A hybrid evolutionary probabilistic forecasting model applied for rainfall and wind power forecast

Guilherme G. Netto, Alexandre C. Barbosa, Mateus N. Coelho, Arthur R. L. Miranda, Vitor N. Coelho, Marcone J. F. Souza, Frederico G. Guimarães and Agnaldo J. R. Reis

***Abstract*— Several works in the literature so far have been focused on deterministic point forecasts, which, usually, indicates the conditional mean of future observations. An increasing need for generating the entire conditional distribution of future observations has been required for the new generation of soft sensors. This study aims the probabilistic forecasts, reporting the use of a hybrid fuzzy forecasting model applied in two different forecasting problems. Our adapted model is applied to predict the rain of the city of Vitoria, in the state of Espírito Santo, Brazil. Real data from a wind farm, provided by the Irish EirGrid institute, was used for analyzing the proposal over a real time series with high fluctuations. Due to the stochasticity of the the hybrid model, which is calibrated through the use of an evolutionary metaheuristic, we adapted it in order to generate future using quantile regression. Computational experiments indicated the ability of the model in finding useful probabilistic quantiles, which were flexible enough in order to limit the lower and upper bounds of the historical datasets. While the probabilistic quantiles suggested the probability of rain and its magnitude, they were also able to predict expected ranges of the amount of energy generated from the wind farm.**

Keywords: ***Rainfall Forecast, Wind Power Forecast, Probabilistic Forecast, Soft Sensors, Hybrid Forecasting Model and Metaheuristics*.**

I. Introduction

POPULATION growth and rising living standards have boosted energy consumption in all sectors [1]. Along aside this modern changing in the Energy Industry is the moving for a new paradigm of energy distribution, known as Smart Grid (SG). In this new electric grid environment, a dynamic scenario fulfilled with uncertainties is reality. Restructure those networks in order to meet the prosperous increasing demand, while it also emerge the need for reducing greenhouse gases and fossil fuel use and emissions, is a huge challenge of the electrical industry of our time [2].

Alexandre C. Barbosa, Guilherme G. Netto, Arthur R. L. Miranda, Mateus N. Coelho and Agnaldo J. R. Reis are with Department of Control and Automation Engineering, Universidade Federal de Ouro Preto, Ouro Preto, MG, Brazil e-mail: (gnguilherme@outlook.com, leamalo@gmail.com, mateus.nazario@yahoo.com.br, arthurlmiranda@hotmail.com and agnreis@gmail.com)

Vitor N. Coelho is with the Graduate Program of Electrical Engineering, Univesidade Federal de Minas Gerais, Belo Horizonte, MG, Brazil e-mail: (vncoelho@gmail.com)

Marcone J. F. Souza is with Department of Computer Science, Universidade Federal de Ouro Preto, Ouro Preto, MG, Brazil e-mail: (marcone@iceb.ufop.br)

Frederico G. Guimarães is with the Departament of Electrical Engineering, Univesidade Federal de Minas Gerais, Belo Horizonte, MG, Brazil e-mail: (frederico.g.guimaraes@gmail.com)

This advancement in technology and information systems have motivated the integration of Renewable Energy Resources (RER), which is playing an important role in the context of providing alternative energy. The potential for RER is growing quickly and countries all over the world are motivating the insertion of these new energy resources [3], [4], [5], [6], [7]. Thus, it is expected that it will, in principle, exponentially exceed the world's energy demand [8]. However, coordinate this RER and take profit of it, in order to enhance the use of self-generated energy, has been challenging researchers [9]. Given the inherent uncertainties associated to these sources of energy, point forecasts are being replaced by the use of entire conditional distribution of future observations. Probabilistic forecasts has been extensively investigated for different forecast problem involving the new renewable energy resources introduced over the SG, such as solar power forecasting in smart grids [10].

Several works in the literature so far has been focused on forecasting the deterministic point forecasts, which indicates the conditional mean of future observations. An increasing need for generating the entire conditional distribution of future observations has been required for the new generation of soft sensors.

This study aims the generation of multiple quantiles covering the requested forecasting horizon of a given time series, reporting the use of a hybrid forecasting model, adapted from the work of Coelho et al. [11], applied in two different forecasting problems. Rainfall forecast is of paramount importance for various applications for water resources management. However, the variability of rainfall in space and time makes this prediction very difficult. This is due to the fact that the amount of rainfall as well as their distribution depend on many variables such as speed and wind direction, pressure, and temperature. With the phenomenon of El Niño [12], [13], slightly variations will be expected over the course of the next year. Thus, the use of flexible and smarter forecasting models, able to generalize data from our given historical data, will be important for understanding these new unseen informations. On the other hand, we also focus on solving a challenge SG problem, the wind power forecast [14]. An effective management of the forthcoming renewable energy resources, such as the wind power turbines, can be useful for coordinating and planning energy storage [15], as well as enhancing self-generated energy use [16].

In special, we consider a historical rainfall dataset from the city of Vitoria, located in the state of Espírito Santo, Brazil. Meanwhile we handle with a real data from a wind farm, provided by the Irish EirGrid institute [17], for analyzing our proposed probabilistic forecasting framework. Results from the hybrid metaheuristic method, based on fuzzy logic concepts, are discussed and analyzed. Results from the hybrid metaheuristic method, based on fuzzy logic concepts, are discussed and analyzed considering the search for a consensual set of parameters. The main contribution of this current paper is to adapt a novel hybrid fuzzy model for performing probabilistic forecast in two different time series scenarios with high fluctuations.

The remainder of this paper is organized as follows. Section II introduces brief literature review and the importance of rainfall and wind power forecast. Section III presents the adaptation proposed in this current work for generating probabilistic quantiles from the hybrid evolutionary forecasting model. Section IV presents the computational experiments, and, finally, Section V draws the final considerations and future work.

II. Literature review

A. Rainfall forecast

Water is the most abundant natural resource on the planet. Nearly ubiquitous way, it is in the daily lives of seven billion people inhabiting the planet. However, it has been experienced severe changes regarding its supply [18]. Currently the management of water resources is undergoing a paradigm shift, which has a strong tradition in controlling the environmental problems assisted by engineering based technical solutions.

Risk management involving tools for predicting extreme scenarios is of great importance due to the limits of current implemented technologies, such as dams and reservoirs. In this sense, the need of novel rainfall forecasting models has been increasing in recent years [19]. It is noteworthy that this topic can be carried out in a sustainable manner, based on the trade-off between social, environmental and economic interests.

Much of the need to forecast hydrological events are linked to global warming and possible adverse effects to humans. A study presented at the 2007 International Panel on Climate Change pointed a variation in climate that occurs due to increased carbon dioxide concentration, largely irreversible for a thousand years after emissions stop [20]. Thus, it is expected that extreme events, with higher fluctuations at its time series, are likely to be more frequent in the future.

In special, rain is one of the most complex and difficult elements of the hydrological cycle to be understood and modeled. The complexity of atmospheric processes, the effects of the solar rain (the current phenomenon of El Niño), forms huge range of variation over a wide range of scales in space and time [21]. French, Krajewski & Cuykendall [21] felt this need of forecasting this complex time series and developed a neural network model for rainfall forecasting based on data from a space-time mathematical rainfall simulation model. Gwangseob & Ana [22] emphasized that rainfall forecasting is one of the biggest challenges of operational hydrology, despite many advances in climate predictions in recent decades. For these reasons, any attempt to predict rainfall has impacts in urban safety, infrastructure and preventing disasters due to flooding and unavailability of water. Besides the economic impact, of course. Furthermore, reliable forecasts can also be used in order for enhancing energy efficiency in hydroelectric power plants. Nowadays, it has been done using short-term [23] and long-term forecasts. The latter has been done since the first dams were built, but, it used to be done at hand by the technicians and operators. With the increasing of novel storage devices, researchers are also investigating the impact of these forecast of pumped-hydro storage plants [24].

The proposal that forecasts should be expressed in probabilistic terms, rather than deterministic, was argued from the common sense and theoretical perspectives for nearly a century. Even though most of the hydrological forecasting operating systems produce deterministic predictions [25], [26], most operational hydrology in research has been devoted of finding the best estimation rather than quantifying the predictive uncertainty [27].

B. Wind power forecast

Smart Grid (SG) is considered as the future of power grid able to manage production, transmission and electricity distribution. The task has been mainly done by using Information and Communication Technologies (ICT), Distributed Systems (DG) and Artificial Intelligence (AI). Due to the need of consistently adapting and integrating new tools to the current grid, SG has become a major challenge for developed and developing nations in both research and utilization aspects [4]. Investing in SG infrastructure is a key enabler for public goods, such as decarbonisation and energy security [28].

In this context, Zhang, Wang & Wang [14] emphasized that probabilistic wind power forecasting is an efficient tool for dealing with randomness and intermittence of wind resources.

The randomness and intermittency of wind resources is the biggest challenge for the integration of wind energy into the power system. The development of accurate forecasting tools for wind power generation is an efficient tool for dealing with such problem. Conventional wind power generation forecasts produce a single future value for each point, depending on a value obtained from past data. However, in any prediction of future values, uncertainty is always involved. Deterministic forecasts define a single value forecast, as a probabilistic forecast define a set of possible values. For decisions in uncertain environments, the probabilistic prediction is a great choice.

In the present state-of-the-art studies, wind power forecast has been performed by probabilistic methods. The latter, compared with other methods, obtains a greater range of values for a given forecasting horizon, more robustness, for the soft sensors, than those using deterministic measurements [14].

III. Methodology

The hybrid forecasting model proposed by Coelho et al. [11] is now adapted for performing probabilistic forecasts. Since the heuristic model is based on a fuzzy model calibrated using a bio-inspired metaheuristic algorithm, the proposal here is to take advantage of the stochasticity of the proposed framework. By running the model several times, it is naturally able to provide different forecasting models that optimize different characteristics from a given time series.

Thus, the core of our idea is to train the hybrid fuzzy model fm times. As mentioned, given the stochasticity of this class of training models which uses metaheuristic procedures, we can achieve different forecasting models only by initializing the training phase with different random seeds. In our current work, the fuzzy model is trained using an algorithm known as GES, which combines the Greedy Randomized Adaptive Search Procedures – GRASP [29] and Evolution Strategies – ES [30]. Thus, our idea is to check if different executions of the proposed framework can be used ensemble in order to generate probabilistic quantiles.

From the set of different forecast models, predicted values are sorted from the lowest to the highest values and, then, quantiles are determined. In our didactic example, we combine the different forecasting models by putting them in order and extracting normal quantiles. As mentioned by Adhikari [31], it is an effective and easy way of obtaining a probabilistic distribution of the forecasts. Basically, a quantile function is defined, which provides a given probability in the probability distribution of a random variable (in our examples, expected rainfall and wind power generation).

In terms of the distribution function F, the quantile function Q returns the value x such that it gives the probability that the values can be above x, as described in Eq. (1). Thus, it provides the value at which the probability of the random variable being less than or equal to this value is equal to the given probability p, provided by the quantiles Q_p. It is also known as the percent point function or inverse cumulative distribution function.

$$F_X(x) := Pr(X \leq x) = p \tag{1}$$

Here, we define quantiles $Q = \{1, ..., 99\}$. Theoretically, the quantile Q_0 is equal to $-\infty$ and $Q_{100} = \infty$, respectively, the lower and upper bounds of any historical time series. In our cases of study, the minimum expected values would be 0 for the the lower quantiles Q_0, given that we know, surely, that we have 0% of chance of having a rainfall or wind power generation lower than 0mm or 0W, respectively. Following the same reasoning, we could define better upper limits for the quantile Q_{100}, looking at the literature and following historical values of the time series. However, in this current paper, we will only focus on the ability of our proposal in obtaining, automatically, the quantiles Q_1 to Q_{99}.

IV. Computational Experiments

The `GES` algorithm was implemented in C++ in the framework OptFrame 2.0 [1] [32], [33] using the same code described in the work of Coelho et al. [11].

The tests were carried out on a OPTIPLEX 9010 Intel Core i7-3770, 3.40 x 8 GHZ with 32GB of RAM, with operating system Ubuntu 12.04.3 precise, and compiled by g++ 4.6.3, using the Eclipse Kepler Release.

A. Historical datasets

The dataset used as didactic example for the wind power turbine was obtained from the EirGrid Free Database. It consists in intraday wind power generation (MW) for the 50 week period from November, 18th of 2013 to February, 18th of 2014 (2160 samples). All experiments used hourly data. The obtained wind power generation time series can be seen depicted in Figure 1, as well as its Autocorrelation – ACF plot 2. As can be noticed, the ACF values decays quickly and shows weak autocorrelation after or before one week. A brief introduction about the current state-of-the-art of the use of ACF can be checked in Hyndman [34].

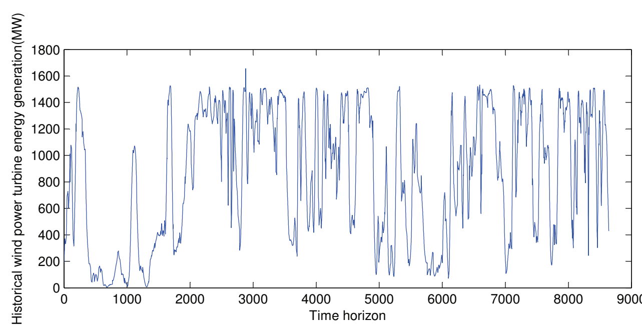

Fig. 1. Historical power generation from a wind turbine

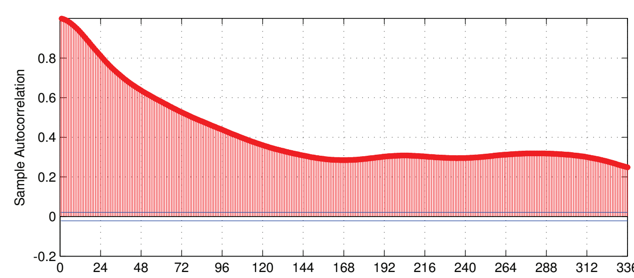

Fig. 2. Autocorrelation function of the power generated from the historical data from the wind turbine

Real data from the city of Vitoria was extracted from the Brazilian “Agência Nacional de Águas”, comprising different years from 1926 to 2013. The maximum monthly rainfall precipitation can be seen depicted in Figure 4, as well as its

[1] Available at http://sourceforge.net/projects/optframe/

ACF plot 4. As can be verified, there is almost no correlation between the maximum monthly rainfall, reinforcing the difficulty of establishing useful inputs/lags for the forecasting model.

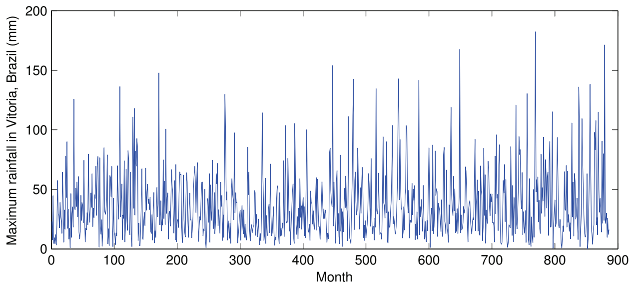

Fig. 3. Maximum rainfall in Vitoria (maximum month per mm)

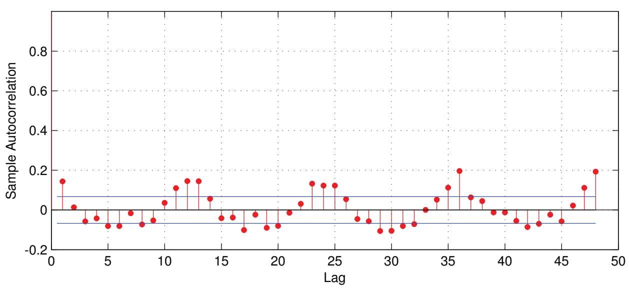

Fig. 4. Autocorrelation function of the monthly maximum rainfall in Vitoria

B. Obtained probabilistic forecasts

The batch of experiments for generating the probabilistic forecasting model was composed of 500 executions of 240 seconds of training. The size of the validation set was set to be 5 times the forecast horizon, thus, for a forecasting horizon of 168 steps ahead (one-week ahead) of wind power generation, 840 samples were used during the training set and the consecutive 168 samples used for comparing the obtained probabilistic forecasts.

In order to show the flexibility of the proposal, the same parameters adopted in the work of Coelho et al. [11] were kept here. Thus, as introduced in Section III, the model was run $tm = 500$ times with different seeds, obtaining different forecasting models.

Figure 5 shows a whole set of forecasts obtained for one week ahead of wind power generation. On the other hand, Figure 6 shows an example of probabilistic quantiles for a forecasting horizon of one-week ahead, the thicker line shows the real measured data.

A reasonable probabilistic approximation can be seen comprised in the quantiles of Figure 6, fitting a reasonable forecasting for one week ahead planning. Quantiles are able to fit the maximum and minimum amount of energy generated, as can be checked analyzing the upper (Q_{99}) and lower bound quantiles (Q_1). A denser concentration of quantile can be found in the middle section of the probabilistic forecast, from the range of 650MW to 900MW.

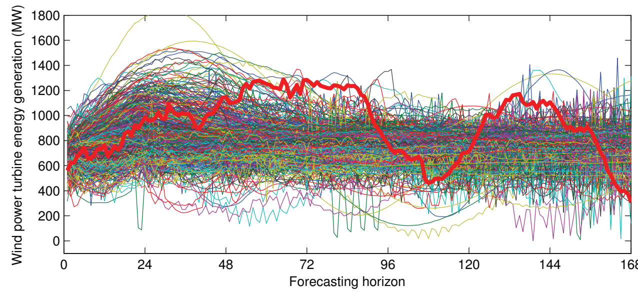

Fig. 5. Obtained hourly forecasts for one week ahead of wind power generation

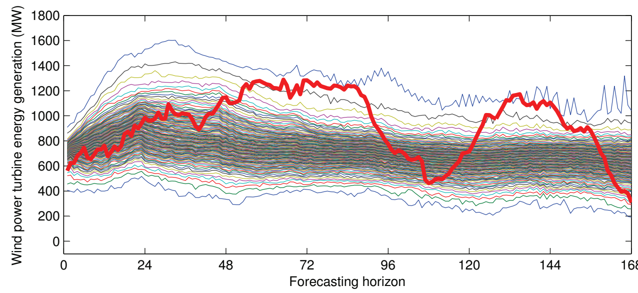

Fig. 6. Probabilistic hourly forecasts for one week ahead of wind power generation

For the rainfall forecasts, a first experiment focused on obtaining one step ahead deterministic forecast. It was initially done in order to check if the hybrid model could, at least, generate visually viable forecasts. As can be verified in Figure 7, the model was able to generate one-step ahead forecast with a maximum error, of rainfall precipitation, around 75 mm, considering a blind testing set of 24 months. This fact motivated a new batch of experiment to check larger forecasting horizons considering probabilistic, which, implicitly, provide mean and variance forecast.

Figures 8 and 9 show two different probabilistic forecasts for one and two years ahead forecasts, respectively, 12 and 24 steps ahead of maximum monthly rainfall. This kind of forecast are handful and useful for decision making for investments in infrastructure and understanding the risk for the next years.

Figure 8 depicts specific quantiles, facilitating the visualization and interpretation of the results, namely Q_1, Q_{25}, Q_{50}, Q_{75}, Q_{99}. As expected, the lower bound were forecasted as 0mm for each month, a fact that occurs in the absence of precipitation. The upper bound limited

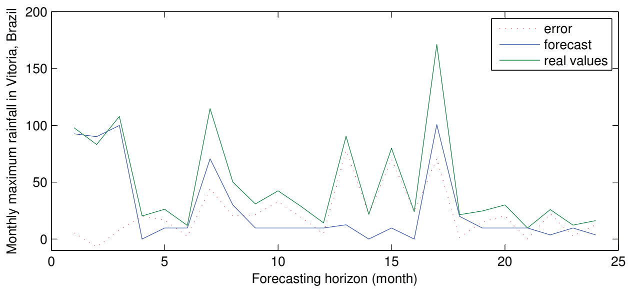

Fig. 7. One step ahead forecast for maximum monthly rainfall

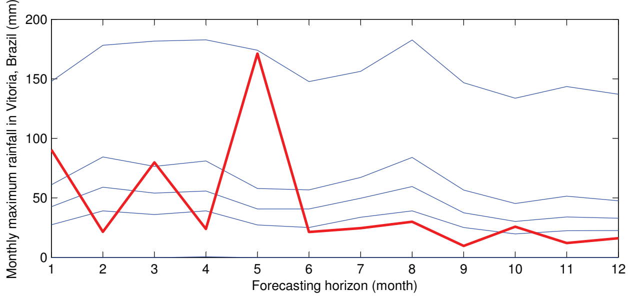

Fig. 8. One year ahead of maximum monthly rainfall for the city of Vitoria in the year of 2013

the maximum raining below an approximated value of 150mm. The probabilistic distribution indicates that for the next year (in the example, 2013), the maximum monthly precipitation had an approximated probability of 75% to 70mm, considering the average of the 12 months. On the hand, it has forecasted with 50% of chance that the rainfall would be close to 50mm.

Finally, analyzing Figure 9, it can be seen that, even for 24 steps ahead, the proposed model was able to produce forecasting quantiles that covered the real measured rainfall.

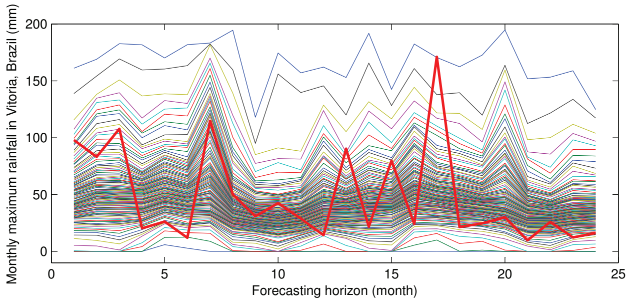

Fig. 9. Two years ahead (24 steps ahead) of maximum monthly rainfall for the city of Vitoria in the years of 2012 and 2013

V. Conclusions and Extensions

In this paper, a novel hybrid fuzzy model was adapted in order to generate probabilistic quantiles. Since the model is calibrated through the use of metaheuristic procedures, the training phase of the proposed methodology was executed several times in order to achieve different forecasting models.

Two different forecasting problems, one for rainfall and another for wind power generation forecast, both with high fluctuation and slopes, were used as a didactic examples. The obtained forecasts from the different models were sorted and quantiles were determined. By analyzing the obtained graphs, evidences pointed out that the model could provide useful forecasts and assist decision making of the new generation of soft/smart sensors.

Future works should focus on comparing the obtained probabilistic functions with well-known indicators, such as a Pinball Function [35]. This kind of comparison would open an interesting field of research for comparing these type of forecasts with the literature. An optimized set of parameters from the metaheuristic algorithm could provide better forecasts guided by the use of these probabilistic quality indicators. The latter would assist the choice of this tunning, providing a way of walking through the solution space of better probabilistic approximations. As future extensions for this work, it is also proposed to tackle other forecasting problems from the energy sector, such as long term load forecast, price forecasts and photovoltaic energy generation.

Acknowledgment

The authors would like to thank Brazilian agency CAPES, CNPq (grants 305506/2010-2, 552289/2011-6, 306694/2013-1 and 312276/2013-3) and FAPEMIG (grant PPM CEX 497-13), for supporting the development of this work.

References

[1] L. Ekonomou, “Greek long-term energy consumption prediction using artificial neural networks,” *Energy*, vol. 35, no. 2, pp. 512 – 517, 2010.

[2] A. Rogers, S. D. Ramchurn, and N. R. Jennings, “Delivering the smart grid: Challenges for autonomous agents and multi-agent systems research,” in *Twenty-Sixth AAAI Conference on Artificial Intelligence (AAAI-12)*, Toronto, CA, 2012, pp. 2166–2172.

[3] M. G. Pereira, C. F. Camacho, M. A. V. Freitas, and N. F. da Silva, “The renewable energy market in brazil: Current status and potential,” *Renewable and Sustainable Energy Reviews*, vol. 16, no. 6, pp. 3786 – 3802, 2012.

[4] C. T. Tugcu, I. Ozturk, and A. Aslan, “Renewable and non-renewable energy consumption and economic growth relationship revisited: Evidence from G7 countries,” *Energy Economics*, vol. 34, no. 6, pp. 1942 – 1950, 2012.

[5] P. Díaz and J. Masó, “Evolution of production and the efficient location of renewable energies. the case of china,” *Energy Procedia*, vol. 40, pp. 15 – 24, 2013.

[6] H.-T. Pao and H.-C. Fu, “Renewable energy, non-renewable energy and economic growth in brazil,” *Renewable and Sustainable Energy Reviews*, vol. 25, no. 0, pp. 381 – 392, 2013.

[7] G. S. Alemán-Nava, V. H. Casiano-Flores, D. L. Cárdenas-Chvez, R. Díaz-Chavez, N. Scarlat, J. Mahlknecht, J.-F. Dallemand, and R. Parra, “Renewable energy research progress in mexico: A review,” *Renewable and Sustainable Energy Reviews*, vol. 32, no. 0, pp. 140 – 153, 2014.

[8] O. Ellabban, H. Abu-Rub, and F. Blaabjerg, "Renewable energy resources: Current status, future prospects and their enabling technology," *Renewable and Sustainable Energy Reviews*, vol. 39, pp. 748 – 764, 2014.

[9] R. Rigo-Mariani, B. Sareni, X. Roboam, and C. Turpin, "Optimal power dispatching strategies in smart-microgrids with storage," *Renewable and Sustainable Energy Reviews*, vol. 40, pp. 649 – 658, 2014.

[10] R. Bessa, A. Trindade, C. S. Silva, and V. Miranda, "Probabilistic solar power forecasting in smart grids using distributed information," *International Journal of Electrical Power & Energy Systems*, vol. 72, pp. 16 – 23, 2015, the Special Issue for 18th Power Systems Computation Conference.

[11] V. Coelho, F. Guimaraes, A. Reis, I. Coelho, B. Coelho, and M. Souza, "A heuristic fuzzy algorithm bio-inspired by evolution strategies for energy forecasting problems," in *Fuzzy Systems (FUZZ-IEEE), 2014 IEEE International Conference on*, July 2014, pp. 338–345.

[12] M. B. Sathicq, D. E. Bauer, and N. Gmez, "Influence of el niño southern oscillation phenomenon on coastal phytoplankton in a mixohaline ecosystem on the southeastern of south america: Río de la plata estuary," *Marine Pollution Bulletin*, vol. 98, no. 1-2, pp. 26 – 33, 2015.

[13] Z. Islam and T. Y. Gan, "Potential combined hydrologic impacts of climate change and el niño southern oscillation to south saskatchewan river basin," *Journal of Hydrology*, vol. 523, pp. 34 – 48, 2015.

[14] Y. Zhang, J. Wang, and X. Wang, "Review on probabilistic forecasting of wind power generation," *Renewable and Sustainable Energy Reviews*, vol. 32, pp. 255 – 270, 2014.

[15] S. Mohammadi, S. Soleymani, and B. Mozafari, "Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices," *International Journal of Electrical Power & Energy Systems*, vol. 54, pp. 525 – 535, 2014.

[16] S. Wang, D. Yu, and J. Yu, "A coordinated dispatching strategy for wind power rapid ramp events in power systems with high wind power penetration," *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 986 – 995, 2015.

[17] E. N. C. Center, 2015, eirGrid National Control Center. [Online]. Available: http://www.eirgrid.com

[18] J. A. LUTZENBERGER, *Fim do Futuro? Manifesto Ecolgico Brasileiro*, ser. 5. So Paulo: Editora Movimento, 1980.

[19] C. Pahl-Wostl, D. Tábara, R. Bouwen, M. Craps, A. Dewulf, E. Mostert, D. Ridder, and T. Taillieu, "The importance of social learning and culture for sustainable water management," *Ecological Economics*, vol. 64, no. 3, pp. 484 – 495, 2008.

[20] S. Solomon, G.-K. Plattner, R. Knutti, and P. Friedlingstein, "Irreversible climate change due to carbon dioxide emissions," *Proceedings of the national academy of sciences*, vol. 106, no. 6, pp. 1704–1709, 2009.

[21] M. N. French, W. F. Krajewski, and R. R. Cuykendall, "Rainfall forecasting in space and time using a neural network," *Journal of Hydrology*, vol. 137, no. 1-4, pp. 1 – 31, 1992.

[22] K. Gwangseob and P. B. Ana, "Quantitative flood forecasting using multisensor data and neural networks," *Journal of Hydrology*, vol. 246, no. 1, pp. 45–62, 2001.

[23] C. Monteiro, I. J. Ramirez-Rosado, and L. A. Fernandez-Jimenez, "Short-term forecasting model for electric power production of small-hydro power plants," *Renewable Energy*, vol. 50, pp. 387 – 394, 2013.

[24] T. Muche, "Optimal operation and forecasting policy for pump storage plants in day-ahead markets," *Applied Energy*, vol. 113, pp. 1089 – 1099, 2014.

[25] J. C. Bennett, D. E. Robertson, D. L. Shrestha, Q. Wang, D. Enever, P. Hapuarachchi, and N. K. Tuteja, "A system for continuous hydrological ensemble forecasting (SCHEF) to lead times of 9 days," *Journal of Hydrology*, 2014.

[26] P. Nastos, K. Moustris, I. Larissi, and A. Paliatsos, "Rain intensity forecast using artificial neural networks in athens, greece," *Atmospheric Research*, vol. 119, pp. 153 – 160, 2013.

[27] R. Krzysztofowicz, "Bayesian theory of probabilistic forecasting via deterministic hydrologic model," *Water Resources Research*, vol. 35, no. 9, pp. 2739–2750, 1999.

[28] S. Hall and T. J. Foxon, "Values in the smart grid: The co-evolving political economy of smart distribution," *Energy Policy*, vol. 74, no. 0, pp. 600 – 609, 2014.

[29] M. G. C. Resende and C. C. Ribeiro, "Greedy randomized adaptive search procedures: Advances, hybridizations, and applications," in *Handbook of Metaheuristics*, 2nd ed., M. Gendreau and J. Potvin, Eds. New York: Springer, 2010, pp. 283–319.

[30] H. G. Beyer and H. P. Schwefel, "Evolution strategies - a comprehensive introduction," *Natural Computing*, vol. 1, pp. 3–52, 2002.

[31] R. Adhikari, "A neural network based linear ensemble framework for time series forecasting," *Neurocomputing*, vol. 157, pp. 231 – 242, 2015.

[32] I. M. Coelho, P. L. A. Munhoz, M. N. Haddad, V. N. Coelho, M. M. Silva, M. J. F. Souza, and L. S. Ochi, "A computational framework for combinatorial optimization problems," in *VII ALIO/EURO Workshop on Applied Combinatorial Optimization*, Porto, 2011, pp. 51–54.

[33] V. Coelho, A. Grasas, H. Ramalhinho, I. Coelho, M. Souza, and R. Cruz, "An ils-based algorithm to solve a large-scale real heterogeneous fleet {VRP} with multi-trips and docking constraints," *European Journal of Operational Research*, vol. 250, no. 2, pp. 367 – 376, 2016.

[34] R. Hyndman, "Better acf and pacf plots, but no optimal linear prediction," *Electronic Journal of Statistics [E]*, vol. 8, no. 2, pp. 2296–2300, 2014.

[35] T. Gneiting, "Quantiles as optimal point forecasts," *International Journal of Forecasting*, vol. 27, no. 2, pp. 197–207, 2011.