ENGENHARIA ELÉTRICA:

Sistemas de energia elétrica e telecomunicações

João Dallamuta
Henrique Ajuz Holzmann
(Organizadores)

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APRESENTAÇÃO

A engenharia elétrica tornou-se uma profissão há cerca de 130 anos, com o início da distribuição de eletricidade em caráter comercial e com a difusão acelerada do telégrafo em escala global no final do século XIX.

Na primeira metade do século XX a difusão da telefonia e da radiodifusão além do crescimento vigoroso dos sistemas elétricos de produção, transmissão e distribuição de eletricidade, deu os contornos definitivos para a carreira de engenheiro eletricista que na segunda metade do século, com a difusão dos semicondutores e da computação gerou variações de ênfase de formação como engenheiros eletrônicos, de telecomunicações, de controle e automação ou de computação.

Não há padrões de desempenho em engenharia elétrica e da computação que sejam duradouros. Desde que Gordon E. Moore fez a sua clássica profecia tecnológica, em meados dos anos 60, a qual o número de transistores em um chip dobraria a cada 18 meses - padrão este válido até hoje – muita coisa mudou. Permanece porem a certeza de que não há tecnologia na neste campo do conhecimento que não possa ser substituída a qualquer momento por uma nova, oriunda de pesquisa científica nesta área.

Produzir conhecimento em engenharia elétrica é, portanto, atuar em fronteiras de padrões e técnicas de engenharia. Também se trata de uma área de conhecimento com uma grande amplitude de subáreas e especializações, algo desafiador para pesquisadores e engenheiros.

Neste livro temos uma diversidade de temas nas áreas níveis de profundidade e abordagens de pesquisa, envolvendo aspectos técnicos e científicos. Aos autores e editores, agradecemos pela confiança e espirito de parceria.

Boa leitura

João Dallamuta
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SUMÁRIO

CAPÍTULO 2

FORECAST METHOD FOR RENEWABLE ENERGY SOURCES: A CASE STUDY OF THE ONTARIO'S ELECTRICAL SYSTEM

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ABSTRACT: Renewable resources can be defined as clean and sustainable energy sources that can be harvest from the environment and do not produce greenhouse gas emissions on the generation process. However, these technologies have some limitations regarding generation output, meaning their power is considered volatile and intermittent, making its predictability difficult. Forecasting methods are essential to fully incorporate renewables to the classic electric system standards, which are able of solving complex and non-linear problems, providing high accurate results for operators to make decisions and act on the coordination of the power plants. This paper has the objective to implement an algorithm for short-term (hourly) forecasting applying Multi-Layer Perceptron (MLP) for photovoltaic solar and wind power generation, using real data from the Ontario Independent Electricity System Operator. The results are compared to the real data operation, and the errors are calculated to provide the accuracy of the method. In addition, the study showed that

the use of MLP can bring satisfactory results for the renewable energy forecast.
KEYWORDS: Power generation forecasting; renewable energy; wind power; photovoltaic solar power; electric system.

MÉTODO DE PREVISÃO PARA FONTES DE ENERGIA RENOVÁVEIS: UM ESTUDO DE CASO DO SISTEMA ELÉTRICO DE ONTÁRIO

RESUMO: Recursos renováveis podem ser definidos como fontes de energia limpas e sustentáveis, as quais são obtidas do meio ambiente, e não produzem emissões de gases de efeito estufa no processo de geração. No entanto, essas tecnologias apresentam algumas limitações em relação à saída de geração, tendo como resultado uma potência volátil e intermitente, o que dificulta sua previsibilidade. Os métodos de previsão são essenciais para incorporar totalmente as energias renováveis aos padrões clássicos do sistema elétrico, pois são capazes de resolver problemas complexos e não lineares, proporcionando resultados de alta precisão para que os operadores tomem decisões e atuem na coordenação das usinas. Este trabalho tem como objetivo implementar um algoritmo de previsão de curto prazo (horário) aplicando o modelo Multi-Layer Perceptron (MLP) para geração de energia solar fotovoltaica e eólica, usando dados reais do Operador Independente do Sistema Elétrico de Ontário. Os resultados são comparados com os dados reais de operação, e os erros são calculados para fornecer a precisão do método. O estudo mostrou que o uso da MLP pode trazer resultados satisfatórios para a previsão de energias renováveis.
PALAVRAS-CHAVE: Previsão de geração de energia; energias renováveis; energia eólica; energia solar fotovoltaica; sistema elétrico.

1 I INTRODUCTION

Most of the electricity generated in the world is currently produced by fossil fuels power plants, especially coal and gas, reaching up to around 63% of the world energy matrix. These fossil fuels are considered some of the main responsible for greenhouse gases and pollution emissions into the environment during the burning process, impacting to the current global climate crises (RITCHIE; ROSER, 2020).

To mitigate the dependency on fossil fuel and move to a carbon-neutral generation many countries are investing heavy on Renewable Energy Sources (RES) and expanding their participation into their electric systems. RES is the term used for describing technologies that are sustainable, meaning they can harvest natural resources that are continually replenished in nature, such as: solar (heat or photovoltaic), wind, hydro (ocean or rivers), biomass and geothermal heat. The electricity generated by these sources are considered clean or green since there is no greenhouse gas emissions or any other pollutant released to the atmosphere (QAZI et al., 2019).

The expansion of RES in many countries can be observed as they push to achieve many established goals that were settled during the Paris Agreement in 2015, substantially reducing global gas emissions to avoid the rise of 1.5°C in the planet temperature (UN, 2015). All this commitment led up to huge investments in new renewable power capacity in the past years, reaching a new annual record in 2021 where around 290 gigawatts (GW) of power were installed around the world (IEA, 2021).

Renewable capacity on the planet has reached around 2800 GW in 2022, around 43% of this power is still based on hydro resources. However, Photovoltaic (PV) and wind technologies are increasing their share faster every year, reaching around 26% of the market in 2022 (IRENA, 2021).

There are many reasons for renewables to be expanding, such as: infinite supply, meaning there is no dependency on any kind of fuel that requires extraction or transportation; zero carbon emissions and no environmental impact when producing electricity; decreasing costs with mass production; technology and efficiency improvements.

However, RES also have challenges and disadvantages, more specifically their high intermittency behavior. Intermittency for RES means a non-continuously power supply for every hour of the day, as their fuel is dependent on weather conditions that can be highly unpredictable. In other words, what this means that their power relies on a very specific sets of weather and physical parameters to proper function and provide energy for the grid. In the case of PV the sun is required to be shinning along with clear skies to reach the maximum energy production, as for the wind production there is a wind speed range that the generator must receive to function at the optimized point (ELAVARASAN et al., 2020).

A classic example of the renewable energy intermittence issue can be observed in California, United States of America, where the increasing deployment of PV system impacted the electric grid to the point of creating a new operation behave called the “duck curve” (NREL, 2018). There is also the example of wind energy problem found in England, as the country expanded their electricity production offshore, reaching around 25% installed capacity. However, during 2021 wind energy was only capable of supplying 7% of the full capacity due to very calm and steady weather conditions and leading to an all-time high of $553 per megawatt-hours (MWh), as coal and gas plants were used to assist the load (MORISON; SHIRYAEVSKAYA, 2021).

As RES expansion around the world speeds up many system operators are searching for strategies that can mitigate the intermittency associated with these sources. Forecasting methods can be implemented to improve this situation and reduce the uncertainty of generation balance. The idea of a forecasting technique is to project future data based on the previous data, involving mathematical and statistical tools that can improve the planning and operation for the electric system.

Thus, this study consists of the short-term generation forecasting for the RES, specifically in wind and PV power generation, with horizons of 12 and 60 hours, evaluating the results with real power data. The method used in this study was the Perceptron Multilayer (MLP) neural network. Finally, the data used on the forecasting model was focused on the Ontario power system data, the Independent Electricity System Operator

(IESO) (IESO, 2022).

2 | FORECAST MODELS

Forecast methods are complex tools that can be used to improve the integration of RES into the electric grid, providing future data of the forecast power that can be generated for many time horizons. Forecast models are basically mathematical algorithms that can perform an analysis based on historical data inputs with the objective to predict future trends and behavior. Fig. 1 and 2 shows an example of a forecasting model applied to wind and PV generation in Germany, showing the power hourly for the real data and the projected one for the same period with the accuracy limits (ZIEHER; LANGE; FOCKEN, 2015).

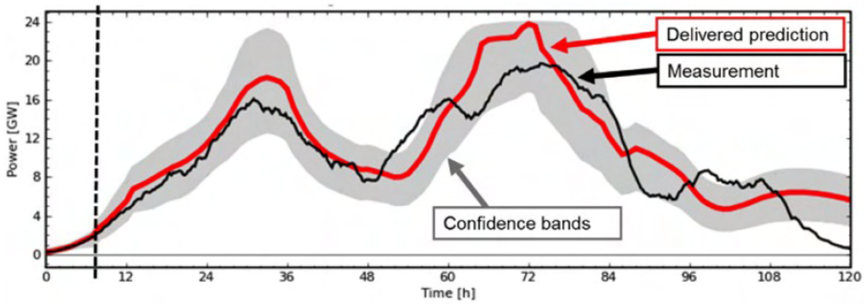

Fig. 1 – Wind power forecast for 5 days horizon.

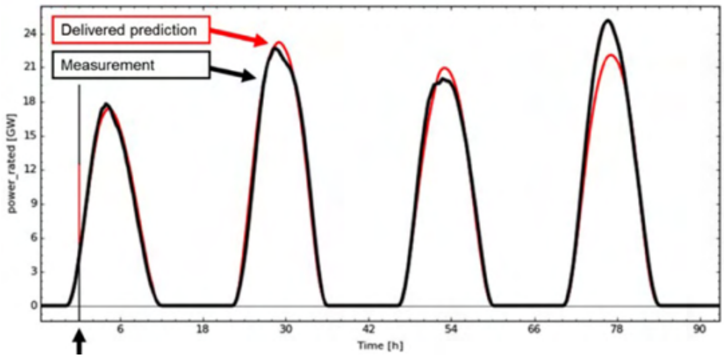

Fig. 2 – PV power forecast for 5 days horizon.

The rapid deployment of renewable resources in the energy sector requires forecasting at multiple timescales in order to proper support the electric system operator on their decisions. These time horizons are very important when deciding which forecasting model to apply depending on the operation challenge, and can be classified as: very short-term (seconds-minutes); short-term (minutes-hours); medium-term (hours-day); long-term (day - week - year) (DEBNATH; MOURSHED, 2018). Fig. 3 show a summary of the these time periods and their applications (HONG; FAN, 2016).

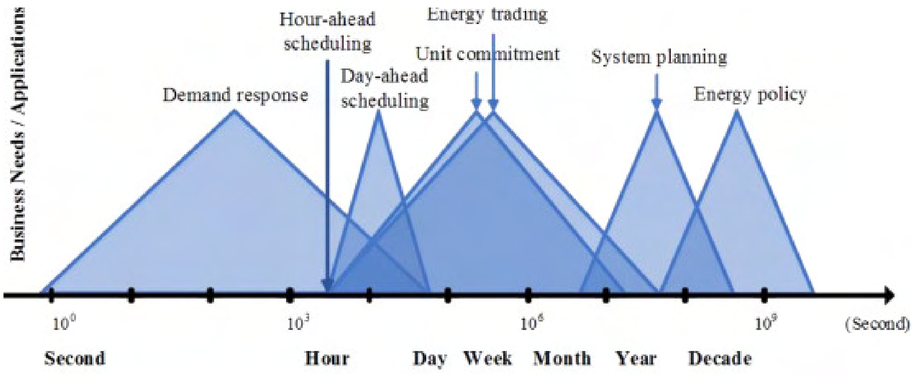

Fig. 3 – Energy forecasting application with the time interval of the forecast.

The energy sector can benefit from forecasting methods for supporting RES as they can be used for improve several operation activities, such as (IRENA, 2020):

- Scheduling and dispatch of power plants, antecipating ramping times;
- Real-time balancing of load and generation, minimizing curtailment;
- Reserves requirements, improving system reliability and flexibility;
- Cost-effect market wholesale, reducing fuel cost;
- Maintenance and contingency planning scheduling improves;
- Market regulation, improving economic signals;

There are many forecasting techniques that can be found in the literature and they can be classified in four mathematical categories: physical, statistical, Artificial Intelligence (AI) and hybrids. Each method has it owns technical parameters (historical data, time-horizons, processing time) along with specific advantages and disadvantages (ESTEVES et al., 2015).

The physical model is based on the weather conditions and meteorological data, using parameters such as: area, topography, location, surface conditions, temperature, humidity, pressure, sun position, sunshine hours, wind speed and direction. The combination of all these parameters is then processed with the Numerical Weather Prediction (NWP) algorithm to estimate the generation data for the RES. This method involves a lot of climatic input data and complex mathematical models, demanding a lot of computational time and consequently increased cost (CHEN et al., 2014).

For the statistical approach the idea is to create correlations between the input data and the future projection, using statistics tools based on historical to measure the impact and influence of specific variables within the data. The historical data is basically a sequence of data points that can present different time periods (hourly, daily, monthly). There are many traditional techniques used for statistical forecasting, the most famous are linear regression and Autoregressive Integrated Moving Average (ARIMA). The main problem with this methodology is the data standards and volume used to perform and obtaining a specific level of quality (RAMIREZ-VERGARA et al., 2022).

The exponential evolution of computational technology resulted in another methodology as an alternative to the classic statistical analysis, the AI. AI is considered a prominent technology that have been applied in many industrial applications: autonomous vehicles, voice and image recognition, automated robots. The expansion of AI methods is mostly due to their learning process capability, as these algorithms can improve their forecasting performance by training with the input data using trial and error over time. Some of the examples of AI methods are: Artificial Neural Network (ANN), Support Vector Machine (SVM), Markov Decision Process, K-nearest Neighbors Regression, Random Forest and Fuzzy Logic (MAKRIDAKIS, 2017).

The main difference between the statistical and AI is the minimization process, as first uses linear equations and the second applies non-linear processes on their error minimization. AI methods have their code based on step-by-step rather then the boolean logic and rules from the traditional programming system, in other words AI are much more complicated to implement and requires greater computational power (VOYANT et al., 2017).

One of the most famous models used by AI is the ANN, able to recognize patters and solve complex non-linear problems reflecting the human learning process. The main advantage of ANN is that it can provide real-time forecasting used for specific time-horizons (very-short or short-term) with notable accuracy. This study is based in a previous study (HAMMERSCHMITT et al., 2022), that makes use of MLP for forecasting energy generation for a centralized electrical system.

2.1 Algorithm Implementation

The implementation of the MLP algorithm for this project was developed with Python programming language and implemented on the Spyder 3.7 platform from the ANACONDA package, in a notebook with 2.4 GHz Intel Core i7 processor, 8 GB of RAM, 2133 MHz DDR 4, video card GeForce 745M, and a Microsoft Windows 10 operating system. To estimate the wind and PV generation potentials, two MLP were designed, where the architecture of both was composed of a 12 entry in the input layer, the hidden layer containing 6 neurons, and only one output for the last layer. This representation presented satisfactory performance, with the all the parameters obtained by the trial-and-error method, observing the error values and processing times.

The parameters of α and η were respectively 1 and 0.01. The MLP were trained following the MAE evolution, in which, for the wind generation MLP, the training criterion was established until the MAE was less than 0.05 (5%), and the MLP for PV generation with training stop criterion with a lower MAE of 0.04 (4%). The normalization of the input data was calculated using the Eq. (1):

$$y_i = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Where, the y_i is the normalized data sample, x is the real data value, x_{max} and x_{min} are the highest and lowest value observed in the real data, respectively.

In the training step, the MLP input data was organized according to their temporal order, on which the input samples have the next sample as learning target, and so on until reaching the last sample of the series data. This process consists of the supervised learning method with delayed inputs. The validation and forecast test followed the same process, with the MLP inputs being the 12 samples prior to the forecast objective and thus estimate power generation for the next hour.

Additionally, after performing the training step of the ANN, the values are submitted to validation tests, where the forecast results are evaluated and the errors are quantified. The validation of the MLP training has the function of monitoring its performance, verifying if the learning is occurring in an adequate means being evaluated by MAE and RMSE, without excessive training, which this a problem that can cause ineffectiveness on the expected forecasting results and impair the ability to generalization. Thus, if the errors are within the desired limits, the ANN will be ready to be applied to the proposed forecast.

Finally, the forecast test step was carried out and the results obtained for the hourly composition of electrical generation expected was expressed and compared to the generation real conditions, thus carrying out the estimates of the PV and wind power generation.

2.2 Renewable energy data

Data is required for developing the MLP method and training the algorithm to be able to forecast the future output for RES. The data used in this project was based on the IESO as they provide public access to their hourly generation output and capacity for the power plant (wind and PV) located in the Ontario region.

For this study PV and wind power plants were selected to be used as training data and also to measure the accuracy of the MLP forecast method developed for the project. The power plants were selected based on the data that were complete from 2018/01/01 to 2019/04/03, all the values were in provided public operator data (IESO, 2022). The historical data from the selected power plants were divided in two data sets, wind and PV, and from there the maximum and minimum values were obtained to perform the normalization mentioned on Eq. (1). These values can be observed in Table I.

Wind Power (MW)		PV Power (MW)	
Max	Min	Max	Min
3950	2	338	0

Table I – Maximum and minimum data values.

After the normalization the data is divided by the application performed on the MLP algorithm:

- 39 Wind and 5 PV Sources (units with complete data) by Ontario IESO
- Training data – 01 hour of 2018/01/01until 24 hours of 2019/03/31.
- Validation data – 01 hour to 12 hour de 2019/04/01.
- Forecasting period for 12-hour interval – 13 hours to 24 hours of 2019/04/01.
- Forecasting period of 60-hour interval – 13 hours of 2019/04/01, to 24 hours of 2019/04/03.

The training, validation and short-term forecasting (12- and 60-hour period) from the MLP method are presented below.

3 I RESULTS AND DISCUSSION

To better express the results obtained for training and validation, and for the two prediction tests that consist of the 12-hour and 60-hour projection, they will be separated into different subchapters. First, the training and validation results will be addressed. Next, the results predicted by the MLP for the 12-hour period will be presented, with the results in their real magnitudes. Finally, the expected results for the period of 60 hours will be presented, also in their real magnitudes.

3.1 Validation

The results obtained by the MLP during training and validation, for wind generation and PV generation, can be observed respectively in Tables II and III.

MAE training (%)	4,98%
Training time (seconds)	20,52
MAE validation (%)	4,77%
RMSE validation (%)	6,17%
Validation time (seconds)	0,012

Table II – Training and validation of wind data.

MAE training (%)	3,99%
Training time (seconds)	10,03
MAE validation (%)	4,18%
RMSE validation (%)	6,29%
Validation time (seconds)	0,014

Table III – Training and validation of PV data.

According to Table II, during the training of the MLP for the wind generation data, an MAE of 4.98% was obtained, with a processing time of 20.52 seconds. For training validation, MAE and RMSE rates were obtained at values of 4.77% and 6.17%, respectively, with a processing time of 0.012 seconds. As for the MLP referred to the PV generation data, observed in Table III, training MAE was obtained in the value of 3.99% with a processing time of 10.03 seconds. The training validation obtained MAE results of 4.19% and RMSE of 6.29%, with a processing time of 0.014 seconds. From these results, the MLP for wind and PV generation was considered ready to be used in the proposed forecasting study.

3.2 Generation forecast – 12 hours

The results for the wind generation forecast test for the period of 12 hours, presented the values of MAE and RMSE of 7.41% and 8.48%, with a processing time of 1.05 seconds. The graphical results of this analysis can be seen in Fig. 4, which depicts the actual and predicted generation curves for the date of 2019/04/01 from 1 am to 12 am on the same day.

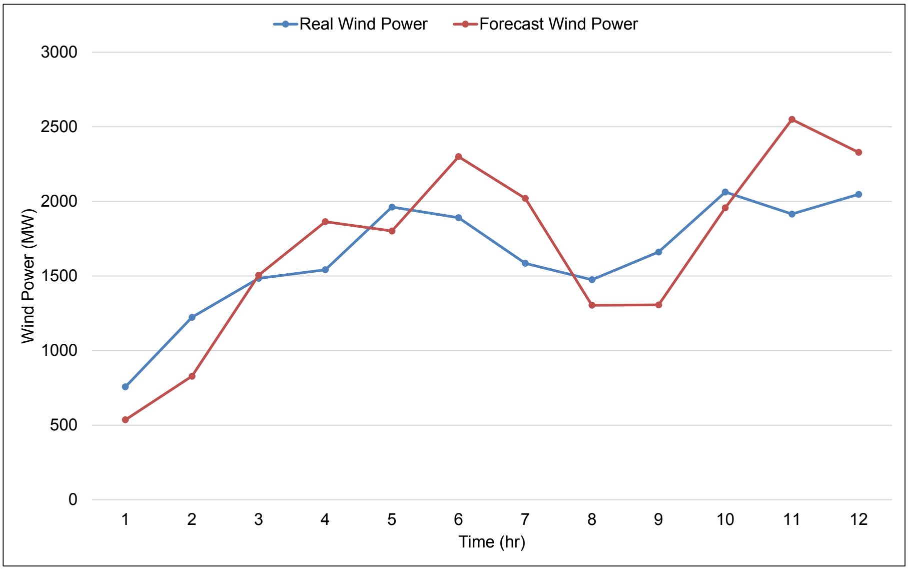

Fig. 4 – Real and forecast wind power for 12 hours periods.

When relating the curves of the actual wind generation and that predicted by the MLP, the greatest variation between the curves is observed at hour 11 am, in the amount of 634 MW. Although there are variations in the profiles of the actual and predicted generation curves, these results are expressive because wind generation is an intermittent energy resource, with low predictability. Furthermore, the effectiveness of the MLP for the prediction of wind generation is proven, observed in Fig. 4 by the similarity of the actual and predicted wind generation curves.

For the PV generation forecasting test for the same period, the MAE and RMSE results were 3.14% and 4.38%, with a processing time of 0.015 seconds. The graphical results of the actual and PV generation forecast are seen in Fig. 5.

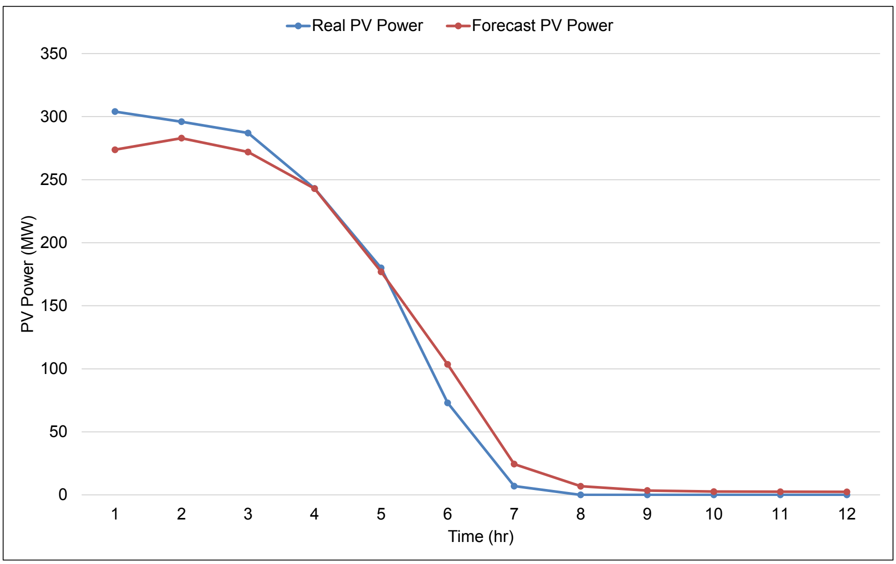

Fig. 5 – Real and forecast PV power for 12 hours periods.

The results obtained for the period of 12 hours of PV generation, portray a certain linearity of the real and predicted curves of the PV generation, a fact that caused the reduction of the forecast errors of the MLP. When observing the actual and predicted curves for PV generation, hour 6 was the biggest difference between the generation curves in the amount of 30 MW occurred. Additionally, as the period of this test coincides with the time of maximum solar intensity, it is possible to observe the reduction of the energy produced from hour 1, which depicts 1 pm on 2019/04/01, with an even more attenuated reduction from hour 3, tending to zero in the hours that followed.

3.3 Generation forecast – 60 hours

When performing the forecast for the period of 60 hours for wind generation, it was observed that the errors quantified by MAE and RMSE were slightly more significant than the case of the forecast for 12 hours. The prediction errors were 7.48% and 8.80%, for MAE and RMSE, respectively, and with a processing time of 1.02 seconds. Fig. 6 expresses the behavior of the actual and predicted wind generation curves by the MLP for the period from 13:00 on 2019/04/01, until 24:00 on 2019/04/03.

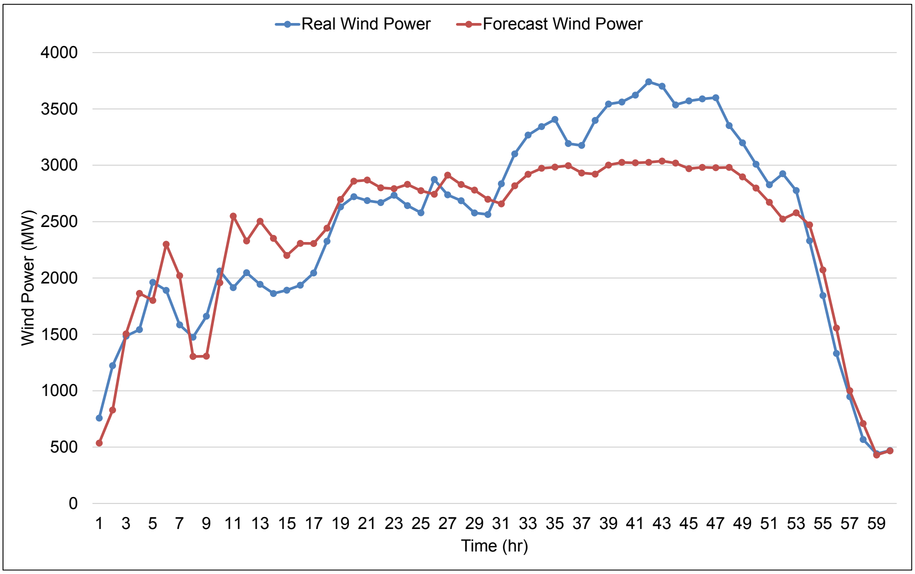

Fig. 6 – Real and forecast wind power for 60 hours periods.

As shown in Fig. 6, the biggest difference between the wind generation curves occurred at hour 42, with a value of 714 MW. When visualizing the wind generation curves in the period of 60 hours, it is noticeable the inconstancy of energy production of this energy resource, and that the disturbances caused by these inconstancies impair its predictability. However, the MLP obtained considerable results for a short-term forecast in view of the difficulties imposed by the intermittence of wind generation.

In terms of PV generation, Fig. 7 expresses the actual and predicted PV generation curves for the 60-hour period. The errors for this forecast test are slightly higher than in the case of the wind generation forecast for the 12-hour period, which were 4.07% and 6.29%, for MAE and RMSE, with a processing time of 0.019 seconds.

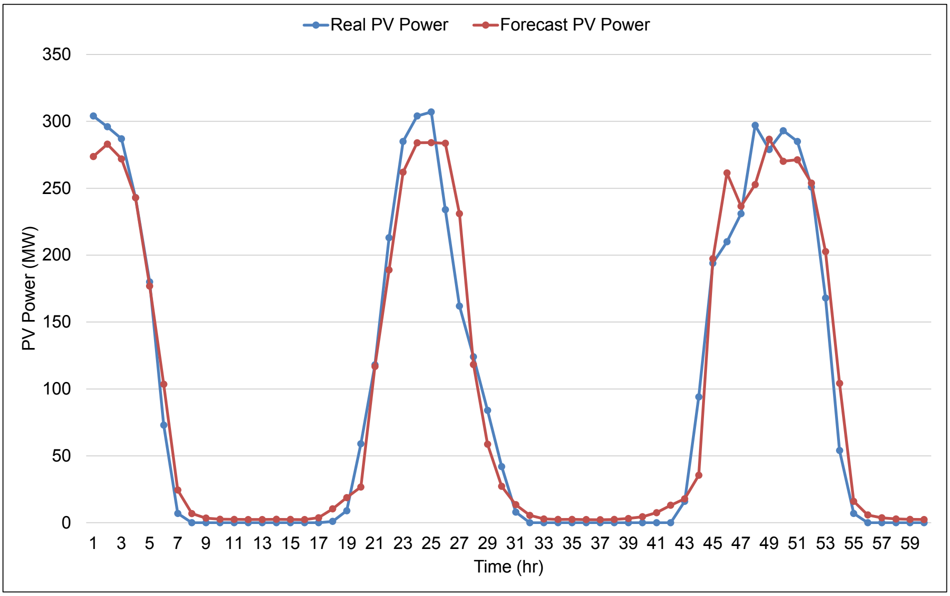

Fig. 7 – Real and forecast PV power for 60 hours periods.

When comparing the curves of real and predicted PV generation by the MLP in Fig. 7, it is possible to observe the pattern of the profiles of daily PV generation, with coincident peaks of maximum power production, a fact that clarifies the efficiency of the MLP for the PV generation forecasting considering the interval of 60 hours. Finally, the biggest difference between the curves was observed at hour 27 with a value of 69MW.

4 | CONCLUSION

Renewable energy is a key solution for the current climate crisis, however it also has a big challenge ahead with the intermittency of their power output, as this variation can impact the electric system in many ways. Generation forecast studies are becoming more essential for introducing higher level of RES, improving the operator decisions to proper control of the electric grid. The expansion of RES will be required increasing computational aid to estimate future data and decrease the generation variation of the system.

There are many methods that can be used to proper forecast depending on the input data, the number of parameters and the time period required by the operator. On this project the MLP algorithm was presented, described and later used with Python programming language to forecast data from RES found in Canada. The selection of this method was based on its capability of solving complex and non-linear problems efficiently.

Thus, this study was developed with the aim of estimating the potential of wind and PV generation for hourly short term. For this, the forecast was carried out considering different periods, 12 and 60 hours, for wind and PV generation. The data results presented a low MAE and RMSE, consistent with errors for the short-term forecast for both applications, proving the effectiveness of MLP for this type of application.

Although wind generation and PV generation have intermittent energy production, and consequently need complementary energy sources to accommodate their generation variations, when estimating their potentials, it is possible to optimize the available energy resources and reduce dependence on fossils fuel for electricity production. Finally, it is worth noting that this study was carried out using only historical data grouped by type of generation source, and that the insertion of other variables, for instance, wind speed, solar radiation and temperature would improve the forecast results.

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