign for anisotropy, therefore we assume that the variation is independent of direction.

Furthermore, we propose an original grid-wide power prediction model by extending the phenomenological equation of wind power (Betz law) to a systemic one and optimizing the solution. Results show that the model is performing well. The out-of-sample fit in Fig 1.5 shows that, indeed, our model is able to capture well the sine-wave shape of wind generation. More error measurements are presented in Chapter III.

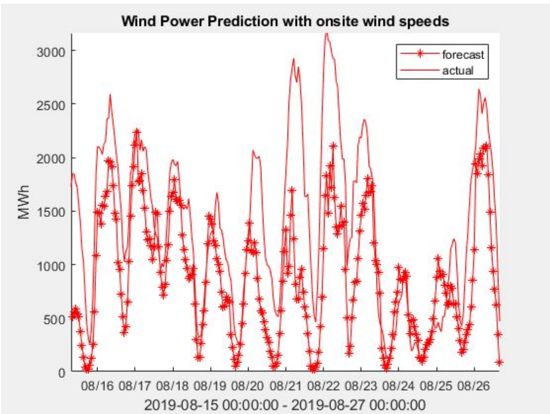


Figure 1.5: Out-of-sample fit of wind power generation

Another important point raised during the study is that of invertibility of

ARMA processes. The property of invertibility ensures that the process has an AR(∞) representation. Nonetheless, invertibility of the newly created time series may be lost during the kriging process. We recover this by creating another statistically identifiable model as explained by Hamilton, 1994 [27].

1.3 Data and computation

Throughout the research, we employ the following three different types of data.

For training the time series model, we count on hourly past operational forecast data from ECMWF in grid format. These forecasts have 6-hourly updates and span over a grid of 0.5°×0.5°resolution. From each forecast, only the shortest horizon until the next update is used. For example, from the 00 (UTC) forecast, we use the values predicted for 00.00-05.00, from the 06 (UTC) forecast we use the 06.00-11.00 values and so on. We end up with a time series of wind speeds in each grid location that we regard as 'actual observation'. Each data point represents the hourly-averaged wind speed at 100 m above ground level (AGL). We will henceforth denominate this the EC dataset.

For model validation, we employ actual observations from aviation reports (METAR) spanning between the grid points. Usually, the measurement locations are airports and the measured variable is wind speed at 10 m AGL. For model benchmarking, we upscale these observations to 100 m AGL by making use of a simplified log wind profile law ((I.1) in Chapter I). METAR report 2 minute-mean wind speed data and there is not necessarily a new update every 2 minutes. For a correct hourly study, we average any such observations to an hourly resolution. By doing so, we obtain the best possible average of almost instantaneous wind speed data. However, this poses a challenge in the sense that there are several hours in these dataset with zero-valued entries. As this behavior is not reproducible by the EC nor by the ERA5 Reanalysis datasets, we replace these values by the bootstraping result of 1000 full-path simulations from our spatio-temporal model.

In order to test the efficiency of our model with respect to other models, we employ ERA5 reanalysis data from ECMWF. This dataset is the result of a forecasting model based on physical atmospheric conditions, similar to a WRF model run ([30]). What is more, the ERA5 dataset comes in grid format with a denser resolution (0.25°×0.25°). This allows us to test the downscaling given by our spatio-temporal model as we are able make predictions in unknown locations.

The timespan of our data is very good. We use hourly in-sample data from 1 February 2015 until 1 July 2019, a total of 38664 entries. We extend this by another 5880 entries between 1 July 2019 and 1 March 2020 as out-of-sample observations. For the initial study, all these values are averaged up to daily resolution. The hourly studies use the raw data. All the three datasets have been kindly provided to us by Refinitiv, an LSEG business.

The wind power generation model was built by use of production data collected by Refinitiv from CAISO Renewable Watch. Further fieldwork was required in order to gather information about the main clusters of wind farms in the Southern California region. For this, we employed the United States Wind Turbine Database [31]. Thereby, we found the evolution of installed capacities per each wind farm, as well as information on turbine types. Then, the Wind Turbine Database [40] would provide the inputs for building realistic power curves (cut-in, cut-out, rated wind speeds and nacelle length from Table A.1 in Chapter 4). All these insights were used in the training of the wind generation model (Eq 1.20).

From the computational standpoint, the model and procedures were built specifically for the study in MATLAB 2018b and RStudio. The spatial variability and the kriging optimization procedures were designed during the study in MATLAB. Some of the most relevant pieces of code are detailed in Appendix A.

The empirical spatial variogram was computed by binning the data every 11 km. The adequate variogram model was found by optimizing in mean-squared error terms the fit from various recommended functions. We tested with several theoretical models such as spherical, pentaspherical, exponential, cubic, sine-hole, gaussian or a combination of these.

Ordinary kriging was performed for 168323 points on a much denser grid of $0.01°\times0.01°$. The total computational time for one parameter in all the grid points was of approximately 30 minutes. The process was carried out for 18 parameters in the first study (Chapter 2), 43 parameters for the second one (Chapter 3) and 45 parameters during the third research stage (Chapter 4).

The studies on hourly data entailed the use of multilinear cokriging for the seasonality profiles. For each month of the year, we derive an hourly intra-day wind speed seasonality profile. We apply this rationale for the mean and variance seasonalities alike. Thus, we have to cokrige twice the 12 monthly profiles, hour-by-hour. The computational time was of approximately 4 seconds per each hourly value in a year period on each grid point. All in all, the multilinear cokriging time for each seasonality vector (eg: p, q) would have been of $4\times24\times168323$= 187 days. As this was far beyond our resources, we reduced the problem to a coarser grid of $0.1°\times0.1°$. The total computation for one seasonality parameter was thus achieved in 23 hours on the University of Oslo's high performance computer Bioint01 (AMD EPYC 7501 CPUs, 128 cores and 128 GB RAM). Then, we linearly interpolate the results to end up to the desired spatial resolution of $0.01°\times0.01°$. These steps are explained in the code presented in Appendix A.2.

1.4 Kriging: theoretical account

Assume Y is a stochastic process defined over the spatial domain $D = \{s_1, s_2, \dots s_L\}$ of all the grid points. In our study, $L = 85$, as seen from Fig 1.3. However, we will hereby introduce the kriging methods on a general term.

We aim at finding $Y(s_0)$ at an unvisited location inside domain D given all the statistical information provided by $Y(s_1), \dots Y(s_L)$ known from observations.

We will henceforth assume the sufficient condition for kriging enunciated by Cressie, 1988 [13]. We assume Y to be an intrinsically stationary process.

Definition 1.4.1. Y is said to be intrinsically stationary if

1.4.1.1. $E[Y(s)] = \mu, \forall s \in D$

1.4.1.2. $Var(Y(s_m) - Y(s_n)) = 2\gamma(s_m - s_n), \forall s_m, s_n \in D$

where γ represents the variogram.

The concept of variogram was first introduced by Matheron in 1963 [39].

Definition 1.4.2. The theoretical semivariogram of Y is the function $\gamma : D \to \mathbf{R}$ defined as

$$\gamma(s_n - s_m) = \frac{1}{2}Var(Y(s_n) - Y(s_m)), \forall s_n, s_m \in D$$

Property 1.4.3. *The following hold for the theoretical semivariogram:*

1. $\gamma(-h) = \gamma(h)$
2. $\gamma(0) = 0$
3. *If* $\lim_{h\to 0} \gamma(h) = C_0 > 0$, *then* C_0 *is called the nugget effect*
4. γ *must be conditionally negative semidefinite:*

$$\sum_{i=1}^{L}\sum_{j=1}^{L} w_i w_j \gamma(s_i - s_j) \leq 0, \quad \forall \{w_k\}_{k=1\ldots L} \ \textit{satisfying} \ \sum_{j=1}^{L} w_j = 0$$

5. *Let* $C(h) = Cov(Y(s), Y(s+h))$ *be the covariance function, then it holds*

$$\gamma(h) = C(0) - C(h)$$

This relation makes the transition between the semivariogram and the covariance function. Note that $C(0)$ *is called the sill of the semivariogram*

Remark 1.4.4. The empirical semivariogram can be estimated from the data with the following formula:

$$\hat{\gamma}(h) = \frac{1}{|N(h)|}\sum_{N(h)}\Big[Y(s_i) - Y(s_j)\Big]^2 \tag{1.1}$$

where $N(h) = \{(s_i, s_j) | \ \ ||s_i - s_j|| = h\}$

1.4.1 Ordinary Kriging

In order to find the optimal ordinary kriging predictor, we assume the mean μ of the process Y unknown. However, we relax further the first condition from Definition 1.4.1 by assuming different unknown constant means in each subregion of domain D.

Ordinary kriging gives the best linear unbiased predictor for $Y(s_0)$:

$$\hat{Y}(s_0) = \sum_{i=1}^{L} \lambda_i Y(s_i) \tag{1.2}$$

where $\boldsymbol{\lambda} = \big(\lambda_1, \lambda_2, \ldots \lambda_L\big)'$ is the solution to the following optimization problem

$$\begin{aligned} &\min_{\boldsymbol{\lambda}} E\Big[(Y(s_0) - \hat{Y}(s_0))^2\Big] \\ &\text{such that} \\ &\sum_{i=1}^{L} \lambda_i = 1 \end{aligned} \tag{1.3}$$

In Appendix I.B, we show that

$$E\Big[(Y(s_0) - \hat{Y}(s_0))^2\Big] = -\sum_{i=1}^{L}\sum_{j=1}^{L} \lambda_i\lambda_j\gamma(s_i - s_j) + 2\sum_{i=1}^{L}\gamma(s_i - s_0) \tag{1.4}$$

Then, we solve (1.3) by the method of Lagrange multipliers. Choosing $L := -2m$, we minimize

$$f(\boldsymbol{\lambda}) = -\sum_{i=1}^{L}\sum_{j=1}^{L} \lambda_i\lambda_j\gamma(s_i - s_j) + 2\sum_{i=1}^{L}\gamma(s_i - s_0) + 2m\bigg(\sum_{i=1}^{L}\lambda_i - 1\bigg) \tag{1.5}$$

which is reduced to a system of linear equations:

$$\begin{aligned} &\sum_{j=1}^{L} \lambda_j\gamma(s_j - s_i) + m = \gamma(s_i - s_0), \qquad i = 1, 2, \ldots L \\ &\sum_{j=1}^{L} \lambda_j = 1 \end{aligned} \tag{1.6}$$

Remark 1.4.5. The predictor $\hat{Y}(s_0)$ is unbiased because

$$E\Big[Y(s_0) - \hat{Y}(s_0)\Big] = E\Big[Y(s_0) - \mu - (\hat{Y}(s_0) - \mu)\Big] = -\sum_{i=1}^{L}\lambda_i E[Y(s_i)] - \mu = 0$$

Remark 1.4.6. The mean-squared error of the optimal solution is:

$$\sigma^2(s_0) = Var(Y(s_0) - \hat{Y}(s_0)) = E\Big[(Y(s_0) - \hat{Y}(s_0))^2\Big] =$$

$$= \sum_{i=1}^{L}\lambda_i\gamma(s_i - s_0) + m - \gamma(0)$$

where $\gamma(0)$ is the nugget effect.

1.4.2 Multilinear Cokriging

Assume now that, instead of being one-dimensional, Y is an $\mathbf{R}^N$ process.

The best unbiased multilinear cokriging predictor for $Y_n(s_0), n = 1 \ldots N$ is of the form:

$$\hat{Y}_n(s_0) = \sum_{i=1}^{L} \sum_{j=1}^{N} \lambda_{ij}^n Y_j(s_i), \qquad n = 1, 2 \ldots N \tag{1.7}$$

The multilinear cokriging predictor $\hat{Y}$ is determined by the solution of the following optimization problem:

$$\begin{aligned} \min_{\boldsymbol{\lambda}^n} \; & E\Big[(Y_n(s_0) - \hat{Y}_n(s_0))^2\Big] \\ & \text{such that} \\ & \sum_{i=1}^{L} \lambda_{in}^n = 1 \\ & \sum_{i=1}^{L} \lambda_{ij}^n = 0, \quad \forall j \neq n, j = 1, \ldots 12 \end{aligned} \tag{1.8}$$

In Appendix II.B (taking $P = Y$) we show that the objective function may be written as

$$\begin{aligned} E\Big[(Y_n(s_0) - \hat{Y}_n(s_0))^2\Big] = & -\sum_{i=1}^{L} \sum_{j=1}^{N} \sum_{i'=1}^{L} \sum_{j'=1}^{N} \lambda_{ij}^n \lambda_{i'j'}^n \gamma_{jj'}(s_i - s_{i'}) + \\ & + 2 \sum_{i=1}^{L} \sum_{j=1}^{N} \lambda_{ij}^m \gamma_{jn}(s_i - s_0) \end{aligned} \tag{1.9}$$

where γ_{ij} represents the cross-semivariogram.

Definition 1.4.7. The theoretical cross-semivariogram of a process Y is the function $\gamma : D \to \mathbf{R}$ such that:

$$\gamma_{ij}(s_l, s_q) = \frac{1}{2} Var(Y_i(s_l) - Y_j(s_q)), \forall s_l, s_q \in D$$

Introducing a Lagrange multiplier $-2L$ into the unbiasedness conditions in (1.8), we obtain the following system of linear equations:

$$\begin{aligned}
&\sum_{i=1,i\neq l}^{L} \sum_{j=1,j\neq q}^{N} \lambda_{ij}^n \gamma_{qj}(s_l - s_i) + 2\lambda_{lq}^n \gamma_{qq}(0) + 2L = 2\gamma_{qn}(s_l - s_0), \\
&l = 1, \dots L, q = 1, \dots N \qquad (1.10) \\
&\sum_{i=1}^{L} \sum_{j=1}^{N} \lambda_{ij}^n = 1
\end{aligned}$$

Therefore, by solving (1.10) we obtain the multilinear cokriging predictors for the multidimensional seasonality process of wind speeds.

1.5 Time series models

Let Y_t be a stationary process with mean 0 defined on a time domain T. The Autoregressive Moving Average (ARMA) class of models have been designed to capture the conditional mean of Y while the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models the conditional variance of it.

1.5.1 ARMA process

Definition 1.5.1. The stationary time series $\{Y_t\}$ is ARMA(p,q) if it can be written as

$$Y_t = \alpha_1 Y_{t-1} + \dots \alpha_p Y_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \dots + \beta_q \varepsilon_{t-q}$$

with $\alpha_p \neq 0$, $\beta_q \neq 0$ and ε a white noise process with $Var(\varepsilon) > 0$.

The first p terms represent the autoregressive (AR) part and the last q terms are the moving average (MA) part.

Remark 1.5.2. An ARMA process can be written in a concise polynomial form:

$$\phi(B)Y_t = \theta(B)\varepsilon_t$$

where B is the lag operator (i.e. $B^p Y_t = Y_{t-p}$).

Property 1.5.3. *Y_t is said to be causal if its characteristic polynomial of the AR part ϕ has all its roots outside the unit circle. In practice, we require the roots $z_1 \dots z_p$ of*

$$\phi(z) = 1 - \alpha_1 z - \dots \alpha_p z^p$$

to fulfill $|z_i| > 1, \forall i = 1 \dots p$.

If the latter holds, Y_t can be written as an $MA(\infty)$ process:

$$Y_t = \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-j}$$

with $\sum_{j=0}^{\infty} |\psi_j| < \infty$ and $\psi_0 = 1$.

Property 1.5.4. *Y_t is said to be invertible if the characteristic polynomial of the MA part θ has all its roots outside the unit circle. In practice, we require the roots $z_1 \dots z_q$ of*

$$\theta(z) = 1 + \beta_1 z + \dots + \dots \beta_q z^q$$

to fulfill $|z_i| > 1, i = 1 \dots q$.

If the latter holds, Y_t can be written as an $AR(\infty)$ process:

$$\varepsilon_t = \sum_{j=0}^{\infty} \pi_j Y_{t-j}$$

with $\sum_{j=0}^{\infty} |\pi_j| < \infty$ and $\pi_0 = 1$.

Remark 1.5.5. If Y_t is causal and invertible and θ and ϕ do not have any common factors, it can be written as

$$Y_t = \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-j}$$

where

$$\psi(z) = \sum_{i=1}^{\infty} \psi_i z^i = \frac{\theta(z)}{\phi(z)}$$

1.5.2 GARCH processes

Definition 1.5.6. Y_t has GARCH(p,q) conditional variance with respect to the filtration $\mathcal{F}_t$ (information up to time t) if it can be written as:

$$Var(Y_t|\mathcal{F}_t) = \sigma_t^2 \varepsilon_t^2 = \sigma_t^2 = \delta_0 + \delta_1 \sigma_{t-1}^2 + \dots \delta_p \sigma_{t-p}^2 + \gamma_1 \varepsilon_{t-1}^2 + \dots \gamma_q \varepsilon_{t-q}^2$$

where ε is a standardly distributed white noise (Gaussian, t-Student etc.).

The GARCH family of models has several variations. We enunciate here those utilized during the research project.

Definition 1.5.7. A zero-mean process Y_t has a GARCH(p,q)-m (GARCH in mean) volatility if it can be written as:

$$Y_t = c\sigma_t^2 + \sigma_t \varepsilon_t \tag{1.11}$$

$$\sigma_t^2 = \delta_0 + \delta_1 \sigma_{t-1}^2 + \dots \delta_p \sigma_{t-p}^2 + \gamma_1 \varepsilon_{t-1}^2 + \dots \gamma_q \varepsilon_{t-q}^2 \tag{1.12}$$

with ε is a standardly distributed white noise.

As [50] point out, one of the main downsides of GARCH models is that they assign the same weight to positive and negative returns. To address this, the following process has been defined by Glosten, Jagannathan and Runkle.

Definition 1.5.8. Y_t has a GJR-GARCH(1,1) conditional variation if it can be expressed as:

$$Var(Y_t|\mathcal{F}_t) = \sigma_t^2 \varepsilon_t^2 = \sigma_t^2 = \delta_0 + \delta_1 \sigma_{t-1}^2 + (\gamma_1 + \gamma_2 \mathbb{1}_{t-1}) \varepsilon_{t-1}^2$$

with $\mathbb{1}_{t-1} = 0$ for $\varepsilon_{t-1} \geq 0$ and $\mathbb{1}_{t-1} = 1$ if $\varepsilon_{t-1} < 0$.

1.6 Power curve modeling

A power curve from turbine manufacturers represents the specific energy profile in standard conditions [1]. As seen from Fig 1.6, power curves are described by:

- Cut-in wind speed (v_{ci}): the minimum wind speed at which the turbine stats producing power
- Rated wind speed (v_r): the wind speed at which a turbine can perform at its maximum capacity
- Cut-out wind speed(v_{co}): the wind speed at which a turbine shuts down to prevent turbine damage
- Rated capacity: the maximum power output attained by a turbine

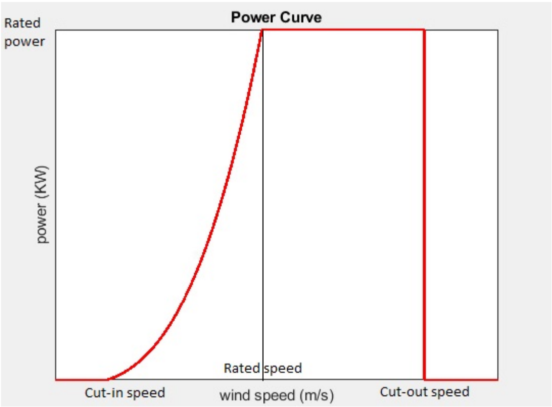


Figure 1.6: Standardized Power Curve

In general, the power potential of the wind crossing the blades of a turbine is described physically from the principle of conservation of mass and the Betz law [1].

$$P = \frac{1}{2} C_p \rho A v^3 \tag{1.13}$$

where v is the wind speed, ρ air density, A the surface swept by the turbine rotors and C_p is a power coefficient that expresses the kinetic energy conversion into mechanical energy. Betz's law claims that C_p cannot exceed 59%.

For wind power generation modeling, we operate with approximations of power curves that describe the curve development between the cut-in and rated wind speeds. Carrillo et al. (2013) [6] review four of the main classes of approximations.

1. Polynomial power curve of second degree

$$P(v) = C_1 + C_2 v + C_3 v^2 \tag{1.14}$$
$$C_1 = \frac{1}{(v_{ci} - v_r)^2}\left[v_{ci}(v_{ci} + v_r) - 4v_{ci}v_r\left(\frac{v_{ci} + v_r}{2v_r}\right)^3\right]$$
$$C_2 = \frac{1}{(v_{ci} - v_r)^2}\left[4(v_{ci} + v_r) - \left(\frac{v_{ci} + v_r}{2v_r}\right)^3 - 3v_{ci} - v_r\right]$$
$$C_3 = \frac{1}{(v_{ci} - v_r)^2}\left[2 - 4\left(\frac{v_{ci} + v_r}{2v_r}\right)^3\right]$$

2. Exponential power curve

$$P(v) = \frac{1}{2}\rho A K_p (v^\beta - v_{ci}^\beta) \tag{1.15}$$

where K_p, β are constants.

3. Cubic power curve, the most similar to the Betz law

$$P(v) = \frac{1}{2}\rho A C_p v^3 \tag{1.16}$$

with C_p a power coefficient, assumed to be constant

4. Approximate cubic curve, which assumes $C_{p,max}$ the Betz limit

$$P(v) = \frac{1}{2}\rho A C_{p,max} v^3 \tag{1.17}$$

The study performed by Carrillo et al. (2013) [6] shows that the exponential and cubic power curves give the lowest errors of energy estimation.

1.7 Daily spatio-temporal wind speed forecasting

The first paper ([47]) initiates the study of wind speeds from a spatio-temporal perspective. The final goal of this is to forecast day-ahead wind speeds in wind farm locations, outside the grid points represented by the ECMWF operation data. This is achieved in four steps.

First, we apply a logarithmic transform on all the 85 time series corresponding to each grid point. By doing so, we symmetrize the data.

Second, we model $W(s_k, t), k = 1 \dots 85$ the wind wind speed in grid point s_k at time t as follows:

$$W(s_k, t) = S(s_k, t) + A(s_k, t) + \varepsilon(s_k, t), \forall s_k \in D \tag{1.18}$$

where

- S is the stationary mean of W, comprised of Fourier series truncated to 6 terms without linear trend

- A is an AR(2) process
- ε is a seasonal volatility function described by 1 daily seasonality series and having standard normal residuals.

The histogram of the final residuals and their Q-Q plots suggest that the assumption of normality is reasonable. Altogether, the estimated parameters of each temporal series is

$$\Theta_k = \{a_0^k, a_1^k, \dots a_{12}^k, \alpha_1^k, \alpha_2^k, b_0^k, b_1^k, b_2^k\}, \forall k \in \{1, 2, \dots 85\}$$

Third, we proceed to the spatial variability study of these parameters. We fit a combination of spherical and sine-hole or gaussian and sine-hole functions to the experimental semivariograms. Then we optimize the ordinary kriging problem (1.3) for each parameter. Results show that seasonality effects are stronger along the coastline. Also, there are high autocorrelation variations in the Mojave Desert area, one of the most complex landscapes from our study. Here, the bias in the seasonal variance term is equally high.

In the fourth step, we make day-ahead spatio-temporal predictions in airport locations with the aim of benchmarking results against the METAR measurements. Results indicate that the model performs very well. The errors are nearly symetrically distributed with respect to their zero mean while very few observations are scattered outside the 95% prediction interval (PI), in the in-sample dataset. In the out-of-sample domain, between 1.22% and 4.9% of observations lie outside the 95% prediction interval (PI).

We conclude that the daily spatio-temporal model is successfully capturing the particularities of the Southern California landscape.

1.8 Hourly spatio-temporal wind speed forecasting

With the second paper ([46]), we address the more challenging problem of spatio-temporal forecasting for hourly data. The models therein are far more complex and need longer computational time. The outcome of this is a 1-hour ahead and full-path prediction method for wind speeds in any unvisited location inside the grid.

Initially, we apply a power transformation to the data that renders it nearly normally-distributed. The choice of the transform is based on the theory of Dubey (1967) [17] which proposes a scaling of the shape parameter to obtain a Weibull distribution with shape 3.6. The latter is proven to be close to a Gaussian distribution.

Furthermore, we work with a similar decomposition as in Eq 1.18. However, the underlying terms have far more intricate processes. The seasonality term is twofold: (1) Fourier series truncated to 6 terms on the hourly frequency and (2) sum of indicator functions that contain the hourly averages for each month of the year. Next, we work with an ARMA(2,24) model, which seems to be the most appropriate, given the autocorrelation effects and the Akaike Information Criterion (AIC). The variance of the residuals exhibit some remaining time dependencies. Similar to the conditional mean, we model the seasonality in the conditional variance by a sum of indicator functions that contain the hourly averages for each month of the year. We approach the remaining heteroskedasticity in the residuals by a GARCH(1,1) process. Therefore, the set of parameters for the time series models is:

$$\Theta_k = \{m_k, a_0^k, a_1^k, \ldots a_{12}^k, p_k, \alpha_1^k, \alpha_2^k, \beta_1^k, \beta_2^k, \ldots \beta_{24}^k, q_k, \delta_0^k, \delta_1^k, \delta_2^k\}$$

where $p_k, q_k \in \mathbf{R}^{288}$.

Moreover, for the spatial model, we perform ordinary kriging for all the variable sin Θ_k except for the multilinear variables. For these, we apply the principles of multilinear cokriging explained in the previous section. By applying such a method, we recognize the fact that the seasonality of wind speeds on a certain hour and month of the year may depend on the values of the other months at the same time of the day. The prediction results for seasonality highlight different micro-climatic regions inside Southern California. In the Mojave Desert, we obtain rather pronounced seasonality terms during the summer months May-August.

Finally, we benchmark our model out-of-sample in the space-time domain. We compare the results with respect to METAR measurements. When we construct the time series in unvisited locations, we encounter the challenge of lack of invertibility in the newly created ARMA(2,24) process. We recover this by inverting the roots of the characteristic polynomial of the MA part and by rescaling the variance to obtain a statistically equivalent model. When comparing to the actual measurements, we see that the predictive capacity of our model 1-hour ahead is very good. It is only in two locations inside Mojave Desert that the rate of observations outside 95% PI exceeds 5%. In addition, we create full-path simulations for the METAR locations and compare. Again, results are promising outside the aforementioned area.

We assess further the performance of the model by comparing it to the performance of the ERA5 reanalysis model. We derive predictions in locations on a 0.25°×0.25°grid and we compare with the ERA5 time series. Once again, the results show an excellent fit between our predictions and the reanalysis data.

Having achieved a trustworthy hourly model, we can run this in order to build a complete wind power generation forecast.

1.9 A Critical study on the improvements in wind power forecasting

Within the third stage of our study ([45]), we aim at quantifying the improvements in wind power prediction given by locational wind speeds. We propose a power generation model that we train successively with wind speed data directly from the grid points and with values from the wind farm locations (according to Fig 1.3). The first model train is called the Base Case and the second Onsite Case. For the latter we take a twofold approach to downscale wind speed data at windmill locations.

On the one hand, we work directly with the hourly wind speeds in grid points. We estimate spatial variograms on the in-sample data that we apply directly to the out-of-sample values. We assume one theoretical semivariogram model per each hour and month of the year. In addition, we give a critical account on why we choose to rule out anisotropy from the study. With this approach, we get rather straightforwardly full-path wind speed data at wind farm locations. The generation estimates produced by this approach will gain the name Actual Base Case and Actual Onsite Case.

On the other hand, we model first the time behavior of wind speed in each of the grid locations. Then, we use ordinary kriging and multilinear cokriging on the parameters thus derived. Thereafter, we obtain models for each points of interest, as described in the previous two studies. In this case, we refine the model to an ARMA(2,24)-AR(1)-GJR-GARCH(1,1) with the skewed t-Student distribution and derive 24-hours ahead predictions.

The next step is to take a bottom-up approach and to build a wind power prediction model. We will seek to upscale windmill data obtained from the U.S Wind Turbine Database [31] to a grid-wide power generation estimate. We depart from the phenomenological equation of wind power production at windmill level (Eq 1.13) and extend that to the whole market via an optimization of weighted power curves. More precisely, for each cluster of wind farms, we design a cubic power curve (Eq 1.16). We find the optimal weighted average of the power curves in mean square error sense.

$$\min_{w_{st}} E\left[\left(Prod_t - \sum_{st=1}^{8} WPP_t(t, st, w_{st})\right)^2\right] \tag{1.19}$$

where $Prod_t$ is the actual wind power generated at time t and $WPP(t, st, w_{st})$ is a wind power production function à la Betz law assigned to each cluster of wind farms (see Appendix III.A).

Thus, we define the wind supply model by:

$$WPP(t, st, w_{st}) = \begin{cases} w_{st} \cdot \frac{1}{2} \cdot A_{st} \cdot 1.225 \cdot W_t(st)^3, & v_{ci}(st) \leq W_t(st) < v_r(st) \\ 0.593 \cdot Cap_t(st), & v_r(st) \leq W_t(st) < v_{co}(st) \\ 0, & \text{otherwise} \end{cases} \tag{1.20}$$

The wind model thus obtain performs well on both Base and Onsite cases. Fig 1.5 gives a snapshot of the fit and the way it captures the sine-wave shape. We note that this shape is due to the clustering of a high installed capacity in certain areas of Southern California (i.e. mainly the Mojave Desert and San Jacinto Valley). Results show that only 2.5% of the values were outside the 95% prediction interval (assuming normality) for the Actual Base Case in-sample and 2.2% for the Actual Onsite case. All in all, we find that locational wind speed data improves the root mean-squared error (RMSE) in-sample by 3.6%. However, the same does not hold for the out-of-sample domain. The paper offers a critical view on this.

We continue benchmarking the model by considering the spatio-temporal wind speed forecasts. We also find improvements from locational wind data in-sample but not out-of-sample.

We take an additional step and we train the model directly with 24-hours ahead spatio-temporal forecasts. The RMSE improves slightly by 1.7% for the Base Case and by 3.6% for the Onsite Case.

This study puts in perspective the analysis done on wind speeds in the previous papers. It scrutinizes several aspects of wind power modeling such as: the presence of anisotropy in wind data, the importance of locational measurements, wind generation model built from descriptive power curves and model calibration on forecasts.

1.10 The Scientific quest

The current work is the crystallised result of many ideas, trials, errors and successes. We will dedicate this part to a reflection on the ideas that did not work as expected and to the questions that these leave open.

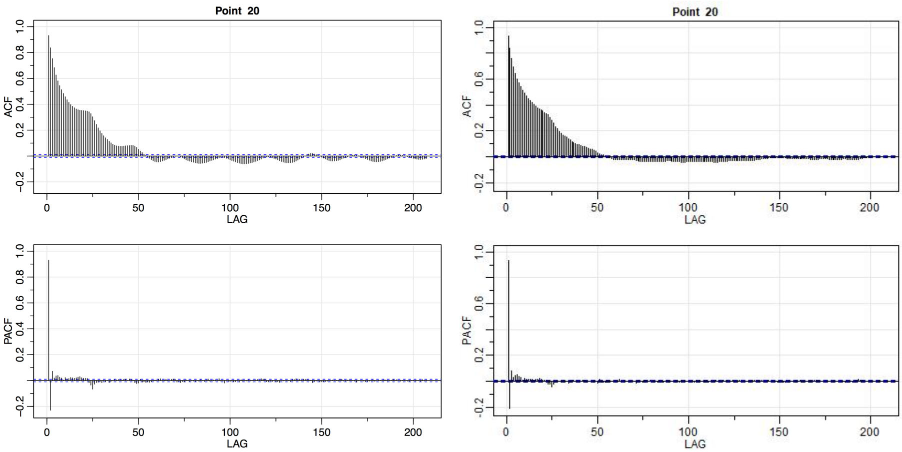
A first point is related to the importance of the theoretical variogram in kriging. The choice for the best variogram model is paramount for a good predictor. This rather intuitive remark has been made also by [41]. In our case, we tested this claim in the third paper. When performing kriging on wind speeds in [45], we chose to fit a generic spherical semivariogram on each hour and month of the year. We found this assumption to be reasonable in most of the cases. In the paper, we exemplify this by March and September charts. We also showed that such a kriging predictor "honors the data" ([13]) rather than smoothes it. However, a more detailed choice of semivariograms may potentially help remove further bias from the final out-of-sample results in the wind power generation study.

A second topic we addressed was seasonality removal from the hourly wind speed time series. As explained earlier, we chose a set of Fourier terms for the yearly seasonality and a sum of indicator functions for each hour and month of the year. The decision for such a model was inspired by [18] after many trials with hourly and daily Fourier terms. The latter method would still not help remove autocorrelation in time series. As seen from Fig 1.7(a), there seems to be a persistent autocorrelation effect at 24 hours lag which disappears with the preferred approach (Fig 1.7(b)).

Consequently, the model choice for seasonality is composed by a yearly trend and a set of seasonality curves specific for each hour of the day.

The third important challenge was related to the spatial study of the seasonality curves. In each grid point, the fitted model would produce $p_k, q_k \in \mathbf{R^{288}}$ corresponding to a series of the type:

$$p_k = (p^k_{Jan,0}, p^k_{Jan,1}, \dots p^k_{Jan,23}, \dots p^k_{Dec,0}, p^k_{Dec,1}, \dots p^k_{Dec,23}) \tag{1.21}$$



(a) (b)

Figure 1.7: Autocorrelation and partial autocorrelation functions after removing seasonality: daily and yearly Fourier seasonality (a); yearly and indicator functions (b)

where $p_{M,h}$ is the averaged wind speed value on month M at hour h. In their innovative study on curve kriging, [24] propose two methods. The first one is called "Cokrige first, fit later", where each entry in the vector would be regarded as an individual value. They will be cokriged individually and we would assume that the vector obtained would honor the global form of the curves p_k, q_k. The second method proposed by the authors was doing the opposite, "Fit first, cokrige later" and it required a parametrization of the curves. Thus, the latter method required a certain fit of the hourly and monthly profiles. Even though there were many options for such parametrization (for example, [23] proposed cubic B-splines), we opted for the first approach. The reason for this was particularly to avoid a similar situation as with the Fourier curve fit explained earlier (we refer to Fig 1.7). Therefore, we employed cokriging for each entry of p_k, q_k and we recomposed the series at new locations. Negative results for the variance term (q_k) were not acceptable albeit inherent in this context. We overcame this challenge by imposing a correction factor on all negative weights $\lambda_{i,j}$. We imposed an algorithm that resets all the negative λ_{ij} from Eq (1.7) to 0 and compensates the remaining positive weights to preserve unbiasedness ([16]).

The remaining heteroskedasticity in the residuals was the fourth challenge. The pure GARCH(1,1) model in [46] seemed to model successfully the conditional variance, but the non-squared residuals exhibit certain autocorrelation at lag 1. This is the reason why in [45] we opt for an additional AR(1) model.

The fifth remark comes from the field of wind generation predictions. Thereby, the model of choice (Eq 1.20) departs from the physical law of wind generation (Eq 1.13) which depends on air density, among other parameters. The choice for an air density approximation is common in the literature and most studies assume the standard conditions of 1.225 kg/m^3 ([42]). Our study is in the same line. However, we are aware that better model results could be obtained if a more complex air density function would be considered. [54] showed that the summer-winter air density variations could give a wind output difference of 2-3%. Prior to the choice of standard air density value, we experimented with a more detailed function.

From the meteorological standpoint, the estimation of air density entails estimating the pressure and virtual temperature (i.e. the temperature at which moist air would have the same density as dry air) [19]. As we did not have any further historical pressure data at our disposal, we attempted to model air density in a seasonal manner.

$$WPP(t,s,w_s) = \begin{cases} w_s \cdot \frac{1}{2} \cdot A_s \cdot 1.225 \cdot f_t(s) \cdot W_t(s)^3, & v_{ci}(s) \leq W_t(s) < v_r(s) \\ 0.593 \cdot Cap_t(s), & v_r(s) \leq W_t(s) < v_{co}(s) \\ 0, & \text{otherwise} \end{cases} \tag{1.22}$$

where

$$f_t(s) = \sum_{i=1}^{4} \left[a^i_{\cos}(s) \cos\left(\frac{2\pi it}{365.25}\right) + a^i_{\sin}(s) \sin\left(\frac{2\pi it}{365.25}\right)\right]$$

and the decision variable for the optimization problem would become

$$\tilde{w}_s = \left(w_s a^1_{\cos}(s), w_s a^1_{\sin}(s) \dots w_s a^4_{\sin}(s) \right)$$

However, we found that a yearly seasonal air density $\rho_t(s) = 1.225 \cdot f_t(s)$ as described earlier and bounded between 0.882 and 1.0780 kg/m^3 would hinder the mean-square error optimization process to the extent that the MATLAB algorithm fmincon would not converge (see Appendix A.3). Therefore, we chose to eliminate seasonality and work with the standard air density value of 1.225 kg/m^3. We believe that further improvements in wind power forecasting could be envisaged if air density is modelled either meteorologically, by considering temperature, air pressure and standard humidity or by a similar model to the one tried during this project.

Taking into consideration the achievements and challenges faced during the research process, we hope to have brought a new perspective on the fundamentals of wind power forecasting as well as on the way we look at market data.

1.11 Model boundaries and beyond

Designing and developing the current research entailed several assumptions and limitations that we shall further discuss. Together with these, we will propose some alternative ways. We shall evoke the model boundaries under three perspectives.

The first point of view stems from the general industrial perspective. Thereby, our model employs ECMWF wind power operational forecasts with a 0.5°× 0.5°spatial resolution to achieve through the spatio-temporal approach a 0.01°× 0.01°resolution. We thus showed that it is possible to transition from grid points located nearly 55 km to 1.11 km apart. Nevertheless, weather forecasts at denser grids can be available to the market. For instance, the German weather forecast provider Deutscher Wetterdienst (DWD) releases four times a day its ICONeu nested high resolution forecast at 0.0625°× 0.0625°. The coverage of this remains, however, limited to European areas.

Along the same line, we must note that the output of our wind speed and, eventually, wind generation model is on hourly resolution. This limitation is intrinsic to the weather forecast as, to the best of our knowledge, there is currently no weather provider in the energy industry that can publish forecasts with 30-minutely or lower time resolution. In this sense, making 1-hour ahead wind power predictions may respond to the intraday market participants by way of market signals. The intraday power markets have evolved significantly in the last years, making it possible to trade hourly, half-hourly or 15-minutely contracts up to 0 minutes before physical delivery. This is the case, for instance, on Europe's most liquid market - EPEX SPOT. In the United States, on the real-time market, the transactioned volumes are the ones corresponding to the deviations between what was settled on the day-ahead market and the system needs in real time. The dispatched volumes and prices are determined on a 5-minutely basis ([20]). Given the granularity of intraday or real-time power contracts, our 1-hour ahead wind model finds its application in the determination of the market signal. For example, a power trader in Germany would check the hour-ahead wind forecast to determine whether the upcoming 4 intraday contracts (corresponding to each 15 minutes) will exhibit a general bullish or a bearish signal with respect to the day-ahead price. Needless to say, a lower granularity in wind generation forecasts would be more beneficial to a trader as it would help determine with more certainty the market signal of the upcoming power contract.

Another aspect worth mentioning is the choice of METAR datasets for model validation. The current study relies on aviation wind observations collected from airport locations. This is due to the fact that airports generally collect these data like any other World Meteorological Organization (WMO) station. A point in favor of this choice was the wide span of airports across Southern California. These allowed us to validate our models in a series of diverse landscapes (flat desert, ridge, mountain valleys, river valleys or plains). Additionally, it is important to mention that such a choice of locations was deemed compatible with our wind farm study. It is recognized the fact that airports are generally built in areas with a uniform pattern of winds and where crosswind levels are minimized ([32]). Further research in this direction, employing other than the METAR datasets, may prevent the negative bias discussed in Section II.5.

The current research develops models and methods that are applied to the Southern California power price area (CAISO SP-15). This choice was made based on the complexity of the terrain and the clustered character of the wind farms that, in turn, trigger a power generation profile akin to a sine-wave. Namely, when the power production surges in the Mojave Desert, across the mountains, in Calexico, this might be rather stagnant. These features rendered wind generation modeling in CAISO SP-15 a challenging task. Nevertheless, one must emphasize the general character of the model hereby developed. We believe that, due to spatial smoothing, the model may render better results in market areas where the wind farms are more scattered, as for example Germany. This is based on the findings of [21], who show that the error reduction due to spatial smoothing can be of as much as 63% when looking at a market with less than 50 wind farms spanning over an area of diameter around 370 km. Thus, we believe that results may improve were the models to be applied to other power markets around the world.

The second perspective is given by the time series models, which carry certain assumptions and limitations that must be taken into account.

Initially, the wind speed time series corresponding to each grid point have gone through a transformation meant to insure approximate Gaussianity. The transformation implied a logarithmic operation (for daily data) or a power operation with a fitted exponent that accommodated the Gaussian assumption (for hourly data). In the three research papers, we operate under the assumption of normal wind speed time series. However, this can be relaxed and the prediction intervals computed accordingly. Additionally, during the temporal model, we assume the weak stationarity condition is fulfilled. We recall that weak stationarity is the characteristic of time series that have a constant mean, a finite variance and an autocovariance function depending solely on the lag between timesteps. In addition, we want to avoid explosive solutions, therefore we assume that our ARMA processes are causal and invertible. When this is not the case, we apply the results described in Section II.4.1.

Furthermore, on the conditional variance part of wind speeds, we chose a GARCH or GJR-GARCH model whereby we assumed that the residuals are normally distributed (Paper II) or that they have a skewed t-student distribution (Paper III), respectively. Recognising that a pure GARCH model assigns the same intensity to the positive or negative innovations, we assumed a GJR-GARCH behavior in the last research paper. Nonetheless, we believe the GJR component of the variance model could be revised given that its weight on the negative shocks does not prevent the apparent negative bias in the model. The in-sample average error of the production model points out to the fact that a pure GARCH process might outperform its more complex variant (see Section III.5).

Moreover, we imposed on the conditional variance model GARCH(1,1) a stationary solution assumption. Namely, under the same notations from Definition 1.5.6, we require that $\delta_1 + \gamma_1 < 1$, provided that $\delta_0 > 0$ and $\delta_1, \gamma_1 \geq 0$.

An alternative to the GARCH process would be a state-space process of the sort of stochastic volatility. Thereby, the innovations could be the result of a hidden linear independent process.

From the third vantage point, the spatial modeling phase also operates with assumptions and limitations to take into account.

The empirical semivariograms derived during this research consider a lag of 11 km and a range between 1 and 800 km. The array of theoretical models to fit these go from spherical, pentaspherical, exponential, gaussian, sine-hole to a combination of these. Since the model of variograms is crucial for the final accuracy of the spatial study, considering Mateérn models in future research might bring improvements.

The ordinary kriging predictor is based on the general assumption that the process is intrinsically stationary in the sense of the Definition 1.4.1. We relaxed this condition by assuming that the spatial unknown mean of the process is only regionally constant. Further enhancements to the current model could consider a universal kriging approach. This relaxes the constant mean requirement to a mean described by a linear trend ([14]).

During the same modeling phase, working under isotropic conditions allowed us to consider the same spatial variability irrespective of direction. In Paper III we challenged this assumption and studied certain directional variograms without finding any notable parameter fitting improvements. However, in future research we might see improvements if one considers anisotropy on a regional basis. Alternatively, we propose working with each wind speed field component, the eastward and westward ones, corresponding to the U and V components under the ECMWF nomenclature.

Therefore, exploring the assumptions under the three vantage points above, the industrial, temporal and spatial modeling one allows us to accommodate further improvements of the present research.

1.12 Further applications and developments

The existing and upcoming challenges in the current energy transition era are multifaceted and demanding for the research world. We take this opportunity to reflect on further applications that this project may have as well as at new research paths to take in the field of wind energy modeling.

Regarding other applications of the models and methods hereby explored, we shall group these into meteorological and non-meteorological related topics.

1.12.1 Meteorological applications

In this field, one can examine several meteorological variables with direct applications to the energy markets.

Temperatures are a paramount factor to watch for any market participant. These drive the power demand, but they may equally impact other contiguous fields such as the generation of power from combined heat and power (CHP) plants, the halt of nuclear plants or the efficiency of solar panels, among many others. [48] apply a spatio-temporal model to daily averaged temperatures measured in Lithuania and assume a linear model for the spatial parameters depending on their location. By the same rationale, one could apply the results derived hereby through kriging and compare them to the ones obtained by the authors. In such a study, unlike for wind speeds, temperatures would have the advantage of being measured, forecasted and validated at the same height (i.e. 2 m AGL).

The solar irradiance is another weather variable crucial to the energy industry. With accurate predictions of the downwards surface solar radiation, the amount of solar photovoltaic (PV) or thermal energy can be computed. This is of utmost interest since Europe is experiencing an upswing in installed power from these technologies. Indeed, being a less intermittent source of renewable energy, solar power can potentially become a baseload energy source in the new energy transition era. [35] model the daily temporal behavior of this meteorological variable through a seasonality function that modulates the total extraterrestrial radiation, an autoregressive part and regime-switching summer-winter residuals. With the research methods developed in the current thesis, one could extend the study of [35] to hourly solar irradiance forecasts and, ultimately, to solar PV production forecasts at grid level. For the spatial grid-wide study of parameters, intrinsic stationarity could be a reasonable assumption. Indeed, we conjecture that there may not exist such a high spatial variation as the one seen from wind speeds. In this context, using an inverse distance weighing method for spatial modeling instead of ordinary kriging might already generate good results. Furthermore, such a study must take into account that surface solar radiation is usually predicted by weather providers as a cumulative variable with less than hourly resolution. Obtaining such a granularity might require certain meaningful pre-processing steps generating more model parameters. Moreover, forecasting the total solar PV generation by a similar method to the one developed in this work (1.20) might require a non-linear model. This is the case because several additional parameters such as the efficiency or the panel tilt have a non-linear relation to the solar irradiance.

Precipitation is a key meteorological parameter for hydropower. Several of the existing research that we consulted on this topic make use of regime-switching models. These capture instances with no precipitation and model the distribution of those with actual precipitation ([4, 49, 51]). For instance, we see potential applications of our method on an extension of the model in [4]. Instead of applying a spatial transformation function involving the NWP forecast, we propose performing a spatial study of the NWP forecast initially and then an ordinary kriging on the temporal parameters.

1.12.2 Non-meteorological application

Another spatio-temporal application could be derived in the nuclear power field.

France has a fleet of 56 nuclear reactors[10] built usually along the main river basins. The water from Rhone or Rhine is used for the cooling of reactors before it is discharged entering back the river. Whenever the water temperature rises or the water stream decreases posing environmental concerns, the plants are

[10] Data updated in 2020 and retrieved from: https://www.edf.fr/groupe-edf/espaces-dedies/l-energie-de-a-a-z/tout-sur-l-energie/produire-de-l-electricite/le-nucleaire-en-chiffres

deemed to halt their production. This occured in particular summer months with heatwaves such as August 2018 or July 2019, causing significant price spikes.

Now, assume that each nuclear plant has its own available capacity curve, meaning a time series depicting how much capacity is available for generation. It is of utmost interest to build a model for the available capacity curves of the French nuclear plants and to make spatial inferences on when and where the next halt will happen. Such an exercise makes use of a similar model as the one we employed during the spatial study (see Section II.3.2, the multilinear cokriging part). In this case, it might become necessary to parametrize the curves and we suggest a B-spline application such as the one in [22]. Otherwise, one could model the temporal behavior of availability in a similar fashion as precipitation or the wind regimes, for example, by a logistic regression model or a Bernoulli distribution.

We have, therefore, proposed several ideas where similar models as the ones in the current research could be applied.

The problem of wind power modeling opens for further developments and techniques. In the sequel, we will explore some of these through the classical and machine learning lens.

Firstly, on the time component, we have used Fourier series truncated to 6 terms to model mean and variance seasonality of the wind speed processes $W(s_k, t)$. Further research could test the use of wavelets to capture seasonality. Given that these allow for time and frequency localization, they may represent better the bumpy behavior in our meteorological parameter (Chapter 5.9 in [29]). Moreover, a regime-switching model could adequately capture low and high wind instances. The academic literature abounds in different methods for this. We could mention using a Bernoulli probability distribution for the zero measurements and Gamma for the rest ([37]), defining zero-inflated binomial models ([26]) or different latent Gaussian processes for the probability of zero-values and for the density distribution of the remaining ones ([4]).

Secondly, on the spatial component, the variability of the parameters could be modelled by the technique of multilayer perceptrons (MLPs) in the spirit of [9]. One could start by the classical sigmoid activation function and by using as input the roughness length coefficients over the whole area under study.

Finally, instead of a phenomenological governing equation, the wind generation model could be formulated the solution of a random forest problem. The inputs could be all the onsite wind speed time series, as well as some other parameters describing air density (i.e. temperature, humidity, air pressure). Another option would be keeping the model from (1.20) but running a selection algorithm that can help choosing the optimal wind farm clusters s. For instance, factor analysis or independent component analysis could identify the optimal loadings (w_s) such that the total power generation is attained in each timestep by some latent variables describing each wind farm:

$$Prod_t = \sum_{i=1}^{n} WPP(t, s_i, w_{s_i})$$

where $WPP(t, s_i, w_{s_i})$ is the wind power produced by wind farm located at s_i at time t and weighted by w_{s_i} as per (1.20).

All aspects considered, we hope that the current research puts wind power modeling in a broader perspective where academic research and market contexts become inextricable.

References

[1] 61400-12-1, I. *Wind turbines–Part 12-1: Power performance measurements of electricity producing wind turbines.* International Standard, Ed. 1.0. 2005.

[2] Amjady, N. and Abedinia, O. "Short Term Wind Power Prediction Based on Improved Kriging Interpolation, Empirical Mode Decomposition, and Closed-Loop Forecasting Engine". In: *Sustainability* vol. 9, no. 11 (2017).

[3] A.Palomares and M.de Castro. "Short-term wind prediction model at the Strait of Gibraltar based on a perfect prognosis statistical downscaling method". In: *Proceedings of European wind energy conference, Madrid, 2003.* 2003.

[4] Berrocal, V. J., Raftery, A. E., and Gneiting, T. "Probabilistic Quantitative Precipitation Field Forecasting Using a Two-Stage Spatial Model". eng. In: *The annals of applied statistics* vol. 2, no. 4 (2008), pp. 1170–1193.

[5] Bowers, R. "Wind has surpassed hydro as most-used renewable electricity generation source in U.S." In: *Today in Energy* (26 February 2020).

[6] Carrillo, C. et al. "Review of power curve modelling for wind turbines". In: *Renewable and Sustainable Energy Reviews* vol. 21 (2013), pp. 572–581.

[7] Carvalho, D. et al. "A sensitivity study of the WRF model in wind simulation for an area of high wind energy". In: *Environ. Model. Softw.* vol. 33 (2012), pp. 23–34.

[8] Cassola, F. and Burlando, M. "Wind speed and wind energy forecast through Kalman filtering of Numerical Weather Prediction model output". In: *Applied Energy* vol. 99 (2012), pp. 154 –166.

[9] Cellura, M. et al. "Wind speed spatial estimation for energy planning in Sicily: A neural kriging application". In: *Renewable Energy* vol. 33, no. 6 (2008), pp. 1251–1266.

[10] Cellura, M. et al. "Wind speed spatial estimation for energy planning in Sicily: Introduction and statistical analysis". In: *Renewable Energy* vol. 33, no. 6 (2008), pp. 1237–1250.

[11] Chang, W.-Y. "A Literature Review of Wind Forecasting Methods". In: *Journal of Power and Energy Engineering* vol. 2 (2014), pp. 161–168.

[12] Costa, A. et al. "A review on the young history of the wind power short-term prediction". In: *Renewable and Sustainable Energy Reviews* vol. 12, no. 6 (2008), pp. 1725–1744.

[13] Cressie, N. “Spatial prediction and ordinary kriging”. In: *Journal of Mathematical Geology* vol. 20, no. 4 (1988), pp. 405–421.

[14] Cressie, N. and Wikle, C. *Statistics for Spatio-Temporal Data*. Wiley series in probability and statistics. ISBN:9780471692744. Wiley (2011).

[15] Damousis, I. G. et al. “A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation”. In: *IEEE Transactions on Energy Conversion* vol. 19, no. 2 (2004), pp. 352–361.

[16] Deutsch, C. “Correcting for negative weights in ordinary kriging”. In: *Computers & Geosciences* vol. 22, no. 7 (1996), pp. 765–773.

[17] Dubey, S. “Normal and weibull distributions”. In: *Naval Research Logistics Quarterly* vol. 14, no. 1 (1967), pp. 69–79.

[18] Ekström, J. et al. “A statistical modeling methodology for long-term wind generation and power ramp simulations in new generation locations”. English. In: *Energies* vol. 11, no. 9 (2018).

[19] Floors, R. and Nielsen, M. “Estimating air density using observations and re-analysis outputs for wind energy purposes”. In: *Energies* vol. 12, no. 11 (2019).

[20] Flores-Espino, F. et al. “Competitive Electricity Market Regulation in the United States: A Primer”. In: (Dec. 2016).

[21] Focken, U. et al. “Short-term prediction of the aggregated power output of wind farms—a statistical analysis of the reduction of the prediction error by spatial smoothing effects”. eng. In: *Journal of wind engineering and industrial aerodynamics* vol. 90, no. 3 (2002), pp. 231–246.

[22] Giraldo, R., Delicado, P., and Mateu, J. “Cokriging and multivariate kriging methods based on data of a functional random field”. In: *Comunicaciones en Estadística* vol. Vol. 10, No.2 (2017), pp. 315–344.

[23] Giraldo, R., Delicado, P., and Mateu, J. “Ordinary kriging for function-valued spatial data”. In: *Environ Ecol Stat* vol. 18 (2011), pp. 411–426.

[24] Goulard, M. and Voltz, M., eds. *Geostatistical Interpolation of Curves: A Case Study in Soil Science.* Vol. vol 5. Soares A. (eds) Geostatistics Tróia ’92. Quantitative Geology and Geostatistics. Dordrecht: Springer, 1993.

[25] Guo, Z. et al. “Multi-step forecasting for wind speed using a modified EMD-based artificial neural network model”. In: *Renewable Energy* vol. 37, no. 1 (2012), pp. 241–249.

[26] Hall, D. B. “Zero-Inflated Poisson and Binomial Regression with Random Effects: A Case Study”. eng. In: *Biometrics* vol. 56, no. 4 (2000), pp. 1030–1039.

[27] Hamilton, J. D. *Time series analysis.* eng. Princeton, N.J: Princeton University Press, 1994.

[28] Haslett, J. and Raftery, A. E. “Space-Time Modelling with Long-Memory Dependence: Assessing Ireland’s Wind Power Resource”. In: *Journal of the Royal Statistical Society. Series C (Applied Statistics)* vol. 38, no. 1 (1989), pp. 1–50.

[29] Hastie, T., Tibshirani, R., and Friedman, J. *The Elements of Statistical Learning : Data Mining, Inference, and Prediction, Second Edition*. 2nd ed. 2009. Springer Series in Statistics. New York, NY: Springer New York, 2009.

[30] Hersbach, H. et al. “The ERA5 global reanalysis”. In: *Quarterly Journal of the Royal Meteorological Society* vol. 146, no. 730 (2020), pp. 1999–2049. eprint: https://rmets.onlinelibrary.wiley.com/doi/pdf/10.1002/qj.3803.

[31] Hoen, B. et al. *United States Wind Turbine Database (ver. 4.1, July 2021): U.S. Geological Survey, American Clean Power (ACP) Association (formerly American Wind Energy Association), and Lawrence Berkeley National Laboratory data release*. 2018.

[32] ICAO International Standards and Recommended Practices. *Annex 14, Aerodromes — Volume I, Aerodrome Design and Operations*. International Standards and Recommended Practices. Montr’éal, Quebec, Canada: International Civil Aviation Organization, Seventh Edition, July 2016.

[33] IEA. “Key World Energy Statistics 2020”. In: *IEA, Paris* (2020).

[34] IEA. *Renewables 2020*. Tech. rep. DAMTP 2000/NA10. Paris: IEA, 2020.

[35] Larsson, K., Green, R., and Benth, F. E. *A Stochastic Time-Series Model for Solar Irradiation*. Tech. rep. Örebro University, Örebro University School of Business, 2021, p. 30.

[36] Lei, M. et al. “A review on the forecasting of wind speed and generated power”. In: *Renewable and Sustainable Energy Reviews* vol. 13, no. 4 (2009), pp. 915 –920.

[37] Lenzi, A. et al. “Spatial models for probabilistic prediction of wind power with application to annual-average and high temporal resolution data”. eng. In: *Stochastic environmental research and risk assessment* vol. 31, no. 7 (2016), pp. 1615–1631.

[38] Marti, I. et al. “Prediction models in complex terrain.” English. In: *European Wind Energy Conference, Copenhagen*. WIP - Renewable Energies, 2001.

[39] Matheron, G. “Principles of geostatistics”. In: *Economic Geology* vol. 58, no. 8 (Dec. 1963), pp. 1246–1266.

[40] Matysik, S. and Bauer, L. *Wind Turbine Database (retrieved in July, 2021)*. 2018.

[41] Nardini, S., Mazzella, A., and Mazzella, A. “The Importance of the Model Choice for Experimental Semivariogram Modeling and Its Consequence in Evaluation Process”. In: *Journal of Engineering* vol. 2013 (2013), p. 960105.

[42] National Aeronautic and Spatial Administration. *U.S Standard Atmosphere*. Tech. rep. NASA-TM-X-74335. Washington D.C: NASA, 1976.

[43] Nfaoui, H., Buret, J., and Sayigh, A. "Stochastic simulation of hourly average wind speed sequences in Tangiers (Morrocco)". In: *Solar Energy* vol. 56, no. 3 (1996), pp. 301–314.

[44] Porter, K and Rogers, J. "Status of Centralized Wind Power Forecasting in North America: May 2009-May 2010". In: (Apr. 2010).

[45] Puica, M. "Improvements in Wind Power Prediction by Considering Locational Wind Speed Estimates: A Critical Analysis". submitted for publication. Norway: University of Oslo.

[46] Puica, M. "On an Hourly Spatio-Temporal Model for Wind Speed Prediction: Applications to Southern California". submitted for publication. Norway: University of Oslo.

[47] Puica, M. and Benth, F. "A Spatio-Temporal Model for Predicting Wind Speeds in Southern California". currently in preprint (2021).

[48] Šaltytė Benth, J., Benth, F. E., and Jalinskas, P. "A Spatial-temporal Model for Temperature with Seasonal Variance". In: *Journal of Applied Statistics* vol. 34, no. 7 (2007), pp. 823–841. eprint: https://doi.org/10.1080/02664760701511398.

[49] Seo, D. et al. "Simulation of precipitation fields from probabilistic quantitative forecast (vol 239, pg 203, 2000)". eng. In: *Journal of hydrology (Amsterdam)* vol. 247, no. 3-4 (2001), pp. 263–263.

[50] Shumway, R. and Stoffer, D., eds. *Time Series Analysis and Its Applications, Fourth Edition*. Springer Texts in Statistics. ISBN:1431-875X. Springer, 2017.

[51] SLOUGHTER, J. M. et al. "Probabilistic quantitative precipitation forecasting using bayesian model averaging". eng. In: *Monthly weather review* vol. 135, no. 9 (2007), pp. 3209–3220.

[52] Tang, B. H. and Bassill, N. P. "Point Downscaling of Surface Wind Speed for Forecast Applications". In: *Journal of Applied Meteorology and Climatology* vol. 57, no. 3 (1Mar. 2018), pp. 659 –674.

[53] Torres, J. et al. "Forecast of hourly average wind speed with ARMA models in Navarre (Spain)". In: *Solar Energy* vol. 79, no. 1 (2005), pp. 65–77.

[54] Ulazia, A. et al. "The Consequences of Air Density Variations over Northeastern Scotland for Offshore Wind Energy Potential". In: *Energies* vol. 12, no. 13 (2019).

[55] Wang, Q. et al. "The value of improved wind power forecasting: Grid flexibility quantification, ramp capability analysis, and impacts of electricity market operation timescales". In: *Applied Energy* vol. 184 (2016), pp. 696–713.

[56] Xia, J., Zhao, P., and Dai, Y. "Neuro-fuzzy networks for short-term wind power forecasting". In: *2010 International Conference on Power System Technology.* 2010, pp. 1–5.