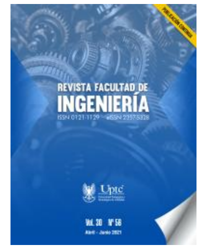
Revista Facultad de Ingeniería
Journal Homepage: https://revistas.uptc.edu.co/index.php/ingenieria



Prediction of Electricity Consumption Profiles Using Potential Polynomials of Degree One and Artificial Neural Networks in Smart Metering Infrastructure

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Received: April 26, 2021 **Accepted:** May 28, 2021 **Published:** June 02, 2021

Citation: P. Urgilés, J. Inga-Ortega, A. Peralta, A. Ortega, "Consumption Profiles Using Potential Polynomials of Degree One and Artificial Neural Networks in Smart Metering Infrastructure," *Revista Facultad de Ingeniería*, vol. 30 (56), e12772, 2021. https://doi.org/10.19053/01211129.v30.n56.2021.12772

Abstract

This work analyzes methods and algorithms for predicting the behavior of electricity consumption based on neural networks using data obtained from the Advanced

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Measurement Infrastructure (AMI) of an educational institution. Also, a contrast between the use of conventional neural networks (ANN), wavelet-based neural networks (WNN) and potential polynomials of degree one (P1P) has been performed. The correlation of each prediction method is analyzed, as well as the behavior of the Mean Square Error (MSE), to finally establish if there is an imbalance in the computational cost through the Big-O analysis and the executing time. The quantitative results of the MSE are below 0.05% for ANN predictions and they use a high computational cost. For P1P, errors around 1.2% are presented, showing as a low computational consumption prediction method but mainly applicable for a short-term analysis. This work is given in response to the need to establish a platform to take advantage of the smart metering structure through the prediction of electricity consumption profile, with the objective of developing a plan for maintenance and management of electricity demand to reduce operating costs from the final consumer to the distribution network operator. For the analysis of projections on the electrical load profile, the statistical characteristics of the consumption are considered to select the prediction algorithms according to the number of days to be projected using data from any of the smart meters, which can be monitored in an electrical network oriented to Smart Grids.

Keywords: AMI; electricity consumption prediction; P1P; smart metering; WNN.

Predicción de perfiles de consumo eléctrico usando polinomios potenciales de grado uno y redes neuronales artificiales en la infraestructura de medición inteligente

Resumen

Este trabajo analiza métodos y algoritmos de predicción del comportamiento de consumo eléctrico basados en redes neuronales, usando datos obtenidos de la infraestructura de medición avanzada (AMI) de una institución educativa. También, se ha realizado un contraste entre el uso de redes neuronales convencionales (ANN), redes neuronales basadas en wavelets (WNN) y los polinomios potenciales de grado uno (P1P). Se analiza la correlación de cada método de predicción, así como el comportamiento del error cuadrático medio (MSE) para finalmente establecer si existe un desbalance en el coste computacional a través del análisis de Big-O y el tiempo de ejecución. Los resultados cuantitativos del error MSE están por debajo del 0,05% para predicciones con ANN y usan un alto costo computacional. Para P1P se presentan errores alrededor del 1,2% mostrando como método de predicción de bajo consumo computacional pero aplicable de forma principal para un análisis a corto plazo. Este trabajo se da en respuesta a la necesidad de establecer una plataforma que permita aprovechar la estructura de medición inteligente, a través de la predicción de perfil de consumo eléctrico con el objetivo de elaborar una planificación de mantenimiento y gestión de la demanda eléctrica para reducir costos de operación desde el consumidor final hasta el gestor de la distribución de energía eléctrica. Para el análisis de las proyecciones sobre el perfil de carga eléctrica se consideran las características estadísticas del consumo para seleccionar los algoritmos de predicción según la cantidad de días a proyectar, usando los datos de cualquiera de los medidores inteligentes, que pueden ser monitoreados en una red eléctrica orientada a las Smart Grids.

Palabras clave: AMI; medición inteligente; P1P; predicción de consumo eléctrico; WNN.

Previsão de perfis de consumo de eletricidade usando polinômios potenciais de grau um e redes neurais artificiais na infraestrutura de medição inteligente

Resumo

Este trabalho analisa métodos e algoritmos de previsão do comportamento do consumo de energia elétrica com base em redes neurais, utilizando dados obtidos na infraestrutura de medição avançada (AMI) de uma instituição de ensino. Além disso, um contraste foi feito entre o uso de redes neurais convencionais (ANN), redes neurais baseadas em wavelet (WNN) e polinômios de potencial de grau um (P1P). É analisada a correlação de cada método de predição, bem como o comportamento do erro quadrático médio (MSE) para finalmente estabelecer se há um desequilíbrio no custo computacional através da análise Big-O e no tempo de execução. Os resultados quantitativos do erro MSE estão abaixo de 0,05% para previsões de RNA e usam alto custo computacional. Para P1P, existem erros em torno de 1,2% mostrando como um método de previsão de baixo consumo computacional, mas principalmente aplicável para uma análise de curto prazo. Este trabalho dá-se em resposta à necessidade de estabelecer uma plataforma que permita tirar partido da estrutura de medição inteligente, através da previsão do perfil de consumo de energia eléctrica, de forma a desenvolver o planeamento da manutenção e gestão da procura de energia eléctrica para reduzir os custos de operação do consumidor final ao gestor da distribuição de energia elétrica. Para a análise das projeções do perfil de carga elétrica, são consideradas as características estatísticas do consumo para selecionar os algoritmos de predição de acordo com o número de dias a serem projetados, utilizando os dados de qualquer um dos medidores inteligentes, que podem ser monitorados em uma rede orientada para Smart Grids.

Palavras-chave: AMI; medição inteligente; P1P; previsão do consumo de eletricidade; WNN.

I. INTRODUCTION

Currently, energy consumption is increasing exponentially due to the large number of new devices, which also implies an increase in the cost of energy consumption. Hence, the flow and availability of energy is fundamental for the interaction between supply and demand of energy systems, such importance is reflected on the behavior of energy production, import, export and consumption by sources and sectors, the latter being a fundamental part in the planning to ensure efficient energy production and consumption [1], [2]. For this reason, smart grids (SG) are applied in advanced measurement infrastructure (AMI), which allow to develop analysis of the electrical energy consumption profile in any environment [3], [4]. Therefore, given the importance of the energy system, it is necessary to implement energy consumption prediction systems that allow adequate planning of electricity consumption to reduce costs; and resource optimization, including the development of models that allow the scaling of networks in response to the demand of energy consumption [5], [6], [7].

According to the aforementioned, there are several methods that allow energy consumption forecasting, however, most of them can result in high computational processing due to the mathematical process inherent in these methods [7], for example, among the various methods is the use of artificial neural networks (ANN) that offer temporal data prediction through adaptive learning, self-organization, fault tolerance, and real-time operation allowing to monitor and track the future behavior of electrical energy consumption or other physical phenomena [8], [9]. The availability of the data universe to be used in a predictive system based on neural networks is extremely important because it allows a better system training with a low error in the prediction [10].

On the other hand, wavelet neural networks (WNN) allow to use the benefits of neural networks combined with the wavelets [11], [12] and using a smaller data universe due to the wavelet decomposition in several levels on the same wave, hence reducing storage and processing resources [13]. However, there are mathematical methods such as the use of Potential Polynomials of Degree One (P1P) that correspond to a computationally efficient mathematical model due to its ability to work even with data compression methods such as Compressive Sensing

(CS), which allows using a source compression process prior to data transmission [14], [15], [16].

According to the aforementioned, electricity consumption data have time series characteristics, therefore, there are several methods that allow the projection of the electricity consumption profile. The various methods aim to predict future events, using mathematical models capable of capturing the most important trends of a Smart Grid and thus contributing to its management. The importance of predictive analysis in Smart Grid is associated with the use of Big Data in recent years due to the large amount of information collected through AMI, some of the advantages of using Big Data in Smart Grids are:

- Restore service promptly in the event of a service interruption
- Reduce operating costs
- Reduce consumer costs
- Reduction in peaks demand
- Greater system efficiency
- Greater security

Therefore, the objective of the case study is to identify the most efficient prediction method considering two neural network structures under three different training methods, contrasting them with the prediction obtained by P1P and WNN, and giving a continuation to the research done by [14]. The metrics analyzed correspond to the mean square error and the computational capacity through Big-O notation [13], [14], [17], [18], thus establishing the advantages in the implementation of each predictive system. Through this analysis, this case study seeks to develop a consumption prediction platform by obtaining data from the AMI network based on WNN as a first stage of prediction, so that educational institutions can evaluate and reduce their electricity consumption.

II. METHODOLOGY

A. Data Processing

Data was collected from 4 smart meters, which are connected to a smart metering network (AMI). This system collects information in 15-minute intervals, generating

DOI: https://doi.org/10.19053/01211129.v30.n56.2021.12772

96 electrical profile data per day. In addition, a 74-week universe was used with parameters such as voltage, current, accumulated electrical energy, accumulated apparent power, accumulated reactive power, and maximum power demand consumed.

In addition, the information is organized by separating the data for each day of the week and differentiating holidays, as the profile statistics changes [ref p1p]. In this context and due to the amount of information, the Big Data paradigm was applied using sorting methods to find the irregular data. The applied process is described in Fig. ***1***.

After having a universe of data without irregularities, the information can be processed using a three-dimensional matrix structure as shown in Figure 2, where the structure for 8 weeks of information is identified in each matrix. Hence, through the 74 weeks obtained by the intelligent measurement system of the Educational Institution for which the prediction platform was developed; 66 sub matrices of 8 weeks were obtained by displacing 1 new week to the previous matrix. This information grouping process facilitated the subsequent analysis with the different prediction techniques used, since each day of the week presents different statistics.

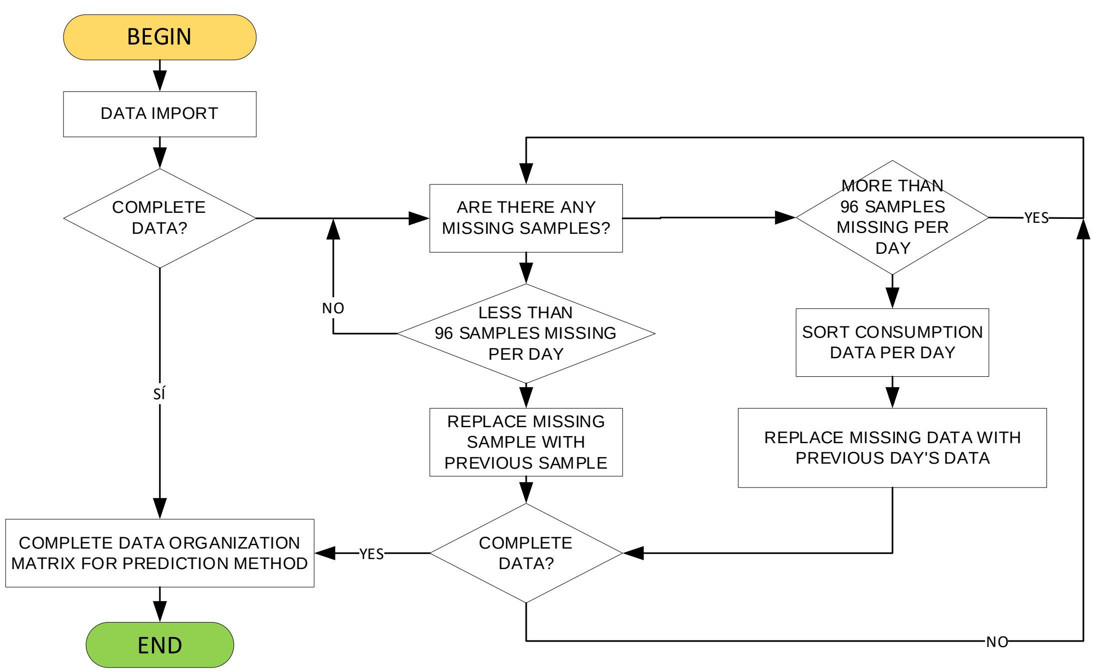


Fig. 1. Algorithm for Big Data Processing.

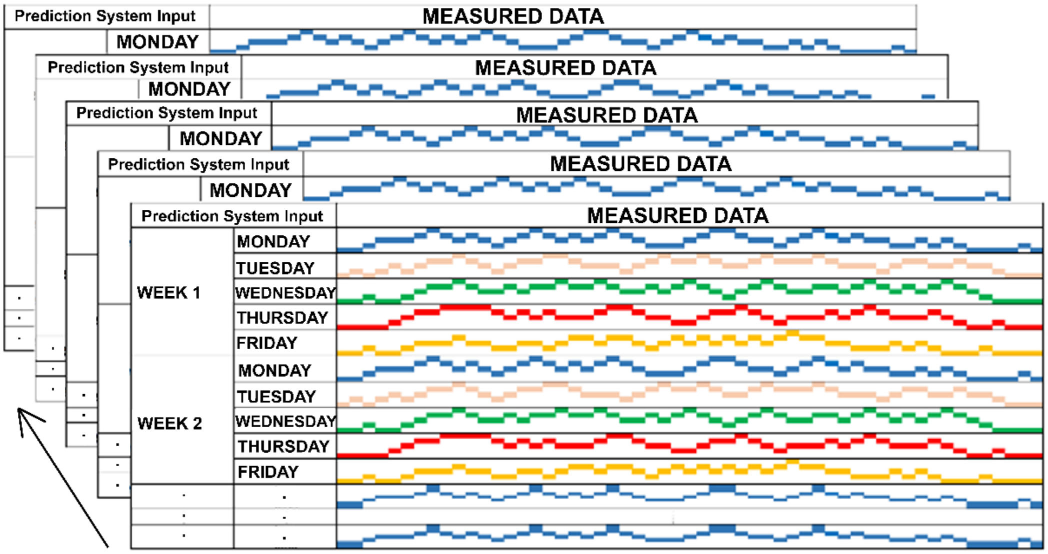


Fig. 2. Three-dimensional matrix of input data to the neural network.

This matrix organizes the data and is developed through the use of a target signal which is the daily electricity consumption profile [14],[16],[19],[20] and which the present case study starts from.

B. Potential Polynomials of Degree 1

The P1P mathematical model allows to obtain data projection by means of polynomial regressions and it also shows characteristics of simplicity and low computational cost in terms of temporal data prediction. This mathematical model has low error and high-performance characteristics in the prediction of electricity consumption data [19]. The objective of this method is to use input data with an unknown internal function to generate a future estimation value. In addition, [14] shows how this method is employed for the projection of electricity consumption data.

The prediction by P1P is governed by equation (1) and (2).

$$B_J = \frac{1}{N}\sum_{i=1}^{N} X_{i,j} \tag{1}$$

$$B_J = c_0 + c_1x + c_2y + c_3z + c_4xy + c_5xz + c_6yz + c_7xyz \tag{2}$$

C. Neural Networks for Data Projection

The projection of electricity consumption data can work with feedforward neural networks and recurrent neural networks, the former being the most suitable for predicting the next value in a time series of data [21]. In this way, neural networks allow knowing the future behavior of the electricity consumption profile using different historical records obtained by the AMI network [22]. Then, according to the characteristics presented by the consumption profile and the reviewed literature, it was decided to use error Backpropagation and Cascade-Correlation (CASCOR) algorithms [18], [23], [24] together with the downward gradient, Resilient Backpropagation and Levenberg-Marquardt training functions [25], [26], [27], [28].

The training method for the Levenberg-Marquardt algorithm is defined by equation (3) [29].

$$w_{i+1} = w_i - (J_i^T J_i + \lambda_i I)^{-1}(2J_i^T e_i) \tag{3}$$

Where J is the Jacobian matrix containing the first derivatives of the squared error with respect to each neural network parameter. Also, in equation (3), if λ tends to zero, Newton's method is obtained using the approximate Hessian; moreover, if λ is very large, it tends to behave in a manner approximating to the downward gradient method. It is advisable to start λ with a high value so that as the algorithm progresses λ decreases to obtain an acceleration in the convergence to the minimum.

As an alternative, it was also decided to work with wavelet neural networks to take advantage of the decomposition of the signal into different levels, through the wavelet functions in order to reduce the computational complexity, which allows multi-scale processing proper to the use of wavelets [30].

For the descending gradient method, a learning rate $\eta = 0.01$ was used, which determines the speed of training or convergence, as shown in the mathematical model of the previous section.

On the other hand, the parameter for the Resilient Back Propagation method was used according to the mathematical model presented in [28], where the values shown in equations (4) - (6) were used.

$$\eta = 1.2; si \ \frac{\partial E^{n-1}}{\partial w_{ij}} \times \frac{\partial E^{n}}{\partial w_{ij}} > 0 \quad (4)$$

$$\eta = 0.5; si \ \frac{\partial E^{n-1}}{\partial w_{ij}} \times \frac{\partial E^{n}}{\partial w_{ij}} < 0 \quad (5)$$

$$\eta = 0.07; si \ \frac{\partial E^{n-1}}{\partial w_{ij}} = 0 \quad (6)$$

In order to analyze the optimization method through the Levenberg-Marquardt algorithm, a damping factor of $\lambda = 0.2$ was used, and according to [30] the initial value reveals a behavior similar to the downward gradient method. The value of λ decreases as the number of iterations of the network training progresses. Thus, as λ decreases, it behaves similarly to Newton's method, in accordance with the needs of the mathematical model shown in equation (3).

D. Training of the neural networks

For each of the implemented neural networks, a total of 8 weeks were used in the input layer considering only working days (Monday to Friday) with a total of 40 days, each containing 96 samples collected by the AMI network (Figure 1).

In order to keep the same ANN and WNN entries, 10 days were used as input data. Therefore, for the WNN, each of these days were broken down into 3 different levels using wavelets, hence obtaining 4 inputs to the neural network for each of the 10 days, thus having a total of 40 days as input data matrix for the neural network. In addition, 15 neurons were used in the hidden layer of the neural network to obtain a lower mean square error according to [17].

In the output layer there are 5 nodes, each of them represents a predicted weekday from Monday to Friday, each of these is a vector with 96 data corresponding to a sampling of every 15 minutes.

On the other hand, the wavelet function used is Daubechies, which according to [18] offers favorable results when employing it in WNNs.

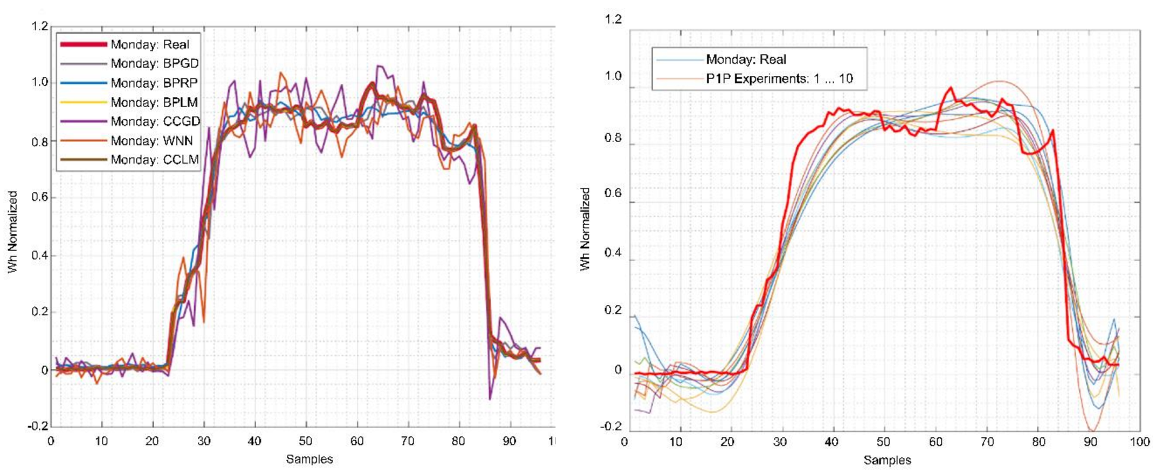
II. ANALYSIS OF RESULTS

The performance analysis of the neural network in contrast with the performance of

DOI: https://doi.org/10.19053/01211129.v30.n56.2021.12772

the P1P and WNN prediction method is supported by the results obtained using the mean square error in the correlation between the power consumption data and the projected data in addition to the Big-O notation. For the analysis case of Big-O, the number of neurons used in the neural network versus the time taken to train each ANN structure mentioned are used as parameters.

The P1P-based projection for the electrical consumption profile shows a fair similarity to the actual values. However, details are lost in the resolution of local maximum or minimum as shown in Fig. ***3***-a. Projection methods based on conventional neural networks or wavelet neural networks demonstrate a much more accurate projection. Fig. ***3***-b shows that the signals projected by the different types of training are closer to the trend of the target wave.



a) b)

Fig. 3. Consumption profile. a) with conventional predictions and wavelet neural networks. b) with polynomial predictions.

A. Mean Squared Error (MSE)

Fig. ***4*** shows that the training method with the lowest possible error was Levenberg-Marquartd with a minimum MSE of 0.2% and a maximum of 0.5% in both training methods, where the MSE curve stabilizes from iteration 50 of training, while the Downward Gradient and Resilient Backpropagation training methods in CASCOR presented the highest MSE with a minimum value of 1. On the other hand, a

DOI: https://doi.org/10.19053/01211129.v30.n56.2021.12772

minimum MSE of 0.18% and a maximum of 0.28% was presented for the Resilient Backpropagation training method, obtaining a stabilization in the training after 30 iterations.

For the projection obtained by the P1P prediction method, values between 1.95% and 0.67% were obtained as maximum and minimum values, respectively.

Fig. ***4*** also shows that the mean square errors of this method oscillate continuously without stabilizing. For the WNNs method, a mean square error of 0.41% was obtained, demonstrating a similar error stability to the Resilient Backpropagation method since they use a similar training method.

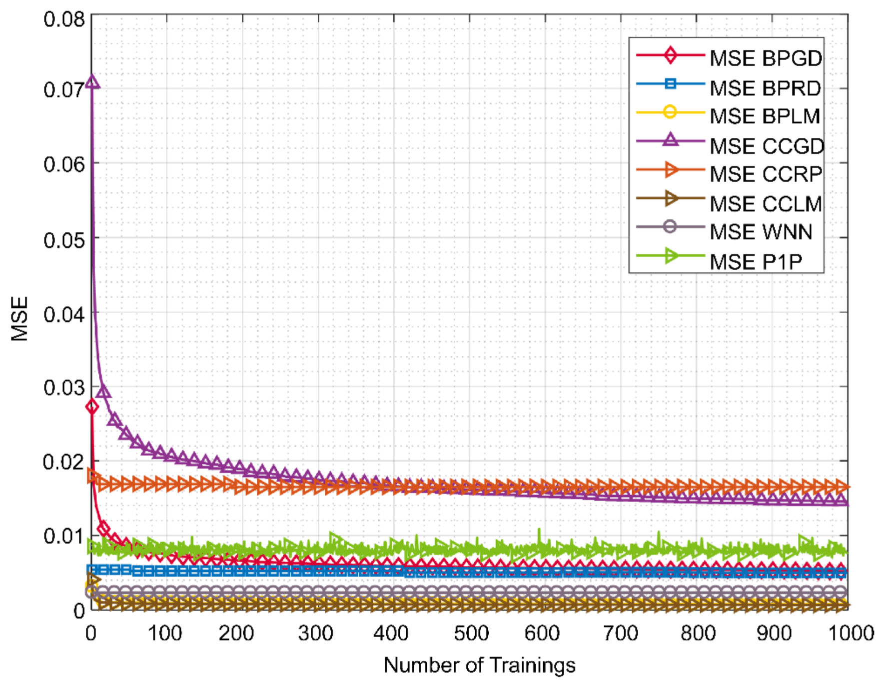


Fig. 4. Mean square error vs. training of the predictive algorithms.

B. System Performance

In the hidden layer, the variation was from 0 to 15 neurons, hence obtaining 15 units of processing time for each prediction method. To know the behavior of each prediction method as a function of the execution time of its algorithms, the Big-O notation was used, which indicates the performance trend of the methods with theoretically smaller errors shown in the previous point.

Fig. ***5*** shows that the Levenberg-Marquardt training method for both network structures, including the WNN method, demonstrate a positive exponential trend, i.e., the processing time increases as the number of neurons in the hidden layer increases. On the other hand, the Back Propagation structure with the downward gradient training method reveals an opposite trend to the Levenberg-Marquardt training method for all analyzed neural network models, including WNN. It is important to mention that for the prediction method using P1P, the MSE is practically constant in all tests.

On the other hand, the Back Propagation structure with the downward gradient training method reveals an opposite trend to the Levenberg-Marquardt training method for all analyzed neural network models, including WNN. It is important to mention that for the prediction method using P1P, the MSE is practically constant in all tests.

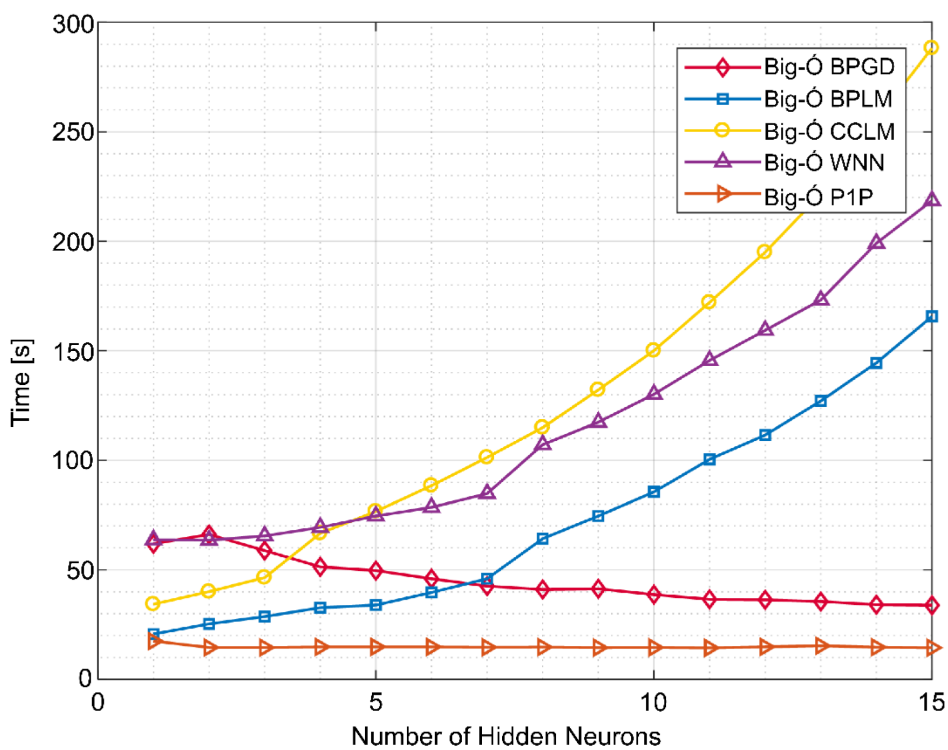


Fig. 5. Evaluation of the computational load of the predictive algorithms.

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III. Conclusion

According to the results obtained, the smallest MSE value is present in the conventional neural network method with Feed Forward Back Propagation structure. Also, the Levenberg-Marquardt training method generates a lower error at a higher computational cost; in the case of WNN, it reduces the error by offering the advantage of using a smaller amount of input data that can be decomposed by wavelets, but it demands a high hardware cost.

The results show that the projections obtained through the P1P method are less accurate than the other methods because their behavior is based on a polynomial function. However, P1P compensates this deficit through computational saving features, optimization and execution times with a low MSE (between 1 and 2%) for little data.

According to the Big-O analysis, it is verified that the performance of the prediction methods depends on the number of neurons existing in the hidden layers of the neural network-based methods. Also, it is observed that the Levenberg-Marquardt method behaves in a positive exponential manner, which expresses a longer execution time as the number of hidden neurons increases. Finally, the downward gradient training method behaves inversely, as the number of neurons in the hidden layer increases the execution time will be shorter, therefore guarantying a low MSE.

Authors' Contribution

Pablo Urgilés: Research, Methodology, Experimental Design, Writing - original draft, Data curation.

Juan Inga-Ortega: Supervision, Experimental Design, Data curation, Writing - original draft.

Arturo Peralta: Methodology, Experimental Design, Validation, Writing - revision and editing.

Andrés Ortega: Methodology, Validation, Writing - revision and editing.

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